People's Democratic Republic of Algeria
Ministry of Higher Education and Scientific Research
Mohamed El Bachir El Ibrahimi University of Borj Bou Arréridj
Faculty of Mathematics and Computer Science
Department of Computer Science

THESIS
In order to obtain the Doctorate degree in LMD (3rd cycle)
Branch: Computer Science
Option: Network and Multimedia

THEME

The Use of big data and data analytics in the prevention, Diagnosis and prediction of long-term diseases.

By: Mecili Oualid

Publicly defended on: 02/10/2025

In front of the jury composed of:

Pr. Abderraouf Bouziane	University of B.B.A	**President**
Dr. Hadj Barkat	University of B.B.A	**Supervisor**
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2025/2026

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Approche Big Data et Data Analytics pour la prévention, la détection et le suivi des maladies de longue durée.

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Abstract

The increasing prevalence of long-term diseases, particularly diabetes, presents significant challenges to global healthcare systems. Early prediction, accurate diagnosis, and continuous monitoring are crucial for improving patient outcomes and reducing healthcare costs. This thesis explores the use of Big Data and data analytics in the prevention, diagnosis, and monitoring of long-term diseases, focusing specifically on diabetes. The core objective is the development of an integrated system that supports individuals throughout the disease lifecycle. The proposed system is structured into three main phases: first, the creation of predictive algorithms capable of estimating an individual's risk of developing diabetes within a ten-year period; second, the application of explainable neural networks to diagnose diabetes based on retinal imaging, ensuring transparency and trust in AI-driven decisions; and third, the development of a digital platform to continuously monitor patients, facilitating proactive management and personalized care. By leveraging machine learning, Big Data technologies, and explainable AI, this work aims to contribute to a more predictive, preventive, and participatory healthcare model for chronic disease management.

Résumé

La prévalence croissante des maladies chroniques, en particulier du diabète, représente un défi majeur pour les systèmes de santé à l'échelle mondiale. La prédiction précoce, le diagnostic précis et le suivi continu sont essentiels pour améliorer les résultats pour les patients et réduire les coûts de santé. Ce mémoire étudie l'utilisation du Big Data et de l'analyse de données dans la prévention, le diagnostic et la surveillance des maladies chroniques, avec un accent particulier sur le diabète. L'objectif principal est de développer un système global qui accompagne les individus tout au long du cycle de la maladie. Ce système est structuré en trois phases principales : tout d'abord, la création d'algorithmes de prédiction capables d'estimer le risque de développer un diabète dans les dix prochaines années ; ensuite, l'utilisation de réseaux neuronaux explicables pour diagnostiquer le diabète à partir d'images rétiniennes, assurant ainsi la transparence et la confiance dans les décisions basées sur l'IA ; enfin, le développement d'une plateforme numérique pour le suivi continu des patients, favorisant une gestion proactive et personnalisée. En exploitant le machine learning, les technologies Big Data et l'intelligence artificielle explicable, ce travail vise à contribuer à un modèle de santé prédictif, préventif et participatif pour la gestion des maladies chroniques.

ملخص

تشكل الزيادة المستمرة في الأمراض المزمنة، وخاصة داء السكري، تحديًا كبيرًا للأنظمة الصحية العالمية. تُعد القدرة على التنبؤ المبكر والتشخيص الدقيق والمتابعة المستمرة ضرورية لتحسين نتائج المرضى وتقليل تكاليف الرعاية الصحية. يتناول هذا البحث استخدام البيانات الضخمة وتحليل البيانات في الوقاية من الأمراض المزمنة وتشخيصها ومراقبتها، مع تركيز خاص على داء السكري. الهدف الرئيسي هو تطوير نظام شامل لدعم الأفراد طوال دورة المرض. يتكون النظام المقترح من ثلاث مراحل رئيسية: أولاً، إنشاء خوارزميات قادرة على التنبؤ بخطر الإصابة بداء السكري خلال السنوات العشر القادمة؛ ثانيًا، استخدام الشبكات العصبية القابلة للتفسير لتشخيص السكري اعتمادًا على صور الشبكية، مما يضمن الشفافية والثقة في القرارات المستندة إلى الذكاء الاصطناعي؛ وأخيرًا، تطوير منصة رقمية لمراقبة المرضى باستمرار، مما يعزز الإدارة الاستباقية والرعاية الشخصية. من خلال الاستفادة من تقنيات التعلم الآلي والبيانات الضخمة والذكاء الاصطناعي القابل للتفسير، يهدف هذا العمل إلى المساهمة في نموذج صحي تنبئي ووقائي وتشاركي لإدارة الأمراض المزمنة.

Dedication and acknowledgements

بِسْمِ اللَّهِ الرَّحْمَٰنِ الرَّحِيمِ

First and foremost, I thank Allah, who has bestowed upon me the ability, motivation, patience, and resources to complete this journey. I am deeply grateful for His guidance and support throughout this process.

وَمَا تَوْفِيقِي إِلَّا بِاللَّهِ ۚ عَلَيْهِ تَوَكَّلْتُ وَإِلَيْهِ أُنِيبُ

I would like to express my deepest gratitude and appreciation to my supervisors. Their invaluable guidance, unwavering support, and constant encouragement have been essential throughout my Ph.D. program.

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Lastly, I extend special thanks to the President of the committee and the examiners for graciously accepting to review my work. Their constructive feedback and insightful criticism will contribute significantly to improving the quality of this thesis.

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List of Abbreviations

ACC	Accuracy
AI	Artificial Intelligence
AUC	Area Under the Curve
CNN	Convolutional Neural Network
CGM	Continuous Glucose Monitoring
DL	Deep Learning
DR	Diabetic Retinopathy
DME	Diabetic Macular Edema
EHR	Electronic Health Records
ETDRS	Early Treatment Diabetic Retinopathy Study
FA	Fluorescein Angiography
F1	F1-Score (Harmonic Mean of Precision and Recall)
FN	False Negative
FP	False Positive
FPR	False Positive Rate
GBM	Gradient Boosting Machine
IDRID	Indian Diabetic Retinopathy Image Dataset
LLE	Locally Linear Embedding
ML	Machine Learning
MESSIDOR	Methodes d'Evaluation des Systemes d'Imagerie Diagnostique de la Retine
OCT	Optical Coherence Tomography
RF	Random Forest

RFE	Recursive Feature Elimination
ROC	Receiver Operating Characteristic
RNN	Recurrent Neural Network
SEN	Sensitivity
SPEC	Specificity
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
TPR	True Positive Rate
VGG	Visual Geometry Group
XDNN	Explainable Deep Neural Network
AdaBoost	Adaptive Boosting
Bagging	Bootstrap Aggregating
CNN	Convolutional Neural Network
DT	Decision Tree
GAN	Generative Adversarial Network
GBM	Gradient Boosting Machine
GMM	Gaussian Mixture Model
GPC	Gaussian Process Classifier
GBC	Gradient Boosting Classifier
GNB	Gaussian Naive Bayes
KNN	K-Nearest Neighbors
LDA	Linear Discriminant Analysis
LSTM	Long Short-Term Memory
LR	Logistic Regression

NB	Naive Bayes
PCA	Principal Component Analysis
QDA	Quadratic Discriminant Analysis
RF	Random Forest
RNN	Recurrent Neural Network
SVM	Support Vector Machine
SVC	Support Vector Classifier
t-SNE	t-Distributed Stochastic Neighbor Embedding
XGBoost	Extreme Gradient Boosting

List of Algorithms

CHAPTER 1

Introduction

In the past few years, the healthcare sector has undergone a data revolution inspired by the advent of big data technologies. With the digitization of medical records, the proliferation of wearable health devices, and advances in medical research, an unprecedented volume of data is now available for analysis. This data explosion has reshaped healthcare, enabling more accurate diagnostics, personalized treatments, and improved long-term management of chronic diseases.

Diabetes is one of the most significant public health challenges worldwide, affecting an estimated 578 million adults worldwide in 2024, and is projected to rise to 783 million by 2045, making it one of the most pressing global health concerns. This significant increase emphasizes the urgent need for innovative solutions in diabetes management, prevention, and prediction to mitigate the growing burden on healthcare systems and improve outcomes for individuals affected by the disease[83].

Diabetes, is an excellent example of how big data is transforming healthcare. By analyzing large datasets from electronic health records (EHRs), continuous glucose monitors, and wearable devices, healthcare providers can track blood sugar levels, predict complications, and personalize treatment plans for diabetic patients. Big data allows for early detection of trends, empowering doctors to make informed decisions that prevent long-term complications. In this way, big data plays a crucial role in managing diabetes, facilitating proactive care, and improving overall patient outcomes.

The growing prevalence of diabetes is driven by multiple factors, including aging populations, increasing prevalence of obesity, sedentary behaviors, and suboptimal nutritional patterns. The disease has a profound impact not only on individuals, but also on healthcare systems, as it is associated with long-term complications such as heart disease, kidney failure, nerve damage, and vision loss. These complications lead to increased mortality and morbidity, as well as rising healthcare costs.

1.1 Overview of Diabetes

Diabetes, when not properly managed, may result in severe complications that impact various organs and systems within the body. These long-term effects, although often preventable, are a significant cause of diabetes. Continuous monitoring, early detection, and personalized care are critical in reducing these risks [86]. The disease occurs when the body cannot produce enough insulin (Type 1 diabetes) or cannot use the insulin it produces effectively (Type 2 diabetes). Type 2 diabetes accounts for approximately 90% of all cases.

One of the most significant complications is cardiovascular disease, and people with diabetes are two to four times more likely to develop heart disease or suffer a stroke [8]. High blood sugar levels contribute to the hardening and narrowing of blood vessels (atherosclerosis), increasing the risk of heart attacks, hypertension, and other cardiovascular problems [120]. Chronic inflammation and damage to endothelial cells that line blood vessels further exacerbate this risk, making cardiovascular disease the primary factor contributing to mortality among individuals diagnosed with diabetes.

Diabetic nephropathy, commonly referred to as kidney disease, is another serious complication. Prolonged elevated glucose levels can damage kidney filtering systems, resulting in chronic kidney disease (CKD) over an extended period, this can progress to end-stage renal disease (ESRD), which often requires dialysis or kidney transplantation [73]. Diabetic nephropathy is one of the most common causes of kidney failure worldwide, affecting 20-40% of people with diabetes. The progression of kidney damage is often gradual, highlighting the need for early intervention and consistent management of blood sugar levels [121].

Another common complication is diabetic neuropathy, which is the result of nerve damage caused by sustained high blood sugar levels. This condition affects up to 50% of individuals with diabetes, causing symptoms such as pain, numbness, and tingling, particularly in the feet and legs [2]. In severe cases, neuropathy can lead to the development of foot ulcers that are challenging to heal as a result of inadequate blood circulation and impaired sensation. Untreated ulcers can become infected and may require amputation. Neuropathy can also affect the autonomic nervous system, leading to problems such as gastrointestinal disturbances, bladder problems, and abnormal heart rhythms [115].

Diabetic retinopathy is the leading cause of blindness in adults with diabetes. High blood sugar levels damage small blood vessels in the retina, causing them to leak fluid or bleed, leading to progressive vision loss. In advanced stages, proliferative diabetic retinopathy can occur, where abnormal blood vessels grow on the surface of the retina, further increasing the risk of blindness. Regular eye examinations and timely treatment can significantly reduce the risk of vision loss, with early intervention preventing up to 95% of diabetes-related blindness cases [61].

Lastly, diabetes greatly affects the body's ability to heal wounds, particularly in the lower extremities. This is compounded by conditions such as peripheral artery disease (PAD), which reduces blood flow to the legs and feet. Combined with neuropathy, even minor injuries can progress to diabetic foot ulcers. These ulcers often become infected and can be extremely difficult to treat. When infections become severe or spread, amputation may be necessary to prevent further complications. Diabetes is responsible for around 85% non-traumatic lower extremity amputations worldwide, underscoring the importance of vigilant foot care and early treatment [74].

These complications highlight the importance of continuous glucose monitoring and the adoption of personalized diabetes management strategies. Modern tools including continuous glucose monitoring devices (CGM), insulin delivery systems, and big data analytics offer significant improvements in diabetes management and prediction of potential complications. A proactive data-driven approach to care, combined with early intervention, is essential to prevent these serious complications and enhance the living standards of individuals diagnosed with diabetes [39].

1.2 Tools for Diabetes Management

Despite advances in medical technology and growing awareness about diabetes, significant challenges remain to effectively prevent, diagnose and predict the disease. These obstacles contribute to the increasing global burden of diabetes and complicate efforts to manage the disease efficiently. One of the primary issues is the limited capacity for early detection and prevention. Currently, diabetes prevention strategies are often reactive and interventions occur only after individuals have developed significant risk factors such as obesity or prediabetes. This delayed approach is exacerbated by fragmented data systems, which store patient information on multiple disconnected platforms, making it difficult to compile a comprehensive view of an individual's health. In addition, inconsistent screening practices and the lack of real-time lifestyle data integration hinder efforts to identify at-risk individuals early and implement personalized prevention strategies.

When it comes to diagnosis, there are also notable limitations. The diagnosis of diabetes usually relies on periodic assessments of blood glucose levels, including fasting blood sugar and hemoglobin A1c tests levels. Although these tests are important, they are often performed intermittently and may not detect early fluctuations in blood sugar or the onset of glucose intolerance, resulting in delayed diagnosis. In many cases, healthcare systems have not fully embraced advanced predictive tools, and current risk assessment models rely heavily on static factors such as age and BMI. This reduces the ability to diagnose diabetes in earlier stages, particularly in resource-limited environments where access to sophisticated diagnostic instruments is restricted, such as continuous glucose monitors (CGM), is limited.

Another significant challenge lies in the prediction of the onset and progression of diabetes. Although big data offers immense potential to enhance prediction accuracy, many healthcare systems have yet to integrate large-scale data analytics effectively. Traditional prediction models often remain static and do not account for real-time changes in patient health or behavior, limiting their utility in predicting hyperglycemic or hypoglycemic events and future complications. Furthermore, privacy concerns surrounding the collection and sharing of large amounts of personal health data hinder the broader adoption of big data analytics for disease prediction, reducing the effectiveness of advanced models in public health.

There are still gaps in personalized care for people living with diabetes. Despite advances in medicine, diabetes treatment often follows a universal strategy that fails to consider individual variations such as genetic differences, lifestyle, and coexisting health conditions. Current care models tend to focus on clinical metrics such as blood sugar levels without adequately integrating behavioral data such as dietary habits and physical activity. This lack of comprehensive and personalized data leads to less effective treatment plans. In addition, while technologies such as CGM and insulin pumps exist, they are not yet universally adopted, further limiting the potential for real-time, data-driven adjustments in patient care.

In the management of diabetes, a variety of tools have emerged to aid in prevention, monitoring, diagnosis, and treatment. These tools span across different technologies, ranging from traditional medical devices to cutting-edge data analytics and artificial intelligence (AI). As diabetes remains a significant public health challenge, these tools are essential to improve patient outcomes, reduce complications, and facilitate personalized care. Below is an overview of some key tools used in diabetes management.

Kidney disease, or diabetic nephropathy, is another severe complication. Elevated glucose levels can impair the renal filtration mechanism, resulting in gradual renal insufficiency. Often, this necessitates dialysis or a kidney transplantation [92]. Nerve damage, known as diabetic neuropathy, often affects the extremities, particularly the lower extremities, including the legs and feet, resulting in discomfort, numbness, and even amputations in severe cases. Additionally, Diabetic retinopathy, characterized by the damage to retinal blood vessels due to elevated blood sugar levels, is a predominant contributor to adult blindness [48]. Poor wound healing, combined with reduced circulation, further increases the risk of amputations, particularly in the lower extremities.

These complications emphasize the importance of ongoing monitoring and individualized care for people with diabetes. New technologies, devices like continuous glucose monitors (CGMs) and insulin pumps offer promising tools for better management, but they must be complemented by data-driven insights and predictive analytics to further reduce the risk of such long-term complications.

In the context of modern diabetes care, the field of explainable deep learning is increasingly recognized for its ability to improve clinical decision-making processes. while offering transparency in predictions. Traditional deep learning models, while powerful in processing large datasets and recognizing patterns, are often criticized as ”black boxes” because their decision-making process is difficult to interpret. Explainable deep learning seeks to bridge this gap by providing insights into how models arrive at specific conclusions [7]. This is particularly important in healthcare, where understanding the reasoning behind predictions such as identifying early signs of diabetic retinopathy or predicting the likelihood of a heart attack can improve trust in AI-driven tools among both healthcare providers and patients. By offering more transparent and interpretable models, explainable deep learning ensures that clinicians can validate AI-generated predictions and adjust treatment plans accordingly, leading to more personalized and precise care.

1.3 Machine Learning Tools for Diabetes

Machine learning (ML) offers a versatile toolkit for addressing various challenges in diabetes management and research. It encompasses classification, prediction, clustering, and anomaly detection. In classification tasks, ML methods can identify high-risk individuals by analyzing factors such as demographics, lifestyle, and genetic data. They employ tools like Logistic Regression, Support Vector Machines (SVMs), and Random Forests. ML also aids in predicting disease complications, such as diabetic retinopathy or nephropathy, using clinical data and imaging, leveraging Convolutional Neural Networks and Gradient Boosting Machines.

For prediction purposes, ML techniques enable forecasting of blood glucose levels to assist patients in adjusting insulin dosage for better glycemic control. This involves Recurrent Neural Networks (RNNs) and Time Series Forecasting models. ML also helps in predicting the risk of hospitalization due to diabetes complications, allowing for early intervention and improved care management. In clustering tasks, ML algorithms group patients with similar characteristics to personalize treatment plans and interventions. Techniques such as K-means clustering and Hierarchical clustering are used. ML also aids in predicting drug response by identifying subgroups likely to respond favorably to specific medications, using unsupervised learning models and dimensionality reduction techniques. Anomaly detection is another area where ML shines, assisting in the identification of unusual blood sugar patterns, as well as other applications relevant to diabetes treatment. Techniques like Isolation Forest, One-Class SVMs, Autoencoders, and Deep Learning models are employed. Additionally, ML techniques, including Computer Vision, play crucial roles in analyzing medical records, extracting insights, and interpreting medical images such as retinal scans for early detection of diabetic complications. Machine learning tools have emerged as promising solutions for improving the management of diabetes. These tools utilize advanced algorithms and techniques to examine extensive datasets of patient data, encompassing blood glucose measurements, lifestyle variables, and medical background.

By identifying patterns and correlations within these data, machine learning algorithms can assist healthcare providers in making more accurate predictions regarding a patient's risk of developing complications or the effectiveness of various treatment strategies. One key application of machine learning in diabetes management is predictive modeling. By leveraging historical data, machine learning algorithms can predict future blood glucose levels or the likelihood of a patient experiencing hypoglycemia or hyperglycemia events. This information enables healthcare providers to proactively intervene and adjust treatment plans to optimize patient outcomes.

Additionally, machine learning tools can enable precision medicine approaches through the customization of therapeutic interventions according to patients' distinct genetic profiles, biomarkers, comorbidities, and treatment responsiveness. Through continuous monitoring and feedback, these tools can adapt and refine their predictions over time, leading to more precise and effective diabetes management strategies. Overall, machine learning offers promising opportunities to revolutionize diabetes care by providing healthcare providers with powerful tools for prediction, diagnosis, and treatment optimization. As these technologies continue to evolve, they have the potential to significantly improve patient outcomes and quality of life for individuals living with diabetes.

1.4 Types of Diabetes

1.4.1 Type 1 Diabetes

Commonly referred to as insulin-dependent diabetes or juvenile diabetes, type 1 diabetes occurs when The immune system erroneously targets and eliminates the insulin-secreting beta cells within the pancreas. Consequently, the body generates minimal to no insulin, resulting in elevated blood glucose levels. Type 1 diabetes generally manifests during childhood or adolescence, although it can arise at any stage of life. The management of type 1 diabetes necessitates continuous insulin therapy, which can be administered via injections or an insulin pump. Patients with type 1 diabetes must also monitor their blood glucose levels regularly and adjust their insulin doses based on their dietary intake and physical activity.

1.4.2 Type 2 Diabetes

Represents the predominant type of diabetes globally, arising when the body either develops insulin resistance or the pancreas fails to produce adequate insulin to regulate blood glucose levels. This condition is frequently linked to factors such as obesity, a lack of physical activity, and genetic factors. In the early stages, adjustments in lifestyle, including dietary changes and increased physical activity, may effectively control type 2 diabetes; however, certain individuals might necessitate the use of oral medications or insulin treatment. Type 2 diabetes can lead to complications such as diabetic retinopathy, diabetic nephropathy, and cardiovascular disease.

1.4.3 Gestational Diabetes

manifests during pregnancy when the body fails to produce sufficient insulin to accommodate the heightened demands, resulting in increased blood glucose levels. This condition typically arises between the 24th and 28th weeks of gestation and generally subsides following delivery. Nevertheless, women who experience gestational diabetes face a higher likelihood of developing type 2 diabetes in the future. Management of gestational diabetes involves dietary modifications, regular physical activity, and, in some cases, insulin therapy. Close monitoring of blood glucose levels is essential to ensure the health of both the mother and the developing fetus.

1.4.4 Monogenic Diabetes

Monogenic diabetes is a rare form of diabetes caused by mutations in a single gene. These genetic mutations affect insulin production and secretion, leading to either decreased insulin production or impaired insulin function. Monogenic diabetes can present in infancy, childhood, or adulthood, and its treatment varies depending on the specific genetic mutation involved.

1.4.5 Prediabetes

Characterized by elevated blood sugar levels that exceed normal ranges but do not meet the criteria for a diagnosis of type 2 diabetes. Those diagnosed with prediabetes face a heightened risk of progressing to type 2 diabetes; however, implementing lifestyle modifications such as weight management, nutritious dietary choices, and consistent physical activity can effectively prevent or postpone the development of this condition.

1.4.6 Other Specific Types of Diabetes

This category includes various other types of diabetes that may result from specific genetic syndromes, pancreatic diseases, drug-induced conditions, or hormonal imbalances. Examples include diabetes associated with cystic fibrosis, steroid-induced diabetes, and diabetes secondary to pancreatic diseases.

1.5 Motivation

The motivation behind undertaking a thesis on diabetes is often deeply rooted in personal experiences, whether through one's own experience with the disease or through the experiences of family members, friends, or patients. Witnessing the daily challenges, complications, and impact of diabetes on individuals and their families can evoke a strong sense of empathy and a desire to create a significant impact on the lives of individuals impacted by diabetes.

Beyond personal experiences, the growing prevalence and public health significance of diabetes globally serve as a compelling motivator for research in this field. Diabetes not only is a major contributor to morbidity and mortality, but also imposes a significant economic burden on healthcare systems and society as a whole. Understanding the underlying mechanisms of diabetes, identifying risk factors and developing effective prevention and management strategies are critical to mitigate the social consequences of this disease.

In addition, diabetes is a complex and multifaceted disease with various etiological factors, ranging from genetic predisposition to environmental and lifestyle influences. This complexity presents an intriguing area for scientific inquiry, with opportunities to explore the intricate interplay between genetics, metabolism, immune function, and environmental factors.

Advancements in technology, such as wearable devices, continuous glucose monitoring systems, mobile health applications, and machine learning algorithms, offer exciting possibilities to revolutionize diabetes management. These technologies have the potential to empower individuals with diabetes to take control of their health, improve adherence to treatment regimens, and enhance communication and collaboration between patients and healthcare providers.

By delving into the complexities of diabetes, researchers aim to uncover new insights into its pathophysiology, identify novel therapeutic targets, and formulate novel strategies for prevention, diagnosis, and therapeutic intervention. Ultimately, the goal of this work on diabetes is to generate knowledge that can translate into tangible improvements in patient care, health outcomes, and quality of life for the well-being of individuals diagnosed with diabetes. Through rigorous research and evidence-based interventions, researchers strive to alleviate the burden of diabetes on individuals, families, and society, ultimately contributing to the collective effort to combat this global epidemic.

1.6 Thesis Objectives

Developing a robust system for diabetes management must not only predict the risk of the disease but also monitor patients' ongoing health metrics to ensure timely interventions. The first component of such a system is a real-time monitoring framework that continuously monitors essential health metrics, including glucose concentrations, blood pressure readings, and body mass index (BMI). This monitoring system gathers patient Information obtained from diverse sources, such as wearable technology and electronic health records, and patient-reported information. By integrating these data into a centralized platform, the system can dynamically assess changes in a patient's health status, identifying potential risk factors in real time. In addition, the system generates alerts when critical thresholds are crossed, signaling healthcare providers or patients to take preventive or corrective action. The continuous monitoring approach is crucial for chronic diseases such as diabetes, where timely interventions can significantly reduce the risk of severe complications.

Building on this monitoring system, the second phase involves the development of a predictive model using machine learning techniques to estimate the likelihood of diabetes onset or progression. After the data is collected and preprocessed, feature selection is carried out to determine the most influential variables, such as age, family history, and lifestyle factors. Machine learning techniques, such as logistic regression, random forests, and support vector machines (SVM), are utilized to discern patterns and correlations within the data. Additionally, advanced models like gradient boosting machines (GBM) and neural networks are explored for their ability to handle complex, non-linear interactions within the dataset. Feature engineering and scaling techniques ensure the data is optimally prepared for these models.

The predictive model is evaluated through metrics such as accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic (ROC) curve (AUC), ensuring that the model provides reliable predictions. Cross-validation techniques are used to avoid overfitting and hyperparameter tuning methods such as grid search are used to optimize model performance. The system is also designed to update its predictions dynamically as new patient data become available through the monitoring system, providing an adaptive framework that evolves with the patient's health status.

Finally, to enhance the transparency and interpretability of this predictive system, an explainable deep neural network (XDNN) is integrated, using a pretrained VGG16 model. VGG16, a convolutional neural network known for its strong performance in image classification tasks, is adapted to process diabetes-related health data see Section 5.2.3. To overcome the "black box" nature of deep learning models, explainability techniques are applied. These methods help in breaking down the model's predictions by identifying the contributions of individual features such as glucose levels or blood pressure changes allowing clinicians to understand why a certain prediction was made.

Incorporating VGG16 into the explainable XDNN model not only boosts prediction accuracy but also provides detailed insights into the underlying factors influencing diabetes risk. This explainable model is crucial in clinical settings, where healthcare providers need to trust and understand the predictions before acting upon them. By leveraging both the predictive power of deep learning and the transparency offered by explainability methods, this system ensures accurate, actionable, and interpretable predictions for diabetes diagnosis and management.

1.7 Thesis Outline

The Introduction section will offer a comprehensive overview of diabetes as a global health concern, highlighting the significance of prompt identification and continuous monitoring to effectively manage the disease. This section will also discuss how recent advances in machine learning and deep neural networks offer significant potential for improving both the prediction and monitoring of diabetes. The problem statement will highlight the challenges faced in detecting diabetes early and continuously tracking its progression, including limitations in current machine learning models that are either predictive or diagnostic but lack real-time monitoring capabilities. The objectives of the thesis will include developing a machine learning-based predictive model for assessing the risk of diabetes. Additionally, building a system capable of real-time monitoring of diabetes progression, and incorporating explainable deep neural networks (XDNN) for transparent, interpretable decision-making. This section will also encapsulate the primary contributions of the thesis, such as combining predictive modeling with real-time monitoring and explainability using the VGG16-based XDNN model. The chapter will conclude by delineating the organization of the thesis and providing a concise overview of the content covered in each section.

