الجمهورية الجزائرية الديمقراطية الشعبية

RepubliqueAlgérienneDémocratiquePopulaire

وزارة التعليم العالي والبحث العلمي

Ministère de l'EnseignementSupérieur de la Recherche Scientifique

Université 20 août 1955 Skikda

جامعة 20 أوت 1955 – سكيكدة

Faculte des Sciences
Departement d'informatique

كلية العلوم
قسم الإعلام الآلي
الرقم: ..../ق/أ/أ/ك-ع/2026

Autorisation de Dépôt de Mémoire de Master

Je soussigné : **Bougamouza Fateh**.....

Certifie que l'étudiant(e) : **Chemaa Sarra** .....

Spécialité : **Réseaux et Systémes Distribués** .....

Ayant soutenu le projet intitulé : **Design and development of an integrated smart system to help Type 1 Diabetes patients in Algeria** ...

A apporté les corrections nécessaires sur son manuscrit de Master.

Signature de l'encadreur

الجمهورية الجزائرية الديمقراطية الشعبية

RepubliqueAlgérienneDémocratiquePopulaire
وزارة التعليم العالي والبحث العلمي

Ministère de l'EnseignementSupérieur de la Recherche Scientifique

Université 20 août 1955 Skikda — جامعة 20 أوت 1955 – سكيكدة

Faculte des Sciences
Departement d'informatique

كلية العلوم
قسم الإعلام الآلي

الرقم: ..../ق/أ/أ/ك.ع/2026

Autorisation de Dépôt de Mémoire de Master

Je soussigné : **Bougamouza Fateh**.....

Certifie que l'étudiant(e) : **Talhi Hadjer**.....

Spécialité : **Intelligence Artificielle**.....

Ayant soutenu le projet intitulé : **Design and development of an integrated smart system to help Type 1 Diabetes patients in Algeria** ...

A apporté les corrections nécessaires sur son manuscrit de Master.

Signature de l'encadreur

الجمهورية الجزائرية الديمقراطية الشعبية

RepubliqueAlgérienneDémocratiquePopulaire
وزارة التعليم العالي والبحث العلمي

Ministère de l'EnseignementSupérieur de la Recherche Scientifique

Université 20 août 1955 Skikda — جامعة 20 أوت 1955 – سكيكدة

Faculte des Sciences
Departement d'informatique

كلية العلوم
قسم الإعلام الآلي

الرقم: ..../ق/أ/أ/ك.ع/2026

Autorisation de Dépôt de Mémoire de Master

Je soussigné : **Bougamouza Fateh**.....

Certifie que l'étudiant(e) : **Moussaoui Hadil** .....

Spécialité : **Intelligence Artificielle**.....

Ayant soutenu le projet intitulé : **Design and development of an integrated smart system to help Type 1 Diabetes patients in Algeria** ...

A apporté les corrections nécessaires sur son manuscrit de Master.

Signature de l'encadreur

الجمهورية الجزائرية الديمقراطية الشعبية
وزارة التعليم لعالي والبحث العلمي

People's Democratic Republic of Algeria
Ministry of Higher Education and Scientific Research
20 Août 1955 University of Skikda
Faculty of Sciences
Department of Computer Science

A project to obtain a master's degree + a start-up institution certificate within the framework of Ministerial Resolution 1275

Project Title

Design and development of an integrated smart system to help Type 1 Diabetes patients in Algeria

Specialty:
Intelligence Artificielle & Réseaux et Systèmes Distribués

Realized by:

- Chemaa Sarra
- Moussaoui Hadil
- Talhi Hadjer

under supervised:

Dr. Bougamouza Fateh

2025-2026

Dedication

بسم الله الرحمن الرحيم

الحمد لله حمداً طيباً مباركاً فيه، والشكر له شكراً يليق بجلال فضله وعظيم إحسانه. فقد أنعم عليّ بتوفيقه، وهداني إلى سواء السبيل، وأعانني على إتمام هذا العمل بعد أن كان عسيراً فجعلته يسيراً. فله الحمد على كل حال، وله الشكر على كل نعمة.

To my dear mother, the light of my eyes and the serenity of my soul,

Your prayers were my weapon, and your satisfaction was my goal. May Allah protect you for me and bestow upon you lasting health and well-being.

To my beloved father, my role model and pillar of support,

Thank you for your immense sacrifices and May Allah reward you abundantly for every value you have instilled in me.

To my only sister, thank you for everything; your presence in my life is a great blessing.

To my friends Hadil and Hadjer, companions of five years,

Thank you for our beautiful memories and the sincere spirit of cooperation that brought us together. May Allah grant you both successes in your paths.

To everyone who supported me with a kind word or a heartfelt prayer,

I offer you my deepest thanks and gratitude.

And finally... to myself,

I thank myself for every sleepless night, for every moment of exhaustion, for every time I rose after failure, and for my belief that every strive earns their share. Today, I conclude one journey to begin another, so praise is to Allah for this completion.

والحمد لله رب العالمين

Sarra

Dedication

بسم الله الرحمن الرحيم

الحمد لله الذي بنعمته تتم الصالحات

I dedicate this humble work

To my beloved parents, whose endless love, sacrifices, prayers, and support have been the foundation of every success in my life. May Allah bless them with health, happiness, and a long life.

To my sister Fadoua, my closest friend and supporter, for her kindness, encouragement, and constant presence in my life.

To my brother Ziad, for his support, laughter, and for always was being a source of strength and joy.

To my dear colleagues Hadjer and Sara, with whom I shared this journey. Thank you for your friendship, support, and all the unforgettable moments we lived together.

To myself, for the late nights, the moments of exhaustion, and the times I almost gave up but didn’t. Thank you for believing in this dream, for your patience and perseverance. This work is proof that hard work and persistence always pay off.

To everyone, near or far, who supported me with a kind word, a prayer, or encouragement thank you from the heart.

Hadil

Dedication

All praise is due to Allah, by whose blessings all good deeds are completed, and who granted me the strength and patience to complete this work.

I dedicate this work to my dear father, my role model and greatest support, who always provided everything I needed to continue my studies and never stopped encouraging me.

To my beloved mother, the source of love, comfort, and endless prayers, whose support was always present in every stage of my life.

To my sisters, for their constant love, encouragement, and motivation.

To my younger brother, who lives with diabetes, and who was the true inspiration for this project. His strength and patience taught me that determination overcomes challenges.

To my uncle, who believed in me from the beginning and encouraged me to pursue this field.

To my dear friends, who shared with me this journey, its challenges, and its beautiful memories.

And to the doctor and therapeutic educator, who were the source of inspiration for this project, with the support and dedication they provided in accompanying diabetic patients and their families, and with the hope and determination they instilled in me to continue. I also dedicate this work to all people living with diabetes and their families, who face daily challenges with patience and hope.

To everyone who supported and believed in me throughout this journey.

And finally, to myself, for the effort, patience, and perseverance that made this achievement possible.

All praise is due to Allah for allowing me to reach this moment and complete this work.

Hadjer

Acknowledgments

First and foremost, we give thanks and praise to Allah the Almighty for granting us the health, strength, and patience necessary to complete this humble work.

الحمد لله رب العالمين

We would like to express our sincere gratitude to our supervisor, Dr. Bougamouza Fateh, for accepting to guide us throughout this project. We are honored to have worked under his supervision, and we pray that Allah rewards him abundantly and grants him continued success in all his endeavors.

Our sincere thanks also go to all the officials and staff of the Incubator of the University of 20 Août 1955 - Skikda for their support, guidance, and the facilities they provided throughout the development of this project.

We extend our heartfelt appreciation to all the professors of the Department of Mathematics and Computer Science, whose knowledge, dedication, and guidance supported us throughout our academic journey.

We would also like to thank the distinguished members of the examination committee for the honor they have bestowed upon us by accepting to evaluate and discuss this thesis.

Our gratitude also goes to all the healthcare professionals and educators who, through their dedication to supporting individuals with diabetes and their families, served as a true source of inspiration for this project and encouraged us to pursue it with hope and determination.

Finally, we wish to thank everyone, near or far, named or unnamed, who contributed in any way to the completion of this modest work.

Thank you all

Abstract

Type 1 Diabetes (T1D) is a chronic autoimmune disease requiring lifelong insulin therapy and precise glycemic control to avoid severe complications such as Hypoglycemia and Diabetic Ketoacidosis. One of the main challenges in daily T1D management is determining the appropriate pre-meal insulin dose, which depends on accurate carbohydrate estimation combined with personalized clinical parameters such as the Insulin-to-Carbohydrate Ratio (ICR) and the Insulin Sensitivity Factor (ISF). However, manual carbohydrate counting remains time-consuming, error-prone, and difficult to apply consistently in everyday life.

In this work, we propose DiabyLife, an AI-based mobile application designed to assist patients with T1D in estimating their pre-meal insulin dose directly from a photograph of their meal. The system relies on a DL model based on the MobileNetV2 architecture, trained using transfer learning to recognize food items and estimate their carbohydrate content. The estimated carbohydrates are then combined with the patient's personalized medical parameters to automatically compute the recommended rapid-acting insulin dose.

Developed using Flutter and integrated with Firebase cloud services, the application also offers additional features such as blood glucose monitoring, meal history tracking, reminder management, and secure storage of medical data. Experimental results show that the optimized model achieved a validation accuracy of 95.4%, demonstrating the feasibility of using computer vision and DL to simplify carbohydrate counting and reduce insulin dosing errors.

This study highlights the potential of combining AI with mobile health applications to improve the daily self-management of T1D and to support patients in achieving better glycemic control.

Résumé

Le diabète de type 1 (DT1) est une maladie auto-immune chronique nécessitant une insulinothérapie à vie ainsi qu'un contrôle glycémique précis afin d'éviter des complications graves telles que l'hypoglycémie et l'acidocétose diabétique. L'un des principaux défis de la gestion quotidienne du DT1 réside dans la détermination de la dose d'insuline pré-prandiale appropriée, laquelle dépend d'une estimation précise des glucides combinée à des paramètres cliniques personnalisés tels que le Ratio Insuline Glucides (ICR) et le Facteur de Sensibilité a L'insuline (ISF). Cependant, le comptage manuel des glucides reste chronophage, sujet à erreurs, et difficile à appliquer de manière cohérente au quotidien.

Dans ce travail, nous proposons DiabyLife, une application mobile basée sur l'intelligence artificielle, conçue pour aider les patients atteints de DT1 à estimer leur dose d'insuline pré-prandiale directement à partir d'une photographie de leur repas. Le système repose sur un modèle d'apprentissage profond basé sur l'architecture MobileNetV2, entraîné par apprentissage par transfert pour reconnaître les aliments et estimer leur teneur en glucides. Les glucides estimés sont ensuite combinés aux paramètres médicaux personnalisés du patient afin de calculer automatiquement la dose recommandée d'insuline rapide.

Développée avec Flutter et intégrée aux services cloud Firebase, l'application propose également des fonctionnalités complémentaires telles que le suivi de la glycémie, l'historique des repas, la gestion des rappels et le stockage sécurisé des données médicales. Les résultats expérimentaux montrent que le modèle optimisé a atteint une précision de validation de 95,4 %, démontrant la faisabilité de l'utilisation de la vision par ordinateur et de l'apprentissage profond pour simplifier le comptage des glucides et réduire les erreurs de dosage de l'insuline.

Cette étude met en évidence le potentiel de l'association entre l'intelligence artificielle et les applications de santé mobile pour améliorer l'autogestion quotidienne du DT1 et aider les patients à atteindre un meilleur contrôle glycémique.

ملخص

يُعد داء السكري من النوع الأول مرضًا مناعيًا ذاتيًا مزمنًا يتطلب علاجًا مدى الحياة بالأنسولين وتحكمًا دقيقًا في مستوى السكر في الدم لتجنب مضاعفات خطيرة مثل نقص السكر الحاد والحماض الكيتوني السكري. ومن أبرز التحديات اليومية في إدارة هذا المرض هو تحديد الجرعة المناسبة من الأنسولين قبل الوجبات، وهو ما يعتمد على تقدير دقيق لكمية الكربوهيدرات المتناولة، إلى جانب معايير طبية شخصية مثل نسبة الأنسولين إلى الكربوهيدرات ومعامل الحساسية للأنسولين. غير أن العد اليدوي للكربوهيدرات يبقى عملية مرهقة وعرضة للأخطاء، ويصعب تطبيقها بشكل منتظم في الحياة اليومية.

في هذا العمل، نقترح تطبيقDiabyLife ، وهو تطبيق هاتفي ذكي يعتمد على الذكاء الاصطناعي، صُمم لمساعدة مرضى السكري من النوع الأول على تقدير جرعة الأنسولين قبل الوجبة مباشرة انطلاقًا من صورة لوجبتهم. يعتمد النظام على نموذج تعلم عميق مبني على معماريةMobileNetV2 ، تم تدريبه باستخدام تقنية التعلم بالنقل للتعرف على الأطعمة وتقدير محتواها من الكربوهيدرات. بعد ذلك، تُدمج هذه القيمة مع المعطيات الطبية الشخصية للمريض لحساب الجرعة الموصى بها من الأنسولين سريع المفعول بشكل تلقائي.

طُوّر التطبيق باستخدام إطار العمل Flutter ومتكامل مع خدمات Firebase السحابية، ويوفر أيضًا ميزات إضافية مثل متابعة مستوى السكر في الدم، وسجل الوجبات، وإدارة التذكيرات، والتخزين الآمن للبيانات الطبية. وأظهرت النتائج التجريبية أن النموذج المحسّن حقق دقة تحقق بلغت 95.4٪، مما يثبت إمكانية استخدام الرؤية الحاسوبية والتعلم العميق لتبسيط عملية عد الكربوهيدرات وتقليل أخطاء حساب جرعات الأنسولين.

تسلط هذه الدراسة الضوء على الإمكانات الكبيرة للجمع بين الذكاء الاصطناعي وتطبيقات الصحة المحمولة في تحسين التسيير الذاتي اليومي لداء السكري من النوع الأول، ومساعدة المرضى على تحقيق تحكم أفضل في مستوى السكر في الدم.

Contents

Dedication.....

Dedication.....

Dedication.....

Acknowledgments.....

Abstract.....VI

Résumé.....VII

ملخص.....VIII

Contents.....IX

List of Figures.....XIII

List of Tables.....XV

List of Abbreviations.....XVI

Introduction général.....1

Chapter 01: Artificial Intelligence.....4

1. Introduction.....5

2. Artificial Intelligence.....5

3. Machine Learning.....6

3.1. Definition.....6

3.2. Machine Learning Paradigms.....6

3.2.1. Supervised Learning.....7

3.2.2. Unsupervised Learning.....8

3.2.3. Reinforcement Learning.....10

3.3. Application Fields of Machine Learning.....11

4. Deep Learning.....12

4.1. Definition.....12

4.2. Origins and Foundations of Deep Learning.....12

4.2.1. Biological neuron.....13

4.2.2. Artificial Neural Networks.....13
.42.3. Activation Functions.....14
.42.4. Loss Functions.....16
4.3. Types of Neural Networks.....17
4.3.1. Feedforward Neural Networks.....17
4.3.2. Convolutional Neural Networks.....18
4.3.3. Recurrent Neural Networks.....19
5. The difference between Deep Learning and Machine Learning.....20
6. Conclusion.....21
Chapter 02: Type 1 Diabetes and Insulin Dosing.....22
1. Introduction.....23
2. Generalities about diabetes.....23
2.1. Definition of Type 1 Diabetes.....23
2.2. Pathophysiology of Type 1 Diabetes.....23
2.3. Importance of Glycemic Control in Type 1 Diabetes.....25
2.4. Complications of Poor Glycemic Control in Type 1 Diabetes.....26
3. Carbohydrate Counting Strategy.....27
3.1. Principles of Carbohydrate Counting.....27
3.2. Why carbohydrates are the main determinant of insulin dosage? 28
3.3. Challenges of accurately estimating carbohydrates manually.....29
4. Medical Calculation of Insulin Dose.....30
4.1. Insulin-to-Carbohydrate Ratio.....30
4.2. Correction Factor.....31
4.3. Insulin Dose Calculation Formula.....31
4.4. Applied clinical example of insulin dose calculation.....32
5. Conclusion.....33

Chapter 03: Design and Implementation.....34

1. Introduction.....35

2. Architecture of the system.....35

2.1. General System Overview.....35

2.2. Dataset.....36

2.3. Data Preprocessing.....37

2.3.1. Resizing.....37

2.3.2. Normalization.....38

2.3.3. Data Augmentation.....38

2.3.4. Validation Set.....39

2.4. Model.....39

2.4.1. MobileNetV2.....39

2.4.2. Transfer Learning.....40

2.4.3. Phase 1: Feature Extraction.....40

2.4.4. Phase 2: Fine-tuning.....41

3. Experiments and Results.....41

3.1. Training Configuration.....41

3.2. Training Results.....42

3.3. Optimization Experiments.....43

3.3.1. Baseline Model.....43

3.3.2. Activation Functions Comparison.....43

3.3.3. Dropout Rate Comparison.....44

3.3.4. Optimizer Comparison.....44

3.3.5. Grid Search.....45

3.3.6. Cross Validation.....46

3.4. Real-World Testing.....47

3.5. Observed Limitations.....47
4. Work Environment and Development Tools.....48
4.1. Hardware Tools.....48
4.2. Software Tools.....50
4.2.1. Google Colaboratory.....50
4.2.2. Android Studio.....50
4.2.3. Flutter & Dart.....51
4.2.4. Libraries and Dependencies.....51
4.2.5. Python Libraries (AI Module).....51
5. Application Interface.....52
5.1. Authentication Screens.....52
5.2. Main Dashboard.....52
5.3. Blood Sugar Tracking.....53
5.4. Diabetes Management Tools.....53
5.5. Insulin Calculator.....54
6. Conclusion.....55
General Conclusion.....56
Bibliography.....58
Webography.....61

LIST OF FIGURES

Figure 1.1: Venn diagram of the components of Artificial Intelligence……5

Figure 1.2: General workflow of a Machine Learning system……..6

Figure 1.3: Overview of ML Paradigms and Their Applications……..7

Figure 1.4: Illustration of Classification and Regression in a medical context…….8

Figure 1.5: Transition from unlabeled to clustered data……9

Figure 1.6: Progressive reduction from 3D to 2D to 1D space……..9

Figure 1.7: Interaction cycle between Agent, Environment, State, Action, and Reward in RL10

Figure 1.8: Deep Learning process input to output……..12

Figure 1.9: Structure of a biological neuron……13

Figure 1.10: Comparison between biological neuron and artificial neuron (perceptron) structure…….……14

Figure 1.11: Structure of a Feedforward Neural Network (FNN) …….18

Figure 1.12: Architecture of a CNN……19

Figure 1.13: Unfolded structure of a RNN across time steps……..20

Figure 2.1: Autoimmune Mechanism Autoimmune β-cell destruction in T1D……..21

Figure 2.2: Long-term complications of hyperglycemia in diabetes……...25

Figure 2.3: Pathophysiology of Diabetic Ketoacidosis (DKA)……...26

Figure 2.4: Common symptoms of Severe Hypoglycemia……..27

Figure 2.5: The diabetes plate method…….28

Figure 3.1: Architecture of the system…….…36

Figure 3.2: Comparison between an original image and its resized version……37

Figure 3.3: Effect of pixel normalization on image appearance…….38

Figure 3.4: Examples of data augmentation transformations applied to training images……38

Figure 3.5: Comparison of MobileNetV1 and MobileNetV2 block structures……39

Figure 3.6: Training and validation accuracy and loss curves across 10 epochs……..43

Figure 3.7: Google colaboratory logo.……..…50

Figure 3.8: Android Studio logo.…….……50

Figure 3.9: Flutter & Dart logo……51

Figure 3.10: Authentication Screens (Login and Registration)……...52

Figure 3.11: Main Dashboard and Side Navigation Menu……..52

Figure 3.12: Measurement Registration……...53

Figure 3.13: Blood Sugar History Calendar, Weekly Table, and Trend Curves (3, 7, and 14 days)……..53

Figure 3.14: Diabetes Management Tools: Overview and Treatment Settings……...54

Figure 3.15: Hyperglycemia and Hypoglycemia Management Screens, Symptoms, ISF, Calculator, and Glucagon Guide……...54

Figure 3.16: Insulin Dose Calculator Screen……...55

LIST OF TABLES

Table 1.1: The difference between DP & ML……21

Table 3.1: Training configuration hyperparameters……41

Table 3.2: Summary of training and validation performance……42

Table 3.3: Baseline model performance……..43

Table 3.4: Validation accuracy across different activation functions…….44

Table 3.5: Validation accuracy across different dropout rates……44

Table 3.6: Validation accuracy across different optimizers.....45

Table 3.7: Best hyperparameter configuration from Grid Search……...45

Table 3.8: 5-Fold Cross Validation results.....46

Table 3.9: Comprehensive comparison of all optimization experiments.....46

Table 3.10: Confidence tier classification.....47

Table 3.11: Hardware specifications of development machines.....49

Table 3.12: Flutter dependencies used in the application.....51

Table 3.13: Python libraries used in the AI training module.....51

List of Abbreviations

AI: Artificial Intelligence

ML: Machine Learning

DL: Deep Learning

T1D: Type 1 Diabetes

T2D : Type 2 Diabetes

CGM: Continuous Glucose Monitoring

HbA1c: Glycated Hemoglobin

RL: Reinforcement Learning

NLP: Natural Language Processing

FNN: Feedforward Neural Networks

CNN: Convolutional Neural Network

RNN: Recurrent Neural Network

MLP: Multilayer Perceptron

LSTM: Long Short-Term Memory

GRU: Gated Recurrent Unit

DKA: Diabetic Ketoacidosis

DCCT: Diabetes Control and Complications Trial

TIR: Time in Range

ICR: Insulin-to-Carbohydrate Ratio

ISF: Insulin Sensitivity Factor

General Introduction

General Introduction

Type 1 Diabetes (T1D) is a chronic autoimmune disease that affects millions of people worldwide. It is characterized by the destruction of pancreatic β-cells, resulting in an absolute deficiency of insulin. Consequently, individuals with T1D require lifelong insulin therapy to maintain blood glucose levels within a healthy range. Poor glycaemic control may lead to severe acute complications, such as Hypoglycemia and Diabetic Ketoacidosis (DKA), as well as long-term complications affecting the eyes, kidneys, nerves, and cardiovascular system. Therefore, maintaining optimal blood glucose levels is essential to improve patients' quality of life and reduce the risk of diabetes-related complications.

