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M. Ameur LATRECHE

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Department of Mechanical Engineering

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By :

Mr. Ameur LATRECHE

Control for robotic assistance and rehabilitation for humans

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First and foremost, I wish to express my deepest gratitude to "Allah" Almighty. Through His grace and mercy, I have reached this significant milestone, a dream I have cherished for many years. I dedicate this work to my beloved mother. May God have mercy on her soul. Despite battling cancer during the second year of my PhD, she remained my steadfast pillar of support and strength, always accompanying me with her prayers and unwavering concern. Her love and resilience have inspired me, and I know that every success I achieve carries her indelible mark. Mom, your spirit lives on in every step I take, and I will continue to seek knowledge in your honour. I pray that God grants you eternal peace in Paradise.

I also dedicate this work to my father, whose kindness and wisdom have always guided me in pursuing knowledge. To my brothers and sisters, who have been my support and strength, and to their children, I extend my heartfelt thanks and love. Your encouragement has been invaluable to me.

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ملخص:

يواجه مشهد الصحة العالمي حاليًا تحديات عديدة، مما يستلزم ايجاد حلول مبتكرة للتأهيل عن بعد. تقدم الأطروحة مساهمتين مهمتين في مجال إعادة التأهيل عن بعد. ترتكز المساهمة الأولى على تطوير وتقييم نظام قائم على MediaPipe لحركة إعادة تأهيل الإنسان، وتقييم موثوقيته وصلاحيته. حاليا، يحظى إنشاء موقع على شبكة الإنترنت لإعادة التأهيل عن بعد بأهمية كبيرة، ليس فقط لقدرته على المتابعة المستمرة لحالة المرضى ولكن أيضًا للفوائد الاقتصادية التي يقدمها للمرضى من خلال التخلص من تكاليف التنقل وغيرها من التكاليف الأخرى.

تضمن الجزء الأول من البحث مقارنة تقنية من تقنية الذكاء الاصطناعي، MediaPipe، مع أدوات القياس التقليدية، بما في ذلك مقياس الزوايا العالمي ومسطرة الزاوية الرقمية، لقياس نطاق الحركة. تم جمع البيانات من حوالي 50 متطوعاً أصحاء بتوجيه من المعالجين الفيزيائيين. تم فحص موثوقية نظام قياس الكتف القائم على MediaPipe بدقة. بالإضافة إلى ذلك، هدفت الدراسة إلى التحقق من صحة النهج من خلال تحديد حدود الاتفاق البالغة 95% ومتوسط الفروق بينMediaPipe والأجهزة التقليدية. أظهرت النتائج بأن تقنية MediaPipe موثوقة وصالحة للإستعمال لإعادة التأهيل عن بعد، خاصة في مراقبة المرضى الذين يتعافون من إصابات عضلية هيكلية محددة، كما يتضح من كسر الرضفة اليمنى.

تقدم المساهمة الثانية من هذه الأطروحة تطوير نظام إعادة التأهيل عن بعد للعلاج الطبيعي في المنزل مدعومًا بدراسة حالة ميدانيا. إعادة تأهيل الحركة أمر أساسي للأفراد المسنين والمرضى الذين يتعافون من إجراءات مثل جراحة الرباط الصليبي الأمامي أو الكتف. في سياق التحديات العالمية المستمرة، بما في ذلك جائحة كوفيد-19 و بمتغيراته دلتا و أوميكرون، برزت إعادة التأهيل عن بعد كإتجاه بارز في أبحاث الرعاية الصحية. وهذا النهج مناسب بشكل خاص في المناطق ذات القيود الجغرافية، مثل المناطق الصحراوية الشاسعة في الجزائر، حيث يمكن أن تكون إمكانية الوصول إلى مرافق الرعاية الصحية محدودة.

نظرا للأسباب المذكورة سابقا، كان الهدف الشامل للمشروع البحثي هو إنشاء موقع ويب لإعادة التأهيل عن بعد لتسهيل جلسات إعادة التأهيل عن بعد، وبالتالي تقليل حاجة المرضى إلى التنقل لمسافات طويلة لتلقي العلاج الطبيعي. علاوة على ذلك،

تسمح هذه المنصة بمراقبة نطاق حركة المرضى (ROM) في الوقت الفعلي باستخدام تقنيات الذكاء الاصطناعي للتحكم في زوايا المفصل أثناء تمارين الحركة بدقة.

كمختصر عام لهذه الدكتوراه، تساهم الأطروحة في تطوير إعادة التأهيل عن بعد من خلال دمج أحدث التقنيات مع ممارسات إعادة التأهيل. بالإضافة إلى دراسة موثوقية وصلاحية النظام القائم على MediaPipe، و توضيح أيضًا جدوى منصة إعادة التأهيل عن بعد خاصة في البيئات الصعبة والنائية.

الكلمات المفتاحية: الصحة الإلكترونية، الصحة العامة، إعادة التأهيل عن بعد، نطاق الحركة، التعلم العميق، شبكة عصبية

Abstract

The global healthcare landscape is currently facing unprecedented challenges, necessitating the exploration of innovative telehealth solutions. This Ph.D. thesis presents two significant contributions to the field of telerehabilitation. The first contribution focuses on developing and evaluating a MediaPipe-Based system for human rehabilitation motion, assessing its reliability and validity. In the era of telehealth, the creation of a telerehabilitation website holds great appeal, not only for its potential to address ongoing epidemics but also for the economic benefits it offers patients by eliminating costly equipment.

The first part of the research involved comparing an artificial intelligence technique, MediaPipe, with conventional measurement tools, including a universal goniometer and a digital angle ruler, to measure the range of motion. Data was collected from approximately 50 healthy volunteers with the guidance of physical therapists. The reliability of the MediaPipe-based shoulder measurement system was rigorously examined. Additionally, the study aimed to validate the approach by determining the 95% limits of agreement and mean differences between MediaPipe and traditional devices. The results unequivocally demonstrated that MediaPipe is reliable and valid for telerehabilitation, particularly in monitoring patients recovering from specific musculoskeletal injuries, as exemplified by a right patella fracture.

The second contribution of this thesis introduces the development of a home-based physiotherapy telerehabilitation system supported by a compelling case study. Motion rehabilitation is fundamental for elderly individuals and patients recovering from procedures like

ACL surgery or a frozen shoulder. In the context of ongoing global challenges, including the COVID-19 pandemic with its delta and omicron variants, telerehabilitation has emerged as a prominent trend in healthcare research. This approach is particularly relevant in regions with geographical constraints, such as the vast desert areas of Algeria, where accessibility to healthcare facilities can be limited.

The research project's overarching goal was to create a comprehensive telerehabilitation website to facilitate remote rehabilitation sessions, thereby reducing the need for patients to travel long distances for their physiotherapy. Moreover, this platform allows real-time monitoring of patients' range of motion (ROM) using artificial intelligence techniques to control joint angles during motion exercises precisely.

In conclusion, this Ph.D. thesis contributes to the advancement of telerehabilitation by integrating state-of-the-art technology with rehabilitation practices. It not only establishes the reliability and validity of the MediaPipe-Based system but also demonstrates the feasibility of a home-based telerehabilitation platform showcasing its potential to revolutionize the rehabilitation process, especially in challenging and remote environments.

Keywords: *E-health; Public health, Telerehabilitation, Rehabilitation informatics, Rehabilitation, Range of motion, MediaPipe, Deep learning, Neural network.*

Résumé

Le paysage mondial des soins de santé est actuellement confronté à des défis sans précédent, ce qui nécessite l'exploration de solutions innovantes de télésanté. Cette thèse de doctorat présente deux contributions significatives au domaine de la télé-rééducation. La première contribution se concentre sur le développement et l'évaluation d'un système basé sur MediaPipe pour le mouvement de rééducation humaine, en évaluant sa fiabilité et sa validité. À l'ère de la télésanté, la création d'un site Web de télé-rééducation présente un grand attrait, non seulement pour son potentiel à lutter contre les épidémies en cours, mais également pour les avantages économiques qu'elle offre aux patients grâce à l'élimination d'équipements coûteux.

La première partie de la recherche impliquait la comparaison d'une technique d'intelligence artificielle, MediaPipe, avec des outils de mesure conventionnels, notamment un goniomètre universel et une règle d'angle numérique, pour mesurer l'amplitude de mouvement. Les données ont été collectées auprès d'environ 50 volontaires en bonne santé sous la direction de physiothérapeutes. La fiabilité du système de mesure de l'épaule basé sur MediaPipe a été rigoureusement examinée. De plus, l'étude visait à valider l'approche en déterminant les limites d'accord à 95 % et les différences moyennes entre MediaPipe et les appareils traditionnels. Les résultats ont démontré sans équivoque que MediaPipe est à la fois fiable et valable pour une utilisation en télé-réadaptation, en particulier pour le suivi de patients se remettant de blessures musculo-squelettiques spécifiques, comme en témoigne une fracture

de la rotule droite.
La deuxième contribution de cette thèse introduit le développement d'un système de télé-réadaptation en physiothérapie à domicile, soutenu par une étude de cas convaincante. La rééducation par le mouvement est une procédure fondamentale pour les personnes âgées et les patients qui se remettent d'interventions telles que la chirurgie du LCA ou une épaule gelée. Dans le contexte des défis mondiaux actuels, notamment la pandémie de COVID-19 avec ses variantes delta et omicron, la télé-réadaptation est devenue une tendance importante dans la recherche sur les soins de santé. Cette approche est particulièrement pertinente dans les régions soumises à des contraintes géographiques, comme les vastes zones désertiques d'Algérie, où l'accessibilité aux établissements de santé peut être limitée.
L'objectif primordial du projet de recherche était de créer un site Web complet de télé-réadaptation pour faciliter les séances de réadaptation à distance, réduisant ainsi la nécessité pour les patients de parcourir de longues distances pour leur physiothérapie. De plus, cette plateforme permet de surveiller en temps réel l'amplitude de mouvement (ROM) des patients à l'aide de techniques d'intelligence artificielle pour contrôler avec précision les angles des articulations pendant les exercices de mouvement.
En conclusion, cette thèse de doctorat contribue à l'avancement de la télé-réadaptation en intégrant une technologie de pointe aux pratiques de réadaptation. Il établit non seulement la fiabilité et la validité du système basé sur MediaPipe, mais démontre également la faisabilité d'une plateforme de télé-réadaptation à domicile, démontrant ainsi son potentiel à révolutionner le processus de réadaptation, en particulier dans les environnements difficiles et éloignés.

Mots cl : *E-santé ; Santé publique, Télé-rééducation, Informatique de Rééducation, Rééducation, Amplitude de mouvement, MediaPipe, Apprentissage profond, Réseau de neuronnes.*

List of Symbols

ROM	Range of motion
AI	Artificial intelligence
CV	Computer Vision
ML	Machine learning
CNN	Conventienal neural network
PTSD	Post-traumatic stress disorder
CBT	Cognitive-behavioral therapy
MAT	Medication-assisted treatment
ICTs	Information and communication technologies
WHO	World Health Organization
ATA	The American Telemedicine Association
CIHI	The Canadian Institute for Health Information
COPD	Chronic obstructive pulmonary disease
VR	Virtual reality
AR	Augmented reality
sEMG	Surface electromyography
CFF	Complementary filter feedback
IMU − POF	Inertial measurement unit-polymer optical fiber
PO	Pelvic obliquity
CPMs	Convolutional Pose Machines
GPU	Graphics Processing Unit
COCO	Common Objects in Context
PAF	Part Affinity Field
INRIA	Institute for Research in Computer Science and Automation
PIFs	Part Intensity Fields
RGB − D	Red Green Blue - Depth
GNNs	Graph Neural Networks
NLP	Natural language processing
RNN	Recurrent neural networks
LSTM	Long short-term memory
RNNLM	Recurrent neural networks-based language model
DETR	Detection Transformer
ViT	Vision Transformer
FPN	Feature Pyramid Networks
SVM	Support vector machine
MSE	Mean squared error
PCKh	Percentage of correct keypoints detected within 50% of the head segment length

NMS	Non-maximum suppression
RMPE	Regional Multi-Person Pose Estimation
CPN	Cascaded Pyramid Network
FLOPs	Floating point operations
PifPaf	Part Intensity Fields and Part Association Fields
HGG	Hierarchical Graph Grouping
SWAHR	Scale and weight adaptive heatmap regression
ROI	Region of interest
ST−GCN	Spatio-Temporal Graph Convolutional Network
ICC	
Go	Clinical goniometer
SEMean	Standard error of the mean
Min	Minimum
Max	Maximum
Med	Median
StDev	Standard deviation
SEM	Standard error of the mean
MDC	Minimal Detectable Change
LOA	Limits of agreement
ACL	The anterior cruciate ligament

General introduction

Artificial intelligence (AI) has brought about transformative changes across various facets of our lives, reverberating significantly within the medical field. The advent of AI has revolutionized conventional healthcare practices and yielded remarkable results, demonstrating its potential to enhance patient care, diagnostics, and treatment methodologies. The ongoing global impact of the COVID-19 pandemic has propelled the exploration of innovative healthcare solutions, prompting scientists and researchers to seek more efficient methods that can effectively address the unprecedented challenges posed by the evolving healthcare landscape. In response to these challenges, numerous studies have emerged, showcasing the integration of AI into various medical domains. Of particular interest is the application of AI in distance rehabilitation. This domain allows healthcare practitioners to monitor patients' conditions remotely using easily accessible equipment, optimizing rehabilitation service delivery.

Within the landscape of remote rehabilitation, the primary objectives are to preserve patient health and alleviate the burdens associated with traditional transportation methods. The challenges of travel, often arduous and physically taxing, can have detrimental effects on the well-being of patients undergoing rehabilitation. In light of these challenges, remote monitoring emerges as an attractive alternative, not only eliminating the physical strains of travel but also significantly reducing associated transportation costs. To address these challenges more effectively, this thesis proposes the development of a dedicated website for

remote rehabilitation tracking. This innovative solution aims to provide a user-friendly platform that ensures continuous monitoring and support for patients undergoing rehabilitation, marking a substantial step toward advancing patient-centric and technology-enhanced healthcare practices.

At the heart of modern research lies integrating technology and AI techniques with the medical field, underscoring the importance of aligning innovation with ethical considerations and patient well-being. This integration necessitates a meticulous approach to ensure patient safety and security, with treatment methods designed to adhere to medical protocols and gain approval from specialists. Furthermore, safeguarding patient data is paramount in the era of digital healthcare. As the healthcare landscape continues to evolve with technological advancements, this research explores the delicate balance between innovation and ethical considerations, aiming to contribute meaningful insights to the growing body of knowledge in AI-powered rehabilitation.

In this thesis, we explore the applications of artificial intelligence in rehabilitation, with a specific focus on telerehabilitation. Chapter 1 sets the stage by providing a contextual background, articulating the problems addressed, and offering a historical overview. Building on this foundation, Chapter 2 delves into the core theme, exploring the intersection of physiotherapy, telerehabilitation, and AI. In this part, we will present the first contribution relating to the state of the art and the comparison of different techniques used. Furthermore, this Chapter narrows the focus to the specific role of AI in rehabilitation, examining its potential to enhance patient outcomes and optimize the rehabilitation process.

In Chapter 3, we conduct a detailed analysis of the reliability and validity of the MediaPipe technique in pose estimation, providing valuable insights into its effectiveness in telerehabilitation applications.

Building upon these research findings, Chapter 4 proposes the development of a novel home-based website for upper and lower-limb telerehabilitation, presenting an innovative platform to facilitate remote rehabilitation processes. The final chapter synthesizes the research outcomes, highlights key findings, and offers insights into the contributions made by the study. This thesis aims to significantly contribute to the understanding and application of AI in rehabilitation, providing practical solutions for optimizing patient care and improving the overall efficiency of rehabilitation practices.

Statement of Contributions

Chapters 3 and 4 contain material from three multi-author papers for which I was the lead author. As the lead author, I was responsible for conceptualizing the studies, carrying out all code development, and drafting and submitting the manuscripts. My co-authors, which included my supervisors Prof. Ridha Kelaiaia and Prof. Ahmed Chemori, provided guidance throughout the process and feedback on draft manuscripts. The references for the three papers are provided below:

1. Ameur Latreche, Ridha Kelaiaia, Ahmed Chemori, Adlen Kerboua. Reliability and validity analysis of MediaPipe-based measurement system for some human rehabilitation motions. Measurement - Journal of the International Measurement Confederation (IMEKO), 2023, pp.112826. ff10.1016/j.measurement.2023.112826ff.
2. Ameur Latreche, Ridha Kelaiaia, Ahmed Chemori, Adlen Kerboua. A New Home-Based Upper- and Lower-Limb Telerehabilitation Platform with Experimental Validation. Arabian Journal for Science and Engineering, 2023, 48 (8), pp.10825-10840. ⟨10.1007/s13369-023-07720-0⟩.
3. Ameur Latreche, Ridha Kelaiaia, Ahmed Chemori. AI-based Human Tracking for Remote Rehabilitation Progress Monitoring. ICAECE 2023 - International Conference on Advances in Electrical and Computer Engineering, May 2023, Tebessa, Algeria. ⟨lirmm-04107931⟩

Chapter

1 Context, problem formulation, and historical overview

1.1 Introduction

The field of physiotherapy has witnessed significant advancements in recent years, with one notable innovation being the integration of telecommunication technologies into rehabilitation services. Telerehabilitation, defined as the delivery of rehabilitation services remotely using telecommunication tools, has emerged as a promising approach to providing efficient and accessible care to patients [25]. Traditional in-person physiotherapy sessions often pose barriers to access, including geographical limitations, transportation difficulties, and scheduling constraints. These challenges can impede patients' ability to receive timely and consistent rehabilitation services, consequently affecting their overall recovery process. Telerehabilitation, on the other hand, offers a solution by leveraging technology to provide remote assessment, monitoring, and intervention.

Telerehabilitation presents several advantages that contribute to improved patient care. Firstly, it eliminates geographical barriers by enabling patients to access rehabilitation services from the comfort of their homes, thereby increasing convenience and reducing travel costs. Secondly, it facilitates regular and continuous monitoring of patients' progress, allowing physiotherapists to track outcomes, adjust treatment plans, and provide timely feedback. Thirdly, telerehabilitation empowers patients by promoting self-management and

active participation in rehabilitation, enhancing motivation and adherence to treatment protocols.

While telerehabilitation offers numerous benefits, it also presents particular challenges. Technological limitations, such as internet connectivity issues or patients' unfamiliarity with technology, can hinder the successful implementation of telecommunication-based rehabilitation services. Additionally, the inability to provide hands-on manual interventions remotely may be a limitation in certain physiotherapy interventions. Ethical considerations related to privacy, data security, and patient consent should also be addressed to ensure the ethical practice of telerehabilitation.

1.2 Context

1.2.1 Telerehabilitation

Telerehabilitation has emerged as a transformative paradigm in the field of rehabilitation medicine, offering innovative solutions to address the challenges of providing effective therapy while ensuring accessibility and convenience for patients. The advent of telecommunication technologies have enabled healthcare professionals to remotely deliver rehabilitation services, thus breaking down geographical barriers and improving the quality of care for individuals with various musculoskeletal and neurological conditions. In an era characterized by an aging population and an increased prevalence of chronic health conditions, the demand for efficient and accessible rehabilitation services have never been greater.

This thesis embarks on a journey to advance the realm of telerehabilitation, focusing on developing a novel home-based upper- and lower-limb telerehabilitation platform. Our research endeavors to bridge the gap between traditional in-clinic rehabilitation and the evolving landscape of remote healthcare delivery. The primary objective of this work is to design, implement, and validate a comprehensive telerehabilitation system that empowers patients to engage in guided upper- and lower-limb exercises from the comfort of their homes.

The context in which this research unfolds is multifaceted and encompasses several crucial dimensions:

Technological Advancements

Recent technological advancements, including high-speed internet connectivity, wearable sensors, and virtual reality interfaces have laid the foundation for the development of sophisticated telerehabilitation platforms. These technologies offer the potential to create immersive and interactive rehabilitation experiences that rival traditional in-person therapy sessions.

Healthcare Access and Disparities

Access to rehabilitation services can be hindered by geographic location, limited mobility, and socioeconomic factors. Telerehabilitation holds the promise of reducing healthcare disparities by providing individuals in underserved areas or with mobility impairments with access to high-quality rehabilitation programs.

Patient Empowerment

Empowering patients to take an active role in their rehabilitation journey is a central theme of this research. A home-based telerehabilitation platform can enhance patient engagement and compliance, fostering a sense of ownership over one's recovery process.

Experimental Validation

A key aspect of this study is the rigorous experimental validation of the developed telerehabilitation platform. We aim to assess its efficacy, safety, and user-friendliness through controlled trials and user feedback, contributing valuable insights to the field.

1.2.2 Artificial intelligence

Artificial intelligence (AI) has become a transformative force across diverse domains, revolutionizing how we approach complex problems and address societal challenges. Within the realm of healthcare, AI has emerged as a potent ally, promising innovative solutions for the enhancement of diagnosis, treatment, and patient care. This thesis is situated at the

intersection of AI and healthcare, specifically focusing on the development of a novel home-based upper- and lower-limb telerehabilitation platform. Within this context, AI serves as an enabling technology that empowers us to create intelligent, adaptable, and patient-centric rehabilitation experiences.

The Ubiquity of Artificial Intelligence

AI, a field rooted in emulating human intelligence through machine learning, neural networks, and data-driven algorithms, has permeated nearly every facet of modern life. Its applications span natural language processing and computer vision to robotics and autonomous systems. AI has catalyzed a revolution in healthcare, driving advancements in medical imaging, drug discovery, predictive analytics, and, most pertinently, rehabilitation.

The integration of AI into rehabilitation services holds immense promise. AI-driven systems can analyze intricate patient data, tailor exercises to individual needs, track progress and offer real-time feedback. In the context of telerehabilitation, AI's capabilities are amplified, enabling remote monitoring, personalized treatment plans, and dynamic adjustments based on the patient performance.

One of the primary strengths of AI in telerehabilitation is its capacity to personalize therapy regimens. By analyzing patient data, including motor function, range of motion, and progress over time, AI algorithms can adapt exercises to optimize outcomes for each individual, accommodating their unique needs and limitations.

AI systems can remotely monitor patient movements during rehabilitation exercises, providing instant feedback and correction when necessary. This real-time interaction enhances patient engagement ensures proper form and reduces the risk of injury.

Through continuous data collection and analysis, AI can generate valuable insights into patient progress, allowing healthcare providers to make informed decisions about treatment adjustments and rehabilitation planning.

AI-Driven Experimental Validation

Crucial to this research is the utilization of AI in the experimental validation of the developed telerehabilitation platform. AI can assist in analyzing data from clinical trials, assessing the platform's effectiveness, and identifying improvement areas. Moreover, AI-powered predictive modeling can help forecast patient outcomes and refine treatment strategies.

1.3 Segments and articulations of the human body

The human body is composed of many different segments and articulations that allow for movement and flexibility. Understanding the structure and function of these segments and articulations are essential for physical therapists, athletes, and anyone interested in human anatomy and movement.

Segments refer to the different regions of the body that are separated by joints or other anatomical landmarks. The major segments of the body include the head and neck, trunk, upper extremities, and lower extremities. These segments are further divided into smaller regions based on their function and anatomy.

1.3.1 The head and neck segment

The head and neck are essential parts of the body that serve multiple functions, including sensory perception, communication, and movement [26]. The head and neck segment includes the skull, face, and neck, each of which has its unique structure and functions [27].

The skull is composed of the cranial bones, which provide protection and support for the brain. The skull is made up of eight bones that are firmly connected by joints called sutures. These bones include the frontal bone, parietal bone, occipital bone, temporal bone, sphenoid bone, and ethmoid bone. The skull also contains several openings for the passage of blood vessels and nerves, including the foramen magnum, which allows the spinal cord to connect to the brain.

The face is located in front of the skull and includes the eyes, nose, mouth, and ears. The eyes are responsible for visual perception and are protected by the bony orbits of the skull. The nose is responsible for the sense of smell and contains the nasal cavity, which is lined with mucus membranes and filled with air. The mouth is responsible for tasting, chewing, and speaking, containing the tongue, teeth, and salivary glands. The ears are responsible for hearing and balance, and they are composed of three parts: the outer ear, middle ear, and inner ear.

The neck comprises the cervical vertebrae and associated soft tissues, including muscles, tendons, and ligaments. The cervical vertebrae provide support for the head and allow for head and neck movement. The neck also contains important blood vessels and nerves, including the carotid arteries, jugular veins, and cervical nerves. The head and neck segment

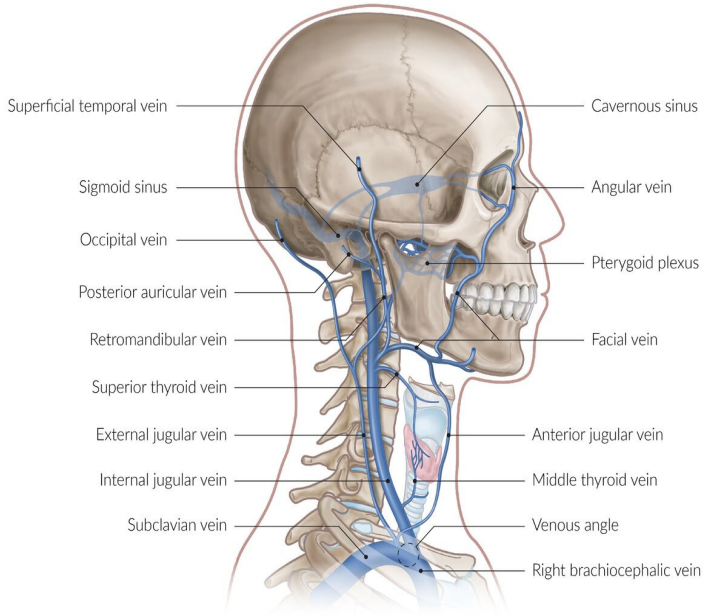


Figure 1.1 : The head and neck anatomy [1].

also has several vital organs and structures, including the brain, spinal cord, and the thyroid gland. The brain is the body's control center and regulates many bodily functions, including movement, sensation, and thought. The spinal cord is a bundle of nerves running from the brain down the neck and back and transmitting sensory and motor signals throughout the body. The thyroid gland is in the neck and produces hormones regulating metabolism and growth.

1.3.2 The trunk segment

The trunk is the central part of the body and provides support and protection for vital organs. It comprises three main regions: the chest, abdomen, and pelvis [28].

The chest region contains the heart and lungs, which are essential for breathing and circulating oxygen. The rib cage, made up of 12 pairs of ribs, protects the chest region. The ribs are attached to the sternum in front and the spine in the back, and they work together to expand and contract during breathing.

The abdomen below the chest contains the digestive organs, including the stomach, intestines, liver, and pancreas. These organs work together to break down food and absorb

nutrients into the body. The diaphragm separates the abdomen from the chest, a thin, dome-shaped muscle that plays a crucial role in breathing by contracting and relaxing to create negative pressure in the chest cavity.

The pelvis region is located at the base of the trunk and comprises the hip bones and sacrum. The pelvis supports the lower extremities and houses the reproductive organs, bladder, and rectum. The hip bones are solid and dense and attach to the sacrum and coccyx to form the pelvis. The pelvis maintains balance and stability during movement, mainly walking, running, and jumping.

The trunk also includes a complex network of muscles, tendons, ligaments, and other connective tissues that work together to provide stability, support, and mobility. The chest muscles, including the major and minor, work together to help move the arms and support the rib cage. The abdomen muscles, including the rectus abdominis and obliques, work together to support the spine and provide stability during movement. The pelvis muscles, including the gluteus maximus and medius, work together to keep the hips and legs.

1.3.3 The upper extremities

The shoulders, in particular, are one of the body's most flexible and mobile joints. They are composed of the clavicle and scapula and work together to provide stability and support to the shoulder joint. The shoulder joint is a ball-and-socket joint that allows for a wide range of motion in the arm, including abduction, adduction, flexion, extension, and rotation [29].

The arm is the segment of the upper extremities that connects the shoulder to the hand. It comprises three bones: the humerus, radius, and ulna. The humerus is the long bone that runs from the shoulder to the elbow and provides the primary support for the arm. The radius and ulna are the two bones in the forearm that run parallel and work together to allow forearm rotation. The radius is on the thumb side of the forearm, while the ulna is on the pinky side [30].

The hand is the final segment of the upper extremities and comprises the carpals, metacarpals, and phalanges. The carpals are eight small bones that make up the wrist and provide stability to the hand. The metacarpals are the five bones that connect the wrist to the fingers and form the palm. The phalanges are the bones in the fingers and thumbs and are responsible for supporting the weight of objects held in the hand [31].

The upper extremities also include muscles, tendons, ligaments, and other connective tissues that work together to provide strength, flexibility, and support to the upper body. The muscles of the shoulder, including the deltoid, rotator cuff muscles, and pectoralis major, work together to provide stability and support to the shoulder joint while also allowing for a wide range of motion. The muscles of the arm, including the biceps brachii and triceps brachial, work together to provide strength and power to the arm during activities such as lifting and throwing. The muscles of the hand, including the intrinsic and extrinsic muscles, work together to allow for fine motor movements and grip strength.

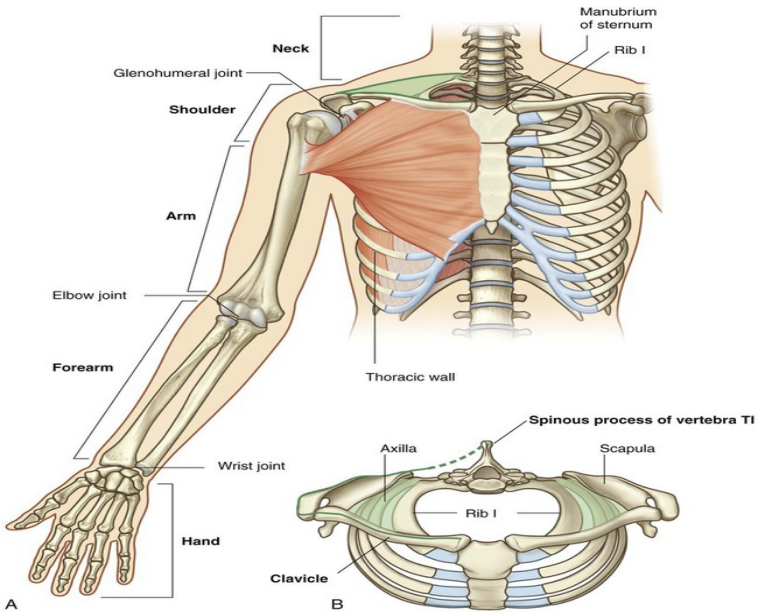


Figure 1.2 : Upper limb. A. Anterior view of the upper limb. B. Superior view of the shoulder [2].

1.3.4 The lower extremities

The lower extremities are critical for movement and mobility, enabling us to walk, run, jump, and perform various other physical activities. The hips, in particular, play a crucial role in facilitating movement in the leg. The hip joint is a ball-and-socket joint that allows for a wide range of motion, including flexion, extension, abduction, adduction, and rotation. These movements are made possible by the pelvic bones and femurs, which work together to create a stable yet flexible joint.

The legs are also vital for movement and support. They comprise two long bones called the tibia and fibula, which run from the knee to the ankle. These bones work together to provide support and stability to the leg while allowing movement. The tibia is the larger of the two bones and is located on the medial side of the leg. It bears most of the body's weight and transmits forces from the knee to the ankle. Conversely, the fibula is located on the lateral side of the leg and is much thinner and smaller than the tibia. It helps to provide additional support and stability to the leg and plays a crucial role in ankle movement [32].

The foot is the final segment of the lower extremities and is composed of the tarsals, metatarsals, and phalanges. The tarsals are a group of seven bones in the ankle that provide support and stability to the foot. The metatarsals are five long bones that connect the tarsals to the phalanges and form the foot's arch [33]. The phalanges are the bones in the toes responsible for supporting the body's weight during activities such as walking and running. Together, the bones of the footwork provide a stable base for the body while also allowing for a wide range of movements.

In addition to the bones, the lower extremities include muscles, tendons, ligaments, and other connective tissues. These structures work together to provide strength, flexibility, and support to the lower body. For example, the hip flexor muscles, including the iliopsoas, rectus femoris, and sartorius, lift the leg forward during walking and running. The calf muscles, including the gastrocnemius and soleus, lift the heel and push the body forward during walking and running.

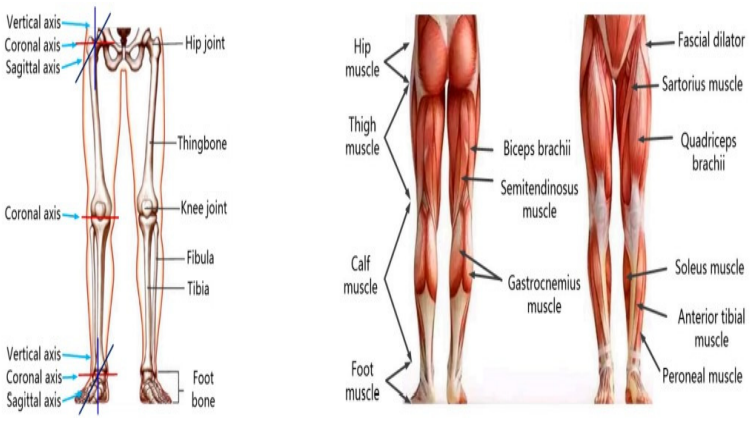


Figure 1.3 : Bones, joints and muscle diagram of human lower limbs [3].

Overall, the lower extremities are essential for movement, balance, and stability. Understanding the anatomy and function of the hips, legs, and feet can help individuals maintain

healthy lower extremities and prevent injury. Regular exercise and proper nutrition can also help to improve the strength and function of the lower extremities, leading to better overall health and wellness.

1.3.5 Note

Articulations refer to the joints between these segments, which allow for movement and flexibility. There are several different types of articulations, including hinge joints, ball-and-socket joints, and pivot joints. Hinge joints, such as the elbow and knee, allow for movement in one plane only. Ball-and-socket joints, such as the shoulder and hip, allow for movement in multiple planes. Pivot joints, such as the joint between the atlas and axis vertebrae, allow for rotation.

1.4 The different modes of rehabilitation

Rehabilitation is the process of restoring physical, mental, and social functions lost or impaired due to injury, illness, or disability. There are different modes of rehabilitation, each of which is designed to meet the specific needs and goals of the individual undergoing rehabilitation. Here are some of the different modes of rehabilitation:

1.4.1 Physical rehabilitation

Physical rehabilitation is a necessary aspect of recovery for individuals who have suffered an injury, illness, or surgery that has impacted their physical ability [34]. This rehabilitation helps individuals regain their independence and improve their quality of life. Physical rehabilitation programs are tailored to the specific needs of each individual, depending on their age, condition, and the extent of their physical limitations.

One of the primary goals of physical rehabilitation is to help individuals regain their strength and endurance. Various exercises, including resistance training, cardiovascular workouts, and stretching, achieve this. Resistance training involves using weights or resistance bands to target specific muscle groups, while cardiovascular workouts are designed to increase heart rate and improve cardiovascular health. Stretching helps to improve flexibility and range of motion.

Physical therapy is a critical component of physical rehabilitation. It involves using specialized techniques and equipment to help individuals regain strength and mobility. Physical therapists work with patients to develop individualized treatment plans that address their needs. These plans may include exercises, manual therapy, and other interventions that help to restore function and mobility.

Occupational therapy is another crucial aspect of physical rehabilitation. It focuses on helping individuals regain the ability to perform daily activities and tasks, such as dressing, grooming, and cooking [35]. Occupational therapists work with patients to develop strategies and adaptations that make these activities more accessible and safer.

In addition to exercises and therapy, physical rehabilitation may also include other interventions, such as assistive devices and technology. These tools can help individuals with physical limitations to perform tasks that would otherwise be difficult or impossible. For example, a wheelchair or a walker may be used to assist individuals with mobility issues move around more easily while voice-activated technology may be used to enable individuals with limited dexterity controls their environment.

Physical rehabilitation is not just crucial for individuals who have suffered an injury or illness. It can also benefit individuals with chronic conditions that impact their physical ability, such as arthritis or multiple sclerosis. In these cases, physical rehabilitation can help to improve function and mobility, reduce pain, and improve overall quality of life.

The benefits of physical rehabilitation are numerous. In addition to improving physical function and mobility. It can also help to reduce pain, improve mental health, and increase social engagement. Physical rehabilitation can also help to reduce the risk of future injuries or complications by improving strength and balance.

1.4.2 Cognitive rehabilitation

Cognitive rehabilitation is a type of rehabilitation that focuses on improving cognitive functioning in individuals who have experienced brain injuries or other cognitive impairments [36]. It is designed to help people regain or develop the skills they need to perform daily activities and improve their quality of life. Cognitive rehabilitation can be used to treat a range of cognitive impairments, including memory loss, attention deficits, language impairments, and executive functioning deficits.

Cognitive rehabilitation programs typically involve a multidisciplinary team of health-

care professionals, including psychologists, occupational therapists, speech therapists, and neuropsychologists. The team works together to develop an individualized treatment plan tailored to each patient's specific needs. The treatment plan may include a variety of interventions, such as cognitive exercises, behavioral therapies, and medication management.

One of the primary goals of cognitive rehabilitation is to improve a patient's ability to perform daily activities [37]. This may include tasks such as cooking, cleaning, and managing finances. Cognitive rehabilitation programs often include training in functional skills to achieve this goal. This involves practicing the skills necessary to perform specific tasks and gradually increasing the difficulty of those tasks as the patient improves.

Another important goal of cognitive rehabilitation is to improve a patient's cognitive abilities. This may involve exercises to improve memory, attention, and problem-solving skills. For example, a patient with memory loss may be asked to practice remembering a list of items, while a patient with attention deficits may be asked to complete tasks that require sustained attention.

Cognitive rehabilitation can also be used to address emotional and psychological issues that can arise following a brain injury or other cognitive impairment [38]. This may involve therapy designed to help patients cope with feelings of frustration, anxiety, or depression. By addressing these emotional issues, cognitive rehabilitation can improve a patient's overall well-being and quality of life.

The effectiveness of cognitive rehabilitation varies depending on the severity of the cognitive impairment and the specific interventions used. However, research has shown that cognitive rehabilitation can be effective in improving cognitive functioning and daily living skills in many patients. Additionally, early intervention is often associated with better outcomes, so it is critical to seek treatment as soon as possible following a brain injury or other cognitive impairment.

1.4.3 Psychological rehabilitation

Psychological rehabilitation is a type of rehabilitation that focuses on addressing the emotional, social, and cognitive aspects of an individual's recovery. It aims to improve an individual's overall well-being and quality of life following a traumatic event, illness, or injury. Psychological rehabilitation can be used to treat a wide range of conditions, including

post-traumatic stress disorder (PTSD), anxiety disorders, depression, and substance abuse disorders [39].

Psychological rehabilitation typically involves a multidisciplinary team of healthcare professionals, including psychologists, psychiatrists, social workers, and occupational therapists. The team works together to develop an individualized treatment plan tailored to each patient's specific needs. The treatment plan may include a variety of interventions, such as psychotherapy, medication management, and behavioral therapies.

One of the primary goals of psychological rehabilitation is to help individuals cope with the emotional and psychological effects of their illness or injury. This may involve therapy designed to help patients address issues such as depression, anxiety, and PTSD. Therapies used in psychological rehabilitation can vary widely, but may include cognitive-behavioral therapy (CBT), exposure therapy, and mindfulness-based interventions.

Another essential goal of psychological rehabilitation is to help individuals rebuild their social and occupational roles. This may involve skills training and vocational rehabilitation, which can help patients improve their ability to manage daily activities, interact with others, and return to work or school.

In addition to treating the symptoms of a specific condition, psychological rehabilitation also aims to promote overall well-being and quality of life. This may involve promoting a healthy lifestyle changes, such as improving diet and exercise habits and developing positive coping strategies to manage stress and other challenges.

The effectiveness of psychological rehabilitation can vary depending on the specific condition being treated, as well as the individual's personal circumstances and treatment history. However, research has shown that psychological rehabilitation can be effective in improving outcomes for many patients. For example, studies have found that CBT can be effective in treating depression, anxiety, and PTSD, while vocational rehabilitation can improve employment outcomes for individuals with disabilities.

1.4.4 Vocational rehabilitation

Vocational rehabilitation is a type of rehabilitation that focuses on helping individuals with disabilities or other barriers to employment to find and maintain meaningful employment [40]. It is designed to help individuals build the skills and knowledge they

need to pursue a successful career, improve their financial independence, and enhance their overall quality of life.