In the Literature Review, the thesis will explore existing research on diabetes prediction and monitoring systems, highlighting both traditional machine learning and more recent deep learning approaches. It will review various techniques for predicting diabetes, including logistic regression, random forests, and support vector machines (SVM), while emphasizing the growing use of deep learning models, such as convolutional neural networks (CNNs), for analyzing health data. The review will cover state of the art systems designed for real-time patient monitoring, especially those integrating wearable technologies and electronic health records. Additionally, it will examine the role of deep learning in medical diagnostics, particularly focusing on how models like VGG16, ResNet, and other CNN architectures have been applied to health problems, including diabetes and other chronic diseases. The literature review will also introduce the concept of explainable AI (XAI), examining the increasing necessity for transparency in machine learning algorithms applied within the healthcare sector. The section will conclude by identifying gaps in current research, such as the limited integration of real-time monitoring systems with predictive models and the lack of interpretable deep learning frameworks for diabetes diagnosis.

The System Design and Architecture chapter will begin with an explanation of the data sources used, including public datasets like the Pima Indians Diabetes Database, as well as real-time information gathered from wearable technology or electronic health records. This section will outline the data preprocessing steps, such as handling missing values, feature selection, and data normalization. The design of the real-time monitoring system will follow, detailing how patient health metrics, including glucose levels and other relevant features, are continuously tracked and evaluated. The system architecture will include mechanisms for generating real-time alerts and risk assessments based on the incoming data. Next, the chapter will describe the machine learning models used for diabetes prediction. Traditional models like logistic regression and random forests will be compared to deep learning approaches, with a focus on how the VGG16 CNN architecture is leveraged for prediction tasks. Finally, the chapter will explain the integration of explainability method, focusing on the VGG16-based XDNN model to provide transparent and interpretable predictions, assisting healthcare professionals in comprehending the reasoning underlying the model's conclusions.

In the System Implementation chapter, the thesis will explore the intricate technical aspects involved in the development of the predictive model and the real-time monitoring system. It will describe the development environment, software tools (such as Python, TensorFlow, and Keras), and the infrastructure needed to deploy the system, potentially in a cloud-based environment. The implementation of the predictive model will be covered in depth, including the training, testing, and evaluation of different machine learning algorithms. The real-time monitoring system will be implemented to integrate continuous data streams and provide timely alerts to healthcare professionals. For the explainable XDNN model, the chapter will describe how the VGG16 architecture was adapted for diabetes prediction.

The Experimental Evaluation section will describe the datasets used in training and validating the models, along with the experimental setup, including hardware and software configurations. This section will present a comparative analysis of different machine learning models, evaluating their accuracy, precision, recall, and AUC (Area Under the ROC Curve) metrics. The performance of the VGG16-based XDNN model will be a central focus, especially in comparison to traditional models. The thesis will also evaluate the real-time monitoring system's effectiveness in tracking patient health data, assessing its responsiveness and reliability in issuing alerts. Additionally, the explainability of the XDNN model demonstrating how interprets individual features and provides transparent predictions. Case studies involving patient data will showcase the system's ability to deliver both accurate predictions and understandable explanations for those predictions.

In the Discussion chapter, the thesis will summarize the key findings from the experimental evaluation, particularly how the combination of predictive modeling, real-time monitoring, and explainable AI contributed to the system's success. A comparison of the developed system with existing diabetes prediction and monitoring systems will highlight its strengths, including its real-time capabilities and the transparency offered by the XDNN model. The discussion will also address the limitations of the current system, such as potential biases in the dataset or issues with model generalization. Suggestions for future work will include improving model accuracy, incorporating additional health metrics into the monitoring system, and exploring other deep learning architectures or explainability techniques.

Finally, the Conclusion will recapitulate the thesis's main contributions, such as the development of a hybrid system that integrates predictive modeling, real-time monitoring, and explainable deep neural networks. It will discuss the potential implications for healthcare, emphasizing how this system could improve diabetes management by providing clinicians with both accurate predictions and interpretable insights. The thesis will close with final remarks on the broader impact of AI and machine learning in the healthcare field and their potential to revolutionize chronic disease management.

1.8 Publications

During the course of our research, we have contributed to several publications in the field of machine learning and healthcare:

- Mecili, O., Hadj, B., Nouioua, F., Attia, A., & Akhrouf, S. (2024). An efficient explainable deep neural network classifier for diabetic retinopathy detection. International Journal of Computers and Applications, 46(9): 795-810.
- Mecili, O., Hadj, B., Nouioua, F., Attia, A., & Akhrouf, S. (2024). Efficient Machine Learning Approach for Diabetes Mellitus Disease Prediction. In Proceedings of the PAIS 2024, pp. 1-8.
- Mecili, O., Hadj, B., Nouioua, F., Akhrouf, S., & Malek, R. (2019). The Use of Big Data and Data Analytics in the Prevention, Diagnosis, and Monitoring of Long-Term Diseases. In IMCL 2019, pp. 879-887.

These publications reflect our contributions to the development of innovative solutions in healthcare through the application of machine learning and data analytics.

Chapter 2

State of the Art

The current cutting-edge advancements in machine learning (ML) and deep learning (DL) for the diagnosis and prediction of diabetes reflects significant improvements in both the accuracy and applicability of these technologies in healthcare. Machine learning techniques, such as random forests, support vector machines (SVMs), and gradient stimulation, have been widely adopted to predict the onset of diabetes, using diverse data sources such as demographics, medical history, and lifestyle factors to identify populations at risk. These models have proven highly effective in early detection, allowing timely interventions that can prevent the progression of the disease. In parallel, deep learning, particularly through the use of convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has revolutionized the field by enhancing diagnostic capabilities, especially in the identification of diabetic retinopathy through retinal imaging and predicting future glucose levels from continuous monitoring data. CNNs have shown exceptional performance in medical imaging, identifying features that may avoid human observation, thereby facilitating earlier and more accurate diagnoses.

2.1 Introduction

With the rapid advancement of mobile health (mHealth) technology, mobile applications have become integral tools in the management of diabetes. These applications offer patients real-time access to their health data, including blood glucose levels, dietary intake, physical activity, and medication adherence. By empowering patients to track their health metrics continuously, these apps enable more informed and timely adjustments to their daily routines, contributing to improved glycemic control and a reduction in diabetes-related complications.

Modern diabetes apps incorporate features such as continuous glucose monitoring (CGM) integration, personalized insights, and alerts for abnormal readings. Many also leverage data analytics to predict trends and offer proactive recommendations, enhancing the accuracy of self-management strategies. Furthermore, some applications use artificial intelligence and machine learning to provide personalized feedback and risk assessments. Research, including studies on the effectiveness of mHealth interventions in chronic disease management, suggests that such applications not only increase patient engagement but also improve clinical outcomes [92].

Exploring the latest advancements in diabetes monitoring applications, including functionalities, data-driven insights, and their integration with wearable devices.Also reviewing challenges and areas for future research, such as data privacy, user adherence, and the integration of AI to improve trust and usability among patients and healthcare providers.

Furthermore, the prediction of diabetes using machine learning has become a transformative area in healthcare, offering potential to significantly improve early detection and preventative measures. Diabetes represents an increasingly significant global health issue, profoundly affecting both individuals and healthcare infrastructures. Early detection facilitates prompt interventions that can avert or postpone the emergence of complications associated with diabetes, thereby enhancing patient well-being and decreasing healthcare expenditures.

Machine learning (ML) models are particularly well-suited for this task due to their capacity to process and analyze large, complex datasets, identifying patterns and risk factors that traditional statistical approaches may overlook. These models utilize a wide range of predictive variables, such as lifestyle habits, genetic factors, and biomarkers, to estimate individual risk. Recent technological advancements have further enriched predictive capabilities by integrating electronic health records, data from wearable devices, and genetic information, enabling more precise and personalized predictions.

Current state-of-the-art approaches employ a variety of algorithms, comprising logistic regression, decision trees, support vector machines, and deep learning algorithms, each offering distinct benefits and challenges regarding interpretability, scalability, and computational demand. Additionally, ensemble and hybrid models have shown promise in enhancing prediction accuracy and robustness by combining multiple model types.

The increasing focus on explainability in AI, particularly in deep learning models, addresses the ”black-box” issue, which is critical in gaining the trust of healthcare professionals and patients. Techniques are now commonly used to provide transparency into how the models make predictions, thus ensuring that they can be reliably integrated into clinical workflows. These advances are gradually being incorporated into clinical practice, with electronic health records (EHRs) serving as key data resources for immediate forecasting and decision-making assistance, despite ongoing issues concerning data standardization and the validation of models. Looking forward, the future of ML and DL in diabetes care is poised to move towards more personalized approaches, leveraging comprehensive datasets that include genomic, lifestyle, and continuous monitoring information to further improve prediction accuracy and individualize patient care. As computational capabilities and data availability continue to grow, these technologies are expected to play an even more pivotal role in improving diabetes outcomes on a global scale.

2.2 Introduction to Machine Learning

Machine Learning (ML) represents a specialized area within artificial intelligence (AI) dedicated to the creation of algorithms that can independently identify patterns in data. These patterns are then used to make predictions or decisions on new, unseen instances. Rather than being explicitly programmed for each task, ML algorithms are designed to improve their performance over time by analyzing data and making predictions or decisions on new instances. Essentially, ML uses statistical and optimization techniques to build models that generalize data patterns, enabling predictions for unseen cases [102].

2.2.1 Types of Machine Learning

ML comprises several approaches, each designed for different tasks and data types: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning.

- **Supervised Learning** Involves training an algorithm on labeled data, where each input is paired with the correct output label. The goal is to minimize the difference between the model's predictions and the actual outputs. Common applications include:
    - *Classification* tasks, where the model predicts categorical labels, such as determining whether a patient is likely to develop diabetes or not based on various health metrics.
    - *Regression* tasks, where the model predicts continuous values, such as estimating a patient's blood glucose levels based on age, weight, and family history. This information can support physicians in managing diabetes [59].
- **Unsupervised Learning** Unsupervised learning operates without labeled data, aiming to uncover hidden patterns or structures within the data itself. Typical tasks include:
    - *Clustering*, which groups data points based on similarities. This allows the algorithm to identify natural clusters in the data without predefined labels.
    - *Dimensionality Reduction*, where the goal is to reduce the number of features in a dataset, retaining only the most informative ones that explain the data's variance. Techniques like Locally Linear Embedding (LLE) and Autoencoders, are often employed for dimensionality reduction.
- **Semi-Supervised Learning** This approach uses a mix of labeled and unlabeled data, which is especially useful when labeled data is limited or costly to obtain. By learning from both data types, the algorithm achieves better accuracy and generalization than it

would from labeled data alone. Semi-supervised learning is highly applicable in medical diagnostics, where labeled samples may be scarce [70].

- **Reinforcement Learning** Reinforcement learning involves an agent interacting with an environment to perform actions that maximize a reward over time. Based on trial and error, the algorithm learns the best actions to take to achieve a cumulative reward. This approach is widely used in robotics and can also apply to certain medical diagnostics tasks. Reinforcement learning techniques include Deep Q-Network and Policy Gradient methods [113].

2.3 Machine Learning Pipeline

The machine learning (ML) pipeline is a framework that organizes the overall process of developing a machine learning model, from data acquisition through to model evaluation. It ensures a systematic and efficient approach to building accurate ML models. This section outlines the key components of the ML pipeline, along with best practices.

- **Data Collection and Preparation**
  The initial stage of the ML pipeline involves gathering and preparing data, including identifying relevant data sources, cleaning the data, and preprocessing it for modeling. Data quality is critical, as it directly impacts model performance. This stage may include exploratory data analysis and partitioning the dataset into training, validation, and testing subsets.

- **Data Exploration and Visualization**
  Statistical methods and data visualization tools, including scatter plots, histograms, and heat maps, are utilized to uncover patterns and relationships among variables. Prior to model training, it is crucial to resolve any data quality concerns, such as absent values or anomalies, to improve the accuracy and dependability of the model.

- **Feature Engineering**
  This stage generally involves feature extraction and feature selection. Feature extraction transforms raw data into formats suitable for ML algorithms. Feature selection, on the other hand, focuses on selecting the most relevant subset of features to reduce redundancy and prevent overfitting. Recursive Feature Elimination (RFE) is a popular method in this stage, which iteratively removes less important features, refining the model to retain only those features that contribute significantly to its predictive performance.

- **Model Selection, Data Split, and Training**
  Based on the problem type, data characteristics, and desired performance, an appropriate ML algorithm is selected, often requiring experimentation with different algorithms.

Typically, The dataset is partitioned into training and testing subsets, typically with a distribution of 70-80% allocated for training and 20-30% reserved for testing, ensuring the testing set remains independent of training. Throughout the training process, the algorithm is calibrated to the training dataset, modifying its parameters or weights to reduce prediction inaccuracies. In the context of clustering tasks, the model seeks to categorize similar data points while distinguishing dissimilar ones by optimizing inter-cluster distances and minimizing intra-cluster distances. In dimensionality reduction tasks, the model seeks to reduce the dimensionality of the data while preserving its essential features.

- **Performance Evaluation**

  The accuracy ratio is defined as the fraction of accurately predicted samples relative to the total number of samples, as expressed in the corresponding Equation[2.3]. Precision is defined as the proportion of true positive predictions relative to the total number of instances classified as positive, as expressed in the following Equation[2.4]. Recall, often referred to as sensitivity or the true positive rate, is defined as the proportion of accurately predicted positive instances relative to the total count of actual positive instances. This metric can be computed using the following Equation[2.5]. Ultimately, the F1-score represents the harmonic mean of precision and recall, serving as a balanced measure between the two metrics. It is expressed mathematically by the following Equation[2.7].

  - **Confusion Matrix:** A confusion matrix serves to illustrate the effectiveness of a model by organizing the actual and predicted class labels into a table format. It includes: True Positive (TP), which refers to the instances that were accurately predicted as positive; False Positive (FP), which denotes instances incorrectly classified as positive; True Negative (TN), representing the instances accurately identified as negative; and False Negative (FN), which indicates instances mistakenly classified as negative. This matrix offers valuable insights into the nature and frequency of errors committed by the model, thereby assisting in the identification of performance shortcomings and the refinement of the model.

$$TrueNegativeRate = \frac{TrueNegative}{TrueNegative + FalsePositive} \tag{2.1}$$

$$TruePositiveRate = \frac{TruePositive}{FalseNegative + TruePositive} \tag{2.2}$$

Table 2.1: Confusion matrix

	Predicted	
Actual	Positive	Negative
Positive	TP	FN
Negative	FP	TN

- **Accuracy** This metric quantifies the ratio of accurately classified instances relative to the total number of instances, thereby assessing the overall accuracy of the model's predictions across all categories. It is formally defined as:

$$Accuracy = \frac{NumberOfCorrectpredictions}{Totalnumberofpredictionsmade} = \frac{TP+TN}{TP+TN+FP+FN} \tag{2.3}$$

  In this context, TP refers to True Positives, FP denotes False Positives, and TN signifies True Negatives. FN represents False Negatives. The accuracy metric is particularly useful in balanced datasets, where the number of instances across different classes is roughly equal. However, it may not be as informative in imbalanced datasets, where one class significantly outnumbers the others. In such cases, relying solely on accuracy can lead to misleading conclusions about the model's performance.

- **Precision** assesses the ratio of true positive predictions relative to the total number of positive predictions generated by the model. This is computed as:

$$Precision = \frac{TP}{TP+FP} \tag{2.4}$$

- **Sensitivity (Recall or True Positive Rate)** The metric represents the proportion of true positive instances accurately recognized by the model out of the total actual positive cases. It quantifies the ratio of correctly identified true positive predictions made by the model. The formula for this metric is as follows:

$$Sensitivity = Recall = \frac{TP}{TP+FN} \tag{2.5}$$

- **Specificity** Referred to as the true negative rate, this metric quantifies the ratio of actual negative cases that the model accurately identifies as negative. It is calculated as follows:

$$Specificity = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}} \tag{2.6}$$

  In this context, TN represents the count of true negatives, while FP denotes the count of false positives.

- **F1-Score** The F1-score represents the harmonic mean of precision and recall, offering a unified metric that reconciles both measurements. Its calculation is as follows:

$$F1-score = 2 * \frac{Precision * Recall}{Precision + Recall} = 2 * \frac{1}{\frac{1}{precision} + \frac{1}{recall}} \tag{2.7}$$

- **ROC-AUC** This metric is extensively utilized to evaluate the efficacy of binary classification models by quantifying the area beneath the Receiver Operating Characteristic (ROC) curve. An elevated ROC-AUC score signifies superior model capability in differentiating between the two classes. The ROC curve illustrates Sensitivity (True Positive Rate) in relation to the False Positive Rate (FPR) across diverse threshold levels. In mathematical terms, ROC-AUC can be expressed as:

$$\text{ROC-AUC} = \int_0^1 \text{Sensitivity}\big(\text{FPR}^{-1}(t)\big)\,dt$$

where $\text{FPR}^{-1}(t)$ represents the inverse function of the False Positive Rate at threshold t.

- **Area Under the Curve (AUC):** The Area Under the Curve (AUC) quantifies the model's capacity to differentiate between distinct classes. The AUC-ROC (Receiver Operating Characteristic) curve illustrates the relationship between the true positive rate (TPR) and the false positive rate (FPR) across a range of threshold values. This metric is measured on a scale from 0 to 1, with a higher AUC value signifying superior model performance due to its enhanced capacity to differentiate between classes [14].

- **Cohen's kappa coefficient (κ):** Cohen's kappa (as shown in Equation 2.8) serves as a statistical tool for evaluating the reliability between raters (or within a single rater) [24]. This measure is frequently regarded as more reliable than basic agreement statistics, as it takes into consideration the probability of agreement happening by mere chance. The definition of Cohen's kappa is as follows:

$$\kappa = \frac{p_o - p_e}{1 - p_e} = 1 - \frac{1 - p_o}{1 - p_e}, \tag{2.8}$$

In this context, p_o denotes the observed level of agreement, while p_e signifies the anticipated level of agreement.

Equation 2.9 further provides a form of Cohen's kappa derived from the confusion matrix, showing how much better the classifier performs compared to a random classifier that guesses according to class frequencies:

$$\kappa = \frac{2 \times (TP \times TN - FN \times FP)}{(TP + FP) \times (FP + TN) + (TP + FN) \times (FN + TN)}, \tag{2.9}$$

In this context, TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively.

In this study, we evaluated classifier effectiveness using the following metrics: **Sensitivity (Precision)**, **Specificity (Recall)**, **Accuracy (ACC)**, **F1-Score (F1)**, and the **Area Under the ROC Curve (AUC-ROC)**.

Model evaluation is essential to determine the model's performance in predicting outcomes for new, unseen data. Various metrics, depending on the problem and model type, are used to evaluate performance, including accuracy, precision, sensitivity (or recall), F1-score, ROC-AUC, and specificity. These metrics reveal model strengths and weaknesses and guide further tuning or model selection.

2.3.1 Model Validation

In the ML pipeline, model validation is crucial to evaluate a model's performance on new data. Common validation techniques include k-fold Cross-Validation and Leave-One-Out Cross-Validation (LOOCV). This work employs k-fold Cross-Validation, in which the dataset is divided into k subsets. The model is trained k times, each time using $k-1$ subsets for training and the remaining subset for validation. After calculating the evaluation metrics for each fold, the average metric is considered as the final performance metric. Algorithm 1 describes the k-fold Cross-Validation process.

Algorithm 1 k-Fold Cross-Validation

```
Require: $X$: training data, $k$: number of folds
Ensure: Average performance metric of the model
Divide $X$ into $k$ equal-sized folds
for $i \leftarrow 1$ to $k$ do
    $X_{\text{test}} \leftarrow i$-th fold
    $X_{\text{train}} \leftarrow X$ with $X_{\text{test}}$ removed
    Train the model on $X_{\text{train}}$
    Test the model on $X_{\text{test}}$
    Calculate performance metric on $X_{\text{test}}$
    Add performance metric to list
end for
Calculate the average of the performance metrics
```

2.3.2 Hyper-Parameter Tuning

Hyper-parameters are parameters that influence the behavior of the learning algorithm, and their optimal selection is crucial for achieving high model performance. Various techniques for hyper-parameter tuning include GridSearch, Random Search, and Bayesian Optimization. In this study, GridSearch was used, which exhaustively searches through a predefined set of hyper-parameters and selects the set that maximizes model performance. The process of GridSearch is illustrated in Algorithm 2.

Algorithm 2 GridSearch for Hyper-Parameter Tuning

```
Require: Set of hyper-parameters, evaluation metric
Ensure: Optimal set of hyper-parameters
for each combination of hyper-parameters do
    Train model with current combination of hyper-parameters
    Evaluate model using chosen evaluation metric
    Record performance and corresponding hyper-parameters
end for
Select the hyper-parameters with the best performance
```

2.4 Diabetes Datasets

2.4.1 Textual Datasets

In the field of diabetes diagnosis and prediction, various datasets play a crucial role in developing and validating machine learning (ML) and deep learning (DL) models. These datasets provide the foundation for training methods for detecting patterns, predict disease onset, and assist in managing the condition.

- **Pima Indians Diabetes Dataset** One of the most widely used datasets [104], which contains medical records of Pima Indian women, including features such as glucose levels, blood pressure, and body mass index (BMI). This dataset is popular due to its well-structured data and has been extensively used to train models that predict diabetes risk based on common health indicators.

- **Diabetes 130-US Hospitals Dataset** [111] is another significant resource, containing clinical care data from 130 U.S. hospitals over ten years. This dataset includes detailed information about patient demographics, diagnoses, lab results, and medications, making it valuable for more complex predictive modeling and analysis of hospital readmission risks for diabetic patients.

- **MIMIC-III Database** For researchers focused on critical care, the (Medical Information Mart for Intensive Care) database [58] is invaluable. It provides comprehensive, anonymized health information from more than 40,000 individuals, including vital signs, lab results, and glucose levels. This dataset is particularly useful for developing models that predict complications and manage diabetes in critical care settings.

- **NHANES Dataset** The NHANES (National Health and Nutrition Examination Survey) dataset [20] offers a broader population-based dataset, including health and nutritional data of U.S. adults and children. This dataset is frequently used to study the impact of various factors, such as diet and lifestyle, on the risk of developing diabetes.
- **UK Biobank** Another large-scale resource is the UK Biobank [112], which contains extensive genetic and health information from half a million UK participants. The dataset includes glucose levels, insulin sensitivity, and other metabolic markers, providing a rich source of data for research into the genetic and environmental factors contributing to diabetes.
- **Diabetes in Children and Adolescents Dataset** In the realm of pediatric diabetes, the Diabetes in Children and Adolescents Dataset [33] focuses on younger populations, providing data that helps in understanding and predicting diabetes onset and progression in children and adolescents. This dataset is crucial for developing age-specific predictive models and understanding the different risk factors in younger patients.
- **Diabetes and Lifestyle Dataset** For studies exploring lifestyle impacts, the Diabetes and Lifestyle Dataset [18] includes information on diet, exercise, and other lifestyle factors alongside medical data. This dataset allows researchers to investigate how lifestyle modifications can reduce diabetes risk or improve management in diagnosed patients.
- **Kaggle Diabetes Datasets** Lastly, the Kaggle Diabetes Datasets [60] offer a variety of community-contributed datasets that cover a wide range of diabetes-related topics. These datasets are often used in competitions and research projects to develop new algorithms and approaches for diabetes prediction and management.

These datasets are integral to advancing research in diabetes, enabling the development of robust ML and DL models that can improve the early diagnosis, prediction, and management of diabetes across different populations and healthcare settings.

2.4.2 Retinal Datasets

This section outlines publicly available retinal image databases commonly used for research in retinal image analysis, specifically for studying diabetic retinopathy and other retinal conditions. These databases, include DRIVE, STARE, DIARETDB, eophtha, HEIMED, Retinopathy Online Challenge (ROC), Messidor, and CHASE_DB1. Each dataset offers unique characteristics, such as image resolution, field of view (FOV), and labeling details, which make them valuable for training and validating machine learning models aimed at automated identification and assessment of retinal disorders.

- **DRIVE Dataset** (Digital Retinal Images for Vessel Extraction) dataset contains 40 color fundus images accompanied by accurate vessel segmentation as the ground truth. This database was sourced from a diabetic retinopathy screening program in the Netherlands. Images were captured using a Canon CR5 non-mydriatic 3CCD camera, with a 45-degree FOV and a resolution of 768×584 pixels at 24-bits per pixel. Each image, JPEG-compressed, has a circular FOV mask of approximately 540 pixels in diameter. The dataset includes a balanced split of 20 images for training and 20 for testing, representing a patient population aged 25 to 90 years[109].
- **STARE Dataset** (Structured Analysis of the Retina) database consists of 20 retinal fundus images, each paired with ground truth vessel segmentation. Captured with a Topcon TRV-50 fundus camera at a 35-degree FOV, the images have a resolution of 605×700 pixels with 24-bits per pixel. Experts manually labeled each image for vessel segmentation [50]
- **ARIA Online Dataset** The ARIA (Automated Retinal Image Analysis) dataset, developed through collaboration between St. Paul's Eye Unit and the University of Liverpool, UK, contains three image sets: 92 images depicting age-related macular degeneration, 59 images of diabetic retinas, and 61 images from a control group. Expert annotations are provided for blood vessels, optic disc, and fovea locations. Each image was captured with a Zeiss FF450+ fundus camera at a 50-degree FOV and a resolution of 768×576 pixels in RGB, stored in uncompressed TIFF format[75]
- **Image-Ret Dataset** consists of two sub-datasets, DIARETDB0 and DIARETDB1. DIARETDB0 includes 130 images, 20 of which are from healthy retinas, while the remaining 110 show various signs of diabetic retinopathy. DIARETDB1 has 89 images, with 5 healthy images and 84 showing mild proliferative diabetic retinopathy signs. Expert annotations identify microaneurysms, hemorrhages, and exudates. Images were captured with a 50-degree FOV, with a resolution of 1500×1152 pixels in PNG format[69]
- **REVIEW Dataset** The REVIEW (Retinal Vessel Image set for Estimation of Widths) dataset includes 16 high-resolution mydriatic images with 193 annotated vessel segments and 5066 labeled profile points, providing data for vessel width estimation. The images are categorized into four distinct subsets: the high-resolution image set (HRIS), the vascular disease image set (VDIS), the central light reflex image set (CLRIS), and the kick point image set (KPIS), supporting detailed analysis of retinal vessel features[3]
- **MESSIDOR Database** The MESSIDOR database comprises 1200 color fundus images in TIFF format, captured by three ophthalmology departments employing a Topcon TRC

NW6 non-mydriatic retinograph featuring a 45-degree field of view. The images, each 8 bits per color plane, come in resolutions of 1440 × 960, 2240 × 1488, or 2304 × 1536 pixels. Of these, 800 images were taken with pupil dilation (using one drop of 0.5% Tropicamide) and 400 without dilation. This database, which is meticulously labeled with diabetic retinopathy (DR) grades for each image, is specifically created to assess and contrast algorithms for retinal lesion segmentation. The images are classified into five separate categories. They are further divided into three groups that align with the ophthalmology departments, with each group containing four compressed subsets of 100 images in TIFF format. Additionally, an Excel file is provided, detailing the medical diagnoses associated with each image. It is important to note that while the MESSIDOR database contains medical diagnoses, it does not include manual annotations like lesion contours or their locations. This extensive database is among the largest accessible resources, aimed at supporting the advancement of Computer-Assisted Diagnosis (CAD) systems for Diabetic Retinopathy (DR). [29].