One of the most challenging aspects of T1D management is determining the appropriate insulin dose before each meal. This process relies on estimating the amount of carbohydrates consumed and combining this information with personalized clinical parameters, including the Insulin-to-Carbohydrate Ratio (ICR) and the Insulin Sensitivity Factor (ISF). However, manual carbohydrate counting is often time-consuming, complex, and prone to estimation errors, particularly when meals contain multiple food items or when nutritional information is unavailable. Even small inaccuracies in carbohydrate estimation may result in inappropriate insulin dosing, leading to episodes of Hypoglycemia or hyperglycaemia and compromising overall glycaemic control.

Traditional approaches for carbohydrate estimation mainly rely on nutrition tables, food labels, mobile applications requiring manual input, or the patient's personal experience. Although these methods are widely used, they require visual estimation and manual calculations that can be inaccurate and burdensome in everyday life. These limitations highlight the need for intelligent and automated solutions capable of simplifying carbohydrate estimation while improving insulin dose accuracy.

Recent advances in Artificial Intelligence (AI), particularly in Deep Learning (DL) and Computer Vision, have opened new opportunities in diabetes management. By automatically analysing food images, deep learning models can accurately recognize different food items and estimate their nutritional composition, including carbohydrate content. Integrating these technologies into mobile healthcare applications enables automatic carbohydrate estimation and personalized insulin dose calculation, reducing human errors and supporting more effective diabetes self-management.

To address this challenge, this dissertation proposes DiabyLife, an AI-based mobile application designed to assist individuals with T1D in estimating their pre-meal insulin dose.

The application employs a DL model based on the MobileNetV2 architecture to recognize food items from a photograph of a meal and estimate their carbohydrate content. The estimated carbohydrates are then combined with each patient's personalized medical parameters, including the ICR and the ISF, to automatically calculate the recommended rapid-acting insulin dose. Developed using Flutter and integrated with Firebase cloud services, DiabyLife also provides additional features such as blood glucose monitoring, insulin dose calculation, meal history, reminder management, and secure storage of medical records, offering a comprehensive solution for daily diabetes management.

This dissertation is organized into three chapters:

The first chapter presents the theoretical foundations of Artificial Intelligence, ML, and DL, together with the neural network architectures used in this work.

The second chapter introduces T1D, emphasizes the importance of glycaemic control, explains carbohydrate counting, and describes the medical calculation of insulin doses.

Finally, the third chapter presents the design, implementation, and evaluation of the proposed DiabyLife system, including its architecture, development tools, experimental results, and mobile application interfaces.

CHAPTER 01:

Artificial Intelligence

1. Introduction

Artificial Intelligence (AI) is a rapidly evolving field that aims to develop intelligent systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, problem-solving, and decision-making.

This chapter provides a comprehensive overview of the fundamental concepts underlying Artificial Intelligence, Machine Learning (ML), and Deep Learning (DL). It begins by introducing AI as a broad scientific discipline and discusses its objectives and key application areas. The chapter then focuses on ML, presenting its main learning paradigms, core techniques, and applications across various domains, particularly healthcare. Finally, it explores DL as an advanced subset of ML based on artificial neural networks, covering its biological inspiration, fundamental components, and major architectures. A comparative analysis between ML and DL is also provided to highlight their differences, strengths, limitations, and complementary roles.

2. Artificial Intelligence

AI is a branch of computer science that aims to design computational systems capable of performing tasks that typically require human intelligence, such as reasoning, learning, decision-making, natural language understanding, and visual perception **[1].**

AI encompasses several subfields, among which ML and DL are the most prominent modern approaches. As illustrated in Figure 1.1, ML is a subset of AI, while DL is a subset of ML, forming a hierarchical relationship between these fields.

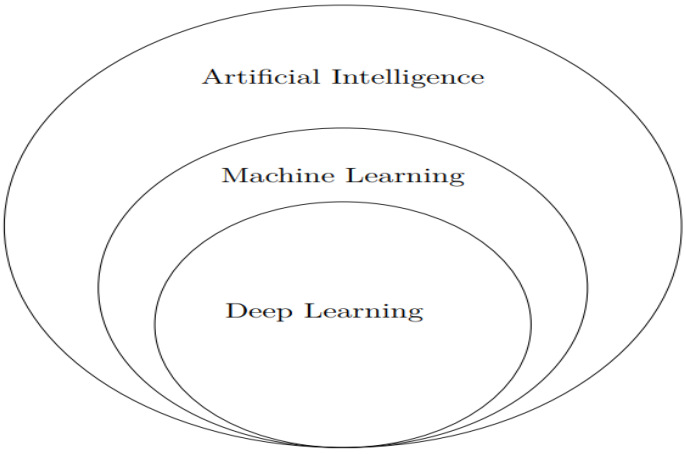


Figure 1.1: Venn diagram of the components of Artificial Intelligence

3. Machine Learning

3.1. Definition

ML is a subfield of AI that focuses on the development of algorithms and statistical models that enable systems to learn from data and improve their performance on specific tasks without being explicitly programmed **[1].**

Unlike traditional programming, where rules are manually defined, ML algorithms identify patterns and relationships within data to make predictions or decisions **[2].** Depending on how the learning process is performed, ML is generally categorized into three main paradigms: Supervised Learning, Unsupervised Learning, and Reinforcement Learning.

The general workflow of a ML system is illustrated in Figure 1.2 During the training phase, a model is built using historical data. Once trained, the model is applied to new input data during the inference phase to generate predictions or support decision-making.

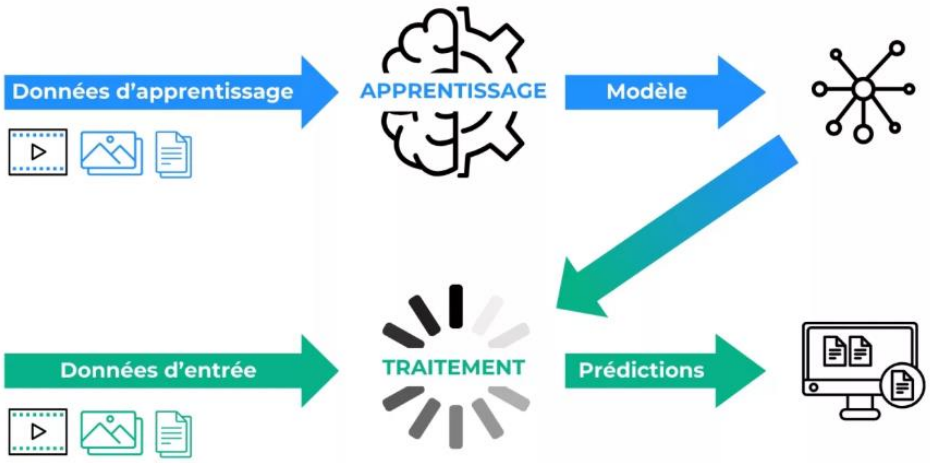


Figure 1.2: General workflow of a Machine Learning system **[Web 01].**

3.2. Machine Learning Paradigms

ML encompasses three fundamental learning paradigms, each distinguished by the nature of the data used and the type of feedback provided to the learning algorithm during the training process. These paradigms are Supervised Learning, Unsupervised Learning, and Reinforcement Learning, as illustrated in Figure 1.3.

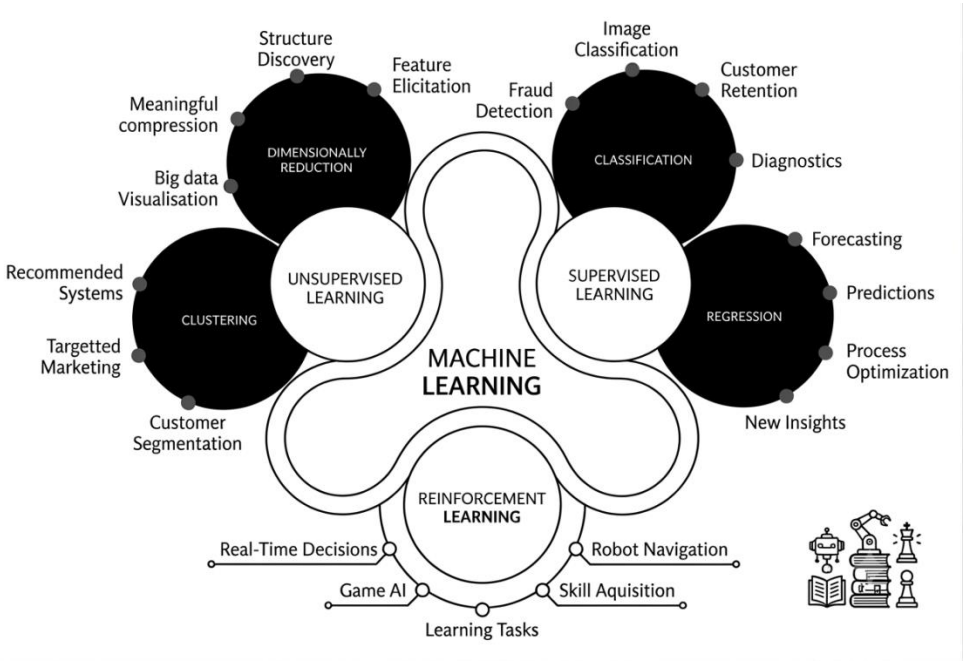


Figure 1.3: Overview of ML Paradigms and Their Applications **[GAI 01].**

3.2.1. Supervised Learning

Supervised Learning is a ML paradigm in which a model is trained using a labeled dataset, where each input sample is associated with a corresponding output label. The objective is to learn a mapping function f(X) =Y, where X represents the input features and Y the target output, allowing the model to make predictions on unseen data **[2].**

During the training phase, the model adjusts its parameters by minimizing a loss function that measures the difference between predicted and actual outputs. The trained model is then evaluated on a separate test set to assess its ability to generalize **[1].**

As illustrated in Figure 1.3, Supervised Learning is mainly divided into two tasks: Classification and Regression.

Classification is the task of assigning input data to predefined categories by learning a decision boundary between classes. It is commonly used in applications such as disease diagnosis (e.g., presence or absence of a condition).

Regression, on the other hand, predicts continuous numerical values by modeling the relationship between input variables and a quantitative output, such as predicting blood glucose levels (See Figure 1.4).

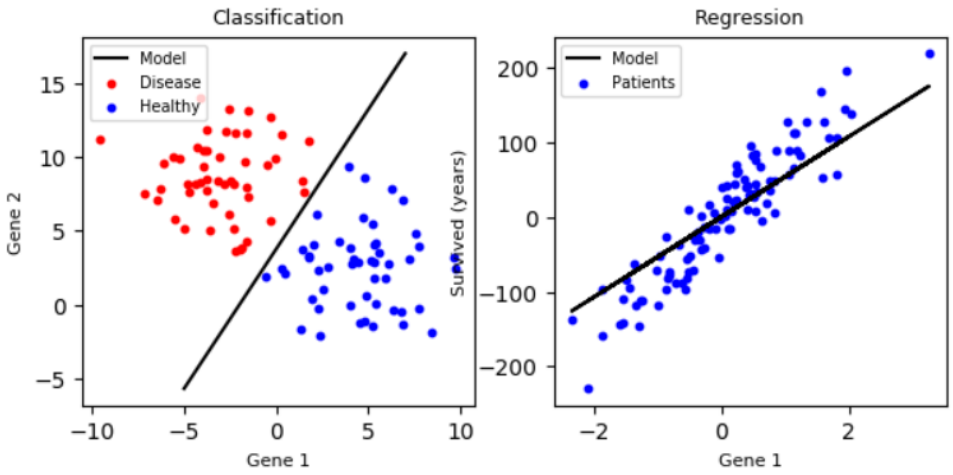


Figure 1.4: Illustration of Classification and Regression in a medical context **[Web 02]**.

Supervised Learning has several advantages, including high prediction accuracy, interpretability, and strong theoretical foundations. However, it also has limitations, such as the need for large labeled datasets and susceptibility to overfitting when data is limited or noisy **[2].**

In the context of Type 1 Diabetes (T1D), Supervised Learning is widely used in clinical decision support systems. Regression models are applied to predict blood glucose levels using Continuous Glucose Monitoring (CGM), insulin dosage, and dietary data, while classification models are used for disease diagnosis based on biomarkers such as HbA1c and C-peptide levels **[3].**

3.2.2. Unsupervised Learning

Unsupervised Learning is a ML paradigm in which a model is trained using an unlabeled dataset, where no predefined output labels are provided. The main objective is to discover hidden patterns, structures, and meaningful representations within the data without external supervision **[2].**

Unlike Supervised Learning, this paradigm relies entirely on the intrinsic properties and statistical distribution of the input data to extract useful information **[1].**

As illustrated in Figure 1.3, Unsupervised Learning is mainly divided into two tasks: Clustering and Dimensionality Reduction.

- **Clustering** involves grouping data points into clusters such that similar samples are placed in the same group. It is widely used in clinical applications such as patient stratification and subgroup identification (See Figure 1.5).

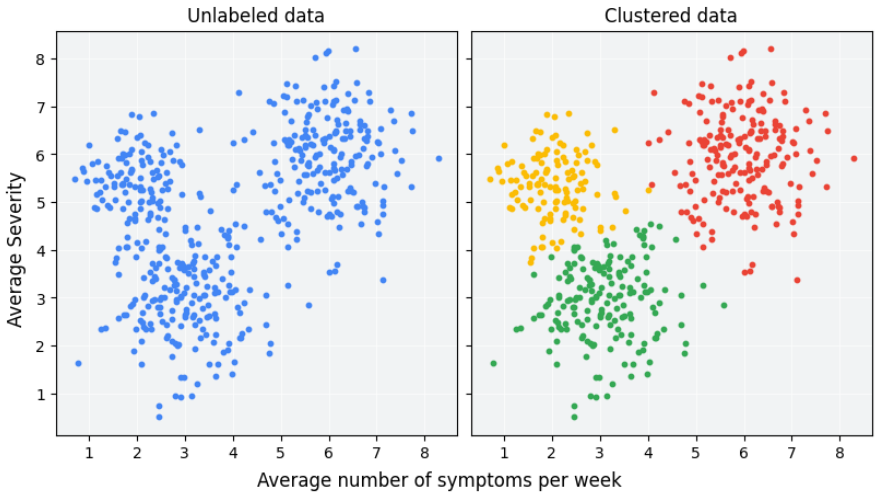


Figure 1.5: Transition from unlabeled to clustered data **[Web 03]**.

- **Dimensionality Reduction** reduces the number of input features while preserving essential information, improving visualization, reducing noise, and enhancing computational efficiency (See Figure 1.6).

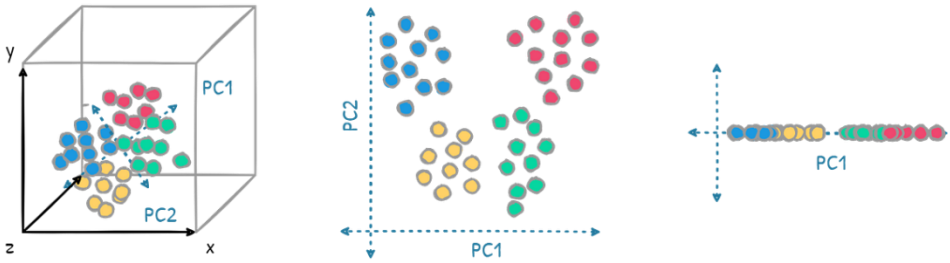


Figure 1.6: Progressive reduction from 3D to 2D to 1D space **[Web 04]**.

Unsupervised Learning has several advantages, including the ability to work with unlabeled data and to discover hidden structures in large datasets. However, its main limitation lies in the difficulty of evaluating results due to the absence of ground truth labels, as well as the potential ambiguity in interpreting discovered patterns **[4].**

In the context of T1D, Unsupervised Learning has been applied in clinical and biomedical research. Clustering algorithms are used to identify patient subgroups based on metabolic profiles, glycemic variability, and insulin sensitivity, enabling more personalized treatment strategies. Dimensionality Reduction techniques are applied to high-dimensional genomic and proteomic data to extract relevant biomarkers and facilitate data visualization **[3].**

3.2.3. Reinforcement Learning

Reinforcement Learning (RL) is a ML paradigm in which an agent learns to make sequential decisions by interacting with a dynamic environment. Unlike Supervised and Unsupervised Learning, no labeled dataset is provided. Instead, the agent learns through feedback in the form of rewards or penalties, aiming to maximize its cumulative reward over time **[1].**

RL is based on three main components: the Agent, the Environment, and the Reward. The agent is the decision-making entity that selects actions based on a policy. The environment represents the external system with which the agent interacts, while the reward is a feedback signal that evaluates the quality of each action.

At each step, the agent observes the current state, selects an action, and receives feedback from the environment. This iterative process allows the agent to continuously improve its policy in order to achieve optimal long-term performance **[5]** (See Figure 1.7).

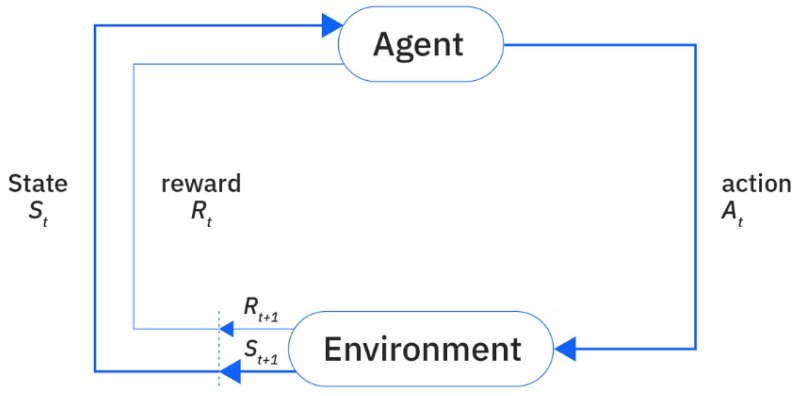


Figure 1.7: Interaction cycle between Agent, Environment, State, Action, and Reward in RL **[Web 05].**

RL has several advantages, including its suitability for sequential decision-making problems, its ability to learn without labeled data, and its capacity to discover optimal strategies through exploration. However, it also has limitations such as high computational cost, sensitivity to reward design, and potential instability in complex environments **[6].**

In the context of T1D, RL has shown significant clinical potential. RL-based algorithms have been applied to optimize insulin dosing in closed-loop artificial pancreas systems, where the agent continuously adjusts insulin delivery based on real-time glucose measurements, meal intake, and physical activity, with the goal of maintaining glycemic levels within a safe therapeutic range **[3].**

This approach improves upon traditional control methods by enabling personalized insulin delivery policies adapted to individual patient metabolic characteristics **[3].**

3.3. Application Fields of Machine Learning

ML has become a key technology in numerous scientific, industrial, and medical fields. Its ability to learn from data and identify complex patterns has enabled the development of intelligent systems capable of prediction, automation, and decision support **[1].**

In healthcare, ML is widely used for disease diagnosis, medical image analysis, drug discovery, and personalized treatment planning. It has shown promising results in the early detection of diseases such as cancer, diabetes, and cardiovascular disorders **[7].**

In Natural Language Processing (NLP), ML supports applications such as machine translation, speech recognition, sentiment analysis, and conversational systems. It is also extensively used in computer vision for tasks including object detection, facial recognition, and medical image interpretation **[1].**

In finance, ML contributes to fraud detection, credit scoring, and market forecasting, while in robotics and autonomous systems, it enables intelligent decision-making and control through interaction with dynamic environments **[8].**

These diverse applications highlight the growing importance of ML and provide the foundation for the emergence of more advanced approaches such as DL, which is presented in the next section.