Vocational rehabilitation programs typically involve a team of professionals, including vocational counselors, job coaches, and rehabilitation specialists. The team works with the individual to assess their abilities, interests, and goals, and then develop a personalized plan to help them achieve their vocational objectives.

One of the primary goals of vocational rehabilitation is to help individuals develop the skills and knowledge they need to succeed in the workforce. This may involve skills training, education, or vocational counseling to help the individual identify their strengths and interests, and determine the best career path for them.

Another important goal of vocational rehabilitation is to help individuals overcome barriers to employment. This may involve assistance with job search activities, such as resume writing and interviewing skills, as well as job placement services and on-the-job training.

Vocational rehabilitation can also involve the use of assistive technology and accommodations to help individuals perform their job duties. This may include specialized equipment, software, or other tools to enable individuals with physical, sensory, or cognitive impairments to perform their job duties effectively.

The advantage of vocational rehabilitation can vary depending on the individual's specific circumstances and the type of program and services used. However, research has shown that vocational rehabilitation can be effective in helping individuals with disabilities achieve employment and improve their quality of life. For example, studies have found that vocational rehabilitation can improve employment outcomes, reduce dependence on public assistance, and increase earnings for disabled individuals.

1.4.5 Substance abuse rehabilitation

Substance abuse rehabilitation is a type of rehabilitation that focuses on helping individuals overcome addiction and regain control over their lives. It aims to address the physical, psychological, and social aspects of addiction, and to help individuals develop the skills and knowledge they need to maintain a sober lifestyle.

Substance abuse rehabilitation programs typically involve a combination of therapies, support groups, and other interventions. The specific program and services used can vary depending on the individual's needs, the severity of their addiction, and other factors.

One of the primary goals of substance abuse rehabilitation is to help individuals detoxify and overcome physical dependence on drugs or alcohol. This may involve medical treatment, such as medication-assisted treatment (MAT) to help manage withdrawal symptoms and reduce the risk of relapse.

Another goal of substance abuse rehabilitation is to help individuals address the underlying psychological and emotional issues that may have contributed to their addiction. This may involve individual or group therapy, cognitive-behavioral therapy (CBT), and other forms of counseling to help individuals develop coping skills and improve their mental health.

Substance abuse rehabilitation also aims to help individuals rebuild their social and occupational roles. This may involve vocational rehabilitation and job training to help individuals find and maintain meaningful employment, as well as family therapy and other support services to help individuals repair relationships with loved ones and develop a strong support network.

The usefulness of substance abuse rehabilitation can vary depending on the individual's specific circumstances, the severity of their addiction, and the program and services used. However, research has shown that substance abuse rehabilitation can be effective in helping individuals overcome addiction and improve their overall quality of life. For example, studies have found that MAT can be effective in reducing the risk of relapse and improving treatment outcomes for individuals with opioid addiction.

1.4.6 Community-based rehabilitation

Community-based rehabilitation (CBR) is a type of rehabilitation that is designed to provide services and support to individuals with disabilities or other rehabilitation needs within their own communities [41]. CBR aims to improve the quality of life for individuals with disabilities and promote their participation in society by addressing barriers to participation and providing access to necessary services and resources.

CBR programs are typically community-driven and involve collaboration between individuals with disabilities, their families, and community members and organizations. The programs may be implemented by government agencies, non-governmental organizations, or community-based organizations, and they may include a range of services, such as education, health care, vocational training, and social support.

One of the primary goals of CBR is to promote social inclusion and community participation for individuals with disabilities [42]. This may involve advocacy and awareness-raising efforts to promote the rights of individuals with disabilities and reduce stigma and discrimination, as well as efforts to increase access to community resources and services.

In addition, CBR is to provide individuals with disabilities with the skills and knowledge they need to live independently and participate in their communities. This may involve skills training, such as vocational training or mobility training, as well as access to assistive devices and technologies to help individuals overcome physical, sensory, or cognitive barriers to participation.

CBR also aims to improve the health and well-being of individuals with disabilities by providing access to necessary health care services and promoting healthy lifestyles. This may involve efforts to increase access to medical care and rehabilitation services as well as initiatives to promote healthy behaviors, such as exercise and good nutrition.

The advantage of CBR can vary depending on the specific program and services used, as well as the social and economic context in which the program is implemented. However, research has shown that CBR can be effective in improving the quality of life for individuals with disabilities and promoting their participation in society. For example, studies have found that CBR can improve access to education, employment, and social support, and reduce social isolation and stigma for individuals with disabilities.

In conclusion, rehabilitation is a multifaceted process that involves different modes of rehabilitation to meet the unique needs and goals of each individual. Whether it's physical, cognitive, psychological, vocational, substance abuse, or community-based rehabilitation, the goal is always to help individuals regain function, independence, and quality of life.

1.5 Exercises recommended for home physiotherapy rehabilitation

Home physiotherapy rehabilitation is a vital component of recovering from injury or illness and can help to restore strength, flexibility, and range of motion. Here are some exercises that are commonly recommended for home physiotherapy rehabilitation:

1.5.1 Range of motion exercises

Range of motion exercises are an essential part of home-based physiotherapy rehabilitation. These exercises improve joint mobility, flexibility, and overall range of motion. Range of motion exercises can be used for individuals recovering from an injury, surgery, or illness that has impacted their physical ability. These exercises also benefit individuals suffering from chronic conditions, such as arthritis or Parkinson's disease.

Range of motion exercises involves moving a joint through its full range of motion, either actively or passively. The individual performs an active range of motion exercises, while a caregiver or healthcare professional performs a passive range of motion exercises. These exercises can be done using bodyweight, resistance bands, or other equipment, depending on the specific needs of the individual.

Range of motion exercises are beneficial for several reasons. First, they help improve joint flexibility and mobility, reducing pain and stiffness. Second, they can improve circulation and lymphatic flow, which can help to reduce swelling and inflammation. Third, range of motion exercises can improve balance and coordination, reducing the risk of falls and other injuries.

There are many different types of range of motion exercises that can be used in home-based physiotherapy rehabilitation. These exercises can be tailored to the specific needs and abilities of the individual. Some examples of the range of motion exercises include:

Shoulder circles

This exercise involves moving the shoulders in a circular motion, both clockwise and counterclockwise. This exercise can help to improve shoulder mobility and flexibility.

Knee bends

This exercise involves bending and straightening the knee, either actively or passively. This exercise can help to improve knee mobility and flexibility.

Ankle circles

This exercise involves moving the ankles in a circular motion, both clockwise and counterclockwise. This exercise can help to improve ankle mobility and flexibility.

Neck stretches

This exercise involves gently stretching the neck in different directions. This exercise can help to improve neck mobility and reduce neck pain.

Hip rotations

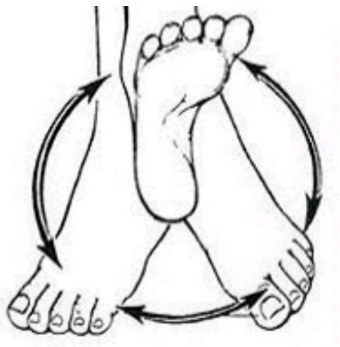


Figure 1.4 : Ankle circles.

This exercise involves rotating the hips in a circular motion, both clockwise and counterclockwise. This exercise can help to improve hip mobility and flexibility.

1.5.2 Strengthening exercises

These exercises are designed to help individuals regain strength in their muscles, which may have been weakened as a result of injury, surgery, or illness. Strengthening exercises are also beneficial for individuals with chronic conditions, such as multiple sclerosis or cerebral palsy, who may experience muscle weakness or fatigue.

Strengthening exercises can be done using bodyweight, resistance bands, or weights, depending on the specific needs and abilities of the individual. These exercises typically involve working the major muscle groups of the body, including the arms, legs, back, and core. Some examples of strengthening exercises include:

Squats

This exercise involves bending the knees and lowering the body into a seated position, then standing back up. Squats can help to strengthen the muscles in the legs and buttocks.

Push-ups

This exercise involves lowering the body to the ground and then pushing back up. Push-ups can help to strengthen the muscles in the chest, shoulders, and arms.

Bicep curls

This exercise involves holding a weight or resistance band and curling it towards the body, working the muscles in the upper arms.

Leg press

This exercise involves pushing the weight away with the legs while sitting or lying down, working the muscles in the legs.

Plank

This exercise involves holding a push-up position while keeping the body straight, working the muscles in the core.

Strengthening exercises are beneficial for a number of reasons. First, they can help to improve overall strength and endurance, which can improve physical function and reduce the risk of falls or other injuries. Second, strengthening exercises can help to increase muscle mass, which can help to improve bone density and reduce the risk of osteoporosis. Third, these exercises can help to improve balance and coordination, which can reduce the risk of falls and other injuries.

It is important to note that strengthening exercises should be done under the guidance of a qualified healthcare professional, such as a physiotherapist or occupational therapist. These professionals can develop a personalized treatment plan that takes into account the individual's specific needs and abilities and can help to monitor progress over time.

1.5.3 Balance exercises

These exercises focus on improving an individual's ability to maintain stability and avoid falls by improving balance and coordination:

Balance exercises

These are especially important for individuals who have suffered from injuries or illnesses that affect their mobility or for older adults who may be at a higher risk for falls.

There are many different types of balance exercises that can be done in the comfort of one's own home. One simple exercise is standing on one foot while holding onto a stable surface, such as a chair or countertop, for balance. This exercise can be progressed by closing the eyes or by standing on a foam pad or unstable surface, which challenges the body's ability to maintain balance.

Another balance exercise that can be done at home is the heel-to-toe walk. This exercise involves walking in a straight line, placing the heel of one foot in front of the toe of the other foot with each step. This exercise challenges balance and coordination and can be progressed by walking backwards or by adding in turns.

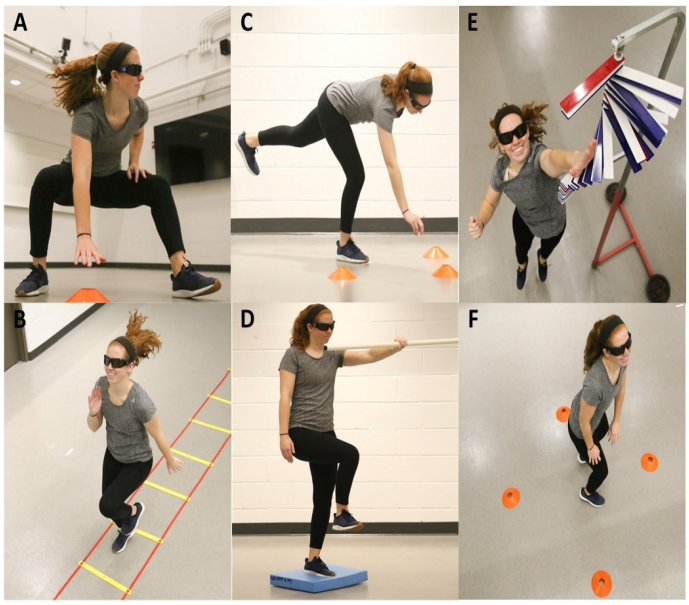


Figure 1.5 : Exercise examples with clinical applications: (A) T-test, (B) Agility ladder drills, (C) Single-leg deadlifts, (D) Single-leg stance (on foam), (E) Vertical jumps, and (F) Squat jumps [4].

Sit to stand exercise

Is another effective balance exercise that can be done at home. This exercise involves sitting in a chair and standing up without using the arms for support. This exercise strengthens the leg muscles and improves balance and coordination.

1.5.4 Stretching exercises

Stretching exercises are a fundamental component of home-based physiotherapy rehabilitation. These exercises are designed to improve flexibility and range of motion, which can help to reduce pain and improve physical function. Stretching exercises are particularly beneficial for individuals who have suffered from injuries or surgeries that limit their mobility and those with chronic conditions such as arthritis.

Stretching exercises can be done using bodyweight or props such as a foam roller, resistance bands, or yoga blocks. These exercises can target specific muscle groups or can be full-body stretches. Examples of stretching exercises include:

Hamstring stretch

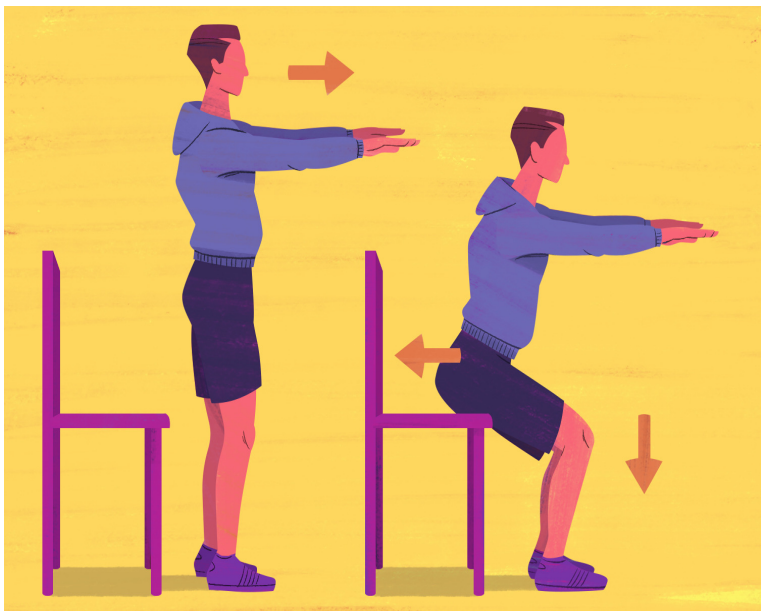


Figure 1.6 : Sit-to-stand [5].

This exercise involves sitting on the floor with legs straight out in front of the body and reaching towards the toes to stretch the hamstring muscles [43].

Figure 1.7 : Flexibility test "chair sit and reach" [6].

Quadriceps stretch

This exercise involves standing with one hand on a wall or other stable surface and pulling one foot up towards the buttocks to stretch the quadriceps muscle [44].

Spinal twist

This exercise involves lying on the back with knees bent and twisting the legs to one side while keeping the shoulders on the ground to stretch the spine and hips [45].

Shoulder stretch

This exercise involves holding a resistance band or towel behind the back and pulling it towards the body to stretch the shoulders [46].

Neck stretch

This exercise involves gently bringing the ear towards the shoulder to stretch the neck muscles [47].

Stretching exercises are important for a number of reasons. First, they can help to improve flexibility and range of motion, which can reduce the risk of injury and improve physical function. Second, stretching exercises can help to reduce muscle tension and soreness, which can alleviate pain and discomfort. Third, stretching exercises can help to improve posture, which can reduce the risk of developing musculoskeletal problems such as back pain.

It is important to note that stretching exercises should be done under the guidance of a qualified healthcare professional, such as a physiotherapist or occupational therapist. These professionals can develop a personalized treatment plan that takes into account the individual's specific needs and abilities and can help to monitor progress over time.

1.5.5 Breathing exercises

These exercises can help to improve lung function, increase oxygen saturation levels, and reduce shortness of breath.

There are many different types of breathing exercises that can be used in home-based physiotherapy rehabilitation, each with its own specific benefits. Some examples of breathing exercises include:

Diaphragmatic breathing

This exercise involves taking deep breaths, allowing the diaphragm to expand and contract fully. It can help to improve oxygenation and reduce shortness of breath [48].

Pursed lip breathing

This exercise involves exhaling slowly through pursed lips, which can help to regulate breathing and reduce shortness of breath [49]. **Inspiratory muscle training**

This exercise involves using a device to provide resistance during inhalation, which can help to strengthen the muscles used in breathing [50]. **Controlled coughing**

This exercise involves taking a deep breath and coughing to clear the lungs of mucus and other secretions [51].

Breathing exercises can be done in a variety of positions, including sitting, standing, and lying down. They can also be combined with other exercises, such as physical therapy exercises, to improve overall physical function and reduce symptoms of respiratory conditions.

In addition to their physical benefits, breathing exercises can also help to reduce stress and anxiety. By focusing on the breath and slowing down the breathing process, individuals can calm their mind and reduce feelings of tension and anxiety.

1.5.6 Posture exercises

Posture exercises are an important component of home-based physiotherapy rehabilitation, particularly for individuals who have poor posture or are recovering from an injury or surgery that has affected their posture. These exercises can help to improve alignment, reduce pain, and prevent further injury.

There are many different types of posture exercises that can be used in home-based physiotherapy rehabilitation, each with their own specific benefits. Some examples of posture exercises include:

Shoulder blade squeeze

This exercise involves squeezing the shoulder blades together while sitting or standing, which can help to improve posture and reduce pain in the upper back and neck [47].

Chin tuck

This exercise involves gently tucking the chin in towards the neck, which can help to align the spine and reduce strain on the neck and shoulders [52].

Wall angels

This exercise involves standing with the back against a wall and slowly raising and lowering the arms, which can help to improve posture and reduce pain in the upper back and shoulders [53].

Cat-camel stretch

This exercise involves moving the spine through a range of motion by alternately arching and rounding the back while on hands and knees, which can help to improve posture and reduce pain in the lower back.

Posture exercises can be done throughout the day, either as part of a structured exercise routine or as simple movements incorporated into daily activities. They can also be combined with other exercises, such as strengthening exercises or range of motion exercises, to improve overall physical function and reduce pain.

In addition to their physical benefits, posture exercises can also help to improve self-confidence and reduce feelings of anxiety or depression. By improving posture, individuals can feel more comfortable and confident in their bodies, which can have a positive impact on their overall mental health.

It is important to note that the specific exercises recommended for home physiotherapy rehabilitation will vary depending on the individual's condition, injury, or illness. It is always recommended to work with a qualified physiotherapist to design a personalized rehabilitation program that is safe and effective for your needs. Additionally, it is important to follow the prescribed exercises consistently and gradually increase intensity or duration under the guidance of a physiotherapist.

1.6 General information on telerehabilitation

1.6.1 General definition of telerehabilitation

Telerehabilitation is a mode of healthcare delivery that uses telecommunication technology to provide rehabilitation services remotely to patients. It can be defined as the delivery of rehabilitation services using information and communication technologies (ICTs), such as videoconferencing, telemonitoring, and mobile health (mHealth) applications. Telerehabilitation can be used to provide a wide range of rehabilitation services, including physical therapy, occupational therapy, speech therapy, and cognitive rehabilitation.

Here are some general definitions of telerehabilitation from authoritative sources:

The World Health Organization (WHO) defines telerehabilitation as "the delivery of rehabilitation services over telecommunication networks and the internet to facilitate the exchange of medical information from one site to another for diagnosis, consultation, treatment, education, and training." (source: WHO, 2010)

The American Telemedicine Association (ATA) defines telerehabilitation is "the application of assessment, intervention, education, and monitoring using telecommunication technologies to assist or support rehabilitation services, including self-management." (source: ATA, 2013)

The Canadian Institute for Health Information (CIHI) defines telerehabilitation is "the use of technology to deliver rehabilitation services, such as physical therapy, occupational therapy, and speech therapy to patients in remote or underserved areas." (source: CIHI, 2016)

Telerehabilitation has the potential to improve access to rehabilitation services for individuals who live in remote or underserved areas, have mobility or transportation limitations, or face other barriers to accessing in-person rehabilitation services. It can also help to reduce healthcare costs, increase patient satisfaction, and improve clinical outcomes. However, it is important to note that telerehabilitation is not a replacement for in-person rehabilitation services and should be used as a supplement to, not a substitute for traditional rehabilitation services when appropriate.

1.6.2 A historical overview of telerehabilitation

Telerehabilitation has its roots in the broader field of telemedicine, which began to emerge in the 1960s with the development of videoconferencing technology. The idea of using this technology to deliver rehabilitation services remotely to patients gained traction in the 1990s, and since then, telerehabilitation has become an increasingly popular mode of healthcare delivery. Here is a historical overview of telerehabilitation:

1990s: Early studies of telerehabilitation [54; 7; 55; 56] focused on the use of videoconferencing technology to deliver rehabilitation services to patients in remote or underserved areas, such figure 1.8. These studies demonstrated that videoconferencing was a feasible and effective way to deliver rehabilitation services and that patients were generally satisfied with the care they received.

2000s: The development of new technologies, such as telemonitoring and mobile health (mHealth) applications, expanded the scope of telerehabilitation beyond videoconferencing. Researchers began to explore the use of telemonitoring to monitor patients' progress and provide feedback, and the use of mHealth applications to deliver rehabilitation exercises and track patients' adherence to treatment plans [57; 58; 59; 60; 61; 8], such show figure 1.9.

2010s: The growing popularity of telerehabilitation led to the development of new tele-

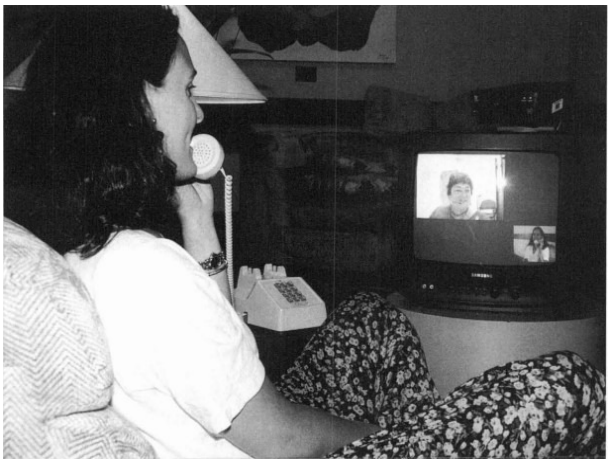


Figure 1.8 : The VC-105 video telephone connected to a standard television and transmitting over POTS. As an option, patient and clinician are able to view both the transmitted and received image, with simultaneous audio. [7].

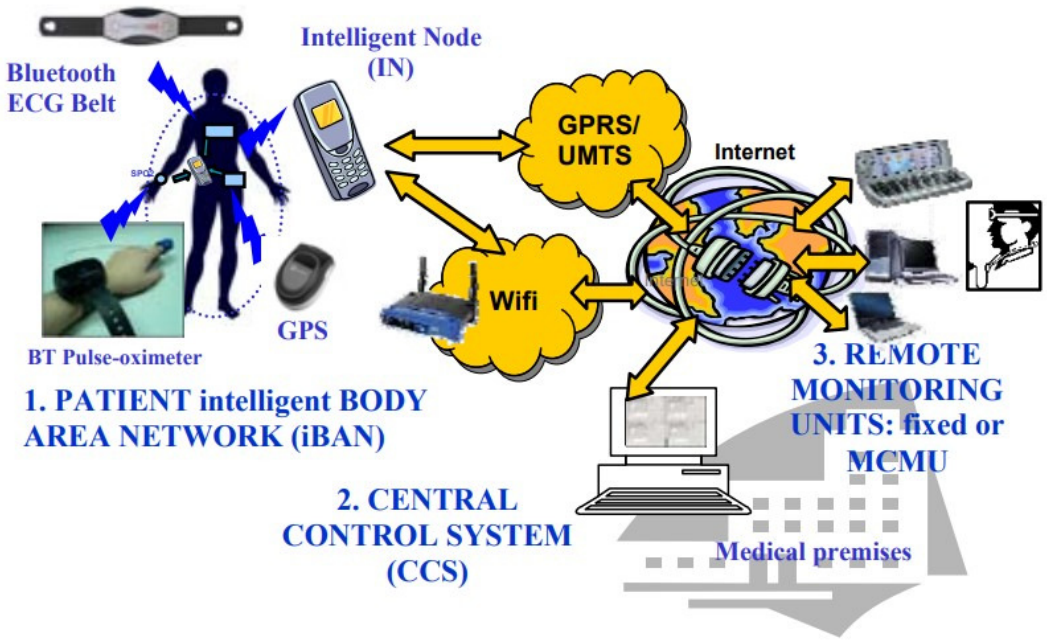


Figure 1.9 : General architecture of the system using wireless Body Area Network based on J2ME for M-Health applications [8].

health policies and regulations, as well as the establishment of telehealth programs in many healthcare organizations. A number of studies demonstrated that telerehabilitation was effective in improving clinical outcomes and reducing healthcare costs, particularly in the areas of stroke rehabilitation and musculoskeletal rehabilitation [62; 63; 64; 65; 66].

2020s: The COVID-19 pandemic accelerated the adoption of telerehabilitation [67; 68; 69; 70; 71; 72; 73], as many healthcare organizations began to offer remote rehabilitation services to patients to reduce the risk of infection. Telerehabilitation is now seen as an essential component of healthcare delivery, and it is likely to continue to grow in popularity in the coming years.

Overall, the history of telerehabilitation has been characterized by a gradual evolution from early studies of videoconferencing to the development of new technologies and the establishment of telehealth programs in healthcare organizations. While telerehabilitation is still a relatively new field, it has shown great promise in improving access to rehabilitation services and reducing healthcare costs.

1.6.3 Domains of the utilization of telerehabilitation

Telerehabilitation can be used across a wide range of domains to provide remote rehabilitation services to patients who are unable to physically attend therapy sessions. Here are some of the domains where telerehabilitation has been found to be effective:

Neurological rehabilitation

Telerehabilitation has been used to provide rehabilitation services to patients with various neurological conditions, such as stroke, Parkinson's disease, multiple sclerosis, and traumatic brain injury [74; 75].

Cardiopulmonary rehabilitation

Telerehabilitation can be used to provide rehabilitation services to patients with heart or lung conditions, such as chronic obstructive pulmonary disease (COPD), heart failure, and pulmonary rehabilitation [76; 77].

Orthopedic rehabilitation

Telerehabilitation can be used to provide rehabilitation services to patients with orthopedic conditions, such as post-operative rehabilitation, joint replacement, and sports injuries [60; 78].

Geriatric rehabilitation

Telerehabilitation can be used to provide rehabilitation services to older adults who have mobility issues or other age-related conditions [79; 80].

Mental health rehabilitation

Telerehabilitation can be used to provide mental health services, such as cognitive-behavioral therapy (CBT) and psychotherapy, to patients with mental health conditions, such as depression, anxiety, and post-traumatic stress disorder (PTSD) [63; 81].

Pediatric rehabilitation

Telerehabilitation can be used to provide rehabilitation services to children with developmental delays, cerebral palsy, and other pediatric conditions [82; 83].

Speech-language pathology

Telerehabilitation can be used to provide speech and language therapy services to patients with speech and language disorders, such as aphasia, dysarthria, and stuttering [58; 84].

Occupational therapy

Telerehabilitation can be used to provide occupational therapy services to patients with conditions that impact their ability to perform daily activities, such as Parkinson's disease, stroke, and spinal cord injury [85; 86].

1.7 Potential applications of physiotherapy telerehabilitation

1.7.1 Postoperative rehabilitation

Postoperative rehabilitation is a critical component of the recovery process for patients who have undergone surgery. Physiotherapy is often used to help patients regain their strength, mobility, and functionality after surgery. With the emergence of telerehabilitation, there is an opportunity to provide postoperative rehabilitation services to patients more conveniently and cost-effectively [87; 88].

One benefit of telerehabilitation for postoperative rehabilitation is that it allows patients to receive care from the comfort of their homes. This can be particularly beneficial for patients who live in remote or rural areas or who have mobility or transportation challenges that make it difficult to attend in-person physiotherapy sessions. By providing care remotely, telerehabilitation can help to ensure that patients receive the support they need to recover and regain their independence.

Another benefit of telerehabilitation for postoperative rehabilitation is that it can provide more personalized and targeted care. By leveraging digital technologies and artificial intelligence, telerehabilitation can give real-time feedback, and monitoring of patient progress. This can help to ensure that patients are following their rehabilitation plans correctly and can allow for adjustments to be made as needed to optimize their recovery.

Telerehabilitation can also help to reduce the burden on healthcare providers and improve the efficiency of care delivery. With telerehabilitation, physiotherapists can simultaneously provide care to multiple patients without traveling to different locations. This can help to reduce costs and improve access to care, particularly for patients who live in areas with limited healthcare resources.

One potential application of physiotherapy telerehabilitation for postoperative rehabilitation is in the area of joint replacement surgery. Joint replacement surgery is a standard procedure for patients with osteoarthritis, and postoperative rehabilitation is critical to ensure that patients regain their mobility and functionality. Telerehabilitation can provide a convenient and an effective way for patients to receive physiotherapy care after joint replacement surgery, particularly for patients who live far away from healthcare providers or who have mobility challenges that make it difficult to attend in-person sessions.

However, there are also some challenges associated with using telerehabilitation for post-operative rehabilitation. For example, not all patients may have access to the technology and internet infrastructure needed to receive telerehabilitation services. Additionally, there may be concerns about the quality and safety of care delivered remotely, particularly for patients with complex needs or who require more hands-on care.

In conclusion, telerehabilitation has the potential to transform the the way that post-operative rehabilitation services are delivered. By providing patients with more convenient and personalized care, telerehabilitation can help to improve patient outcomes and reduce the burden on healthcare providers. However, there are also challenges that need to be addressed, such as ensuring that patients have access to the necessary technology and infrastructure, and ensuring that the quality and safety of care are not compromised. With continued innovation and investment in this area, physiotherapy telerehabilitation is poised to become an increasingly important component of postoperative rehabilitation in the years to come.

1.7.2 Chronic conditions management

Chronic conditions are long-term medical conditions that require ongoing management and support. These conditions can be physical, such as chronic pain or arthritis, or they can be mental health conditions, such as depression or anxiety. Physiotherapy is a critical component of chronic condition management, as it can help patients improve their physical functioning, reduce pain, and improve their quality of life. With the emergence of telerehabilitation, there is an opportunity to provide physiotherapy services to patients with chronic conditions in a more convenient and accessible way [89; 90].

One of the benefits of using telerehabilitation for chronic condition management is that it can help to improve patient access to care. Patients with chronic conditions often require ongoing support from healthcare providers, which can be challenging to access due to factors such as geographical barriers, mobility limitations, or transportation challenges. By providing care remotely, telerehabilitation can help to ensure that patients receive the support they need to manage their condition, regardless of where they live or their ability to travel to healthcare facilities.

Another benefit of telerehabilitation for chronic condition management is that it can provide patients with greater control over their care. With telerehabilitation, patients can

access care on their schedule and can receive support from healthcare providers in real-time through video conferencing, messaging platforms, or other digital means. This can help empower patients to take an active role in managing their condition, which can improve their engagement and motivation to make positive changes to their health behaviors.

Telerehabilitation can also help improve care delivery efficiency and reduce healthcare costs. By providing care remotely, healthcare providers can reach more patients in less time without having to travel to different locations. This can help to reduce overhead costs, which can translate into cost savings for patients and healthcare systems. Additionally, telerehabilitation can help to prevent the need for unnecessary emergency room visits or hospitalizations, which can be costly and disruptive to patients' lives.

One potential application of physiotherapy telerehabilitation for chronic condition management is in the area of chronic pain management. Chronic pain is a common condition that affects millions of people worldwide, and it can be challenging to manage with traditional approaches. Physiotherapy can help to reduce pain and improve physical functioning, but access to physiotherapy services can be limited due to factors such as geographical barriers or high costs. Telerehabilitation can provide a more convenient and accessible way for patients to access physiotherapy services, which can help to improve pain management and reduce the need for medication or other more invasive treatments.

However, some challenges are associated with telerehabilitation for chronic condition management. For example, not all patients may have access to the technology and internet infrastructure needed to receive telerehabilitation services. Additionally, there may be concerns about the quality and safety of care delivered remotely, particularly for patients with complex needs or who require more hands-on care.

1.7.3 Injury rehabilitation

Injury rehabilitation is an essential aspect of physiotherapy, as it helps patients to recover from injuries and regain their physical functioning. Whether it's a sports injury or an injury resulting from an accident, physiotherapy can be a vital component of the rehabilitation process. With the emergence of telerehabilitation, there is an opportunity to provide physiotherapy services to patients with injuries in a more convenient and accessible way. In the literature, there are many types of research on this topic [91; 92]

One of the benefits of using telerehabilitation for injury rehabilitation is that it can help

to improve patient access to care. Patients with injuries often require ongoing support from healthcare providers, which can be challenging to access due to factors such as geographical barriers, mobility limitations, or transportation challenges. By providing care remotely, telerehabilitation can help to ensure that patients receive the support they need to recover from their injuries, regardless of where they live or their ability to travel to healthcare facilities.

Another benefit of telerehabilitation for injury rehabilitation is that it can give patients greater control over their care. With telerehabilitation, patients can access care on their schedule and can receive support from healthcare providers in real-time through video conferencing, messaging platforms, or other digital means. This can help to empower patients to take an active role in their recovery, which can improve their engagement and motivation to make positive changes to their health behaviors.

Telerehabilitation can also help improve care delivery efficiency and reduce healthcare costs. By providing care remotely, healthcare providers can reach more patients in less time without having to travel to different locations. This can help to reduce overhead costs, which can translate into cost savings for patients and healthcare systems. Additionally, telerehabilitation can help to prevent the need for unnecessary emergency room visits or hospitalizations, which can be costly and disruptive to patients' lives.

One potential application of physiotherapy telerehabilitation for injury rehabilitation is in the area of sports injury rehabilitation. Sports injuries are common, particularly among athletes, and can be challenging to manage with traditional approaches. Physiotherapy can help to reduce pain and inflammation, improve range of motion and flexibility, and strengthen the affected area to prevent further injury. Telerehabilitation can provide a more convenient and accessible way for athletes to access physiotherapy services, which can help them recover faster and return to their sports activities sooner.

Finally, some challenges are associated with using telerehabilitation for injury rehabilitation. For example, not all injuries may be suitable for remote care, particularly those that require more hands-on or specialized care. Additionally, there may be concerns about the quality and safety of care delivered through remote means, particularly for patients with complex needs or who require more intensive rehabilitation.

1.7.4 Elderly care

Elderly care is a growing concern for healthcare providers worldwide. With an increasing elderly population and the rising prevalence of chronic conditions such as arthritis, osteoporosis and stroke, there is a need for innovative approaches to deliver effective and accessible care to this population. One potential solution is the use of physiotherapy telerehabilitation [93], which has the potential to provide elderly patients with a more convenient and accessible way to receive care.

One of the primary benefits of using telerehabilitation for the elderly care is that it can help to improve patient access to care. Many elderly patients have mobility limitations or other health conditions that make it challenging for them to travel to healthcare facilities for in-person appointments. By providing care remotely, telerehabilitation can help to ensure that elderly patients receive the support they need to manage their conditions, regardless of their location or mobility status.

Another benefit of telerehabilitation for elderly care is that it can help to improve patient engagement and motivation. Older adults often face social isolation and may experience feelings of loneliness, which can contribute to poor health outcomes. By providing remote care, telerehabilitation can help to provide a sense of connection and engagement with healthcare providers, which can motivate patients to be more proactive about their health and well-being.

Telerehabilitation can also help to reduce healthcare costs and improve the efficiency of care delivery. By providing care remotely, healthcare providers can reach more patients in less time without traveling to different locations. This can help to reduce overhead costs and translate into cost savings for patients and healthcare systems. Telerehabilitation can also help prevent unnecessary emergency room visits or hospitalizations, which can be costly and disruptive to elderly patients' lives.

One potential application of physiotherapy telerehabilitation for elderly care is in the area of fall prevention. Falls are a significant concern for older adults and can lead to severe injuries such as hip fractures or head trauma. Physiotherapy can help improve balance and mobility, reducing the risk of falls. Telerehabilitation can provide a convenient and accessible way for elderly patients to receive physiotherapy services, which can help prevent falls and improve overall quality of life.

There are also challenges associated with using telerehabilitation for elderly care. For

example, not all elderly patients may have access to the necessary technology or infrastructure to participate in remote care. Additionally, there may be concerns about the quality and safety of care delivered through remote means, particularly for elderly patients with complex needs or who require more intensive rehabilitation.

1.7.5 Pediatrics

Pediatrics is a specialized area of healthcare that focuses on the physical, cognitive, and emotional development of children. Physiotherapy plays an essential role in the treatment and management of various pediatric conditions, such as cerebral palsy, muscular dystrophy, and developmental delays [94]. The use of physiotherapy telerehabilitation in pediatrics has the potential to provide children with a more accessible, convenient, and engaging way to receive care.

One of the primary benefits of using telerehabilitation for pediatric physiotherapy is that it can help to improve patient access to care. Many children with disabilities or chronic conditions face challenges in accessing care due to mobility limitations or the need for specialized care. By providing care remotely, telerehabilitation can help to ensure that children receive the support they need to manage their conditions, regardless of their location or mobility status.

Another benefit of telerehabilitation in pediatrics is that it can help to increase patient engagement and motivation. Children often have shorter attention spans and may struggle with in-person physiotherapy sessions. Telerehabilitation can provide a more engaging and interactive platform for physiotherapy, using games, videos, and other multimedia tools to keep children motivated and interested in their therapy sessions.

Physiotherapy telerehabilitation can also help to reduce healthcare costs and improve the efficiency of care delivery. By providing care remotely, healthcare providers can reach more patients in less time without traveling to different locations. This can help to reduce overhead costs and translate into cost savings for patients and healthcare systems. Additionally, telerehabilitation can help prevent the need for unnecessary emergency room visits or hospitalizations, which can be costly and disruptive to children's lives.

One potential application of physiotherapy telerehabilitation in pediatrics is in the area of early intervention for developmental delays. Early identification and intervention for developmental delays can improve children's outcomes and reduce the need for more intensive

interventions later in life. Telerehabilitation can provide a convenient and accessible way for children to receive early intervention services, which can improve developmental outcomes and overall quality of life.

But, there are also defiances associated with using telerehabilitation in pediatrics. For example, younger children may need help with using technology or may need access to the necessary equipment or internet connection. Additionally, telerehabilitation may not be suitable for children with complex conditions or who require more intensive rehabilitation.

In conclusion, physiotherapy telerehabilitation has the potential to transform the way that care is delivered to pediatric patients. By providing more accessible, convenient, and engaging care, telerehabilitation can help to improve patient outcomes, reduce healthcare costs, and enhance patient engagement and motivation. However, some challenges need to be addressed, such as ensuring that patients have access to the necessary technology and infrastructure, and ensuring that the quality and safety of care are not compromised. With continued innovation and investment in this area, physiotherapy telerehabilitation is poised to become an increasingly important component of pediatric care in the years to come.

1.7.6 Athlete rehabilitation

Athlete rehabilitation is a specialized area of physiotherapy that focuses on the recovery and rehabilitation of athletes following injury or surgery [95]. Traditionally, athlete rehabilitation has been conducted in person, with athletes working closely with physiotherapists to develop customized treatment plans and exercises to aid in their recovery. However, the use of physiotherapy telerehabilitation in athlete rehabilitation has the potential to revolutionize the way that care is delivered, providing athletes with a more accessible, convenient, and personalized ways to receive care.

One of the primary benefits of using telerehabilitation in athlete rehabilitation is that it can help to improve patient access to care. Many athletes, particularly those who compete at the elite level, travel frequently, and may struggle to attend in-person appointments with their physiotherapists. By providing care remotely, telerehabilitation can help to ensure that athletes receive the support they need to recover from their injuries, regardless of their location or travel schedule.

Another benefit of using telerehabilitation in athlete rehabilitation is that it can help to improve patient engagement and motivation. Athletes are often highly motivated indivi-

duals who are focused on their recovery and returning to competition as quickly as possible. Telerehabilitation can provide a more engaging and interactive platform for physiotherapy, using video analysis and other multimedia tools to help athletes better understand their injuries and the rehabilitation process.

Telerehabilitation can also help to reduce healthcare costs and improve the efficiency of care delivery. By providing care remotely, healthcare providers can reach more patients in less time without traveling to different locations. This can help to reduce overhead costs and translate into cost savings for athletes and healthcare systems. Additionally, telerehabilitation can help prevent the need for unnecessary emergency room visits or hospitalizations, which can be costly and disruptive to athletes' lives.

One potential application of physiotherapy telerehabilitation in athlete rehabilitation is in the area of injury prevention. Telerehabilitation can provide athletes with access to customized exercise programs and injury prevention strategies that can help to reduce the risk of future injuries. Additionally, telerehabilitation can give the athletes real-time feedback on their form and technique, helping to ensure that they are performing exercises correctly and safely.

In the realm of athlete rehabilitation, the utilization of telerehabilitation is challenging. For example, athletes may require specialized equipment or tools to aid their rehabilitation, which may not be available in all locations. Additionally, telerehabilitation may not be suitable for athletes with complex injuries or who require more intensive rehabilitation.

1.7.7 Mental health

Physiotherapy telerehabilitation is a promising avenue for managing mental health conditions. Mental health disorders are common and can cause significant impairment in individuals' daily lives. Physiotherapy telerehabilitation offers a flexible and convenient way to access care, particularly for those living in rural or remote areas or with difficulty traveling to in-person appointments.