- **APTOS Dataset** The APTOS dataset, hosted on Kaggle, comprises 3662 color fundus images captured using various cameras, resulting in different sizes and quality levels, reflecting real-world variations due to different camera settings at the capture centers. Curated by Aravind Eye Hospital in India and associated with the Asia Pacific Tele-Ophthalmology Society (APTOS), the dataset aids in developing and evaluating algorithms for automated diabetic retinopathy (DR) detection and classification. The images are categorized into five severity levels of DR: No DR, Mild DR, Moderate DR, Severe DR, and Proliferative DR. The ground truth labels for the training set are publicly available, including expert annotations. The dataset exhibits significant class imbalance, with a majority of images showing normal retinas (1805 images) and a smaller number depicting severe Non-Proliferative Diabetic Retinopathy (NPDR) (183 images), posing a challenge for model training due to potential bias towards the majority class. Techniques like oversampling, undersampling, or using class-weighted loss functions may be necessary to address this imbalance. The variability in image quality and resolution due to different camera settings adds to the dataset's value, as it simulates real-world conditions and helps test the robustness and generalization capabilities of Computer-Assisted Diagnosis (CAD) systems for DR. Accessible on Kaggle, the APTOS dataset supports competitions and research initiatives aimed at improving automated DR detection, providing a benchmark for researchers and practitioners to compare and advance their models in ophthalmic AI applications [108].

- **IDRiD Dataset** The IDRiD (Indian Diabetic Retinopathy Image Dataset) serves as a comprehensive and publicly accessible resource dedicated to diabetic retinopathy research, comprising 516 high-resolution retinal fundus images collected from diabetic patients. These images are strategically divided into training and testing sets, each meticulously annotated with diabetic retinopathy (DR) severity levels and detailed markings of lesions such as microaneurysms, hemorrhages, soft exudates, and hard exudates. Captured using high-resolution fundus cameras, the images reflect the diversity and variability found in clinical practice, enhancing the robustness of models trained on this data. The dataset supports a wide range of applications, including DR classification and fine-grained grading, lesion detection, and segmentation, making it invaluable for developing and evaluating machine learning algorithms. Widely embraced in the research community, the IDRiD dataset facilitates the advancement of Computer-Assisted Diagnosis (CAD) systems, aiding in early detection and treatment of diabetic retinopathy. Its public availability ensures global access, fostering collaboration and accelerating progress in the field. As a cornerstone of diabetic retinopathy research, IDRiD's comprehensive annotations and high-quality images are critical for improving the accuracy and reliability of automated DR detection and assessment systems [90].

These datasets are valuable resources for developing and testing machine learning algorithms for retinal image analysis, particularly in the diagnosis and management of diabetic retinopathy and other retinal conditions [76].

2.5 Related Work

2.5.1 Medical Mobile Applications for Diabetes Management

The growing mobile platform offers significant advantages to both healthcare professionals and patients through the advancement of various medical mobile applications. Millions of people gain access to essential healthcare services, simplifying their daily lives. A simple search on Google Play or the Apple Store reveals numerous applications focused on diabetes self-management. However, only a few are openly accessible, while others offer some functionalities as premium features for an additional cost.

The features across these applications generally include reminders, medication tracking, and blood glucose level logging. Some applications also provide guidance on diet, physical exercise, weight management, and blood pressure control. Additional features in certain apps include alerts/notifications and integration with social media platforms such as Facebook and Twitter.

In an investigation of a digital community designed for individuals with type 2 diabetes to document, track, and voluntarily share their recent hemoglobin A1c levels via a geographic interface, researchers discovered that the data submitted by patients was up-to-date, with 83.1% of the latest HbA1c values recorded within the preceding 90 days. [103]. According to El-Gayar et al. [34], providing patients with individual analysis and interpretation of their health data would be advantageous. However, most applications only offer insulin dosage suggestions based on data recorded on the patient's device, limiting the app's effectiveness as it lacks the integration of the patient's clinical history [57]. Furthermore, research indicates that self-management education positively impacts clinical outcomes for diabetes patients [17].

A comprehensive review of mobile apps for diabetes management by Demidowich et al. [30] identified challenges in achieving widespread adoption due to concerns over data security and privacy. Similarly, research by Kebede et al. [64] emphasized the importance of involving healthcare professionals in app development to ensure clinical relevance and accuracy.

One significant issue not fully addressed by developers is usability, which is crucial for ensuring ease of use and delivering an effective, efficient, and satisfying user experience [106]. Developing reliable and legally compliant medical applications is essential to support adoption by both patients and healthcare providers. Medical mobile apps fall into five common categories as shown in Fig. 2.1 [32]. Unfortunately, not all digital interventions are successful. Many medical mobile apps fail to meet user expectations due to poor user experience, confusing interfaces, and limited functionality.

To improve diabetes management applications, several strategies can be adopted:

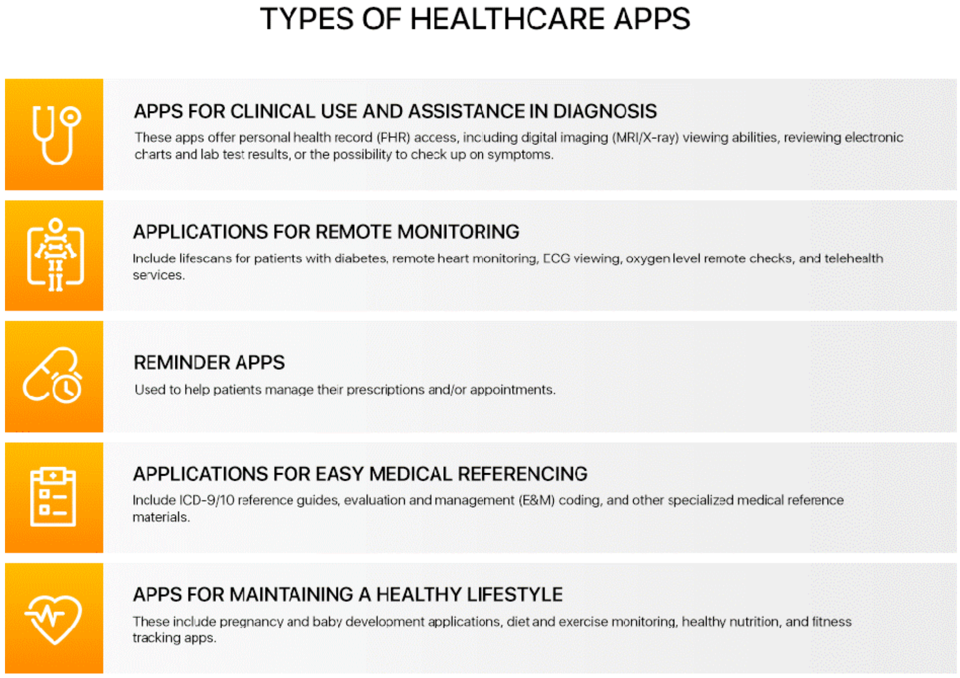
- **Integration with Clinical Systems:** Linking apps with electronic health records (EHR) can provide a complete view of a patient's history [88].
- **Personalized Recommendations:** Using machine learning and AI to tailor advice based on individual user data [72].
- **Advanced Analytics:** Providing actionable insights by analyzing trends in blood glucose levels and other health metrics [95].
- **Enhanced Usability:** Conducting extensive user testing to ensure intuitive interfaces and workflows [41].

The development of medical mobile apps for diabetes management presents an excellent opportunity to enhance patient care and support self-management. However, challenges such as usability, functionality, and clinical data integration need to be addressed to maximize their impact. Future efforts should focus on improving user experience, ensuring reliability, and aligning with healthcare standards to increase adoption and effectiveness.

2.5.2 Prediction

The prediction of diabetes remains a complex challenge with significant implications for public health. This review examines existing research on machine learning approaches for diabetes prediction, identifying key findings, limitations, and opportunities for improvement.

To predict diabetes, Sisodia et al [101] study achieved a reported accuracy of 76.3% utilizing three distinct machine learning methods: Decision tree (DT), naive Bayes classifier (NB), and support vector machine (SVM). The dataset employed for their analysis is the Pima Indians Diabetes Database (PIMA), sourced from the UCI machine learning repository [101].



TYPES OF HEALTHCARE APPS

APPS FOR CLINICAL USE AND ASSISTANCE IN DIAGNOSIS

These apps offer personal health record (PHR) access, including digital imaging (MRI/X-ray) viewing abilities, reviewing electronic charts and lab test results, or the possibility to check up on symptoms.

APPLICATIONS FOR REMOTE MONITORING

Include lifescans for patients with diabetes, remote heart monitoring, ECG viewing, oxygen level remote checks, and telehealth services.

REMINDER APPS

Used to help patients manage their prescriptions and/or appointments.

APPLICATIONS FOR EASY MEDICAL REFERENCING

Include ICD-9/10 reference guides, evaluation and management (E&M) coding, and other specialized medical reference materials.

APPS FOR MAINTAINING A HEALTHY LIFESTYLE

These include pregnancy and baby development applications, diet and exercise monitoring, healthy nutrition, and fitness tracking apps.

Figure 2.1: Common Features in Diabetes Management Mobile Applications

A data mining pipeline is used by Dagliati et al. [27] to develop a set of prediction models for type 2 diabetes Mellitus (T2DM). The obtained accuracy is up to 83.8%.

In their study, Faruque et al. [37] used several machine learning algorithms, including Support Vector Machine (SVM), Naive Bayes (NB), K-Nearest Neighbor (KNN) and the C4.5 Decision Tree, to predict diabetes mellitus. Specifically, the C4.5 classifier achieved a recall rate of 74% on a data set that contains numerous characteristics or risk factors related to diabetes mellitus, encompassing information from 200 patients.

K-means clustering techniques and Naive Bayes Tree and C4.5 decision tree-based classification algorithms are utilized by Fiarni and colleagues [40] using a diabetic medical record from three sources, in Indonesia. The suggested model's total accuracy is 68 %.

In [80], Nongyao et al. use data from 26 primary Care units they evaluated four classification techniques: decision tree, artificial neural network, logistic regression, and Naive Bayes. All were subjected to further bagging and boosting, as well as the random forest. All the participants' greatest accuracy is between 84 and 86

Hasan et al. [49] employed a comprehensive approach, including outlier rejection, data standardization, feature selection, K-fold cross-validation, and various machine learning classifiers (k-nearest Neighbor, Decision Trees, Random Forest, AdaBoost, Naive Bayes, and XGBoost), along with Multilayer Perceptron (MLP). They achieved an impressive 95% area under the curve (AUC) using the Pima Indian Diabetes Dataset.

Kaur and colleagues [63] utilized supervised machine learning algorithms such as linear kernel support vector machine (SVM-linear), radial basis function (RBF) kernel support vector machine, k-nearest neighbor (k-NN), artificial neural network (ANN), and multifactor dimensionality reduction (MDR). They obtained AUC values of 90% and 92% for the SVM-linear and k-NN models, respectively.

On the Pima Indian Diabetes Dataset, Nnamoko et al. [82] performed data preprocessing methods such as the IQR algorithm, enhanced the data with oversampling, and tackled class imbalances with SMOTE. For classification, they use Naïve Bayes, SVM-RBF, C4.5, and RIPPER, and they get 89.5% accuracy, 90% precision, 89.4% recall, 89.5% F-score, and 83.5% Kappa.

For diabetic classification and prediction applied on the PIMA Indian Diabetes dataset, a fine-tuned MLP and LSTM proposed by Butt et al.[19] get an accuracy of 86.083% and 87.26%, respectively.

Wang et al.[116] propose an organized framework for diabetes prediction using ML algorithms. However, the classification accuracy of the proposed system is not good. They present a pipeline strategy to predict diabetes and improve classification accuracy.

A condensed overview drawn from state-of-the-art methods in diabetes prediction is shown in Table 2.2, summarizing challenges in accurate diagnosis, the effectiveness of machine learning algorithms, and the crucial role of preprocessing medical data. It also presents performance metrics achieved by various models, offering insights for further research to improve the precision and reliability of diabetes prediction. While machine learning algorithms have emerged as promising tools in this endeavor, their full potential has yet to be realized, indicating a need for further investigation and refinement. Particularly noteworthy is the significant influence of preprocessing medical data, which poses a substantial hurdle in accurately categorizing patients. Additionally, the optimization of hyper-parameters through techniques such as fine-tuning is essential for enhancing prediction accuracy and robustness.

2.5.3 Diagnosis

Timely identification of Diabetic Retinopathy (DR) is essential for successful treatment, The condition frequently presents without symptoms during its early phases. Automated detection systems offer considerable advantages, such as enhanced screening efficiency, greater access to healthcare in isolated regions, and the promotion of proactive disease management. These innovations lead to improved patient outcomes and assist in alleviating the overall impact of the disease.

Despite the development of various models, significant improvements are still needed, particularly in multiclass classification. Numerous machine learning (ML) models have been explored in research, but their classification performance remains suboptimal, even though they are less complex than deep learning (DL) models. To address these limitations, researchers have increasingly turned to transfer learning (TL) models, which are designed to enhance per-

Table 2.2: Comparative performance of the state-of-the-art works on the same dataset.

Reference	Dataset	Preprocess Methods	Classifiers	Performance
[101]	PIMA	—	NB, SVM, DT	ACC:76.30% PR:75.9% Rec:76.3%
[27]	clinical data from the EHR	missing data using random forest (RF), handle class imbalance	LR	ACC:83.8%
[37]	Medical Centre Chittagong (MCC)		SVM, NB, KNN and C4.5	Rec:74%
[40]	Diabetic medical record from three sources	—	SVM, NB, KNN and C4.5	ACC:68%
[80]	Data from 26 primary Care units	—	DT, ANN, LR, NB, Bagging and Boosting	ACC:85.56%
[49]	PIMA	outlier rejection, filling missing values, standardization	KNN, DT,RF, AdaBoost, XGBoost and Multilayer Perceptron (MLP)	AUC:0.95%
[63]	PIMA	—	SVM-linear, RBF, k-NN, ANN and MDR	AUC:0.92%
[82]	PIMA	IQR, SMOTE	Naïve Bayes, SVM-RBF, C4.5 and RIPPER	ACC:89.5%
[19]	PIMA	—	MLP, LSTM	ACC:87.26%
[116]	PIMA	filling missing values, Feature selection, SMOTE	nCART	ACC:87.10%

formance. However, TL models present a challenge: their large number of parameters and layers results in prolonged training times.

Nguyen et al. [81] proposed a five-class classification framework to detect and categorize Diabetic Retinopathy (DR) across five severity stages, from 0 (no DR) to 4 (proliferative DR). They implemented transfer learning techniques utilizing VGG-16 and VGG-19 models and evaluated their method on the EyePacs dataset. Their best results reported an accuracy of 82.0%, a sensitivity of 80.0%, and a specificity of 82.0%. However, performance for classes 3 and 4 was comparatively lower, mainly due to class imbalance issues. Although the authors applied data augmentation techniques, the scarcity of samples for classes 3 and 4 was not adequately mitigated.

In another study, Zhang [122] employed EfficientNet-B3 as the core architecture for developing Diabetic Retinopathy (DR) detection models, using a dataset comprising 38,788 labeled images. On the test set, the proposed model achieved a Kappa score of 93.5%. The author claimed that the model's diagnostic performance was comparable to that of experienced human specialists.

In [51], Hossen et al. proposed a Diabetic Retinopathy (DR) detection technique based on the DenseNet-121 architecture. The method was evaluated on the APTOS dataset and demonstrated strong performance, achieving an accuracy of 94.9%, a sensitivity of 92.6%, and a specificity of 97.1%. Additionally, their model attained a weighted Kappa score of 88%.

In [68], Kumar et *al.* introduced ensemble classification methods along with vessel segmentation for the identification of diabetic retinopathy. Although the paper presents a novel and potentially effective approach for predicting retinal diseases through deep learning techniques, it lacks comprehensive information regarding the datasets employed for testing the proposed method and the performance metrics applied to assess its efficacy. This absence of critical details hampers the ability to compare and evaluate the proposed techniques in relation to existing methods in the research literature.

Alam et al. [4] introduced an innovative approach for the early detection of proliferative diabetic retinopathy by integrating a Deep Convolutional Neural Network (DCNN) with vascular segmentation techniques. Evaluated on the MESSIDOR-2 dataset, their method achieved a remarkable area under the curve (AUC) of 96.9%, along with an accuracy of 94.1%, specificity of 95.7%, and sensitivity of 92.7%. These outcomes demonstrate the effectiveness of their system in differentiating between healthy and pathological retinal images.

Diware and colleagues implemented a machine learning model using the DN121-L architecture and evaluated its performance on the Messidor2 dataset. Their model achieved an accuracy of 90.3% and an F1-score of 81.8% in diabetic retinopathy detection[31]

Saeed Parsa et al utilize self-supervised learning, specifically the BYOL technique, for pretraining neural networks on unlabeled data, combined with deep ensemble learning for diabetic retinopathy (DR) grading they validate their approach on the IDRiD and Messidor datasets, achieving notable accuracies of 71.84% and 75.42%, specificities of 88.76% and 87.13%, with AUC values of 86.02% and 86.54%, respectively [87].

Extensive experiments conducted using the APTOS 2019 DR dataset demonstrated that the baseline model, DenseNet-121, achieved an average accuracy of 0.9746 and an AUC of 0.995. Upon integrating the local branch, the AG-CNN significantly improved performance, reaching an average accuracy of 0.9848 and an AUC of 0.998. This represents a notable advancement in state-of-the-art performance within the field [78].

The research conducted by Santos et al. [94] presents an innovative Siamese Convolutional Neural Network (SCNN) aimed at predicting diabetic retinopathy (DR), which is applicable for use by primary care practitioners. This SCNN evaluates pairs of eye fundus images and employs shared weights throughout its layers to extract critical features, facilitating the assessment of similarity between the outputs of the neural network. The model was evaluated on four datasets (IDRiD, APTOS, Messidor-1, DIARETDB0), achieving accuracy rates that varied from 67.23% (APTOS) to 96.85% (DIARETDB0).

Also HRUNet achieves accuracy rates of 94% on the Asia Pacific Tele-Ophthalmology Society (APTOS) dataset and 91% on the KAGGLE dataset. The model has a total of 6,315,732 trainable parameters. [93].

Yipeng Wang and colleagues [117] employ a graph convolutional network (MDGNet) with dynamic weight fusion of multi-scale local features for diabetic retinopathy grading. Their approach yields results on both the Aptos and DDR datasets, achieving an accuracy of 84.31% and 81.25% respectively. For the Aptos dataset, they report an F1-score of 69.69%, precision of 72.27%, recall of 67.84%, and AUC of 81.89%. For the DDR dataset, they report an F1-score of 59.18%, precision of 63.91%, recall of 56.93%, and AUC of 75.34%.

The original DCNN Inception-Resnet-v2 was refined by modifying the fully connected layers. Subsequently, this optimized CNN was trained on the EyePACS dataset utilizing a cosine learning rate decay with a warm-up phase. Ultimately, the developed model underwent evaluation on eight publicly available datasets as reported by Chetoui et al.[23]. They achieved their best result with an AUC of 99.0% on the UoA-DR dataset.

Ioannou et al [54] used three distinct CNN-based network architectures: DenseNet, InceptionV3 and EfficientNetB0. The models underwent training for Diabetic Retinopathy (DR) grading classification on IDRiD and DDR datasets independently. Image augmentation techniques, including random zooms, rotations, and flips, were applied. EfficientNetB0 proved to be the most suitable architecture for this task, achieving an overall accuracy of 60.19% on IDRiD and 73.56% on DDR.

Boreiko et al [13] involved ensembling a conventional model with an adversarially robust counterpart, intending to maintain high accuracy while improving the interpretability of visual explanations. Notably, the ensemble demonstrated the capacity to generate meaningful visual counterfactuals, complementing traditional saliency-based techniques. The experiments utilized three publicly available datasets of retinal fundus images annotated with Diabetic Retinopathy (DR) grades. The ensemble achieved an accuracy of 89.7% on Kaggle dataset and 87.9% on Messidor.

Jang et al [55] presented an explainable diabetic retinopathy classification method based on neural-symbolic learning which generated a high-level symbolic representation via a segmentation network. The DR severity is predicted by the fully connected network, which was trained using the extended symbolic representation achieved 63.11% accuracy on kaggle Dataset.

In [96] Shorfuzzaman et al propose the development of an explainability approach that utilizes gradient-weighted class activation mapping and Shapley adaptive explanations to emphasize areas in fundus images indicative of various Diabetic Retinopathy (DR) stages. This enables medical professionals, particularly ophthalmologists, to comprehend the decision-making process of their model. The evaluation results, conducted across three distinct datasets (APTOS, MESSIDOR, IDRiD), showcase the effectiveness of their model. It achieved superior classification rates, boasting high precision (97.0%), sensitivity (98.0%), and AUC (97.8%).

Utilizes a comprehensive multi-phase approach that includes data pre-processing, feature extraction through a hybrid CNN-SVD model, and classification employing Improved Support Vector Machine-Radial Basis Function (ISVM-RBF), Decision Trees (DT), and K-Nearest Neighbors (KNN) methodologies. Thoroughly evaluated on the IDRiD dataset, which is categorized into five levels of severity, the hybrid model demonstrates exceptional performance metrics, achieving an accuracy of 99.18%, sensitivity of 98.15%, and specificity of 100% in the detection of Vision-Threatening Diabetic Retinopathy (VTDR) [10].

Another study [12] introduces “NIMEQ-SACNet,” a novel hybrid model combining the Enhanced Quantum-Inspired Binary Grey Wolf Optimizer (EQI-BGWO) with a self-attention capsule network for improved VTDR classification. The proposed approach advances Binary Grey Wolf Optimization with Quantum Computing methodologies and applies the enhanced EQI-BGWO to finely tune SACNet’s parameters.

Bilal et al [11] this study introduces an innovative AI-based framework for the detection of VTDR, which employs a majority voting mechanism to integrate various models. The methodology encompasses thorough preprocessing, data augmentation, and feature extraction through a hybrid convolutional neural network-singular value decomposition (CNN-SVD) model. Classification is executed using an advanced Support Vector Machine with Radial Basis Function (SVM-RBF), in conjunction with decision trees (DT) and K-nearest neighbors (KNN). Our model, validated on the IDRiD dataset, demonstrates remarkable performance metrics, achieving an accuracy of 99.89%, a sensitivity of 84.40%, and a specificity of 100%.

Mercaldo et al [77] introduced a method for automated identification of diabetic retinopathy presence in ocular angiography through the utilization of convolutional neural networks. The two proposed models serve distinct purposes: the first model aims to differentiate between healthy eyes and those with retinopathy, while the second model focuses on distinguishing non-proliferative retinopathy from weakly and severely proliferative retinopathy, achieving an accuracy of 98.00% for the first model and 91.00% for the second model.

Law Kumar Singh et al. assesses the performance of four machine learning classifiers, K-Nearest Neighbour (KNN), Support Vector Machine (SVM), Naive Bayes, and Decision Tree, trained on the given dataset. The system’s effectiveness is evaluated using the widely accepted DRIVE dataset, employing key performance metrics such as precision, sensitivity, specificity, area under the curve (AUC), and accuracy for blood vessel segmentation from fundus images. The results are as follows: KNN achieved an accuracy of 0.9623, SVM 0.9463, Naive Bayes 0.9459, and Decision Tree 0.9624.[98]

Also used the Genetic Search Optimization Algorithm (GSOA) to optimize model performance. Successfully developed and trained six machine learning models tailored to selected features, achieving a notable accuracy of 95.36%. Proficient in evaluating model performance through comprehensive statistical analysis and validation techniques including split testing and cross-validation [99].

They used the Emperor Penguin Optimization (EPO) and Bacterial Foraging Optimization (BFO) algorithms, along with a hybrid approach combining both techniques, which are utilized for feature selection in machine learning. Seven machine learning classifiers are employed to assess the selected features, computing eight statistically based performance metrics and measuring execution time. The method achieves notable results, including the highest specificity of 0.9940, sensitivity of 0.9347, and maximum accuracy of 96.5%.[100]

In another research [67], this study presents three innovative Convolutional Neural Networks (CNNs) based on deep learning techniques for the prediction of diabetic retinopathy. The initial network is constructed from the ground up, the second comprises an ensemble of five high-performing networks, and the third integrates a Convolutional Neural Network with Long Short Term Memory (CNN-LSTM) architecture. These networks are rigorously evaluated against twenty-one established image nets to assess their effectiveness. The evaluation spans across seven experiments using three Kaggle datasets independently and in combination. Key performance indicators such as accuracy, F1 score, sensitivity, and AUC score are computed, with the proposed models achieving notable results: The highest recorded accuracy is 0.9545 (with an average peak of 0.9368), the maximum F1 score achieved is 0.9685 (averaging at 0.9374), the peak sensitivity is 0.9566 (with an average of 0.9420), and the maximum AUC score is 0.9769 (averaging at 0.9395).

A separate study by [122] leveraged the EfficientNet-B3 architecture as the foundation for developing deep learning-based diabetic retinopathy detection models, utilizing a dataset of 38 788 annotated images. The model achieved a Kappa value of 93.5% on the test set, with the author claiming that its performance matched the level of expertise exhibited by human experts.

The paper addresses the challenge of detecting diabetic retinopathy (DR) by introducing an innovative framework that effectively integrates transfer learning (TL) and deep learning (DL) models. The proposed architecture adopts a modular and layered design, which ensures both flexibility and scalability. By optimizing the balance between performance and complexity, the framework seeks to enhance classification accuracy while significantly reducing the number of parameters and layers, thereby improving efficiency and minimizing computational costs.

This study employs a preprocessing approach for fundus images (FI) depicting diabetic retinopathy. A circle mask is used to eliminate the extraneous black regions around the eyes, ensuring focus on the critical areas. Following this, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to enhance DR lesions. These preprocessing steps effectively highlight essential features in the images, optimizing their utility for classification within the proposed framework.

Table 2.3: Summary of models and results applied by other related works

Reference	Database	Methods	Results
[81]	EyePacs	CNN, VGG16, VGG19	ACC:82% Sen:82% Spec:80% AUC:90.4%
[51]	APTOS	DenseNet-121	ACC:94.9% Sen:97.1% Spec:92.6%
[68]	MESSIDOR-2 and APTOS	Efficient Net B0, VGG 16, ResNet-152 throughout vessel blood segmentation, ensemble approach	Acc:99.71% Sen:98.63% Spec:98.52%
[4]	MESSIDOR-2	Deep Convolutional Neural Network with vascular segmentation	Acc:94.1% Sen:95.7% Spec:92.7% AUC:96.9%
[31]	MESSIDOR2	DenseNet121-L	Acc:90.3%
[87]	IDRID, MESSIDOR	self-supervised Learning	Acc:71.84% Sen:75.42% AUC:88.76% Acc:87.13% Sen:86.02% AUC:86.54%
[78]	APTOS2019	DenseNet121,AG-CNN	Acc:97.4% AUC:99.5%
[94]	IDRID, MESSIDOR2, APTOS, DIARETB0	Siames CNN	Acc:90.3%
[93]	APTOS, Kaggle	HRUNet	Acc:94% Acc:91%
[117]	Aptos, DDR	Graph Convolutional Network	Acc:84.13% Sen:81.25% Acc:81.89% Sen:75.34%
[119]	MESSIDOR-2, e-ophtha, and APTOS	ViT	AUC:95.6% AUC:97.7% AUC:94.7%

[47]	MESSIDOR-2	vision transformer with a residual module	Acc:89.3% AUC:98.1%
[1]	MESSIDOR-2 and APTOS	ensemble of transformer-based models linked with attention maps	AUC:97.7% AUC:91.2%
[23]	EyePACS	DCNN Inception-Resnet-v2	Sen:99.00%
[54]	IDRiD and DDR	DenseNet, InceptionV3 and EfficientNetB0	Acc:60.19% Acc:73.56%
[55]	Kaggle	neural-symbolic learning	Acc:63.11%
[96]	APTOS, MESSIDOR, IDRiD	explainability gradient-weighted and SHAP	97.00% 98.00% 97.8%
[10]	IDRID	ISVM-RBF	Acc:99.18% Sen:98.15% Spec:100%
[11]	IDRID	SVM-RBF	Acc:99.89% Sen:84.40% Spec:100%
[98]	DRIVE	KNN, SVM, NB, DT	Acc:96.23% Acc:94.63% Acc:94.59% Acc:96.24%
[100]	-	EPO, BFO	Acc:96.5% Sen:93.4% Spec:99.4%
[67]	Kaggle	CNN-LSTM	Acc:95.45% F1: 96.85% Sen:95.66% AUC:97.69%

2.6 Conclusion

The review of literature reveals that advancements in mobile health applications, machine learning (ML), and deep learning (DL) have significantly transformed diabetes management and detection strategies. Mobile apps play a pivotal role in empowering patients to self-manage diabetes by providing features like blood glucose tracking, insulin dosage reminders, and dietary recommendations. The potential of such applications to improve clinical outcomes is evident, yet their utility is often hindered by challenges like usability, limited functionality, and lack of integration with clinical records. These barriers emphasize the need for more intuitive designs, robust features, and adherence to medical regulations.