4. Deep Learning

4.1. Definition

DL is a subfield of ML that utilizes Artificial Neural Networks (ANNs) with multiple layers to automatically learn hierarchical representations of data **[6].**

The term deep refers to the large number of interconnected layers through which data is progressively transformed into increasingly abstract feature representations **[8].**

Unlike traditional ML approaches that rely on manual feature engineering, DL models can automatically extract relevant features directly from raw data, such as images, text, audio, and numerical signals **[6].**

Owing to their ability to learn complex patterns from large-scale datasets, DL techniques have achieved remarkable success in various domains, including computer vision, natural language processing, speech recognition, and healthcare applications **[1].**

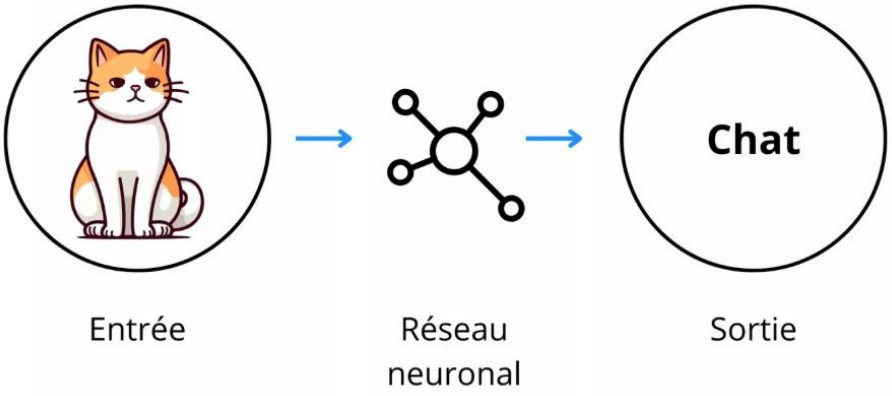


Figure 1.8: Deep Learning process input to output **[Web 06].**

4.2. Origins and Foundations of Deep Learning

The development of DL is rooted in decades of interdisciplinary research spanning neuroscience, mathematics, and computer science. Inspired by the structure and functioning of the human brain, researchers developed computational models capable of simulating certain aspects of biological intelligence, leading to the emergence of artificial neural networks **[6].**

Over time, advances in optimization algorithms, the availability of large-scale datasets, and increasing computational power enabled the evolution of simple neural models into the deep architectures that characterize modern DL systems **[8].**

The following subsections present the fundamental concepts underlying DL, including the biological neuron, artificial neural networks, activation functions, and loss functions.

4.2.1. Biological neuron

The biological neuron is the basic functional unit of the human nervous system. It is responsible for receiving, processing, and transmitting information through electrochemical signals. A typical neuron consists of three main components: dendrites, which receive incoming signals; the cell body (soma)**,** which processes the received information; and the axon, which transmits signals to other neurons through synaptic connections **[9].** (See Figure 1.9).

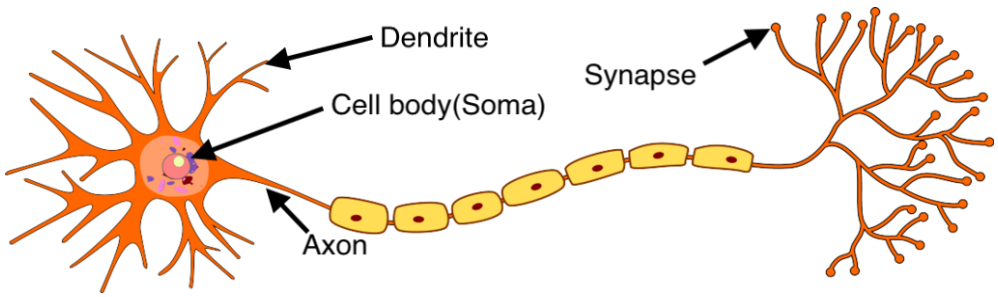


Figure 1.9: Structure of a biological neuron **[Web 07].**

Neural communication is based on a threshold mechanism. When the accumulated input signals exceed a certain threshold, the neuron generates an electrical impulse that propagates along the axon. Otherwise, no signal is transmitted **[6].**

This mechanism inspired the development of ANNs, where artificial neurons emulate the behavior of biological neurons by receiving inputs, processing them, and producing outputs.

4.2.2. Artificial Neural Networks

ANNs are computational models inspired by the structure and functioning of biological neural networks. They consist of interconnected processing units, called artificial neurons, organized into layers that learn patterns and relationships from data **[6].**

A typical ANN is composed of three main layers: the input layer, which receives the input data; one or more hidden layers, which process the information through a series of transformations; and the output layer, which produces the final prediction or classification result **[2].**

Connections between neurons are associated with numerical weights that determine the influence of one neuron on another. During training, these weights are adjusted to improve the network's performance and reduce prediction errors **[6].**

The relationship between biological and artificial neurons is illustrated in Figure 1.10. In this analogy, dendrites correspond to input signals, the soma performs information processing, and the axon represents the transmission of the output to subsequent neurons.

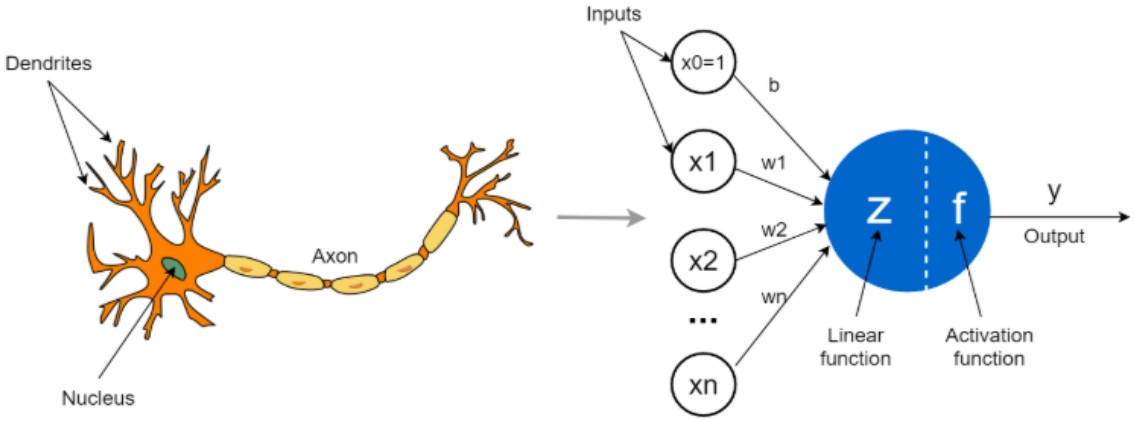


Figure 1.10: Comparison between biological neuron and artificial neuron (perceptron) structure **[Web 08].**

4.2.3. Activation Functions

Activation functions are a fundamental component of ANNs. They introduce non-linearity into the model, enabling it to learn complex patterns beyond linear relationships. Without them, a neural network would behave as a simple linear model regardless of its depth **[6].**

Formally, a neuron computes a weighted sum:

$$Z = \sum w_i \, x_i + b \quad (1)$$

This is then transformed by an activation function f to produce the output:

$$y = f(z) \quad (2)$$

The choice of activation function has a significant impact on model performance, including learning stability and convergence speed **[2].**

- **Logistics function**

The Logistics function (Sigmoid) maps input values to the range (0, 1), making it suitable for binary classification and probability estimation:

$$\sigma(\mathrm{Z}) = \frac{1}{1 + \mathrm{e}^{-\mathrm{z}}} \quad (3)$$

However, it suffers from the vanishing gradient problem in deep networks, which limits its use in hidden layers **[6].**

- **Hyperbolic Tangent**

The hyperbolic tangent (TanH) function maps inputs to the range (-1, 1):

$$\sigma(\mathrm{Z}) = \frac{\mathrm{e}^{\mathrm{z}} - e^{-z}}{\mathrm{e}^{\mathrm{z}} + e^{-z}} \quad (4)$$

It is zero-centered, which improves optimization compared to Sigmoid, but it still suffers from vanishing gradients in deep architectures **[2].**

- **Rectified Linear Unit**

The Rectified Linear Unit (ReLU) is widely used in modern DL:

$$\mathrm{ReLU}(\mathrm{Z}) = \max(0, \mathrm{Z}) \quad (5)$$

It improves training efficiency and reduces vanishing gradient issues, but may suffer from the “dying ReLU” problem where neurons become inactive **[2].**

- **Gaussian Error Linear Unit**

The Gaussian Error Linear Unit (GELU) is a smooth, probabilistic activation function that can be interpreted as a weighted version of ReLU, where inputs are scaled according to the probability of being positive under a Gaussian distribution.

Its exact formulation is given by:

$$GELU(z) = Z.\Phi(\mathrm{Z}) \quad (6)$$

Where $\Phi(\mathrm{Z})$ denotes the cumulative distribution function of the standard normal distribution.

In practice, GELU is commonly approximated using the following expression:

$$\mathrm{GELU(Z)} = 0.5\mathrm{Z}(1 + \tan[\sqrt{\frac{2}{\pi}}(Z + 0.044715Z^3)]) \quad (7)$$

GELU has been widely adopted in state-of-the-art transformer-based architectures such as BERT and GPT due to its strong empirical performance in DL tasks **[10].**

- **Softmax**

Softmax is used in the output layer of multi-class classification problems:

$$softmax\,(\vec{Z})_i = \frac{e^{Z_i}}{\sum_{j=1}^{K} e^{Z_i}} \quad (8)$$

It converts raw scores into a probability distribution over classes **[6].**

4.2.4. Loss Functions

A loss function is a mathematical measure used to quantify the difference between the predicted outputs of a neural network and the actual target values. During training, optimization algorithms minimize this function by iteratively updating the model parameters using backpropagation, with the goal of improving prediction accuracy **[6].**

- **Mean Squared Error**

Mean Squared Error (MSE) is one of the most widely used loss functions in regression problems. It computes the average squared difference between predicted values $\hat{y}_i$ and actual values $y_i$over n samples, and is defined as:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \quad (9)$$

The squaring operation ensures non-negative error values and penalizes larger deviations more heavily than smaller ones, making MSE particularly sensitive to outliers. Due to its differentiable nature, it is well-suited for gradient-based optimization methods such as gradient descent **[2].**

In regression tasks such as blood glucose prediction in T1D management, MSE is commonly used to evaluate prediction accuracy and guide model optimization **[3].**

4.3. Types of Neural Networks

DL has developed a wide variety of neural network architectures, each designed to address specific types of data and learning problems. Although these architectures share the same fundamental principle of layered computation and representation learning, they differ in their structure, connectivity, and information processing mechanisms **[6].**

The choice of an appropriate architecture depends on the nature of the input data and the target task. Different data types, such as tabular data, images, and sequential data, require specialized models to effectively capture their underlying patterns **[8].**

The following subsections present three fundamental neural network architectures that form the basis of modern DL: Feedforward Neural Networks (FNN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN).

4.3.1. Feedforward Neural Networks

A FNN, also known as a Multilayer Perceptron (MLP), is the most basic architecture in DL. It is characterized by a unidirectional flow of information from the input layer, through one or more hidden layers, to the output layer, without any cycles or feedback connections. In

this structure, each neuron is fully connected to all neurons in the subsequent layer, forming a dense (fully connected) network **[6].**

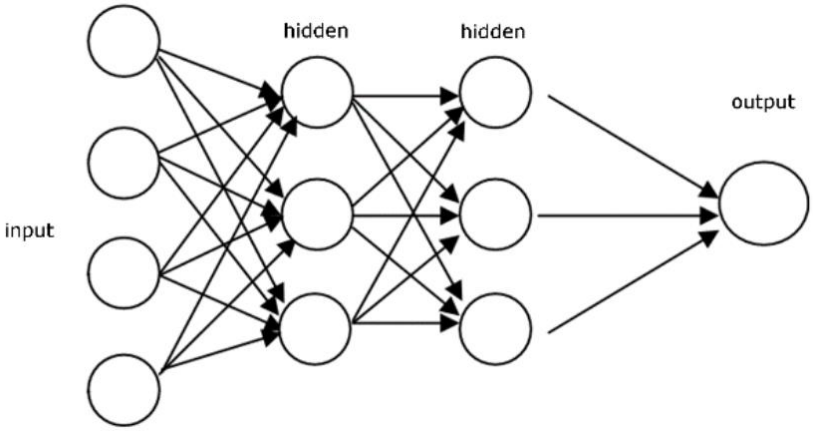


Figure 1.11: Structure of a Feedforward Neural Network (FNN) **[Web 09].**

During the forward pass, input data is propagated through successive layers, where each layer applies a linear transformation followed by a non-linear activation function. Through training, the network learns an optimal mapping between inputs and outputs by adjusting its internal parameters **[2].**

FNNs are mainly suitable for structured and tabular data, where spatial or temporal dependencies are not dominant. However, their fully connected structure can become computationally expensive and may lead to overfitting when applied to high-dimensional data such as images or sequential signals, which motivates the use of more specialized architectures **[6].**

In the context of T1D, FNNs have been used for tasks such as predicting insulin dosage and classifying glycemic risk levels based on clinical features including HbA1c, body mass index, and fasting glucose levels **[3].**

4.3.2. Convolutional Neural Networks

A CNN is a DL architecture specifically designed for processing data with spatial structure, such as images and two-dimensional signals. Unlike Feedforward Neural Networks, CNNs exploit local connectivity and parameter sharing through convolutional filters, allowing them to efficiently capture spatial features such as edges, textures, and shapes **[6].**

A typical CNN consists of two main parts, as illustrated in Figure 1.11. The feature extraction stage includes convolutional layers, which apply filters to extract feature maps, followed by pooling layers that reduce spatial dimensions and improve robustness to small transformations. The classification stage consists of fully connected layers followed by a Softmax layer for final prediction **[11].**

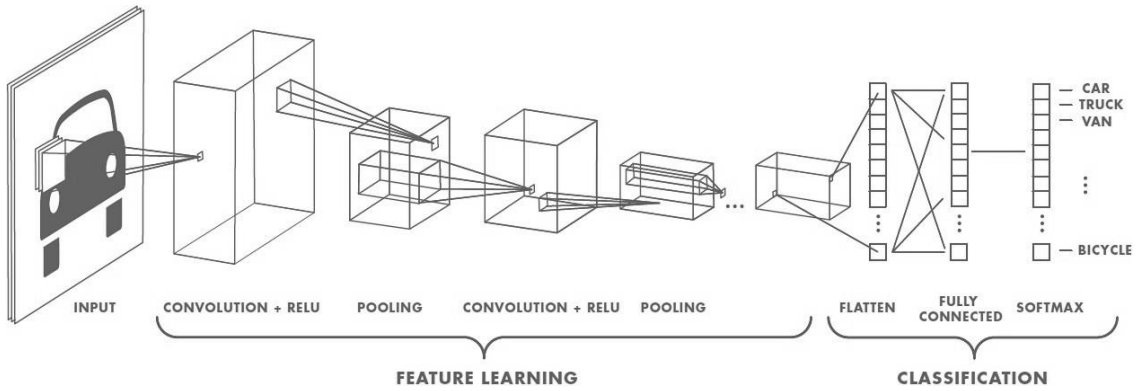


Figure 1.12: Architecture of a CNN **[Web 10].**

The convolution operation can be expressed as:

$$(f * g)(t) = \sum f(\tau)\mathrm{g}(\mathrm{t} - \tau) \quad (10)$$

Where f represents the input signal and g represents the convolution filter.

CNNs have achieved strong performance in computer vision tasks and are widely used in medical image analysis. In the context of Type 1 Diabetes, CNNs have been applied to retinal fundus image analysis for the detection of diabetic retinopathy, a serious complication of the disease, achieving high diagnostic accuracy **[3].**

4.3.3. Recurrent Neural Networks

A RNN is a DL architecture designed for processing sequential and temporal data. Unlike Feedforward and CNN, RNNs incorporate recurrent connections that allow information to persist across time steps, enabling the model to capture temporal dependencies through an internal memory (hidden state) **[6].**

As illustrated in Figure 1.12, at each time step t,, the network receives an input x_t and combines it with the previous hidden state h_{t-1} to produce a new hidden state $h_t$and an output y_t. This process can be mathematically expressed as:

$$h_t = f(W_t x_t + W_h h_{t-1} + b) \quad (11)$$

Where $W_t$and W_h are learnable weight matrices, and b is a bias term **[12].**

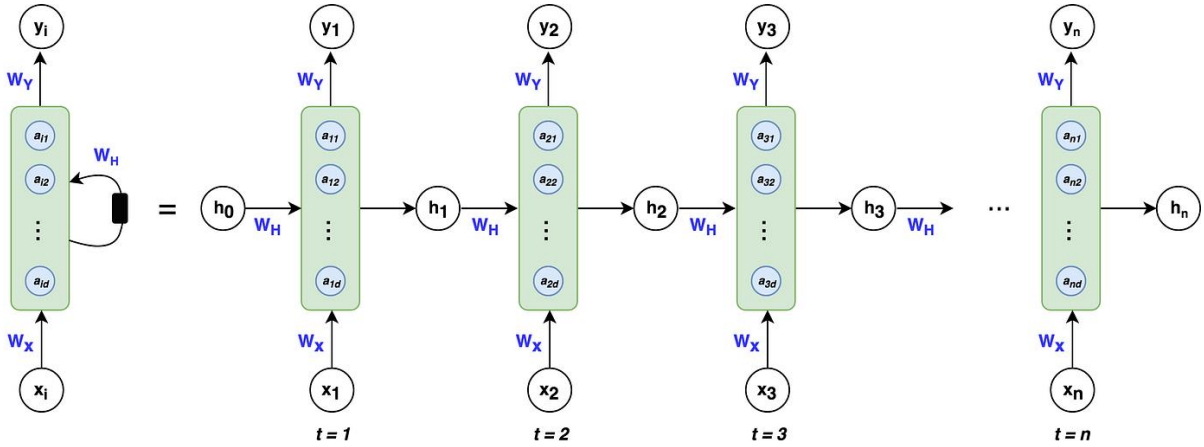


Figure 1.13: Unfolded structure of a RNN across time steps **[Web 11].**

Despite their ability to model sequential data, standard RNNs suffer from the vanishing gradient problem, which limits their effectiveness in learning long-term dependencies. This limitation has led to the development of more advanced variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) **[6].**

In healthcare applications, RNNs are widely used for time-series prediction tasks, particularly in forecasting blood glucose levels using CGM data, supporting real-time decision-making in T1D management **[3].**

5. The difference between Deep Learning and Machine Learning

ML and DL both are subsets of AI but there are many similarities and differences between them, this table illustrates that:

Aspect	Machine Learning	Deep Learning
Definition	Uses algorithms to learn patterns from data	Subset of ML using multi-layer neural networks
Feature Engineering	Requires manual feature extraction	Automatically learns features from raw data
Data Type	Mainly structured data	Structured and unstructured data (images, text, audio)
Model Complexity	Simpler models (e.g., SVM, Decision Trees)	Complex deep neural networks (CNN, RNN, etc.)
Data Requirement	Works well with small to medium datasets	Requires large datasets for good performance
Computational Power	Lower computational cost	High computational cost (GPU often needed)
Training Time	Faster training	Slower training due to deep architectures
Performance	Good for simpler tasks	Higher accuracy for complex tasks
Examples	Linear Regression, SVM, Random Forest	CNN, RNN, LSTM, Transformers

Table 1.1: The difference between DL & ML.

6. Conclusion

This chapter has presented the essential foundations of AI, ML, and DL. It has shown that AI serves as the general field, within which ML and DL represent progressively more specialized and powerful approaches.

The next chapter presents the fundamental concepts and methods related to diabetes managements, with a focus on nutrition and insulin dosing.

CHAPTER 02:

Type 1 Diabetes and Insulin Dosing

1. Introduction

Building on the foundational concepts of AI, ML, and DL introduced in the previous chapter, this chapter shifts the focus to the clinical domain, where these technologies find one of their most impactful applications. It explores the principles of carbohydrate counting and insulin dose calculation in Type 1 Diabetes (T1D) management, highlighting the relationship between dietary carbohydrate intake and insulin requirements. It also describes the main methods used for determining accurate insulin doses, including the insulin-to-carbohydrate ratio and the insulin sensitivity factor.

2. Generalities about diabetes

2.1.Definition of Type 1 Diabetes

T1D is a chronic metabolic disorder characterized by an absolute deficiency of insulin resulting from the destruction of pancreatic β-cells **[13].** Insulin is an essential hormone involved in the regulation of blood glucose levels by facilitating glucose uptake and utilization in peripheral tissues. The absence or severe reduction of endogenous insulin leads to persistent hyperglycemia and disruption of normal metabolic homeostasis.

According to current clinical classifications, T1D is distinguished from T2D by the near-total or completes absence of insulin production, rather than insulin resistance, which is the predominant mechanism in T2D **[14].** As a result, individuals with T1D are dependent on lifelong exogenous insulin therapy to maintain glycemic control and prevent acute metabolic decompensation.

T1D can occur at any age, although it is most frequently diagnosed in childhood and adolescence. Early identification and appropriate insulin management are essential to reduce the risk of acute complications and to ensure long-term metabolic stability **[14].**

2.2.Pathophysiology of Type 1 Diabetes

The pathophysiology of T1D is characterized by a progressive autoimmune process that leads to the selective destruction of pancreatic β-cells. In genetically susceptible individuals, environmental factors such as viral infections or other external triggers are thought to initiate an abnormal immune response against pancreatic islet cells.