One potential application of physiotherapy telerehabilitation in mental health is for the treatment of anxiety and depression. These are among the most common mental health conditions, and physiotherapy can be an effective adjunct to traditional therapies. Physiotherapy telerehabilitation can provide patients access to evidence-based interventions such as exercise, relaxation techniques, and breathing exercises. Patients can receive instruction

and guidance from their physiotherapist via video conferencing, making it easier to fit therapy into their schedules and reduce travel time.

Another potential application of physiotherapy telerehabilitation in mental health is for the treatment of post-traumatic stress disorder (PTSD). PTSD can develop after exposure to a traumatic event, and individuals with PTSD may experience a range of physical and mental symptoms. Physiotherapy telerehabilitation can offer virtual sessions that provide safe exposure therapy, relaxation techniques, and physical exercise programs that can help manage PTSD symptoms.

Telerehabilitation can also be helpful in the management of chronic pain, which can have a significant impact on mental health. Pain can cause depression, anxiety, and sleep disturbances, which in turn can worsen pain symptoms. Physiotherapy telerehabilitation can provide patients with customized exercise programs that can help manage pain and improve mood. Patients can also receive education on pain management strategies and advice on modifying their activities to reduce pain.

Physiotherapy telerehabilitation can also be effective in the treatment of substance abuse disorders. Substance abuse is a significant public health concern, and individuals with substance abuse disorders are often stigmatized and have limited access to care. Physiotherapy telerehabilitation can provide access to treatment for individuals who may not have access to traditional in-person rehabilitation programs. Patients can receive guidance and support from their physiotherapists through exercises, breathing techniques, and mindfulness-based interventions.

However, one of the main challenges is ensuring the quality and safety of care. Physiotherapists need to be adequately trained to provide care through telehealth platforms and must be able to identify patients who may not be appropriate candidates for virtual care. Additionally, some individuals may require more intensive in-person care, and telerehabilitation may not be suitable for all mental health conditions.

1.8 Physiotherapy telerehabilitation outcomes and challenges

1.8.1 Outcomes of physiotherapy telerehabilitation

Physiotherapy telerehabilitation, which involves the use of technology to deliver physiotherapy interventions remotely, has been shown to have several positive outcomes. These include:

Improved Access to Care

Telerehabilitation allows patients to access physiotherapy services from the comfort of their own homes, which can be especially beneficial for individuals with mobility issues, those who live in remote areas, or those who have difficulty traveling.

Increased Patient Compliance

Telerehabilitation has been shown to improve patient compliance with their rehabilitation program, as it allows patients to complete their exercises at home and on their own schedule. This can lead to better outcomes and faster recovery times.

Cost Savings

Telerehabilitation can be less expensive than traditional in-person physiotherapy, as it eliminates the need for patients to travel to appointments and reduces the need for physical therapy facilities.

1.8.2 Challenges of Physiotherapy Telerehabilitation

Technology Limitations

Telerehabilitation requires reliable technology, such as high-speed internet and video conferencing software, which may not be available to all patients. In addition, some patients may have difficulty using the technology, which could limit their ability to participate in telerehabilitation.

Lack of Personal Interaction

Telerehabilitation may not provide the same level of personal interaction between the patient and physiotherapist as traditional in-person physiotherapy. This could limit the physiotherapist's ability to provide hands-on care or make adjustments to the patient's treatment plan based on their physical response.

Privacy and Security Concerns

Telerehabilitation raises concerns about the privacy and security of patient information. Physiotherapy practices must ensure that they are using secure technology and following best practices for data protection to ensure patient confidentiality is maintained. Overall, despite the challenges, telerehabilitation has the potential to improve access to physiotherapy services, increase patient compliance, and reduce costs. With continued advancements in technology and increased adoption of telerehabilitation by physiotherapy practices, it is likely that telerehabilitation will become an increasingly important part of physiotherapy treatment in the future.

1.9 How we can improve the physiotherapy telerehabilitation?

There are several ways to improve physiotherapy telerehabilitation, including:

Customized treatment plans

Creating personalized treatment plans for patients based on their individual needs and goals.

Interactive exercises

Using interactive exercises and gamification to make the rehabilitation process engaging and fun for patients.

Real-time feedback

Providing real-time feedback to patients during their exercises to improve their technique and motivate them.

Remote monitoring

Using technology to remotely monitor patients' progress and adjust their treatment plans accordingly.

Wearable devices

Using wearable devices to track patients' movements and provide feedback to both patients and therapists.

Videoconferencing

Utilizing videoconferencing allows patients to interact with their therapists in real-time and receive guidance and support.

Tele-assessment

Conducting tele-assessments to evaluate patients' progress and determine if adjustments need to be made to their treatment plans.

Accessible platforms

Ensuring that telerehabilitation platforms are accessible and easy to use for patients of all ages and abilities.

Collaborative approach

Encouraging a collaborative approach between patients, therapists, and healthcare providers to ensure the best outcomes.

Adapting to new technology

Continuously adapting to new technology and incorporating it into telerehabilitation to improve patient outcomes.

Continuous evaluation

Continuously evaluating the effectiveness of telerehabilitation programs and making necessary adjustments to improve outcomes.

1.10 Objectives of the thesis

The objectives of this thesis are to present an artificial intelligence technique integrated into a website to control the rehabilitation progress of some patients. But firstly, we need to study the reliability and validity of the MediaPipe technique and compare it with other popular techniques such as the clinical goniometer and the angle ruler.

The proposed website and the technique used in it will be validated through real experiments.

1.11 Main contributions of the thesis

The main contributions can be listed as follows:

Contribution 1: State of the art

In this part, we will present the first contribution relating to the state of the art and the comparison of different techniques used. It encompasses critical areas like usability, accessibility, privacy, customization, technical support, social support, feedback, patient engagement, and the latest technology trends in motion tracking, 3D animation, and telecommunication. Additionally, it explores the state of the art in physiotherapy telerehabilitation, including virtual reality, gamification, sensors, robotics devices, and computer vision techniques. The section concludes with a discussion on challenges and solutions in AI-driven physiotherapy telerehabilitation.

Contribution 2: Reliability and validity analysis of MediaPipe-based measurement system for some human rehabilitation motions

Our first contribution involves a comprehensive comparison between the MediaPipe technique, a universal goniometer, and a digital angle ruler for measuring range of motion. With the help of physical therapists, data was gathered from approximately 50 healthy volunteers for shoulder movements and 25 healthy persons from knee movements. The reliability of the MediaPipe-based shoulder and knee measurement system was evaluated. To validate this approach, the study determined the 95% limits of agreement and mean difference between the MediaPipe and the other two devices. The results demonstrate the MediaPipe's reliability and validity in the context of telerehabilitation for the specific movements analyzed.

Contribution 3: A new home-based upper- and lower-limb telerehabilitation platform with experimental validation

Introducing a tele-rehabilitation website that serves as a valuable tool for remote rehabilitation. This platform employs the MediaPipe technique to actively monitor and analyze patients' real-time range of motion (ROM). By accurately tracking the angles of limb movement around joints, it significantly aids in assessing progress.

1.12 Organization of the thesis

Chapter 2 provides a state of the art and comparison of different techniques used in physiotherapy telerehabilitation. Section 2.1 describes the human factors for designing a telerehabilitation platform. Section 2.2 shows the technologies and techniques used for physiotherapy telerehabilitation. Section 2.3 presents a comparison of techniques and devices used in physiotherapy telerehabilitation.

Section 2.4 talks about the state on the principal algorithms for detecting and tracking human body keypoints. Section 2.5 details the utilization of human pose estimation in the medical domain. The last section is the conclusion of the chapter.

Chapter 3 introduces the reliability and validity analysis of the MediaPipe-based measurement system for some human rehabilitation motions. It begins with an introduction. Section 3.2 presents the MediaPipe pose estimation technique. Section 3.3 talks about graph construction. Section 3.4 analyzes the reliability and validity of the MediaPipe-based measurement system for some human rehabilitation motions, even in the upper and lower limbs.

Chapter 4 provides the development of a human-based physiotherapy telerehabilitation system with the case study. Section 4.1 is an introduction to the chapter. Section 4.2 presents a survey and open challenge. Section 4.3 describes the proposed system "DzTelerehab". Section 4.4 provides the new home upper- and lower-limb telerehabilitation platform. Section 4.5 presents a patient experimental validation. Section 4.6 presents and discusses the results obtained. Section 4.7 is the conclusion of the chapter.

The last chapter provides a general conclusion and perspectives of the thesis.

1.13 Conclusion

In this chapter, we provide an introduction to artificial intelligence and telerehabilitation. To further explore the fields of physiological rehabilitation, we present a comprehensive overview of the segments and articulations of the human body. Subsequently, we introduce various modes of rehabilitation, along with the exercises specialists recommend for distance rehabilitation. These exercises are simple and can be performed by most individuals. Following that, we define telerehabilitation and provide a historical perspective on its development and application areas. We then discuss the prospects and challenges associated with telerehabilitation, as well as potential methods for improvement.

Finally, we identify the objectives of this thesis and its main contributions. This thesis will thoroughly discuss and examine these points in detail.

Chapter

2 Contribution 1: State of the art

2.1 Human factors for designing telerehabilitation platform

Designing a telerehabilitation platform that is effective and user-friendly requires consideration of a range of human factors. Here are some key human factors to consider when designing a telerehabilitation platform:

Usability

Usability in telerehabilitation is crucial for effective patient and healthcare provider use, impacting care quality and outcomes [96]. The platform must be intuitive, user-friendly, and accessible on various devices, accommodating patients with physical or cognitive impairments. It should facilitate effective communication and engagement through features like video conferencing and educational materials while supporting evidence-based interventions.

Accessibility

Telerehabilitation provides remote access to rehabilitation services, making accessibility crucial. Accessibility involves usability, compatibility, and adaptability.

Privacy and security

Patients' sensitive health information must be protected from unauthorized access and cyberattacks, making compliance with privacy and security regulations essential for telehealth platforms.

Encryption is a key approach, securing data both in transit and at rest. Additionally, data must be stored securely, with access restricted to authorized personnel.

User authentication and access control are crucial. Unique credentials and two-factor authentication ensure only authorized users can access the system, with role-based controls limiting access to relevant data.

Customizability

Customizability is crucial in telerehabilitation, allowing tailored rehabilitation programs to improve patient engagement, motivation, satisfaction, and outcomes.

The integration of multiple healthcare providers and caregivers facilitates communication and coordination, leading to a comprehensive rehabilitation program that considers the patient's medical history, preferences, and goals.

The user interface should also be customizable to meet specific patient needs, such as large fonts for the elderly or accessible features for disabled patients.

Technical support

Telerehabilitation success hinges on well-maintained technology requiring reliable technical support for smooth operation. This support encompasses hardware and software upkeep, troubleshooting, and updates, crucial for maintaining platform functionality and swiftly resolving issues. Accessibility to support is vital for patients and clinicians, who may need aid with setup, connectivity, or data monitoring. A dedicated support team reachable via phone, email, or live chat ensures prompt assistance and uninterrupted rehabilitation progress.

Social support

Patients benefit greatly from social support during rehabilitation, improving adherence and outcomes. Telerehabilitation platforms should integrate features like peer communication, family involvement, and social network integration. Peer-to-peer communication fosters motivation through shared experiences facilitated by chat rooms or forums. Family involvement encourages adherence and emotional support, achievable through virtual sessions or shared educational materials. Social network integration expands support networks beyond the program, enhancing patient connection and motivation. Professional support is

vital, too, with platforms offering virtual appointments or messaging systems for patient-provider communication.

Feedback and monitoring

Telerehabilitation offers real-time feedback and monitoring, which is crucial for effective rehabilitation. Immediate guidance through verbal cues and progress tracking enhances patient outcomes by promptly refining techniques. Remote monitoring via wearable sensors and video recordings allows therapists to track progress and adjust treatment plans accordingly, intervening swiftly to prevent setbacks. This personalized approach, catering to individual needs and motivation levels, ensures patient engagement and achievement of rehabilitation goals.

Patient engagement

Enhancing patient engagement in telerehabilitation is crucial for program effectiveness. Gamification, utilizing game-like elements, boosts motivation through rewards and challenges, fostering adherence. Personalized rehabilitation programs tailored to patient needs and preferences improve relevance and motivation, leveraging patient data for customization. Social support, facilitated through online communities, enhances engagement by fostering connection and motivation.

2.2 State of the art on physiotherapy telerehabilitation

2.2.1 Virtual reality

Virtual reality (VR) is an innovative technology that is increasingly being used in the field of telerehabilitation. The use of VR in telerehabilitation allows patients to participate in immersive, interactive, and engaging exercises that can improve their functional outcomes. The technology has the potential to revolutionize telerehabilitation by providing patients with access to more personalized and effective treatments that can be delivered remotely.

The use of VR in telerehabilitation has been widely studied and has demonstrated positive outcomes in various clinical populations. A recent systematic review of the literature found that the use of VR in telerehabilitation was associated with significant improvements in upper limb function, balance, and gait speed in stroke patients. Another review found that

VR-based telerehabilitation effectively improved arm function and quality of life in patients with multiple sclerosis.

In addition, studies have shown that VR-based telerehabilitation can be as effective as in-person rehabilitation while also providing patients with greater flexibility and convenience. For example, a randomized controlled trial of VR-based telerehabilitation for stroke patients found that the technology was as effective as in-person therapy in improving upper limb function while also improving patient satisfaction and reducing healthcare costs.

The use of VR in telerehabilitation is not limited to stroke and multiple sclerosis patients and the technology has shown promise in improving outcomes for a wide range of clinical populations. For example, studies have shown that VR-based telerehabilitation can improve mobility and balance in patients with Parkinson's disease and reduce pain and disability in patients with chronic low back pain.

Despite the promising results of studies on the use of VR in telerehabilitation, there are still some challenges that need to be addressed. These include the need for more standardized and user-friendly VR platforms, the need for more research on the long-term effects of VR-based telerehabilitation, and the need for more extensive training for healthcare providers on how to use VR technology in their practices.

2.2.2 Serious games

Games have been used as an effective tool in telerehabilitation to promote motivation, engagement, and adherence to therapy programs. The use of games in telerehabilitation has shown promising results in improving functional outcomes in various clinical populations.

A recent systematic literature review found that many researchers use game techniques in telerehabilitation. We can cite some examples:

Reinkensmeyer et al. [97] introduced a telerehabilitation system designed explicitly for arm and hand therapy after a stroke. This system encompasses a web-based library featuring status tests, therapy games, and progress charts. It offers flexibility by supporting various input devices, including a low-cost force-feedback joystick capable of providing assistance or resistance during movements.

In another study, Karime et al. [98] presented a telerehabilitation system known as 'Tele-

Wobble.' This system incorporates a modified version of a wobbleboard equipped with sensors and actuators, a software training game, and a web-service architecture. The purpose of this system is to enable remote control and monitoring of an individual's training progress. It aims to provide doctors with essential performance measurements obtained during training sessions. The outcomes suggested that the Tele-Wobble system could serve as an effective and affordable solution for home-based rehabilitation, explicitly targeting patients with ankle deficiencies.

Molteni et al. [99] developed the HEAD platform, a telerehabilitation system focused on restoring limb motor functions. This system emphasizes the utilization of low-cost sensors, which are connected to a gaming module designed for cognitive-motor rehabilitation. The system connects patients at home and hospital therapists through an infrastructure. The therapists supervise the rehabilitation exercises remotely. The HEAD platform aims to provide accessible and cost-effective rehabilitation solutions.

Octavia et al. [100] created a mobile game application to facilitate hand rehabilitation for stroke patients. This alternative therapy approach employs the interaction design lifecycle model to address specific patient needs within the mobile game application. The study revealed that patients exhibited diverse reactions to the mobile game app, and the games motivated them to work on improving their hand skills. The findings demonstrated the potential of mobile game applications as a valuable tool in hand rehabilitation for stroke patients.

Sierra et al. [9] focused on the development and implementation of a functional telerehabilitation system "SmartRehab" (show figure 2.1), for patients with limited upper- and lower-limb movement due to cerebral palsy. This system utilized interactive virtual environments and biomedical technologies. The system facilitated therapeutic intervention through telerehabilitation by employing video games developed in Scratch® and utilizing Kinect as a movement acquisition interface. The authors developed a video game using a configurable programming language that therapists could easily modify and adjust based on each patient's progress. This interactive and user-friendly approach motivated patients to continue their rehabilitation journey. The study significantly improved upper and lower limb mobility for children with cerebral palsy.

Figure 2.1 : Patients with cerebral palsy using SmartRehab [9].

2.2.3 Sensors

Sensors have emerged as an essential tool in telerehabilitation for monitoring patient progress and providing personalized feedback. The use of sensors in telerehabilitation has shown promising results in improving functional outcomes in various clinical populations.

In movement analysis, sensors can capture data on joint angles, muscle activity, and movement patterns. This data can be used to provide personalized patient feedback and monitor their progress over time. Wearable sensors such as accelerometers and gyroscopes can also be used to measure activity levels and detect changes in physical activity patterns, providing insight into the effectiveness of telerehabilitation programs.

In physiotherapy telerehabilitation, researchers have widely utilized sensors to enhance the effectiveness of rehabilitation programs. Montoya et al. [101] A study involving 24 healthy individuals was conducted to test a physiologically adapted video game, Force Defense. This study aimed to create an immersive virtual rehabilitation experience and implement biocybernetic adaptation for upper-limb rehabilitation. The method utilized surface electromyography (sEMG) signals in real-time to detect fatigue stages and adjust the game interactively. Feedback from participants indicated that the system was both entertaining and beneficial. Interestingly, users of the immersive system achieved perfect results compared to users of the non-immersive system.

In another study, Cesarini et al. [10] introduced a real-time monitoring program designed to support telerehabilitation sessions for the functional recovery of patients' lower limbs. The program used low-cost wearable sensors to monitor limb movements during re-

habilitation exercises. It provided multimodal biofeedback to patients, enhancing the quality of their actions. The system also assisted therapists in defining suitable exercises for each patient and enabled the collection of historical data for monitoring therapy effects and further analysis. This cloud-based approach facilitated remote monitoring and improved the overall effectiveness of telerehabilitation sessions.

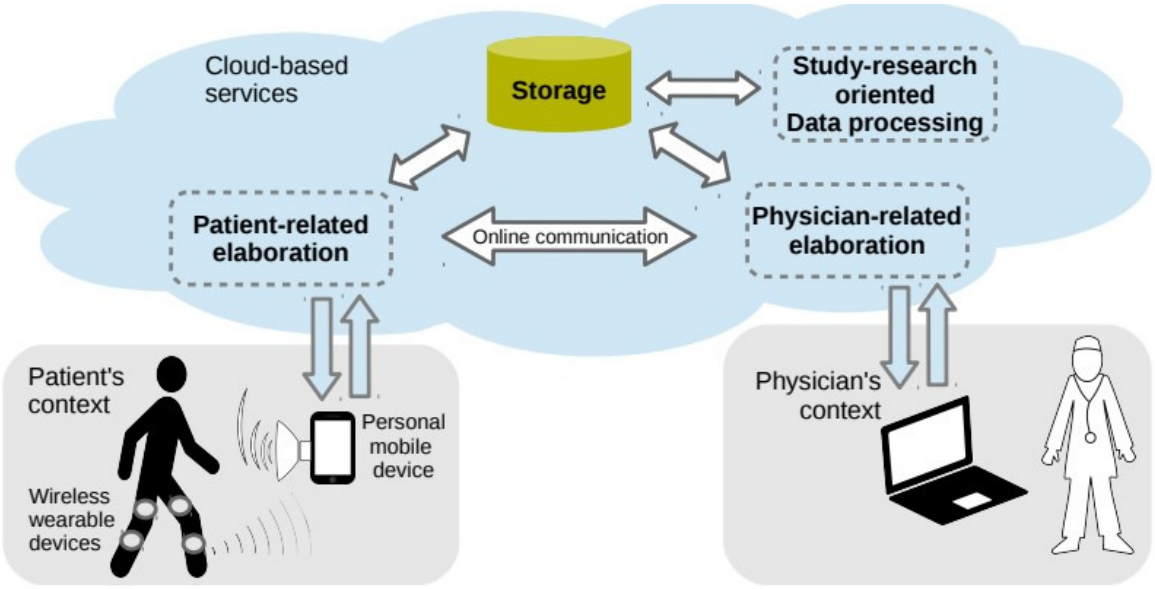


Figure 2.2 : The complete system usage [10].

Ongvisatepaiboon et al. [102] proposed a machine learning method for estimating the angle of rotation of the arm using data from an accelerometer sensor. They focused on utilizing raw readings from the sensor to achieve accurate estimations. Parisi et al. [11] suggested a body-sensor-network-based approach using wireless inertial nodes (Figure 2.3). Their system aimed to diagnose Parkinson's disease automatically and could be employed for telerehabilitation, enabling the remote monitoring of Parkinson's patients. This approach provided a convenient and efficient means of monitoring the disease's progression from a distance.

Bariga et al. [12] presented a general approach utilizing 3D cameras and neural network-based algorithms. The system detected static postures for control purposes and autonomously assisted elderly individuals in rehabilitation exercises. It also could identify abnormal behavior.

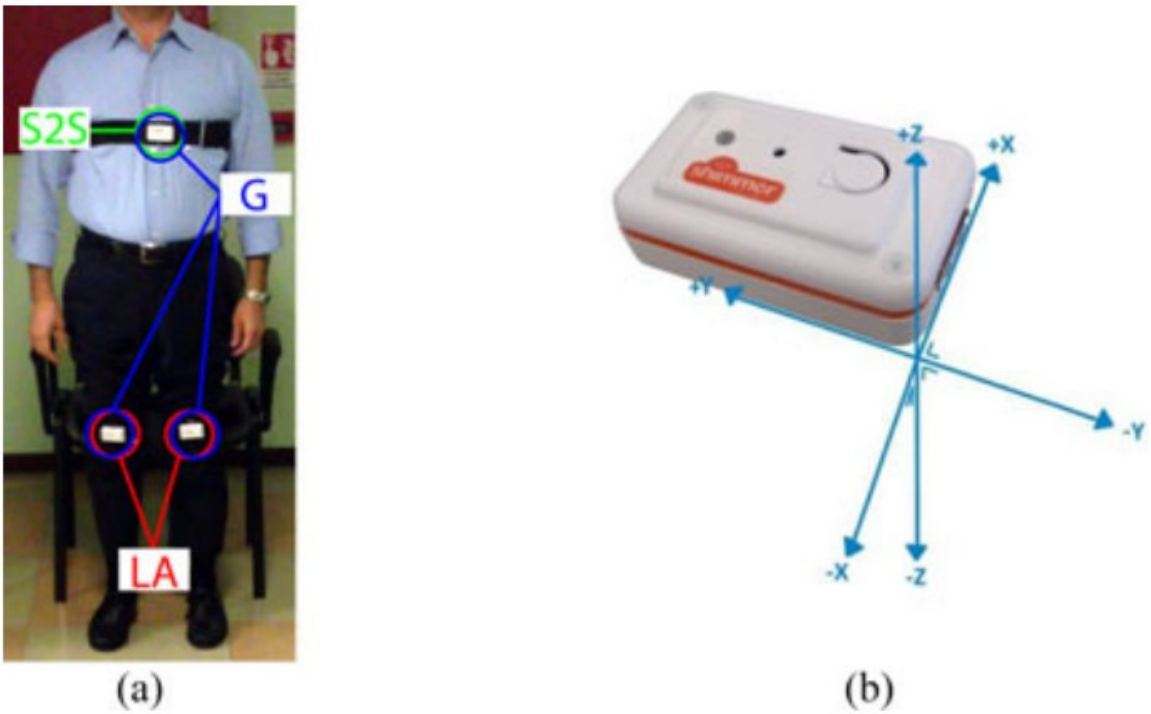


Figure 2.3 : (a) Inertial BSN designed for the evaluation of the three UPDRS tasks of interest (LA, S2S, G): the subsets of nodes used in each task are marked with different colors. (b) Shimmer device (IMU) and its reference coordinate system [11].

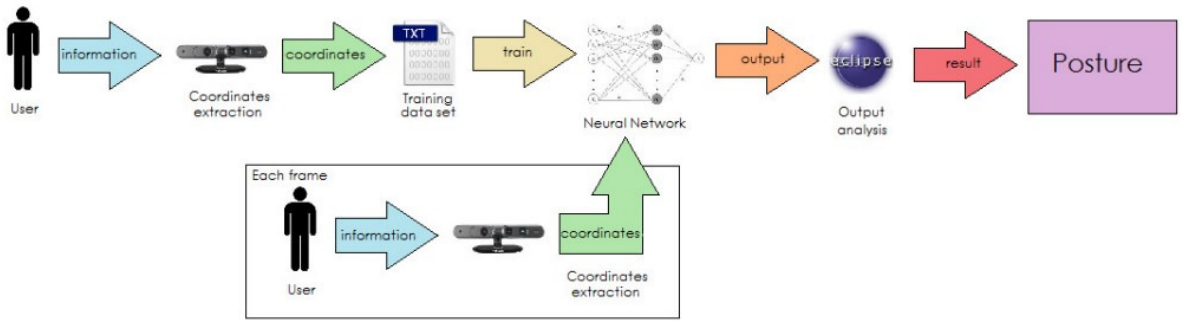


Figure 2.4 : System architecture [12].

Yean et al. [13] proposed two fusion algorithms, namely complementary filter feedback (CFF) and gradient descent using a quaternion-based Kalman filter (KFGD). These algorithms aimed to provide accurate, drift-free 3D orientation estimates for early-stage rehabilitation. The evaluation demonstrated that CFF effectively corrected drifting trends while KFGD outperformed other methods and exhibited good alignment with reference values. These algorithms offered reliable results and addressed issues related to drift and direction changes.

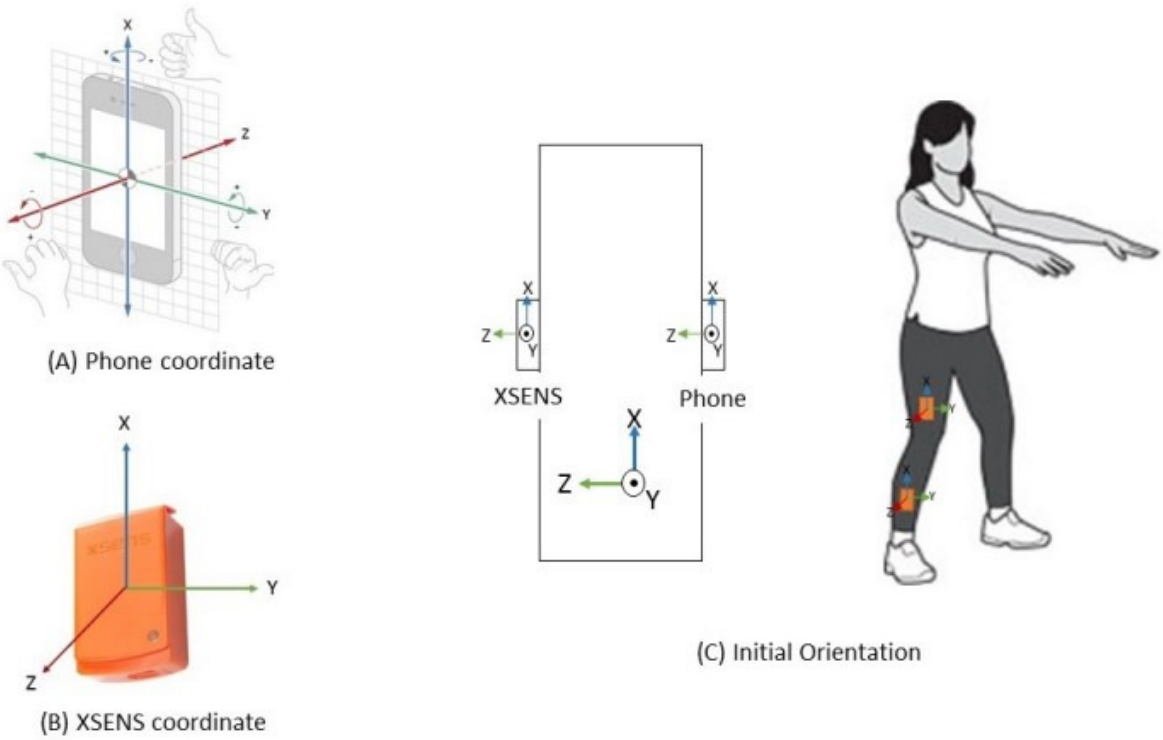


Figure 2.5 : Placement and Initial Orientation of Sensors to avoid Gimbal Lock [13].

Buonocunto et al. [14] developed a platform for reinforcing the functional recovery of limbs through a telerehabilitation program. They designed a low-cost, wearable sensor capable of real-time data processing. The sensor featured a simple interface that met doctors' requirements and addressed common issues associated with sensors available in the market.

Naembadi et al. [103] implemented a telerehabilitation program in northern Denmark

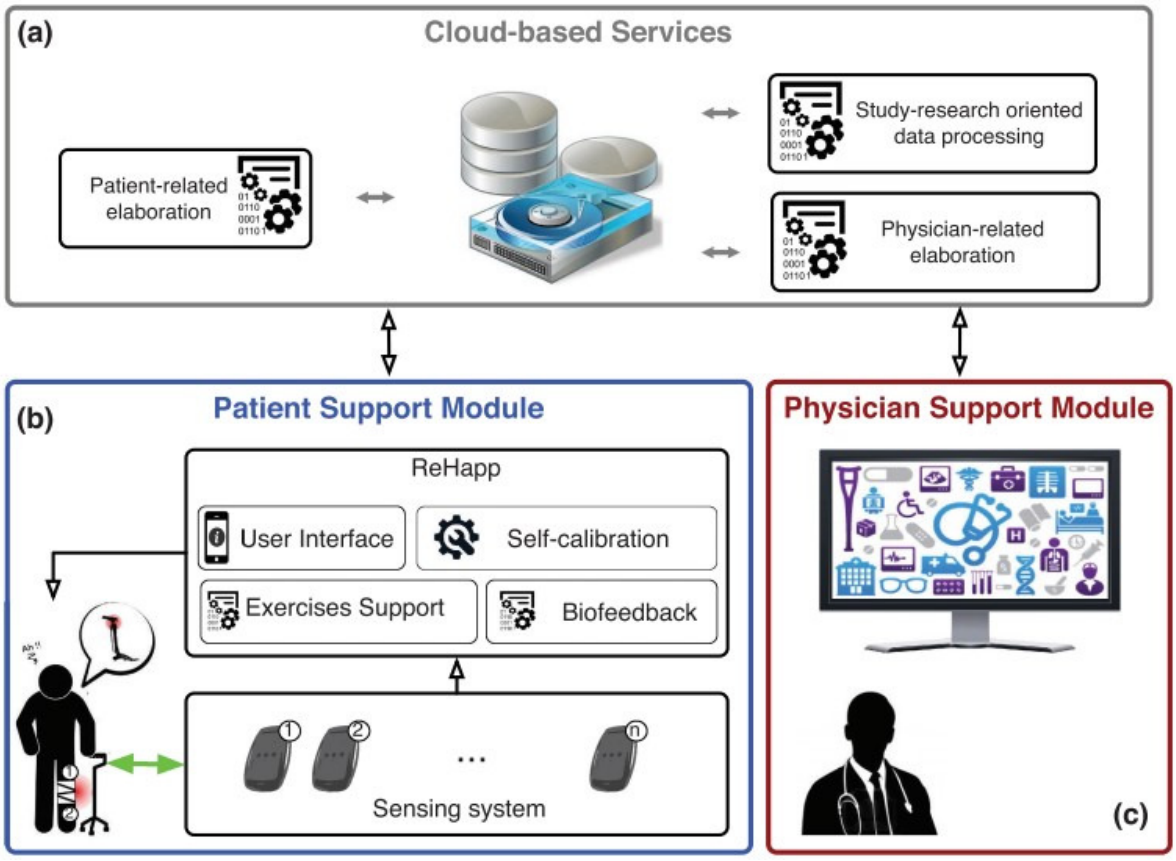


Figure 2.6 : The proposed telerehabilitation framework: (a) Patient Support Module, (b) Cloud-based Services, and (c) Physician Support Module. [14].

to evaluate its feasibility as a substitute for self-training programs for individuals who had been discharged after knee surgery.

Valencia et al. [15] proposed an IMU-POF (inertial measurement unit-polymer optical fiber) sensor fusion system that utilized a knee sleeve to predict knee flexion-extension angles. This system facilitated accurate knee placement determination and could be utilized in online applications with some adaptations. Additionally, it showed potential for exoskeleton and soft-robotics applications. Antunes et al. [104] employed two IMU sensors connected to the lower limb above and below the knee using a dual-patch system to measure knee flexion in patients recovering from knee replacement surgery at home.

To conclude, sensors have emerged as an essential tool in telerehabilitation for monitoring patient progress and providing personalized feedback. The use of sensors in telereha-

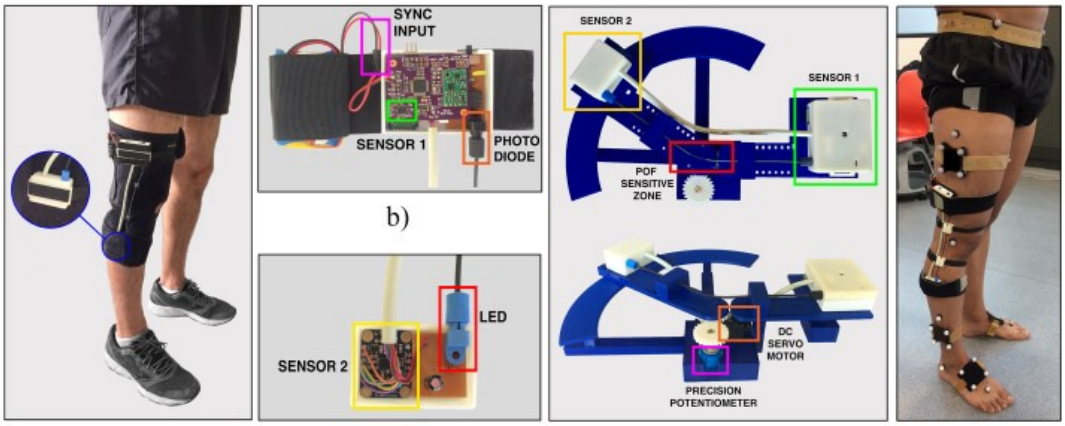


Figure 2.7 : (a) Knee sleeve system placed on a participant. Instrumented part: (b) main hardware unit and (c) second unit. (d) Experimental setup for POF curvature sensor characterization, (e) marker set (Plug-in-Gait lower body model), marker clusters and IMU-POF system placed on a participant [15].

bilitation has shown promising results in improving outcomes for patients with Parkinson's disease, stroke, and other clinical populations. While there are some limitations to the use of sensors in telerehabilitation, continued research, and development have the potential to address these limitations and further improve the effectiveness and accessibility of sensor-based telerehabilitation programs.

2.2.4 Robotics devices

Recently, a growing interest has been in using robotics devices for physiotherapy telerehabilitation. Robotic devices, such as exoskeletons and robot-assisted therapy, have shown great promise in enhancing the effectiveness of telerehabilitation. Exoskeletons are wearable robotics devices that can assist patients with lower limb paralysis in walking and standing. These devices use motors and sensors to detect the patient's movements and provide the necessary assistance. They can be controlled remotely by a physiotherapist, allowing telerehabilitation sessions to occur. Robot-assisted therapy involves using robots to guide and assist patients in performing exercises. These robots can provide feedback on the patient's movements and adjust the level of assistance based on their performance.

The use of robotics devices in telerehabilitation has several benefits. First, it allows patients to receive rehabilitation services from the comfort of their own homes, which can

increase accessibility and reduce the need for travel. Second, these devices can provide real-time feedback and adjust the level of assistance based on the patient's performance, which can enhance the effectiveness of rehabilitation. Third, robotics devices can create a safe and controlled environment for patients to practice their movements, reducing the risk of injury.

Various examples in literature have showcased the use of robotics devices in telerehabilitation. For instance, Park et al. [16] proposed a portable teleassessment system for remote estimation of elbow impairments in patients with neurological disorders (show figure 2.8). They used a controller device and an agent device to control a mannequin arm and the subject's arm sequentially and measured the elbow flexion angle and torque. The physiotherapist could observe the movement of the mannequin arm to assess the spasticity/contracture of the subject's elbow and set the active range of motion (ROM) accordingly. Two different methods of teleoperation were utilized to address network latency issues based on the speed of the tasks. The first method used real-time teleoperations for lazy movements, while the second one, teach-and-replay teleoperations, was used for functions involving rapid movements. This system allowed doctors to check several aspects of a stroke survivor's elbow, including range of motion, muscle strength, and spasticity.

Another example is the mechatronics master-slave setup for hand telerehabilitation, as suggested by Cortese et al. [17], which includes a sensorized glove and a powered hand exoskeleton (show figure 2.9). This setup offers three key benefits. Firstly, it provides physiotherapists with an intuitive interface for controlling the rehabilitation exercises. Secondly, the exoskeleton can offer efficient therapy outside of the hospital without the physical presence of the physiotherapist. Thirdly, a sensorized object is integrated into the setup, allowing manipulation exercises and patient development recording. In light of the COVID-19 situation, Bouteraa et al. [18] presented a portable and easy-to-use remote rehabilitation solution for wrist movements, such as flexion-extension and ulnar-radial movement. To ensure a convenient and secure rehabilitation operation, they integrated a fuzzy logic-based decision-making system into the control architecture to control the pain level (show figure 2.10). Biofeedback, current, and position sensors were used to estimate the pain level.

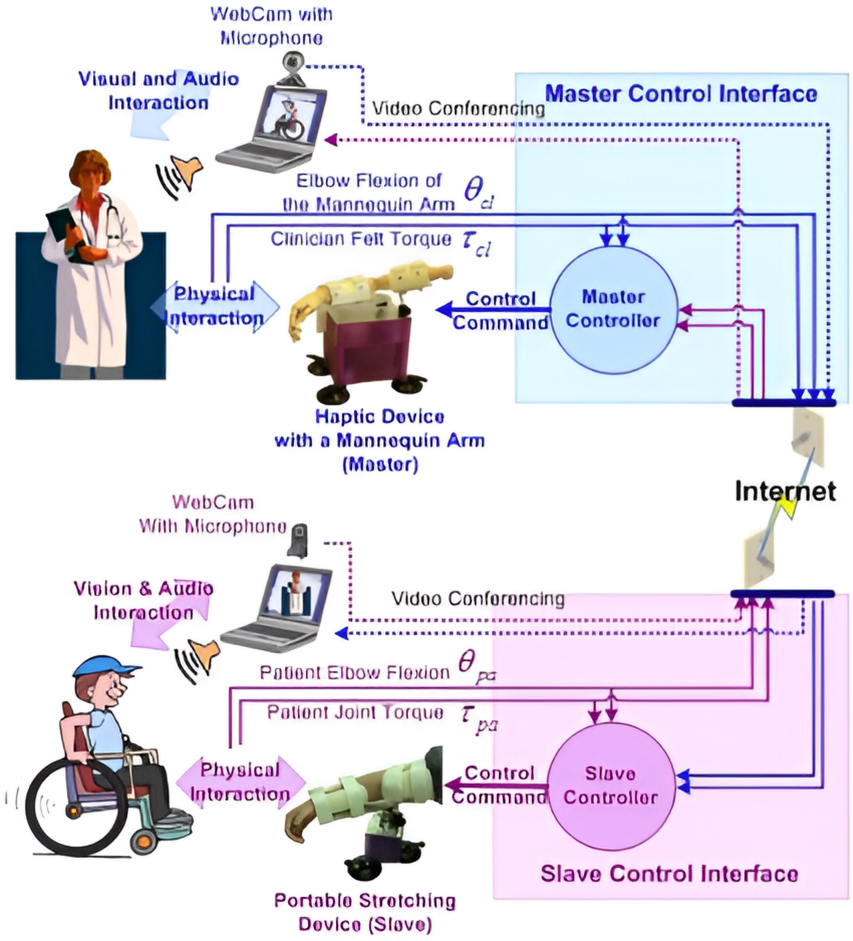


Figure 2.8 : Schematic diagram of the telerehabilitation system. The master and the slave devices provide physical interactions between the doctor and the patient with remote controls based on the position and torque measurements at both devices. In addition, the doctor and the patient can see and talk to each other utilizing a pair of webcameras and microphones [16].