In addition to self-management tools, automated diagnostic technologies have shown promise in addressing complications like diabetic retinopathy and improving risk prediction models. DL models, particularly convolutional neural networks (CNNs), have demonstrated high accuracy in analyzing retinal images for early detection of retinopathy, thus mitigating one of diabetes's most severe complications. This automated detection not only improves diagnostic efficiency but also reduces reliance on specialized expertise, making these solutions accessible in resource-constrained settings.

Similarly, the application of ML techniques for predicting diabetes, such as the use of the PIMA Indians Diabetes Dataset, has been explored extensively in literature. These predictive models leverage features like age, BMI, and glucose levels to identify individuals at risk. Textual analysis-based prediction systems, when integrated into apps, can provide users with a personalized risk profile, enabling early intervention and lifestyle adjustments.

Despite these advancements, gaps remain in the scalability, personalization, and generalization of these technologies. Current retinopathy detection models often require large, labeled datasets for training, which may not always be available. Similarly, predictive models based on textual data face challenges in achieving high accuracy and explainability, which are critical for trust and adoption.

In summary, while mobile apps, ML, and DL technologies have made significant strides in managing and predicting diabetes, the literature underscores the need for further innovation. By integrating automated diagnostic tools like retinopathy detection, textual prediction models, and enhanced mobile app functionalities, the next generation of diabetes management systems can become comprehensive, user-friendly, and effective. These systems have the potential not only to improve patient outcomes but also to alleviate the burden on healthcare providers.

Diabetes is a chronic health condition affecting millions of people worldwide. Managing this disease requires continuous monitoring, timely interventions, and personalized treatment strategies. Advancements in mobile health applications, machine learning (ML), and deep learning (DL) have significantly transformed diabetes management and detection strategies. These technologies are redefining how healthcare providers approach disease management, enabling more accurate diagnostics, effective treatment, and improved patient engagement [65, 66].

The integration of artificial intelligence (AI) in diabetes care provides innovative tools to analyze complex datasets, predict disease progression, and assist in early detection. Furthermore, mobile applications equipped with AI capabilities are empowering patients with real-time monitoring and self-management tools, revolutionizing the conventional healthcare model [52].

Machine learning algorithms have proven effective in analyzing clinical and behavioral data to diagnose diabetes. Techniques such as support vector machines (SVM), decision trees, and random forests have demonstrated high diagnostic accuracy by identifying patterns in patient data [65]. For instance, random forest classifiers have been used to predict diabetes onset based on large datasets, facilitating early interventions and better disease management [66].

Deep learning (DL), particularly convolutional neural networks (CNNs), has shown tremendous potential in medical imaging, such as detecting diabetic retinopathy through retinal scans [52]. These models can extract meaningful features from raw data, enabling precise diagnosis. A notable study employed DL models to analyze retinal images, achieving sensitivity and specificity levels exceeding 90%, thus aiding in early detection of diabetes-related complications [62].

In addition to imaging, ML models have also been applied to structured datasets, such as the Pima Indians Diabetes Dataset, to predict diabetes based on clinical features. By leveraging algorithms like logistic regression and neural networks, researchers have achieved high predictive accuracy, highlighting the potential of ML in structured data analysis [66].

AI-powered mobile applications have transformed diabetes management by providing real-time insights, personalized recommendations, and automated reminders. These applications enable patients to log blood glucose levels, track insulin dosages, and monitor their diet and physical activity. For example, apps integrating continuous glucose monitoring (CGM) systems provide instant feedback, allowing patients to make informed decisions regarding their treatment plans [52].

Moreover, advancements in mobile health technologies have introduced features such as AI-driven chatbots that assist patients in managing their condition by answering questions and providing tailored advice. The integration of patient-generated health data (PGHD) with electronic health records (EHRs) further enhances the personalization of care, enabling healthcare providers to make data-driven decisions [62].

While the advancements in AI and mobile health applications present significant opportunities, several challenges must be addressed to ensure successful implementation. One major issue is data privacy and security, as handling sensitive patient information requires strict compliance with regulations like GDPR and HIPAA [52].

Another challenge is the interpretability of ML and DL models. Healthcare professionals often require transparent decision-making processes to trust AI-driven recommendations [65]. Additionally, the lack of standardized evaluation metrics and benchmarks complicates the comparison of different models, hindering the selection of the most effective solutions [66].

The integration of AI in diabetes management offers transformative potential for improving diagnostics, treatment, and patient engagement. Machine learning and deep learning models are revolutionizing how diabetes is detected and managed, from analyzing clinical datasets to interpreting retinal images for diabetic retinopathy detection. Mobile health applications further enhance self-management by providing real-time monitoring and personalized care.

However, addressing challenges related to data privacy, model interpretability, and usability is critical for ensuring the successful adoption of these technologies. By striking a balance between innovation and ethical considerations, AI and mobile health applications can pave the way for a future where diabetes care is more efficient, accessible, and patient-centric.

Chapter 3

Methodologies and Tools

Rapid advancements in medical technology and the widespread adoption of digital health records have led to an unprecedented accumulation of healthcare data, often referred to as ”big data.” This data encompasses a vast array of information, including electronic health records (EHRs), genomic sequences, medical imaging, and data from wearable devices, among others. The potential to harness this wealth of information for improving healthcare outcomes has become a focal point of research, particularly in the context of managing long-term diseases. Big data analytics offers a transformative approach to the prevention, diagnosis, and monitoring of chronic conditions. By leveraging advanced computational tools and algorithms, healthcare providers can now analyze complex datasets to uncover patterns, predict disease onset, and tailor interventions to individual patients. This shift towards data-driven decision-making promises not only to enhance the accuracy and timeliness of diagnoses but also to enable personalized medicine, where treatments are customized based on the unique characteristics of each patient. Despite the immense potential, the integration of big data into healthcare is fraught with challenges, including issues related to data privacy, the interoperability of disparate data sources, and the need for robust analytical frameworks. This chapter explores these dynamics, offering insights into how big data analytics is being applied to revolutionize the management of long-term diseases while also addressing the ethical and practical challenges that accompany this evolution. A critical aspect of applying advanced analytics in healthcare is the development and use of explainable neural networks. Traditional neural networks, while powerful, often operate as ”black boxes,” providing little insight into how they reach their decisions. This opacity can be a significant drawback in healthcare, where understanding the rationale behind a diagnosis or treatment recommendation is crucial for clinical acceptance and trust. Explainable neural networks (XNNs) aim to address this issue by making the decision-making process of these models more transparent. By incorporating techniques such as attention mechanisms, feature importance scoring, and model interpretability tools, XNNs allow healthcare professionals to understand and verify the steps taken by the model to arrive at a conclusion. This not only enhances trust in the system but also aids in identifying potential biases or errors in the model, ensuring that the use of such technology aligns with the ethical standards required in healthcare.

3.1 Introdcution

Machine Learning (ML) is a subfield of Artificial Intelligence (AI) that focuses on developing algorithms capable of automatically learning patterns from data to make predictions or decisions on new, unseen instances without explicit programming. Unlike traditional programming, where rules are manually defined by the programmer, ML allows computers to improve their performance on a specific task by analyzing data and learning from it. This learning process involves using statistical techniques and optimization algorithms to create models that can identify patterns within the data. Once these patterns are recognized, the models can generalize them to predict outcomes or make decisions when presented with new data. The primary goal of ML is to enable computers to learn and adapt based on experience, thereby increasing their effectiveness over time.

3.2 Machine Learning Techniques for Diabetes

Machine Learning (ML) is a specialized area within Artificial Intelligence (AI) that focuses on developing systems capable of learning and improving from experience without the need for explicit programming. This field involves creating algorithms that can identify patterns in data and use these patterns to make predictions or decisions when faced with new, unseen data. Unlike traditional programming, where every task is hard-coded with specific instructions, ML empowers computers to learn from examples and adjust their responses based on the data they process, allowing for more flexible and dynamic problem-solving. Within ML, several approaches are commonly used, each tailored to different types of tasks.

Supervised Learning is one such approach, where the model is trained on a labeled dataset, meaning that the correct output is provided for each input. The objective is to enable the model to accurately predict the output for new inputs by learning from the training data. This method is widely used in applications such as image recognition, where the model is trained to identify objects in images by learning from a large set of labeled examples.

In contrast, Unsupervised Learning involves training a model on data that has no labeled outcomes. The model's goal is to find underlying structures or patterns within the data, such as grouping similar data points together (clustering) or reducing the dimensionality of the data while retaining its essential features. This approach is particularly useful in exploratory data analysis, where the objective is to uncover hidden patterns or groupings within the data.

Another important ML approach is Reinforcement Learning, which involves training an agent to make decisions by interacting with an environment and receiving feedback in the form of rewards or penalties. The agent learns to optimize its actions to maximize cumulative rewards over time. This method is often used in areas like robotics, gaming, and autonomous systems, where the agent must learn to navigate complex environments and make decisions that lead to favorable outcomes.

Additionally, Semi-Supervised and Self-Supervised Learning approaches combine elements of both supervised and unsupervised learning. These methods use a small amount of labeled data along with a large amount of unlabeled data to improve learning efficiency and accuracy. This is particularly useful in situations where labeled data is scarce or expensive to obtain, allowing models to learn effectively from limited supervision.

ML models rely heavily on statistical methods and optimization techniques to analyze data, identify trends, and make predictions. The success of ML systems depends on the quality and quantity of data available, the choice of algorithms, and the computational resources used to train these models. As a result, ML is becoming increasingly essential across various industries, including healthcare, finance, and marketing, where it helps automate tasks, provide valuable insights, and enhance decision-making processes.

3.3 Machine Learning Pipline

A machine learning pipeline is a systematic sequence of processes designed to transform raw data into meaningful insights and predictive models. The journey begins with data collection, where relevant data is gathered from various sources such as databases, APIs, or sensors. The quality and comprehensiveness of this data are crucial, as they form the foundation for the entire pipeline. Once collected, the data undergoes preprocessing, a vital step that involves cleaning the data by handling missing values, removing duplicates, and correcting errors. Additionally, data transformation techniques like normalization, standardization, and encoding of categorical variables are applied to prepare the data for analysis. Feature engineering may also be performed during this stage to create new variables or modify existing ones, enhancing the model's ability to learn from the data.

After preprocessing, the dataset is typically split into training and testing subsets. The training set is used to train the machine learning model, while the testing set is reserved for evaluating its performance. This separation ensures that the model can generalize well to new, unseen data. The next step is model selection, where an appropriate machine learning algorithm is chosen based on the problem type—be it classification, regression, clustering, or another task. Common algorithms include decision trees, support vector machines, neural networks, and others, each with its strengths and suitable applications.

With the model selected, the training phase begins. During training, the algorithm learns from the training data by adjusting its internal parameters to minimize the error between its predictions and the actual outcomes. This process often involves optimizing a loss function that quantifies the model's performance. Once trained, the model undergoes evaluation using the testing dataset. Evaluation metrics such as accuracy, precision, recall, F1 score, mean squared error, or R-squared are used to assess how well the model performs and to ensure it generalizes effectively to new data.

Following evaluation, hyperparameter tuning is performed to fine-tune the model's performance. Hyperparameters are settings that are not learned from the data but are set prior to training, such as the learning rate, number of trees in a random forest, or the architecture of a neural network. Techniques like grid search, random search, or Bayesian optimization are employed to find the optimal combination of hyperparameters that enhance the model's accuracy and robustness.

Once the model is trained, evaluated, and fine-tuned, it is ready for deployment. Deployment involves integrating the model into a production environment where it can make real-time predictions or decisions based on new incoming data. This stage requires ensuring that the model is scalable, reliable, and capable of handling the expected data load. After deployment, continuous monitoring and maintenance are essential to ensure the model remains effective over time. Monitoring involves tracking the model's performance and detecting any degradation or drift in its predictions as new data patterns emerge. Periodic retraining with updated data and adjustments to the pipeline may be necessary to maintain the model's accuracy and relevance.

In summary, a machine learning pipeline encompasses a series of interconnected stages—from data collection and preprocessing to model deployment and maintenance—that work together to create effective and reliable predictive models. Each stage is crucial for ensuring that the final model is accurate, robust, and capable of providing valuable insights in real-world applications.

3.4 Overview of Machine Learning Algorithms

Machine learning algorithms are the backbone of machine learning, enabling computers to learn from data, identify patterns, and make decisions with minimal human intervention. These algorithms can be broadly categorized based on the type of learning they facilitate: supervised, unsupervised, semi-supervised, reinforcement, and deep learning algorithms. Each category addresses different types of problems and uses different methodologies to learn from data.

3.4.1 Supervised Learning Algorithms

Supervised learning algorithms are trained on labeled data, where the input-output pairs are known. The goal is to learn a mapping from inputs to outputs that can be used to predict the output for new, unseen data. Common supervised learning algorithms include:

- **Linear Regression:** Used for predicting a continuous target variable based on one or more predictor variables.
- **Logistic Regression:** Used for binary classification tasks where the outcome is categorical.
- **Decision Trees:** A tree-like model used for both classification and regression tasks, where decisions are made based on feature splits.
- **Random Forests:** An ensemble method that combines multiple decision trees to improve accuracy and reduce overfitting.
- **Support Vector Machines (SVM):** A classification method that finds the hyperplane that best separates the classes in the feature space.
- **k-Nearest Neighbors (k-NN):** A non-parametric method used for classification and regression, where the output is based on the closest training examples in the feature space.

3.4.2 Unsupervised Learning Algorithms

Unsupervised learning algorithms work with unlabeled data, meaning that the model tries to identify patterns or structure within the data without any guidance on what the correct output should be. Common unsupervised learning algorithms include:

- **k-Means Clustering:** A method of partitioning a dataset into k distinct, non-overlapping subsets (clusters) based on similarity.
- **Hierarchical Clustering:** Builds a hierarchy of clusters by either merging or splitting them iteratively.
- **Principal Component Analysis (PCA):** A dimensionality reduction technique that transforms data into a set of linearly uncorrelated components.
- **t-Distributed Stochastic Neighbor Embedding (t-SNE):** A technique for reducing high-dimensional data to two or three dimensions for visualization.
- **Gaussian Mixture Models (GMM):** A probabilistic model that assumes the data is generated from a mixture of several Gaussian distributions.

3.4.3 Reinforcement Learning Algorithms

Reinforcement learning involves training an agent to make decisions by interacting with an environment. The agent learns to maximize cumulative rewards by taking actions and receiving feedback in the form of rewards or penalties. Key reinforcement learning algorithms include:

- **Q-Learning:** A model-free algorithm that seeks to learn the value of an action in a particular state by using a Q-table.
- **Deep Q-Networks (DQN):** Combines Q-Learning with deep neural networks to handle high-dimensional state spaces.
- **Policy Gradient Methods:** Algorithms that directly optimize the policy by adjusting the parameters in the direction that increases the expected reward.

3.4.4 Deep Learning Algorithms

Deep learning algorithms are a subset of machine learning that uses neural networks with many layers (hence ”deep”). These algorithms excel at handling large, complex datasets and are widely used in applications like image recognition, natural language processing, and speech recognition. Common deep learning algorithms include:

- **Convolutional Neural Networks (CNNs):** Specialized for processing grid-like data such as images, using convolutional layers to detect spatial hierarchies.
- **Recurrent Neural Networks (RNNs):** Designed for sequential data, such as time series or text, where the output depends on previous inputs.
- **Long Short-Term Memory Networks (LSTMs):** A type of RNN that can capture long-term dependencies in sequential data, useful for tasks like language modeling.
- **Generative Adversarial Networks (GANs):** Consist of two networks (generator and discriminator) that are trained together to produce realistic data samples.

3.4.5 Semi-Supervised and Self-Supervised Algorithms

Semi-supervised learning algorithms use a small amount of labeled data alongside a larger amount of unlabeled data to improve learning efficiency. Self-supervised learning is a form of unsupervised learning where the data itself provides the supervision. Examples include:

- **Semi-Supervised Support Vector Machines (S3VM):** An extension of SVMs that incorporates both labeled and unlabeled data.

- **Autoencoders:** Neural networks used for unsupervised representation learning, which can also be adapted for semi-supervised tasks.

These algorithms are fundamental to the success of machine learning applications across various industries, from healthcare and finance to autonomous driving and entertainment. Each algorithm has its strengths and is chosen based on the specific requirements of the problem at hand.

3.5 Introduction to Deep Learning

Deep learning is a subset of machine learning that focuses on algorithms inspired by the structure and function of the brain, known as artificial neural networks. These networks are composed of layers of interconnected nodes, or neurons, that can learn to represent data in increasingly abstract ways. Unlike traditional machine learning models, which rely heavily on feature engineering by humans, deep learning models automatically discover and learn representations from raw data, making them particularly powerful for complex tasks.

At its core, deep learning aims to model high-level abstractions in data by using multiple layers of transformations. Each layer in a deep neural network processes the input data and passes the transformed output to the next layer, enabling the network to build up a hierarchy of features. For example, in image recognition, the first layers may detect edges, the middle layers might identify shapes or textures, and the final layers could recognize objects or faces.

One of the key advantages of deep learning is its ability to handle large, high-dimensional datasets, such as images, video, and text. Deep learning has revolutionized many areas of artificial intelligence, including computer vision, natural language processing, and speech recognition. Techniques such as Convolutional Neural Networks (CNNs) have achieved state-of-the-art performance in image classification, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs) have become standard tools for sequence-based tasks like language modeling and machine translation.

The success of deep learning is largely attributed to the availability of large datasets, advances in computing power, particularly Graphics Processing Units (GPUs), and the development of more sophisticated algorithms and architectures. However, deep learning models require significant amounts of data and computational resources to train, and they can be difficult to interpret, leading to a growing interest in explainable AI.

Overall, deep learning represents a significant leap forward in the field of artificial intelligence, providing powerful tools for solving complex problems across a wide range of domains. Its ability to automatically extract features and learn from data with minimal human intervention has opened up new possibilities in technology, science, and industry.

3.6 Explainable Deep Learning in Healthcare

As deep learning models have become increasingly prevalent in fields such as healthcare, finance, and autonomous systems, the demand for explainability has grown alongside their adoption. While these models, particularly deep neural networks, have demonstrated remarkable performance in various complex tasks, they are often criticized for being ”black boxes”—providing little insight into how they arrive at their decisions. This opacity poses significant challenges in domains where understanding the decision-making process is crucial, not only for gaining trust from end-users but also for ensuring compliance with regulatory standards.

Explainable deep learning (XDL) seeks to address this challenge by developing methods that make the decision processes of deep learning models more transparent and interpretable. The goal of XDL is to produce models that not only perform well but also provide explanations for their predictions that are understandable to humans. These explanations can take various forms, such as highlighting which features or inputs were most influential in a decision, visualizing the inner workings of the neural network, or generating natural language descriptions of the reasoning behind a model’s output.

Several techniques have been developed to enhance the explainability of deep learning models. For example, attention mechanisms in neural networks allow models to focus on specific parts of the input when making decisions, thereby providing insight into what the model deems most relevant. Another popular approach is the use of feature importance methods, such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations), which quantify the contribution of each feature to the model’s prediction. Visualization techniques, like saliency maps or heatmaps, are also widely used to interpret how models process visual data.

The importance of explainable deep learning is particularly pronounced in high-stakes applications. In healthcare, for instance, a model used to diagnose diseases must provide interpretable results that clinicians can trust and act upon. Similarly, in autonomous driving, understanding why a vehicle’s AI made a particular decision is essential for safety and accountability.

Despite the progress in XDL, there remain challenges in balancing explainability with model performance. Often, making a model more interpretable can lead to trade-offs in accuracy or complexity. Moreover, there is an ongoing debate about what constitutes a ”good” explanation, as the needs for interpretability can vary significantly between different users and contexts.

In conclusion, explainable deep learning is a rapidly evolving field that aims to bridge the gap between the powerful capabilities of deep learning models and the need for transparency and trust. As AI systems continue to integrate into critical aspects of society, the ability to explain and justify their decisions will be key to their widespread acceptance and ethical deployment.

3.7 Machine Learning and Deep Learning for Diabetes

Machine learning (ML) and deep learning (DL) have become pivotal tools in the diagnosis and prediction of diabetes, significantly enhancing the accuracy, speed, and efficiency of identifying individuals at risk or already suffering from the disease. These technologies leverage vast amounts of healthcare data to uncover patterns that may not be apparent through traditional statistical methods, providing both clinicians and patients with actionable insights.

3.7.1 ML in Diabetes Diagnosis and Prediction

Machine learning algorithms have been widely applied in diabetes management, particularly in predicting the onset of diabetes and assisting in early diagnosis. Supervised learning techniques, such as decision trees, support vector machines (SVM), and random forests, are often used to analyze patient data, including demographics, medical history, and lifestyle factors, to predict the likelihood of developing diabetes. For instance, logistic regression models can predict the probability of a patient developing diabetes based on their blood glucose levels, body mass index (BMI), and other risk factors.

Unsupervised learning approaches, such as clustering algorithms, can be used to segment patients into groups with similar characteristics, allowing for more personalized care plans. These algorithms can identify patterns within the data that correlate with high-risk groups, thereby enabling more targeted interventions.

3.7.2 DL in Diabetes Diagnosis and Prediction

Deep learning, a subset of machine learning that uses neural networks with many layers, has shown great promise in improving the accuracy and efficiency of diabetes diagnosis and prediction. Convolutional Neural Networks (CNNs) are particularly effective in analyzing medical images, such as retinal scans, to detect diabetic retinopathy—a common complication of diabetes that can lead to blindness if not treated early. By training on large datasets of retinal images, CNNs can identify subtle features indicative of disease progression that might be missed by human clinicians.

Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs) are also utilized in predicting diabetes by analyzing time-series data, such as continuous glucose monitoring data. These models can learn from past glucose readings to predict future glucose levels, helping to manage and prevent hypoglycemic events in diabetic patients.

Additionally, deep learning models can integrate various types of data, including genetic information, electronic health records (EHRs), and lifestyle data, to provide a comprehensive risk assessment for diabetes. This holistic approach allows for the identification of complex interactions between different risk factors, leading to more accurate predictions.

Impact and Challenges The use of ML and DL in diabetes care has significantly improved early diagnosis and personalized treatment plans, leading to better patient outcomes. However, there are challenges that need to be addressed, including data privacy concerns, the need for large and diverse datasets to train models effectively, and the ”black box” nature of deep learning models, which can make it difficult to interpret their decisions.

Explainable AI (XAI) techniques are increasingly being developed to make these models more transparent, ensuring that clinicians can understand and trust the decisions made by AI systems. As research in this area continues to evolve, the integration of ML and DL into diabetes care is expected to become even more prevalent, offering new possibilities for managing and potentially preventing this widespread disease.

In conclusion, machine learning and deep learning are transforming the landscape of diabetes diagnosis and prediction, providing powerful tools that enhance the ability to identify, manage, and treat diabetes more effectively. As these technologies continue to advance, they hold the promise of improving the quality of life for millions of people worldwide.

3.8 Conclusion

In conclusion, the integration of machine learning (ML) and deep learning (DL) into the diagnosis and prediction of diabetes represents a significant advancement in healthcare. These technologies enable the analysis of vast and complex datasets, allowing for earlier detection, more accurate predictions, and personalized treatment strategies. By leveraging ML algorithms, healthcare providers can identify individuals at risk of developing diabetes and tailor interventions accordingly, improving patient outcomes. Similarly, DL techniques, particularly through neural networks, enhance the accuracy of diagnosing diabetes-related complications, such as diabetic retinopathy, by analyzing medical images and other forms of health data.

However, the deployment of these technologies is not without challenges. Issues such as data privacy, the need for extensive and diverse datasets, and the interpretability of DL models must be addressed to ensure their successful implementation in clinical settings. Ongoing research into explainable AI (XAI) is crucial for making these models more transparent and trustworthy, thereby increasing their acceptance among healthcare professionals and patients.

Overall, ML and DL are set to play an increasingly vital role in the fight against diabetes, offering new possibilities for early intervention, management, and potentially even prevention of the disease. As these technologies continue to evolve, they promise to significantly enhance the quality of diabetes care and improve the lives of millions of people affected by this condition worldwide.

Chapter 4

Prediction

Diabetes mellitus, often referred to as a silent killer, is a chronic disease that disrupts insulin production, leading to high blood sugar levels and complications in vital organs such as the eyes, kidneys, and nerves. Despite extensive research, machine learning methods for diabetes classification face challenges such as missing data and imbalanced class distributions, which limit their performance. This paper introduces a novel approach, **Diabetes Mellitus classification for Imbalanced data with Missing values (DMIM)**, to overcome these issues.

The proposed method involves three key steps. First, missing values are handled using the **Isolation Forest** method, which normalizes the data and addresses outliers. Next, the **Smote T-link** adaptive synthetic sampling technique is applied to balance the class distribution and mitigate the impact of data imbalance. Finally, a **Random Forest (RF)** classifier is employed for classification. Experiments were conducted on the **Pima Indians Diabetes Dataset** from the University of California to evaluate the approach.

The DMIM method achieved outstanding results, including an **Area Under the Curve (AUC)** of 97.2%, **Specificity** of 91.7%, and **Recall** of 92.3%. The proposed method was also benchmarked against other machine learning models, such as k-Nearest Neighbors, Decision Trees, AdaBoost, Naive Bayes, XGBoost, and Extra Trees, consistently demonstrating superior performance.

These results highlight the effectiveness of the DMIM approach in addressing the challenges of missing data and class imbalance, significantly improving the accuracy of diabetes classification. This work provides a robust framework for advancing machine learning applications in healthcare and enhancing diagnostic precision for diabetes.

4.1 Introduction

Diabetes is a long-term condition that necessitates continuous medical care, can lead to serious complications like blindness, heart, and kidney disease if left untreated. Early prediction is crucial for preventing these consequences and initiating prompt management.

Particularly concerning is the rising incidence of diabetes in children and adolescents, with experts predicting a significant increase by 2045. This is linked to factors like obesity, lack of physical activity, and family history.