This autoimmune reaction is primarily mediated by autoreactive $CD4^+$ and $CD8^+$ T lymphocytes, which infiltrate the islets of Langerhans, leading to chronic inflammation known as insulitis. This cellular immune response plays a central role in the gradual loss of functional β-cell mass **[15].** (See Figure 2.1)

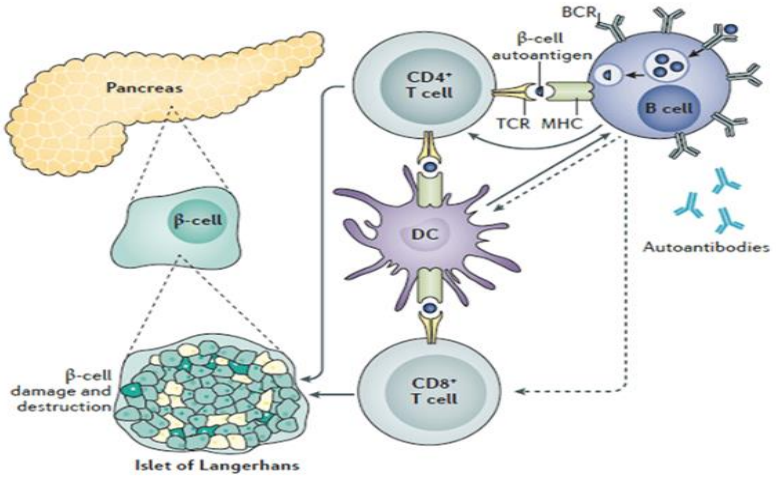


Figure 2.1: Autoimmune Mechanism Autoimmune β-cell destruction in T1D **[Web 12].**

In parallel, humoral immune markers are commonly detected during the preclinical phase. Autoantibodies directed against key β-cell antigens, including Glutamic Acid Decarboxylase (GAD65), Insulinoma-Associated protein 2 (IA-2), and Zinc Transporter 8 (ZnT8), may appear in the circulation years before the onset of clinical symptoms **[16].** These immunological markers are widely used to identify individuals at risk and to characterize disease progression.

As β-cell destruction advances, insulin secretion progressively declines, resulting in a transition through preclinical stages of dysglycemia before the onset of overt diabetes. Clinical manifestations typically appear when a critical proportion of β-cell function is lost, leading to significant insulin deficiency and impaired glucose regulation **[17].**

At the time of diagnosis, the majority of pancreatic β-cell mass is already destroyed, which explains the immediate and lifelong dependence on exogenous insulin therapy required for survival and metabolic control **[15].**

2.3. Importance of Glycemic Control in Type 1 Diabetes

Maintaining optimal glycemic control is a fundamental component of T1D management. Due to the absolute deficiency of insulin characteristic of the disease, achieving and maintaining target blood glucose levels is essential not only for normal metabolic functioning but also for preventing long-term diabetes-related complications.

The main clinical indicator used to evaluate long-term glycemic control is glycated hemoglobin (HbA1c). This biomarker reflects the average blood glucose levels over the previous two to three months and is widely used as a predictor of the risk of developing chronic diabetes complications **[18].**

Sustained hyperglycemia is strongly associated with the development and progression of both microvascular and macrovascular complications, including retinopathy, nephropathy, neuropathy, and cardiovascular disease (See Figure 2.2). In contrast, achieving improved glycemic control, particularly with HbA1c levels below 7%, has been shown to significantly reduce the risk and delay the progression of these complications **[19].**

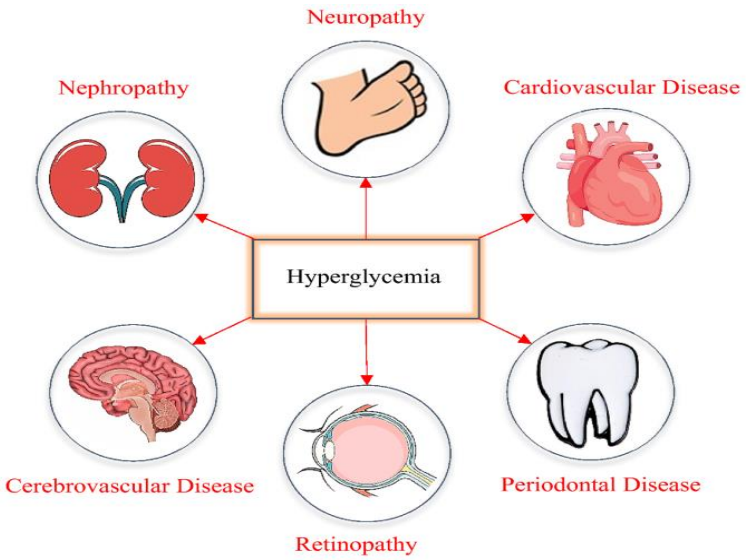


Figure 2.2: Long-term complications of hyperglycemia in diabetes **[Web 13].**

This relationship was clearly demonstrated in the Diabetes Control and Complications Trial (DCCT), which provided strong evidence that intensive insulin therapy aimed at near-normal glycemia significantly reduces the incidence of long-term complications in individuals with T1D **[19].**

In addition to HbA1c, modern diabetes care increasingly incorporates metrics derived from Continuous Glucose Monitoring (CGM), such as Time in Range (TIR), time above range, and time below range. These parameters offer a more comprehensive and dynamic assessment of glycemic control, supporting more precise and individualized therapeutic decision-making **[19].**

2.4.Complications of Poor Glycemic Control in Type 1 Diabetes

Poor glycemic control in T1D is strongly associated with the occurrence of acute metabolic complications that may be life-threatening if not promptly recognized and managed. Among the most clinically significant complications are Diabetic Ketoacidosis (DKA) and Severe Hypoglycemia.

- **Diabetic Ketoacidosis**

DKA is an acute and potentially fatal complication resulting from severe insulin deficiency. In the absence of sufficient insulin, the body shifts to alternative energy sources, leading to increased lipolysis and the production of ketone bodies (See Figure 2.3). The accumulation of ketones results in metabolic acidosis, dehydration, and significant electrolyte imbalance. Clinically, DKA is characterized by hyperglycemia, ketonemia, and metabolic acidosis, and it remains one of the leading causes of hospitalization among patients with T1D **[20].**

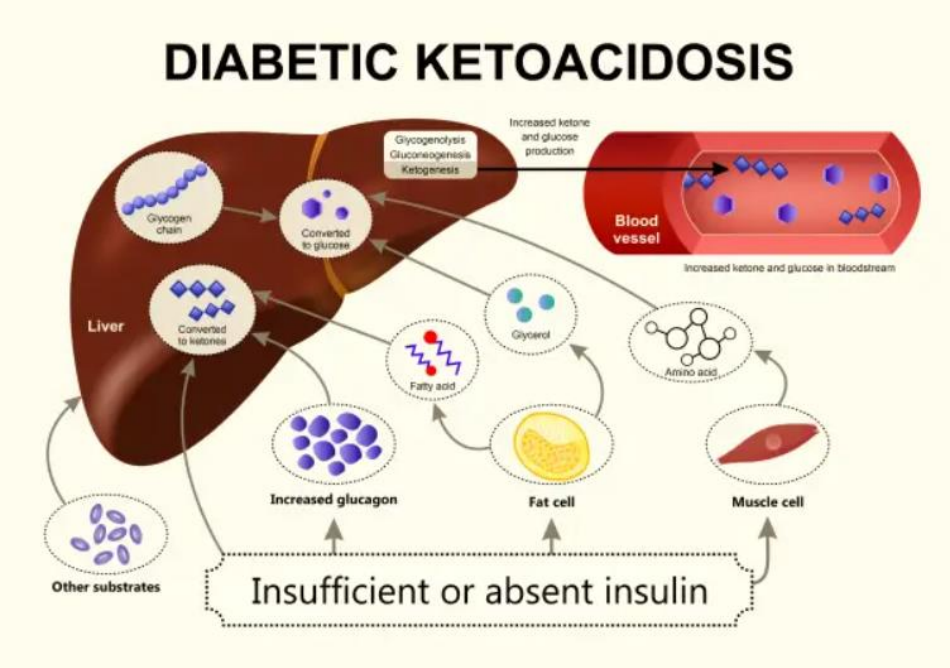


Figure 2.3: Pathophysiology of Diabetic Ketoacidosis (DKA) **[Web 14].**

- **Severe Hypoglycemia**

Severe hypoglycemia is another critical complication associated with diabetes management, particularly in patients receiving insulin therapy. It occurs when blood glucose levels fall below the physiological threshold required for normal neurological function. Clinically, it may present with confusion, loss of consciousness, seizures, or even coma if not rapidly treated (See Figure 2.4). Severe hypoglycemia is often linked to an imbalance between insulin administration, carbohydrate intake, and physical activity **[21].**

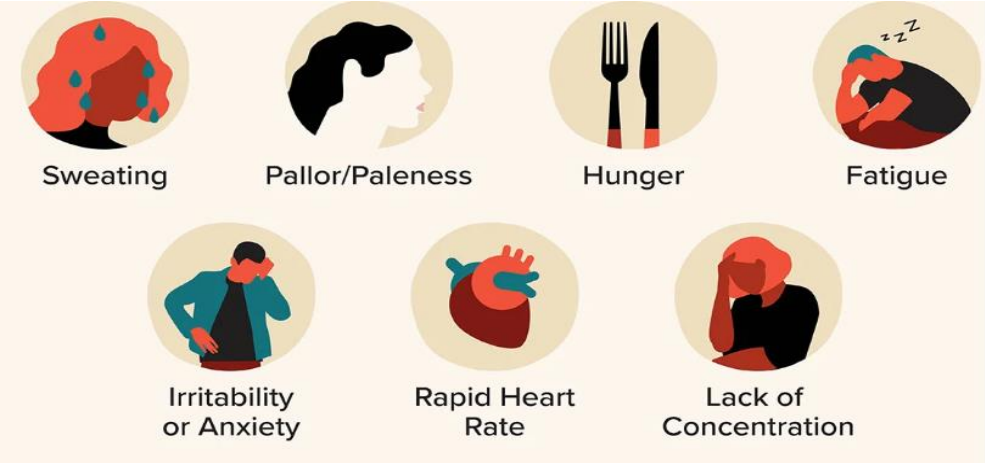


Figure 2.4: Common symptoms of Severe Hypoglycemia **[Web 15].**

Overall, both DKA and severe hypoglycemia represent opposite extremes of glycemic imbalance and highlight the importance of maintaining precise and stable glycemic control in individuals with T1D.

3. Carbohydrate Counting Strategy

3.1. Principles of Carbohydrate Counting

Carbohydrate counting is a dietary management approach widely used in T1D to estimate the amount of carbohydrates consumed in meals and to adjust insulin doses accordingly. This method is based on the physiological principle that carbohydrates have the most immediate and significant effect on postprandial blood glucose levels compared to proteins and fats **[22].**

The core principle of carbohydrate counting involves quantifying the carbohydrate content of foods, typically expressed in grams (See Figure .25). This estimation enables individuals to match their rapid-acting insulin dose with the expected rise in blood glucose

after meals, thereby improving postprandial glycemic control and overall metabolic stability **[23].**

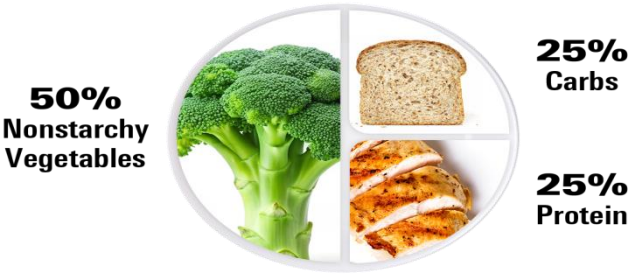


Figure 2.5: The diabetes plate method.

Carbohydrate counting can be applied using different levels of complexity. A basic approach focuses on estimating carbohydrate portions using standardized serving sizes, while a more advanced approach involves precise calculation of carbohydrate grams and their conversion into insulin units using individualized parameters such as the Insulin-to-Carbohydrate Ratio (ICR) **[24].**

The effectiveness of this strategy depends on the patient's ability to correctly identify carbohydrate-containing foods, interpret nutritional labels, and apply accurate portion estimation techniques. For this reason, carbohydrate counting requires structured diabetes education and continuous patient training to ensure correct implementation and optimal glycemic outcomes **[23].**

Overall, carbohydrate counting is considered a fundamental component of modern T1D self-management, as it provides a flexible framework that aligns dietary intake with insulin therapy and supports improved glycemic control **[24].**

3.2. Why carbohydrates are the main determinant of insulin dosage?

Carbohydrates represent the primary macronutrient responsible for postprandial increases in blood glucose levels. Upon ingestion, dietary carbohydrates are rapidly digested and converted into glucose, leading to a predictable rise in plasma glucose concentration. In individuals with T1D, who lack endogenous insulin secretion, this glucose load must be managed through externally administered insulin **[25].**

Rapid-acting insulin doses are therefore primarily calculated based on the quantity of carbohydrates consumed, as this macronutrient has the most immediate and direct impact on glycemic excursions after meals. In contrast, proteins and fats have a delayed and less pronounced effect on postprandial glucose levels, making carbohydrates the most reliable predictor for prandial insulin requirements **[26].**

The physiological relationship between carbohydrate intake and blood glucose response forms the basis of the ICR, which allows for individualized insulin dosing. This ratio reflects how many grams of carbohydrates are covered by one unit of insulin and is essential for achieving postprandial glycemic control **[27].**

However, this relationship can be influenced by several factors, including individual insulin sensitivity, gastrointestinal absorption rates, meal composition, and physical activity. Despite these variations, carbohydrate counting remains the most practical and evidence-based method for determining prandial insulin requirements in clinical practice **[26].**

Overall, the predominance of carbohydrates in determining insulin dosage is rooted in their direct metabolic effect on blood glucose levels, making them the central component in meal-related insulin adjustment strategies.

3.3. Challenges of accurately estimating carbohydrates manually

Although carbohydrate counting is effective in adjusting insulin doses for patients with T1D, its real-world application faces several challenges that limit its accuracy and consistency:

- Carbohydrate counting is limited by the natural variability in carbohydrate content between similar food items, making precise estimation difficult in everyday practice **[23].**
- Nutritional labeling is not always available or applicable, especially for homemade meals, restaurant food, or mixed dishes, which forces patients to rely on approximations **[22].**
- The accuracy of carbohydrate estimation is influenced by individual skills such as visual portion estimation, numeracy, and overall health literacy, which vary significantly between patients **[22].**
- Even small errors in carbohydrate estimation can lead to clinically significant fluctuations in postprandial blood glucose levels and insulin dosing accuracy **[28].**

- Lifestyle factors such as eating outside the home, cultural dietary habits and irregular meal compositions further complicate consistent carbohydrate counting **[23].**
- These limitations highlight the importance of structured diabetes education and continuous training to improve patient competency in carbohydrate estimation techniques.

Despite these challenges, carbohydrate counting remains an essential component of prandial insulin adjustment in T1D management due to its proven clinical effectiveness **[28].**

4. Medical Calculation of Insulin Dose

4.1. Insulin-to-Carbohydrate Ratio

The ICR is a key parameter used in T1D management to individualize prandial insulin dosing. It defines the amount of rapid-acting insulin required to metabolize a specific quantity of carbohydrates, usually expressed as the number of grams of carbohydrates covered by one unit of insulin.

ICR is based on the physiological relationship between carbohydrate intake and postprandial blood glucose rise. Since carbohydrates are the primary determinant of meal-related glycemic excursions, matching insulin dose to carbohydrate intake allows for more precise control of blood glucose levels after meals **[25].**

In clinical practice, the ICR varies significantly between individuals due to differences in insulin sensitivity, age, body weight, physical activity, and overall metabolic control. For example, an individual with high insulin sensitivity may require one unit of insulin to cover a larger amount of carbohydrates, whereas insulin-resistant individuals may require more insulin for the same carbohydrate intake **[27].**

ICR is typically determined empirically and adjusted over time based on blood glucose monitoring data. It is often used in combination with other dosing parameters, such as the correction factor (Insulin Sensitivity Factor), to calculate the total insulin dose required for a meal **[29].**

Mathematically, ICR can be expressed as:

$$\textbf{ICR = grams of carbohydrates covered by 1 unit of insulin} \quad (12)$$

This relationship forms the foundation of flexible insulin therapy, allowing patients to adapt insulin doses according to meal composition rather than following fixed insulin schedules.

4.2. Correction Factor

The correction factor, also known as the ISF, is a clinical parameter used to estimate how much one unit of rapid-acting insulin will lower an individual's blood glucose level. It is an essential component of insulin dose adjustment, particularly when pre-meal blood glucose levels are above the target range.

The main purpose of the correction factor is to address pre-existing hyperglycemia before food intake. Unlike the ICR, which focuses on meal-related glucose rise, the correction factor specifically targets elevated blood glucose levels independent of carbohydrate consumption.

The ISF varies significantly between individuals and is influenced by factors such as age, body weight, total daily insulin dose, and insulin sensitivity. Patients with higher insulin sensitivity experience a greater reduction in blood glucose per unit of insulin, whereas insulin-resistant individuals require more insulin to achieve the same effect **[25].**

In clinical practice, the correction factor is often used alongside ICR to calculate the total mealtime insulin dose using a structured formula.

Mathematical expression:

$$\textbf{Correction Dose} = (\textbf{Current Blood Glucose} - \textbf{Target Blood Glucose}) \div \textbf{ISF} \quad (13)$$

4.3. Insulin Dose Calculation Formula

The total prandial insulin dose in T1D is determined by combining two key components: the insulin required covering carbohydrate intake and the insulin required to correct pre-meal hyperglycemia. This dual-component approach enables more precise and individualized insulin therapy.

The carbohydrate coverage component is calculated using the ICR, which defines how many grams of carbohydrates are covered by one unit of insulin. The correction component is

calculated using the ISF, which estimates the expected decrease in blood glucose per one unit of insulin **[25].**

$$\textbf{Insulin Dose} = (\textbf{Carbohydrates (g)} \div \textbf{ICR}) + (\textbf{Current BG} - \textbf{Target BG}) \div \textbf{ISF} \quad (14)$$

This formula is primarily applied for rapid-acting insulin administered at mealtimes. It allows clinicians and patients to adjust insulin doses dynamically based on both meal composition and current glycemic status. Individual variability in insulin sensitivity requires periodic reassessment of both ICR and ISF to maintain optimal glycemic control.

4.4. Applied clinical example of insulin dose calculation

To illustrate the practical application of insulin dose calculation, consider the following clinical scenario in a patient with T1D using intensive insulin therapy.

- **Clinical Data**
  - Total carbohydrate intake: 75 g
  - ICR: 1 unit per 15 g of carbohydrates
  - Current blood glucose: 210 mg/dL
  - Target blood glucose: 120 mg/dL
  - ISF: 1 unit reduces 50 mg/dL
- **Step 1: Carbohydrate Coverage Dose**
  - Carbohydrates ÷ ICR
  - 75 ÷ 15 = 5 units
- **Step 2: Correction Dose**
  - (Current BG − Target BG) ÷ ISF
  - (210 − 120) ÷ 50 = 90 ÷ 50 = 1.8 units ≈ 2 units
- **Step 3: Total Insulin Dose**
  - 5 + 1.8 = **6.8 units**
  - Rounded clinically to: **7** units of rapid-acting insulin

- **Clinical Interpretation**

This example demonstrates how insulin dosing is individualized by combining both meal-related glucose load and pre-existing hyperglycemia correction. In real clinical practice, dose rounding is applied based on insulin pen or pump precision, and patient-specific factors such as physical activity or insulin sensitivity may further influence the final dose.

5. Conclusion

After presenting the theoretical foundations of AI, ML, and DL in the first chapter, this chapter addressed the clinical aspects related to the management of T1D, with a particular focus on carbohydrate counting and insulin dose determination.

The following chapter moves on to the practical phase, which aims to integrate the technical and clinical aspects into a unified, fully integrated system based on Artificial Intelligence to support patients with T1D.

CHAPTER03 :

Design and Implementation

1. Introduction

In the previous chapters, we covered the theoretical foundations of T1D management as well as the core concepts of deep learning and computer vision. This chapter focuses on the practical implementation of the proposed system.

The objective is to present the complete development of an IA-based mobile application designed to assist T1D patients in estimating their pre-meal insulin dose from a simple meal image. This includes the dataset used, preprocessing techniques, model architecture, training strategy, and experimental results. In addition, the hardware and software environments that enabled the development and deployment of the system are described in detail.

2. Architecture of the system

2.1. General System Overview

The proposed system is an IA-based mobile application designed to assist patients with T1D in estimating their pre-meal insulin dose from a simple image of their meal. Its primary objective is to bridge the gap between dietary intake and insulin management by automating carbohydrate estimation through artificial intelligence.

The system consists of four main components: the Flutter mobile application, which serves as the user interface; Firebase, which manages communication and backend services; a Python-based AI module responsible for food recognition and carbohydrate estimation; and Cloud Firestore, which provides persistent data storage.

As illustrated in Figure 3.1, the system operates through a sequential workflow. First, the patient captures an image of the meal using the mobile application and enters additional information, such as the meal weight. The request is then transmitted to Firebase, where it is validated before being forwarded to the AI module for analysis.

The AI module processes the image in three consecutive stages. It first identifies the food items present in the meal, then estimates their serving sizes, and finally calculates the total carbohydrate content in grams. The analysis results are returned to Firebase, which retrieves the required reference data from Cloud Firestore and computes the recommended insulin dose using Firebase Cloud Functions. The calculation is personalized according to the patient's ICR and correction factor.

Finally, the calculated results are sent back to the Flutter application, where the patient is presented with the estimated carbohydrate content, recommended insulin dose, and meal information. All relevant data, including meal history, carbohydrate values, and user records, are securely stored in Cloud Firestore to support continuous monitoring and future improvements of the system.