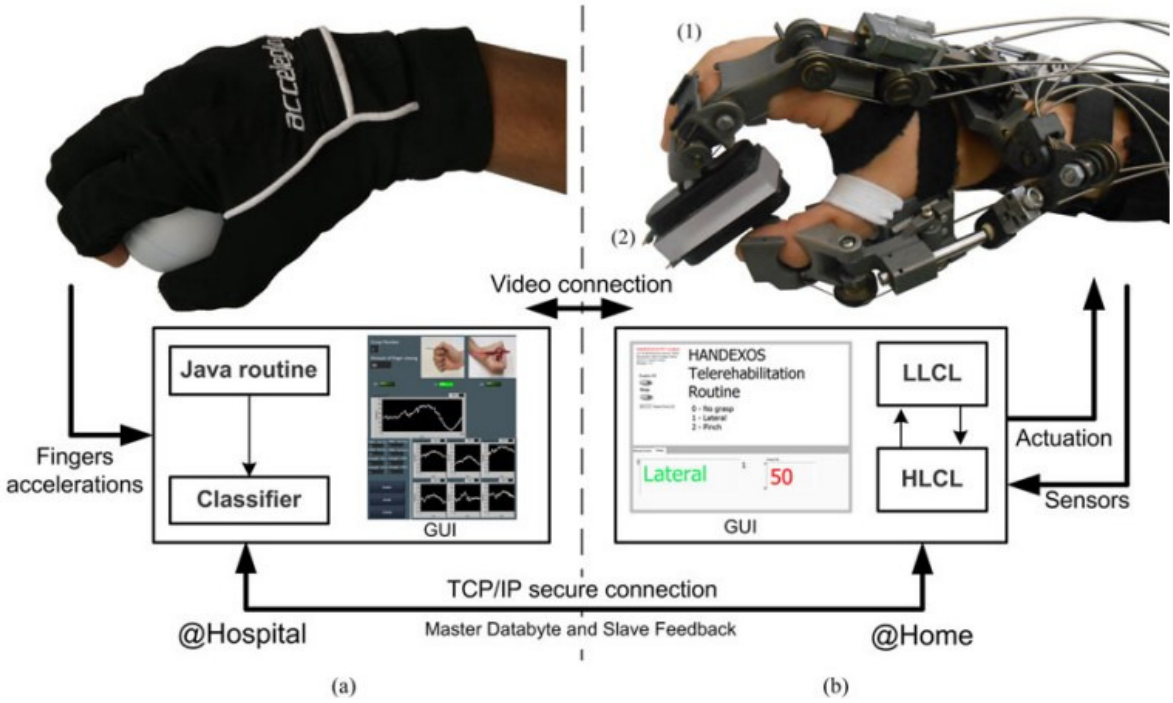


Figure 2.9 : Overview of the master–slave telerehabilitation system (a) Master unit: Acceleglove worn by the therapist. (b) Slave unit: (1) the hand exoskeleton worn by the patient and (2) the sensorized object [17].

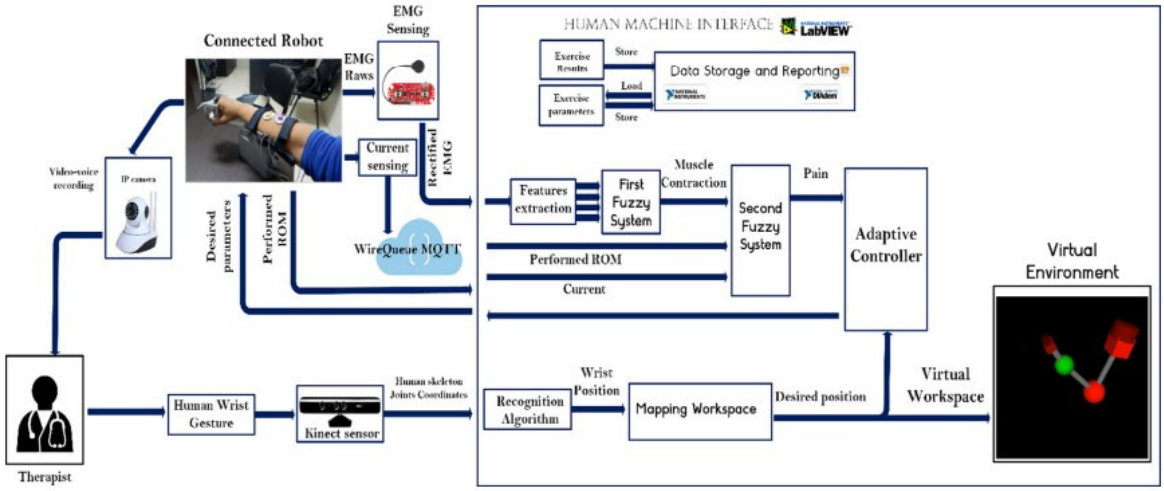


Figure 2.10 : Control Architecture Overview [18].

2.2.5 Computer vision techniques

These techniques involve the use of computer algorithms to analyze video recordings of patients' movements and provide feedback to physiotherapists, which can aid in remote diagnosis and monitoring of patients.

One of the most commonly used computer vision techniques in physiotherapy telerehabilitation is markerless motion capture. This technique involves using computer vision algorithms to track the movements of a patient's body without the need for physical markers or sensors. By analyzing video recordings of the patient's movements, the computer can accurately capture joint angles, positions and velocities, allowing for a more accurate assessment of the patient's range of motion and motor function such [19] (show figure 2.11).

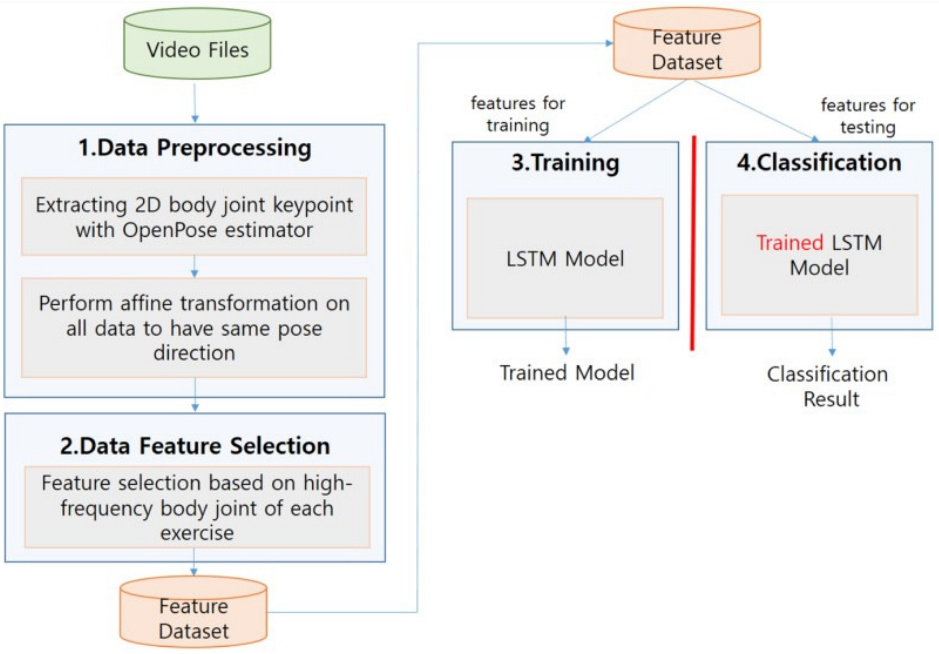


Figure 2.11 : Overall process of proposed system [19].

Another computer vision technique that is frequently used in physiotherapy telerehabilitation is gait analysis. By analyzing video recordings of a patient's gait, computer vision algorithms can detect abnormalities in walking patterns, such [20]. This information can then be used by physiotherapists to develop tailored rehabilitation programs that target specific areas of weakness or imbalance in the patient's gait.

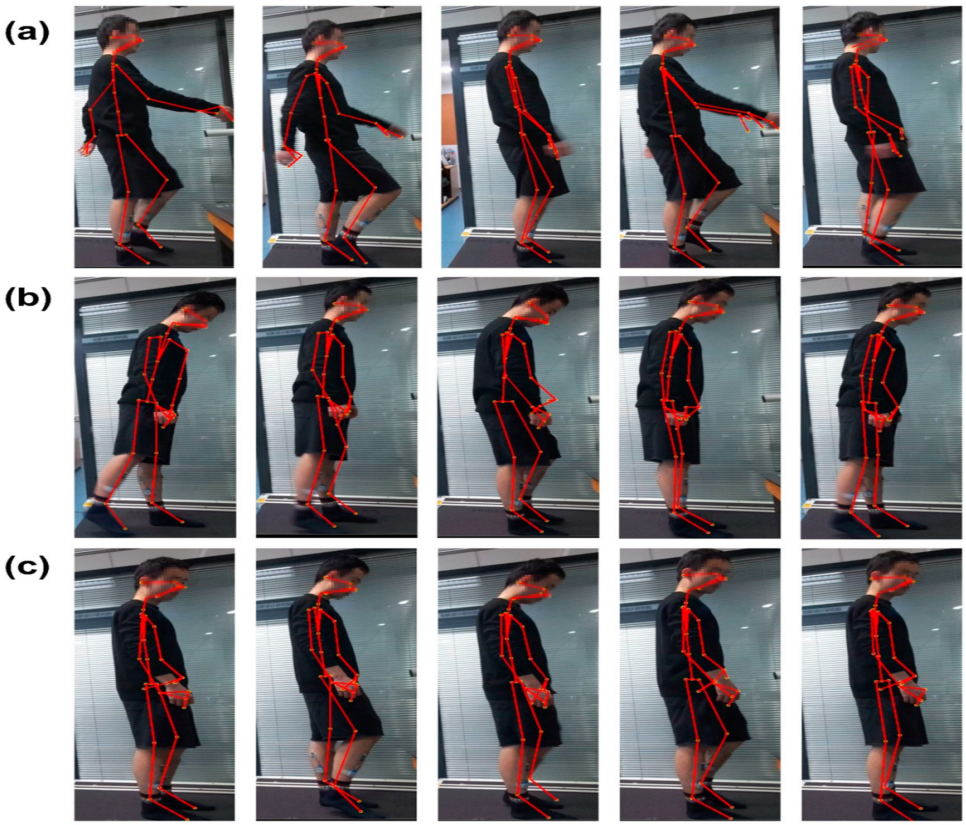


Figure 2.12 : Illustration of gait kinematics information acquisition, including angles and velocity of the joints using Kinect skeletal tracking SDK, Open CV, and Visual Studio software. Kinematics information of 3 gait patterns was obtained for offline data analysis. (a) The tracking sequence of normal gait (NG); (b) The tracking sequence of pelvic obliquity (PO) gait; (c) The tracking sequence of knee hyperextension (KH) gait [20].

Computer vision techniques can also be used to assess posture and balance in patients with conditions such as Parkinson's disease or stroke. By analyzing video recordings of patients performing specific movements, computer vision algorithms can detect abnormalities in posture, such as slouching or leaning to one side, and provide feedback to physiotherapists on how to address these issues.

2.3 Comparison of techniques and devices used in physiotherapy telerehabilitation

Telehealth technologies have significantly advanced the landscape of physiotherapy, offering various solutions for remote rehabilitation. In this section, we explore and compare different techniques and devices utilized in physiotherapy telerehabilitation, highlighting their advantages and disadvantages.

In order to compare telehealth technologies we must take in consideration different points before:

2.3.1 Accuracy and reliability

Accuracy and reliability are among the most significant challenges of using AI for physiotherapy telerehabilitation. While AI has the potential to enhance the quality and effectiveness of telerehabilitation services; it is critical to ensure that the algorithms and models used are accurate and reliable. Here are some key points to consider:

Data quality

The accuracy and reliability of AI models in physiotherapy telerehabilitation depend heavily on the quality of the data that is used to train them. Ensuring that the data is accurate, reliable, and representative of the patient population served is essential. This can be challenging, as data may be incomplete, inconsistent, or biased in various ways.

Algorithmic bias

AI models can also be biased in various ways, leading to inaccurate or unreliable results. For example, if an AI model is trained on data from a particular demographic group, it may not be as effective for other groups. To address this, it is important to ensure that AI models are trained on diverse and representative data sets.

Interpretability

Another challenge associated with using AI in physiotherapy telerehabilitation is the interpretability of the models. It can be challenging to understand how an AI model arrived at a particular result, making it difficult to trust and use the model effectively. Researchers are working to develop techniques for making AI models more interpretable, such as by visualizing the decision-making process. **Clinical validation**

To ensure the accuracy and reliability of AI models in physiotherapy telerehabilitation, it is essential to validate them through rigorous clinical trials. This can help to identify any limitations or potential biases in the models and ensure that they are effective for the patient population being served.

User feedback

Finally, it is essential to gather feedback from patients and clinicians who use AI-enabled telerehabilitation services. This feedback can help to identify any issues with the accuracy or reliability of the AI models and inform improvements to the technology.

2.3.2 Personalization

While AI has the potential to enhance the quality and effectiveness of telerehabilitation services, it is critical to ensure that the algorithms and models used can be tailored to the individual needs and characteristics of each patient. Here are some key points to consider:

Data collection

Personalized physiotherapy telerehabilitation requires collecting and analyzing a wide range of data, including patient health records, medical images, and patient-generated data such as motion tracking and activity level. It is vital to ensure that data collection is done in a secure and privacy-preserving manner.

Machine learning

Machine learning algorithms can analyze patient data and identify patterns that can help inform personalized treatment plans. For example, machine learning can remember which exercises are most effective for a patient based on their previous performance and feedback. However, it is crucial to ensure that the machine learning algorithms are trained on diverse and representative data sets to avoid algorithmic bias.

User interface

The user interface of the telerehabilitation platform should be designed to enable personalization. For example, the platform should be able to adapt to the individual needs and preferences of each patient, such as adjusting the difficulty level of exercises or providing real-time feedback.

Patient feedback

Personalization requires ongoing feedback from patients to inform adjustments to their

treatment plans. This feedback can be collected through various means, such as patient surveys or patient-generated data such as motion tracking and activity level.

Clinical validation

To ensure that personalized physiotherapy telerehabilitation is effective, it is essential to validate it through rigorous clinical trials. This can help to identify any limitations or potential biases in the treatment plan and ensure that it is effective for the patient population being served.

2.3.3 Accessibility

Accessibility is one of the most significant challenges associated with using AI for physiotherapy telerehabilitation. Here are some key points to consider:

Technology access

One of the main challenges of using AI for physiotherapy telerehabilitation is ensuring that patients have access to the necessary technology to use the platform. This includes reliable internet access, appropriate devices, and software. Ensuring accessibility may require providing additional support to patients, such as loaning equipment or providing technical support.

Language and cultural barriers

Another challenge is ensuring that the platform is accessible to patients with different language and cultural backgrounds. The platform should be designed to support multiple languages and cultural preferences to ensure that patients can understand and engage with the treatment plan.

Disability accessibility

The platform should be designed to support patients with disabilities, such as visual, hearing, or motor impairments. This may require incorporating assistive technologies or adjusting the user interface to accommodate different needs.

Cost and affordability

The cost of accessing the telerehabilitation platform may be a significant barrier for patients, particularly for those who do not have insurance coverage or have limited financial resources. Addressing affordability may require working with insurance providers, government agencies, or non-profit organizations to ensure that patients have access to the necessary resources.

Digital literacy

Not all patients may be comfortable or familiar with using technology, which can make accessing the telerehabilitation platform difficult. Providing training and support to patients can help to address this barrier and ensure that patients can fully engage with the platform.

2.3.4 Privacy and security

Privacy and security are crucial challenges associated with using AI for physiotherapy telerehabilitation. Here are some key points to consider:

Patient data protection One of the primary concerns with using AI for physiotherapy telerehabilitation is ensuring the privacy and security of patient data. Patient data should be encrypted during transmission and stored securely to protect against data breaches or unauthorized access.

Compliance with regulations

The platform must comply with local and national regulations governing the collection, storage, and use of patient data. For example, in the United States, platforms must comply with the Health Insurance Portability and Accountability Act (HIPAA) to ensure the confidentiality of patient health information.

User authentication and access control

The platform should use strong user authentication protocols and access controls to ensure that only authorized individuals can access patient data. This includes implementing multi-factor authentication and role-based access control.

Transparency and informed consent

Patients must be fully informed about how their data will be collected, stored, and used. This includes providing patients with clear and concise information about the platform's data privacy and security practices and obtaining their informed consent to participate in the program.

Cybersecurity threats

The platform must be designed to protect against cyber attacks, such as phishing attempts or ransomware attacks. This requires implementing security controls, such as firewalls, intrusion detection systems, and anti-malware software.

Privacy and security are significant challenges associated with using AI for physiotherapy telerehabilitation. Addressing these challenges requires attention to patient data pro-

tection, compliance with regulations, user authentication and access control, transparency and informed consent, and cybersecurity threats. By addressing these challenges, it may be possible to increase patient trust and confidence in the platform and ensure the confidentiality, integrity, and availability of patient data.

2.3.5 Integration

Integrating AI into physiotherapy telerehabilitation can be challenging for several reasons. Here are some details about these challenges:

Limited access to data AI requires large amounts of high-quality data to be effective, but in physiotherapy, access to such data can be limited. Patients may not have access to sensors or wearables that can track their movements, and there may be privacy concerns around collecting and sharing patient data.

Lack of standardization

There is no standardization in the types of data collected or the methods used to collect data in physiotherapy. This can make it difficult for AI systems to learn and make accurate predictions.

Interpretation of data

Physiotherapists use their clinical expertise to interpret patient data and make decisions about treatment plans. AI systems may not have the same level of clinical knowledge and may struggle to interpret data accurately.

Technical challenges

Integrating AI into physiotherapy telerehabilitation requires technical expertise, including knowledge of machine learning algorithms, data analysis, and software development. This expertise may not be readily available in the physiotherapy field.

Ethical considerations

The use of AI in healthcare raises ethical concerns, such as ensuring patient privacy and avoiding bias in the algorithms used. These issues must be addressed before AI can be fully integrated into physiotherapy telerehabilitation.

Despite these challenges, there are potential benefits to integrating AI into physiotherapy telerehabilitation, such as providing personalized treatment plans, remote monitoring, and predictive analytics. However, overcoming the challenges will require collaboration between

healthcare providers, researchers, and technical experts to develop and implement effective AI solutions.

2.3.6 Cost-effectiveness

Cost-effectiveness is one of the most significant challenges of using AI in physiotherapy telerehabilitation. Here are some details about this challenge:

Initial investment

One of the major challenges of integrating AI into physiotherapy telerehabilitation is the high initial investment required. This includes the development of AI algorithms, software, and hardware. Smaller healthcare providers may find these costs prohibitive, and this could limit the adoption of AI technology in the field.

Maintenance costs

Once an AI system is implemented, there are ongoing costs associated with maintenance, including software updates and hardware repairs or replacement. These maintenance costs can be significant, particularly for smaller healthcare providers with limited resources.

Training costs

Healthcare providers may require training to effectively use AI technology in their practices. This training can be costly and time-consuming and may require additional resources, such as specialized trainers.

Reimbursement policies

In some countries, reimbursement policies for telehealth and AI technology are not well established. This can make it challenging for healthcare providers to recover their investment costs.

Uncertainty in return on investment

The return on investment for using AI in physiotherapy telerehabilitation can be uncertain. While AI technology has the potential to improve patient outcomes and reduce costs, it may take some time to realize these benefits.

Despite these challenges, the potential benefits of using AI in physiotherapy telerehabilitation, such as personalized treatment plans, remote monitoring, and predictive analytics, may outweigh the costs over time. Healthcare providers and policymakers need to carefully consider the costs and benefits of implementing AI technology and ensure that it is used effectively and efficiently to maximize its potential.

2.3.7 Discussion

Telerehabilitation, particularly in the field of physiotherapy has emerged as a promising approach to provide remote healthcare services to patients. Advancements in technology, such as robotics devices, sensors, and artificial intelligence (AI) techniques have significantly contributed to the development of telerehabilitation systems. In this chapter, we discussed the state of the art in physiotherapy telerehabilitation, focusing on the utilization of these technologies and the challenges they present, along with potential solutions.

Integrating robotics devices in physiotherapy telerehabilitation has revolutionized the field by enabling remote patient assessment and treatment. These devices offer various benefits, including precise movement tracking, customized therapy, and real-time feedback. Patients can receive guided rehabilitation exercises tailored to their specific needs by incorporating robotic assistance. Additionally, robotic devices can assist in motor control training and provide therapists with objective measurements of patient progress.

Sensors play a crucial role in physiotherapy telerehabilitation systems as they facilitate the collection of valuable patient data. Sensor technologies, such as accelerometers, gyroscopes, and force sensors, enable the accurate monitoring of movements, muscle activity, and balance. This data can be used to evaluate patient performance, track progress, and detect abnormalities. Sensors also allow for remote monitoring of patients' vital signs, ensuring their safety during rehabilitation sessions.

The application of AI techniques in physiotherapy telerehabilitation has further enhanced the capabilities of these systems. Machine learning algorithms can analyze large datasets from patients' sensor readings and identify patterns or anomalies. This information can assist in assessing patient progress, predicting outcomes, and personalizing treatment plans. AI can also be used to develop intelligent virtual assistants or chatbots that provide personalized guidance and support to patients, enhancing their engagement and adherence to therapy protocols.

Despite the potential benefits, several challenges exist in using AI for physiotherapy telerehabilitation. One major concern is the need for robust and reliable data transmission and storage infrastructure to ensure the secure transfer of patient information. Additionally, privacy and data protection issues must be I have carefully addressed this to protect patient confidentiality. Another challenge lies in the integration and interoperability of different technologies and systems to provide a seamless telerehabilitation experience.

To overcome these challenges, various solutions can be considered. Firstly, collaboration between researchers, clinicians, engineers, and policymakers is vital to establishing standards and guidelines for developing and implementing telerehabilitation systems. This collaboration can ensure the ethical use of AI and adherence to privacy regulations. Secondly, advancing data analytics techniques, including AI algorithms, can help extract meaningful insights from patient data, leading to improved clinical decision-making. Furthermore, investing in developing secure and scalable telecommunication infrastructure can enhance data transmission efficiency and security.

The following table provides an overview of key approaches, each presenting unique features that cater to different aspects of patient assessment and engagement.

Technique / Device	**Advantages**	**Disadvantages**
Teleassessment Systems	Simple and cost-effective; enables remote assessment of physical function through video conferencing.	May not provide as accurate an assessment as other techniques. Limited ability to conduct hands-on evaluations.
Markerless Motion Capture	More accurate assessment of range of motion and motor function without physical markers; utilizes computer vision algorithms.	Requires advanced technology and expertise; may have higher implementation costs. Limited in capturing fine details of movement.
Wearable Sensors	Provides objective data on patient progress; facilitates tailored rehabilitation programs.	Can be expensive and inaccessible to certain patient populations. Continuous monitoring may lead to potential privacy concerns.
Virtual Reality	Offers an immersive rehabilitation experience simulating real-world movements; aids in improving physical function and reducing injury risk.	High cost of virtual reality technology; limited accessibility for all patients. May cause motion sickness in some individuals.
Robot-Assisted Therapy	Provides consistent and controlled rehabilitation experience using robotic devices.	Requires advanced technology; may not be accessible to all patients. Lack of adaptability to individual patient needs.

Table 2.1 : Advantages and Disadvantages of Techniques and Devices in Physiotherapy Telerehabilitation

2.4 State of the art on the principal algorithms for detecting and tracking human body keypoints

2.4.1 Tflite

TFLite, or TensorFlow Lite, is a lightweight version of TensorFlow optimized for mobile and embedded devices, enabling high-performance, low-latency machine learning applications directly on devices like smartphones and wearables. A key feature is human body pose estimation, used in fitness tracking, motion capture, and augmented reality, with pre-trained models available for immediate use or customization.

TFLite's human pose estimation models use a technique called Convolutional Pose Machines (CPMs), which is a deep learning architecture that can accurately estimate human body keypoints in real-time. CPMs use a sequence of convolutional neural networks to estimate the probability of each keypoint location [21; 105; 106]. The the output of each network is then used as input to the next network, enabling the model to refine its estimate of the keypoints at each stage of the network.

GPU (Graphics Processing Unit) can be used in conjunction with TFLite (show figure 2.13)to accelerate machine learning computations on mobile and embedded devices. TFLite is a lightweight version of TensorFlow designed explicitly for such platforms.

When using TFLite with a GPU, the workflow typically involves the following steps: model conversion, GPU backend selection, model inference, memory management, parallel processing, and post-processing.

In addition to pose estimation, TFLite also supports a range of other machine learning tasks, including object detection [107], image classification [108] , and natural language processing [109]. TFLite is designed to work seamlessly with TensorFlow allows developers to train and deploy machines easily learning models on a variety of platforms, including mobile and embedded devices.

2.4.2 OpenPose

OpenPose is an open-source library for real-time multi-person keypoint detection and pose estimation. Developed by researchers at Carnegie Mellon University, OpenPose utilizes deep neural networks to identify and track human body keypoints [110; 111], such as the wrists, elbows, and knees, in real-time, from a video or image stream.

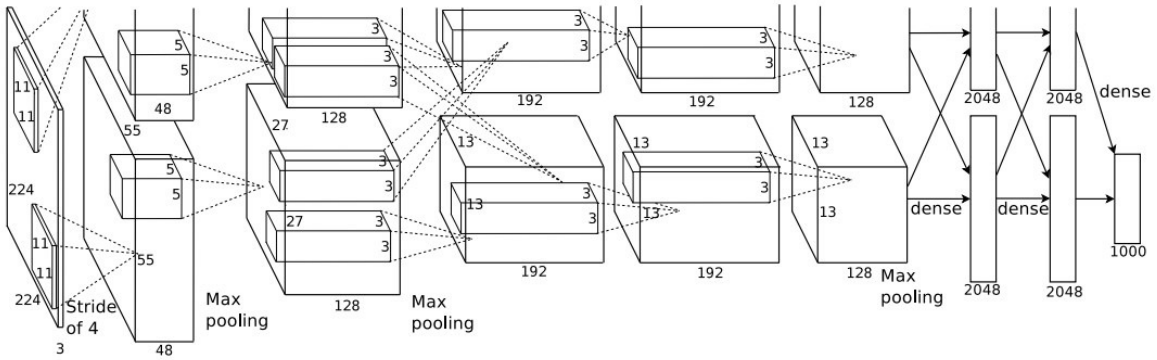


Figure 2.13 : An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440−186,624−64,896−64,896−43,264−4096−4096−1000. [21].

OpenPose's keypoint detection algorithm is based on the concept of part affinity fields (PAFs) [112]. PAFs are a set of two-dimensional vectors that encode the association between two body parts, such as the shoulders and elbows. These vectors estimate the likelihood of a particular body part being connected to another body part.

OpenPose uses a deep neural network architecture known as a Convolutional Pose Machine (CPM) to estimate the probability of each keypoint location. The CPM consists of convolutional neural networks that refine the keypoint estimate at each network stage. This allows OpenPose to estimate the pose of multiple people accurately in real-time.

One of the unique features of OpenPose is its ability to handle occlusion and partial body poses. Occlusion occurs when a body part is hidden or obstructed from view, while partial body poses occur when only part of the body is visible. OpenPose uses the Part Affinity Field (PAF) to address these challenges. The PAF is a two-dimensional vector field that encodes the association between body parts. Using the PAF, OpenPose can accurately estimate the location of body parts, even when they are partially occluded or only partially visible.

OpenPose has many applications in areas such as sports analysis [113], entertainment, and robotics [114]. It can be used to track athletes' movements, animate 3D characters in video games and movies, and control robotic systems. OpenPose is also used in the deve-

lopment of human-robot interaction systems, where it is used to enable robots to recognize and respond to human gestures and movements.

2.4.3 Pifpaf

PifPaf is a state-of-the-art algorithm for multi-person pose detection and estimation. Developed by researchers at the French Institute for Research in Computer Science and Automation (INRIA) [22], PifPaf uses deep neural networks to identify and track human body keypoints, such as the elbows, shoulders, and hips.

The PifPaf algorithm is based on the concept of Part Intensity Fields (PIFs) and Part Association Fields (PAFs). PIFs are two-dimensional intensity maps that represent the probability of each pixel belonging to a specific body part, while PAFs are two-dimensional vector fields that encode the association between body parts.

To detect and estimate the poses of multiple people, PifPaf first detects the PIFs and PAFs in an input image using a deep neural network. It then uses a greedy decoding algorithm to group the PIFs and PAFs into individual poses.

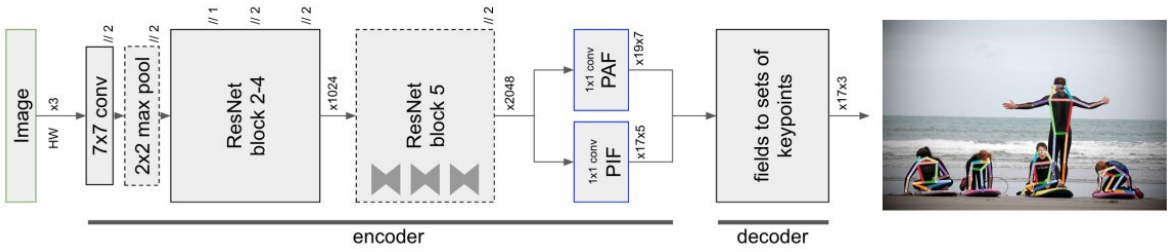


Figure 2.14 : Model architecture. The input is an image of size (H, W) with three color channels, indicated by "x3". The neural network based encoder produces PIF and PAF fields with 17×5 and 19×7 channels. An operation with stride two is indicated by "//2". The decoder is a program that converts PIF and PAF fields into pose estimates containing 17 joints each. Each joint is represented by an x and y coordinate and a confidence score [22].

One of the unique features of PifPaf is its ability to handle occlusion and cluttered backgrounds. Occlusion occurs when one body part is hidden or obstructed from view, while cluttered backgrounds happen when the image contains multiple objects or people. PifPaf uses a technique called multi-scale testing to address these challenges. Multi-scale testing

involves processing the image at different scales to capture the full range of pose variations and to ensure that all body parts are detected even when partially occluded.

Another vital feature of PifPaf is its high accuracy and real-time performance. PifPaf has achieved state-of-the-art results on several benchmark datasets, including the COCO dataset, which is widely used to evaluate pose detection algorithms. Additionally, PifPaf can operate in real-time on a single CPU, making it suitable for mobile and embedded systems.

PifPaf has a wide range of applications, including sports analysis, robotics, and human-robot interaction [115]. It can be used to track the movements of athletes, control robotic systems, and enable robots to recognize and respond to human gestures and movements.

2.4.4 Tfjs (Resnet 50)

Tfjs (Resnet 50) is a deep learning algorithm for detecting and tracking human body keypoints. It is based on the ResNet-50 architecture, which is a deep neural network consisting of 50 layers. The algorithm is designed to detect and track keypoints such as the head, shoulders, elbows, wrists, hips, knees, and ankles in real-time video and image data [116].

One of the critical advantages of Tfjs (Resnet 50) is that it can be run directly in the web browser using TensorFlow.js, a JavaScript library for training and deploying machine learning models. This means that the algorithm can be easily integrated into web-based applications, making it accessible to a broader audience.

Tfjs (Resnet 50) uses convolutional neural networks (CNNs) to detect and track keypoints. CNNs are a deep neural network specifically designed for processing images and can learn to recognize patterns in the data.

The algorithm first processes the input image using a series of convolutional layers to detect keypoints. These layers extract features from the image and identify areas likely to contain keypoints. The algorithm then uses a set of regression layers to predict the location of each keypoint within the image.

One of the strengths of Tfjs (Resnet 50) is its ability to handle complex pose variations and occlusions. The algorithm is trained on large datasets of labeled images and can learn to recognize a wide range of pose variations, including body shape, size, and orientation. It can also handle occlusions, where one body part may be wholly or partially hidden from view.

Another advantage of Tfjs (Resnet 50) is its real-time performance. The algorithm can

process video data at high frame rates, making it suitable for real-time applications such as video-based gaming and augmented reality.

In addition to its applications in detecting and tracking human body keypoints, Tfjs (Resnet 50) has many applications in computer vision and image processing. It can be used for object detection, image classification, and image segmentation.

2.4.5 TFJS (MobileNet)

TFJS (MobileNet) is a deep learning algorithm that can be used for detecting and tracking human body keypoints. This algorithm is based on the MobileNet architecture, which is designed to be lightweight and efficient for deployment on mobile devices. MobileNet uses depthwise separable convolutions, which separate the spatial and channel-wise operations in the convolutional layers, reducing the number of parameters and computations required for training and inference.

The TFJS (MobileNet) algorithm analyzes images or video frames and detects critical points on the human body, such as the shoulders, elbows, wrists, hips, knees, and ankles. These key points are essential for various applications, such as fitness tracking, motion capture, and gesture recognition. The algorithm can also track the movement of these critical points over time, allowing for the analysis of dynamic movements and activities.

One of the advantages of using TFJS (MobileNet) for human body keypoints detection and tracking is its speed and efficiency. The lightweight architecture of MobileNet allows the algorithm to run efficiently on mobile devices, making it ideal for applications such as fitness tracking and rehabilitation exercises. The algorithm can also be run in real-time, allowing immediate performance and movement feedback.

Another advantage of TFJS (MobileNet) for human body keypoints detection and tracking is its accuracy. The algorithm is trained on a large dataset of labeled human body images, allowing it to accurately detect and track key points even in challenging conditions, such as low lighting or occlusions. The algorithm's accuracy can be improved by fine-tuning the model on specific datasets or tasks.

The TFJS (MobileNet) algorithm has numerous potential applications in various fields, such as sports science, healthcare, and entertainment. For example, the algorithm can be used to track the movement of athletes during training or competition, providing coaches and trainers with insights into their technique and performance. In healthcare, the algorithm

can be used for rehabilitation exercises or assessing the progress of patients with movement disorders. In entertainment, the algorithm can be used for motion capture in video games or animation.

However, there are some limitations to using TFJS (MobileNet) for human body keypoints detection and tracking. One limitation is the need for a large and diverse dataset for training the algorithm. Such a dataset can be time-consuming and expensive, particularly for niche applications. Additionally, the algorithm may struggle to detect and track critical points in complex poses or movements or when multiple people are present in the frame.

2.4.6 BlazePose

BlazePose is developed by Google; this algorithm uses deep learning techniques to accurately identify critical points in the human body, including the shoulders, elbows, wrists, hips, knees, and ankles. This information can be used for various applications, such as motion tracking, fitness tracking, and gesture recognition [117].

One of the main advantages of BlazePose is its accuracy. The algorithm is trained on a large dataset of labeled images and videos, which allows it to detect and track key points accurately even in challenging conditions such as low lighting or occlusions. This high level of accuracy makes BlazePose well-suited for applications such as fitness tracking, where precise measurements of movement and posture are essential.

Another advantage of BlazePose is its speed. The algorithm is optimized for real-time performance, which means that it can analyze video frames quickly and efficiently. This makes BlazePose ideal for applications such as motion tracking and gesture recognition, where real-time analysis is necessary for immediate feedback or control.

BlazePose combines deep convolutional neural networks and geometric constraints to detect and track critical points in the human body. The algorithm first segments the body part to identify the person's location in the image or video. It then uses a regression model to estimate the location of the key points and a geometric model to refine the estimated critical points based on their spatial relationships.

BlazePose has numerous potential applications in various fields. For example, in fitness tracking, BlazePose can monitor a person's posture and movement during exercise, providing feedback on form and technique. In sports science, BlazePose can analyze athletes' movements during training or competition, providing insights into their technique and per-

formance. In healthcare, BlazePose can be used for rehabilitation exercises or assessing the progress of patients with movement disorders.

However, there are also some limitations to BlazePose. One limitation is that the algorithm may struggle to detect and track critical points in complex poses or movements or when multiple people are present in the frame. Additionally, BlazePose requires significant computational resources, which may limit its use in specific applications or on specific devices.

BlazePose is a robust computer vision algorithm that accurately detects and tracks human body key points. It's high level of accuracy, real-time performance, and potential applications in various fields make it a valuable tool for researchers, developers, and practitioners. While the algorithm has some limitations, its strengths make it a promising technology for the future of human body tracking and analysis. The table 2.2 represents a comparison of Keypoint Detection Algorithms

Table 2.2 : Comparison of Keypoint Detection Algorithms

Algorithm	**Advantages**	**Disadvantages**
Tflite	— Optimized for mobile and embedded devices — Low latency and efficient performance — Supports a variety of models — Easy integration with TensorFlow ecosystem	— Performance may not match heavier models on high-end devices — Limited flexibility compared to full TensorFlow

Continued on next page

Algorithm	Advantages	Disadvantages
OpenPose	— High accuracy and detailed keypoint detection — Supports multi-person detection — Open-source and widely used — Robust and reliable for various applications	— Computationally expensive — Requires powerful hardware for real-time performance — Large model size
Pifpaf	— High precision and real-time performance — Suitable for various applications — Open-source and actively maintained — Good performance on person detection	— Still relatively new and evolving — Requires fine-tuning for specific applications — Limited support compared to more established methods
Tfjs (ResNet 50)	— Runs directly in the browser without server-side processing — Leveraging ResNet-50 for high accuracy — Utilizes GPU acceleration when available — Easy to integrate with web applications	— Higher latency compared to native mobile or desktop solutions — Resource-intensive, can slow down browsers — Model size and complexity may limit usage in low-end devices

Continued on next page

Algorithm	Advantages	Disadvantages
Tfjs (MobileNet)	— Optimized for performance in web browsers — Lower latency and resource usage compared to ResNet-50 — Suitable for a wide range of devices — Easy to integrate with web applications	— Lower accuracy compared to ResNet-50 — May still be resource-intensive for low-end devices — Limited to capabilities of the browser environment
BlazePose	— Highly efficient and lightweight — Designed specifically for real-time applications on mobile — Good accuracy with low computational requirements — Integrated with MediaPipe framework	— Limited to single-person detection — May not provide the same level of detail as heavier models — Specific to certain use cases, less versatile than some alternatives

2.5 Overview of pose estimation

Pose estimation is an essential technique in telerehabilitation, as it allows physiotherapists to accurately monitor and analyze a patient's movements and posture during therapy sessions. Here is a state-of-the-art overview of pose estimation in telerehabilitation:

A- Marker-based motion capture [118; 119; 120]

B- Markerless motion capture [121; 122; 123; 124]

Table 2.3 represents a comparison of Marker-based and Markerless Motion Capture Technologies.

Technology	Advantages	Disadvantages
Marker-based Motion Capture	— High accuracy and precision in tracking — Robust data collection with minimal noise — Widely used in industry and research — Effective in controlled environments	— Requires preparation time to attach markers — Can be uncomfortable for subjects — Limited to controlled environments with special equipment — Potential occlusion issues with markers — Expensive setup and maintenance
Markerless Motion Capture	— No need for physical markers, more comfortable for subjects — Greater flexibility and natural movement — Can be used in various environments, including outdoors — Cost-effective, using standard cameras — Easier and quicker setup	— Generally lower accuracy and precision compared to marker-based systems — More susceptible to environmental factors like lighting and background — Higher computational requirements for real-time processing — Potential issues with occlusion and complex movements — Varies significantly depending on the algorithm used

Table 2.3 : Comparison of Marker-based and Markerless Motion Capture Technologies

2.5.1 Real-time pose estimation

Real-time pose estimation is the process of estimating a patient's pose and movement in real-time. This allows physiotherapists to provide immediate feedback and guidance during therapy sessions. However, this approach requires specialized algorithms and hardware, such as GPUs or FPGAs, to perform the necessary computations quickly enough for real-time use. Real-time pose estimation can be highly effective for telerehabilitation, but it requires specialized expertise and resources to set up and use.

The state-of-the-art in pose estimation for telerehabilitation is rapidly evolving, with new algorithms and techniques being developed and tested in research studies. The choice of pose estimation technique will depend on the specific needs and goals of the patient and physiotherapist, as well as the available resources and expertise.

2.5.2 Datasets of human pose detection

Recent advancements in human pose estimation have been supported by datasets like MPII [125] and COCO [24], with MPII comprising over 25,000 images and 40,000 people engaged in everyday activities, while COCO includes large sets for training, validation, and testing. Wei et al. introduced the LHPD for head pose prediction [126], and Guler et al. developed Human3.6M providing 2D and 3D pose coordinates [127]. However, none of these datasets cover rehabilitation exercises, highlighting the need for specialized datasets to evaluate and enhance pose estimation algorithms in this domain, essential for developing telerehabilitation systems.

2.5.3 Attention mechanism

Attention mechanisms are pivotal in natural language processing (NLP), notably for tasks like summarization, translation, and question-answering systems. RNNs have historically played a crucial role in temporal dynamics and sequence modeling, including character order in text. Despite their effectiveness in tasks like language translation with the encoder-decoder structure, RNNs struggle with long-range dependencies and gradient decay over cycles. Solutions include LSTM to mitigate gradient issues [128], RNNLM extensions [129], and efficient word representation methods [130]. Attention mechanisms, introduced by Vaswani et al. [23], significantly enhance handling of long-range relationships in NLP tasks (see figure 2.15).