Effective prediction methods can help identify children at risk, allowing for early intervention and potentially preventing the development of diabetes altogether.

According to the International Diabetes Federation (IDF)[84], Type 2 Diabetes is characterized by a persistent elevation of glucose levels in the bloodstream. While there is no long-term cure for the disease, it can be effectively managed and potentially even prevented through healthy lifestyle choices and early diagnosis[9].

The prediction of diabetes is a challenging and crucial task and hence, obtaining a higher accuracy rate in diabetes prediction is decisive. The use of data analytics in the healthcare system has several advantages including providing insights, augmenting diagnoses, improving outcomes, and lowering costs among other things. Specifically, successful implementation of machine learning Improving medical practitioners' skills and increasing the effectiveness of the healthcare system.

The purpose is to assess several diabetes incidence prediction models based on shared risk variables and identify the most accurate one for predicting individual diabetes risk without requiring a blood test or hospital visit. To achieve this, we rigorously analyze various popular classifiers, combined with multiple common data preprocessors. We meticulously tune their parameters to maximize accuracy and compare their performance. Ultimately, we propose a novel approach to diabetes prediction using the PIMA Indians Diabetes dataset.

Data preprocessing plays a crucial role in our contribution. We introduce a unique preprocessing step that integrates several techniques within a single framework. This includes outlier rejection, missing value imputation, data standardization, feature selection, and K-fold cross-validation. Additionally, we employ the Smote T-Link method to address the challenge of class imbalance, where the number of individuals with and without diabetes is significantly different. This imbalance can bias prediction models towards the majority class. By incorporating Smote T-Link, we ensure that the model accurately predicts for both groups.

Furthermore, we analyze the significance of each attribute within the dataset. This knowledge will be valuable for future studies aimed at further refining and improving our prediction model. By employing this comprehensive approach, we hope to identify the most accurate and non-invasive method for predicting diabetes risk, potentially leading to earlier diagnosis and improved patient outcomes.

4.2 Proposed Framework

Diabetes prediction faces challenges like outliers, missing data, class imbalance, and classifier performance. This paper proposes a framework illustrated in Figure 4.1 that tackles these issues, focusing on data preprocessing as a crucial step. Preprocessing includes outlier rejection (OR), missing value imputation (MV), standardization (S), and feature selection (FS), each playing a key role in improving data quality and model accuracy.

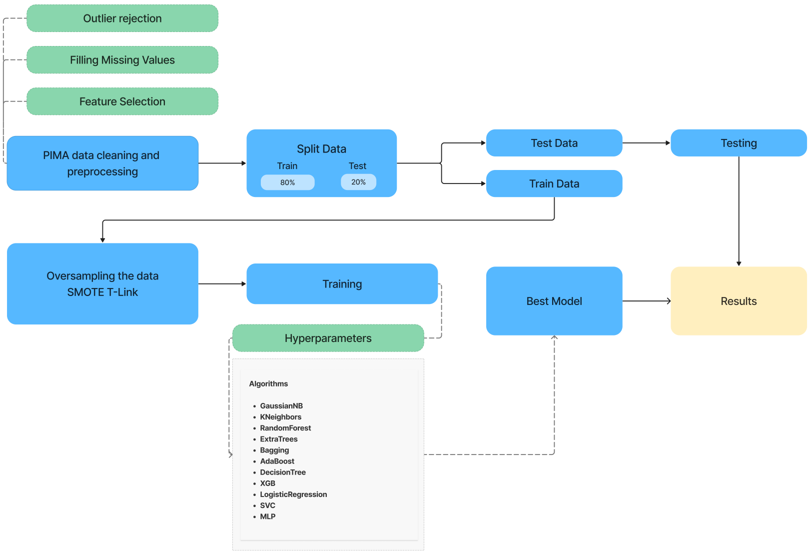


Figure 4.1: The framework of the proposed method.

Following preprocessing, we evaluate several machine learning algorithms (SVM, Random Forest...etc) for their classification performance in predicting diabetes.

4.2.1 The Used Dataset

The machine learning models were trained and evaluated using a dataset of 768 female diabetes patients from the Pima Indian community near Phoenix, Arizona [105], which is publicly available at:https://www.kaggle.com/datasets/uciml/pima-indians-diabetes-database. There are 268 diabetes individuals (positive) and 500 non-diabetic patients (negative) in this dataset, each with eight distinct features see Figure 4.2.

The study focuses on examining eight specific features pertinent to health analysis. These features encompass various aspects such as the number of pregnancies, plasma glucose concentration post a two-hour oral glucose tolerance test, diastolic blood pressure (measured in mmHg), triceps skin fold thickness (measured in mm), 2-hour serum insulin levels (measured in mu U/ml), body mass index (BMI), diabetes pedigree function, age (in years), and a binary class variable represented by 0 or 1, In this context, a class value of 1 indicates that the individual has tested positive for diabetes, while a class value of 0 signifies that the individual has tested negative for diabetes. These selected features serve as the core elements under investigation, providing valuable insights into health-related phenomena.

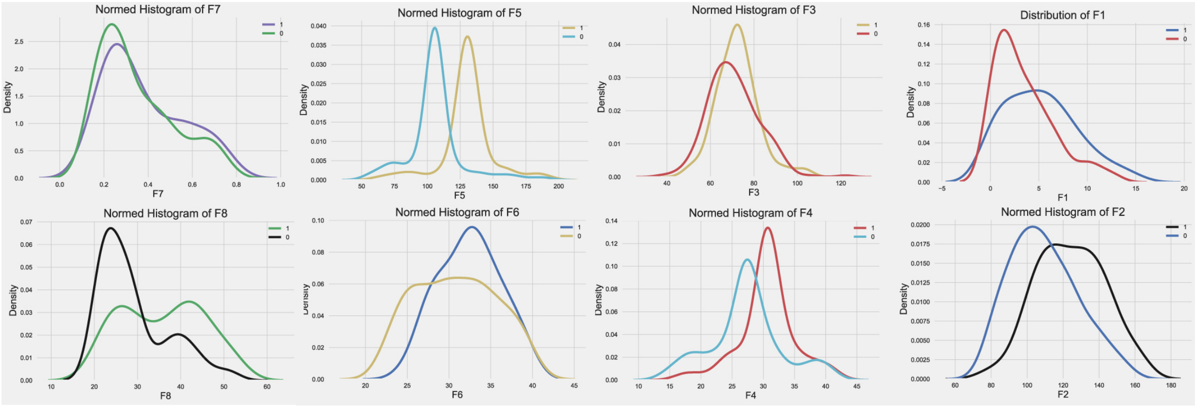


Figure 4.2: The distribution of various attributes within the Pima Indian diabetes dataset, where distinct color representations indicate the non-diabetic and diabetic classifications.

4.2.2 Preprocessing

The preprocessing step includes Outlier rejection (with Isolation Forest Algorithm[71]), filling missing values (Replace Zero values with the mean), standardization, and the selection of features pertaining to the attributes is succinctly outlined as follows:

4.2.2.1 Outlier Rejection

An outlier is an observation that differs significantly from the rest. It must be excluded from data distribution since classifiers are extremely sensitive to data range and attribute distribution. We have used the Isolation Forest Algorithm [71] which is a machine learning algorithm for anomaly detection. Isolation algorithms, which aim to separate instances from the rest of the data, are particularly effective for identifying anomalies. This is because anomalies, being "few and different," tend to be isolated more easily compared to normal data points. An anomaly score is required for any anomaly detection method. It is an unsupervised learning algorithm that identifies anomalies by isolating outliers in the data. The technique returns the average path length of an unsuccessful search in the Binary Search Tree given a data set of n instances as follows:

$$c(n) = 2H(n-1) - (2(n-1)/n) \tag{4.1}$$

where $H(i)$ is the harmonic number, which may be calculated using $ln(i) + 0.5772156649$ (Euler's constant). The mathematical formula for outlier rejection is as follows:

$$S(x,n) = 2^{-\frac{E(h(x))}{c(n)}} \tag{4.2}$$

In Equation (4.2), $E(h(x))$ represents the average of $h(x)$ computed from a set of isolation trees. The relationship between $E(h(x))$ and the anomaly score S is defined as follows: when

$E(h(x))$ approaches $c(n)$, S approaches 0.5; when $E(h(x))$ tends to 0, S tends to 1; and when $E(h(x))$ approaches $n-1$, S approaches 0. Here, S is a monotonic function of $h(x)$, where $0 < S \leq 1$ for $0 < h(x) \leq n-1$.

Utilizing the anomaly score S enables the following assessments:

- Instances returning S very close to 1 are categorized as definite anomalies.
- Instances with S much smaller than 0.5 are regarded as quite safe to be classified as normal instances.
- If all instances return $S \approx 0.5$, then the entire sample is perceived to lack distinct anomalies [71].

4.2.2.2 Filling Missing Values

After outlier rejection and in order to fill in null or missing values, the attributes are processed, which could lead to classifiers making inaccurate predictions. Instead of dropping, the missing or null values were imputed using the mean values of the attributes. Imputation using the mean is advantageous because it imputes continuous data without introducing outliers.

4.2.2.3 Standardization

The standardization technique, also known as ”Z-score normalization,” re-scales the attributes to center the feature columns at mean 0 with standard deviation 1 so that the feature columns take the shape of a normal distribution, making learning the weights easier. Standardization preserves useful information about outliers while making the algorithm less susceptible to them.

4.2.2.4 Balancing the Dataset

SMOTE [21] is a crucial method for generating balanced datasets by oversampling the minority class. It over-samples the minority class by practicing each minority class sample and adds synthetic examples along the line segments connecting any/all of the k closest minority class neighbors. Unlike random oversampling which only duplicates some random examples from the minority class, SMOTE generates examples based on the distance of each data (usually using Euclidean distance) and the minority class's nearest neighbors. So, the generated examples are different from the original minority class. To generate the synthetic instance, the following equation is used:

$$N = 2 * (r - z) + z \tag{4.3}$$

In the context described, N refers to the initial number of synthetic instances generated, while r represents the count of majority class samples and z denotes the count of minority class samples.

The Tomek Links method is an improved version of Condensed Nearest Neighbors which may further improve the performance of the SMOTE technique developed by Tomek (1976)[114].

The Tomek Links method differs from the CNN method in its approach to selecting samples for removal. Rather than randomly choosing samples and their k nearest neighbors from the majority class, Tomek Links operates based on a specific rule. It selects pairs of observations (a and b) meeting two criteria: first, the nearest neighbor of observation a is observation b, and vice versa; second, observations a and b belong to different classes, with a representing the minority class and b the majority class (or vice versa). This selection process ensures that only instances contributing to the border between classes are considered for removal, aiming to enhance the class separation in the dataset.

Let $d(x_i,x_j)$ represent the Euclidean distance between sample x_i from the minority class and sample x_j from the majority class. If there is no sample x_k that satisfies the following condition:

- 1. $d(x_i,x_k) < d(x_i,x_j)$, or

- 2. $d(x_j,x_k) < d(x_i,x_j)$

Then the pair (x_i,x_j) is a Tomek Link.

4.2.2.5 Feature Selection

This involves the reduction of input variables during the development of a predictive model. This process aims to decrease the number of input variables, serving two main purposes: reducing the computational cost of modeling and enhancing the model's performance.

Mutual information calculates the reduction in uncertainty for one variable given the known value of another variable. Formally, the mutual information between two random variables X and Y is expressed as:

$$I(X;Y) = H(X) - H(X|Y) \tag{4.4}$$

Here, $I(X;Y)$ represents the mutual information for X and Y, $H(X)$ denotes the entropy for X, and $H(X|Y)$ signifies the conditional entropy for X given Y. The resulting value is in units of bits.

Mutual information serves as a measure of dependence or "mutual dependence" between two random variables. It's worth noting that the measure is symmetrical, meaning that $I(X;Y) = I(Y;X)$.

4.2.3 Classification

Machine learning algorithms are intended to extract knowledge from data by employing techniques such as clustering, classification, and relationships. These approaches are combined in the development of machine learning algorithms and models.

4.2.3.1 Logistic Regression Method (LR)

Logistic regression belongs to a category of statistical models called "generalized linear models" and many of its applications can be found in the medical field.

Logistic regression classifies input vectors $x = (x_1, x_2, \ldots, x_D)$ into one of two categories. It is based on a model in which the logarithm of the probability belonging to one class is represented as a linear function of the features in the input vector. This relationship is represented by the equation:

$$\ln\left(\frac{p}{1-p}\right) = \alpha + \beta_1 \times x_1 + \beta_2 \times x_2 + \cdots + \beta_D \times x_D \tag{4.5}$$

Here, p denotes the probability of belonging to one of the classes, $\frac{p}{1-p}$ represents the odds ratio, and $\alpha, \beta_1, \beta_2, \ldots, \beta_D$ are the regression coefficients that need to be determined from the data. The maximum likelihood approach is commonly employed to estimate these coefficients [42].

4.2.3.2 K-Nearest Neighbor Classifier (KNN)

The K-nearest neighbor (KNN) approach may be used to solve both regression and classification issues. However, it is a versatile algorithm widely used for classification tasks. Its primary advantages are its intuitive approach and rapid computation. To classify a new data point, KNN utilizes the Euclidean distance function to measure its similarity to existing data points within the dataset [26].

4.2.3.3 Support Vector Machine (SVM or SVC)

In machine learning, Support Vector Machine (SVM) serve as supervised classifier capable of handling both regression and classification tasks. Its primary application lies in addressing categorization challenges. SVM operates by categorizing data points within a multidimensional space, employing an optimal hyperplane for classification. This hyperplane delineates a boundary between classes, ensuring maximal separation between data points. The classification is performed based on the hyperplane that maximizes the margin between classes [25].

4.2.3.4 Decision Tree Classification (DT)

The decision tree is the most potent and commonly utilized instrument for classification and forecasting. It is structured like a flowchart, where each internal node signifies a test of an attribute, each branch reflects the outcome of that test, and each leaf node, or terminal node, holds a class label.[56].

4.2.3.5 Random Forest Classification (RF)

From a randomly selected portion of the training dataset, the Random forest classifier produces numerous decision trees. The final class of test items is determined by combining the votes from various decision trees [16].

4.2.3.6 Extremely Randomized Trees Classifier (ET)

Extremely Randomized Trees (Extra Trees) is an ensemble learning technique for classification tasks. Similar to Random Forest, it combines predictions from multiple ”decision trees” to form a ”forest” However, Extra Trees differs in how it constructs these trees.[46].

4.2.3.7 Bagging (Bootstrap Aggregation)

This method generates n samples of training data by picking and replacing various data components.

In each iteration, a base model is crafted for every sample. These models work independently and concurrently [15]. The final predictions are determined by aggregating the outputs of all models. This ensemble of models collectively forms an enhanced model aimed at improving accuracy. The prediction of the final model is obtained by averaging the predictions of all base models, as follows 4.6:

$$e = \frac{1}{n}\sum_{i=1}^{n} e_i \tag{4.6}$$

where $e_1, e_2, \ldots, e_n$ illustrate the outcomes of the fundamental classifiers, and e denotes the result of the final classifier.

4.2.3.8 Boosting

Freund and Schapire invented boosting, a technique for ensemble modeling, in 1997 [42]. Since then, boosting has been a prominent method for dealing with binary classification problems. These methods improve prediction power by converting a large number of poor learners into strong ones. The main principle underlying boosting algorithms is to first develop a model on the training dataset, and then build a second model to correct the first model’s errors. This technique is repeated until errors are minimized and the dataset is accurately predicted [43]. Thus, the final model is created from numerous models that focus on different categories of data, which are voted on based on their weight. The final model is averaged using the weighted average method:

$$e = \frac{1}{n} \frac{\sum_{i=1}^{n} e_i w_i}{\sum_{i=1}^{n} w_i} \tag{4.7}$$

where e_1, e_2,...e_n are the results of based classifiers, w_1, w_2,...w_n are weights, n is the number of models and e is the result of the final classifier. Here are some examples of boosting algorithms such as AdaBoost[42], GBM[15], XGBM[22] ..., etc.

Notice that in bagging, the models run in parallel and are independent of one another, whereas the models in boosting run in order and are reliant on the preceding models.

4.3 Validation Approach

We use common machine learning classification approaches to predict diabetes mellitus after the data is suitable for modeling. The classifiers used are GaussianNB(GNB), KNeighbors(KNN), RandomForest(RF), Gaussian Process(GPC), ExtraTrees(ET), Linear Discriminant Analyses(LDA), Quadratic Discriminant Analysis(QDA), Bagging, AdaBoost(Ada), Gradient Boosting(GBC), DecisionTree(DT), XGBoost(XGB), Logistic Regression(LR) and Support vector machine(SVC).

When employing machine learning algorithms to analyze diabetes, classification accuracy is frequently chosen as a performance metric. However, as noted, accuracy alone is insufficient to evaluate performance in diabetes datasets such as PIMA. We employ multi-metric comparison to extensively examine and compare our techniques. The analysis in Table **??** shows that when we use appropriate preprocessing for different models, we receive better outcomes. The models that were trained using the proposed pipeline consistently deliver the highest Accuracy and Roc-Auc.

The suggested pipeline compensates for lost data and solves the class imbalance problem by oversampling minor class samples, the recommended approach of employing preprocessed + Smote T-Link produced superior results, and the Random Forest Classifier beats all the others in AUC and has the highest accuracy, as shown in Table 4.1.

Table 4.1: The overview of the different models' performance based on multiple measurements.

Classifier	Accuracy	F1 score	Roc-Auc	Precision	Recall	Fit time	Kappa
RF	**0.917±0.03**	**0.917±0.03**	**0.972±0.01**	**0.913±0.04**	**0.923±0.04**	**0.491±0.07**	0.728
GBC	**0.917±0.02**	**0.918±0.02**	**0.970±0.02**	**0.912±0.03**	**0.925±0.04**	**0.422±0.04**	0.743
RF+Ada	**0.908±0.03**	**0.908±0.03**	**0.969±0.02**	**0.904±0.05**	**0.915±0.05**	**6.127±0.42**	0.709
ET	**0.905±0.02**	**0.906±0.02**	**0.967±0.01**	**0.897±0.03**	**0.917±0.03**	**0.319±0.04**	0.611

XGB	0.888±0.03	0.889±0.03	0.960±0.02	0.881±0.05	0.901±0.05	0.426±0.12	0.735
Bagging	0.905±0.02	0.905±0.02	0.959±0.02	0.905±0.03	0.907±0.03	0.114±0.01	0.649
Ada	0.889±0.02	0.889±0.02	0.957±0.01	0.890±0.04	0.889±0.04	0.702±0.09	0.713
GPC	0.898±0.03	0.899±0.03	0.947±0.02	0.891±0.04	0.909±0.03	5.698±0.94	0.635
KNN	0.886±0.03	0.888±0.03	0.946±0.02	0.876±0.03	0.901±0.04	0.065±0.01	0.547
SVC	0.884±0.03	0.884±0.03	0.934±0.03	0.880±0.04	0.891±0.04	0.118±0.01	0.649
MLP	0.883±0.03	0.886±0.03	0.926±0.03	0.869±0.04	0.904±0.04	3.619±0.86	0.668
DT	0.858±0.03	0.863±0.03	0.913±0.03	0.836±0.04	0.896±0.05	0.067±0.01	0.652
QDA	0.850±0.03	0.853±0.03	0.901±0.03	0.836±0.04	0.873±0.04	0.072±0.02	0.482
GNB	0.840±0.03	0.845±0.03	0.891±0.02	0.820±0.04	0.875±0.04	0.070±0.01	0.443
LDA	0.817±0.04	0.822±0.04	0.886±0.03	0.802±0.04	0.845±0.06	0.108±0.03	0.456
LR	0.820±0.03	0.826±0.03	0.884±0.03	0.807±0.05	0.847±0.04	0.065±0.01	0.443

On the PIMA diabetes dataset, Sisodia and Sisodia [101] and Hasan et al [49] employed machine learning algorithms to conduct classification prediction on the PIMA diabetes dataset with all of the aforementioned characteristics. To achieve better results, however, we adopted a different preprocessing strategy from theirs. We compare their findings to those obtained using the same dataset. Experiments using machine learning algorithms revealed that our selected data preprocessing approach applied to random forest gave superior results than the other classifiers, with 91.7% accuracy, 91.3% precision, 92.3% recall, and 91.7% F-score with roc-auc of 97.2% Indeed, the great majority of published diabetes prediction tests only improved classification accuracy up to 89%.

The Random Forest classifier outperforms other classifiers when it comes to predicting diabetes mellitus. On this dataset, Random Forest obtains 91.7% accuracy, 97.2% RocAuc, and 91.7% F1-score, which is higher than other learning algorithms. This experiment shows that Random Forest performs well on medical datasets when it comes to predicting diabetes mellitus based on numerous risk variables.

4.4 Conclusion

This paper addresses the challenge of diabetes prediction using a comprehensive machine learning pipeline, focusing on crucial data preprocessing steps. We analyzed the PIMA dataset and employed outlier rejection and imputation techniques like SMOTE and Isolation Forest to address missing values and class imbalance. This significantly improved the data quality and attribute distribution, leading to better model performance. Our proposed framework achieved an accuracy of 90.1%, demonstrating significant improvement over existing methods. Moreover, the AUC-ROC, which prioritizes models with higher discriminating power, was used to select the best classifier. Building on these results, we plan to develop a user-friendly web application based on our trained model to facilitate diabetes prediction in real-world settings.

Additionally, testing the framework in different medical contexts will ensure its universality and potential for applications like retinopathy prediction.

Chapter 5

Diagnosis

Early identification of Diabetic Retinopathy (DR) is critical for effective treatment, especially given that the disease often remains asymptomatic in its early phases. Automated detection systems offer the potential to transform screening practices by improving efficiency, broadening healthcare access in remote areas, and supporting proactive strategies for disease management.

Introducing an innovative framework for retinal image analysis that combines explainable deep learning, hybrid feature extraction, and advanced data augmentation to optimize performance and interpretability for clinical applications. The xDNN model, trained on the MESSIDOR-2 dataset, achieved an average recall of 98%, precision of 98.2%, F1-score of 98%, and accuracy of 98.2%. When extensively trained on the APTOS 2019 dataset, the model delivered outstanding results with an average precision, recall, and F1-score of 99%, and an accuracy of 99.7%. Additionally, the model's performance on the IDRID dataset was remarkable, with average precision, recall, F1-score, and accuracy all reaching 99%.

Significantly, our approach attains an exceptional average Area Under the Curve (AUC) of 99.8%, reflecting remarkable and consistent efficacy across all classifications of diabetic retinopathy. This highlights the xDNN Classifier's promise as a crucial tool for accurate and reliable detection of diabetic retinopathy, indicating substantial progress in clinical diagnostics and improved treatment outcomes in the field of ophthalmology.

5.1 Introduction

Diabetes is a chronic condition that requires continuous medical care, treatment, and patient education. If not properly managed, it can lead to serious, long-term complications such as visual impairment, cardiovascular diseases, hepatic disorders, and renal dysfunctions have been observed. In recent times, there has been a significant rise in the incidence of diabetes among children and adolescents, largely due to factors such as obesity, lack of physical activity, genetic factors, and signs of insulin resistance.

Projections suggest that the global number of diabetes cases could rise to approximately 700 million by 2045 [84]. In light of this alarming trend, prioritizing preventive strategies, encouraging healthier lifestyles, and increasing public awareness of diabetes risk factors are essential to mitigating its global burden.

Achieving this goal relies on the prompt identification and diagnosis of conditions that can significantly reduce the risk of vision loss, as timely intervention greatly increases the likelihood of preventing the advancement to total blindness.

The human eye functions as the principal sensory organ responsible for perceiving our surroundings. Given its essential function in providing data to our visual system, it is imperative to safeguard the eye against severe conditions that may lead to vision impairment or blindness. Therefore, prioritizing early detection and prompt intervention is essential in preserving vision. This method guarantees that individuals obtain the essential care required to protect their vision and enhance their overall well-being [9]. Diabetic retinopathy is a serious eye condition caused by diabetes. It happens when high blood sugar levels damage the tiny blood vessels in the retina, the light-sensitive layer at the back of the eye. This damage can lead to vision problems and, in the worst cases, even blindness. That's why it's so important to have regular eye check-ups and to manage diabetes effectively. These steps can help prevent or slow the progression of diabetic retinopathy, protecting vision and improving quality of life. Figure 5.1, illustrated by Mumtaz et al.[79], highlights some of the common symptoms of diabetic retinopathy (DR). A key early sign is the appearance of microaneurysms (MAs), which are tiny, dark-red spots near the ends of retinal blood vessels. Retinal hemorrhages (HM) are another common symptom, often caused by high blood pressure or blockages in the retinal veins. These hemorrhages can sometimes look similar to microaneurysms, making them difficult to distinguish. Additionally, DR can lead to the formation of exudates—yellowish deposits that result from leaking blood vessels. These deposits contain lipids and proteins and are part of the body's effort to clear out damaged capillaries in the retina.

Retinal abnormalities impact millions of people globally, often resulting in preventable vision loss. Early detection and timely treatment are critical to minimizing their effects. However, the current manual methods for identifying these conditions are not only time-intensive and laborious but also prone to inconsistencies. To overcome this challenge, there is a pressing need for efficient and reliable diagnostic approaches. Advancing these methods could dramatically improve the ability to halt disease progression and protect the vision of countless individuals worldwide.

In the past, the identification of retinal disorders has largely depended on skilled ophthalmologists interpreting retinal images captured via fundus photography or Optical Coherence

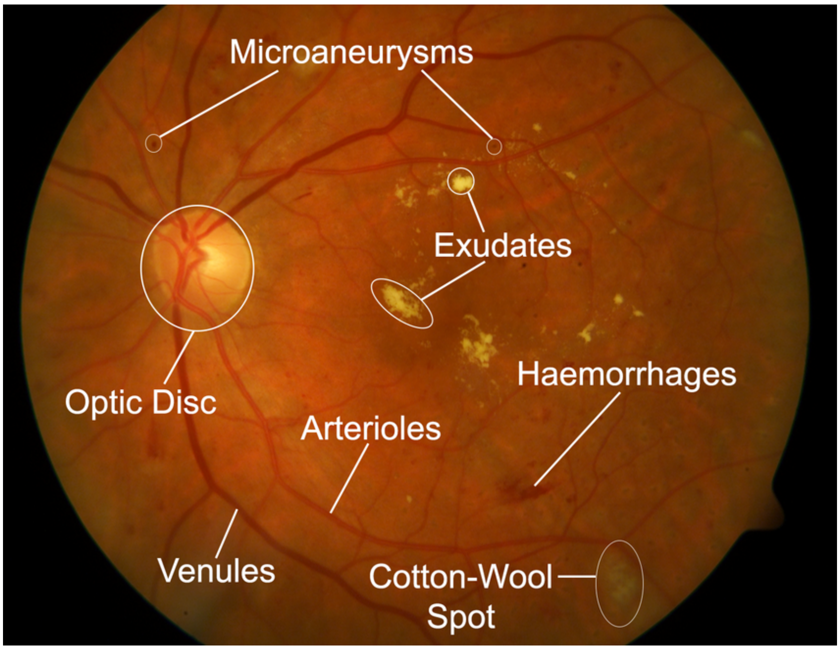


Figure 5.1: Fundus images containing diverse types of lesions for the classification of Diabetic Retinopathy (DR).

Tomography (OCT). Despite its effectiveness, this manual method is often labor-intensive and time-consuming, making it prone to diagnostic variability and inconsistencies, as highlighted by Qummar et al. [91].