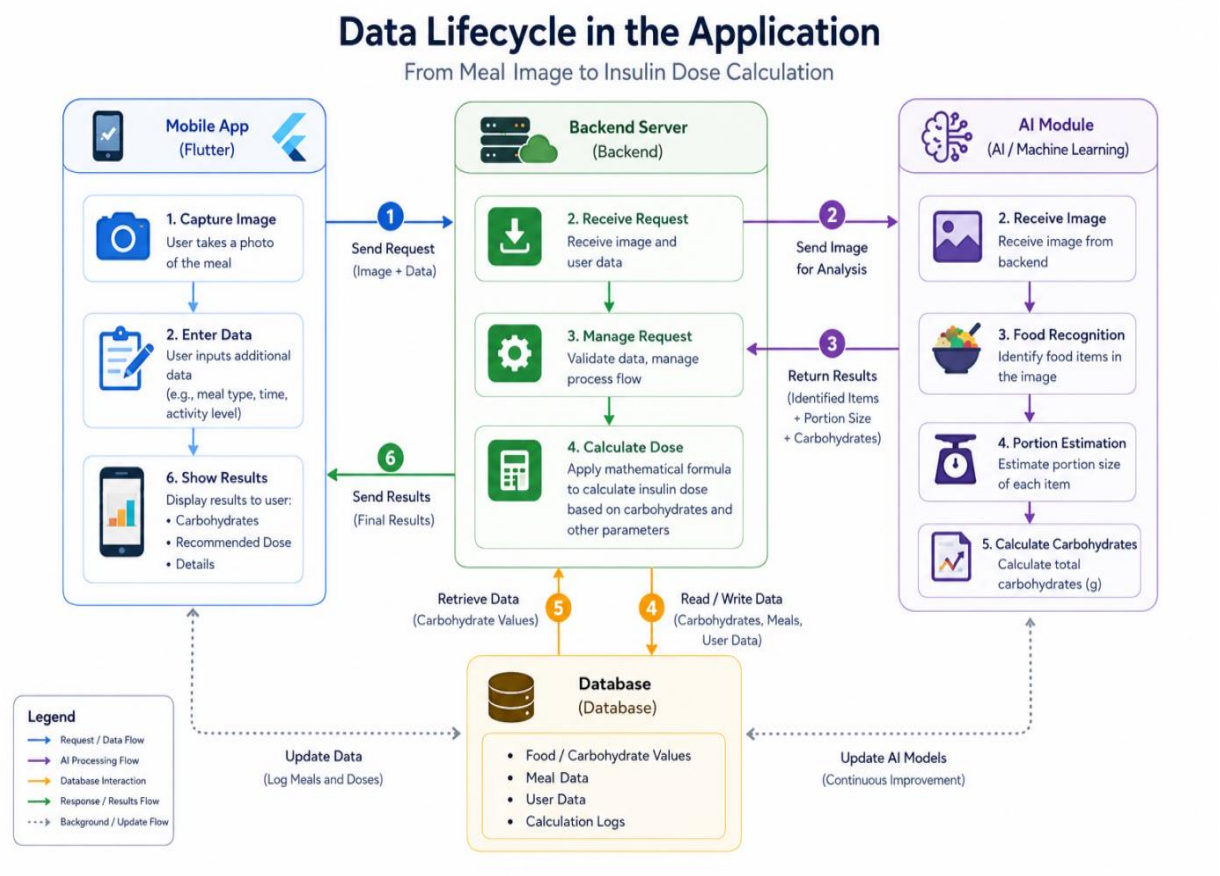


Figure 3.1: Architecture of the system **[GAI 02].**

2.2. Dataset

One of the initial challenges in developing the AI module was selecting a dataset that is both reliable and suitable for the target application. The objective was to use real food images that are accurately labeled and sufficiently diverse to reflect the types of meals a patient may capture in real-life scenarios using a mobile device.

After evaluating several available options, an open-source dataset of fruits and vegetables was selected. This dataset provides a structured and well-annotated collection of images with the following characteristics:

- **Total images:** 3,581 images.
- **Classes:** 36 categories of common fruits and vegetables.
- **Training/Validation split:** 2,872 images (80%) for training and 709 images (20%) for validation.
- **Diversity:** Each class contains multiple images captured from different angles, backgrounds, and lighting conditions, which enhances the model's ability to generalize to real-world scenarios.

This dataset was chosen for two main reasons. First, it provides a clean and well-structured foundation for applying transfer learning with MobileNetV2, eliminating the need for extensive manual data collection and annotation. Second, the diversity across 36 classes ensures sufficient variability for training a robust model capable of recognizing a wide range of food items commonly encountered in daily meals.

2.3. Data Preprocessing

Before any image goes into the model, it needs to be prepared. Images coming from different sources are not consistent they vary in size, brightness, and orientation. Feeding them raw into the network would not work, so preprocessing was a necessary first step.

2.3.1. Resizing

All images are resized to a fixed resolution of 224×224 pixels (See Figure 3.2). This size is required by the MobileNetV2 architecture, which expects a standardized input dimension. Resizing ensures that all input images share the same spatial dimensions regardless of their original format, enabling uniform processing by the network.



Figure 3.2: Comparison between an original image and its resized version.

2.3.2. Normalization

Pixel values are normalized from the range [0, 255] to [0, 1] by dividing each pixel value by 255. This normalization step helps stabilize the training process by keeping input values within a consistent range, which improves gradient behavior and accelerates model convergence.

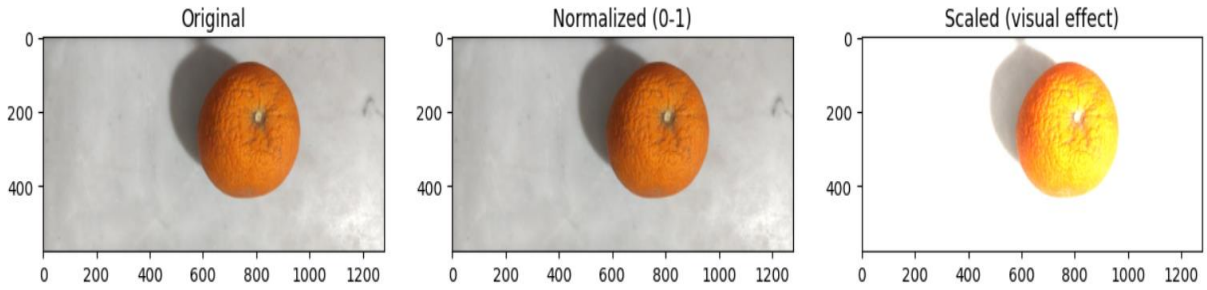


Figure 3.3: Effect of pixel normalization on image appearance.

2.3.3. Data Augmentation

Given the relatively small size of the dataset (3,581 images across 36 classes), data augmentation is used to reduce the risk of overfitting. During training, random transformations such as horizontal flipping, rotation, and zooming are applied to the images (See Figure 3.3). These transformations help the model learn more robust and invariant features, focusing on the intrinsic characteristics of food items rather than variations in position, angle, or scale.

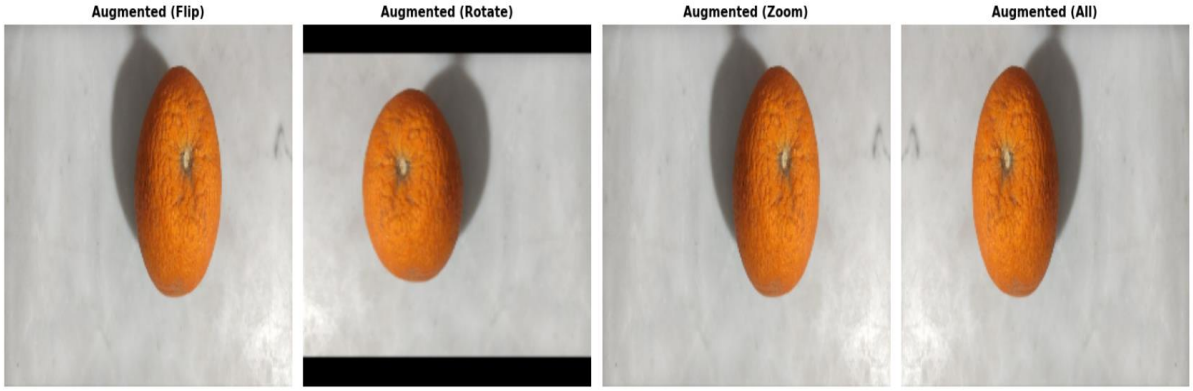


Figure 3.4: Examples of data augmentation transformations applied to training images.

2.3.4. Validation Set

The validation set remains untouched throughout the training process. Only normalization is applied, while no augmentation techniques are used. This ensures that validation results provide an unbiased estimate of the model's generalization performance on real, unseen data.

2.4. Model

2.4.1. MobileNetV2

MobileNetV2 is a lightweight convolutional neural network developed by Google, designed for mobile and resource-constrained environments. It achieves a good balance between accuracy and computational efficiency.

Its main innovations are Inverted Residual Blocks and Linear Bottlenecks**.** The network first expands the input features using a 1×1 convolution, then applies a 3×3 depth wise convolution, and finally projects them back to a lower-dimensional space using another 1×1 convolution. Shortcut connections are placed between bottleneck layers to improve gradient flow while reducing memory usage.

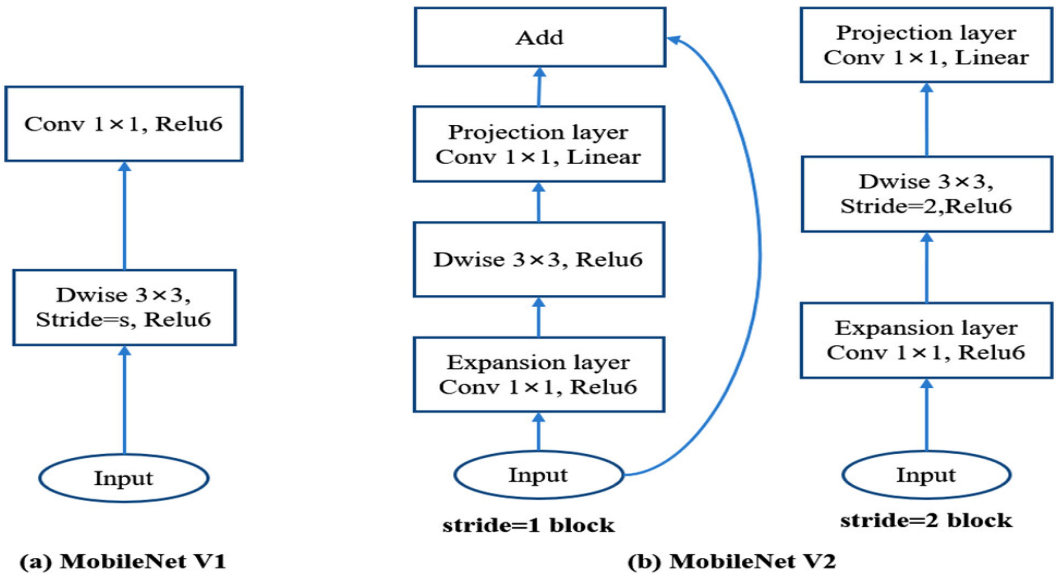


Figure 3.5: Comparison of MobileNetV1 and MobileNetV2 block structures **[Web 16].**

MobileNetV2 also uses depth wise separable convolutions**,** which split standard convolution into a depth wise operation (per channel) followed by a pointwise convolution. This significantly reduces computation and model size.

To preserve information in compact feature spaces, the model removes non-linear activation functions from bottleneck layers, using linear activations instead. This helps maintain representational quality in low-dimensional spaces.

Thanks to these optimizations, MobileNetV2 is well-suited for mobile applications, with around 3.4 million parameters and strong performance despite its low computational cost **[30].**

2.4.2. Transfer Learning

For the food recognition task, MobileNetV2 was used as the base model due to its efficiency in mobile environments. Instead of training the network from scratch, a Transfer Learning approach was applied using pre-trained weights from ImageNet, a large-scale dataset containing over 14 million images across 1,000 categories. This allows the model to reuse previously learned visual features such as edges, textures, and shapes, and adapt them to the target task.

The original classification head of MobileNetV2 was removed and replaced with a custom head adapted to the dataset. This new head includes a Conv2D layer with 32 filters for feature refinement, followed by a GlobalAveragePooling2D layer to reduce spatial dimensions, a Dropout layer (0.2) to reduce overfitting, and a final dense layer with Softmax activation for classification into 36 food categories.

The training process was performed in two phases, which are described in the following sections.

2.4.3. Phase 1: Feature Extraction

In the first phase, all layers of the MobileNetV2 base model were frozen, meaning their pre-trained weights were kept fixed while only the newly added classification head was trained. This allows the model to reuse generic visual features learned from ImageNet, such as edges and textures, while focusing the learning process on mapping these features to the 36 food classes. Freezing the base model also reduces the number of trainable parameters, which speeds up training and helps prevent overfitting on a relatively small dataset.

2.4.4. Phase 2: Fine-tuning

After the classification head converged, the last layers of the MobileNetV2 base model were unfrozen and retrained with a lower learning rate. This step allows the model to slightly adjust high-level feature representations to better fit the specific characteristics of the food dataset.

Fine-tuning improves sensitivity to fine-grained details such as texture, color, and shape, while preserving general visual knowledge learned from ImageNet. The combination of feature extraction and fine-tuning results in a better balance between generalization and specialization.

This two-phase training strategy achieved a training accuracy of 97.76% and a validation accuracy of 78.56%.

3. Experiments and Results

3.1. Training Configuration

Before presenting the results, it is important to document the training configuration, as hyperparameters directly influence the learning behavior and final performance of the model.

The model was trained using the following setup:

Parameter	Value
Optimizer	Adam
Loss Function	Categorical Crossentropy
Epochs	10
Batch Size	64
Input Image Size	224 × 224 × 3
Train/Validation Split	80% / 20%
Dropout Rate	0.2
Phase 2 Learning Rate	Reduced (fine-tuning)

Table 3.1: Training configuration hyperparameters.

The Adam optimizer was chosen due to its adaptive learning rate mechanism, which adjusts parameter updates using first and second moment estimates of gradients, making it effective for deep learning tasks on relatively small datasets.

Categorical Crossentropy was used as the loss function, as it is suitable for multi-class classification problems where each sample belongs to a single class among the 36 food categories.

Training was conducted for 10 epochs with a batch size of 64, providing a balance between computational efficiency and stable gradient updates. The experiments were executed on Google Colaboratory using a Tesla T4 GPU to accelerate training.

3.2. Training Results

After completing both training phases, the model was evaluated on the validation set to assess its generalization performance. The results are summarized in the table below:

Metric	Training Set	Validation Set
Accuracy	97.76%	78.56%
Loss	—	—

Table 3.2: Summary of training and validation performance.

The model achieved a training accuracy of 97.76% compared to a validation accuracy of 78.56%. This noticeable gap indicates a degree of overfitting, which is common when training deep learning models on relatively small datasets (3,581 images across 36 classes).

Despite this, the model demonstrates reasonable generalization ability, especially considering the complexity of the classification task and the variability of real-world food images. The use of data augmentation and the two-phase training strategy helped reduce overfitting and improve robustness.

Further insight into the learning behavior can be observed through the training curves (accuracy and loss over epochs), which are presented in Figure 3.4.

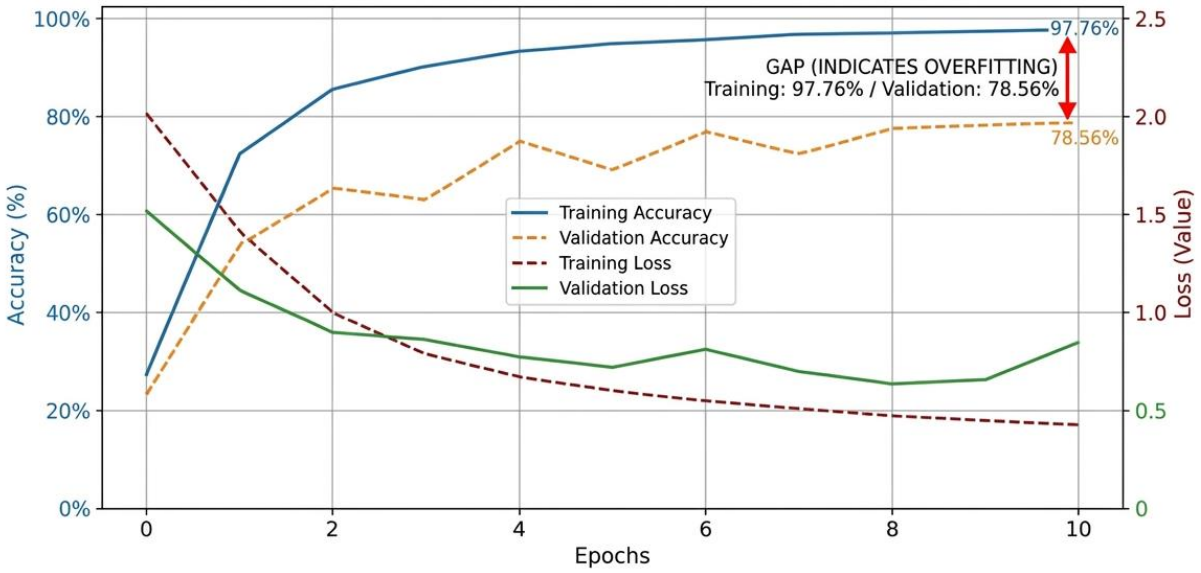


Figure 3.6: Training and validation accuracy and loss curves across 10 epochs.

3.3. Optimization Experiments

To improve upon the baseline performance, a series of controlled experiments were conducted. Each experiment targeted a specific component of the model configuration, including the activation function, regularization strategy, and optimization algorithm. The goal was to systematically identify the combination of hyperparameters that yields the best validation accuracy while maintaining generalization ability.

3.3.1. Baseline Model

The first step was to establish a reference performance using a standard configuration. MobileNetV2 was used as a feature extractor with a dense classification layer containing 36 output neurons and a Softmax activation function, without any additional optimization. This baseline serves as the reference point against which all subsequent experiments are compared.

Model	Accuracy
MobileNetV2 Baseline	93.2%

Table 3.3: Baseline model performance.

3.3.2. Activation Functions Comparison

The impact of different activation functions on classification performance was evaluated by replacing the default ReLU activation with two alternatives: PReLU and GELU.

ReLU eliminates negative values and accelerates training, but may discard potentially useful information. PReLU addresses this by allowing the model to learn a slope for negative values rather than setting them to zero. GELU provides a smoother activation curve and preserves additional information during forward propagation.

Activation	Accuracy
ReLU	93.2%
PReLU	94.0%
GELU	94.5%

Table 3.4: Validation accuracy across different activation functions.

GELU achieved the highest validation accuracy, indicating better feature representation compared to ReLU and PReLU. It was therefore selected for subsequent experiments.

3.3.3. Dropout Rate Comparison

To assess the effect of regularization strength, four dropout rates were tested while keeping all other parameters constant. Dropout randomly deactivates a fraction of neurons during training, which reduces co-adaptation and helps prevent overfitting.

Dropout Rate	Accuracy
0.10	94.6%
0.20	95.0%
0.30	94.8%
0.50	92.9%

Table 3.5: Validation accuracy across different dropout rates.

A dropout rate of 0.20 provided the best trade-off between regularization and information retention. Higher rates such as 0.50 led to underfitting, while lower rates offered insufficient regularization.

3.3.4. Optimizer Comparison

Three widely used optimizers were compared to evaluate their effect on convergence speed and final classification accuracy.

SGD updates weights using a fixed learning rate, which can result in slow or unstable convergence. RMSProp adapts the learning rate based on recent gradient magnitudes, improving stability. Adam combines the advantages of both momentum and adaptive learning rates, making it particularly effective for deep learning tasks on relatively small datasets.

Optimizer	Accuracy
SGD	91.8%
RMSProp	94.4%
Adam	95.0%

Table 3.6: Validation accuracy across different optimizers.

Adam achieved the best convergence speed and classification accuracy and was confirmed as the optimal choice for this task.

3.3.5. Grid Search

Following the individual experiments, a systematic Grid Search was performed to identify the optimal combination of hyperparameters. The search space covered three key parameters: learning rate, batch size, and dropout rate.

The following values were explored:

- Learning Rate: 0.01, 0.001, 0.0001
- Batch Size: 16, 32, 64
- Dropout Rate: 0.2, 0.3, 0.5

The best configuration identified through this search is summarized below:

Parameter	Optimal Value
Learning Rate	0.001
Batch Size	32
Dropout Rate	0.20
Optimizer	Adam

Table 3.7: Best hyperparameter configuration from Grid Search.

This configuration achieved a validation accuracy of 95.4%, representing a notable improvement over the baseline.

3.3.6. Cross Validation

To verify the stability and generalizability of the optimized model, a 5-Fold Cross Validation was performed. This technique divides the dataset into five equal subsets, training the model five times while using a different fold as the validation set each time. It provides a more reliable estimate of generalization performance by reducing the influence of any particular data split.

Fold	Accuracy
Fold 1	95.1%
Fold 2	94.8%
Fold 3	95.5%
Fold 4	94.9%
Fold 5	95.3%
Average	**95.12%**
Std. Deviation	**0.27%**

Table 3.8: 5-Fold Cross Validation results.

The low standard deviation of 0.27% confirms that the model performs consistently across different data splits, indicating stable generalization rather than dependence on a specific training-validation division.

The table below consolidates the results of all experiments conducted throughout this section, providing a comprehensive view of how each optimization step contributed to the progressive improvement of model performance.

Experiment	Accuracy
Baseline MobileNetV2	93.2%
ReLU	93.2%
PReLU	94.0%
GELU	94.5%
Dropout 0.10	94.6%
Dropout 0.20	95.0%
Dropout 0.30	94.8%
Dropout 0.50	92.9%
SGD	91.8%
RMSProp	94.4%
Adam	95.0%
Grid Search Best Model	95.4%
5-Fold Cross Validation	95.12%

Table 3.9: Comprehensive comparison of all optimization experiments.