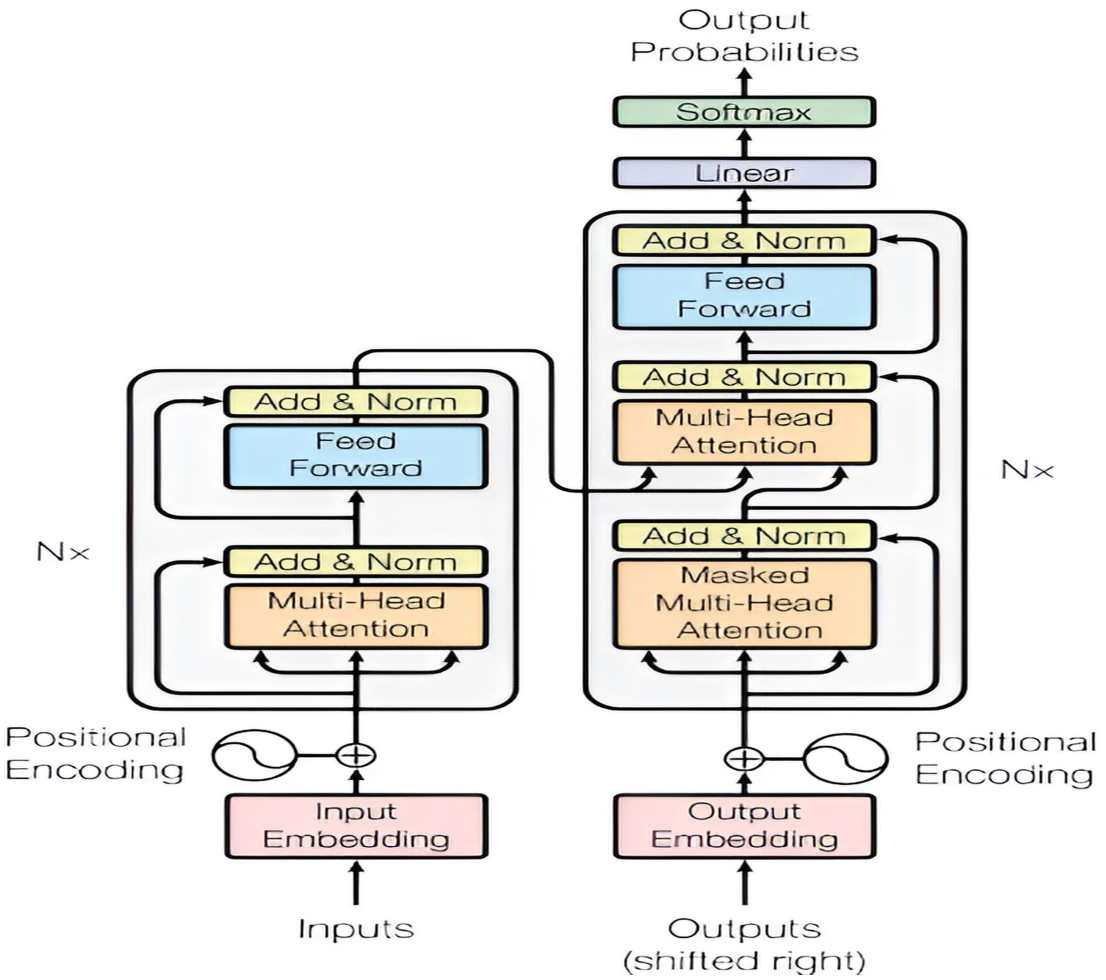


Figure 2.15 : The Transformer - model architecture [23].

The Transformer model introduced by Vaswani et al. [23] eliminates recurrent networks and convolutions, relying solely on self-attention for input-output representations. It features a stacked encoder-decoder structure with six identical layers, each containing a multi-head attention layer followed by a feed-forward layer. This design allows efficient learning of long-range dependencies and simultaneous attention to multiple positions within input sequences, enhancing accuracy in capturing source-target dependencies. Moreover, the model processes sequences in parallel, surpassing the sequential processing limitations of RNN-based models. The interpretability and efficiency gains of self-attention were fur-

ther explored in BERT by Devlin et al. [131], revolutionizing language representation and task-specific model fine-tuning.

2.5.4 Transformer in computer vision

The success of self-attention in NLP has spurred applications of transformer architectures across various computer vision tasks, including object detection [132; 133; 134; 135] and segmentation [136; 137; 138], alongside image classification. Despite the longstanding dominance of convolutional neural networks (CNNs) in computer vision, transformers like DETR [132] and Vision Transformer (ViT) [139] have emerged as promising alternatives. ViT, treating images as sequences of patches, achieved state-of-the-art results in image classification without traditional CNN components. Experimental models like TransPose [140], Swin Transformer [141], and EvoPose2D [142] further explore transformer capabilities in capturing global relations and reducing computational costs, albeit requiring training on large-scale datasets for optimal performance.

2.5.5 Image feature fusion

Feature fusion methods in computer vision integrate multi-level features effectively [143]. HyperNet [144] concatenates representations pre-prediction, Spatial Pyramid Pooling [145] explores multi-scale filters, and feature pyramids by Felzenszwalb et al. [146] utilize scale-invariant properties. Feature Pyramid Networks (FPN) by Lin et al. [147] enhance object detection by combining strong low-resolution with weak high-resolution features in a pyramidal hierarchy from ConvNet [21]. Image feature fusion integrates features from diverse sources like modalities or scales into a unified representation, leveraging complementary information to boost model performance through concatenation, summation, or attention-based fusion methods.

2.5.6 Part-Based Models (pre-Deep learning)

Before deep learning, object recognition in computer vision often used part-based models. These models represent objects as collections of parts, each characterized by specific features. Popular examples include the deformable part model (DPM) introduced by Felzenszwalb et al. in 2008, which uses a hierarchical structure and is trained with a variant of the SVM algorithm, and articulated pose estimation models for estimating human body

poses with kinematic constraints. While part-based models were widely used, their performance generally lags behind deep learning-based approaches, which can learn more complex representations.

Since Fischler and Elschlager [148] first developed pictorial structures, a deformable component model, in 1973, to distinguish facial characteristics in images, there has been interested in the notion of employing image processing to detect human traits. Coincidentally, the first article from Dr. Geoffrey E. Hinton, a renowned scientist in the deep learning field, dealt with the challenge of arranging random sets of rectangles into a puppet-like forms [149] (1976). Hinton later made a significant contribution to work that popularized the backpropagation algorithm [150]. In 2000, Felzenszwalb and Huttenlocher [151] proposed an effective global matching algorithm for pictorial structures and used it to predict articulated human postures using a geometric human body model made up of object pieces, which was inspired by the early work of Fischler and Elschlager. The first object part models comprised of manually defined rectangles with fixed aspect ratios, an average color, and color variance. They then improved their technique by employing maximum likelihood estimation to learn the object model parameters from 10 sample training photos [152].

The large plurality of methods leading up to the deep learning era were focused on deformable part models / pictorial structures but utilized competing machine learning methods for detecting body parts and modeling their connections [153; 154; 155; 156; 157; 158; 159; 160; 161; 162; 163; 164; 165; 166; 167]. To summarize a few, Ronfard et al. [154] trained support vector machines (SVMs) [168] to classify image patches based on features extracted utilizing Gaussian filters: Ramanan and Sminchisescu [155; 156] Proposed conditional random fields; Andriluka et al. [159] utilized shape context descriptors to train AdaBoost [169] classifiers; and Pishchulin et al. [170] conditioned pictorial structures on poses [171] focused on histograms of oriented gradients [172]. The development of CNNs, which automatically learn visual characteristics from image data, has rendered manual part-based models useless. Due to the public release of huge keypoint datasets like LSP [173; 161], FLIC [167], and MPII [125], there was also a move toward regressing keypoint positions rather than detecting body sections.

2.5.7 Single-person human pose estimation using deep learning

Single-person human pose estimation using deep learning is a popular task in computer vision that aims to estimate the 2D or 3D locations of a person's body joints or keypoints in an image or video. Deep learning-based methods have achieved state-of-the-art results in this task, especially using convolutional neural networks (CNNs).

Here are some popular deep learning-based methods for single-person human pose estimation:

- OpenPose

OpenPose is a real-time pose estimation method using a multi-stage CNN architecture for detecting and refining body part locations.

- Hourglass network

The Hourglass network, a CNN architecture for human pose estimation, employs an encoder-decoder structure with skip connections for enhanced accuracy.

- PoseNet

PoseNet is a CNN method directly estimating 2D or 3D body joint coordinates from input images, utilizing a single-stage architecture with a regression layer.

- Mask R-CNN

Mask R-CNN, a versatile two-stage CNN, excels in object detection, instance segmentation, and single-person pose estimation, with broad applications including 3D pose estimation.

Toshev and Szegedy [174] pioneered DeepPose in 2014 with a 7-layer CNN for direct keypoint recovery from RGB photos, influencing subsequent CNN-based advancements [175; 112; 176; 177; 178]. Tompson et al. [179] explored nonlinear pose vector regression, noting challenges in convolutional translational equivariance and the utility of fully-convolutional networks for spatial mapping [180; 181].

Tompson et al. [179] introduced keypoint heatmaps using Gaussian fields centered on keypoints, training with MSE loss. This approach influenced subsequent work on heatmap

predictions [182; 183; 184], alongside their pioneering of multi-scale feature fusion [185], still prevalent in modern pose estimation methods [177; 186; 178].

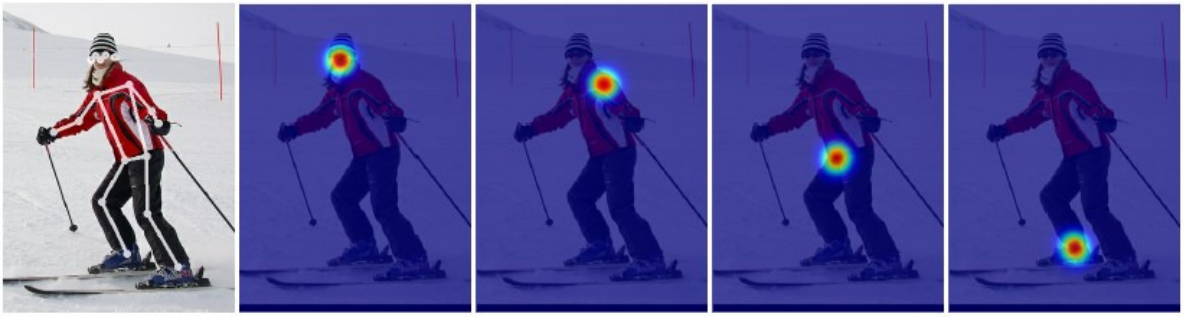


Figure 2.16 : Sample keypoint heatmap predictions made using EvoPose2D, the 2D human pose estimation network [24].

In 2016, Wei et al. introduced Convolutional Pose Machines [175], employing iterative heatmap refinement with intermediate supervision across multiple convolutional stages. Concurrently, Newell et al. utilized "hourglass" convolutional modules with recurrent top-down, bottom-up processing [176], influenced by U-net [187] and ResNet's success [188]. The Stacked Hourglass network spurred further research and adaptations [189; 190; 191; 192; 193; 194; 195]. Quantitative comparisons on the MPII dataset show substantial accuracy gains from early pictorial structures models [152] to Tompson et al.'s first deep learning heatmap-based method [179] and Newell's Stacked Hourglass approach, representing over 100% relative improvement in three years.

2.5.8 Two-Stage Multi-Person human pose estimation

Multi-person human pose estimation in computer vision aims to localize 2D or 3D body keypoints for multiple individuals in images or videos, requiring detection and association of body parts across multiple people, unlike single-person pose estimation.

Here are the key steps involved in two-stage multi-person human pose estimation:

- Person detection

- Person grouping

- Pose estimation

Here are some popular two-stage, multi-person human pose estimation methods:
- Mask R-CNN

- Associative embedding

- OpenPose

2.5.9 Single-Stage Multi-Person human pose estimation

Single-stage multi-person pose estimation in computer vision directly estimates 2D or 3D body keypoints for multiple individuals in images or videos using a single neural network, unlike two-stage methods that separate person detection and body part association steps.

Here are some popular single-stage multi-person human pose estimation methods: CenterNet, HigherHRNet, SimpleBaseline

2.6 Human pose estimation and utilization in medical domain

Human pose estimation has a wide range of applications in the medical domain. One critical application is analyzing medical images such as X-rays, CT scans, and MRIs. Pose estimation can be used to locate and quantify the accurately position and orientation of various anatomical landmarks, which can aid in diagnosis, treatment planning, and surgical guidance.

Here are some specific use cases of human pose estimation in the medical domain:

2.6.1 Orthopedics

One of the most promising applications of this technology is in the field of medical imaging, where it can be used to analyze X-rays and CT scans to locate and quantify the accurately position and orientation of various anatomical landmarks.

By accurately identifying the position and orientation of landmarks such as the hip, knee, and spine, pose estimation algorithms can help healthcare professionals diagnose various

orthopedic conditions. For example, in cases of arthritis, pose estimation can help quantify the severity of joint damage and guide treatment decisions. Similarly, in cases of fractures, pose estimation can help to accurately locate the site of the fracture and assess the extent of the damage.

Another area where pose estimation is proving to be particularly valid in the diagnosis and treatment of scoliosis. Scoliosis is a condition that causes the spine to curve abnormally, and it can lead to a wide range of health problems, including chronic pain and difficulty breathing. By using pose estimation to measure accurately the curvature of the spine, doctors can more accurately diagnose the condition and plan a course of treatment that is tailored to the patient's specific needs.

The use of pose estimation in medical imaging is still in its early stages, but it holds great promise for improving the accuracy and efficiency of orthopedic diagnosis and treatment. As the technology continues to develop, we will likely see more and more healthcare applications of pose estimation, helping doctors to better understand and treat a wide range of medical conditions. In the future, it may even be possible to use pose estimation to monitor the progress of treatment and predict the likelihood of future health problems, further improving the quality of care for patients around the world.

2.6.2 Radiation therapy

Radiation therapy is a common treatment for many forms of cancer, but it can be a complex and challenging process. One of the key challenges in radiation therapy is ensuring that the radiation is delivered precisely to the target area while minimizing damage to healthy tissue. This requires a high degree of accuracy in the positioning of the patient during treatment.

This is where human pose estimation can be of great help. By using advanced computer vision algorithms to track the position and orientation of the patient in real-time, pose estimation can ensure that the radiation is delivered precisely to the target area while avoiding damage to healthy tissue. This is particularly important in cases where the target area is close to critical organs or other sensitive structures.

Moreover, pose estimation can detect and correct any movements or changes in the patient's position during treatment, ensuring that the radiation continues to be delivered ac-

curately throughout treatment. This can be especially important in cases where the patient may be in discomfort or pain and may move or shift position during treatment.

The use of human pose estimation in radiation therapy is still a relatively new field, but it is already showing great promise in improving the accuracy and effectiveness of treatment. As the technology continues to develop; we will likely see more and more applications of pose estimation in medical settings, helping to improve the quality of care and outcomes for patients around the world.

2.6.3 Surgical planning and guidance

In surgical planning and guidance, pose estimation can be used to provide surgeons with real-time feedback on the position and movement of surgical instruments, as well as the location of important anatomical structures.

One application of pose estimation in surgical planning and guidance is in the field of orthopedics. Orthopedic surgeons often use surgical robots to assist with joint replacement surgeries, which require precise alignment of the implant components. Pose estimation can be used to track the movement of the robotic arm and the position of the surgical instruments in real-time, allowing the surgeon to make adjustments as needed.

Another application of pose estimation in surgical planning and guidance is in neurosurgery. In neurosurgery, surgeons must navigate complex structures such as the brain and spinal cord while avoiding essential blood vessels and nerves. Pose estimation can track the position and orientation of the surgical instruments and the location of crucial structures such as the ventricles and the thalamus. This information can be used to create 3D maps of the surgical site and to guide the surgeon's movements during the procedure.

Pose estimation can also be used in surgical planning, particularly for procedures that involve complex movements or difficult-to-reach areas. For example, in minimally invasive surgery, where the surgeon operates through small incisions, pose estimation can be used to provide the surgeon with a virtual view of the surgical site, allowing them to see around corners and visualize the location of hidden structures.

Overall, the use of pose estimation in surgical planning and guidance has the potential to improve the accuracy and safety of surgical procedures. By providing surgeons with real-time feedback on the position and movement of surgical instruments, as well as the location of critical anatomical structures pose estimation can help to reduce the risk of complications

and improve patient outcomes. However, the technology is still in its early stages, and further research is needed to validate its effectiveness and optimize its use in surgical settings.

2.6.4 Physical therapy

Physical therapy is a crucial part of the treatment plan for many patients with various medical conditions. It involves using exercises, stretching, and other techniques to help patients regain mobility, strength, and function following an injury or illness. However, tracking physical therapy progress can be challenging, as it often requires careful observation and measurement of the patient's movements and range of motion.

This is where human pose estimation can be instrumental. By using advanced computer vision algorithms to track the movements of the patient during therapy sessions pose estimation can accurately measure the patient's range of motion, movement patterns, and other important parameters. This can provide valuable data that can be used to track progress over time and to adjust therapy plans as needed.

Moreover, pose estimation can detect abnormalities or asymmetries in the patient's movements, an essential indicator of underlying medical conditions. For example, patients with stroke or cerebral palsy often exhibit abnormal movement patterns, which can be detected and quantified using pose estimation. This can aid in diagnosing these conditions and can also help tailor therapy plans to each patient's specific needs.

Similarly, patients with Parkinson's disease often experience difficulties with movement and balance, which can be accurately measured and monitored using pose estimation. This can help therapists to design targeted exercise and therapy plans that address the specific needs of each patient, improving their overall quality of life and function.

2.7 Conclusion

In conclusion, this thesis chapter explores the the fascinating field of human pose estimation and its applications, with a specific focus on the utilization of artificial intelligence (AI) techniques. The research conducted shed light on the advancements and challenges in human pose estimation and its significance in the medical domain.

The study investigated various techniques employed in human pose estimation, ranging from traditional computer vision methods to cutting-edge deep learning approaches. These

techniques demonstrated the ability to accurately estimate the human body's pose, including joint positions and orientations from images or video sequences. AI-based algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have proven to be highly influential in this regard, offering enhanced performance and robustness.

Furthermore, examining human pose estimation in the medical domain revealed its substantial potential for revolutionizing healthcare. Accurate and real-time pose estimation can significantly contribute to medical diagnosis, treatment, and rehabilitation. For instance, it can aid in assessing musculoskeletal disorders, enabling precise measurements of joint angles and range of motion. This information is invaluable for clinicians to design personalized treatment plans and track patients' progress throughout their rehabilitation journey.

Moreover, human pose estimation in the medical domain has the potential to facilitate telemedicine and remote patient monitoring. With the advent of telehealth, patients can receive expert guidance and feedback from healthcare professionals from the comfort of their homes. Real-time pose estimation can enable remote assessment of patients' movements and exercise techniques, allowing therapists to provide accurate guidance and corrections. This technology extends healthcare access to individuals in remote areas or with limited mobility.

Despite the remarkable progress made in human pose estimation and it's potential in the medical field, several challenges remain. Robustness to occlusions, variations in lighting conditions, and complex poses are ongoing research areas. Furthermore, the ethical considerations surrounding data privacy, security, and consent must be carefully addressed to ensure patient confidentiality and trust.

In conclusion, this thesis chapter has provided a state of the art in physiotherapy telerehabilitation and a comprehensive overview of human pose estimation techniques and their applications, with a specific focus on its relevance in the medical domain. The research conducted highlights the significant impact that AI-based pose estimation algorithms can have on healthcare, particularly in diagnosis, treatment, rehabilitation, and remote patient monitoring. By addressing the remaining challenges and continuing to advance the field, human pose estimation has the potential to transform healthcare delivery and improve patient outcomes in the coming years.

Chapter

3 Contribution 2: MediaPipe-Based system for human rehabilitation motion: reliability and validity analysis

3.1 Intoduction

The objective of machine learning and computer vision is to empower computers with the capability to perceive data, comprehend it, and make decisions based on past and current occurrences. Currently, computer vision and machine learning are in their initial phases of advancement. Several instances of computer vision include identifying objects, detecting poses and gestures, and other related fields. To classify human postures or activities and estimate human behavior by analyzing RGB image sequences from a video, one could employ a deep learning technique.

3.2 MediaPipe pose estimation

3.2.1 MediaPipe basic concepts

MediaPipe BlazePose is a machine learning system designed for precise tracking of body postures, which can infer 33 3D landmarks and generate background segmentation masks for the entire body based on RGB video frames [117]. Although BlazePose can run on various devices such as modern mobile phones, laptops/desktops, and even the web using Python, advanced techniques typically rely on powerful desktop environments for efficient inference.

The solution utilizes a two-step detector-tracker ML pipeline. Initially, the pipeline employs a detector to locate the region of interest (ROI) corresponding to the subject/pose within each frame. Subsequently, the tracker takes the cropped frame of the ROI as input to predict the pose landmarks and segmentation mask within that specific region. The detector is only invoked when necessary, such as for the first frame or if the tracker fails to detect a body pose in the previous frame. For subsequent frames, the pipeline calculates the ROI based on the pose landmarks obtained from the previous frame. This approach allows for extracting the landmarks or key points of a subject, thereby enhancing the real-time performance of the pipeline.

3.2.2 Data transformation

The process involves applying computer vision techniques to extract individual frames from each video. Then, the pose estimation framework MediaPipe BlazePose is utilized to extract key points from each frame. The resulting data is subsequently divided into separate subsets for training and testing purposes. Considering the presence of multiple videos in the dataset, a batch size of N is chosen, with each batch containing T frames. Each frame can potentially detect up to M individuals, with each individual having C coordinates or channels for each key point. The total number of key points is denoted as V. As a result, the final data will have dimensions of $N \times T \times V \times C \times M$.

3.2.3 Constructing skeleton graphs

In each frame of a skeleton sequence, the 3D coordinates accurately represent the position of each human joint. These skeletal sequences are organized in a hierarchical manner using a spatial-temporal graph. When dealing with N skeleton sequences, each consisting of T frames and containing both intra-body and inter-frame connections, a spatial-temporal graph is constructed. For each skeleton sequence, an undirected graph G is created. The structure of this graph is determined by its nodes, denoted as V, and its edges, denoted as E.

$$G = (V, E) \tag{3.1}$$

The set of nodes in the sequence V will include values equal to $T \times N$ as shown below:

$$V = \{v_{i(t)} \mid i = 1, \ldots, N \text{ and } t = 1, \ldots, T\} \tag{3.2}$$

The construction of the spatial-temporal graph for the skeleton sequences involves two steps. Firstly, edges are created to connect the joints within a frame, following the natural connectivity of the human body. Additionally, each joint is connected to the corresponding joint in the subsequent frame. This process results in the creation of two separate sets of edges: inter-frame edges and intra-skeleton edges.

Inter-frame edges establish connections between a joint in one frame and the corresponding joint in the next frame. On the other hand, intra-skeleton edges connect joints within the same frame to other joints within that frame. These two sets of edges, inter-frame edges (EF), and intra-skeleton edges, are defined as follows.

$$E_F = \{v_{it} \cdot v_{i(t+1)} \mid i = 1, \ldots, N \text{ and } t = 1, \ldots, T\} \tag{3.3}$$

Likewise, the connections between nodes within the same frame can be represented as intra-skeleton edges. Let's denote these edges as ES. In this case, the definition of ES for any given frame can be expressed as follows.

$$E_F = \{v_{it} \cdot v_{jt} \mid (i,j) \in \text{Set of natural human joints and } t = 1, \ldots, T\} \tag{3.4}$$

3.2.4 Design specification

The overall architecture of the pipeline consists of several components. Firstly, the video data is organized into a folder structure before being passed into the pipeline. A visual representation of the pipeline can be seen in Figure 3.1, and a detailed description of each step is provided below.

Pose Estimation using MediaPipe BlazePose

The process begins by reading the videos and converting them into individual frames using OpenCV. Subsequently, MediaPipe BlazePose is utilized to extract the landmarks or key points representing the skeletal data from each frame.

Skeletal data

The extracted landmark data from MediaPipe BlazePose is stored in a .NPY file, while the corresponding labels are stored in a pickle file. This dataset is subsequently divided into

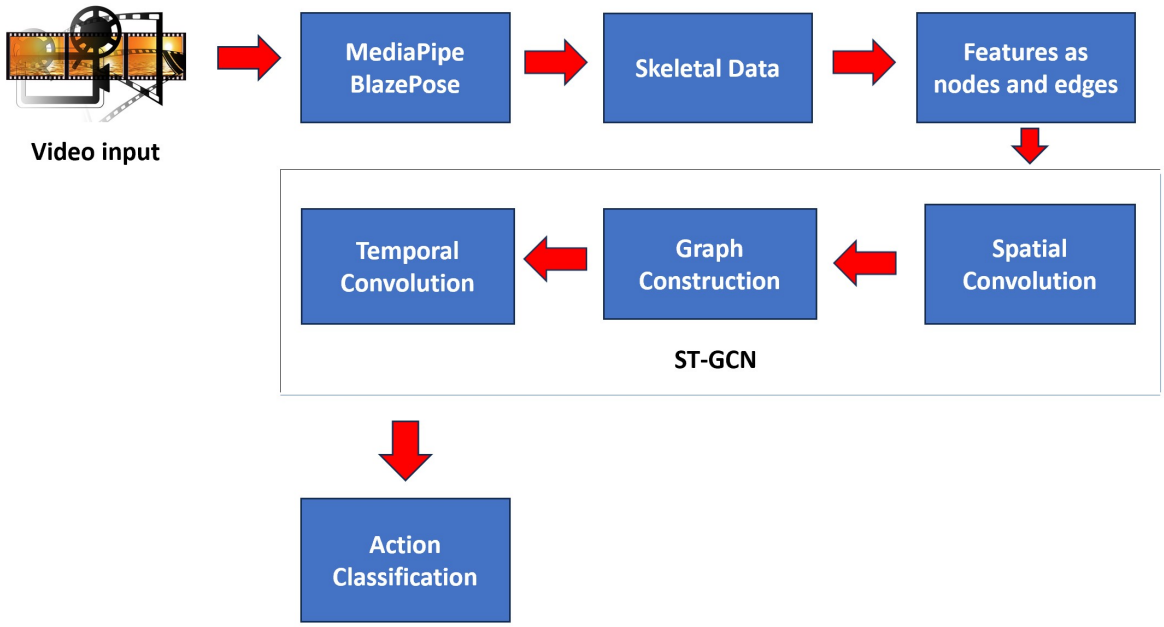


Figure 3.1 : Overview of the pipeline.

a training set and a testing set for further analysis.

Features as nodes and edges

Next, the skeletal data is partitioned into two distinct components: edges and nodes. These specific features are subsequently inputted into ST-GCN (Spatio-Temporal Graph Convolutional Network) for further processing and analysis.

ST-GCN

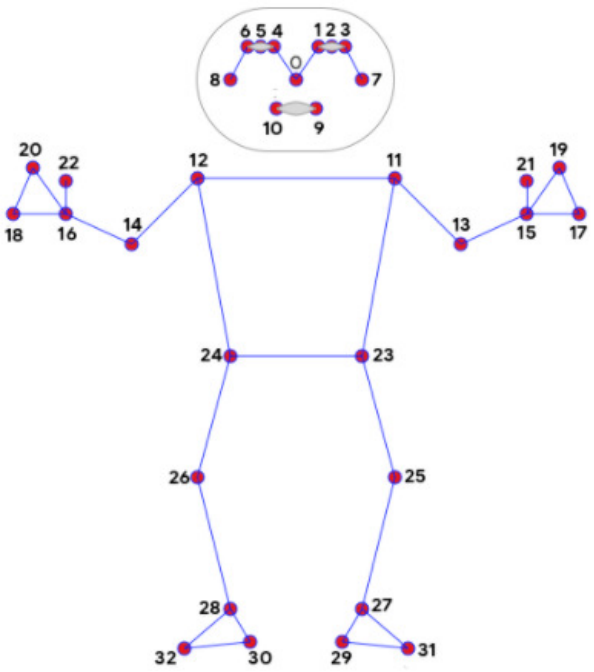
During the training phase, the data is fed to the model in batches for training purposes. The model employed in this study is a Spatial-Temporal Graph Convolutional Neural Network (ST-GCN). This network utilizes Spatial-Temporal Convolution operations for feature extraction. The ST-GCN block is implemented by leveraging the constructed graph, along with spatial convolution and temporal convolution techniques.

Action classification

After the ST-GCN model processes the input data, its output is fed into a softmax classifier, which is responsible for classifying the activity at the final stage of the pipeline.

3.3 Graph construction

The construction of the graph involves the utilization of a Graph Class. The manual definition of two sets of edges is carried out. The first set comprises intra-skeleton edges connecting nodes within the same frame. For instance, if node 32 is chosen, it will be linked to nodes 30 and 28. This linkage is established by identifying natural human joints using the landmark information provided by MediaPipe BlazePose, as depicted in figure 3.2. The second set consists of inter-frame edges that connect nodes in one frame with the corresponding node in the subsequent frame. These edges are structured as (i, i), indicating that node 1 in the current frame will be connected to node 1 in the next frame, resulting in an edge with the structure (1, 1). A function is programmed to get the data. Then, this function



0. nose
1. left_eye_inner
2. left_eye
3. left_eye_outer
4. right_eye_inner
5. right_eye
6. right_eye_outer
7. left_ear
8. right_ear
9. mouth_left
10. mouth_right
11. left_shoulder
12. right_shoulder
13. left_elbow
14. right_elbow
15. left_wrist
16. right_wrist
17. left_pinky
18. right_pinky
19. left_index
20. right_index
21. left_thumb
22. right_thumb
23. left_hip
24. right_hip
25. left_knee
26. right_knee
27. left_ankle
28. right_ankle
29. left_heel
30. right_heel
31. left_foot_index
32. right_foot_index

Figure 3.2 : BlazePose model 33 human Poses.

calculates the angles at each human body joint. The angle made between the two lines is calculated by using analytic geometry. For example, we have three points (show figure 3.3), A(x1,y1), B(x2,y2), and C(x3,y3). We suggest that AB and BC as skeletal structures, or two bones. The intersection between the lines AB and BC is on point B. The angle between

AB and BC can be determined as follows: Slope of AB is:

$$d1 = (y2 - y1)/(x2 - x1). \tag{3.5}$$

BC slope is:

$$d2 = (y3 - y2)/(x3 - x2). \tag{3.6}$$

Now, we can determine the angle between AB and BC :

$$tan\theta = (d1 - d2)/(1 + d1.d2). \tag{3.7}$$

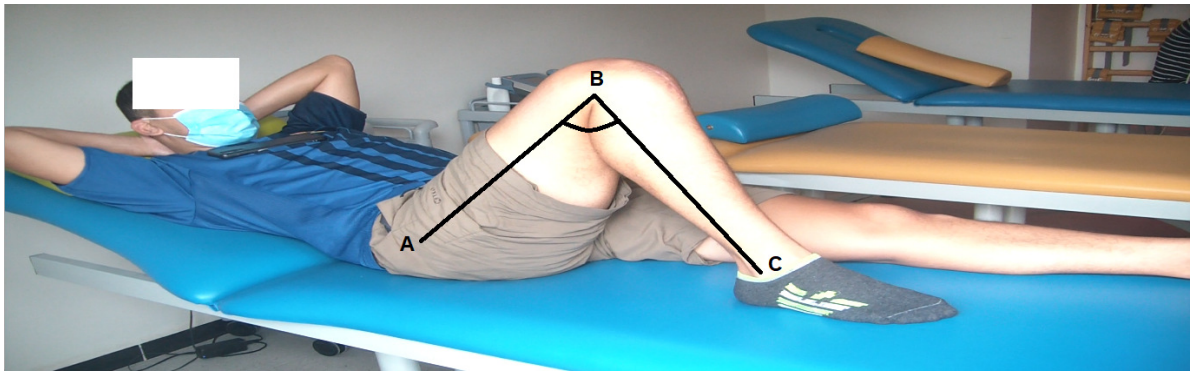


Figure 3.3 : Angle joint calculation.

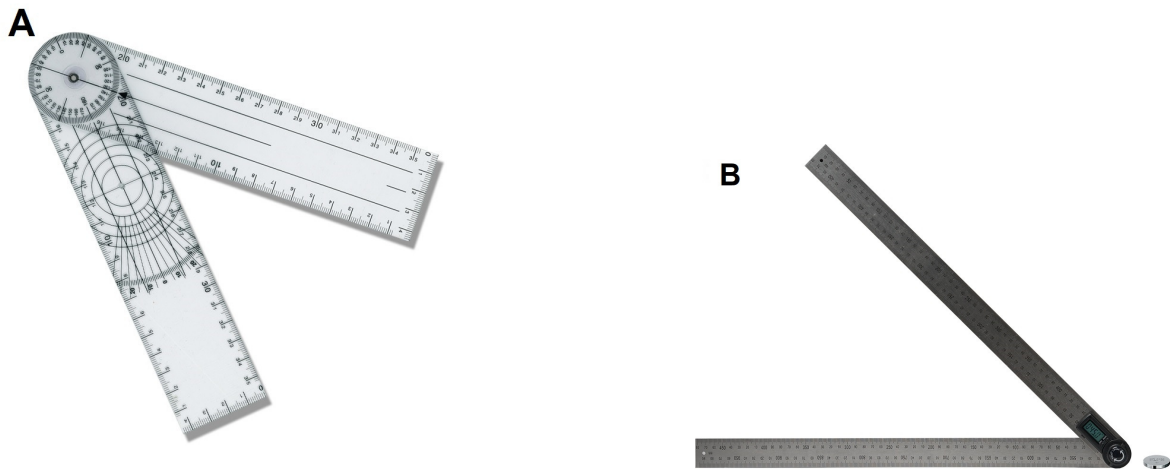
3.4 Reliability and validity of MediaPipe based measurement system

3.4.1 Reliability analysis of the proposed shoulder movements

A total of 50 volunteers have participated "for the upper-limb movements", and 25 for the knee flexion-extension; their ages range from 21 to 42. Most of the data were taken at the University of Skikda. This study adheres to the principles outlined in the Declaration of Helsinki, a set of ethical guidelines for biomedical research involving human subjects. All participants provided informed consent prior to their involvement in the study. The principles of confidentiality, voluntary participation, and the right to withdraw without prejudice have been strictly observed throughout the research process. This study is committed

to upholding the highest ethical standards as stipulated in the Declaration of Helsinki. All participants were measured using three methods: MediaPipe with a camera on a computer, Dell Intel(R) The second instrument is a clinical goniometer (figure 3.4). The third is a digital instrument called Angle Ruler 50, a 360° digital protractor 2x50 cm ADA (see figure 3.4). The measurement accuracy is about 0.3°, power: 3V, 1 x CR 2032. Data are visualized on the built-in LCD digital display.

This study measures four ranges of motion, shoulder abduction, adduction, flexion, and extension for the upper limb. For the lower limb, we studied knee flexion/extension. Before beginning to measure the movements, we obtained consent from all volunteers to publish their data in this research. We had a physical therapist explain the method to each individual and take measurements. We first started by measuring the four movements with MediaPipe in three repetitions. This procedure aims to calculate the ICC to prove the reliability of the technique. The physiotherapist did just one measurement with the goniometer and the angle ruler.



((a)) Goniometer ((b)) Angle ruler

Figure 3.4 : Instruments used in the measurement of ROM.

In Figure 3.6, the results of the active range of motion (ROM) values for shoulder abduction, adduction, extension, and flexion were compared using three different visualization methods. Each method was represented by a different color to indicate the differences between them. In order to provide a more detailed analysis of the results, histogram graphics

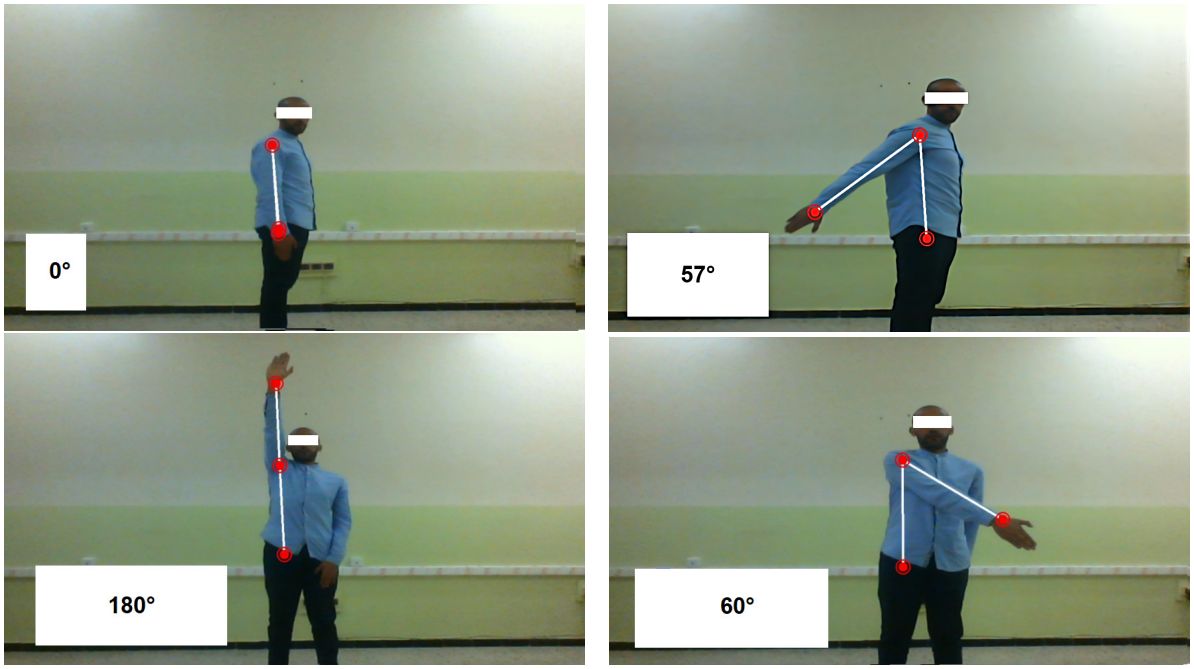


Figure 3.5 : Some pose estimation.

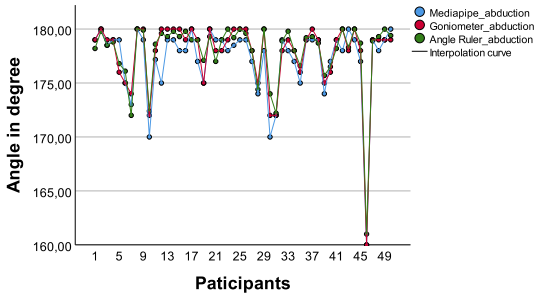
Table 3.1 : Data of four shoulder motions obtained using a universal goniometer, angle ruler and MediaPipe.

Movement	Meth	Mean	SE Mean	StDev	Min	Q1	Med	Q3	Max
Abduction	Go	177.76°	0.48°	3.41°	160°	177.5°	179°	180°	180°
	AR	177.86°	0.45°	3.20°	161°	177.07°	178.95°	179.65°	180°
	Me	177,20°	0,49°	3,49°	160°	177°	178,50°	179°	180°
Flexion	Go	169.12°	0.88°	6.28°	155°	163.75°	174°	174°	180°
	AR	169.54°	0.89°	6.30°	157.50°	163.87°	170°	175.10°	179.7°
	Me	169,40°	0,93°	6,61°	155°	165°	170°	176°	180°
Adduction	Go	64.50°	0.94°	6.66°	51.00°	59.75°	60°	64°	75.00°
	AR	64.95°	0.95°	6.71°	51.20°	60.25°	64.20°	70°	75.10°
	Me	64.40°	0.95°	6.76°	50.00°	60°	64°	70°	75.00°
Extension	Go	56.89°	0.49°	3.51°	45.00°	55.00°	58.50°	59.00°	60.00°
	AR	57.24°	0.51°	3.63°	44.80°	56.10°	58.50°	60.00°	60.90°
	Me	56.88°	0.51°	3.63°	45.00°	55.00°	58.20°	60.00°	60.00°

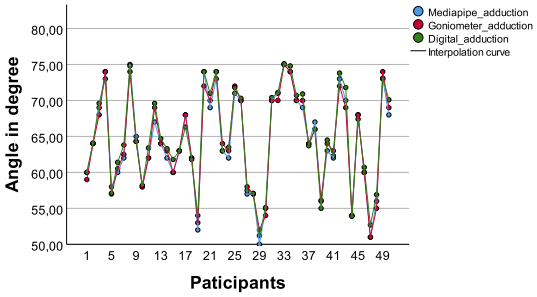
. Abbreviation : Meth : method, Go : clinical goniometer, AR : Angle Ruler, Me : MediaPipe, SE Mean :standard error of the mean, StDev : Standard deviation, Min : minimum, Med : median, Max : maximum.

were generated and presented in Figures 3.7, 3.8, 3.9 These histograms showed the distribution of the active range of motion for each of the four shoulder movements previously mentioned. To better understand the data, the histograms were overlaid with black curves representing the Gaussian distribution, also known as the normal distribution. This distribution is a probability distribution that is symmetric about the mean and is often used to analyze data in statistical analyses. The results indicated that there were no significant differences between the three visualization methods used to compare the ROM values for the four shoulder movements. This finding was supported by Table 3.1, which summarizes the results of the analysis.