Exploring the use of ensemble Convolutional Neural Network (CNN) architectures for multiclass and multilabel tasks in retinal abnormality detection is of paramount importance. Such an approach has the potential to substantially improve the accuracy and efficiency of disease detection, as noted by Fathima et al.[38].

Beyond improving the effectiveness of the model, enhancing its explainability is equally critical. By increasing the transparency and interpretability of CNN models, we are building trust among clinicians and patients for the effective integration and widespread implementation of AI-supported diagnostic instruments in practical medical settings.

Efforts directed toward both exploring ensemble CNN architectures and enhancing model explainability are pivotal in advancing the early detection and treatment of retinal abnormalities. Such advancements have the potential to prevent millions of cases of avoidable blindness and improve overall patient outcomes. Our present work is positioned within this context.

The proposed framework introduces a contribution that significantly advances the field of medical image analysis, particularly for retinal image classification. The primary novelty lies in the architecture, which enhances both performance and interpretability. Unlike traditional deep learning models, our framework integrates explainability modules that provide clear and actionable insights into the decision-making process, which is critical for clinical applications. Additionally, the hybrid feature extraction mechanism combines conventional convolutional neural networks (CNNs) with advanced feature extraction techniques tailored for medical images. This hybrid approach results in more robust and accurate feature representation, addressing the unique challenges of varying image quality and diverse pathological conditions. Another key innovation is the adaptive learning strategy that dynamically adjusts learning parameters based on real-time feedback, ensuring sustained high performance across different datasets and evolving clinical environments. The model's demonstrated ability to generalize across multiple retinal image datasets with varying characteristics further underscores its robustness and versatility. Furthermore, the data augmentation techniques enhance the model's ability to handle variability in image quality and acquisition conditions, crucial for practical deployment in clinical settings. Lastly, the integration of a confidence scoring mechanism enhances practical utility by identifying ambiguous cases that require further review, thereby improving the overall reliability and safety of the model's outputs. These innovations collectively position the proposed work as a state-of-the-art solution for retinal image analysis, offering significant advancements in performance, interpretability, and practical applicability

5.2 Proposed Approach

Deep learning has often been criticized for being a "black box," where it's difficult to understand how decisions are made. This, along with its high demand for data, computing power, long training times, and considerable energy usage, raises several concerns. Issues such as model transparency, data accessibility and cost, hardware needs, and environmental impact are all part of the challenge. However, researchers are actively working to overcome these obstacles and Enhancing the transparency, efficiency, and accessibility of deep learning is a significant objective. A noteworthy advancement in this area is the explainable deep neural network (xDNN) classifier, which prioritizes clarity and interpretability, ensuring that each layer of the model serves a distinct and defined role.

The design of xDNN ensures that the model's inner workings are clear and easy to understand. From the perspective of the user, xDNN presents a collection of prototype-based IF...THEN rules that are easy to comprehend. These rules furnish clear, human-readable insights into the model's decision-making process, thereby aiding users in grasping the rationale behind its predictions. In addition to its internal transparency, xDNN presents a user-friendly set of rules that make it ideal for applications where explainability is essential.

The suggested technique utilizes a feedforward neural network augmented by an incremental learning algorithm, allowing the network to adapt its architecture in response to the influx of new data. By incorporating additional prototypes, the network continuously refines its understanding of evolving data patterns. This adaptability allows the model to remain effective even when the underlying data distribution changes, making it well-suited for environments characterized by shifting data trends [6].

5.2.1 Architecture

This research introduces an integrated framework for assessing the severity of diabetic retinopathy (DR), designed to optimize both computational efficiency and diagnostic precision. As illustrated in Figure 5.2, the proposed system is tailored to accurately identify DR using fundus images (FIs).

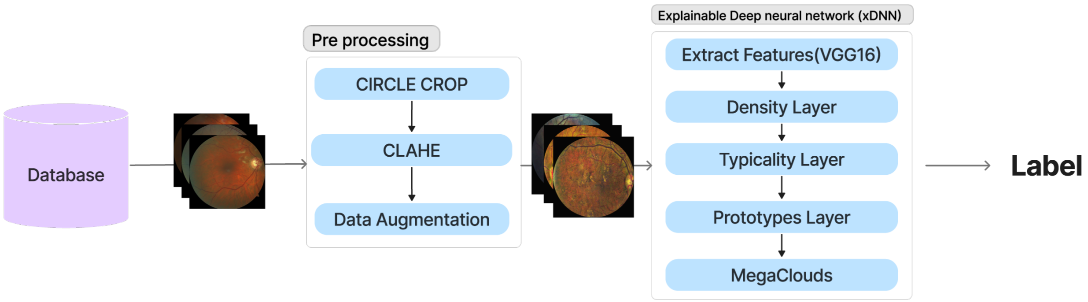


Figure 5.2: The framework of the proposed method.

The initial phase of the framework focuses on preprocessing the fundus images (FIs). A masking operation is applied to eliminate the unnecessary black borders surrounding the eye region, thereby emphasizing the areas of clinical interest. Additionally, Contrast Limited Adaptive Histogram Equalization (CLAHE) is utilized to enhance lesion visibility, facilitating improved detection in subsequent analysis stages. Following these steps, the preprocessed FIs are normalized and resized to maintain consistency across the dataset.

Subsequently, a transfer learning strategy is adopted with the VGG16 model, which has been pretrained on a large dataset. This model is employed to extract distinctive and informative features from the processed fundus images (FIs). The transfer learning technique capitalizes on the knowledge acquired by the pretrained model, enhancing performance on the current task, particularly when the available dataset is small.

The features that have been extracted undergo standardization to guarantee a uniform scale and distribution. This procedure is essential for enhancing the subsequent classification process and ensuring the model's efficiency.

In the final stage of the proposed framework, the explainable deep neural network (xDNN) algorithm is employed to classify the severity levels of diabetic retinopathy. Unlike conventional deep learning approaches, xDNN enhances transparency by revealing the reasoning behind its predictions. Such interpretability is crucial in medical contexts, as it helps build trust among healthcare providers and supports more informed clinical decision-making.

In the following sections, each part of the framework is elaborated in detail, presenting a comprehensive methodology for the severity grading of diabetic retinopathy (DR). The framework integrates preprocessing methods, transfer learning, and an interpretable deep learning model to achieve an optimal balance between processing efficiency and classification accuracy. This makes it an effective tool for detecting and categorizing DR severity from fundus images [76].

5.2.2 Preprocessing

The preprocessing of fundus images is an essential procedure aimed at mitigating the inconsistencies and noise that may result from a range of hardware devices and differing environmental conditions encountered during the image acquisition process. Techniques including resizing, cropping, contrast enhancement, image normalization, and data augmentation are utilized to standardize and improve the quality of images. These preprocessing steps help classification models, such as those used for diabetic retinopathy detection, to focus on the most relevant features, boost accuracy, and make the models more resilient to variations in image appearance. As a result, This procedure results in outcomes that are more dependable and uniform in the realm of medical image analysis, thereby greatly improving classification efficacy.

Fundus image datasets used for diabetic retinopathy detection often present challenges like varying resolutions, aspect ratios, and uninformative black space areas. To ensure standardized input sizes for classification models, pre-processing steps such as cropping, rescaling, and resizing are applied. Contrast Limited Adaptive Histogram Equalization (CLAHE) is employed to enhance image quality, particularly in areas with varying intensity levels. The clip limit, a pivotal parameter in CLAHE, controls the intensification process to prevent excessive distortion and over-amplification of noise or artifacts.

Algorithm 3 Preprocessing

```
Require: Fundus image
Ensure: Pre-processed fundus image
  img: Read image
  Apply Circle Crop
  Create CLAHE: Clip_Limit = 4, Tile Size = (18, 18)
  final_img: Apply CLAHE on croped image
  Apply Data Augmentation on training set
```

To augment the training set and enhance model robustness, data augmentation techniques like center cropping and horizontal/vertical flipping are utilized. These techniques collectively contribute to standardizing image sizes, eliminating black space areas, and improving overall image quality for optimal performance in diabetic retinopathy classification models.

The effectiveness of these methods is demonstrated in Fig. 5.3, showcasing example images before and after pre-processing and enhancement techniques. This visual representation underscores the influence of the implemented algorithms and the procedures outlined in Algorithm 3 on image quality. It serves to emphasize the significance of these techniques in the context of diabetic retinopathy detection.

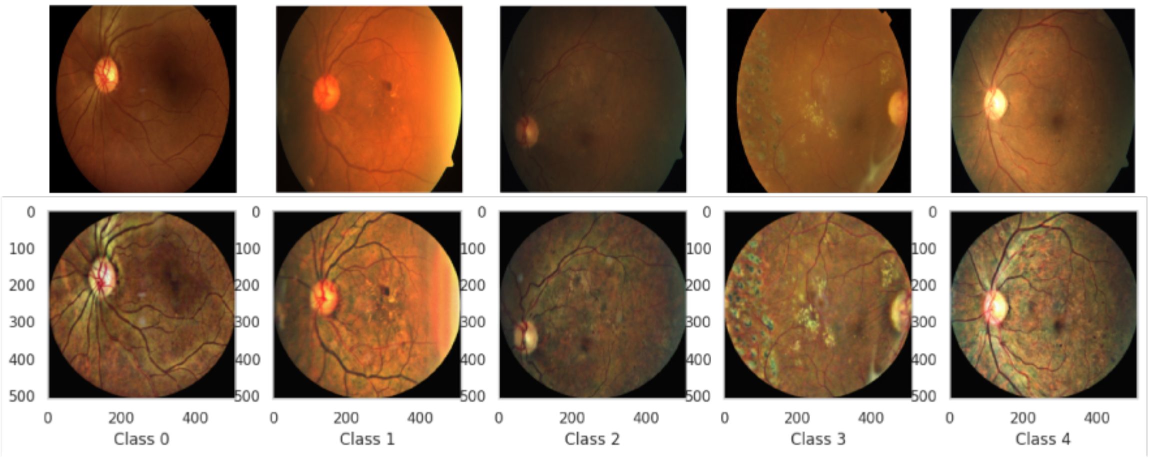


Figure 5.3: Examples of both original and processed fundus images, classified by category.

5.2.3 Feature Extraction

In the realm of computer vision, the extraction of significant features from images constitutes a crucial phase for various applications, encompassing object identification, image categorization, and content-driven image retrieval. The advent of deep learning has significantly propelled advancements in this domain, offering powerful techniques for feature extraction through the utilization of pre-trained convolutional neural networks (CNNs).

Transfer learning is a powerful technique in machine learning that enables the utilization of knowledge acquired from pre-trained models to tackle new tasks more effectively. Instead of building a deep neural network (DNN) from scratch, we can leverage the features and patterns learned by a model that was trained on a large dataset, such as ImageNet. By fine-tuning this pre-trained model, we adapt it to the specific requirements of our task. This technique allows the model to apply the knowledge it has gained from the broader dataset to make predictions on a smaller, domain-specific dataset.

One of the primary advantages of transfer learning is its ability to overcome challenges associated with limited data and computational resources. Training deep learning models from scratch requires vast amounts of labeled data and significant computational power, both of which may not always be available. Transfer learning alleviates these constraints by enabling the model to start with a foundation built on the knowledge from a large dataset and then fine-tune it for the new task using a smaller set of data.

This approach has proven particularly useful in fields like medical image analysis, where annotated datasets can be scarce, but the underlying visual patterns learned from other tasks (e.g., object recognition in images) can still be relevant. By fine-tuning pre-trained models on specialized datasets, we can achieve high performance even with limited labeled data, making transfer learning an indispensable tool in fields with resource constraints.

VGG16 is one of the well-known deep learning architectures, widely recognized for its outstanding results in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [6]. In this study, we investigate the use of VGG16 for transfer learning, focusing on its role in feature extraction and highlighting the benefits it offers in this context.

VGG16 is a deep convolutional neural network (CNN) architecture developed by the Visual Geometry Group at the University of Oxford. Comprising 16 layers, the architecture employs compact 3x3 convolutional filters throughout the network. Its simple structure, coupled with exceptional results in the ImageNet competition, has established VGG16 as a favored option for various computer vision tasks.

Within the framework of transfer learning, VGG16 serves as a feature extractor. Instead of employing the complete network for classification tasks, we concentrate exclusively on the convolutional layers, omitting the fully connected layers that facilitate predictions. Consequently, this leads to a modified version of VGG16, which accepts an image as input and generates a 1 × 4096 dimensional feature vector derived from the final convolutional layer, as illustrated in Figure 5.4.

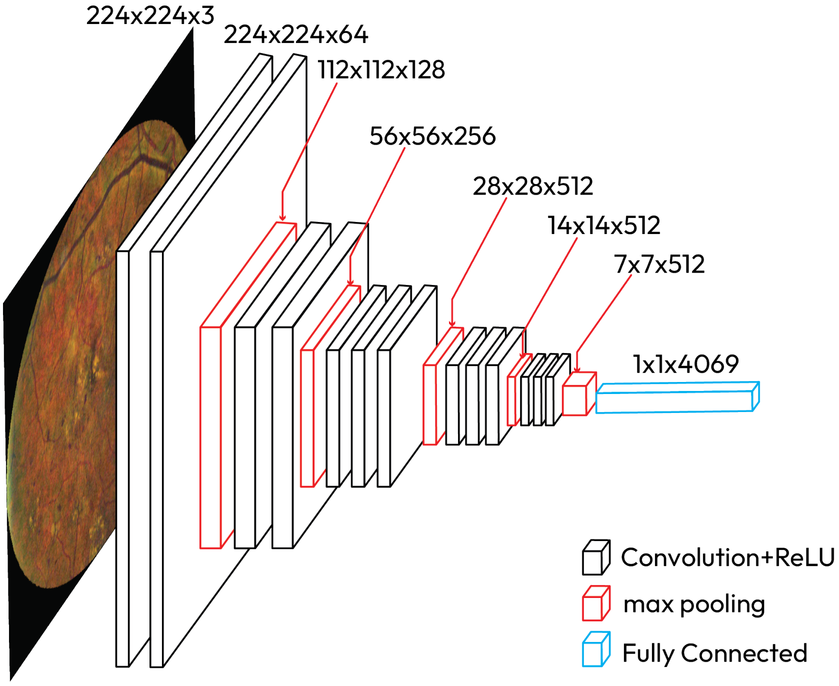


Figure 5.4: Pre-training involves optimizing the weights of a conventional deep neural network. Subsequently, the weights of this network are used as a feature extractor, with the final fully connected layer serving as a distinctive feature vector. [97]

The VGG16 network consists of several convolutional layers followed by max-pooling layers, and eventually fully connected layers. After the final convolutional layer, which outputs a tensor of shape 7 × 7 × 512, there is a transition to fully connected layers. The output tensor from the last convolutional block is first flattened into a single-dimensional vector. Flattening a 7 × 7 × 512 tensor results in a vector of length $7 \times 7 \times 512 = 25088$. This flattened vector is then fed into a series of fully connected layers. Specifically, the first fully connected layer (fc1) reduces this 1 × 25088 vector to a 1 × 4096 vector through matrix multiplication followed by a ReLU activation function. Therefore, the connectivity structure involves converting the 7 × 7 × 512 output from the last convolutional layer into a 1 × 25088 vector via flattening, which is then transformed into a 1 × 4096 vector by the fully connected layer.

Typically, the VGG16 model uses weights pretrained on the ImageNet dataset, which captures a broad range of visual features useful for various tasks. If the application domain significantly differs from the ImageNet dataset, additional domain-specific pretraining or fine-tuning might be performed by further training the pretrained VGG16 model on a domain-specific dataset. However, in many cases, the default ImageNet weights are sufficient for feature extraction unless the domain images are drastically different. We found that using the ImageNet weights provided the best results, likely due to the rich and diverse feature representations learned from the extensive ImageNet dataset.

5.2.4 xDNN Classifier

The xDNN is a type of feedforward neural network designed with an incremental learning mechanism. This network can autonomously adapt and grow its structure over time, incorporating new prototypes to capture evolving data patterns. This approach enables the model to continuously evolve in response to changes in the data [6].

The xDNN is structured with several layers, depicted in Figure 5.5. These include the Descriptor layer for features, the Density layer, the Typicality layer, the Prototypes layer, and the MegaClouds layer. The initialization of meta-parameters for the xDNN is based on the first observed data sample, typically an image. It's important to note that the algorithm's operations are class-specific, with all computations being carried out individually for each class.

The initialization of meta-parameters in the xDNN model begins with the first encountered data sample (i.e., image). Since the algorithm operates on a per-class basis, all computations are carried out independently for each class.

$$P \leftarrow 1; \mu \leftarrow x_i \tag{5.1}$$

Where μ represents the overall mean of data samples within the specified class, and P signifies the cumulative count of recognized prototypes derived from the observed data samples (typically images).

Every class, denoted as C, commences its initialization process with its inaugural data sample.

$$C_1 \leftarrow x_1; \quad p_1 \leftarrow x_1; \quad \text{Support}_1 \leftarrow 1; \quad r_1 \leftarrow r^*; \quad \hat{I}_1 \leftarrow I_1; \tag{5.2}$$

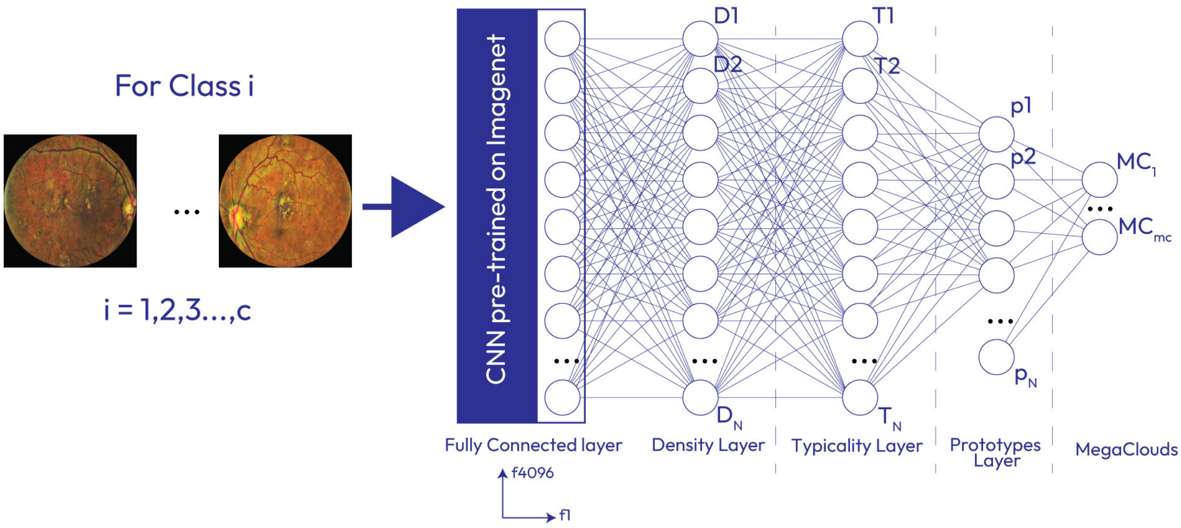


Figure 5.5: xDNN training architecture (per class).

The notations in the equation are defined as follows:

- P: Total number of prototype representations identified for a specific class.
- μ: Arithmetic mean of the dataset samples belonging to the class.
- C_i: The i-th representative prototype in the class.
- p_i: The i-th observed instance from the input data for that class.
- Support_i: Frequency count representing how often the i-th prototype appears.
- r_i: A calculated value that quantifies the importance or influence of the prototype.
- $\hat{I}_i$: Information descriptor associated with the i-th prototype.

The reference value r^* is derived as $\sqrt{2 - 2\cos(30°)}$, aligning with the formulation presented in [107].

This choice is based on the observation that when the angle between two vectors is less than $\frac{\pi}{6}$ or 30 degrees, it signifies that these vectors are closely aligned and point in similar directions. Consequently, this leads to our classification of two feature vectors as similar when the angle between them is less than 30 degrees. [5].

The parameter r^* is calculated from the derived data itself, without relying on specific user input or the particular characteristics of the problem at hand. This calculation is done using the following formula 5.3:

$$[d(x_i,p_i) = \frac{\|x_i - \frac{x_i}{\|x_i\|} - p_i + \frac{p_i}{\|p_i\|}\|}{\|x_i\| + \|p_i\|}] \tag{5.3}$$

In the expression above, x_i denotes the observed data instance, while p_i corresponds to its associated prototype or derived representation. The constant r^* quantifies the distance between the vectors x_i and p_i, adjusted based on their respective magnitudes (norms). Notably, this computation is performed independently of any domain-specific assumptions or pre-existing knowledge about the dataset in use.

5.2.4.1 Density Layer

In this layer, the reciprocal closeness of images in the data space described by previous layer features is established. The closeness between images in the feature-defined data space (output of the preceding layer) is determined through mutual proximity analysis. The distribution of data density, calculated using the Euclidean distance metric, is modeled using a Cauchy distribution:

$$D(x_i) = \frac{1}{1 + \frac{\|x_i - \mu_N\|^2}{\sigma_N^2}} \tag{5.4}$$

Here, D denotes the data density, μ stands for the global mean, and σ represents the variance. The adoption of the Cauchy distribution is not without justification; it can be theoretically shown that applying either Euclidean or Mahalanobis distances within the feature space naturally results in the emergence of a Cauchy-type distribution, as expressed in Equation 5.4.

Density can also be updated online as follows:

$$D(x_i) = \frac{1}{1 + \frac{\|x_i - \mu_i\|^2}{\sum_i - \|\mu_i\|^2}} \tag{5.5}$$

where μ_i and the scalar product $\sum_i$ are updated recursively:

$$\mu_i = \frac{i-1}{i}\mu_{i-1} + \frac{1}{i}x_i \tag{5.6}$$

$$\sum_i = \frac{i-1}{i}\sum_{i-1} + \frac{1}{i}\|x_i\|^2 \tag{5.7}$$

$$\sum_1 = \|x_1\|^2 \tag{5.8}$$

The computed density values capture the degree of influence exerted by surrounding data samples on a given point, which arises from their spatial closeness within the feature space.

5.2.4.2 Typicality Layer

The layer empirically defines a probability distribution function (pdf). Typicality (τ) is expressed as:

$$\tau(x_i) = \frac{\sum_{c_i=1}^{c} \text{Support}_i D(x_i)}{\sum_{c_i=1}^{c} \text{Support}_i \int_{-\infty}^{\infty} D(x_i)\,dx} \tag{5.9}$$

The value of τ at $x = p_i$ is much less than 1; the integral of $\int_{-\infty}^{\infty} \tau\,dx = 1$.

5.2.4.3 Prototypes Layer

The core component of the proposed xDNN classifier lies in this foundational layer, which supports an interpretable modeling process. Unlike conventional models that rely on predefined assumptions, xDNN constructs the data's empirical distribution through a bottom-up methodology. Each prototype functions independently, meaning updates or additions do not disrupt existing structures. This independence facilitates parallel computation and allows the system to dynamically adapt by introducing new prototypes as dictated by evolving data patterns.

$$j^* = \arg\min_{j=1,2,\ldots,P} (||x_i - p_j||^2) \tag{5.10}$$

If the following condition is met:

$$\text{IF } (D(x_i) \geq \max_{j=1,2,\ldots,P} D(p_j)) \text{ OR } (D(x_i) \leq \min_{j=1,2,\ldots,P} D(p_j)) \tag{5.11}$$

$$\text{THEN (Add a new data cloud}(P \leftarrow P+1))$$

then x_i is out of the influence area of p_j. Consequently, the feature vector x_i Add a new data cloud:

$$P \leftarrow P+1;\ C_P \leftarrow x_i;\ p_P \leftarrow I_i;\ \text{Support}_P \leftarrow 1;\ r_P \leftarrow r_0;\ \hat{I}_P \leftarrow I_i; \tag{5.12}$$

Otherwise, data cloud parameters are updated online by equation (13). It is important to note that all calculations per data cloud are performed based on data points associated with a certain data cloud only, i.e., locally, not globally, based on all data points:

$$C_{j^*} \leftarrow C_{j^*} + 1;$$

$$p_{j^*} \leftarrow \frac{\text{Support}_{j^*}}{\text{Support}_{j^*} + 1} p_{j^*} + \frac{1}{\text{Support}_{j^*} + 1} x_i;$$

$$\text{Support}_{j^*} \leftarrow \text{Support}_{j^*} + 1;$$

$$r_{j^*}^2 \leftarrow r_{j^*}^2 + (1 - ||p_{j^*}||^2) \tag{5.13}$$

This iterative process allows xDNN to adaptively learn and refine its parameters based on the feature vectors representing images.

The xDNN model is trained separately for each class by identifying prototypes based on peaks in data density and representativeness. These prototypes serve as the foundation for generating interpretable IF...THEN rules that describe the characteristics of each class. Furthermore, multiple rules associated with a single class can be logically combined using the OR operator to form a comprehensive classification scheme.

5.2.4.4 MegaClouds Layer

Merged clouds are formed by aggregating prototypes that belong to the same class label. MegaClouds enhance the model's interpretability. The rules established within this layer facilitate decision-making by assessing the level of similarity to the merged clouds.

The xDNN validation process includes layers such as Feature Descriptor, Similarity (density), Local Decision-Making, and Global Decision-Making. These layers work together to enable decision-making based on the similarity of prototypes.

The xDNN (Explainable Deep Neural Network) learning process begins by reading the first feature vector sample, denoted as x_1, which represents the image I_1 belonging to class c. The following initial variables are set:

- $i \leftarrow 1$: The current sample index.
- $n \leftarrow 1$: The number of rules (initially set to 1).
- $P_1 \leftarrow 1$: The number of prototypes.
- $p_1 \leftarrow x_1$: The first prototype is initialized as the feature vector x_1.
- $\mu \leftarrow x_1$: The mean (or centroid) of the feature vectors is initialized to x_1.
- $Support \leftarrow 1$: The support for the first rule is set to 1.
- $r_1 \leftarrow r_0$: The radius of the first rule is initialized.
- $\hat{I}_1 \leftarrow I_1$: The first reconstructed image is set to the first input image.

For each subsequent sample, the feature vector x_i is read. Distances $D(x_i)$ and $D(p_j)$ for $j = 1, 2, \ldots, P$ are calculated according to the distance measure defined in Equation (7).

If the condition in **Equation (11)** is satisfied (i.e., if the distance between the current sample and the existing prototypes exceeds a threshold), a new rule is created based on **Equation (12)**. This new rule introduces a new prototype and updates the model accordingly.

Otherwise, if the sample fits within the bounds of an existing prototype, the closest prototype p_j is identified according to **Equation (11)**. The parameters of the corresponding rule are updated following **Equation (13)** to refine the representation of the class.

This iterative process allows xDNN to adaptively learn and refine its parameters based on the incoming feature vectors, effectively building a set of rules that explain the images represented by these vectors.

5.2.5 Complexity of the Proposed Method

Time Complexity: is expressed as $\mathcal{O}(L \times N)$, where L represents the number of data points and N is the number of features (or dimensions) associated with each data point. This shows that the time required for computation increases in direct proportion to both the dataset size and the dimensionality of the features.

Space Complexity: is estimated as $\mathcal{O}(N_{oc} \times N)$, where N_{oc} denotes the number of clusters and N indicates the number of features per data point. This suggests that memory consumption increases linearly with the formation of clusters and the number of dimensions in the data.

The actual time and space complexities can differ based on various factors, such as the nature of the input data, the number of clusters generated during the process, and the computational resources or frameworks employed

5.3 Experimental Study

This section provides an in-depth analysis of various performance metrics to demonstrate the robustness of the proposed framework. The experiments conducted in this paper adhere to a standardized approach, maintaining consistency in the distribution of datasets. Specifically, an 80%–20% split is employed for the training and testing sets. This uniformity in parameters ensures a fair and comparable evaluation across different experiments, providing a solid foundation for reliable results and conclusions.