These results demonstrate that the combination of GELU activation, a dropout rate of 0.20, the Adam optimizer, and the hyperparameters identified through Grid Search yielded the most significant performance gains, improving validation accuracy from 93.2% in the baseline to 95.4% with the optimized configuration.

3.4. Real-World Testing

Beyond validation metrics, the model was evaluated using real photographs captured directly from a mobile phone camera to assess its performance under practical conditions similar to actual patient usage.

For simple cases, such as clear and well-lit images containing a single centered food item, the model demonstrated strong and consistent performance. For example, when tested on an image of a banana, the model achieved a confidence score of 98.45%, indicating high prediction reliability under favorable conditions.

To help users interpret prediction quality, three confidence levels were defined as shown below:

Confidence Level	Range	Interpretation
Excellent	> 80%	Reliable prediction
Good	60% – 80%	Acceptable result, verification recommended
Low	< 60%	Unreliable prediction, image should be retaken

Table 3.10: Confidence tier classification.

Each model output includes the predicted food category along with its confidence score. These results are displayed within the Flutter application interface, enabling users to evaluate prediction reliability before proceeding with insulin dose estimation.

3.5. Observed Limitations

Although the system achieved promising results under controlled conditions, real-world testing revealed several limitations that must be acknowledged. These limitations are mainly related to dataset constraints and the scope of the project.

- **Lighting conditions:**

Model performance decreases significantly under low or uneven lighting. Since the training data mainly consists of well-lit images, the model struggles in darker environments, which are common when users capture meals indoors or in the evening.

- **Image angle and orientation:**

Unusual or highly variable camera angles can lead to misclassification. The dataset does not fully represent the range of viewpoints expected in real user scenarios, limiting robustness to perspective changes.

- **Multiple food items:**

The model is trained on single-food images and is therefore not designed to handle complex meals containing multiple items. In such cases, it tends to focus on the most dominant object, which may result in incomplete or inaccurate predictions for mixed dishes.

- **Dataset size:**

With 3,581 images across 36 classes, the dataset remains relatively small for deep learning tasks. This limits generalization performance and contributes to the observed gap between training and validation accuracy.

These limitations are expected given the academic scope of the project and highlight clear directions for future improvements, which are discussed in the conclusion.

4. Work Environment and Development Tools

4.1. Hardware Tools

The development and testing of this project involved multiple hardware environments, each serving a specific role within the workflow, including development, model training, and real-world application testing.

- **Personal Computers Development & Initial Testing**

Three personal computers were used for software development, code implementation, and preliminary testing. Their specifications are summarized below:

Machine	Brand	CPU	RAM	Operating System
1	Lenovo	Intel Core i5-10210U @ 1.60GHz	8 GB	Windows 10 Pro
2	HP	Intel Core i5-6200U @ 2.30GHz	4 GB	Windows 10 Pro
3	Lenovo	Intel Core i3-5005U @ 2.00GHz	4 GB	Windows 10 Pro

Table 3.11: Hardware specifications of development machines.

- **Google Colab Model Training**

Due to the computational requirements of DL training, Google Colaboratory was used as the primary training environment. It provided access to the following resources:

- CPU: 2× Intel Xeon @ 2.30GHz
- RAM: 12 GB
- GPU: Tesla T4
- Disk: 55 GB

The availability of the Tesla T4 GPU significantly reduced training time compared to local hardware configurations.

- **Test Mobile Device**

The Flutter application was evaluated on a physical mobile device to assess real-world performance under realistic usage conditions:

- Device: Poco X3 NFC
- RAM: 6 GB
- Operating System: Android 12 (SKQ1.211019.001)

4.2. Software Tools

4.2.1. Google Colaboratory

Google Colaboratory was used as the primary environment for training the MobileNetV2 model. Training DL models on a personal computer without a dedicated GPU would be inefficient in terms of time and computational resources. Colab provided free access to a Tesla T4 GPU, which significantly reduced training time. Its browser-based environment also simplified setup, requiring only dataset upload and notebook execution without complex local configuration.



Figure 3.7: Google colaboratory logo.

4.2.2. Android Studio

Android Studio was used for Android-specific development tasks, including application configuration, debugging, and build management. It provided the necessary tools to compile and deploy the Flutter application on a physical device for real-world testing.



Figure 3.8: Android Studio logo.

4.2.3. Flutter & Dart

Flutter was chosen as the mobile development framework due to its cross-platform capabilities, enabling a single codebases for both Android and iOS platforms. The application interface, logic, and integration with Firebase and the AI module were fully implemented using Dart, Flutter's programming language.



Figure 3.9: Flutter & Dart logo.

4.2.4. Libraries and Dependencies

Library	Version	Purpose
Tflite	^1.1.2	TensorFlow Lite inference on-device
image_picker	^0.8.0	Camera and gallery image access
firebase_core	—	Firebase initialization
cloud_firestore	—	Database interaction
firebase_auth	—	User authentication
firebase_storage	—	Meal image storage

Table 3.12: Flutter dependencies used in the application.

4.2.5. Python Libraries (AI Module)

Library	Purpose
TensorFlow 2.x	Deep learning framework and model training
Keras	High-level API for building neural networks
NumPy	Numerical computations and array manipulation
Matplotlib	Visualization of training curves and results
TensorFlow Lite Converter	Conversion of trained model to TFLite format for mobile deployment

Table 3.13: Python libraries used in the AI training module.

5. Application Interface

The following section presents the main screens of the DiabyLife mobile application. Each screen was designed to provide an intuitive experience for T1D patients, covering all key functionalities from authentication to insulin dose calculation.

5.1. Authentication Screens

The application entry point consists of two screens: a login screen and a registration screen.



Figure 3.10: Authentication Screens (Login and Registration).

5.2. Main Dashboard

The home screen displays the most recent blood sugar reading with its status and quick access to all core features. The side navigation menu provides access to the personal profile, treatment settings, and appointment management.

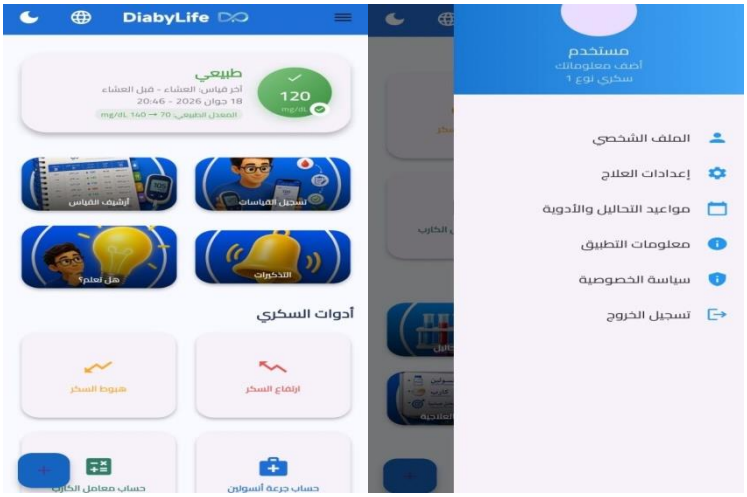


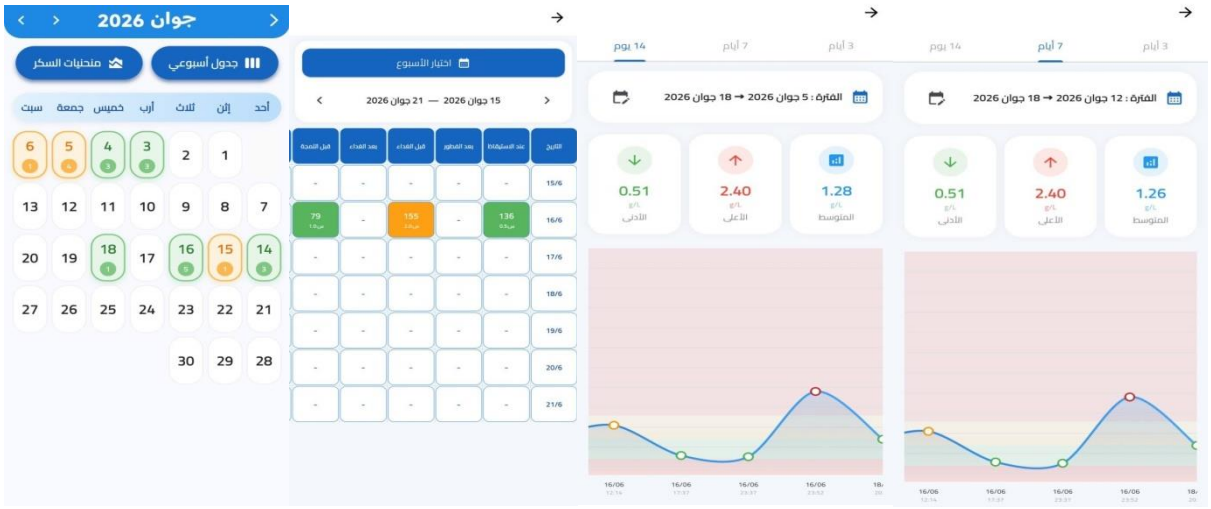
Figure 3.11: Main Dashboard and Side Navigation Menu.

5.3. Blood Sugar Tracking

The tracking module allows patients to log and monitor glucose readings over time. Measurements are entered manually with insulin doses, meal period, and optional notes. History is visualized through a monthly calendar, a weekly table, and graphical curves over 7 or 14-day periods.



Figure 3.12: Measurement Registration.



. **Figure 3.13:** Blood Sugar History Calendar, Weekly Table, and Trend Curves (3, 7, and 14 days).

5.4. Diabetes Management Tools

This section centralizes clinical utilities for managing both hyperglycemia and hypoglycemia. It includes personalized treatment settings, symptom guides, an insulin sensitivity factor calculator, and a step-by-step glucagon injection tutorial.



Figure 3.14: Diabetes Management Tools: Overview and Treatment Settings.

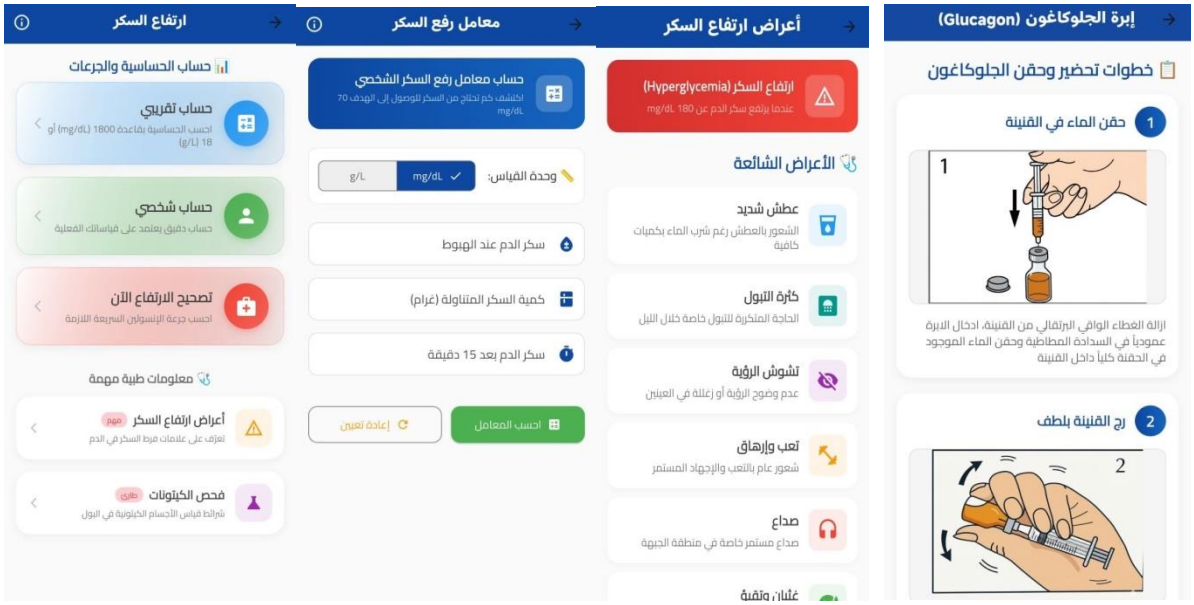


Figure 3.15: Hyperglycemia and Hypoglycemia Management Screens, Symptoms, ISF Calculator, and Glucagon Guide.

5.5. Insulin Calculator

The insulin calculator allows the patient to estimate their required dose based on meal carbohydrate content. The user selects the meal type, adds food items manually or via camera, and enters the weight in grams. Total carbohydrates and the recommended insulin dose are computed and displayed in real time.



Figure 3.16: Insulin Dose Calculator Screen.

6. Conclusion

This chapter presented the full implementation of an AI-based mobile application designed to assist T1D patients in estimating their pre-meal insulin dose. Despite promising results under controlled conditions, real-world testing revealed limitations related to dataset size and scope. Future work will focus on expanding the dataset, handling complex meals, and conducting clinical validation to improve the system's overall reliability.

General Conclusion

General Conclusion

In conclusion, the management of T1D requires accurate insulin dose calculation before every meal, making it a daily challenge for patients. In this dissertation, we proposed DiabyLife, an intelligent mobile application that uses Artificial Intelligence and Deep Learning to recognize food from images, estimate the amount of carbohydrates, and automatically calculate the appropriate insulin dose based on each patient's medical parameters. The application also provides several features to help patients monitor and manage their diabetes more easily.

The results obtained show that combining Artificial Intelligence with mobile applications is a promising approach to improving the daily management of T1D. It can simplify carbohydrate counting, reduce calculation errors, and provide patients with a faster and more accurate way to estimate their insulin dose.

Although the proposed system achieved encouraging results, there are still several opportunities for future improvement. Future work will focus on expanding the food database to include more local, traditional, and international dishes, as well as improving the model's ability to recognize mixed meals containing multiple food items. We also plan to develop a web platform for healthcare professionals connected to the mobile application, allowing doctors to monitor their patients remotely. In addition, the application could be integrated with a smart food scale that automatically measures the weight of the meal while capturing its image, providing more accurate carbohydrate estimation and insulin dose calculation. Other planned improvements include multilingual support, dark mode, smarter notifications, and integration with CGM systems.

Finally, we hope that DiabyLife will be a first step toward developing intelligent AI-based healthcare solutions that support people living with T1D, improve diabetes management, and contribute to a better quality of life.

Bibliography

[1] Russell, S., & Norvig, P. (2020). *Artificial intelligence: A modern approach* (4th ed.). Pearson.

[2] Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer.

[3] Contreras, I., & Vehi, J. (2018). Artificial intelligence for diabetes management and decision support. *Journal of Medical Internet Research, 20*(5), e10775. https://doi.org/10.2196/10775

[4] Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning* (2nd ed.). Springer.

[5] Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction* (2nd ed.). MIT Press.

[6] Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

[7] Obermeyer, Z., & Emanuel, E. J. (2016). Predicting the future — big data, machine learning, and clinical medicine. *New England Journal of Medicine, 375*(13), 1216–1219. https://doi.org/10.1056/NEJMp1606181

[8] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444. https://doi.org/10.1038/nature14539

[9] Kandel, E. R., Schwartz, J. H., Jessell, T. M., Siegelbaum, S. A., & Hudspeth, A. J. (2013). *Principles of neural science* (5th ed.). McGraw-Hill.

[10] Hendrycks, D., & Gimpel, K. (2016). *Gaussian error linear units (GELUs)*. arXiv preprint arXiv:1606.08415. https://arxiv.org/abs/1606.08415

[11] OpenGenus Tech Review Team. (2018, November 18). *When to use convolutional neural networks (CNN)?* OpenGenus IQ. Retrieved June 8, 2026, from https://iq.opengenus.org/when-to-use-convolutional-neural-network-cnn/

[12] Towards AI. (2021). *Whirlwind tour of RNNs*. Towards AI. Retrieved June 8, 2026, from https://pub.towardsai.net/whirlwind-tour-of-rnns-a11effb7808f

[13] Sapra, A., & Bhandari, P. (2024). *Type 1 diabetes*. In StatPearls. StatPearls Publishing. https://www.ncbi.nlm.nih.gov/books/NBK507713/

[14] American Diabetes Association. (2024). Diagnosis and classification of diabetes: Standards of care in diabetes—2024. *Diabetes Care, 47*(Suppl. 1), S20–S42. https://doi.org/10.2337/dc24-S002

[15] Burrack, A. L., Martinov, T., & Fife, B. T. (2017). T cell-mediated beta cell destruction: Autoimmunity and alloimmunity in the context of type 1 diabetes. *Frontiers in Endocrinology, 8*, 343. https://doi.org/10.3389/fendo.2017.00343

[16] Marre, M. L., et al. (2025). The role of immune dysregulation in the pathogenesis of type 1 diabetes: A paradigm shift in prevention strategies. *PMC*. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC12078776/

[17] Sanofi. (2025). *The pathophysiology of autoimmune type 1 diabetes*. https://pro.campus.sanofi/global/t1d/articles/the-pathophysiology-of-autoimmune-type-1-diabetes

[18] Łaba, A., et al. (2023). Factors influencing the control of diabetes measured via glycated hemoglobin concentrations in adults with type 1 diabetes. *Nutrients, 15*(20). https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10606861/

[19] American Diabetes Association. (2024). Glycemic goals and hypoglycemia: Standards of care in diabetes—2024. *Diabetes Care, 47*(Suppl. 1), S111–S125. https://doi.org/10.2337/dc24-S006 ,https://pmc.ncbi.nlm.nih.gov/articles/PMC10725808/

[20] Kitabchi, A. E., Umpierrez, G. E., Miles, J. M., & Fisher, J. N. (2009). Hyperglycemic crises in adult patients with diabetes. *Diabetes Care, 32*(7), 1335–1343. https://doi.org/10.2337/dc09-9032

[21] Seaquist, E. R., Anderson, J., Childs, B., Cryer, P., Dagogo-Jack, S., Fish, L., Heller, S. R., Rodriguez, H., Rosenzweig, J., & Vigersky, R. (2013). Hypoglycemia and diabetes: A report of a workgroup of the American Diabetes Association and the Endocrine Society. *Diabetes Care, 36*(5), 1384–1395. https://doi.org/10.2337/dc12-2480

[22] American Diabetes Association. (2024). *Facilitating behavior change and well-being to improve health outcomes: Standards of care in diabetes—2024*. Diabetes Care, 47(Suppl. 1), S77–S110. https://doi.org/10.2337/dc24-S005

[23] Smart, C. E., Annan, F., Higgins, L. A., Jelleryd, E., Lopez, M., & Acerini, C. L. (2014). ISPAD Clinical Practice Consensus Guidelines 2014. Nutritional management in children and adolescents with diabetes. *Pediatric Diabetes*, *15*(S20), 135–153. https://doi.org/10.1111/pedi.12175

[24] Franz, M. J., et al. (2017). *American Diabetes Association nutrition therapy for adults with diabetes or prediabetes: A consensus report*. Diabetes Care, 40(10), 1323–1334. https://doi.org/10.2337/dci17-0045

[25] American Diabetes Association. (2024). *Pharmacologic approaches to glycemic treatment: Standards of care in diabetes—2024*. Diabetes Care, 47(Suppl. 1), S145–S159. https://doi.org/10.2337/dc24-S009

[26] Bell, K. J., Smart, C. E., Steil, G. M., Brand-Miller, J. C., & King, B. (2015). Impact of fat, protein, and glycemic index on postprandial glucose control in type 1 diabetes. *Diabetes Care*, *38*(6), 1008–1015. https://doi.org/10.2337/dc15-0100

[27] Walsh, J., & Roberts, R. (2017). *Using insulin-to-carbohydrate ratios in diabetes management*. Diabetes Spectrum, 30(3), 183–190. https://doi.org/10.2337/ds16-0074

[28] Dose Adjustment For Normal Eating (DAFNE) Study Group. (2002). Training in flexible, intensive insulin management to improve diabetes control. *BMJ*, *325*(7367), 746. https://doi.org/10.1136/bmj.325.7367.746

[29] Kaufman, F. R. (2012). Role of insulin-to-carbohydrate ratios in diabetes management. *Endocrine Practice, 18*(S1), 23–28. https://doi.org/10.4158/EP12115.RA

[30] Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L.-C. (2018). MobileNetV2: Inverted residuals and linear bottlenecks. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 4510–4520. https://arxiv.org/abs/1801.04381

Webography

[Web 01] Florent, M. (2024, February 5). *Machine learning : l'apprentissage automatique des systèmes*. Tree Learning. Retrieved June 8, 2026, from https://www.tree-learning.fr/plateforme-lms-elearning/machine-learning/ *(Last modified: February 27, 2024)*

[Web 02] Petercour. (2019, July 19). *Machine learning classification vs regression*. DEV Community. Retrieved June 8, 2026, from https://dev.to/petercour/machine-learning-classification-vs-regression-1gn *(Last modified: June 8, 2026)*

[Web 03] Google for Developers. (2025, October 1). *Qu'est-ce que le clustering ?* Google Machine Learning. Retrieved June 8, 2026, from https://developers.google.com/machine-learning/clustering/overview?hl=fr *(Last modified: October 1, 2025)*

[Web 04] Taha, M. (2025, March 10). *Dimensionality reduction in machine learning*. Medium. Retrieved June 8, 2026, fromhttps://muhammadtaha01.medium.com/dimensionality-reduction-in-machine-learning-46d45747eaee

[Web 05] Murel, J., & Kavlakoglu, E. (n.d.). *What is reinforcement learning?* IBM. Retrieved June 8, 2026, from https://www.ibm.com/think/topics/reinforcement-learning

[Web 06] Florent, M. (2024, February 19). *Deep learning : des systèmes inspirés du cerveau humain*. Tree Learning. Retrieved June 8, 2026, from https://www.tree-learning.fr/plateforme-lms-elearning/deep-learning/ *(Last modified: February 21, 2024)*

[Web 07] Mhatre, S. (2020, June 6). *What is the relation between artificial and biological neuron?* Medium. Retrieved June 8, 2026, from https://saurabhnativeblog.medium.com/what-is-the-relation-between-artificial-and-biological-neuron-18b05831036

[Web 08] Pramoditha, R. (2021, December 26). *The concept of artificial neurons (perceptrons) in neural networks*. Towards Data Science. Retrieved June 8, 2026, from https://towardsdatascience.com/the-concept-of-artificial-neurons-perceptrons-in-neural-networks-fab22249cbfc/ *(Last modified: January 19, 2025)*

[Web 09] ResearchGate. (2021). *Structure of a feedforward neural network*. Retrieved June 8, 2026, from https://www.researchgate.net/figure/Structure-of-a-feedforward-neural-network_fig2_343452701

[Web 10] OpenGenus Tech Review Team. (2018, November 18). *When to use convolutional neural networks (CNN)?* OpenGenus IQ. Retrieved June 8, 2026, from https://iq.opengenus.org/when-to-use-convolutional-neural-network-cnn/*(Last modified: November 18, 2018)*

[Web 11] Khuong, B. (2019, June 24). *Whirlwind tour of RNNs*. Towards AI. Retrieved June 9, 2026, from https://pub.towardsai.net/whirlwind-tour-of-rnns-a11effb7808f

[Web 12] Med Learning Group. (2024). *Etiopathogenesis of type 1 diabetes* [Figure: Pathogenesis of Type 1 Diabetes]. DETECT T1D Clinician Portal. Retrieved June 9, 2026, from https://detect-t1d.com/clinician-portal/etiopathogenesis-of-t1d/

[Web 13] Zahedifar, R., & Keymasi Khalaji, A. (2022). Control of blood glucose induced by meals for type-1 diabetics using an adaptive backstepping algorithm. *Scientific Reports, 12*, 12228. https://doi.org/10.1038/s41598-022-16535-2

[Web 14]Care Hospitals. (n.d.). *Diabetic ketoacidosis*. Retrieved June 9, 2026, from https://www.carehospitals.com/raipur/diseases-conditions/diabetic-ketoacidosis

[Web 15] Healthline. (n.d.). *Hypoglycemia: Symptoms, causes, diagnosis, and treatment* .Retrieved June 9, 2026, from https://www.healthline.com/health/hypoglycemia#symptoms

[Web 16] Shi, H. (2023). A lightweight image splicing tampering localization method based on MobileNetV2 and SRM. IET Image Processing, 17, 1883–1892. Retrieved June 10, 2026, from https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/ipr2.12763

Generate by IA

[GAI 01] Google. (2024). *Overview of Machine Learning Paradigms and Their Applications* [AI-generated image]. Google Gemini (Imagen).