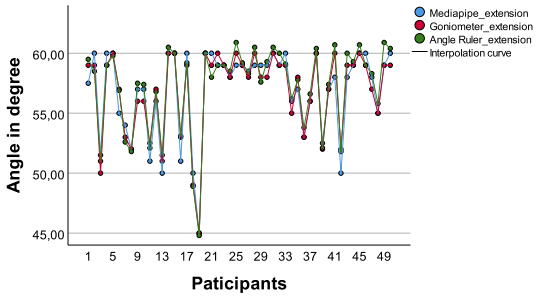
Overall, the analysis presented in this text aimed to compare and evaluate the effectiveness of different visualization methods for analyzing the active range of motion in the shoulder. Through the use of histograms and Gaussian distributions, the study was able to provide a more detailed and nuanced analysis of the results.



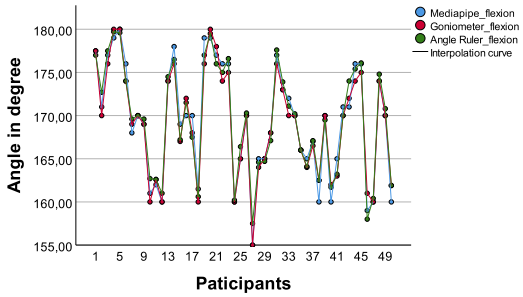
((a)) Comparison of shoulder abduction with three techniques.



((b)) Comparison of shoulder adduction with three techniques.



((c)) Comparison of shoulder extension with three techniques.



((d)) Comparison of shoulder flexion with three techniques.

Figure 3.6 : Comparison of the three methods of measurement in studied motions.

In our study, we used MediaPipe, a popular AI-based tool for motion analysis, to assess the reliability of shoulder motion pose. We conducted a test with multiple participants, measuring their shoulder motion pose at three different times. The results of the test are presented in Table 3.2, which includes the pose of the proposed movements with Mean, StDev, SEM, MDC, and ICC values.

The ICC value is a measure of reliability that ranges from 0 to 1, with values closer to 1 indicating higher reliability. In our study, the ICC values for all proposed movements were greater than 0.81, indicating excellent reliability. These results suggest that MediaPipe is a reliable tool for assessing shoulder motion pose, and it can be used effectively in clinical and research settings.

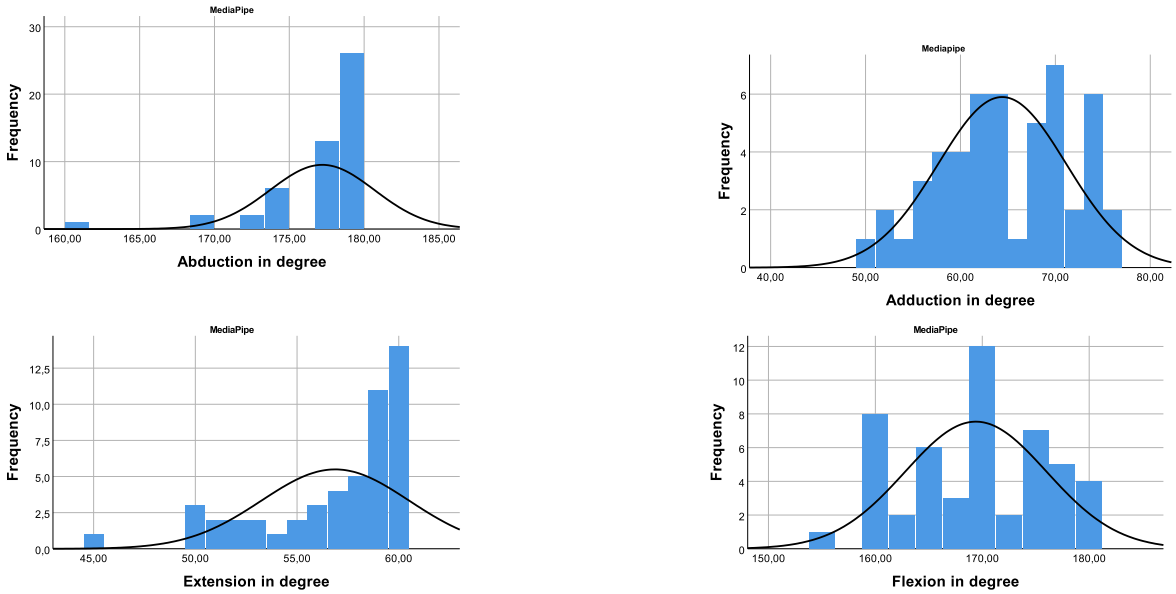


Figure 3.7 : Shoulder ROMs frequencies with MediaPipe method of measurement.

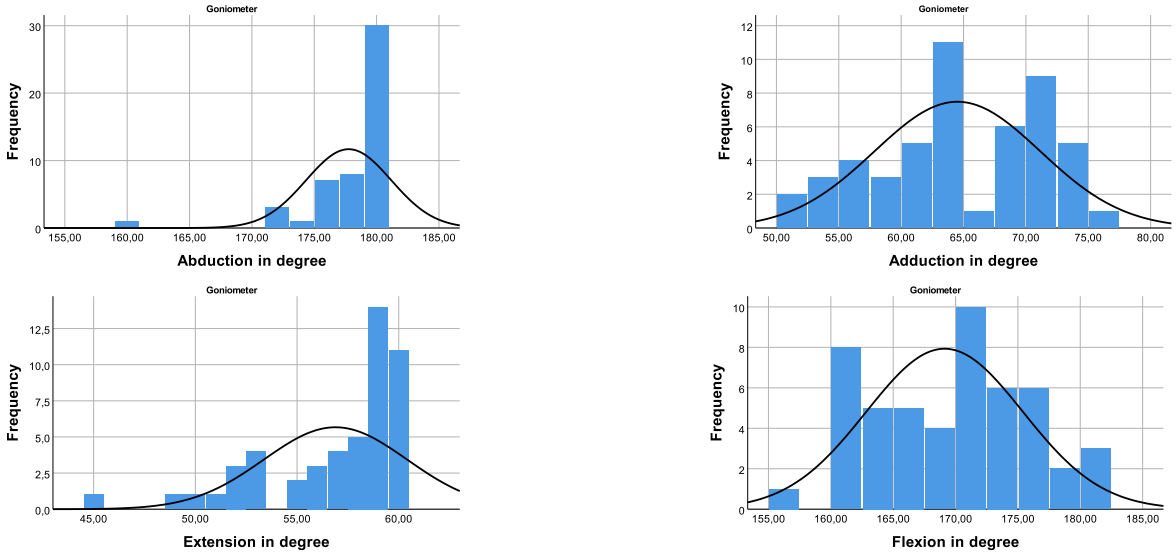


Figure 3.8 : Shoulder ROMs frequencies with goniometer method of measurement.

3.4.2 Validity analysis of the proposed shoulder movements

To obtain the validity of the MediaPipe, a 95% limit of agreement (LOA) between MediaPipe-based measurement and the two other instruments was calculated as follows:

$$\text{Upper limit} = \text{Mean}(\text{bias}) + 1{,}96 \,.\, \text{StDev} \tag{3.8}$$

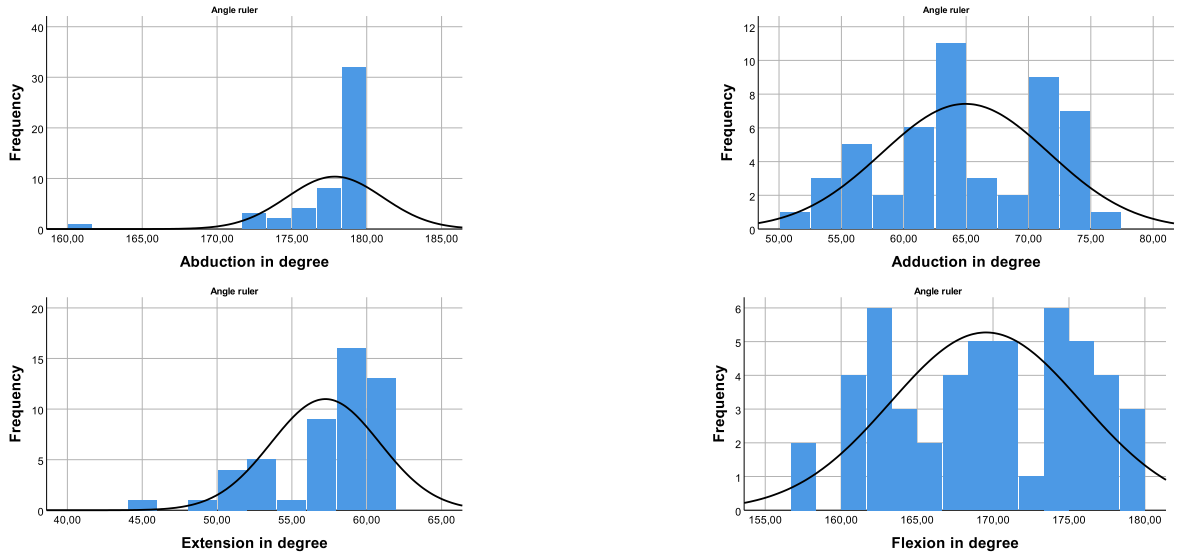


Figure 3.9 : Shoulder ROMs frequencies with angle ruler method of measurement.

Table 3.2 : Reliability results of the MediaPipe based measurement system.

	ICC	StDev	SEM	MDC
Abduction	0.968	2.11°	0.377°	1.046°
Adduction	0.99	5.778°	0.5778°	1.601°
Extension	0.99	4.296°	0.4296°	1.190°
Flexion	0.992	6.725°	0.6725°	1.864°

$$\text{Lower limit} = \text{Mean}(\text{bias}) - 1{,}96 \,.\, \text{StDev} \tag{3.9}$$

In addition to assessing the reliability of MediaPipe, we also compared the results obtained using this tool with those obtained using traditional measurement instruments, such as the goniometer and angle ruler. The results of the Bland-Altman plots comparing the two instruments with MediaPipe are presented in Table 3.3.

In the shoulder extension, the mean differences between the goniometer and MediaPipe technique were -0.01°, -0.108° in adduction, -0.55° in abduction, and -0.14° in flexion. In

comparison, the mean differences between the angle ruler and MediaPipe technique were -0.36°, -0.552° in adduction, -0.6604° in abduction, and -0.14° in flexion.

Table 3.3 : Bland–Altman analysis results of shoulder joint data acquired utilizing Universal goniometer, angle ruler and MediaPipe.

	Goniometer vs MediaPipe		Angle ruler vs MediaPipe	
ROM	Mean bias	95% LOA	Mean bias	95% LOA
Shoulder abduction	-0,55°	-2,9436° to 1,8308°	-0,6604°	-3,2865° to 1,9657°
Shoulder adduction	-0,108°	-1,774° to 1,558°	-0,552°	-2,44° to 1,34°
Shoulder extension	-0,01°	-1,8916° to 1,87°	-0,36°	-2,4327° to 1,7127°
Shoulder flexion	-0,14°	-2,5998° to 2,3198°	-0,14°	-2,5998° to 2,3198°

The Bland-Altman plots (Figure 3.10)show that the differences in the studied pose angles acquired by the two measurement methods are not distributed in a systematic way. Instead, they demonstrate a random distribution for all the studied motions. These values fall within a narrow range, whether comparing MediaPipe with the goniometer or the angle ruler, indicating a generally superior agreement. The comparison of the results obtained using MediaPipe with those obtained using traditional measurement instruments is crucial as it helps validate the accuracy of AI-based tools in motion analysis. The results obtained in our study demonstrate the effectiveness of MediaPipe in measuring shoulder motion pose and highlight the potential of AI-based tools in motion analysis.

Moreover, the good results obtained in the validity analysis for all proposed motion poses, as indicated by [196], further emphasize the reliability of MediaPipe. This finding is particularly significant as it shows that MediaPipe can be used effectively in various clinical and research settings to assess shoulder motion pose accurately.

The results of this study have important implications for the field of physiotherapy and rehabilitation. One of the significant advantages of using MediaPipe is its potential application in telerehabilitation. With the increasing demand for telehealth services, the ability to accurately measure and track a patient's movement remotely is becoming increasingly important. The use of AI-based tools, such as MediaPipe, can help improve the accuracy and reliability of remote assessments, leading to more effective treatment plans and better patient outcomes. Furthermore, the results of this study suggest that the proposed new technology

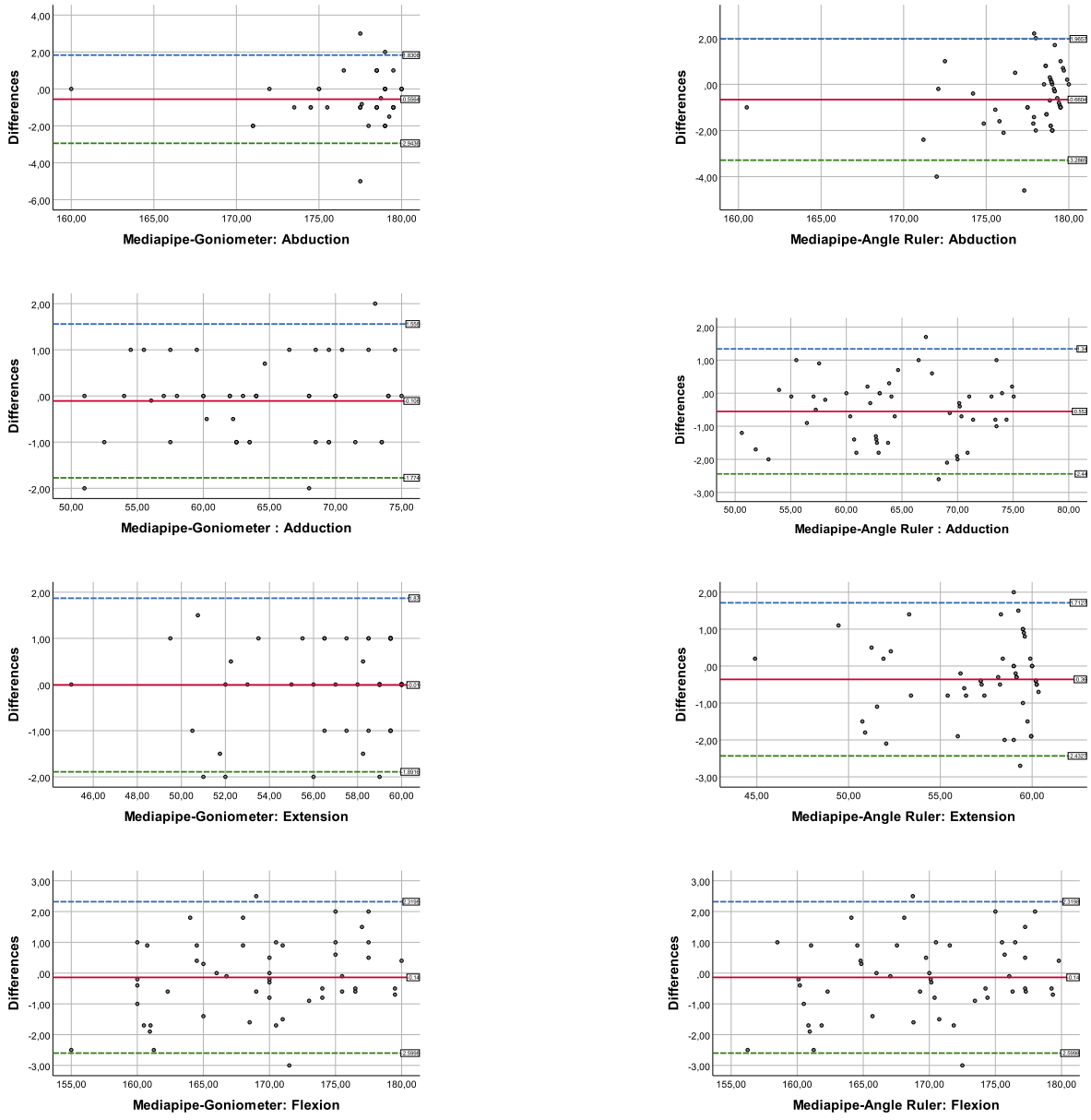


Figure 3.10 : Bland–Altman plots a comparison between MediaPipe and UG and MediaPipe and an AR.

could be a useful addition to clinical rehabilitation settings. The ability to accurately measure shoulder and knee motions in real-time can help clinicians assess the effectiveness of various interventions and track a patient's progress over time. Moreover, the use of AI-based tools, such as MediaPipe, can provide valuable insights into the underlying mechanisms of movement disorders, helping clinicians develop more targeted and effective treatment plans.

3.4.3 Reliability analysis of knee flexion and extension

A total of 25 participants, ranging in age from 21 to 40, took part in this study and investigation. The majority of the data was collected at Skikda University. This study adheres to the principles outlined in the Declaration of Helsinki, a set of ethical guidelines for biomedical research involving human subjects. All participants provided informed consent prior to their involvement in the study. The principles of confidentiality, voluntary participation, and the right to withdraw without prejudice have been strictly observed throughout the research process. This study is committed to upholding the highest ethical standards as stipulated in the Declaration of Helsinki. The MediaPipe and universal goniometer were used to measure all participants. We began by measuring the four motions in three repeats with MediaPipe. The purpose of this approach is to compute the ICC in order to demonstrate the technique's reliability. The goniometer was only used once by the physiotherapist. As reported in Table 3.5, the MediaPipe technique has excellent reliability because the ICC

Table 3.4 : Data of knee flexion and extension obtained using universal goniometer and MediaPipe.

Movement	Meth	Mean	SE Mean	StDev	Min	Med	Max
Flexion	Go	20,40°	0.16°	0.81°	19°	21°	22°
	Me	20,00°	0,17°	0,86°	19°	20°	22°
Extension	Go	179.20°	0.18°	0.91°	178°	180°	180°
	Me	179.08°	0.18°	0.90°	177°	179°	180°

. Abbreviation : Meth : method, Go : clinical goniometer, AR : Angle Ruler, Me : MediaPipe, SE Mean :standard error of the mean, StDev : Standard deviation, Min : minimum, Med : median, Max : maximum.

results of both knee flexion and extension are between 0.81 and 1.0.

Table 3.5 : Reliability results of the MediaPipe based measurement system.

	ICC	StDev	SEM	MDC
Flexion	0.92	0.81°	0.23°	0.63°
Extension	0.87	0.91°	0.33°	0.91°

3.4.4 Validity analysis of knee flexion and extension

A 95% limit of agreement (LOA) amidst MediaPipe-based measurement and the universal goniometer calculated, is calculated; results are in table 3.6:

Table 3.6 : Bland–Altman analysis results of knee flexion/extension data acquired using goniometer and MediaPipe.

	Mean bias	95% LOA
Flexion	0,40°	-0,98° to 1,78°
Extension	0,20°	-0,60° to 1,00°

As shown in [196], the table 3.6 and Figure 3.11 and Figure 3.12, the MediaPipe is valid for using to measure the knee flexion extension in the telerehabilitation platform.

3.5 Discussion

The use of AI-based tools in motion analysis has many potential advantages over traditional measurement methods. For example, it can provide a more objective and accurate assessment of human motion, reduce measurement errors, and improve the efficiency of data analysis. Additionally, AI-based tools can provide valuable insights into the underlying mechanisms of movement disorders, helping researchers and clinicians develop more effective treatments.

The evaluation of range of motion plays a critical role in musculoskeletal exploration . While goniometers are commonly used by kinetherapists, their manual nature prompts the exploration of modern, more accurate, and patient-friendly methods with the advance-

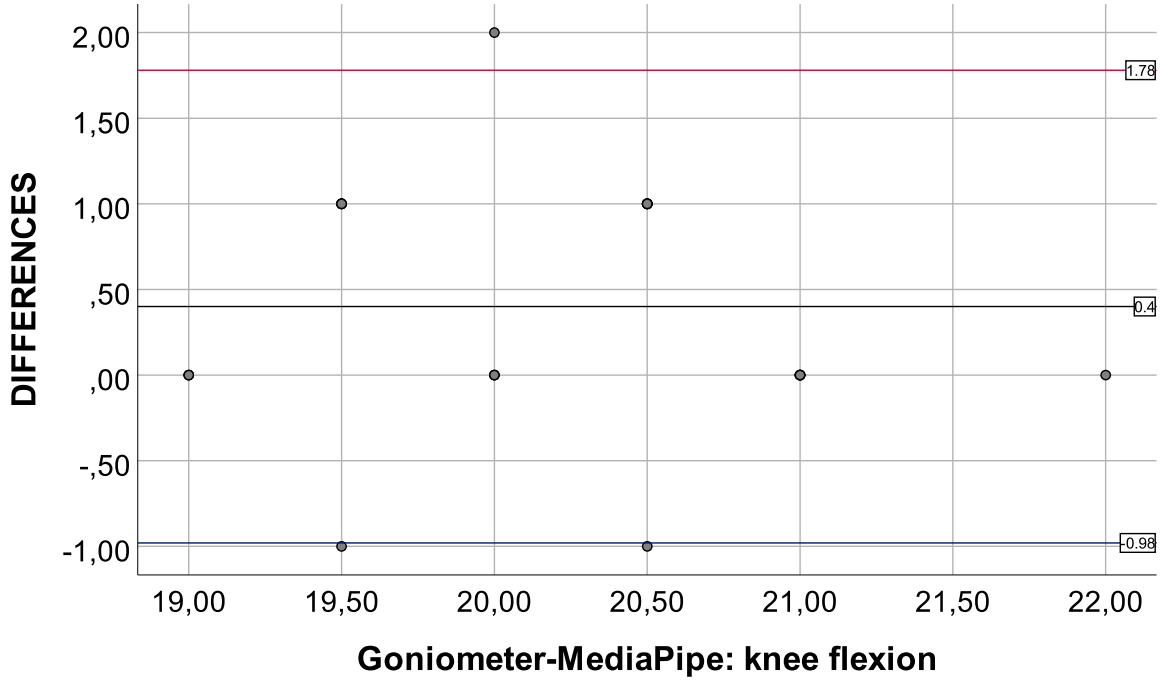


Figure 3.11 : Bland–Altman plots a comparison between MediaPipe and goniometer for flexion.

ment of telerehabilitation techniques. This study examines the reliability and validity of a MediaPipe-based system for measuring four active shoulder ranges of motion. The results indicate that the MediaPipe technique demonstrates excellent reliability and relatively high accuracy, as compared to the clinical goniometer and Kinect results presented in table 4.

Based on our experience, careful positioning in front of the camera is crucial for accurate detection, as an arbitrary position can impact pose estimation. Furthermore, optimal lighting conditions are recommended, as experiments have indicated noise introduction due to lighting variations.

3.6 Conclusion

In conclusion, our study highlights the potential of AI-based tools, such as MediaPipe, in motion analysis. The results demonstrate the reliability and validity of MediaPipe in measuring shoulder motion pose, indicating its potential use in various clinical and research settings. However, it is essential to consider the limitations and potential biases of AI-based

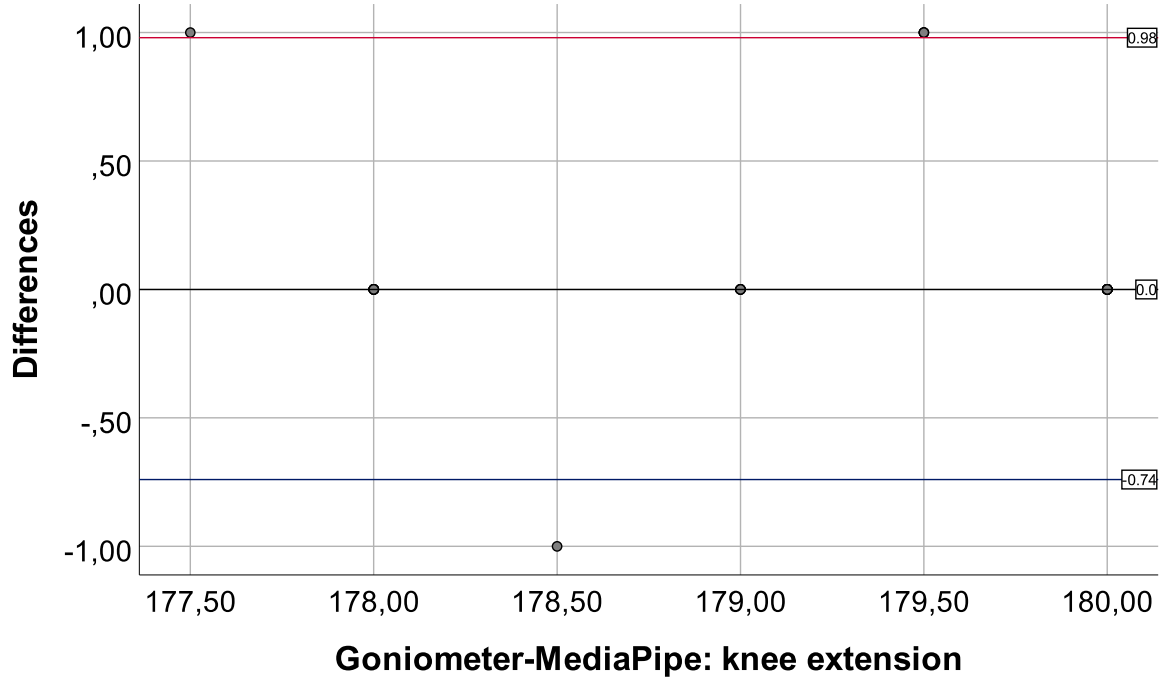


Figure 3.12 : Bland–Altman plots a comparison between MediaPipe and goniometer for extension.

tools and ensure that the results are interpreted correctly by trained professionals. With continued advancements in AI technologies, we can expect more sophisticated and accurate tools for motion analysis in the future.

Chapter

4 Contribution 3: Development of a home-based physiotherapy telerehabilitation system

4.1 Introduction

Remarkable technological advancements have made telecare and telerehabilitation captivating subjects in medicine. These advancements allow patients to interact with their physicians from the comfort of their own homes. As discussed in previous chapters, rehabilitation exercises are frequently essential for treating various musculoskeletal conditions and facilitating postoperative recovery. Patients should engage in rehabilitation programs within a home-based setting to address specific challenges.

One crucial factor considered before embarking on the study of "telerehabilitation" was the mobility difficulties faced by individuals with lower or upper extremity injuries. Additionally, the vast expanse of Algeria, spanning approximately two and a half million square kilometers presents a significant obstacle. Accessing hospitals becomes particularly challenging in desert areas or remote villages, often necessitating journeys of 300 kilometers or more across the Sahara. The inhabitants of these areas face multiple issues, including limited or nonexistent transportation options. Moreover, the scorching desert temperatures challenge patients, especially the elderly, who struggle to move around and perform exercises.

Reducing patient costs, such as transportation expenses, is one of the primary objectives of this study. Most patients can efficiently engage in rehabilitation exercises with the widespread availability of telerehabilitation technology and equipment. Additionally,

telecommunication-based solutions are frequently required, given the necessity of social distancing during the COVID-19 pandemic. Furthermore, due to significant overcrowding, patients often experience lengthy waiting periods of at least three weeks before commencing their rehabilitation sessions.

In light of these circumstances, this chapter introduces a telerehabilitation website designed to enhance the ease and comfort of rehabilitation for patients, physicians, and physiotherapists.

4.2 Survey and open challenge

In this thesis, many factors have been considered before developing the proposed system. The first is COVID-19, and all other epidemics necessitate finding a solution. The second factor is Algeria's surface. Most of it is considered a desert [197]. Traveling through this region is difficult due to the climate, especially in the summer. Also, the citizen sometimes travels more than 200 km to the nearest hospital. Another defy is to reduce the costs of transportation and materials used in telerehabilitation. So, we decided to find a solution with low cost. The majority of the questionnaire was sent electronically.

Before beginning the development of the system, we surveyed 142 citizens in Algeria. The survey is a simple random sample. The most critical questions that were included in the questionnaire are the following:

4.2.1 Age

Our research considers the average age of Algerian citizens, as it plays a significant role in mobility limitations, particularly in the elderly population. As depicted in Figure 4.1, the range of ages of the survey respondents was examined to gain insight into the age demographics of our study. Understanding the population's age distribution is crucial in determining the most appropriate telerehabilitation strategies for different age groups. The study results may provide insight into how age affects the adoption of telerehabilitation technology and the challenges that may arise, particularly in older age groups.

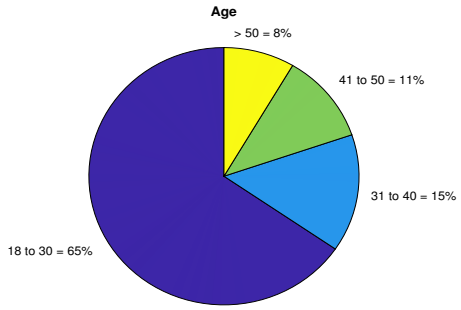


Figure 4.1 : The age range of the participants in the questionnaire.

4.2.2 Place of residence

The distribution of the participants in the questionnaire is depicted in figure 4.2, where the highest percentages are concentrated in both urban and rural areas. It is essential to note that these locations vary regarding the resources available for rehabilitation. For instance, cities have more resources, such as hospitals, transportation, and other necessary facilities for rehabilitation, while rural areas may have fewer resources. On the other hand, the countryside is even more challenging to deal with, as it has a more complex and diverse environment that may hinder access to rehabilitation. Therefore, our research considers the geographical location of patients and the resources available to ensure that telerehabilitation is effective.

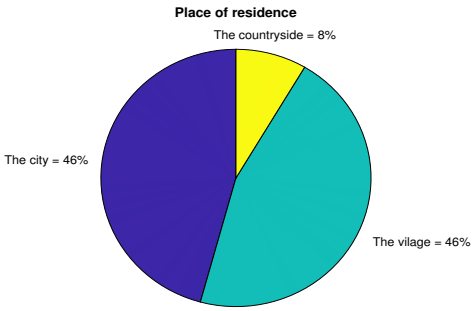


Figure 4.2 : The place of residence of the participants in the questionnaire.

4.2.3 Distance and proximity to the hospital

The factor of distance and proximity to the hospital: The distance between patients' homes and the nearest rehabilitation center is a crucial aspect that was studied in this research, as illustrated in figure 4.3. Transportation is a significant challenge for Algerian citizens, particularly in remote areas and municipalities, which can make it difficult for patients to access rehabilitation centers. Furthermore, overcrowding in major cities can pose a risk to a patient's health when they travel to and from the hospital. The results of 4.3 highlight the challenges that patients face in accessing rehabilitation centers, with many respondents reporting distances greater than 50 km. This makes it even more important to provide accessible and convenient rehabilitation services to patients, particularly those who live in remote areas.

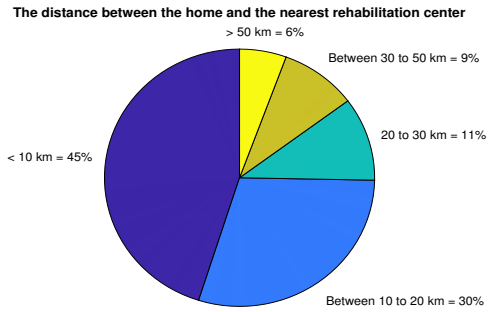


Figure 4.3 : The distance between the homes of the participants in questionnaire and the nearest rehabilitation center.

4.2.4 The buildings

Figure 4.4 illustrates the distribution of participants based on the type of housing they reside in. Our research took into account the type of housing, specifically social buildings, which are commonly referred to as tours, and private housing. Social buildings typically have more than five floors and are usually old buildings without electric elevators. Private housing, on the other hand, is often in the form of a house or a small building with few floors. It is essential to consider the type of housing and the floor number to conduct a more accurate analysis. This is because living on a higher floor can pose a significant challenge, particularly for those with lower extremity problems or the elderly, who may find it

difficult to move around. Therefore, this factor is crucial to our research as it can significantly affect a patient's rehabilitation process.

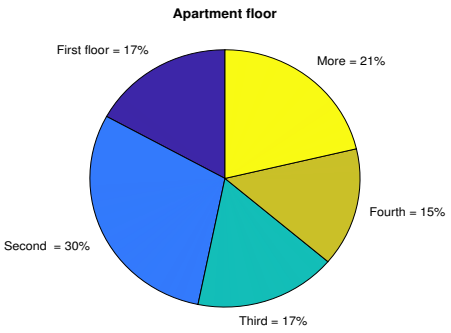


Figure 4.4 : The positioning of the apartment in the social housing.

4.2.5 The availability of a laptop in the house

The availability of computers among participants was analyzed in our research, and the results are presented in figure 4.5. In the survey, we asked whether there was at least one laptop computer or tablet in the participant's house. The computer or tablet only needed a camera and an internet connection for our proposed tele-rehabilitation system to work. As shown in 4.5, 80.4% of the participants responded positively to this question, indicating the presence of a computer or tablet in their homes. In contrast, 19.6% responded negatively, indicating the absence of a computer or tablet in their homes. It is noteworthy that our proposed website and application can be accessed from a mobile phone, which provides more convenience to the patients who do not have a computer or tablet.

4.2.6 The mastery of the use of computers

We conducted a survey among the participants to assess their computer proficiency, and the results showed that 86.6% of the respondents reported having mastered the use of computers, while the remaining 13.4% expressed a lack of computer skills. This information is crucial for our proposed system, as it will help us determine the level of technical support required for the patients who may face difficulties in using the platform. Therefore, we plan to provide adequate guidance and assistance to those who need it, to ensure a seamless user experience for everyone., and we also asked this question of **elderly persons**

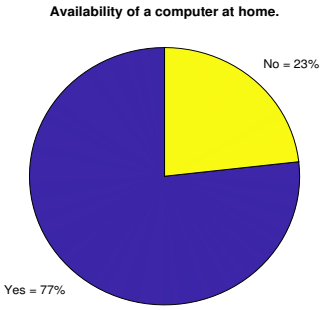


Figure 4.5 : Availability of a laptop at home.

(Figure 4.6 which represents computer proficiency for the elderly). We also considered **the availability of the Internet at home**: 84.1% of the participants have Internet access.

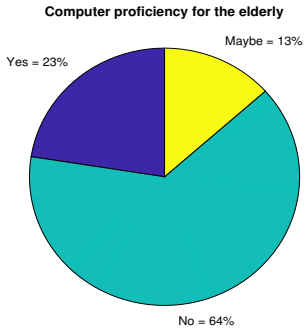


Figure 4.6 : Computer proficiency for the elderly.

The findings from the questionnaire underscore the significance of developing a website that can assist citizens and patients in overcoming various challenges and expenses. Additionally, the results highlight the importance of further promoting and advancing telehealth in the medical industry, given its numerous benefits.

4.3 Proposed system "DzTelerehab"

This thesis proposes a website called DZtelerehab that utilizes an artificial intelligence technique to support remote rehabilitation procedures. The website employs computer vision to detect real-time angles and positions of the patient's body, which can be

achieved using a web camera connected to a computing device, tablet, or even just a phone call. The computer vision system enables physiotherapists to assess the patient's range of motion in real-time, allowing them to save exercise data and compare it with future results. This feature facilitates monitoring the patient's progress, obtaining rehabilitation outcomes, and digitizing the data, eliminating the need for paper records, which are prone to damage and require large storage space. The proposed system utilizes deep learning, a subfield of machine learning, to compute the output. The deep learning model learns hierarchical data patterns and weights these hierarchies to compute the desired output. Deep learning has proven to be useful in various health informatics applications. Figure 4.7 depicts the architecture of the DZtelerehab system.

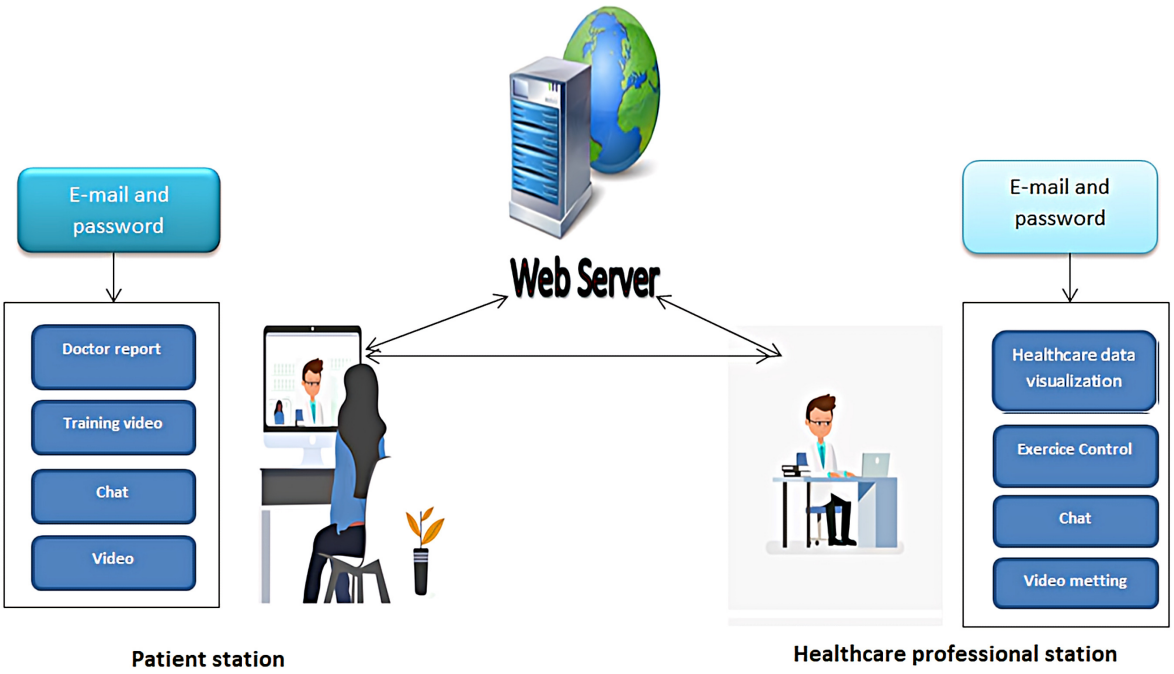


Figure 4.7 : Architecture of the proposed system.

4.4 DZtelerehab telerehabilitation platform

DZtelerehab is a website that comprises three significant entities, namely the administrator, doctor, and patient. The administrator's primary responsibility is to arrange and manage the website's workflow. The administrator plays a crucial role in the registration of

both doctors and patients on the platform. To maintain the security and confidentiality of patients' information, the administrator uses identification and password systems. As seen in figure 4.8, the patient's account registration portal displays the measures in place to guarantee privacy and security. Only the administrator has access to the patient's portal, and no other person can access it. This ensures that patient data is safe and secure on the website.

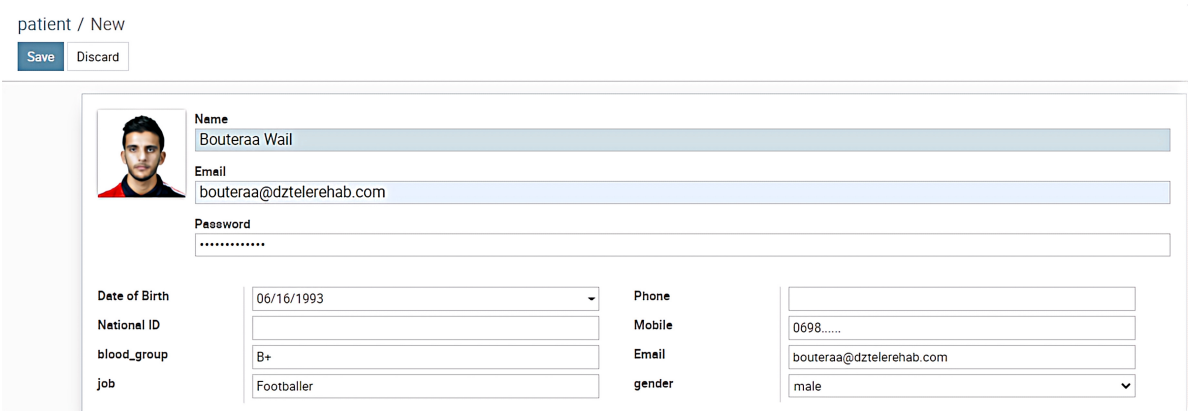


Figure 4.8 : Registration for a patient account.