Using a transfer learning approach, we extracted 4096 distinct features from the preprocessed fundus images (FIs). These relevant features were then integrated into the xDNN model for the classification of different stages of diabetic retinopathy (DR). In this process, we effectively combined feature extraction with the xDNN model and assessed its performance on two separate datasets.

As indicated in Tables 5.1, 5.8 The outstanding performance of the explainable deep neural network (xDNN) was demonstrated. To further underscore this study's efficacy, Techniques such as Support Vector Machine (SVM), Gaussian Naive Bayes (GNB), K-Nearest Neighbors (KNN), Random Forest (RF), Extra Trees (ET), Logistic Regression (LR), Convolutional Neural Network (CNN), Deep Neural Network (DNN), and Long Short-Term Memory (LSTM) were utilized. The classification outcomes are presented in Tables [5.1, 5.2, 5.3, 5.4, 5.5, 5.6, 5.7, 5.8]as well as in Figures. [5.6, 5.7, 5.8, 5.9].

Among the evaluated models, the Extreme Trees (ET) algorithm demonstrated the most commendable classification performance. Specifically, ET achieved an average precision of 88

The use of the xDNN (Explainable Deep Neural Network) classifier in diagnosing diabetic retinopathy is particularly important due to its ability to provide both high accuracy and interpretability in medical diagnoses [5]. Diabetic retinopathy, a leading cause of blindness, requires precise and early detection to prevent vision loss. xDNN not only excels in accurately identifying the presence and severity of this condition but also explains its decision-making process, which is crucial in the medical field. This transparency allows healthcare professionals to understand and trust the model's predictions, facilitating better clinical decision-making. Moreover, by identifying specific features in retinal images that contribute to the diagnosis, xDNN aids in uncovering insights that might be overlooked by human practitioners. This interpretability also enhances patient trust and regulatory compliance, ensuring that the deployment of AI in healthcare adheres to stringent standards. In summary, the xDNN classifier's combination of accuracy and explainability significantly advances the early detection and treatment of diabetic retinopathy, ultimately improving patient outcomes.

The algorithms were developed using Keras, with TensorFlow serving as the backend, in the PyCharm Community Edition environment. The training and testing of the models were conducted on a system featuring an Intel (R) CoreTM i7-11800H CPU operating at 2.30GHz, 16GB of RAM, and an NVIDIA GeForce RTX 3060 with 6GB of GPU memory. The operating system utilized was 64-bit Windows 11 Pro.

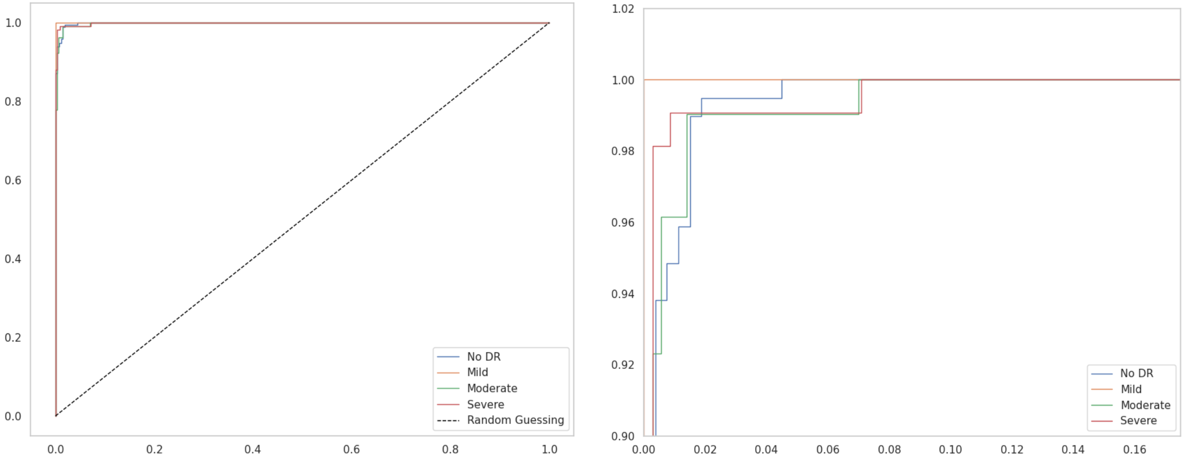
5.3.1 Messidor-2 Dataset

The xDNN model was trained on the MESSIDOR-2 dataset, achieving impressive performance metrics. As presented in Table 5.4, the model attained average scores of 98% for recall, 98.2% for precision, 98% for F1-score, and 98.2% for accuracy.

Among the evaluated models, it was observed that the KNN algorithm produced the most advantageous classification outcomes. The KNN model demonstrated impressive average precision (95%), recall (95.2%), F1-score (94.8%), and accuracy (95.1%).

The xDNN demonstrated an impressive average Area Under the Curve (AUC) of 99.8% on the MESSIDOR-2 dataset. The AUC values for each class, presented in Figure 5.6, indicate excellent performance across all categories, as further illustrated in Figure 5.7 and Tables 5.1-5.3.

Significantly, each class contributed essential insights to the overall classification results, attaining AUC values exceeding 95% in all categories. This underscores that, even with an uneven class distribution, the proposed framework effectively identified all types of Diabetic Retinopathy (DR).



(a) The Multiclass Receiver Operating Characteristic

(b) Zooming In on Significant Changes: Multiclass Receiver Operating Characteristic

Figure 5.6: Illustration of both the comprehensive and detailed perspectives of notable alterations in the multiclass receiver operating characteristic (ROC) curve pertaining to the MESSIDOR-2 dataset.

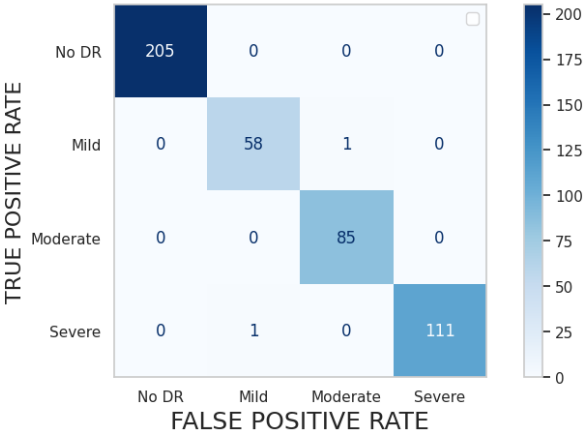


Figure 5.7: Confusion Matrix for Messidor-2

Table 5.1: A comparison of classification performance in the MESSIDOR-2 dataset can be conducted based on precision.

	Precision									
	Our	SVM	GB	KNN	RF	ET	LR	DNN	CNN	LSTM
None	**0.99**	0.53	0.81	0.95	0.90	0.91	0.61	0.61	0.84	0.53
Mild DR	0.97	0.00	0.20	0.91	**1.00**	**1.00**	0.29	1.00	0.83	0.00
Moderate DR	**0.98**	0.00	0.43	0.92	0.95	0.96	0.47	0.75	0.62	0.00
Severe DR	**0.98**	0.73	0.66	0.97	0.98	0.95	0.66	0.76	1.00	0.82
Avg	**0.98**	0.41	0.63	0.95	0.94	0.94	0.56	0.72	0.83	0.42

Table 5.2: A comparison of classification performance in the MESSIDOR-2 dataset can be conducted based on F1-score.

	F1-Score									
	Our	SVM	GB	KNN	RF	ET	LR	DNN	CNN	LSTM
None	**0.99**	0.68	0.37	0.95	0.94	0.95	0.71	0.74	0.86	0.69
Mild DR	**0.98**	0.00	0.32	0.92	0.92	0.92	0.06	0.04	0.81	0.00
Moderate DR	**0.98**	0.00	0.37	0.93	0.92	0.92	0.37	0.51	0.72	0.00
Moderate DR	**0.97**	0.61	0.31	0.96	0.94	0.93	0.61	0.73	0.78	0.68
Avg	**0.98**	0.45	0.40	0.95	0.94	0.94	0.45	0.60	0.80	0.47

Table 5.3: A comparison of classification performance in the MESSIDOR-2 dataset can be conducted based on Recall.

	Recall									
	Our	SVM	GB	KNN	RF	ET	LR	DNN	CNN	LSTM
None	**0.99**	0.96	0.24	0.95	0.99	0.99	0.85	0.92	0.87	0.98
Mild DR	**1.00**	0.00	0.93	0.93	0.86	0.86	0.04	0.02	0.79	0.00
Moderate DR	**0.99**	0.00	0.32	0.94	0.90	0.89	0.31	0.39	0.84	0.00
Severe DR	**0.96**	0.52	0.41	0.94	0.91	0.92	0.63	0.70	0.63	0.58
Avg	**0.98**	0.56	0.38	0.95	0.94	0.94	0.60	0.66	0.80	0.58

Table 5.4: A comparison of classification performance in the MESSIDOR-2 dataset can be conducted based on All Metrics.

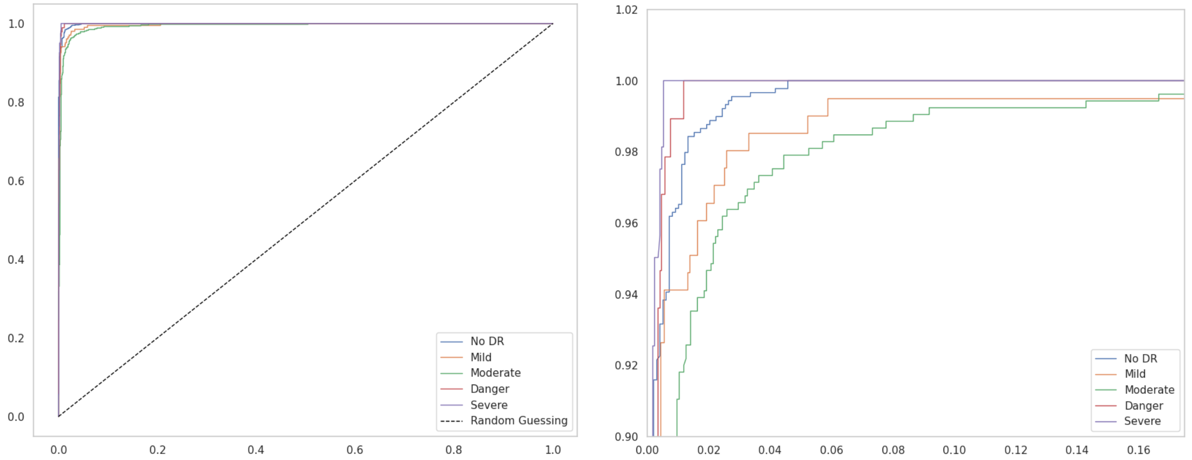
	All Metrics					
	ACC	F1-Socre	Roc	Precision	Recall	CK
GB	0.38	0.40	0.71	0.63	0.38	0.23
KNN	0.95	0.95	0.89	0.95	0.95	0.92
RF	0.94	0.94	0.98	0.94	0.94	0.90
ET	0.94	0.94	0.98	0.94	0.94	0.90
LR	0.60	0.55	0.80	0.55	0.60	0.36
SVM	0.56	0.45	0.79	0.45	0.56	0.24
CNN	0.80	0.80	0.95	0.83	0.80	0.710
DNN	0.65	0.60	0.84	0.72	0.66	0.440
LSTM	0.57	0.47	0.70	0.42	0.58	0.270
Our	**0.98**	**0.98**	**0.99**	**0.98**	**0.98**	**0.96**

5.3.2 Aptos-2019 Dataset

The conducted experiments unequivocally illustrate the efficacy of the proposed xDNN methodology, yielding remarkably precise outcomes that surpass existing state-of-the-art techniques across a range of demanding datasets. Notably, xDNN achieves not only outstanding accuracy but also delivers results characterized by a significant degree of interpretability.

The xDNN model underwent comprehensive training with the APTOS 2019 dataset, resulting in outstanding evaluation outcomes. As shown in Table 5.8, the model achieved notable performance metrics, featuring an average precision of 99%, a recall of 99%, an F1-score of 99%, and an accuracy rate of 99.7%.

The xDNN model demonstrated an impressive average Area Under the Curve (AUC) of 99.8% on the APTOS 2019 dataset. Figure 5.8 presents the AUC values for each class, highlighting exceptional performance across all categories. Importantly, each class significantly contributed to the overall classification success as shown in Figure 5.9, with AUC values surpassing 95% for all classes. This underscores that, despite an imbalanced class distribution, the proposed framework consistently detected all classes of Diabetic Retinopathy (DR).



(a) The Multiclass Receiver Operating Characteristic

(b) Zooming In on Significant Changes: Multiclass Receiver Operating Characteristic

Figure 5.8: An illustration depicting the standard view alongside a detailed examination of notable variations in the multiclass receiver operating characteristic for the APTOS2019 datasets.

The findings are articulated through diverse and informative formats, including IF…THEN logical constructs and empirical distributions of typicality, all within a cohesive analytical framework. Such representations facilitate a more profound analysis, enhancing comprehension of the fundamental patterns and decision-making mechanisms.

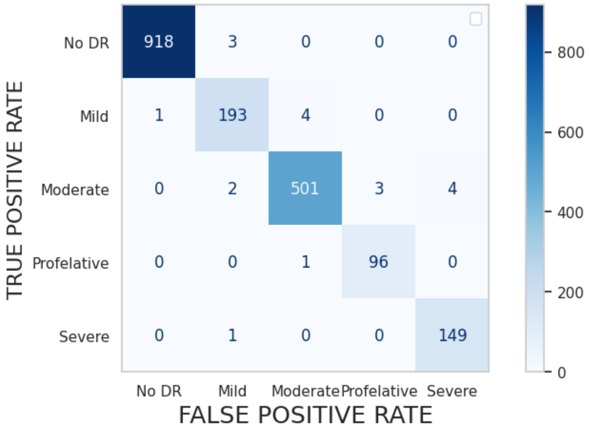


Figure 5.9: Confusion Matrix of Aptos2019 dataset using xDNN Classifier

Table 5.5: Comparison of classification performance based on F1-score for the Aptos2019 dataset.

	F1-score									
	Our	SVM	GB	KNN	RF	ET	LR	DNN	CNN	LSTM
No DR	**1.00**	0.92	0.58	1.00	0.99	0.99	0.94	0.94	0.86	0.82
Mild	0.98	0.07	0.28	0.97	**0.94**	**0.94**	0.48	0.52	0.81	0.00
Moderate	**0.99**	0.68	0.18	0.98	0.96	0.95	0.72	0.72	0.72	0.58
Severe	0.97	0.00	0.41	0.96	**0.93**	0.92	0.35	0.59	0.78	0.36
Proliferative DR	**0,98**	0.01	0.38	0.96	0.93	0.93	0.38	0.57	0.99	0.07
Avg	**0.99**	0.64	0.42	0.98	0.97	0.97	0.75	0.79	0.81	0.58

Table 5.6: Comparison of classification performance based on Precision metrics for Aptos2019.

	Precision									
	Our	SVM	GB	KNN	RF	ET	LR	DNN	CNN	LSTM
No DR	**1.00**	0.87	0.92	1.00	0.99	0.98	0.90	0.98	0.84	0.99
Mild	**0.99**	0.62	0.16	0.96	0.97	0.97	0.67	0.58	0.83	0.00
Moderate	**0.99**	0.55	0.70	0.98	0.93	0.93	0.64	0.64	0.62	0.42
Severe	**0.99**	0.00	0.38	0.97	0.98	0.97	0.74	0.60	1.00	0.42
Proliferative DR	**0.97**	1.00	0.36	0.96	0.98	0.97	0.55	0.67	0.99	0.75
Avg	**0.99**	0.72	0.70	0.98	0.97	0.97	0.77	0.80	0.83	0.69

Table 5.7: Comparison of classification performance based on Recall for the Aptos2019 dataset.

	Recall									
	Our	SVM	GB	KNN	RF	ET	LR	DNN	CNN	LSTM
No DR	**1.00**	0.98	0.43	0.99	1.00	0.99	0.98	0.90	0.87	0.70
Mild	**0.97**	0.04	0.88	0.98	0.92	0.91	0.38	0.47	0.79	0.00
Moderate	**0.99**	0.90	0.11	0.98	0.98	0.97	0.83	0.83	0.84	0.95
Severe	**0.99**	0.00	0.45	0.94	0.89	0.88	0.23	0.59	0.63	0.32
Proliferative DR	**0.99**	0.01	0.41	0.96	0.89	0.89	0.29	0.49	0.99	0.04
Avg	**0.99**	0.72	0.39	0.98	0.97	0.97	0.78	0.79	0.80	0.62

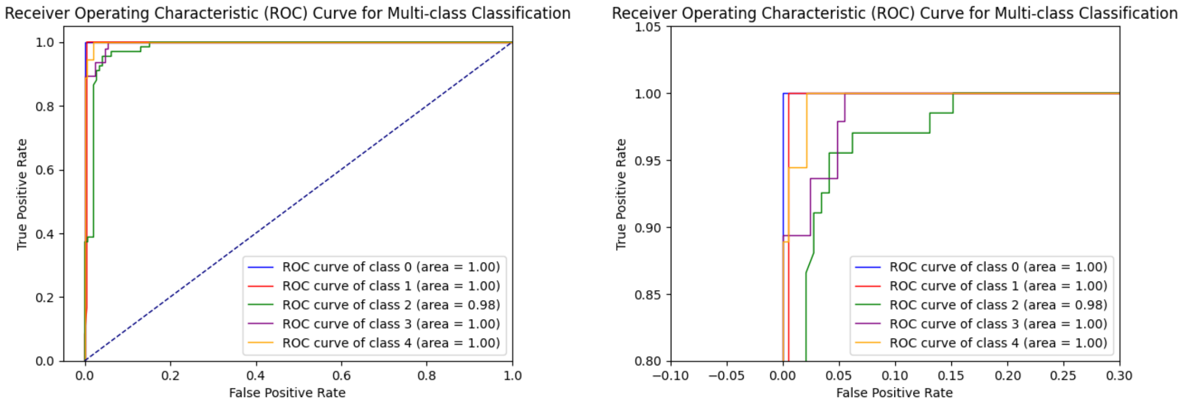
Table 5.8: A comparative analysis of classification performance using AllMetrics for Aptos2019.

	All Metrics					
	ACC	F1-Socre	Roc	Presicion	Recall	CK
GB	0.39	0.42	0.51	0.50	0.39	0.54
KNN	0.98	0.98	0.95	0.98	0.98	0.986
RF	0.97	0.97	0.96	0.97	0.97	0.970
ET	0.96	0.97	0.96	0.97	0.97	0.972
LR	0.78	0.75	0.75	0.77	0.78	0.800
SVM	0.72	0.64	0.70	0.72	0.72	0.730
CNN	0.80	0.80	0.95	0.83	0.80	0.710
DNN	0.79	0.79	0.94	0.80	0.79	0.680
LSTM	0.61	0.58	0.86	0.69	0.62	0.420
Our	0.99	0.99	0.99	0.99	0.99	0.994

5.3.3 IDRID Dataset

The xDNN model underwent thorough training on the IDRID dataset, resulting in remarkable evaluation outcomes. As presented in Table 5.12, the model exhibited impressive performance metrics, including average precision, recall, F1-score, and accuracy rate, all reaching 99.7%.

Moreover, the xDNN model showcased exceptional results on the IDRID dataset, attaining an average Area Under the Curve (AUC) of 99.8%. The individual AUC values for each class are visually depicted in Figure 5.10, illustrating outstanding performance across all categories, emphasized in Figure 5.11, with AUC values surpassing 95% for all classes. This underscores the robustness of the proposed framework, consistently detecting all classes of Diabetic Retinopathy (DR).



(a) The Multiclass Receiver Operating Characteristic

(b) Zooming In on Significant Changes: Multiclass Receiver Operating Characteristic

Figure 5.10: Visualization of the normal and the zooming in on significant changes in the multiclass receiver operating characteristic of IDRID datasets.

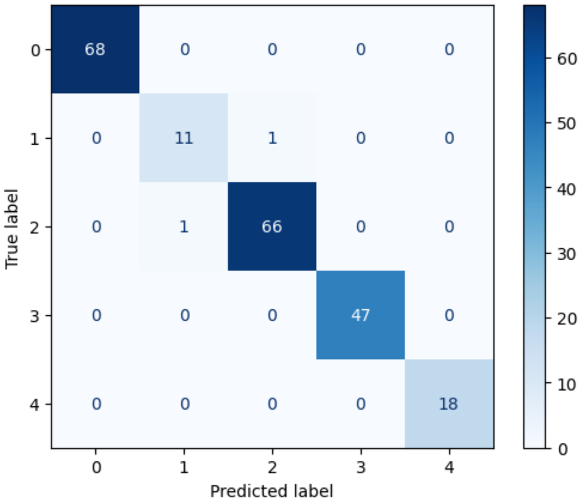


Figure 5.11: Confusion Matrix of IDRID dataset using xDNN Classifier

Table 5.9: Classification performance comparison by F1-score for IDRID.

	F1-score									
	Our	SVM	GB	KNN	RF	ET	LR	DNN	CNN	LSTM
No DR	**1.00**	0.90	0.56	1.00	0.99	0.99	0.94	0.87	0.87	0.76
Mild	0.92	0.1	0.28	0.96	0.94	0.94	0.48	0.99	0.29	0.00
Moderate	**0.99**	0.70	0.18	0.98	0.96	0.95	0.72	0.81	0.81	0.58
Severe	1.00	0.00	0.41	0.95	**0.93**	0.92	0.35	0.81	0.72	0.30
Proliferative DR	**0,98**	0.10	0.40	0.96	0.93	0.93	0.38	0.69	0.77	0.00
Avg	**0.99**	0.64	0.42	0.98	0.91	0.97	0.75	0.79	0.80	0.49

Table 5.10: Classification performance comparison by Precision for IDRID.

	Precision									
	Our	SVM	GB	KNN	RF	ET	LR	DNN	CNN	LSTM
No DR	**1.00**	0.87	0.92	1.00	0.99	0.98	0.90	0.83	0.98	0.73
Mild	**0.99**	0.62	0.16	0.96	0.97	0.97	0.67	1.00	0.67	0.00
Moderate	**0.99**	0.55	0.70	0.98	0.93	0.93	0.64	0.75	0.70	0.46
Severe	**0.99**	0.00	0.38	0.97	0.98	0.97	0.74	0.84	0.96	0.50
Proliferative DR	**0.97**	1.00	0.36	0.96	0.98	0.79	0.55	0.65	0.99	0.00
Avg	**0.99**	0.72	0.70	0.98	0.97	0.97	0.77	0.81	0.84	0.49

Table 5.11: Classification performance comparison by Recall for IDRID.

	Recall									
	Our	SVM	GB	KNN	RF	ET	LR	DNN	CNN	LSTM
No DR	**1.00**	0.98	0.43	0.99	1.00	0.99	0.98	0.91	0.78	0.79
Mild	**0.97**	0.04	0.88	0.98	0.92	0.91	0.38	0.17	0.67	0.00
Moderate	**0.99**	0.90	0.11	0.98	0.98	0.97	0.83	0.87	0.96	0.78
Severe	**0.99**	0.00	0.45	0.94	0.89	0.88	0.23	0.79	0.57	0.21
Proliferative DR	**0.99**	0.01	0.41	0.96	0.89	0.89	0.61	0.94	0.99	0.00
Avg	**0.99**	0.72	0.39	0.98	0.97	0.97	0.78	0.80	0.80	0.55

Table 5.12: Classification performance comparison by AllMetrics for IDRID.

	All Metrics					
	ACC	F1-Socre	Roc	Presicion	Recall	CK
GB	0.39	0.42	0.51	0.50	0.39	0.54
KNN	0.98	0.98	0.95	0.98	0.98	0.986
RF	0.97	0.97	0.96	0.97	0.97	0.97
ET	0.96	0.97	0.96	0.97	0.97	0.972
LR	0.78	0.75	0.75	0.77	0.78	0.800
SVM	0.72	0.64	0.70	0.72	0.72	0.730
CNN	0.79	0.80	0.97	0.84	0.80	0.720
DNN	0.81	0.79	0.97	0.81	0.80	0.720
LSTM	0.54	0.49	0.81	0.49	0.55	0.530
Our	0.99	0.99	0.99	0.99	0.99	0.994

One of the primary benefits of the xDNN methodology is its recursive, non-iterative, and nonparametric nature. These attributes facilitate the creation of exceptionally efficient computational implementations. The recursive framework enhances execution efficiency, whereas the non-iterative and nonparametric aspects streamline processes and minimize computational burden.

In conclusion, the suggested xDNN methodology not only demonstrates remarkable accuracy on difficult datasets but also provides a clear and interpretable framework for displaying outcomes, rendering it a powerful and effective instrument for a range of applications.

5.3.4 Ablation Study

To assess the impact of the proposed method on the pipeline, an ablation study was conducted. Tables 5.13a,5.13b and 5.13c present results for various components, including resizing (RS), CLAHE preprocessing (CL), and data augmentation (DA), shedding light on their individual contributions to the overall performance.

	Acc	CK
RS	0.37	0.11
RS+CL	0.41	0.17
RS+CL+DA	0.99	0.98

(a) MESSIDOR-2.

	Acc	CK
RS	0.61	0.43
RS+CL	0.71	0.53
RS+CL+DA	0.99	0.98

(b) Aptos-2019.

	Acc	CK
RS	0.30	0.07
RS+CL	0.42	0.19
RS+CL+DA	0.99	0.98

(c) IDRID.

Table 5.13: Ablation study of individual contributions to the overall performance on the three datasets (MESSIDOR-2, Aptos-2019, IDRID).

Resizing the images emerges as a pivotal factor, laying the groundwork for subsequent improvements. Clahe Preprocessing significantly enhances accuracy, and when synergistically combined with data augmentation, it forms the optimal and most effective pipeline. In essence, the resizing, preprocessing, and data augmentation combination proves to be the most effective configuration for our work, showcasing a harmonious impact on overall performance. The observed accuracy increase of approximately 1% with the inclusion of Clahe Preprocessing underscores its pivotal role within the method's pipeline. Furthermore, the positive impact on accuracy resulting from the integration of data augmentation reinforces the notion that the combined pipeline, encompassing both preprocessing and data augmentation, emerges as the most effective and beneficial approach for our work. This highlights the interconnected benefits derived from the complementary use of these techniques in enhancing the overall performance of the method.

5.4 Conclusion

In this study, we present an innovative method for the effective identification of diabetic retinopathy, utilizing an explainable deep neural network (xDNN). This method is designed to overcome the shortcomings of conventional deep learning approaches by offering a clear and interpretable internal structure. It not only surpasses current methodologies in accuracy but also enhances training efficiency and model interpretability.

Efficiency and Training Speed: A significant benefit of the xDNN approach is its impressive efficiency in terms of both computational resources and training time. Unlike traditional deep learning methods, which typically require GPUs and extended training periods, xDNN can function effectively with minimal computational resources

Prototype-Based Architecture: The architecture employs a prototype-based paradigm, utilizing genuine training data samples (images) that represent local maxima within the distribution of data observed or collected from real-world sources. These prototypes indicate typicality and data density. The generative model derived from these prototypes is fully characterized in a closed form, obviating the need for user-specific thresholds, parameters, or manual intervention. This distinctive feature guarantees that the model is fully driven by data and is generated automatically from the training dataset..