[GAI 02] OpenAI. (2026). *Data lifecycle in the application: From meal image to insulin dose calculation* [AI-generated image]. ChatGPT (GPT-4o).

الجمهورية الجزائرية الديمقراطية الشعبية

وزارة التعليم لعالي والبحث العلمي

République algérienne démocratique et populaire

Ministère de l'enseignement supérieur et de la recherche scientifique

20 août 1955 Université de Skikda

Un projet d'obtention d'un certificat de démarrage dans le cadre de la résolution ministérielle 1275

Titre du projet

Conception et développement d'un système intelligent intégré pour aider les patients atteints de diabète de type 1 en Algérie

Nom commercial

DiabyLife

2025-2026

Carte d'information

A propose de l'équipe d'encadrement du groupe de travail

1- Equipe d'encadrement :

Equipe d'encadrement	
Encadrant principal : Bougamouza Fateh	Spécialité : Intelligence artificielle

2- Equipe de projet :

Equipe de projet	faculté	spécialité
Etudiant 01 : Moussaoui Hadil	Faculté de sciences	Intelligence artificielle
Etudiant 02 : Talhi Hadjer	Faculté de sciences	Intelligence artificielle
Etudiant 03 : Chemaa Sarra	Faculté de sciences	Réseaux et systèmes distribué

Table des matières

Premier axe : Présentation du projet	4
1. l'idée de projet	5
2. les valeurs suggérées	5
3. l'équipe	6
4. les objectifs du projet	7
5. le planning de réalisation du projet	9
Deuxième axe : Aspects innovants	10
1. la nature des innovations	11
2. les domaines d'innovation	12
Troisième axe : Analyse stratégique du marche	13
1. le segment du marché	14
2. la mesure de l'intensité de la concurrence	15
3. la stratégie marketing	17
Quatrième axe : Plan de production et organisation	20
1. le processus de production	21
2. l'approvisionnement	22
3. la main d'œuvre	23
4. les principaux partenaires	24
Cinquième axe : Plan financier	25
1. les couts et les charges	26
2. le chiffre d'affaires	27
3. les comptes de résultats escomptés	28
4. le plan de trésorerie	28
Sixième axe : Prototype expérimental	30
Septième axe : Modèle d'entreprise BMC	35

Premier axe :

Présentation du projet

1. L'idée de projet

La vie avec le diabète de type 1 représente une charge quotidienne constante, comparable à une activité à plein temps qui ne s'arrête jamais, même pendant le sommeil. Il ne s'agit pas uniquement d'une maladie, mais d'un état de vigilance permanente, où le patient doit estimer les glucides et calculer les doses d'insuline avec une grande précision avant chaque repas. La moindre erreur peut entraîner des conséquences importantes, telles qu'une hyperglycémie ou une hypoglycémie, impactant directement la santé et la qualité de vie du patient. Cette réalité engendre une pression psychologique continue et une anxiété permanente.

Face à cette problématique, notre projet vise à simplifier cette charge quotidienne en proposant une solution intelligente et accessible. Nous avons développé une application mobile agissant comme un véritable compagnon numérique du patient diabétique. Grâce à l'intelligence artificielle, l'utilisateur peut analyser ses repas via la caméra de son smartphone, estimer automatiquement les glucides, et obtenir des recommandations de dosage d'insuline adaptées à son profil médical. L'application intègre également des rappels de prise de médicaments, de suivi médical et un système de communication simplifié avec le médecin pour assurer un suivi continu.

Sur le plan technique, nous avons adopté une architecture moderne et fiable. L'interface utilisateur a été développée avec Flutter afin de garantir une expérience fluide sur Android, tandis que le traitement des données et des images repose sur Python, utilisé comme moteur principal de l'intelligence de l'application. Le processus de développement a suivi une méthodologie Agile, permettant une évolution progressive du projet ainsi que des tests réguliers en conditions réelles, afin d'assurer la fiabilité et la sécurité des résultats.

Ce projet est le fruit d'une collaboration entre compétences techniques et encadrement médical, assurée par un médecin spécialiste intervenant à chaque étape pour valider les aspects cliniques. L'objectif principal n'est pas seulement de développer une application, mais de contribuer à améliorer la qualité de vie des patients diabétiques en leur offrant plus d'autonomie, de sécurité et de sérénité dans leur quotidien.

2. Les valeurs proposées

Ce projet apporte une valeur ajoutée à travers :

- Cette application facilite le calcul des doses d'insuline au lieu de compter sur des

calculs manuels complexes, car elle les calcule automatiquement et avec précision.

- Le patient peut facilement identifier les repas en prenant une photo, car l'application estime la quantité de glucides grâce à l'intelligence artificielle, ce qui lui fait gagner du temps et des efforts.
- Il contribue à réduire les erreurs que le patient peut faire lors du calcul des doses, et aide ainsi à éviter les problèmes de glycémie élevée ou basse.
- Il fournit au patient un seul endroit pour enregistrer toutes les mesures de glycémie et de repas, ce qui l'aide à mieux surveiller son état de santé.
- Il permet au patient d'être connecté à son médecin, ce qui facilite le processus de suivi sans avoir à y aller à chaque fois.
- L'application est conçue pour être adaptée à l'utilisateur arabe, en particulier en termes de qualité des aliments et d'habitudes alimentaires.
- L'application aide à réduire le stress associé à la maladie, car elle rend le processus de suivi plus facile et plus clair.

3. Equipe de travail

L'équipe du projet est composée des membres suivants :

- Etudiant 01 : MOUSSAOUI Hadil, étudiante en Master 2, spécialisée en intelligence artificielle. Elle a suivi des formations en finance et a également complété une formation de niveau Sonatrach.
- Etudiant 02 : TALHI Hadjer, étudiante en Master 2, spécialisée en intelligence artificielle. Elle a suivi des formations en finance et a également complété une formation de niveau Sonatrach.
- Etudiant 03 : CHEMAA Sarra, étudiante en Master 2, spécialisée en réseaux et systèmes distribués. Elle a suivi des formations en finance et a également complété une formation de niveau Sonatrach.

En ce qui concerne l'organisation du travail, nous nous sommes appuyés sur le principe de 'la bonne personne à la bonne place.' Nous avons réparti les tâches entre nous de manière très équilibrée, afin que chacun d'entre nous se concentre sur le côté dans lequel il est créatif ; Il y a ceux qui se plongent dans les complexités des algorithmes d'intelligence artificielle, ceux qui construisent des interfaces d'application avec des touches artistiques en utilisant Flutter, tandis que d'autres construisent le « nerf » du projet via le backend en utilisant Python pour s'assurer que toutes les parties sont connectées les unes aux autres de manière fluide.

Parce que nous nous occupons de la santé des gens, nous ne voulions rien laisser au hasard ; c'est pourquoi, nous sommes accompagnés dans ce voyage par un médecin spécialiste, qui nous guide avec son expérience et surveille attentivement les aspects médicaux, veiller à ce que chaque fonctionnalité que nous fournissons soit une solution sûre et efficace pour les patients.

La meilleure chose à propos de ce projet est l'esprit qui nous unit ; nous travaillons dans un environnement plein de coopération et d'enthousiasme. Il n'y a pas de décisions individuelles, nous nous asseyons toujours, échangeons des idées et prenons nos décisions ensemble. C'est cette atmosphère qui fait que chacun de nous se sent partie intégrante de ce rêve, et notre première motivation à donner le meilleur de nous-mêmes.

4. Objectifs du projet

Objectifs commerciaux

- Entrer sur le marché de la santé numérique (e-santé) et proposer une solution innovante alliant intelligence artificielle et applications médicales.
- Faciliter la communication entre les patients et les médecins et améliorer la qualité des services de santé.
- Parvenir à une adoption progressive de l'application par les cliniques et les médecins sur le marché local.
- Constituer une base d'utilisateurs actifs (patients + médecins) au cours des premières étapes du lancement.
- Créer un modèle de profit durable basé sur les abonnements et les services payants.
- Réduire les coûts et le temps de suivi des conditions médicales par rapport aux méthodes traditionnelles.
- Développer le projet en une plateforme de santé numérique qui peut être étendue au niveau national puis régional.
- Renforcer la confiance dans la solution grâce à une supervision médicale qui garantit l'exactitude et la fiabilité du contenu et des services.

Estimer la part de marché cible

- **Court terme (0 – 2 ans)**

Objectif : Lancer MVP et tester l'idée sur le marché local

Part de marché cible : 1 % à 3 % des patients diabétiques de type 1 localement

Focus:

- Recueillir les premiers utilisateurs (premiers utilisateurs)
- Collaborer avec un nombre limité de médecins
- Améliorer la précision du calcul de dose et l'intelligence artificielle

- **Moyen terme (3 – 5 ans)**

Objectif : S'étendre au sein du pays et connecter un réseau plus large de médecins

Part de marché cible : 5 % à 12 %

Focus:

- Approbation de la demande dans les cliniques et centres de traitement du diabète
- Amélioration des algorithmes d'analyse d'images alimentaires
- Lancement officiel de la plateforme Docteur et connexion des patients à celle-ci

- **Long terme (5 – 10 ans)**

Objectif : Devenir une plateforme régionale dans la gestion du diabète et de la e-santé

Part de marché cible : 15 % à 25 %+

Focus:

- Expansion à l'extérieur du pays (Afrique du Nord / pays arabes)
- Partenariats avec les hôpitaux et les compagnies d'assurance maladie
- Développer un système d'intelligence artificielle avancé pour prédire le sucre et répartir les doses

5. Calendrier de réalisation du projet

Phase	Durée	principaux résultats
Phase 01 : Étude et analyse	1 à 2 mois	- Étudier les besoins des patients diabétiques de type 1 - Définir les exigences de l'application -Analyser les solutions existantes et la concurrence
Phase 02 : Conception (UI/UX)	1 mois	- Concevoir les interfaces de l'application (Flutter UI) - Créer une expérience utilisateur simple et intuitive - Réaliser un prototype
Phase 03 : Développement du MVP	2 à 3 mois	- Développer l'application mobile avec Flutter - Implémenter le calcul de dose d'insuline et des glucides - Mettre en place le backend en Python et la base de données
Phase 04 : Intelligence artificielle	2 à 3 mois (en parallèle)	- Développer le modèle de reconnaissance des repas par image - Estimer l'impact des aliments sur la glycémie - Améliorer progressivement la précision du modèle
Phase 05 : Plateforme médecin	1 à 2 mois	- Créer la plateforme destinée aux médecins - Mettre en place le système de codes pour les patients - Activer le suivi à distance des patients
Phase 06 : Tests et validation	1 mois	- Tester l'application avec de vrais utilisateurs - Corriger les bugs et améliorer les performances - Recueillir les retours des médecins et patients
Phase 07 : Lancement initial	1 mois	- Lancer la première version (Beta / Version 1) - Cibler les premiers utilisateurs
Phase 08 : Évolution et extension	Continu	- Ajouter de nouvelles fonctionnalités - Améliorer l'intelligence artificielle - Développer le projet au niveau national puis régional

Deuxième axe :

Aspects innovants

1. Nature des innovations

Ce projet propose une approche moderne de la santé numérique pour gérer le diabète de type 1, en combinant plusieurs niveaux d'innovation de manière intégrée.

- **Innovation radicale**

L'innovation radicale est une refonte complète de la façon dont le diabète est traité. Le projet ne se limite pas à l'ajout d'une fonctionnalité distincte, mais combine plutôt le calcul de la dose d'insuline, l'estimation des glucides et le suivi médical au sein d'une seule plateforme intégrée. Cette intégration transforme les modèles traditionnels qui reposent sur des outils disparates et sans rapport entre eux.

- **Innovation de marché**

Le projet se concentre sur une catégorie définie avec précision : les patients diabétiques de type 1, ce qui permet d'élaborer une solution personnalisée adaptée à leurs besoins quotidiens. Cela contribue à créer de la valeur ajoutée sur le marché de la santé numérique, en particulier dans le contexte local, en fournissant un service plus spécialisé par rapport aux applications générales.

- **Innovation technologique**

Le projet repose sur l'utilisation de technologies modernes, en particulier l'intelligence artificielle, pour analyser les images des aliments et identifier les repas, dans le but d'estimer leur impact sur les niveaux de sucre. Les techniques de développement modernes sont également utilisées pour construire une application mobile et une plateforme dorsale qui assurent des performances de traitement de données efficaces et intégrées.

- **Innovation progressive**

Le projet est basé sur le principe du développement continu, où les algorithmes et les fonctions sont progressivement améliorés en fonction de l'utilisation réelle et des retours. Cela garantit une précision et une efficacité accrues au fil du temps.

- **Innovation dans le modèle de suivi médical**

Le projet propose une nouvelle façon d'organiser la relation médecin-patient grâce à un système de code qui permet un suivi numérique continu. Ce modèle réduit le recours aux visites traditionnelles et améliore la continuité des soins médicaux.

- **Intégration technique**

L'importance du projet est également évidente dans l'intégration de plusieurs technologies (Flutter, Python et intelligence artificielle) en un seul système intégré, permettant

La fourniture d'une solution numérique unifiée et efficace dans le domaine de la gestion des maladies chroniques.

2. Domaines d'innovation

À partir des cas ci-dessus, les innovations peuvent inclure les domaines suivants :

- **Nouveaux processus**

Le projet vise à introduire une nouvelle approche de la gestion du diabète en intégrant le calcul des doses d'insuline, l'analyse des glucides et le suivi de la santé dans une seule application, plutôt que de s'appuyer sur des outils et processus traditionnels séparés.

- **Nouvelles expériences**

L'application offre une expérience différente pour le patient, car il peut suivre son état de santé sur une base quotidienne et facile, avec une interface simple et une interaction directe avec le médecin, ce qui améliore l'expérience utilisateur et la rend plus continue et confortable.

- **Nouvelles fonctionnalités**

Le projet comprend des fonctionnalités innovantes telles que la reconnaissance des repas à partir de photos, le calcul de l'effet de la nourriture sur les niveaux de sucre, un système d'alerte intelligent et une communication directe entre les patients et les médecins via des codes spéciaux.

- **Nouveaux clients**

Le projet cible un groupe sous-utilisé dans les applications actuelles, à savoir les patients diabétiques de type 1, en plus des médecins spécialisés dans le suivi de ce type de maladie, ce qui ouvre un marché spécialisé et spécifique.

- **Nouvelles offres**

Le projet propose un nouveau modèle pour les services de santé numériques, composé d'abonnements destinés aux patients et aux médecins, avec la possibilité de fournir des services supplémentaires tels que l'analyse intelligente et les recommandations nutritionnelles.

- **Nouveaux modèles**

Le projet est basé sur un modèle de plateforme de santé numérique (Health Platform Model) qui connecte en continu le patient et le médecin, tout en intégrant l'intelligence artificielle dans la prise de décision, au lieu du modèle traditionnel basé uniquement sur les visites médicales.

Troisième axe :

Analyse stratégique du marche

1. Le segment du marché

- **Marché potentiel**

Le marché potentiel comprend toutes les parties qui pourraient bénéficier de l'application ou acheter ses services, à savoir :

- Diabétiques de type 1 (utilisateurs principaux de l'application).
- Les diabétiques en général qui peuvent avoir besoin d'une surveillance nutritionnelle et de la mesure de la glycémie.
- Médecins spécialisés en diabète et endocrinologie.
- Cliniques privées et centres médicaux.
- Plus tard : Les compagnies d'assurance maladie et les établissements de santé.

Qu'est-ce qui les motive à utiliser le produit ?

- La nécessité d'une surveillance attentive et continue du sucre et de l'insuline.
- Difficulté à calculer manuellement les glucides et les doses.
- Désir de réduire les erreurs de santé quotidiennes.
- La nécessité d'un suivi médical à distance au lieu de mouvements fréquents.
- Gagnez du temps et améliorez la qualité des soins de santé.

Où sont-ils situés ?

- Hôpitaux et cliniques spécialisés dans le diabète.
- Centres médicaux privés.
- Communautés locales pour diabétiques.
- À un niveau plus large : d'abord dans les grandes villes, puis au niveau national.

Leur taille approximative

- Patients diabétiques à l'échelle mondiale : des centaines de millions (avec une grande proportion de type 1 et 2).
- Dans tous les pays, les diabétiques représentent un segment important et croissant chaque année en raison du mode de vie.
- Spécialistes : Un segment plus petit mais avec un impact significatif sur l'adoption et la diffusion de l'application.

- **Marché cible (Segmentation)**

Puce principale :

Patients diabétiques de type 1, en particulier les jeunes et les adultes qui dépendent quotidiennement de l'insuline.

Segment secondaire :

- Endocrinologues et diabétiques.
- Cliniques privées intéressées par le suivi numérique.

- **Justifications du choix de ce marché cible**

- Un besoin quotidien et urgent de gérer les doses d'insuline avec précision.
- Manque de solutions locales globales qui combinent nutrition, insuline et suivi médical.
- Il est facile pour les patients de se fier aux applications téléphoniques dans leur vie quotidienne.
- Le coût élevé du suivi traditionnel et la difficulté des déplacements fréquents de médecins.
- Il existe une lacune évidente sur le marché des solutions intelligentes pour le diabète de type 1.

- **La possibilité de conclure des contrats avec des clients importants**

À l'avenir, le projet pourra conclure des partenariats et des contrats avec :

- **Cliniques privées de diabète et d'endocrinologie :** Adoption de l'application comme méthode formelle de suivi pour les patients.
- **Médecins indépendants :** utilisez la plateforme du médecin pour suivre à distance leurs patients pour un abonnement.
- **Hôpitaux :** Intégration du système dans les services de suivi numériques.
- **Compagnies d'assurance maladie :** utilisation de l'application pour réduire les coûts de traitement et les complications.

Ces contrats peuvent dépendre de :

- Abonnement mensuel pour chaque médecin ou institution.
- Ou les accords d'utilisation par les patients de groupe au sein des cliniques.

2. Mesure de l'intensité de la concurrence

Le marché de la santé numérique en Algérie, notamment en ce qui concerne la gestion du diabète, est en pleine croissance et n'est pas encore saturé par les technologies numériques.

La dépendance principale reste aux méthodes traditionnelles telles que le suivi médical direct, les dispositifs manuels et les cahiers papier, avec une présence très limitée de solutions numériques spécialisées.

- **Concurrents directs**

Ce sont des solutions ou applications numériques qui offrent des fonctions similaires (surveillance du diabète, calcul de mesures, enregistrement de données de santé).

Il n'existe pas d'applications locales fortes spécifiquement destinées aux personnes atteintes de diabète de type 1.

Le recours à des applications étrangères est souvent nécessaire, telles que : MySugr, Glucose Buddy…, Ou utilisez des solutions simples et non intégrées.