4.4.1 Design of the website

Python and Node.js are the programming languages utilised in this project. To enable real-time assessment, two additional modules are developed. The first module facilitates data analysis using a RESTful API, while the second module acquires movement data through a client application. These modules can connect via the JSON data format, allowing for the analysis of patient movements and the delivery of outcomes. The patient's movements are recorded utilising a computer camera. Bootstrap 4.1.3 and JQuery 1.11.4 were utilised in building the web interface. The operating system used is Ubuntu, and Nginx 1.10.3 is used as a reverse proxy.

4.4.2 Administrator role

The platform administrator plays a crucial role in facilitating communication between doctors and patients. As illustrated in figure 4.9, the administrator arranges and schedules virtual meetings for patients and doctors to interact and discuss various aspects of their treatment plans. During these meetings, doctors can evaluate the patient's progress, provide

feedback, and adjust the rehabilitation program accordingly. The administrator also ensures that the meeting runs smoothly and that both parties have access to the necessary tools and resources, such as a virtual whiteboard or exercise videos. Overall, the administrator plays a vital role in ensuring that the telerehabilitation process is effective and efficient for both patients and doctors.

Figure 4.9 : Meeting portal creating.

4.4.3 Doctor portal

The doctor has the responsibility of organising the rehabilitation sessions, which includes setting the date and time, and selecting specific exercises for the patient. Following this, the doctor can liaise with the administrator to schedule appointments. Communication between the doctor and patient takes place through the internet. To facilitate the rehabilitation session and guide the patient, the physiotherapist can send video examples, website links, or any tutorial procedure. During the exercise, the physiotherapist can display the

range of motion in real-time, as demonstrated in figure 4.10. Additionally, the doctor can record the session, provide feedback, give instructions, and prepare a report on the session. The physiotherapist can store the recorded data in various formats, including XLS, CSV, PDF, JPEG, or PNG. The patient can access this information, view reports and instructions from the doctor, and send messages to the physiotherapist for advice or recommendations.

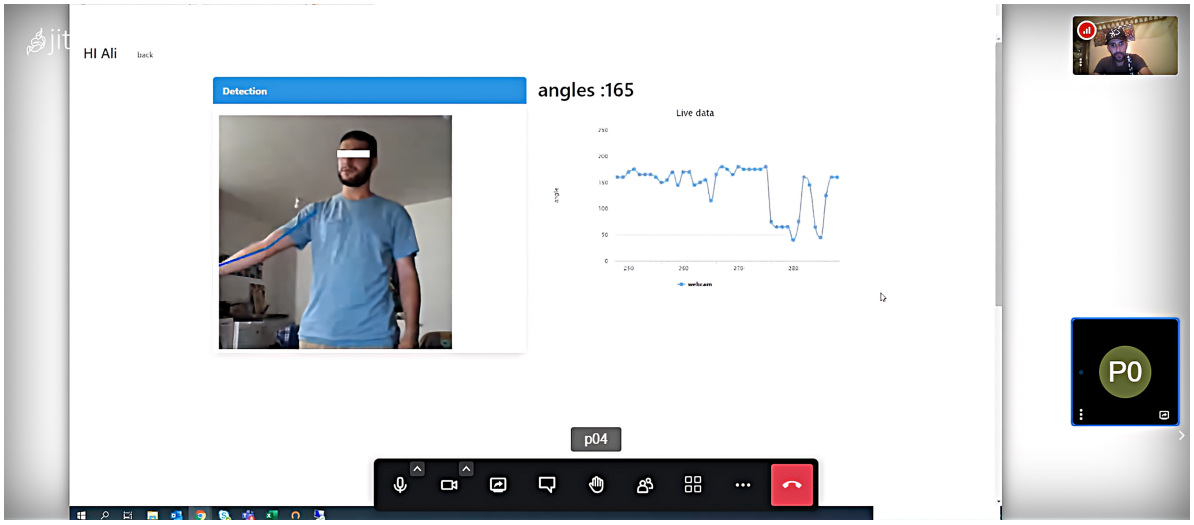


Figure 4.10 : Physiotherapist view during the session.

4.4.4 Patient portal

Apart from its user-friendliness, the system also features a comprehensive guide or user manual to assist patients in navigating it. In the patient portal, we have focused on simplicity and ease of use; it can be used by patients of different educational levels. As part of the telerehabilitation evaluation process, the doctor engages in a face-to-face interaction with the patient. This typically entails conducting an interview, performing a physical examination, making observations, conducting movement examinations, and administering standardized tests.

4.4.5 Rehabilitation session method

To commence the rehabilitation session, the patient and doctor must first attend a virtual meeting, during which the patient should position themselves in front of the camera. The first step of telerehabilitation involves launching and loading the pose module. Next,

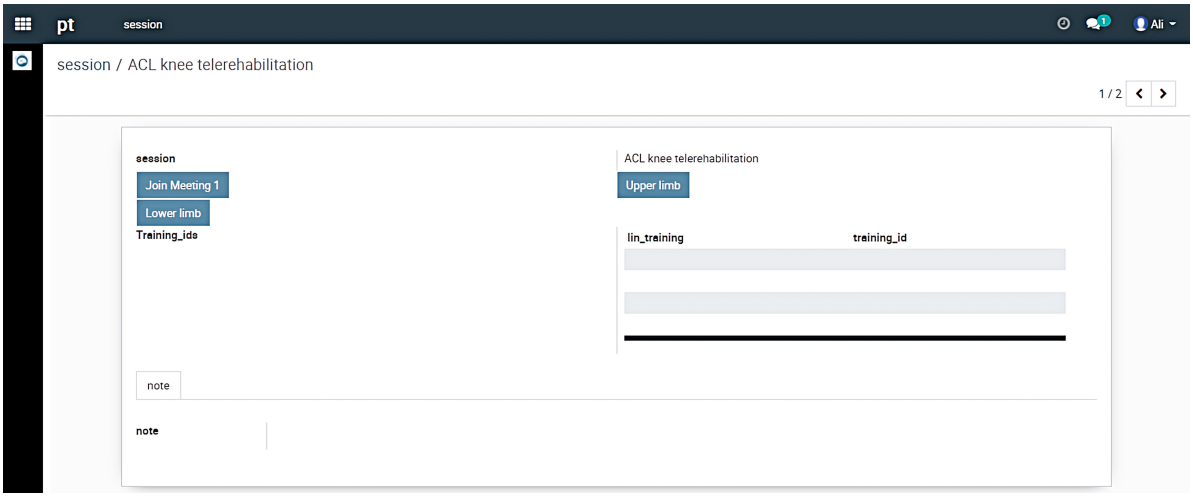


Figure 4.11 : Patient station view.

the doctor sends the patient a video tutorial of the exercise to be performed or provides verbal instructions. The patient then begins to practice the exercise, and the physiotherapist guides them on the number of repetitions to perform. During the session, the doctor can view the patient in real-time, alongside the values of the angles and a graphical representation of the data, allowing for comparison with previous sessions or the data of a healthy individual. Once the session is complete, the doctor can save the data and compare it with that of subsequent sessions to assess the patient's progress. The platform can detect the range of motion of both the upper and lower limbs, facilitating a wide range of rehab exercises, including those for ACL knee reconstruction and frozen shoulder rehab. The system is summarised in the flowchart depicted in figure 4.12.

4.5 Patient experimental validation

This study adheres to the principles outlined in the Declaration of Helsinki, a set of ethical guidelines for biomedical research involving human subjects. All participants provided informed consent prior to their involvement in the study. The principles of confidentiality, voluntary participation, and the right to withdraw without prejudice have been strictly observed throughout the research process. This study is committed to upholding the highest ethical standards as stipulated in the Declaration of Helsinki. Our experimental test aimed to evaluate the effectiveness of telerehabilitation in guiding patients through

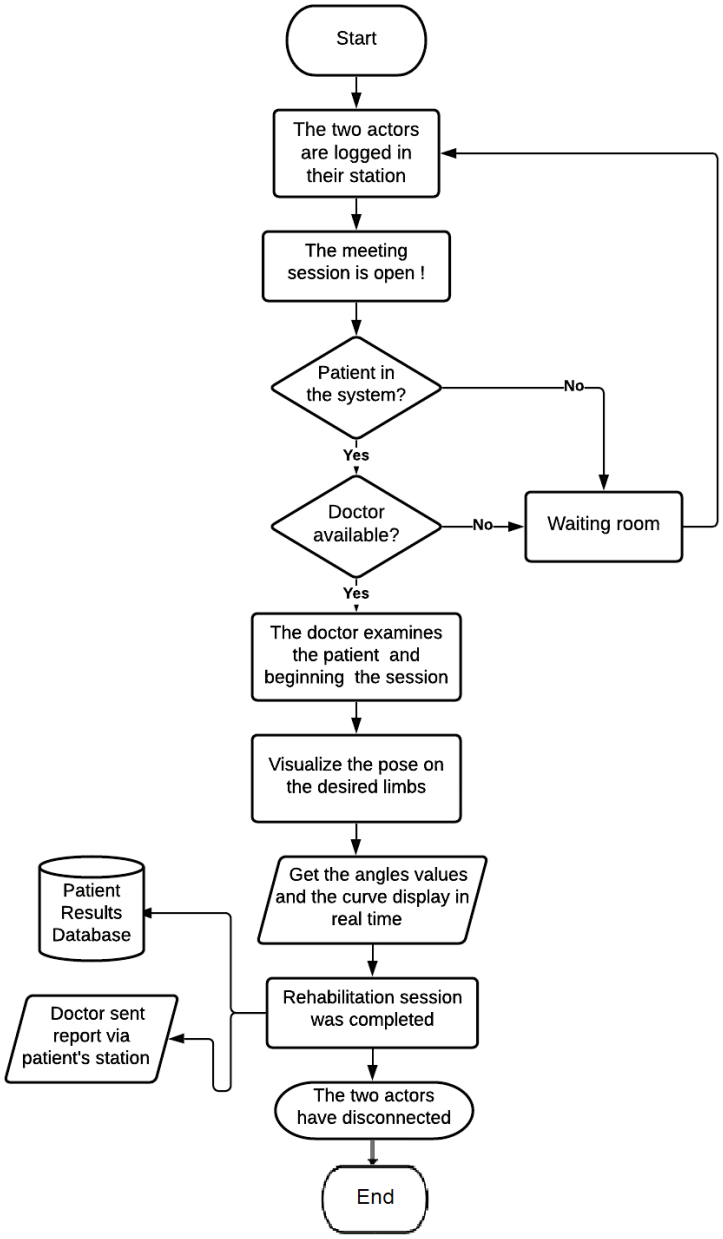


Figure 4.12 : Proposed system process.

the rehabilitation exercises required after an ACL knee reconstruction. The ACL is a vital ligament that connects the femur to the tibia and helps stabilize the knee joint during movement. However, a torn ACL can result from over-rotation or direct trauma to the knee. In such cases, surgery may be necessary to repair the ACL. During the arthroscopic procedure, the surgeon removes the damaged ACL and replaces it with a graft attached to the tibia and femur through small tunnels. After the surgery, the patient begins supervised physical therapy within a few days to help recover. The initial phase of physical therapy focuses on assisting the patient in coping with the surgery's trauma and restoring knee motion. One such exercise, depicted in 4.13, is heel slides and quad sets, which are designed to improve the knee's range of motion and rebuild the front thigh muscles. As rehabilitation progresses, the patient can move on to more advanced exercises such as single-leg balance exercises to improve balance and inner range quad and static quad exercises to enhance the knee's mobility.

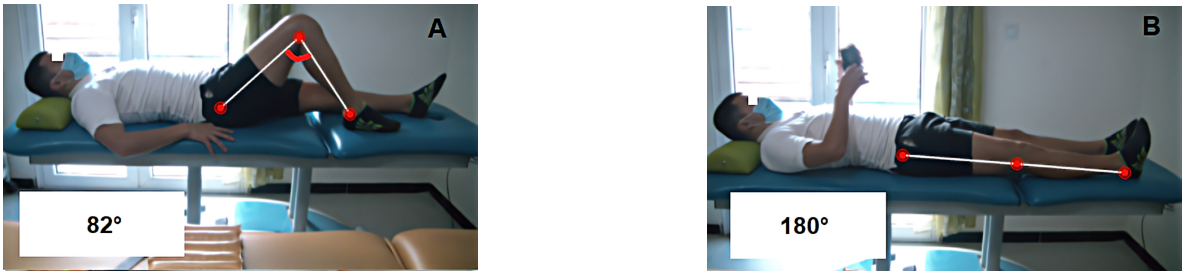


Figure 4.13 : A. Heel slides: to lie on the back with legs straight, then to bend the knee and slide the heel up toward the buttocks. B. Quad sets: to try to engage the quad muscles while lying on the back with the leg straight.

Typically, physiotherapists use goniometers or sensors to evaluate the patient's range of motion and progress, which they then document in a report. However, in this project, an artificial intelligence technique is proposed to measure the range of motion. Using this technique makes it apparent that a healthy person can achieve flexion of 20°, as shown in the 'Healthy' graph in Fig. 18. However, the patient undergoing ACL reconstruction rehabilitation cannot reach this range of motion and shows a significant difference from a healthy individual. Specifically, patients with ACL reconstruction find it challenging to flex their knees and must do so gradually to achieve the desired results. With the the proposed technique, patients can receive remote assistance throughout their rehabilitation sessions and track their progress, comparing each session's results with the previous ones. Using these

graphs, physiotherapists can analyze the effectiveness of the rehabilitation and tailor the treatment to suit each patient's needs.

4.5.1 Patient 1 follow-Up

The study involved two participants, a 24-year-old individual and a 28-year-old male who was 175 cm tall and weighed 68 kg. The 24-year-old patient suffered a football injury five years prior, and an MRI of their right knee revealed the following findings:
- Subtotal rupture of the anterior cruciate ligament;
- Grade 3 lesion of the posterior horn of the internal meniscus;
- Grade 3B lesion of the posterior horn of the external meniscus.

On October 5, 2021, the patient underwent surgery, and on October 10, 2021, the first rehabilitation session took place. During this session, the patient managed to achieve a flexion angle of 120°, but he experienced pain during the exercises, which slowed down the rehabilitation process. After ten days, the patient was able to reach 100°, indicating a slight improvement in the speed of the exercise. However, on November 16, the patient experienced some swelling in the knee, followed by pain, and achieved only 86° (record 3). After nine weeks, on December 28, 2021, the patient reached 67° (record 4), with some improvement in the speed of flexion and extension. Unfortunately, the patient stopped doing the rehabilitation exercises for more than a month and a half, and there was no improvement during this period. However, the following week, there was a slight improvement in the patient's condition, which is indicated by the curve of record 6. The first patient was a 24-year-old man with a height of 175 cm and a weight of 68 kg. He sustained an injury while playing football five years ago, as revealed by an MRI of his right knee.

4.5.2 Patient 2 follow-Up

The second patient underwent surgical management for anterointernal laxity of the right knee using a KJ-type ligamentoplasty on September 26, 2021. The patient's rehabilitation progress was measured using heel slides and quad set exercises, and the results are presented in the graphs. The rehabilitation sessions began on September 30, 2021, with simple exercises, and the effectiveness of rehabilitation was analyzed using these curves. Record 1 in the graph represents the results from the first week after the operation. As the

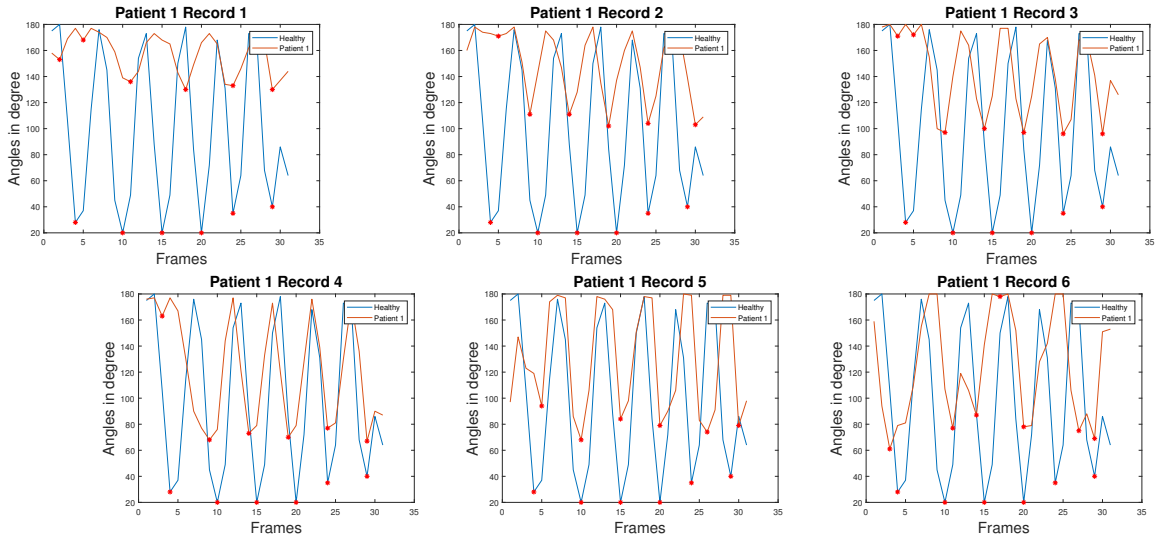


Figure 4.14 : RoM of knee flexion-extension of patient 1.

patient could only reach a flexion angle of 125°, the extension and flexion of the knee were challenging, and progress was slow. However, there was a remarkable improvement after ten days, and the patient reached 98° (record 2). Although the speed of flexion and extension remained small, the patient experienced some pain relief during this period. The patient reached a flexion angle of 62° on record 4 (see Figure 4.15) within the first month of rehabilitation, indicating significant improvement. The patient moved at an average speed in just one week, slightly improving the flexion. On December 20 (record 5), the patient could reach 47°, and on January 3, 2022 (record 6), the patient got a flexion angle of 40°. These results demonstrate the effectiveness of the rehabilitation program and the progress made by the patient over time.

4.5.3 Patients data comparison

In order to evaluate and compare the effectiveness of the trained models, it is necessary to quantify the error between the actual and predicted values. This is achieved by computing the root mean square error (RMSE) using the unstandardized prediction data. Figure 4.16 visually represents the differences between a healthy individual's range of motion and the patient's progress over four months. The RMSE value is calculated by taking the square root of the average of the squared differences between the predicted and actual

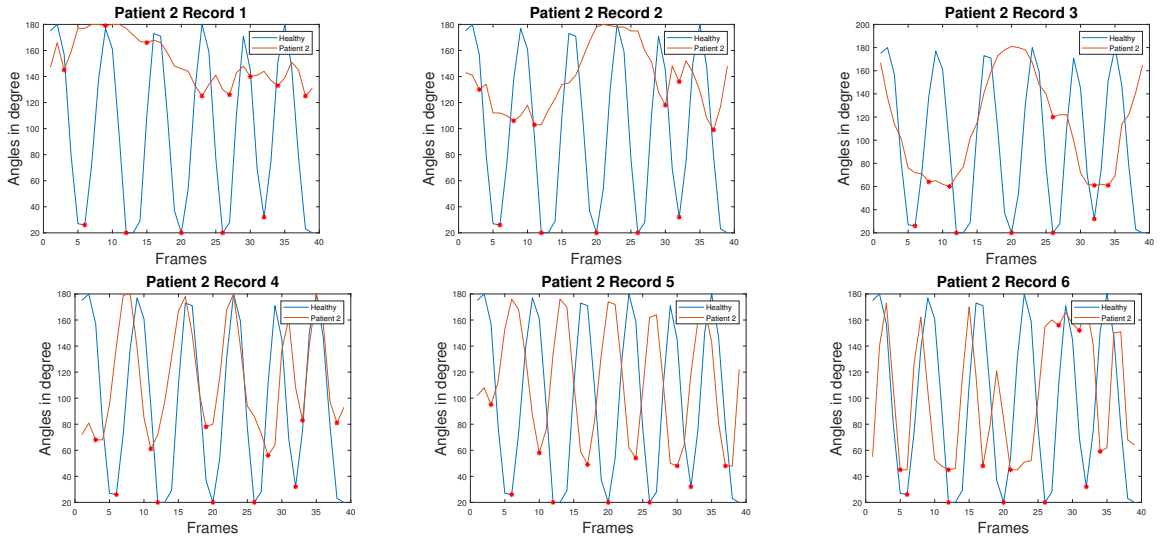


Figure 4.15 : RoM of knee flexion extension of patient 2.

values. A lower RMSE indicates that the model's predictions are closer to the fundamental values, while a higher RMSE suggests a greater degree of error in the model's predictions. By comparing the RMSE values of the trained models, we can determine which model performs better in predicting the range of motion for the patients.

$$\mathrm{RMSE} = \sqrt{\frac{1}{R}\Sigma_{i=1}^{R}(t_i - y_i)^2} \tag{4.1}$$

where t_i is the mean of the minima (per training session) of the angles of flexion of the patient, y_i represents the flexion angle of a healthy person, and R is the number of training . Table 1 illustrates the flexion progression of the patients over six records.

Upon examining and following up with the two patients, we observed that the second patient exhibited faster progress than the first, mainly because the second patient attended the rehabilitation sessions consistently. We also noted that if the patient discontinues the rehabilitation process, they may lose the progress they have made, and the process of flexion and extension may become more tiring. In four months, the second patient reached a flexion angle of 40°, whereas the first patient only managed to get a flexion angle of 60°. The physical therapist advised the patient to perform the exercises consistently, even at home, to aid in the patient's speedy recovery. The therapist emphasized the importance of continuing reha-

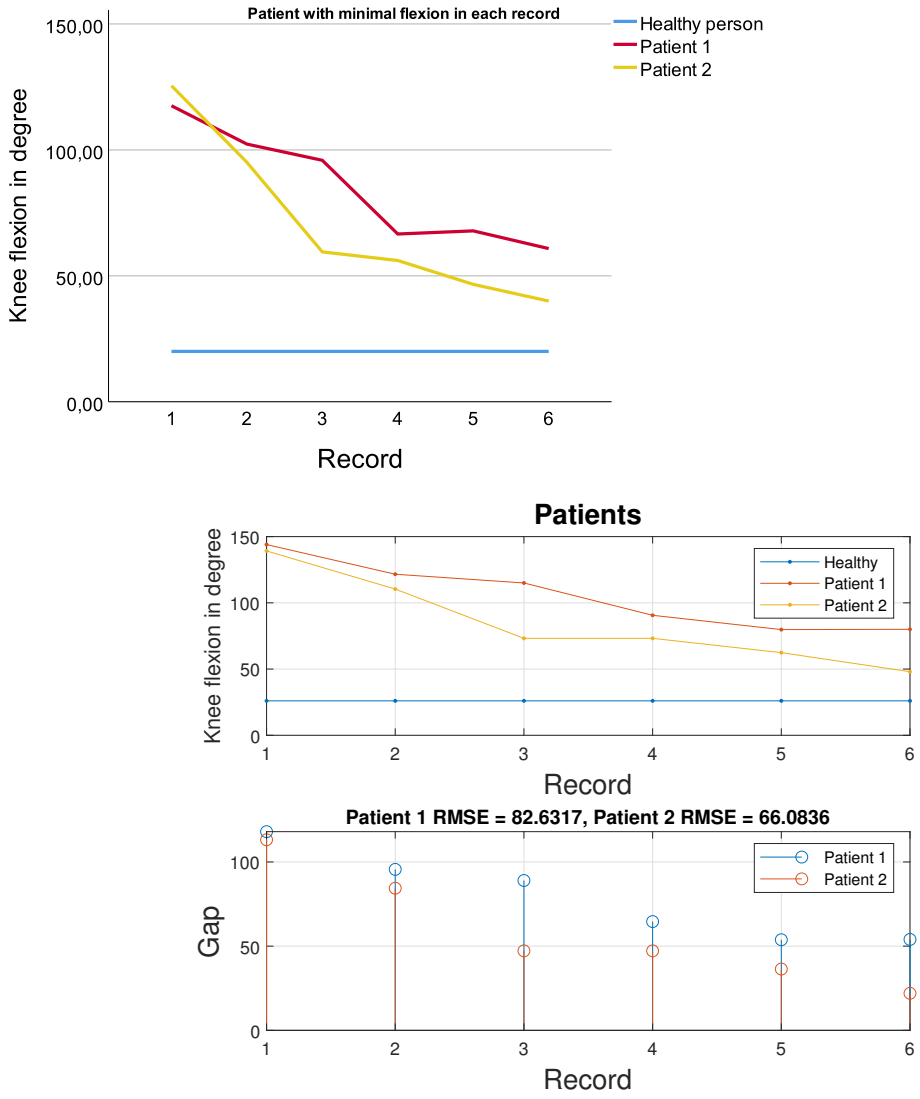


Figure 4.16 : Flexion differences between a healthy subject with the progression of the patients through 4 months.

Table 4.1 : Optimal patients flexion progression during six records.

Optimal flexion	Patient 1	Patient 2
R1	130.00°	125.49°
R2	102.32°	98.00°
R3	95.86°	59.00°
R4	66.60°	56.10°
R5	67.83°	46.62°
R6	60.83°	40.00°

R: record.

bilitation until the patient reaches their desired results. This way, the patient can maintain and improve the flexibility of the knee joint.

4.5.4 Health staff and patients' feedback

In conclusion, we administered a survey to gather feedback on the project's impact on patients and medical staff. The medical staff, including the doctor and physiotherapist, provided input on the system's technical aspects and potential impact on patients. The doctor noted that the system's reliability in angle measurement was excellent and could be crucial in aiding patients' rehabilitation from a distance. The affordability of the equipment used in the system made it an accessible solution for patients. The doctor also suggested expanding the project to include other medical fields that could benefit from remote interventions.

The physiotherapist was pleased with the ability to monitor patients remotely, which reduced their workload in the clinic. The data collected on the website was also helpful in tracking patients' progress, which was time-efficient compared to in-person monitoring. However, the physiotherapist mentioned that internet connectivity issues sometimes remained an obstacle.

The patients who participated in the survey provided positive feedback on their experience with the system. One patient found the website easy to use, and the progress displayed on graphs motivated them to continue their rehabilitation sessions. Another patient appreciated the system's convenience, saving them from traveling to a center and incurring high expenses.

Overall, the survey results were highly positive, with suggestions for expanding the project's reach and increasing the use of modern medical technologies in the region. The system's affordability and accessibility make it an excellent tool for aiding patients' rehabilitation from a distance. The data collected from the system also provides valuable insights into patients' progress, making it an essential tool for medical staff. The project has the potential to benefit many patients and medical professionals and should be developed further.

4.6 Results and discussion

In this research, we propose a novel method to address the challenge of prolonged rehabilitation periods, which often extend beyond ten weeks. Our approach enables doctors to inspect and monitor patients remotely, offering numerous benefits that alleviate obstacles during this extended duration. By adopting telerehabilitation, patients can avoid various hardships, including travel difficulties, burdens, and financial costs. Our system provides several advantages that enhance patient comfort and eliminate numerous stress-inducing, arduous, and expensive factors. Furthermore, it significantly facilitates the work of doctors.

Compared to alternative solutions, "DzTelerehab" such as Microsoft Kinect or other sensor-based approaches, our method is more cost-effective and user-friendly. Notably, the risk of obtaining inaccurate readings due to misplaced sensors are mitigated, and patients can avoid the discomfort associated with prolonged attachment of sensors to their bodies.

One of the critical considerations is the protection of the patient data, as medical information, is susceptible, and maintaining medical privacy is of utmost importance. Implementing such an application can enable safer and more motivational home workout practices while enhancing accessibility.

However, it is crucial to acknowledge and address specific challenges that arise when implementing our remote rehabilitation approach. The first limitation pertains to older individuals' need for familiarity with technology, which may hinder their ability to use the system, mainly if they are alone effectively. To mitigate this issue, we have simplified the patient's page on the website as much as possible, aiming to make it user-friendly for individuals of all ages. Additionally, some individuals prefer face-to-face interactions and may not readily participate in remote rehabilitation. They believe having a physiotherapist physically present during rehabilitation sessions is more beneficial than remote sessions conducted over the phone.

Another limitation that must be considered is the potential instability of the patient's Internet connection. In some cases, a poor connection can hinder the effectiveness of telerehabilitation sessions. To address this concern, we propose a secondary solution: Recording the exercise session and sending it to the physiotherapist for later evaluation of the patient's progress. This approach allows for a more flexible assessment that is not entirely dependent on real-time internet connectivity.

By recognizing and addressing these limitations, we aim to optimize the implementation of remote rehabilitation, making it more accessible, efficient, and accommodating to a wide range of patients' needs and preferences.

4.7 Conclusion

Telerehabilitation is gaining significant importance and witnessing unprecedented growth and demand due to its effectiveness in providing services, particularly to patients. Especially during critical situations like the ongoing coronavirus pandemic, where staying at home to prevent infection and limit the spread of the virus is crucial, telerehabilitation emerges as an invaluable resource. It proves incredibly beneficial for patients with lower-limb injuries or individuals facing mobility difficulties, as it allows them to perform rehabilitation exercises from the comfort of their homes. The elderly population also benefits significantly from these remote rehabilitation services.

The advancement of digital technology in various fields, including medicine, has opened doors for extensive research and practical solutions to address such challenges. In the present era, exploring innovative approaches that minimize costs while ensuring efficient access to services is imperative. Telecare significantly enhances the quality of patient care, improves patient outcomes, and reduces overall healthcare expenses.

General conclusion

In conclusion, this thesis has made significant contributions to the field of human rehabilitation through the application of mediapipe-based measurement systems and the development of a novel home-based telerehabilitation platform. The research focused on two main objectives: the reliability and validity analysis of the mediapipe-based measurement system for assessing human rehabilitation motions, and the design and experimental validation of a new telerehabilitation platform for upper and lower limb rehabilitation.

The first contribution of this work involved the rigorous analysis of the MdiaPipe-based measurement system. Through extensive experiments and statistical analyses, the reliability and validity of the system were assessed, providing valuable insights into its accuracy and effectiveness in measuring and evaluating human rehabilitation motions. This analysis not only established the system's suitability for clinical and research applications but also highlighted areas for improvement and further development.

The second contribution of this thesis was the proposal and implementation of a home-based telerehabilitation platform for upper and lower limb rehabilitation. This platform aimed to address the limitations of traditional in-clinic rehabilitation programs by providing a flexible and accessible solution for patients to engage in rehabilitation exercises remotely. The experimental validation of the platform demonstrated its feasibility and effectiveness in promoting rehabilitation outcomes, empowering patients to actively participate in their own recovery process.

Throughout this thesis, the contextual background, problem formulation, and historical overview provided a foundation for understanding the significance and relevance of the research. The related works chapter presented a comprehensive review of existing literature, identifying gaps and opportunities for innovation in the field of human rehabilitation. Additionally, the exploration of artificial intelligence in rehabilitation highlighted the potential of advanced technologies to enhance the effectiveness and efficiency of rehabilitation interventions.

Overall, this research contributes to the advancement of human rehabilitation by combining state-of-the-art measurement systems with innovative telerehabilitation platforms. The findings and insights obtained from this work can inform the development of future measurement tools, enhance the design of tele-rehabilitation systems, and ultimately improve the quality of care provided to individuals undergoing rehabilitation. The outcomes of this research have the potential to positively impact the lives of patients, healthcare professionals, and researchers in the field of human rehabilitation.

In our future work, we aim to leverage AI to estimate muscle force during complicated movements such as reach-and-grasp. This will involve developing advanced machine learning models that can analyze high-fidelity motion capture data and biomechanical simulations to understand the dynamics of these complex actions. Additionally, we will explore sensor-free AI approaches, using computer vision and deep learning algorithms to estimate muscle force purely from visual data, eliminating the need for wearable sensors. This approach will enhance the accessibility and practicality of telerehabilitation by allowing accurate muscle force estimation through standard cameras, thereby simplifying the setup and increasing patient compliance.

Bibliography

[1] H Gray. Standring s. gray's anatomy: the anatomical basis of clinical practice, 2005. Cited on pages 1 and 24.

[2] Upper limb. Online access: October, 2023. Cited on pages 1 and 26.

[3] Qiying Su, Zhongcai Pei, Zhiyong Tang, and Quan Liang. Design and analysis of a lower limb loadbearing exoskeleton. In *Actuators*, volume 11, page 285. MDPI, 2022. Cited on pages 1 and 27.

[4] Timothy R Wohl, Cody R Criss, and Dustin R Grooms. Visual perturbation to enhance return to sport rehabilitation after anterior cruciate ligament injury: a clinical commentary. *International Journal of Sports Physical Therapy*, 16(2):552, 2021. Cited on pages 1 and 38.

[5] Health Central 10 best strength exercises for ms. https://www.healthcentral.com/slideshow/best-strength-exercises-for-ms. Accessed: 2023-05-26. Cited on pages 1 and 39.

[6] M Matos-Duarte, Vicente Martínez-de Haro, Ismael Sanz-Arribas, AGP Andrade, and Mauro H Chagas. Estudio longitudinal de la flexibilidad funcional en mayores físicamente activos. *Revista Internacional de Medicina y Ciencias de la Actividad Física y del*

Deporte/International Journal of Medicine and Science of Physical Activity and Sport, 17 (65):121–137, 2017. Cited on pages 1 and 39.

[7] Richard B Burns, Deb Crislip, Pat Daviou, Ann Temkin, Susan Vesmarovich, John Anshutz, Cathy Furbish, and Michael L Jones. Using telerehabilitation to support assistive technology. *Assistive Technology*, 10(2):126–133, 1998. Cited on pages 1, 43, and 44.

[8] MJ Moron, JR Luque, and AA Bottela. Development of wireless body area network based on j2me for m-health applications. In *2nd European Computing Conf.*, pages 83–88, 2008. Cited on pages 1, 43, and 44.

[9] Liliana Rodríguez Tovar, Javier E Sierra, Claudia Pachón Flórez, and Meryene Barrios Barreto. Functional telerehabilitation system in interactive virtual environments and biomedical technologies. *Utopía y praxis latinoamericana: revista internacional de filosofía iberoamericana y teoría social*, (11):195–203, 2020. Cited on pages 1, 67, and 68.

[10] Daniel Cesarini, Pasquale Buonocunto, Mauro Marinoni, and Giorgio Buttazzo. A telerehabilitation framework for lower-limb functional recovery. In *Proceedings of the 9th International Conference on Body Area Networks*, pages 54–61, 2014. Cited on pages 1, 68, and 69.

[11] Federico Parisi, Gianluigi Ferrari, Matteo Giuberti, Laura Contin, Veronica Cimolin, Corrado Azzaro, Giovanni Albani, and Alessandro Mauro. Body-sensor-network-based kinematic characterization and comparative outlook of updrs scoring in leg agility, sit-to-stand, and gait tasks in parkinson's disease. *IEEE journal of biomedical and health informatics*, 19(6):1777–1793, 2015. Cited on pages 1, 69, and 70.

[12] Angela Barriga, José M Conejero, Juan Hernández, Elena Jurado, Enrique Moguel, and Fernando Sánchez-Figueroa. A vision-based approach for building telecare and telerehabilitation services. *Sensors*, 16(10):1724, 2016. Cited on pages 1, 69, and 70.

[13] Seanglidet Yean, Bu Sung Lee, Chai Kiat Yeo, Chan Hua Vun, and Hong Lye Oh. Smartphone orientation estimation algorithm combining kalman filter with gradient descent. *IEEE Journal of biomedical and health informatics*, 22(5):1421–1433, 2017. Cited on pages 1 and 71.

[14] Pasquale Buonocunto, Andrea Giantomassi, Mauro Marinoni, Davide Calvaresi, and Giorgio Buttazzo. A limb tracking platform for tele-rehabilitation. *ACM Transactions on Cyber-Physical Systems*, 2(4):1–23, 2018. Cited on pages 2, 71, and 72.

[15] Laura Susana Vargas-Valencia, Felipe BA Schneider, Arnaldo G Leal-Junior, Pablo Caicedo-Rodriguez, Wilson A Sierra-Arevalo, Luis E Rodriguez-Cheu, Teodiano Bastos-Filho, and Anselmo Frizera-Neto. Sleeve for knee angle monitoring: An imu-pof sensor fusion system. *IEEE journal of biomedical and health informatics*, 25(2): 465–474, 2020. Cited on pages 2, 72, and 73.

[16] Hyung-Soon Park, Qiyu Peng, and Li-Qun Zhang. A portable telerehabilitation system for remote evaluations of impaired elbows in neurological disorders. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 16(3):245–254, 2008. Cited on pages 2, 74, and 75.

[17] Mario Cortese, Marco Cempini, Paulo Rogério de Almeida Ribeiro, Surjo R Soekadar, Maria Chiara Carrozza, and Nicola Vitiello. A mechatronic system for robot-mediated hand telerehabilitation. *IEEE/ASME transactions on mechatronics*, 20(4):1753–1764, 2014. Cited on pages 2, 74, and 76.

[18] Yassine Bouteraa, Ismail Ben Abdallah, Khaled Alnowaiser, and Atef Ibrahim. Smart solution for pain detection in remote rehabilitation. *Alexandria Engineering Journal*, 60(4):3485–3500, 2021. Cited on pages 2, 74, and 76.

[19] Boldmaa Solongontuya, Kyung Joo Cheoi, and Mi-Hye Kim. Novel side pose classification model of stretching gestures using three-layer lstm. *The Journal of Supercomputing*, 77:10424–10440, 2021. Cited on pages 2 and 77.

[20] Biao Chen, Chaoyang Chen, Jie Hu, Zain Sayeed, Jin Qi, Hussein F Darwiche, Bryan E Little, Shenna Lou, Muhammad Darwish, Christopher Foote, et al. Computer vision and machine learning-based gait pattern recognition for flat fall prediction. *Sensors*, 22(20):7960, 2022. Cited on pages 2, 77, and 78.

[21] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. *Communications of the ACM*, 60(6):84–90, 2017. Cited on pages 2, 87, 88, and 99.

[22] Sven Kreiss, Lorenzo Bertoni, and Alexandre Alahi. Pifpaf: Composite fields for human pose estimation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 11977–11986, 2019. Cited on pages 2 and 89.

[23] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017. Cited on pages 2, 97, and 98.

[24] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V 13*, pages 740–755. Springer, 2014. Cited on pages 2, 97, and 102.

[25] Kazuko Shem, Ingebjørg Irgens, and Marcalee Alexander. Getting started: Mechanisms of telerehabilitation. In *Telerehabilitation*, pages 5–20. Elsevier, 2022. Cited on page 19.

[26] Temple Grandin. Calming effects of deep touch pressure in patients with autistic disorder, college students, and animals. *Journal of child and adolescent psychopharmacology*, 2(1):63–72, 1992. Cited on page 23.

[27] Netanel Ofer, Daniel R Berger, Narayanan Kasthuri, Jeff W Lichtman, and Rafael Yuste. Ultrastructural analysis of dendritic spine necks reveals a continuum of spine morphologies. *Developmental neurobiology*, 81(5):746–757, 2021. Cited on page 23.

[28] Richard Drake, A Wayne Vogl, and Adam WM Mitchell. *Gray's anatomy for students E-book*. Elsevier Health Sciences, 2009. Cited on page 24.

[29] Malcolm Peat. Functional anatomy of the shoulder complex. *Physical therapy*, 66(12): 1855–1865, 1986. Cited on page 25.

[30] Ruth A Miller. Functional adaptations in the forelimb of the sloths. *Journal of Mammalogy*, 16(1):38–51, 1935. Cited on page 25.

[31] Terri M Skirven, A Lee Osterman, Jane Fedorczyk, and Peter C Amadio. *Rehabilitation of the hand and upper extremity, 2-volume set E-book: expert consult*. Elsevier Health Sciences, 2011. Cited on page 25.

[32] P David Polly and BK Hall. Limbs in mammalian evolution. *Fins into limbs: evolution, development and transformation*, pages 245–268, 2007. Cited on page 27.

[33] Stephen H Scott and David A Winter. Biomechanical model of the human foot: kinematics and kinetics during the stance phase of walking. *Journal of biomechanics*, 26 (9):1091–1104, 1993. Cited on page 27.