Part de marché estimée :

- L'utilisation des applications numériques dans ce domaine est encore faible.
- Estimation de part : Moins de 5 % des patients utilisent efficacement les solutions numériques.

Points forts :

- Technologies relativement avancées.
- Bonnes interfaces utilisateur.
- Fournit certaines fonctionnalités de suivi.

Points faibles :

- Non destiné au marché algérien.
- Absence de langue et de contexte local.
- Manque de contact direct avec les médecins locaux.
- Intelligence artificielle faible ou absente dédiée à l'alimentation locale.

- **Concurrents indirects**

Ce sont les alternatives traditionnelles sur lesquelles comptent actuellement les patients pour gérer leur diabète.

Exemples :

- Médecins et cliniques spécialisées.
- Glucomètres (glucomètres).
- Suivi papier ou cahiers médicaux.
- Consultations médicales directes uniquement.

Part de marché :

Ces solutions représentent plus de 90% de la prise en charge actuelle du diabète en Algérie.

Points forts :

- Confiance élevée du patient.

- Accréditation officielle au sein du système de santé.
- Présence directe du médecin.

Points faibles :

- Suivi non continu.
- Erreurs humaines dans les calculs.
- Difficulté de suivi quotidien.
- Coût et effort du transport médical.

Le marché du diabète en Algérie se caractérise par une faible concurrence numérique et une forte dépendance aux méthodes traditionnelles, ce qui fait du projet une excellente opportunité de se positionner comme une solution numérique innovante dans le secteur de la santé.

3. La stratégie marketing

Dans ce projet, nous nous appuyons sur une stratégie marketing basée sur la compréhension des besoins des patients atteints de diabète de type 1, tout en utilisant les technologies modernes et l'intelligence artificielle pour fournir une réelle valeur ajoutée, tout en atteignant un équilibre entre les éléments du mix marketing (Marketing Mix) assurer le succès du projet et sa diffusion sur le marché.

- **Objectifs de la stratégie marketing :**

Sensibilisation et éducation :

Sensibiliser à l'importance d'un suivi intelligent pour le diabète de type 1, et au rôle de la technologie dans l'amélioration de la vie des patients et la gestion des doses et de la nutrition.

Génération de la demande :

Encouragez les patients et les médecins à adopter l'application comme principal outil quotidien pour surveiller le sucre, compter les glucides et ajuster avec précision les doses d'insuline.

Positionnement :

L'application se positionne comme une solution digitale intelligente et innovante dans le domaine de la santé numérique, en combinant intelligence artificielle et suivi médical au sein d'une plateforme intégrée.

- **Clés de la stratégie marketing :**

Division et ciblage:

- Ciblant principalement les patients atteints de diabète de type 1.
- Ciblant les médecins spécialisés en endocrinologie et diabète.
- Coopérer avec les cliniques et les centres médicaux en tant qu'utilisateurs institutionnels.
- Adapter le message marketing à chaque catégorie (patient / médecin / institution).

Positionnement :

- Fournir l'application comme une solution complète et intégrée pour la gestion quotidienne du diabète.
- Soulignant la précision du calcul de dose, l'analyse des repas et la facilité du suivi médical.
- Comparer la solution avec les méthodes traditionnelles (livres, calcul manuel, suivi non continu) pour montrer la valeur ajoutée.
- Concentrez-vous sur le fait que l'application n'est pas seulement une alternative, mais un assistant médical intelligent.

Communication & Promotion :

- Utiliser les réseaux sociaux (Facebook, Instagram, TikTok) pour atteindre les patients.
- Collaborer avec les médecins pour diffuser l'application auprès de leurs patients (référence médicale).
- Organiser des démonstrations pour expliquer comment utiliser l'application.
- Produire du contenu de sensibilisation sur le diabète, la nutrition et l'insuline.

Tarification :

- Adopter un modèle d'abonnement flexible (mensuel / annuel).
- Fournir une version gratuite avec des fonctionnalités de base pour attirer les utilisateurs (Fermium).
- Fournir un abonnement spécial aux médecins pour utiliser la plateforme de suivi.
- Maintenir des prix raisonnables pour le marché local algérien.

Distribution :

- Distribuez l'application via Google Play et App Store.

- Collaborer avec les médecins et les cliniques en tant que principal canal de distribution.
- Intégration ultérieure de l'application au sein des établissements de santé.
- Assurer la facilité de téléchargement et d'utilisation sans complexité technique.

Budget marketing :

- Définissez un budget limité au départ, en mettant l'accent sur le marketing numérique à faible coût.
- Investir dans du contenu de sensibilisation plutôt que dans des publicités coûteuses.
- Améliorer le retour sur investissement (ROI) en ciblant soigneusement les patients et les médecins.
- Rediriger les ressources en fonction de l'utilisation et des résultats d'interaction.

La stratégie marketing est basée sur une approche progressive et réfléchie, alliant sensibilisation, ciblage précis, et construction de la confiance avec les utilisateurs, dans le but d'introduire l'application sur le marché algérien de la santé comme une solution digitale innovante et efficace dans la gestion du diabète de type 1.

Quatrième axe :

Plan de production et organisation

1. Le processus de production

Concrètement, notre processus de production n'a rien de traditionnel : ici, pas d'usine ni de produits physiques. Comme notre projet est 100 % digital, tout se joue dans la conception logicielle et la gestion ultra-sécurisée des données de santé. C'est à travers une organisation technique rigoureuse que nous transformons notre concept initial en une plateforme intelligente et performante, pensée pour faciliter le quotidien des patients atteints de diabète de type 1 et optimiser le suivi des médecins spécialistes.

Le processus de production passe par les étapes suivantes :

Étape 1 : Collecte et traitement des données

Les données sont la base sur laquelle repose un système intelligent. Cette étape comprend :

- Collecter diverses images de régimes pour construire une base de données d'entraînement.
- Collecter des données médicales relatives aux taux de sucre et aux doses d'insuline.
- Classer et traiter les données pour garantir leur exactitude.
- Sécurisez les données en utilisant des protocoles de sécurité qui garantissent la confidentialité des utilisateurs.

Étape 2 : Développement et formation d'un modèle d'IA

À ce stade, le modèle responsable de l'analyse des images nutritionnelles et de l'estimation de leur effet sur les niveaux de sucre est développé, grâce à :

- Construire des algorithmes de reconnaissance d'images.
- Entraîner le modèle à l'aide des données disponibles.
- Tester et améliorer continuellement la précision des résultats.
- Augmentez l'efficacité du traitement et la vitesse de réponse.

Étape 3 : Développement de l'application

Cette phase comprend la conception et le développement de l'application en utilisant Flutter, avec un accent sur :

- Créer des interfaces utilisateur simples et faciles à comprendre.
- Permettre à l'utilisateur de saisir ses données de santé quotidiennes.
- Présenter clairement ses conclusions et recommandations.

- Ajoutez des alertes pour les médicaments et les mesures.

Étape 4 : Architecture back-end et développement de bases de données

Cette étape comprend :

- Configuration des serveurs cloud.
- Concevoir une base de données sécurisée.
- Veiller à ce que les données soient stockées et récupérées rapidement et efficacement.
- Sécurisez la connexion entre l'application et la base de données.

Étape 5 : Essais et vérification

Avant le lancement final, le système est testé par :

- Tests techniques :

Pour vérifier la vitesse de performance et détecter et corriger les erreurs logicielles.

- Vérification médicale :

En coopération avec un médecin spécialiste, l'exactitude des résultats et recommandations de santé est assurée.

Étape 6 : Publication et mise à jour continues

Après avoir terminé les tests :

- Publier l'application via des boutiques d'applications officielles.
- Surveiller les performances du système.
- Recueillir les commentaires des utilisateurs.
- Développer des mises à jour périodiques pour améliorer les performances et la fonctionnalité.

2. Approvisionnement

Le processus de restauration dans ce projet consiste à fournir diverses ressources techniques et logicielles nécessaires au développement de l'application et à assurer sa continuité, en mettant l'accent sur les outils numériques plutôt que sur les matériaux physiques.

Politique d'achat : La politique d'approvisionnement repose sur le choix d'outils et de technologies fiables, performants et rentables, en s'appuyant autant que possible sur des

Solutions open source, et en n'utilisant des services payants que lorsque cela est nécessaire, notamment en ce qui concerne les serveurs cloud et les services avancés.

Matières premières et fournitures : Les matériaux et fournitures comprennent des données numériques (photos de repas et données médicales), ainsi que des ordinateurs et des smartphones utilisés dans le développement et les tests, avec un accès internet et des comptes de développeurs d'applications.

Logiciel : Le projet s'appuie sur un ensemble de logiciels centraux tels que Flutter pour le développement d'applications, Python pour l'intelligence artificielle, ainsi que TensorFlow, OpenCV pour le traitement d'images et des bases de données telles que Firebase pour le stockage de données.

3. Main-d'œuvre

Le projet nécessite une équipe multidisciplinaire et peut contribuer à la création de plusieurs postes liés au développement et à l'exploitation de l'application.

Postes de travail possibles

- Développeurs (2 postes) : Développer et maintenir l'application et ajouter des fonctionnalités.
- Support technique (1 poste) : Aider les utilisateurs, résoudre des problèmes et recueillir des commentaires.
- Spécialiste en intelligence artificielle (2 poste) : Développer un modèle d'analyse des repas et améliorer la précision.

Nature du travail

Main-d'œuvre techniquement qualifiée dans :

- Développement d'applications (Flutter / Python)
- Intelligence artificielle et analyse de données
- Communication et support technique

Lieux de présence

- Universités et établissements d'enseignement supérieur.
- Incubateurs et startups.
- Entreprises technologiques et centres de recherche.

4. Les principaux Partenaires

Le succès de ce projet repose sur un ensemble de partenariats clés qui contribuent à son développement et en assurent la continuité. Ces partenariats comprennent des institutions de santé telles que les hôpitaux et les médecins spécialistes du diabète, qui contribuent à fournir un soutien médical et à vérifier l'exactitude des résultats et des recommandations. Le projet s'appuie également sur des partenariats techniques avec des sociétés de développement logiciel et des fournisseurs de services cloud, dans le but de fournir l'infrastructure numérique et les outils de développement nécessaires. En outre, des partenariats académiques tels que les universités et les laboratoires de recherche contribuent à soutenir l'aspect scientifique et technique du projet. Les associations et institutions du diabète soutenant des projets émergents peuvent également être mises à contribution afin de faciliter la diffusion de l'application et d'atteindre les utilisateurs ciblés.

Cinquième axe :

Plan financier

1. Les couts et les charges

Les coûts associés au développement d'une application intelligente pour le diabète comprennent une combinaison d'équipement de base, de développement, de dépenses opérationnelles et de marketing. Puisque le projet se fait dans un petit cadre (startup) et que le travail est effectué à domicile, les coûts restent relativement limités dans la première phase.

Coûts de la fondation (une fois)

- Ordinateurs (3 ordinateurs) : environ 300 000 – 450 000 DZD
- Smartphones à tester (2 à 3) : environ 60 000 – 120 000 DZD
- Équipement et fournitures Internet : environ 10 000 – 20 000 DZD

Frais de fonctionnement mensuels

- Services Cloud et Firebase : 0 – 10 000 DZD
- Outils de développement et d'IA : 5 000 – 30 000 DZD
- Internet : environ 2000 – 4000 DZD par mois

Marketing et publicité

- Publicités Facebook / Instagram (Phase 1) : 20 000 – 50 000 DZD par mois au lancement
- Campagnes marketing plus importantes lors de l'expansion : 100 000 DZD ou plus selon l'étape

Mobilité et consultations médicales

Transferts simples pour consulter un médecin : environ 5 000 – 15 000 DZD par mois (irrégulier)

Ressources humaines (équipe)

L'équipe se compose de 3 personnes travaillant ensemble sur le projet :

- Développeur d'application (Flutter + Backend)
- Spécialiste en intelligence artificielle (IA + données)
- Concepteur UI/UX + Support général du projet

Puisque l'équipe est la fondatrice du projet, les salaires peuvent être pris en compte :

- Initialement : sans salaires fixes (auto-investissement)
- Ou plus tard lors du développement : environ 40 000 – 70 000 DZD par membre et par mois

Modes et sources de financement

- Autofinancement par l'équipe fondatrice

- Soutenir les incubateurs universitaires
- Programmes de financement de startups
- Investisseurs privés (lors de l'expansion)

Recouvrement des coûts

Les coûts peuvent être récupérés via :

- Abonnement mensuel à l'application
- Services payants d'analyse alimentaire et d'IA
- Partenariats avec des cliniques ou des médecins
- Soutien et investissement des incubateurs ou investisseurs

Coûts initiaux : 370 000 – 590 000 DZD

Coûts mensuels : 32 000 – 99 000 DZD

Estimation annuelle approximative :

Entre 750 000 DZD et 1 800 000 DZD la première année

2. Le chiffre d'affaires

L'abonnement est fixé au prix de 500 DZD par mois

Scénario optimiste

Année	N	N+1	N+2	N+3	N+4	N+5
Nombre d'utilisateurs	50	200	600	1200	2500	5000
Chiffre d'affaires (DA)	300000	1200000	3 600000	7 200000	15 000000	3 000 000

Scénario pessimiste

Année	N	N+1	N+2	N+3	N+4	N+5
Nombre d'utilisateurs	20	80	200	400	800	1200
Chiffre d'affaires (DA)	120000	480 000	1 200 000	2 400 000	4 800 000	7 200 000

Le chiffre d'affaires attendu reste positif du fait que le projet est basé sur un modèle d'abonnement numérique ce qui réduit les coûts fixes et augmente la marge bénéficiaire. Sa croissance est également directement liée au nombre d'utilisateurs réels et à l'étendue de la diffusion de l'application sur le marché de la santé.

3. Les comptes de résultats escomptés

Grâce à un tableau de calcul des résultats attendus sur cinq ans, le projet montre une forte capacité de croissance à moyen et long terme, en particulier dans un scénario optimiste, où les revenus augmentent constamment en raison de l'augmentation du nombre d'utilisateurs et de l'expansion de l'application. Les coûts restent également relativement maîtrisés, ce qui permet d'augmenter les bénéfices. Dans un scénario pessimiste, le projet atteint une croissance plus lente, mais reste progressivement développable et peut atteindre la rentabilité au fil du temps.

Année	Chiffre d'affaires (optimiste) DA	Total des charges DA	Résultat (optimiste) DA	Chiffre d'affaires (pessimiste) DA	Total des charges DA	Résultat (pessimiste) DA
2026	9 600 000	1 300 000	+8 300 000	2 400 000	1 300 000	+1 100 000
2027	15 000 000	1 400 000	+13 600 000	3 600 000	1 400 000	+2 200 000
2028	22 000 000	1 500 000	+20 500 000	5 000 000	1 500 000	+3 500 000
2029	28 000 000	1 600 000	+26 400 000	6 500 000	1 600 000	+4 900 000
2030	35 000 000	1 700 000	+33 300 000	8 000 000	1 700 000	+6 300 000

Total sur 5 ans (Cumul)

Indicateur	Optimiste	Pessimiste
Chiffre d'affaires total	109 600 000 DA	25 500 000 DA
Total des charges	7 500 000 DA	7 500 000 DA
Résultat total	+102 100 000 DA	+18 000 000 DA

4. Le plan de trésorerie

Grâce au plan de trésorerie, nous pouvons prévoir et déterminer les dépenses et les revenus totaux du projet. Le projet devrait enregistrer un léger déficit au début de l'activité, en raison de l'augmentation des coûts initiaux, puis s'améliorer progressivement avec l'augmentation du nombre de contributions et des revenus mensuels, entraînant un excédent financier positif au cours des mois suivants et une stabilité financière à la fin de la première année.

Mois	Encaissements (recettes)	Décaissements (dépenses)	Solde mensuel
Janvier	300 000	400 000	-100 000
Février	350 000	350 000	0
Mars	400 000	320 000	+80 000
Avril	450 000	300 000	+150 000
Mai	500 000	300 000	+200 000
Juin	550 000	310 000	+240 000

Juillet	600 000	320 000	+280 000
Août	650 000	330 000	+320 000
Septembre	700 000	340 000	+360 000
Octobre	750 000	350 000	+400 000
Novembre	800 000	360 000	+440 000
Décembre	850 000	370 000	+480 000

Sixième axe :

Prototype expérimental

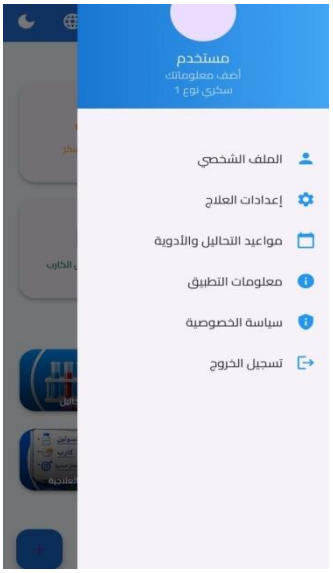
This section presents the main screenshots of the developed mobile application, illustrating its key interfaces from authentication to insulin dose calculation.





The application starts with a login screen and a registration form collecting basic patient information.





The dashboard displays the latest blood sugar reading and quick access to core features, while the side menu provides access to profile and treatment settings.



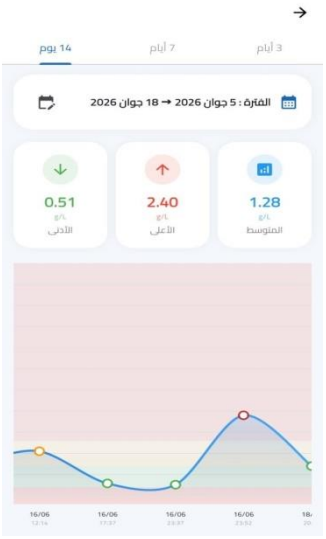


This section centralizes the diabetes management tools and allows the patient to configure personalized parameters such as the insulin-to-carbohydrate ratio.











These screens allow patients to log and visualize their blood sugar history through calendars, tables, and trend curves.









These tools help patients manage hyperglycemia episodes, recognize symptoms, calculate their sensitivity factor, and follow emergency glucagon injection steps.



This screen represents the core feature of the application, calculating the recommended insulin dose based on the carbohydrate content of the meal.

Septième axe :

Modèle d'entreprise BMC

<table>
<tr>
<td rowspan="2">Principaux partenaires
▪ Médecins spécialisés en diabète et endocrinologie
▪ Cliniques et hôpitaux (publics et privés)
▪ Pépinières d'entreprises (pépinières de startups)
▪ Entreprises de développement d'IA et d'informatique en nuage
▪ Laboratoires d'analyses médicales
▪ Institutions de santé numérique (partenaires de l'e-santé)</td>
<td>Activités principales
▪ Développement d'applications mobiles (Flutter)
▪ Développement d'algorithmes d'intelligence artificielle pour l'analyse des repas
▪ Calculer les doses d'insuline et de glucides
▪ Développement d'une plateforme pour les médecins (tableau de bord web)
▪ Tester et améliorer continuellement la précision du système
▪ Collecte de données et amélioration du modèle médical</td>
<td rowspan="2">Valeur fournie
▪ Une application intelligente complète pour la gestion du diabète de type 1
▪ Calcul précis des doses d'insuline et de glucides
▪ Analyser des repas à partir d'images en utilisant l'intelligence artificielle
▪ Suivi médical à distance entre le médecin et le patient
▪ Réduire les erreurs quotidiennes et améliorer la qualité de vie des patients
▪ Une alternative numérique intégrée aux méthodes traditionnelles (livre + compte manuel)</td>
<td>Relations clients
▪ Prise en charge dans l'application (Support / Centre d'aide)
▪ Suivi continu de l'état du patient
▪ Lien direct entre le médecin et le patient via des codes
▪ Notifications et rappels de médicaments intelligents
▪ Contenu de sensibilisation sur le diabète et la nutrition
▪ Interaction personnelle basée sur les données utilisateur</td>
<td rowspan="2">Segments de clientèle
▪ Patients diabétiques de type 1 (cible principale)
▪ Les diabétiques en général
▪ Médecins spécialisés dans les glandes et le diabète
▪ Cliniques et centres de santé
▪ Plus tard : Les compagnies d'assurance maladie</td>
</tr>
<tr>
<td>Ressources clés
▪ Équipe de développement (mobile + backend + IA)
▪ Modèle d'intelligence artificielle pour l'analyse d'images
▪ Base de données médicale sécurisée
▪ Application pour téléphone et plateforme médicale
▪ Ressources humaines (techniciens + support + marketing)
▪ Architecture cloud pour le stockage de données</td>
<td>Les Canaux
▪ Google Play / App Store
▪ Médecins et cliniques (canal principal)
▪ Réseaux sociaux (Facebook, Instagram, TikTok)
▪ Campagnes de sensibilisation médicale
▪ Partenariats avec des établissements de santé
▪ Spectacles en direct à l'intérieur des cliniques</td>
</tr>
</table>

Structure des coûts	**Sources de revenus**
▪ Développement d'applications et intelligence artificielle ▪ Hébergement de serveurs (services cloud) ▪ Marketing et publicité numérique ▪ Maintenance et mise à jour du système ▪ Salaires de l'équipe technique ▪ Coûts du partenariat médical	▪ Abonnements patients mensuels/annuels ▪ Abonnements pour les médecins afin d'utiliser la plateforme ▪ Advanced AI Analysais Services (fonctionnalités d'IA premium) ▪ Partenariats avec des cliniques et des établissements de santé ▪ Plus tard : Les compagnies d'assurance maladie