[34] Edward Taub, Gitendra Uswatte, Rama Pidikiti, et al. Constraint-induced movement therapy: a new family of techniques with broad application to physical rehabilitation-a clinical review. *Journal of rehabilitation research and development*, 36(3):237–251, 1999. Cited on page 28.

[35] PATRICIA KEARNEY, TAMI MCGOWAN, JENNIFER ANDERSON, and DEBRA STROSAHL. The role of the occupational therapist on the neuro-rehabilitation team. *Acquired brain injury: An integrative neuro-rehabilitation approach*, pages 215–237, 2007. Cited on page 29.

[36] Keith D Cicerone, Tasha Mott, Joanne Azulay, and John C Friel. Community integration and satisfaction with functioning after intensive cognitive rehabilitation for traumatic brain injury. *Archives of physical medicine and rehabilitation*, 85(6):943–950, 2004. Cited on page 29.

[37] Aaron T Beck and Marjorie Weishaar. *Cognitive therapy*. Springer, 1989. Cited on page 30.

[38] Barbara A Wilson. Cognitive rehabilitation: How it is and how it might be. *Journal of the International Neuropsychological Society*, 3(5):487–496, 1997. Cited on page 30.

[39] Jonathan Bisson and Martin Andrew. Psychological treatment of post-traumatic stress disorder (ptsd). *Cochrane database of systematic reviews*, (3), 2007. Cited on page 31.

[40] Alo Dutta, Robert Gervey, Fong Chan, Chih-Chin Chou, and Nicole Ditchman. Vocational rehabilitation services and employment outcomes for people with disabilities: A united states study. *Journal of occupational rehabilitation*, 18:326–334, 2008. Cited on page 31.

[41] Paul Chappell and Christa Johannsmeier. The impact of community based rehabilitation as implemented by community rehabilitation facilitators on people with disabilities, their families and communities within south africa. *Disability and rehabilitation*, 31(1):7–13, 2009. Cited on page 33.

[42] Stacy Clifford Simplican, Geraldine Leader, John Kosciulek, and Michael Leahy. Defining social inclusion of people with intellectual and developmental disabilities: An ecological model of social networks and community participation. *Research in developmental disabilities*, 38:18–29, 2015. Cited on page 34.

[43] C Jessie Jones, Roberta E Rikli, Julie Max, and Guillermo Noffal. The reliability and validity of a chair sit-and-reach test as a measure of hamstring flexibility in older adults. *Research quarterly for exercise and sport*, 69(4):338–343, 1998. Cited on page 39.

[44] Bob Anderson. *Stretching: 20th anniversary*. Shelter Publications, Inc., 2000. Cited on page 40.

[45] Carlos E Rivera. Core and lumbopelvic stabilization in runners. *Physical Medicine and Rehabilitation Clinics*, 27(1):319–337, 2016. Cited on page 40.

[46] Phillip Page and Todd S Ellenbecker. *Strength band training*. Human Kinetics Publishers, 2019. Cited on page 40.

[47] Bethany Valachi and Keith Valachi. Preventing musculoskeletal disorders in clinical dentistry: strategies to address the mechanisms leading to musculoskeletal disorders. *The Journal of the American Dental Association*, 134(12):1604–1612, 2003. Cited on pages 40 and 41.

[48] Rik Gosselink. Breathing techniques in patients with chronic obstructive pulmonary disease (copd). *Chronic respiratory disease*, 1(3):163–172, 2004. Cited on page 40.

[49] Yongqiang Qin, Chris J Vincent, Nadia Bianchi-Berthouze, and Yuanchun Shi. Airflow: designing immersive breathing training games for copd. In *CHI'14 Extended Abstracts on Human Factors in Computing Systems*, pages 2419–2424. 2014. Cited on page 41.

[50] JinHong Kim, Jun Hyuck Park, and Jongeun Yim. Effects of respiratory muscle and endurance training using an individualized training device on pulmonary function

and exercise capacity in stroke patients. *Medical science monitor: international medical journal of experimental and clinical research*, 20:2543, 2014. Cited on page 41.

[51] James B Fink. Forced expiratory technique, directed cough, and autogenic drainage. *Respiratory care*, 52(9):1210–1223, 2007. Cited on page 41.

[52] Barbara M Wilson Arboleda and Arlette L Frederick. Considerations for maintenance of postural alignment for voice production. *Journal of Voice*, 22(1):90–99, 2008. Cited on page 41.

[53] Mark Kluemper, Tim Uhl, and Heath Hazelrigg. Effect of stretching and strengthening shoulder muscles on forward shoulder posture in competitive swimmers. *Journal of sport rehabilitation*, 15(1):58, 2006. Cited on page 41.

[54] Michael J Rosen. Telerehabilitation. *NeuroRehabilitation*, 12(1):11–26, 1999. Cited on page 43.

[55] Susan Vesmarovich, Tracy Walker, Roxanne Pickett Hauber, Ann Temkin, and Richard Burns. Use of telerehabilitation to manage pressure ulcers in persons with spinal cord injuries. *Advances in Skin & Wound Care*, 12(5):264, 1999. Cited on page 43.

[56] Corinna E Lathan, Audrey Kinsella, Michael J Rosen, Jack Winters, and Cheryl Trepagnier. Aspects of human factors engineering in home telemedicine and telerehabilitation systems. *Telemedicine Journal*, 5(2):169–175, 1999. Cited on page 43.

[57] Jack M Winters, Yu Wang, and JILL M Winters. Wearable sensors and telerehabilitation. *IEEE Engineering in Medicine and Biology Magazine*, 22(3):56–65, 2003. Cited on page 43.

[58] Deborah Theodoros, Trevor Russell, and R Latifi. Telerehabilitation: current perspectives. *Studies in health technology and informatics*, 131(1):191–210, 2008. Cited on pages 43 and 46.

[59] Linn Wakeford, Peggy P Wittman, Matthew Wesley White, and Mark R Schmeler. Telerehabilitation position paper. *AJOT: American Journal of Occupational Therapy*, 59(6):656–661, 2005. Cited on page 43.

[60] Grigore Burdea, Viorel Popescu, Vincent Hentz, and Kerri Colbert. Virtual reality-based orthopedic telerehabilitation. *IEEE Transactions on Rehabilitation Engineering*, 8(3):430–432, 2000. Cited on pages 43 and 46.

[61] Jerry CK Lai, Jean Woo, Elsie Hui, and WM Chan. Telerehabilitation—a new model for community-based stroke rehabilitation. *Journal of telemedicine and telecare*, 10(4): 199–205, 2004. Cited on page 43.

[62] Tim Johansson and Claudia Wild. Telerehabilitation in stroke care–a systematic review. *Journal of telemedicine and telecare*, 17(1):1–6, 2011. Cited on page 45.

[63] Michael McCue, Andrea Fairman, and Michael Pramuka. Enhancing quality of life through telerehabilitation. *Physical Medicine and Rehabilitation Clinics*, 21(1):195–205, 2010. Cited on pages 45 and 46.

[64] Alessandro Peretti, Francesco Amenta, Seyed Khosrow Tayebati, Giulio Nittari, Syed Sarosh Mahdi, et al. Telerehabilitation: review of the state-of-the-art and areas of application. *JMIR rehabilitation and assistive technologies*, 4(2):e7511, 2017. Cited on page 45.

[65] Lucy Dodakian, Alison L McKenzie, Vu Le, Jill See, Kristin Pearson-Fuhrhop, Erin Burke Quinlan, Robert J Zhou, Renee Augsberger, Xuan A Tran, Nizan Friedman, et al. A home-based telerehabilitation program for patients with stroke. *Neurorehabilitation and neural repair*, 31(10-11):923–933, 2017. Cited on page 45.

[66] Huidi Tchero, Maturin Tabue Teguo, Annie Lannuzel, and Emmanuel Rusch. Telerehabilitation for stroke survivors: systematic review and meta-analysis. *Journal of medical Internet research*, 20(10):e10867, 2018. Cited on page 45.

[67] Janet Prvu Bettger and Linda J Resnik. Telerehabilitation in the age of covid-19: an opportunity for learning health system research. *Physical therapy*, 100(11):1913–1916, 2020. Cited on page 45.

[68] Pamela W Duncan and Julie Bernhardt. Telerehabilitation: has its time come? *Stroke*, 52(8):2694–2696, 2021. Cited on page 45.

[69] Wenguang Xia, Chao Zhan, Shouguo Liu, Zhifei Yin, Jiayue Wang, Yufei Chong, Chanjuan Zheng, Xiaoming Fang, Wei Cheng, Jan D Reinhardt, et al. A telerehabilitation programme in post-discharge covid-19 patients (tereco): a randomised controlled trial. *Thorax*, 77(7):697–706, 2022. Cited on page 45.

[70] Kurt D Knepley, Jennifer Z Mao, Peter Wieczorek, Frederick O Okoye, Abhi P Jain, and Noam Y Harel. Impact of telerehabilitation for stroke-related deficits. *Telemedicine and e-Health*, 27(3):239–246, 2021. Cited on page 45.

[71] Marcelo Dalbosco-Salas, Rodrigo Torres-Castro, Andres Rojas Leyton, Franco Morales Zapata, Elisabeth Henriquez Salazar, Gabriel Espinoza Bastias, Maria Elizabeth Beltran Diaz, Kris Tapia Allers, Daniela Mornhinweg Fonseca, and Jordi Vilaro. Effectiveness of a primary care telerehabilitation program for post-covid-19 patients: a feasibility study. *Journal of clinical medicine*, 10(19):4428, 2021. Cited on page 45.

[72] Mark A Havran and Douglas E Bidelspach. Virtual physical therapy and telerehabilitation. *Physical Medicine and Rehabilitation Clinics*, 32(2):419–428, 2021. Cited on page 45.

[73] Mark W Werneke, Daniel Deutscher, David Grigsby, Carole A Tucker, Jerome E Mioduski, and Deanna Hayes. Telerehabilitation during the covid-19 pandemic in outpatient rehabilitation settings: A descriptive study. *Physical therapy*, 101(7):pzab110, 2021. Cited on page 45.

[74] Sherindan Ayessa Ferreira de Brito, Aline Alvim Scianni, Paula da Cruz Peniche, and Christina Danielli Coelho de Morais Faria. Measurement properties of outcome measures used in neurological telerehabilitation: A systematic review using cosmin checklist. *Clinical Rehabilitation*, 37(3):415–435, 2023. Cited on page 45.

[75] Arturo Nuara, Maddalena Fabbri-Destro, Emilia Scalona, Stefano Elio Lenzi, Giacomo Rizzolatti, and Pietro Avanzini. Telerehabilitation in response to constrained physical distance: an opportunity to rethink neurorehabilitative routines. *Journal of neurology*, 269(2):627–638, 2022. Cited on page 45.

[76] Dixie Aragaki, Jerry Luo, Elizabeth Weiner, Grace Zhang, and Babak Darvish. Cardiopulmonary telerehabilitation. *Physical Medicine and Rehabilitation Clinics*, 32(2): 263–276, 2021. Cited on page 45.

[77] Renata Główczyńska, Ewa Piotrowicz, Dominika Szalewska, Ryszard Piotrowicz, Ilona Kowalik, Michael J Pencina, Wojciech Zaręba, Maciej Banach, Piotr Orzechowski, Sławomir Pluta, et al. Effects of hybrid comprehensive telerehabilitation on cardiopulmonary capacity in heart failure patients depending on diabetes mellitus: subanalysis of the telereh-hf randomized clinical trial. *Cardiovascular Diabetology*, 20(1):106, 2021. Cited on page 45.

[78] Jose Manuel Pastora-Bernal, Rocio Martín-Valero, Francisco Javier Barón-López, and María José Estebanez-Pérez. Evidence of benefit of telerehabitation after orthopedic surgery: a systematic review. *Journal of medical Internet research*, 19(4):e142, 2017. Cited on page 46.

[79] Mooyeon Oh-Park, Henry L Lew, and Preeti Raghavan. Telerehabilitation for geriatrics. *Physical Medicine and Rehabilitation Clinics*, 32(2):291–305, 2021. Cited on page 46.

[80] Mathieu Hamel, Rejean Fontaine, and Patrick Boissy. In-home telerehabilitation for geriatric patients. *IEEE Engineering in Medicine and Biology Magazine*, 27(4):29–37, 2008. Cited on page 46.

[81] Deepak Jayarajan, Thanapal Sivakumar, John B Torous, and Jagadisha Thirthalli. Telerehabilitation in psychiatry. *Indian Journal of Psychological Medicine*, 42(5_suppl): 57S–62S, 2020. Cited on page 46.

[82] Amy E Rabatin, Mary E Lynch, Matthew C Severson, Joline E Brandenburg, and Sherilyn W Driscoll. Pediatric telerehabilitation medicine: Making your virtual visits efficient, effective and fun. *Journal of pediatric rehabilitation medicine*, 13(3):355–370, 2020. Cited on page 46.

[83] Kelly Tanner, Rachel Bican, Jamie Boster, Catie Christensen, Candace Coffman, Kristin Fallieras, Rene Long, Christine Mansfield, Sara O'ROURKE, Lindsey Pauline, et al. Feasibility and acceptability of clinical pediatric telerehabilitation services. *International Journal of Telerehabilitation*, 12(2):43, 2020. Cited on page 46.

[84] David M Brennan, Amy C Georgeadis, Christine R Baron, and Linsey M Barker. The effect of videoconference-based telerehabilitation on story retelling performance by

brain-injured subjects and its implications for remote speech-language therapy. *Telemedicine Journal & e-Health*, 10(2):147–154, 2004. Cited on page 46.

[85] Goris Hung KN and Kenneth NK Fong. Effects of telerehabilitation in occupational therapy practice: A systematic review. *Hong Kong Journal of Occupational Therapy*, 32(1):3–21, 2019. Cited on page 46.

[86] Hassan Izzeddin Sarsak. Telerehabilitation services: A successful paradigm for occupational therapy clinical services. *International Physical Medicine & Rehabilitation Journal*, 5(2):93–98, 2020. Cited on page 46.

[87] SA Bini and J Mahajan. Clinical outcomes of remote asynchronous telerehabilitation are equivalent to traditional therapy following total knee arthroplasty: a randomized control study. *Journal of telemedicine and telecare*, 23(2):239–247, 2017. Cited on page 47.

[88] Yuan-Yuan Zhang, Yin-Guang Zhang, Zhen Li, Shi-Hao Li, and Wei-Guo Xu. Effect of home-based telerehabilitation on the postoperative rehabilitation outcome of hip fracture in the aging population. *Orthopaedic Surgery*, 14(8):1768–1777, 2022. Cited on page 47.

[89] Roxanna M Bendixen, Kathleen Horn, and Charles Levy. Using telerehabilitation to support elders with chronic illness in their homes. *Topics in Geriatric Rehabilitation*, 23(1):47–51, 2007. Cited on page 48.

[90] Yuh Morimoto, Tetsuya Takahashi, Ryuichi Sawa, Masakazu Saitoh, Tomoyuki Morisawa, Nobuyuki Kagiyama, Takatoshi Kasai, Birthe Dinesen, Malene Hollingdal, Jens Refsgaard, et al. Web portals for patients with chronic diseases: scoping review of the functional features and theoretical frameworks of telerehabilitation platforms. *Journal of medical Internet research*, 24(1):e27759, 2022. Cited on page 48.

[91] Tamara Ownsworth, Urska Arnautovska, Elizabeth Beadle, David HK Shum, and Wendy Moyle. Efficacy of telerehabilitation for adults with traumatic brain injury: a systematic review. *The Journal of head trauma rehabilitation*, 33(4):E33–E46, 2018. Cited on page 49.

[92] Joseph H Ricker, Mitchell Rosenthal, Edward Garay, John DeLuca, Anneliese Germain, Klaus Abraham-Fuchs, and Kai-Uwe Schmidt. Telerehabilitation needs: a survey of persons with acquired brain injury. *The Journal of Head Trauma Rehabilitation*, 17(3): 242–250, 2002. Cited on page 49.

[93] James Barlow, Debbie Singh, Steffen Bayer, and Richard Curry. A systematic review of the benefits of home telecare for frail elderly people and those with long-term conditions. *Journal of telemedicine and telecare*, 13(4):172–179, 2007. Cited on page 51.

[94] Isabel Rodríguez-Costa, Vanesa Abuín-Porras, Paula Terán-García, Andrea Férez-Sopeña, Victoria Calvo-Fuente, Concepción Soto-Vidal, and Soraya Pacheco-da Costa. Effectiveness of a telecare physical therapy program in improving functionality in children and adolescents with cerebral palsy: A cases study. *Children*, 10(4):663, 2023. Cited on page 52.

[95] Hitesh Lal, Shwetasri Mohanta, Jaswant Kumar, Mohit Kumar Patralekh, Lavanya Lall, Himansu Katariya, and RK Arya. Telemedicine-rehabilitation and virtual reality in orthopaedics and sports medicine. *Indian Journal of Orthopaedics*, 57(1):7–19, 2023. Cited on page 53.

[96] Jorge Luis Pérez Medina, Mario González, Hennry Mauricio Pilco, Karina Beatríz Jimenes Vargas, Patricia Acosta-Vargas, Sandra Sanchez-Gordon, Tania Calle-Jimenez, Danilo Esparza, and Yves Rybarczyk. Usability study of a web-based platform for home motor rehabilitation. *IEEE Access*, 7:7932–7947, 2019. Cited on page 63.

[97] David J Reinkensmeyer, Clifton T Pang, Jeff A Nessler, and Christopher C Painter. Web-based telerehabilitation for the upper extremity after stroke. *IEEE transactions on neural systems and rehabilitation engineering*, 10(2):102–108, 2002. Cited on page 66.

[98] Ali Karime, Hussein Al-Osman, Jihad Mohamad Alja'am, Wail Gueaieb, and Abdulmotaleb El Saddik. Tele-wobble: A telerehabilitation wobble board for lower extremity therapy. *IEEE Transactions on Instrumentation and Measurement*, 61(7):1816–1824, 2012. Cited on page 66.

[99] Franco Molteni, Cristina Gramigna, Samuela Canobbio, Milena Peverelli, Silvia Aggujaro, Mauro Rossini, Giovanna Palumbo, Giandomenico Caruso, Mario Covarrubias,

et al. Tele-rehabilitation platform for upper and lower limb in elderly patients, the head project. In *eTELEMED 2017, The Ninth International Conference on eHealth, Telemedicine, and Social Medicine*, pages 117–122, 2017. Cited on page 67.

[100] Johanna Renny Octavia and Livia Natasha. Design of a mobile game application to support hand rehabilitation of stroke patients in indonesia. *IJTech*, 8(2):250, 2017. Cited on page 67.

[101] Maria F Montoya, John E Muñoz, and Oscar A Henao. Enhancing virtual rehabilitation in upper limbs with biocybernetic adaptation: the effects of virtual reality on perceived muscle fatigue, game performance and user experience. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 28(3):740–747, 2020. Cited on page 68.

[102] Kanmanus Ongvisatepaiboon, Jonathan H Chan, and Vajirasak Vanijja. Smartphone-based tele-rehabilitation system for frozen shoulder using a machine learning approach. In *2015 IEEE Symposium Series on Computational Intelligence*, pages 811–815. IEEE, 2015. Cited on page 69.

[103] MReza Naeemabadi, Birthe Dinesen, Ole Kæseler Andersen, Niels Kragh Madsen, Ole Højgaard Simonsen, and John Hansen. Developing a telerehabilitation programme for postoperative recovery from knee surgery: specifications and requirements. *BMJ Health & Care Informatics*, 26(1), 2019. Cited on page 71.

[104] Ricardo Antunes, Paul Jacob, Andrew Meyer, Michael A Conditt, Martin W Roche, and Matthias A Verstraete. Accuracy of measuring knee flexion after tka through wearable imu sensors. *Journal of Functional Morphology and Kinesiology*, 6(3):60, 2021. Cited on page 72.

[105] Yangqing Jia, Evan Shelhamer, Jeff Donahue, Sergey Karayev, Jonathan Long, Ross Girshick, Sergio Guadarrama, and Trevor Darrell. Caffe: Convolutional architecture for fast feature embedding. In *Proceedings of the 22nd ACM international conference on Multimedia*, pages 675–678, 2014. Cited on page 87.

[106] Le Gao, Yongjie Huang, Xin Zhang, Qiyuan Liu, and Zequn Chen. Prediction of prospecting target based on resnet convolutional neural network. *Applied Sciences*, 12(22): 11433, 2022. Cited on page 87.

[107] Muhammad Faique Shakeel, Nabit A Bajwa, Ahmad Muhammad Anwaar, Anabia Sohail, and Asifullah Khan. Detecting driver drowsiness in real time through deep learning based object detection. In *Advances in Computational Intelligence: 15th International Work-Conference on Artificial Neural Networks, IWANN 2019, Gran Canaria, Spain, June 12-14, 2019, Proceedings, Part I 15*, pages 283–296. Springer, 2019. Cited on page 87.

[108] Vishal Shah and Neha Sajnani. Multi-class image classification using cnn and tflite. *International Journal of Research in Engineering, Science and Management*, 3(11):65–68, 2020. Cited on page 87.

[109] Kun Han, Junwen Chen, Hui Zhang, Haiyang Xu, Yiping Peng, Yun Wang, Ning Ding, Hui Deng, Yonghu Gao, Tingwei Guo, et al. Delta: a deep learning based language technology platform. *arXiv preprint arXiv:1908.01853*, 2019. Cited on page 87.

[110] Weiming Chen, Zijie Jiang, Hailin Guo, and Xiaoyang Ni. Fall detection based on key points of human-skeleton using openpose. *Symmetry*, 12(5):744, 2020. Cited on page 87.

[111] Paul Hur and Nigel Bosch. Tracking individuals in classroom videos via post-processing openpose data. In *LAK22: 12th International Learning Analytics and Knowledge Conference*, pages 465–471, 2022. Cited on page 87.

[112] Zhe Cao, Tomas Simon, Shih-En Wei, and Yaser Sheikh. Realtime multi-person 2d pose estimation using part affinity fields. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 7291–7299, 2017. Cited on pages 88 and 101.

[113] Takumi Kitamura, Hitoshi Teshima, Diego Thomas, and Hiroshi Kawasaki. Refining openpose with a new sports dataset for robust 2d pose estimation. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 672–681, 2022. Cited on page 88.

[114] Liang-Yan Gui, Kevin Zhang, Yu-Xiong Wang, Xiaodan Liang, José MF Moura, and Manuela Veloso. Teaching robots to predict human motion. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 562–567. IEEE, 2018. Cited on page 88.

[115] Huiying Zhou, Geng Yang, Baicun Wang, Xingyu Li, Ruohan Wang, Xiaoyan Huang, Haiteng Wu, and Xi Vincent Wang. An attention-based deep learning approach for inertial motion recognition and estimation in human-robot collaboration. *Journal of Manufacturing Systems*, 67:97–110, 2023. Cited on page 90.

[116] Sinan Chen, Sachio Saiki, and Masahide Nakamura. Nonintrusive fine-grained home care monitoring: Characterizing quality of in-home postural changes using bone-based human sensing. *Sensors*, 20(20):5894, 2020. Cited on page 90.

[117] Valentin Bazarevsky, Ivan Grishchenko, Karthik Raveendran, Tyler Zhu, Fan Zhang, and Matthias Grundmann. Blazepose: On-device real-time body pose tracking. *arXiv preprint arXiv:2006.10204*, 2020. Cited on pages 92 and 109.

[118] Yaqin Tao and Huosheng Hu. A novel sensing and data fusion system for 3-d arm motion tracking in telerehabilitation. *IEEE Transactions on Instrumentation and Measurement*, 57(5):1029–1040, 2008. Cited on page 95.

[119] Anargyros Chatzitofis, Dimitrios Zarpalas, Petros Daras, and Stefanos Kollias. Democap: low-cost marker-based motion capture. *International Journal of Computer Vision*, 129(12):3338–3366, 2021. Cited on page 95.

[120] Elise Klæbo Vonstad, Xiaomeng Su, Beatrix Vereijken, Kerstin Bach, and Jan Harald Nilsen. Comparison of a deep learning-based pose estimation system to marker-based and kinect systems in exergaming for balance training. *Sensors*, 20(23):6940, 2020. Cited on page 95.

[121] Els Knippenberg, Jonas Verbrugghe, Ilse Lamers, Steven Palmaers, Annick Timmermans, and Annemie Spooren. Markerless motion capture systems as training device in neurological rehabilitation: a systematic review of their use, application, target population and efficacy. *Journal of neuroengineering and rehabilitation*, 14:1–11, 2017. Cited on page 95.

[122] Winnie WT Lam and Kenneth NK Fong. The application of markerless motion capture (mmc) technology in rehabilitation programs: A systematic review and meta-analysis. *Virtual Reality*, pages 1–16, 2022. Cited on page 95.

[123] Ashish Shingade and Archana Ghotkar. Animation of 3d human model using markerless motion capture applied to sports. *arXiv preprint arXiv:1402.2363*, 2014. Cited on page 95.

[124] F José Racero, Salvador Bueno, and M Dolores Gallego. Predicting students' behavioral intention to use open source software: A combined view of the technology acceptance model and self-determination theory. *Applied Sciences*, 10(8):2711, 2020. Cited on page 95.

[125] Mykhaylo Andriluka, Leonid Pishchulin, Peter Gehler, and Bernt Schiele. 2d human pose estimation: New benchmark and state of the art analysis. In *Proceedings of the IEEE Conference on computer Vision and Pattern Recognition*, pages 3686–3693, 2014. Cited on pages 97 and 100.

[126] Wei Sun, Yezhao Fan, Xiongkuo Min, Shihao Peng, Siwei Ma, and Guangtao Zhai. Lphd: A large-scale head pose dataset for rgb images. In *2019 IEEE International Conference on Multimedia and Expo (ICME)*, pages 1084–1089. IEEE, 2019. Cited on page 97.

[127] Rıza Alp Güler, Natalia Neverova, and Iasonas Kokkinos. Densepose: Dense human pose estimation in the wild. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 7297–7306, 2018. Cited on page 97.

[128] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997. Cited on page 97.

[129] Tomas Mikolov, Martin Karafiát, Lukas Burget, Jan Cernockỳ, and Sanjeev Khudanpur. Recurrent neural network based language model. In *Interspeech*, volume 2, pages 1045–1048. Makuhari, 2010. Cited on page 97.

[130] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*, 2013. Cited on page 97.

[131] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018. Cited on page 99.

[132] Nicolas Carion, Francisco Massa, Gabriel Synnaeve, Nicolas Usunier, Alexander Kirillov, and Sergey Zagoruyko. End-to-end object detection with transformers. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part I 16*, pages 213–229. Springer, 2020. Cited on page 99.

[133] Ying Li, Chenxi Wang, Yu Cao, Benyuan Liu, Yan Luo, and Honggang Zhang. A-hrnet: Attention based high resolution network for human pose estimation. In *2020 Second International Conference on Transdisciplinary AI (TransAI)*, pages 75–79. IEEE, 2020. Cited on page 99.

[134] Zinan Xiong, Chenxi Wang, Ying Li, Yan Luo, and Yu Cao. Swin-pose: Swin transformer based human pose estimation. In *2022 IEEE 5th International Conference on Multimedia Information Processing and Retrieval (MIPR)*, pages 228–233. IEEE, 2022. Cited on page 99.

[135] Zhiqing Sun, Shengcao Cao, Yiming Yang, and Kris M Kitani. Rethinking transformer-based set prediction for object detection. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 3611–3620, 2021. Cited on page 99.

[136] Jieneng Chen, Yongyi Lu, Qihang Yu, Xiangde Luo, Ehsan Adeli, Yan Wang, Le Lu, Alan L Yuille, and Yuyin Zhou. Transunet: Transformers make strong encoders for medical image segmentation. *arXiv preprint arXiv:2102.04306*, 2021. Cited on page 99.

[137] Matthew Chung Hai Lee, Kersten Petersen, Nick Pawlowski, Ben Glocker, and Michiel Schaap. Tetris: Template transformer networks for image segmentation with shape priors. *IEEE transactions on medical imaging*, 38(11):2596–2606, 2019. Cited on page 99.

[138] Sixiao Zheng, Jiachen Lu, Hengshuang Zhao, Xiatian Zhu, Zekun Luo, Yabiao Wang, Yanwei Fu, Jianfeng Feng, Tao Xiang, Philip HS Torr, et al. Rethinking semantic segmentation from a sequence-to-sequence perspective with transformers. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 6881–6890, 2021. Cited on page 99.

[139] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Syl-

vain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*, 2020. Cited on page 99.

[140] Sen Yang, Zhibin Quan, Mu Nie, and Wankou Yang. Transpose: Keypoint localization via transformer. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 11802–11812, 2021. Cited on page 99.

[141] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. Swin transformer: Hierarchical vision transformer using shifted windows. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 10012–10022, 2021. Cited on page 99.

[142] William McNally, Kanav Vats, Alexander Wong, and John McPhee. Evopose2d: Pushing the boundaries of 2d human pose estimation using accelerated neuroevolution with weight transfer. *IEEE Access*, 9:139403–139414, 2021. Cited on page 99.

[143] Jiang Deng, Sun Bei, Su Shaojing, and Zuo Zhen. Feature fusion methods in deep-learning generic object detection: A survey. In *2020 IEEE 9th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, volume 9, pages 431–437. IEEE, 2020. Cited on page 99.

[144] Tao Kong, Anbang Yao, Yurong Chen, and Fuchun Sun. Hypernet: Towards accurate region proposal generation and joint object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 845–853, 2016. Cited on page 99.

[145] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Spatial pyramid pooling in deep convolutional networks for visual recognition. *IEEE transactions on pattern analysis and machine intelligence*, 37(9):1904–1916, 2015. Cited on page 99.

[146] Pedro F Felzenszwalb, Ross B Girshick, David McAllester, and Deva Ramanan. Object detection with discriminatively trained part-based models. *IEEE transactions on pattern analysis and machine intelligence*, 32(9):1627–1645, 2009. Cited on page 99.

[147] Tsung-Yi Lin, Piotr Dollár, Ross Girshick, Kaiming He, Bharath Hariharan, and Serge Belongie. Feature pyramid networks for object detection. In *Proceedings of the IEEE*

conference on computer vision and pattern recognition, pages 2117–2125, 2017. Cited on page 99.

[148] Martin A Fischler and Robert A Elschlager. The representation and matching of pictorial structures. *IEEE Transactions on computers*, 100(1):67–92, 1973. Cited on page 100.

[149] G Hinton. Using relaxation to find a puppet. In *Proceedings of the 2nd Summer Conference on Artificial Intelligence and Simulation of Behaviour*, pages 148–157, 1976. Cited on page 100.

[150] David E Rumelhart, Geoffrey E Hinton, and Ronald J Williams. Learning internal representations by error propagation. Technical report, California Univ San Diego La Jolla Inst for Cognitive Science, 1985. Cited on page 100.

[151] Pedro F Felzenszwalb and Daniel P Huttenlocher. Efficient matching of pictorial structures. In *Proceedings IEEE Conference on Computer Vision and Pattern Recognition. CVPR 2000 (Cat. No. PR00662)*, volume 2, pages 66–73. IEEE, 2000. Cited on page 100.

[152] Pedro F Felzenszwalb and Daniel P Huttenlocher. Pictorial structures for object recognition. *International journal of computer vision*, 61:55–79, 2005. Cited on pages 100 and 102.

[153] Sergey Ioffe and David Forsyth. Human tracking with mixtures of trees. In *Proceedings Eighth IEEE International Conference on Computer Vision. ICCV 2001*, volume 1, pages 690–695. IEEE, 2001. Cited on page 100.

[154] Remi Ronfard, Cordelia Schmid, and Bill Triggs. Learning to parse pictures of people. In *Computer Vision—ECCV 2002: 7th European Conference on Computer Vision Copenhagen, Denmark, May 28–31, 2002 Proceedings, Part IV 7*, pages 700–714. Springer, 2002. Cited on page 100.

[155] Deva Ramanan. Learning to parse images of articulated bodies. *Advances in neural information processing systems*, 19, 2006. Cited on page 100.

[156] Deva Ramanan and Cristian Sminchisescu. Training deformable models for localization. In *2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06)*, volume 1, pages 206–213. IEEE, 2006. Cited on page 100.

[157] Vittorio Ferrari, Manuel Marin-Jimenez, and Andrew Zisserman. Progressive search space reduction for human pose estimation. In *2008 IEEE Conference on Computer Vision and Pattern Recognition*, pages 1–8. IEEE, 2008. Cited on page 100.

[158] Marcin Eichner, Vittorio Ferrari, and S Zurich. Better appearance models for pictorial structures. In *Bmvc*, volume 2, page 5. London, UK, 2009. Cited on page 100.

[159] Mykhaylo Andriluka, Stefan Roth, and Bernt Schiele. Pictorial structures revisited: People detection and articulated pose estimation. In *2009 IEEE conference on computer vision and pattern recognition*, pages 1014–1021. IEEE, 2009. Cited on page 100.

[160] Yi Yang and Deva Ramanan. Articulated pose estimation with flexible mixtures-of-parts. In *CVPR 2011*, pages 1385–1392. IEEE, 2011. Cited on page 100.

[161] Sam Johnson and Mark Everingham. Learning effective human pose estimation from inaccurate annotation. In *CVPR 2011*, pages 1465–1472. IEEE, 2011. Cited on page 100.

[162] Yang Wang, Duan Tran, and Zicheng Liao. Learning hierarchical poselets for human parsing. In *CVPR 2011*, pages 1705–1712. IEEE, 2011. Cited on page 100.

[163] Kun Duan, Dhruv Batra, and David J Crandall. A multi-layer composite model for human pose estimation. In *BMVC*, volume 2, page 5. Surrey, UK, 2012. Cited on page 100.

[164] Leonid Pishchulin, Arjun Jain, Mykhaylo Andriluka, Thorsten Thormählen, and Bernt Schiele. Articulated people detection and pose estimation: Reshaping the future. In *2012 IEEE Conference on Computer Vision and Pattern Recognition*, pages 3178–3185. IEEE, 2012. Cited on page 100.

[165] Yuandong Tian, C Lawrence Zitnick, and Srinivasa G Narasimhan. Exploring the spatial hierarchy of mixture models for human pose estimation. In *ECCV (5)*, pages 256–269, 2012. Cited on page 100.

[166] Leonid Pishchulin, Mykhaylo Andriluka, Peter Gehler, and Bernt Schiele. Poselet conditioned pictorial structures. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 588–595, 2013. Cited on page 100.

[167] Ben Sapp and Ben Taskar. Modec: Multimodal decomposable models for human pose estimation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3674–3681, 2013. Cited on page 100.

[168] Corinna Cortes and Vladimir Vapnik. Support-vector networks. *Machine learning*, 20: 273–297, 1995. Cited on page 100.

[169] Yoav Freund and Robert E Schapire. A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of computer and system sciences*, 55 (1):119–139, 1997. Cited on page 100.

[170] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. *nature*, 521(7553): 436–444, 2015. Cited on page 100.

[171] Lubomir Bourdev and Jitendra Malik. Poselets: Body part detectors trained using 3d human pose annotations. In *2009 IEEE 12th International Conference on Computer Vision*, pages 1365–1372. IEEE, 2009. Cited on page 100.

[172] Navneet Dalal and Bill Triggs. Histograms of oriented gradients for human detection. In *2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05)*, volume 1, pages 886–893. Ieee, 2005. Cited on page 100.

[173] Sam Johnson and Mark Everingham. Clustered pose and nonlinear appearance models for human pose estimation. In *bmvc*, volume 2, page 5. Aberystwyth, UK, 2010. Cited on page 100.

[174] Alexander Toshev and Christian Szegedy. Deeppose: Human pose estimation via deep neural networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1653–1660, 2014. Cited on page 101.

[175] Shih-En Wei, Varun Ramakrishna, Takeo Kanade, and Yaser Sheikh. Convolutional pose machines. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pages 4724–4732, 2016. Cited on pages 101 and 102.

[176] Alejandro Newell, Kaiyu Yang, and Jia Deng. Stacked hourglass networks for human pose estimation. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part VIII 14*, pages 483–499. Springer, 2016. Cited on pages 101 and 102.

[177] Yilun Chen, Zhicheng Wang, Yuxiang Peng, Zhiqiang Zhang, Gang Yu, and Jian Sun. Cascaded pyramid network for multi-person pose estimation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 7103–7112, 2018. Cited on pages 101 and 102.

[178] Wenbo Li, Zhicheng Wang, Binyi Yin, Qixiang Peng, Yuming Du, Tianzi Xiao, Gang Yu, Hongtao Lu, Yichen Wei, and Jian Sun. Rethinking on multi-stage networks for human pose estimation. *arXiv preprint arXiv:1901.00148*, 2019. Cited on pages 101 and 102.

[179] Jonathan J Tompson, Arjun Jain, Yann LeCun, and Christoph Bregler. Joint training of a convolutional network and a graphical model for human pose estimation. *Advances in neural information processing systems*, 27, 2014. Cited on pages 101 and 102.

[180] Maurice Weiler, Fred A Hamprecht, and Martin Storath. Learning steerable filters for rotation equivariant cnns. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 849–858, 2018. Cited on page 101.

[181] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3431–3440, 2015. Cited on page 101.

[182] Joao Carreira, Pulkit Agrawal, Katerina Fragkiadaki, and Jitendra Malik. Human pose estimation with iterative error feedback. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4733–4742, 2016. Cited on page 102.

[183] Umer Rafi, Bastian Leibe, Juergen Gall, and Ilya Kostrikov. An efficient convolutional network for human pose estimation. In *BMVC*, volume 1, page 2, 2016. Cited on page 102.

[184] Adrian Bulat and Georgios Tzimiropoulos. Human pose estimation via convolutional part heatmap regression. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part VII 14*, pages 717–732. Springer, 2016. Cited on page 102.

[185] Jonathan Tompson, Ross Goroshin, Arjun Jain, Yann LeCun, and Christoph Bregler. Efficient object localization using convolutional networks. In *Proceedings of the IEEE*

conference on computer vision and pattern recognition, pages 648–656, 2015. Cited on page 102.

[186] Ke Sun, Bin Xiao, Dong Liu, and Jingdong Wang. Deep high-resolution representation learning for human pose estimation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 5693–5703, 2019. Cited on page 102.

[187] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18*, pages 234–241. Springer, 2015. Cited on page 102.

[188] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016. Cited on page 102.

[189] Xiao Chu, Wei Yang, Wanli Ouyang, Cheng Ma, Alan L Yuille, and Xiaogang Wang. Multi-context attention for human pose estimation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1831–1840, 2017. Cited on page 102.

[190] Wei Yang, Shuang Li, Wanli Ouyang, Hongsheng Li, and Xiaogang Wang. Learning feature pyramids for human pose estimation. In *proceedings of the IEEE international conference on computer vision*, pages 1281–1290, 2017. Cited on page 102.

[191] Guanghan Ning, Zhi Zhang, and Zhiquan He. Knowledge-guided deep fractal neural networks for human pose estimation. *IEEE Transactions on Multimedia*, 20(5):1246–1259, 2017. Cited on page 102.

[192] Yu Chen, Chunhua Shen, Xiu-Shen Wei, Lingqiao Liu, and Jian Yang. Adversarial posenet: A structure-aware convolutional network for human pose estimation. In *Proceedings of the IEEE international conference on computer vision*, pages 1212–1221, 2017. Cited on page 102.

[193] Chia-Jung Chou, Jui-Ting Chien, and Hwann-Tzong Chen. Self adversarial training for human pose estimation. In *2018 Asia-Pacific Signal and Information Processing*

Association Annual Summit and Conference (APSIPA ASC), pages 17–30. IEEE, 2018. Cited on page 102.

[194] Lipeng Ke, Ming-Ching Chang, Honggang Qi, and Siwei Lyu. Multi-scale structure-aware network for human pose estimation. In *Proceedings of the european conference on computer vision (ECCV)*, pages 713–728, 2018. Cited on page 102.

[195] Zhiqiang Tang, Xi Peng, Shijie Geng, Lingfei Wu, Shaoting Zhang, and Dimitris Metaxas. Quantized densely connected u-nets for efficient landmark localization. In *Proceedings of the European conference on computer vision (ECCV)*, pages 339–354, 2018. Cited on page 102.

[196] Paul W Stratford, Jill M Binkley, and Daniel L Riddle. Health status measures: strategies and analytic methods for assessing change scores. *Physical therapy*, 76(10): 1109–1123, 1996. Cited on pages 121 and 124.

[197] Eugène Fromentin. *Between sea and Sahara: an Algerian journal*. Ohio University Press, 1999. Cited on page 128.