Synergistic Reasoning and Learning: xDNN integrates reasoning and learning in a cohesive, non-iterative, and non-parametric approach, which greatly enhances its efficiency and interpretability. This integration allows human users to easily understand the proposed approach, as it provides a transparent and interpretable classifier.

Outstanding Performance: The empirical findings of our research demonstrate that xDNN surpasses state-of-the-art deep learning techniques, such as VGG-VD-16, regarding accuracy, training efficiency, and the clarity of its decision-making explanations.

While our study demonstrates promising results, we acknowledge several limitations that need addressing to ensure broader applicability. Firstly, the datasets used, including MESSIDOR-2, Aptos-2019, and IDRID, may not fully capture the geographic and demographic diversity necessary for global generalizability. Despite rigorous preprocessing, variability in image quality remains a concern, and the range of retinal pathologies in the datasets is limited primarily to diabetic retinopathy and related conditions. Furthermore, the practical interpretability of the model's decisions by clinicians, especially in fast-paced clinical settings, requires further validation. To address these limitations, future work will focus on acquiring more diverse datasets that include a wider range of demographics and retinal pathologies. Additionally, advanced preprocessing and augmentation techniques, along with adaptive learning methods, will be explored to enhance the model's robustness. We also plan to conduct pilot studies in various clinical settings to validate the model's performance and gather feedback for improving its integration into healthcare systems. Developing more intuitive explanation interfaces and interactive training modules for clinicians will be essential for ensuring the model's practical utility. Our assumptions included the effectiveness of preprocessing techniques in standardizing image quality and the representativeness of the datasets, as well as the clinical relevance of the model's explanations, all of which need further empirical validation. Future work will explore adaptive learning techniques for minimal intervention updates and develop advanced monitoring tools for deeper performance insights. By addressing these limitations and pursuing the outlined future directions, we aim to develop a comprehensive and reliable model suitable for diverse clinical applications.

Chapter 6

Monitoring

The integration of the app and website creates a seamless experience for users, allowing them to access their health information anytime, anywhere. By combining education, personalization, and data-driven insights, the platform not only helps users manage their diabetes effectively but also fosters a supportive environment for long-term health and well-being. Together, the app and website empower users to take control of their health and live their best lives. In this context, a strategy for social media in healthcare has become essential. When implemented effectively, social media becomes a powerful tool for building trust, reaching a larger patient base, and disseminating valuable medical information. Additionally,The progress in mobile technology, along with the extensive adoption of smartphones and tablets, is expected to enhance the quality of healthcare services.

6.1 Introduction

Diabetes is a persistent medical condition that requires ongoing healthcare, patient education, and effective management. This serious illness can result in various long-term complications such as vision impairment, liver dysfunction, cardiovascular disease, and renal failure. Timely identification and forecasting of diabetes are essential for prompt intervention, which can halt the advancement of the disease and reduce the likelihood of these complications.

The International Diabetes Federation (IDF) reported that in 2017, the MENA region had the second highest prevalence of diabetes (9.2%), with nearly 40 million people affected, following North America and the Caribbean. with an annual cost of approximately 567 USD per diabetic individual [53].

In early 2024, Algeria had approximately 64.7 million internet users, which represents about

146.7% of the population, indicating that many people have multiple accounts or devices [28], The exchange of health information within an online community has been demonstrated to enhance the management of the diseases encountered by its members. Recent developments in information and communication technology include the emergence of social networks and the proliferation of user-friendly mobile devices. These platforms can serve as a cornerstone in the prevention and treatment of diabetes through proper awareness initiatives. In addition to their success and popularity, social media holds great potential for exploring new use cases in healthcare.

The proliferation of mobile health applications is remarkable, with over 31,000 health and medical apps presently accessible for download [45], driving the expansion of the market size [110].

Apps designed for healthcare professionals can assist in diagnosing diseases, accessing medication information, performing clinical calculations, searching for scientific evidence, sharing clinical experiences, enhancing chronic disease management, and conducting healthcare research [89].

From a healthcare perspective, the utilization of mobile phones by clinicians holds potential to enhance clinical communication, foster the implementation of evidence-based medicine, and provide access to informational resources at the point of care. This could ultimately lead to improved patient outcomes and more effective treatment strategies.

This study outlines the design and implementation of a computer system intended to aid diabetes patients in forecasting and self-managing their health condition, while ensuring effective communication with healthcare providers. Our goal is to design and develop a specialized social network tailored to the diabetes community, providing a platform for individuals to discuss their challenges. These discussions will be moderated by doctors and specialists to ensure accurate and reliable information. The following sections of this paper outline the related work and describe the project methodology. We then present the system architecture, followed by a conclusion and discussion of future work.

The creation of a mobile application designed to track health conditions and nutritional status can enhance access to fundamental healthcare services. Countless individuals depend on their mobile devices to streamline their daily activities and promote their overall health.

A quick search on Google Play or the Apple Store reveals numerous applications related to diabetes self-management. However, only a few of these apps are fully accessible to everyone, with others offering premium features at an additional cost.

The functionalities of all the analyzed applications include timely insulin dosage or medication tracking and the recording of blood glucose levels. Some of these apps also provide features for diet management, physical exercise, weight control, and blood pressure monitoring. Additionally, others offer support through alerts/notifications and integration with social media platforms such as Facebook and Twitter.

A study of an online community designed for type 2 diabetic patients to report, chart, and optionally share latest hemoglobin HbA1c levels through a geographic interface revealed that 83.1% of the reported HbA1c values were up to date, with the most recent data obtained within the preceding 90 days [118].

El-Gayar [35] suggests that providing patients with individual analysis and interpretation of results would be beneficial. However, most applications primarily offer insulin dosage suggestions based on data recorded on the patient's mobile device [44]. A significant limitation of these applications is the lack of consideration for the patient's clinical history.

Furthermore, diabetes researchers have found that self-management education positively impacts clinical outcomes [85]. However, one factor that has not been adequately addressed by developers is usability. Usability refers to the quality or attribute that represents how easily a human-computer interface can be used to provide an effective, efficient, and satisfying experience [36]. The development of meaningful, reliable solutions that comply with legal standards represents an essential phase in encouraging The utilization of medical applications by patients and healthcare professionals. Although numerous categories of medical mobile applications exist, the majority can be classified into five primary types [110], as shown in Fig. 3. Nonetheless, not all digital interventions achieve success. Numerous medical mobile applications do not fulfill user expectations, often due to inadequate user experience, perplexing interfaces, and subpar functionality.

In this context, the authors aim to develop a computer system designed to assist in the prediction and self-management of diabetes for patients, with monitoring by healthcare professionals. This system will be multiplatform, consisting of a mobile application for patients and a web application for doctors, nutritionists, and fitness experts.

The rise in diabetes cases worldwide underscores the need for accessible, real-time monitoring and management tools. Digital platforms provide an opportunity to collect, analyze, and predict health metrics, aiding patients and healthcare providers. This project aims to create a comprehensive platform that includes a web application, a mobile app, and a backend database. The platform uses machine learning for predictive insights, Firebase for real-time data storage, and React.js/React Native for user interfaces.

6.2 Methodology

High-quality design is crucial for all mobile applications, particularly when creating apps intended for sensitive user groups, such as individuals utilizing medical mobile applications. Several factors must be considered when designing an app to ensure it is easily adoptable by users, as well as reliable and secure. To successfully develop a mobile health application, it is crucial to identify the primary needs of the target audience and center the development around implementing those essential features. Emphasizing the requirements of the end user is crucial, as is the commitment to providing a superior user experience. If the application does not guarantee safety and security for both patients and healthcare professionals, the overall system's efficacy is compromised. To develop the system, a cyclical methodology was employed, consisting of four key phases: conception, prototype development, testing, and result analysis. This structured approach ensures that each stage of the system's development is carefully planned and evaluated, leading to a more effective and user-centered final product. Given that a significant number of individuals in this demographic may be older, possess sensory disabilities or other impairments, or may not have the same level of technical proficiency as younger mobile application users, it is crucial to adopt a forward-thinking design approach. This involves prioritizing accessibility, usability, and inclusivity in every aspect of the application.

Trust in medical applications is paramount, particularly when handling sensitive health data. Encryption is implemented to safeguard data at all levels, whether stored, transmitted, or exchanged across networks. Common targets for encryption include databases, server files, communication channels, and other sensitive transmissions. Additionally, compliance with regulations such as GDPR and HIPAA is emphasized to ensure data protection and legal adherence.

The proposed mobile application includes several features to support diabetes management. A key functionality is the FINDRISC questionnaire, which predicts the likelihood of developing diabetes based on a series of questions. The system also allows healthcare professionals to configure patient profiles and clinical histories through a synchronized web application.

Patients can record daily blood glucose levels, blood pressure, and other health data, along with personal notes such as dietary changes, medication, and exercise routines. The application sends timely notifications for medication reminders, upcoming consultations, and other health-related alerts. Recorded data is analyzed and displayed in charts and tables, with normal ranges customized for the patient's age.

A chat feature facilitates secure communication between patients and healthcare professionals, while an education module provides tailored information about diabetes and healthcare. The application also supports seamless data transfer between healthcare professionals and patients, ensuring that educational materials, diet plans, and other resources are always accessible. Alerts are sent to healthcare professionals when abnormal values are detected, enabling timely intervention.

6.3 Technical Implementation

6.3.1 Database Setup

Firebase is used as the backend, providing secure, scalable data storage, real-time data synchronization, and authentication.

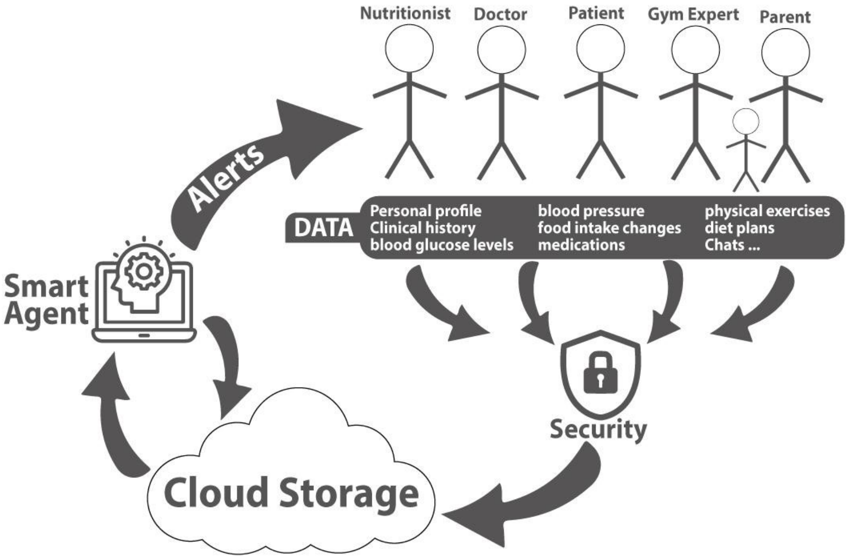


Figure 6.1: System Architecture of the Diabetes Management Platform

- **Database Structure:** Data is organized around user collections, storing health metrics such as blood glucose, dietary intake, and medication.
- **Authentication:** Secure login methods to protect user data and privacy.
- **Real-Time Database:** Firebase's real-time features keep the platform synchronized across devices.

6.3.2 Web Application Development with React.js

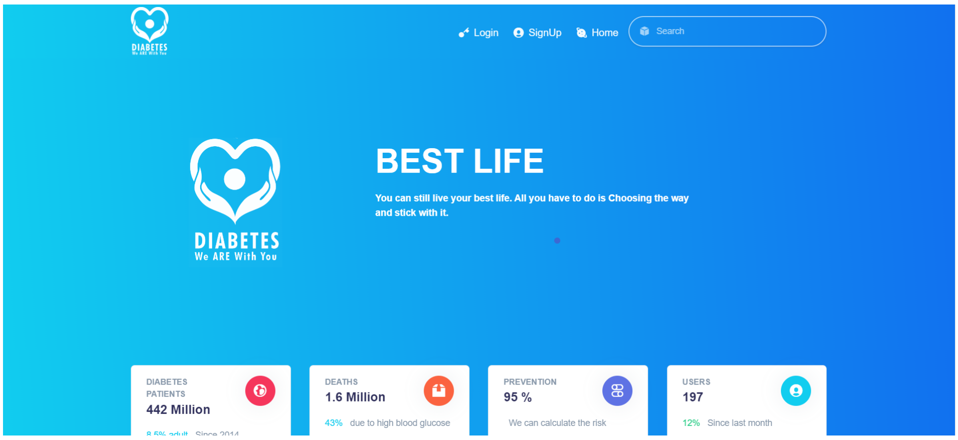
The web application, built using React.js, allows users to visualize data, analyze trends, and receive predictive insights.

Homepage

The homepage of the website features a motivational message: ”You can still live your best life. All you have to do is choose the way and stick with it.” This sets a positive and encouraging tone for users. The page also highlights key statistics about diabetes, such as:

- **N**umber of people affected by diabetes.
- **N**umber of deaths annually.
- **P**ercentage of cases that are preventable.
- **U**sers currently using the platform.

These statistics emphasize the importance of diabetes management and the role of the platform in helping users reduce their risk.



BEST LIFE

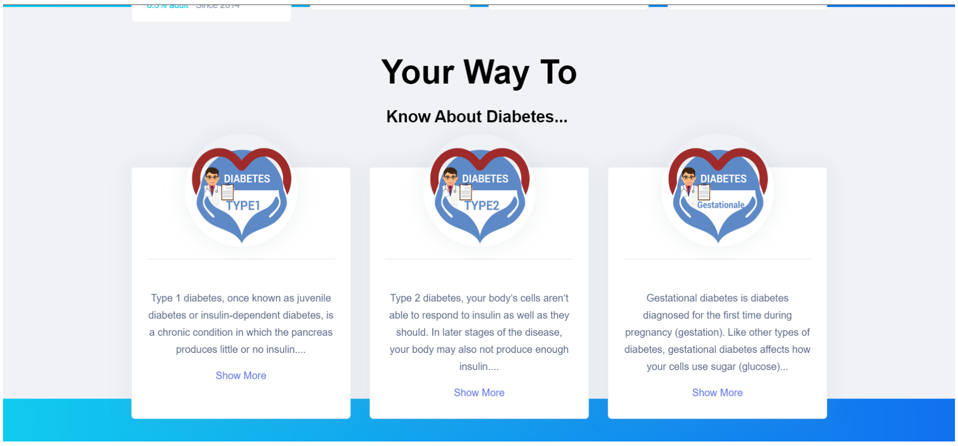
You can still live your best life. All you have to do is Choosing the way and stick with it.

Diabetes Information Page

This page provides detailed information about different types of diabetes:

- **Type 1 Diabetes**: A chronic condition where the pancreas produces little or no insulin.
- **Type 2 Diabetes**: A condition where the body's cells do not respond effectively to insulin, and insulin production may decrease over time.
- **Gestational Diabetes**: Diabetes diagnosed for the first time during pregnancy, affecting how cells use glucose.

Each section includes a "Show More" button, allowing users to expand the information and learn more about each type of diabetes.



Your Way To

Know About Diabetes...

Type 1 diabetes, once known as juvenile diabetes or insulin-dependent diabetes, is a chronic condition in which the pancreas produces little or no insulin....

Type 2 diabetes, your body's cells aren't able to respond to insulin as well as they should. In later stages of the disease, your body may also not produce enough insulin....

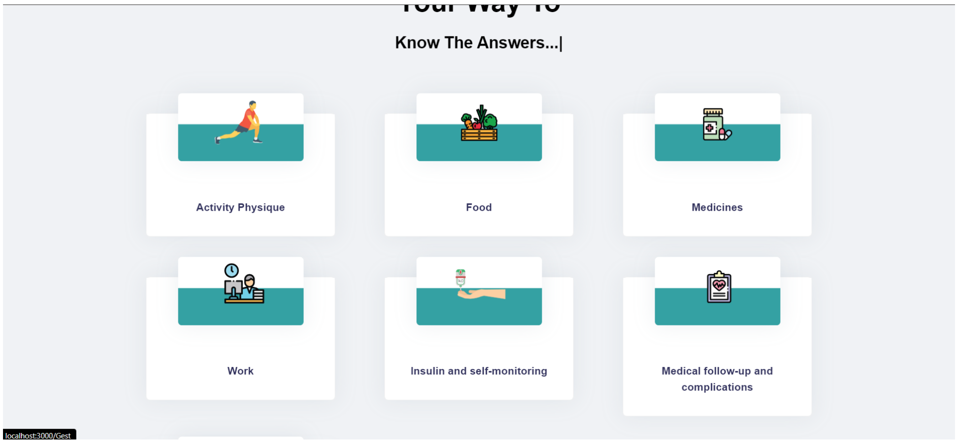
Gestational diabetes is diabetes diagnosed for the first time during pregnancy (gestation). Like other types of diabetes, gestational diabetes affects how your cells use sugar (glucose)...

Knowledge Section - ”Know The Answers”

This section focuses on key aspects of diabetes management, including:

- **Physical Activity**: The importance of exercise in managing diabetes.
- **Food**: Dietary recommendations for diabetes patients.
- **Medicines**: Information on medications and insulin.
- **Work**: Balancing work and diabetes management.
- **Insulin and Self-Monitoring**: The role of insulin and regular health monitoring.
- **Medical Follow-Up and Complications**: The importance of regular check-ups and managing potential complications.

This section serves as a comprehensive guide for users to understand and manage their condition effectively.

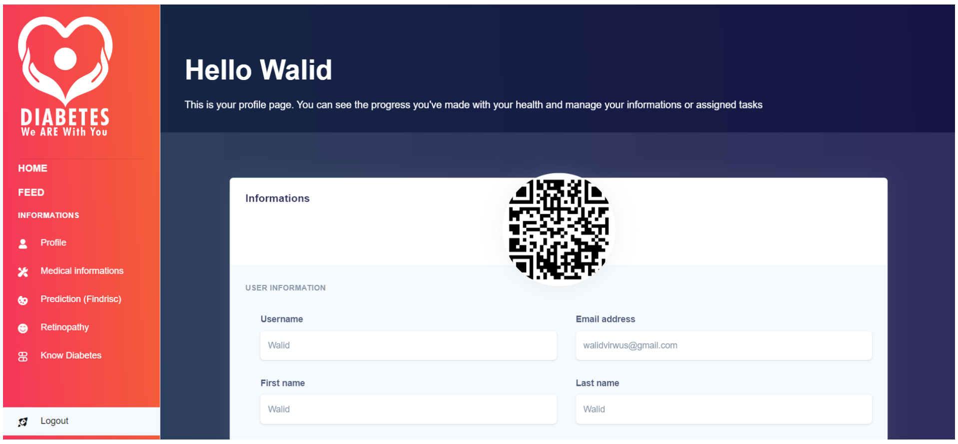


User Profile Page

The user profile page, personalized allows users to track their health progress and manage their information. Key features include:

- **User Information**: Displays the user’s username, email address, first name, and last name.
- **Medical Information**: Tracks health metrics such as weight, insulin levels, height, tension, waist size, and glucose levels.
- **Tasks and Progress**: Users can view their progress and manage assigned tasks related to their health.

This page provides a centralized location for users to monitor their health and access relevant information.



Hello Walid

This is your profile page. You can see the progress you've made with your health and manage your informations or assigned tasks

Informations

USER INFORMATION

Username: Walid

Email address: walidvirwus@gmail.com

First name: Walid

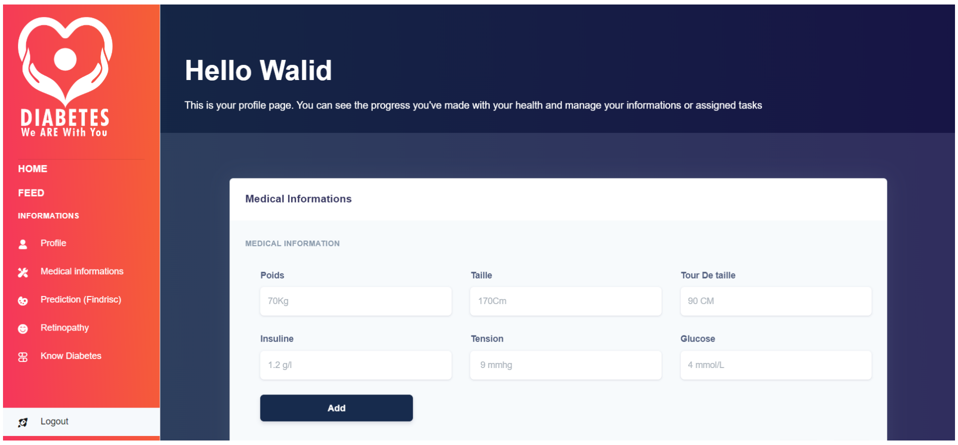
Last name: Walid

Medical Information Page

This page provides a detailed overview of the user's medical data, including:

- **Weight**
- **Insulin**
- **Height**
- **Tension**
- **Waist Size**
- **Glucose**

Users can add new data and view their health metrics in a structured format. The page also includes options to view data in a graph or table format, making it easier to track trends over time.



Hello Walid

This is your profile page. You can see the progress you've made with your health and manage your informations or assigned tasks

Medical Informations

MEDICAL INFORMATION

Poids: 70Kg

Taille: 170Cm

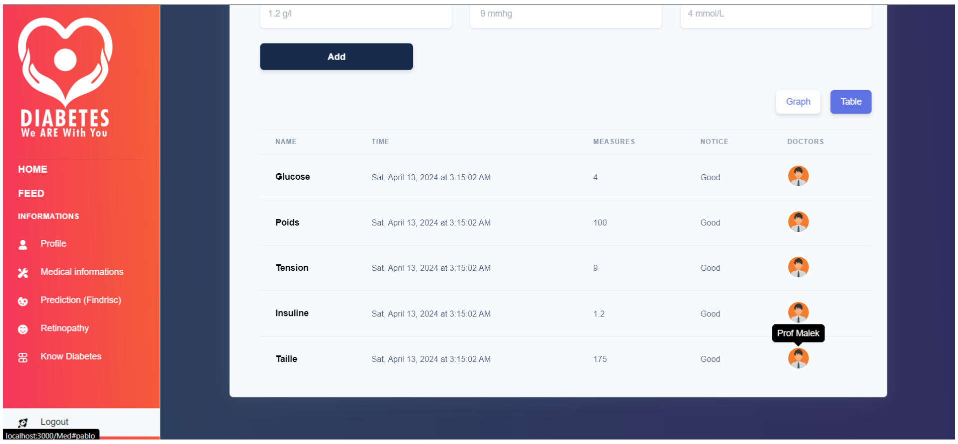
Tour De taille: 90 CM

Insuline: 1.2 g/l

Tension: 9 mmhg

Glucose: 4 mmol/L

Each entry includes the date and time of measurement, the measured value, and a notice (e.g., "Good"). This table allows users to track their health metrics over time and share them with healthcare providers.



NAME	TIME	MEASURES	NOTICE	DOCTORS
Glucose	Sat, April 13, 2024 at 3:15:02 AM	4	Good	
Poids	Sat, April 13, 2024 at 3:15:02 AM	100	Good	
Tension	Sat, April 13, 2024 at 3:15:02 AM	9	Good	
Insuline	Sat, April 13, 2024 at 3:15:02 AM	1.2	Good	
Taille	Sat, April 13, 2024 at 3:15:02 AM	175	Good	

Summary of Features

The website is designed to support diabetes management through:

- **Educational Content**: Information about different types of diabetes and management strategies.
- **User Profiles**: Personalized profiles for tracking health metrics and progress.
- **Data Visualization**: Graphs and tables for monitoring health data.
- **Community Support**: Encouraging messages and statistics to motivate users.

6.3.3 Mobile Application Development with React Native

The mobile app allows users to log metrics on the go, with real-time data synchronization through Firebase.

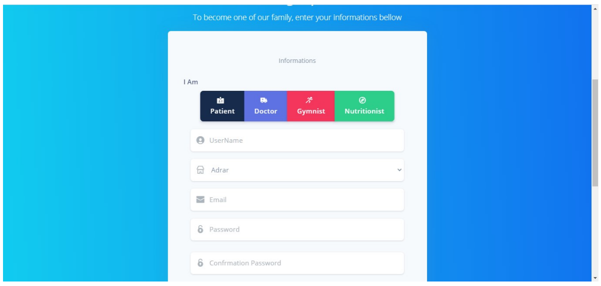
Logo and Branding

The app features a distinctive logo with the text "DIABETES We ARE With You." This branding emphasizes the app's mission to support individuals managing diabetes, creating a sense of community and care. The logo is simple yet impactful, setting the tone for the app's purpose.

DIABETES
We ARE With You

Signup Page

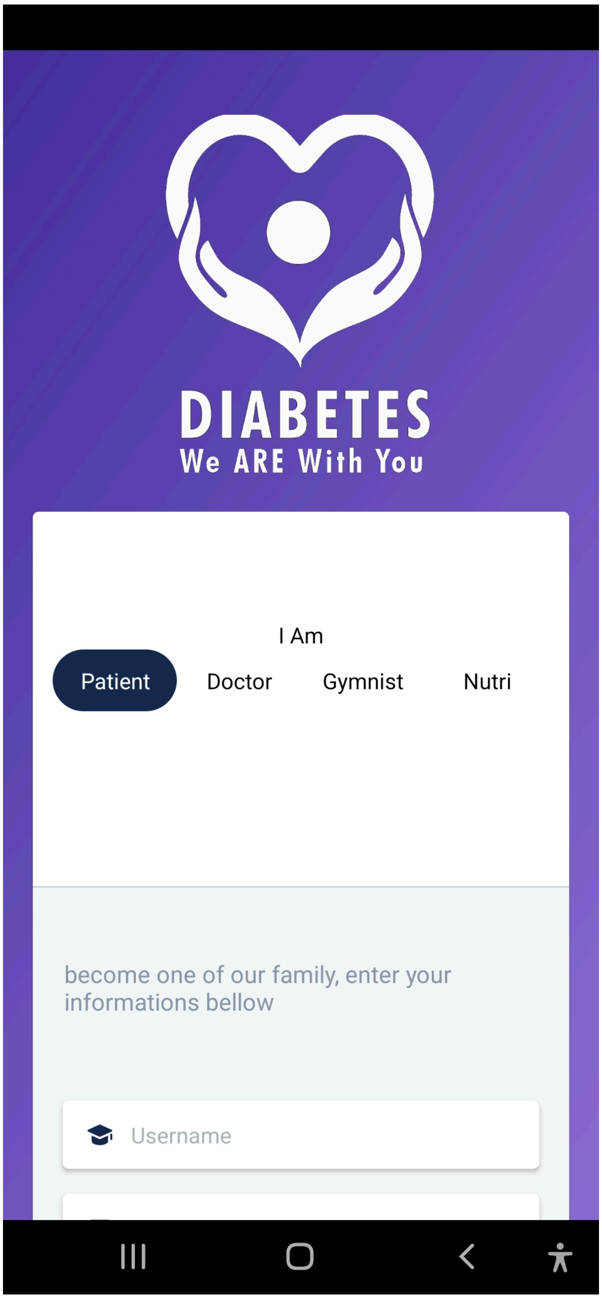
The signup page is designed to onboard new users by allowing them to select their role: Patient, Doctor, Gymnist, or Nutritionist. Users are required to enter basic information such as their username, email, and password, with a confirmation field for the password. This role-based approach ensures that the app caters to a diverse audience, including healthcare professionals and patients.



To become one of our family, enter your informations bellow

Welcome Screen

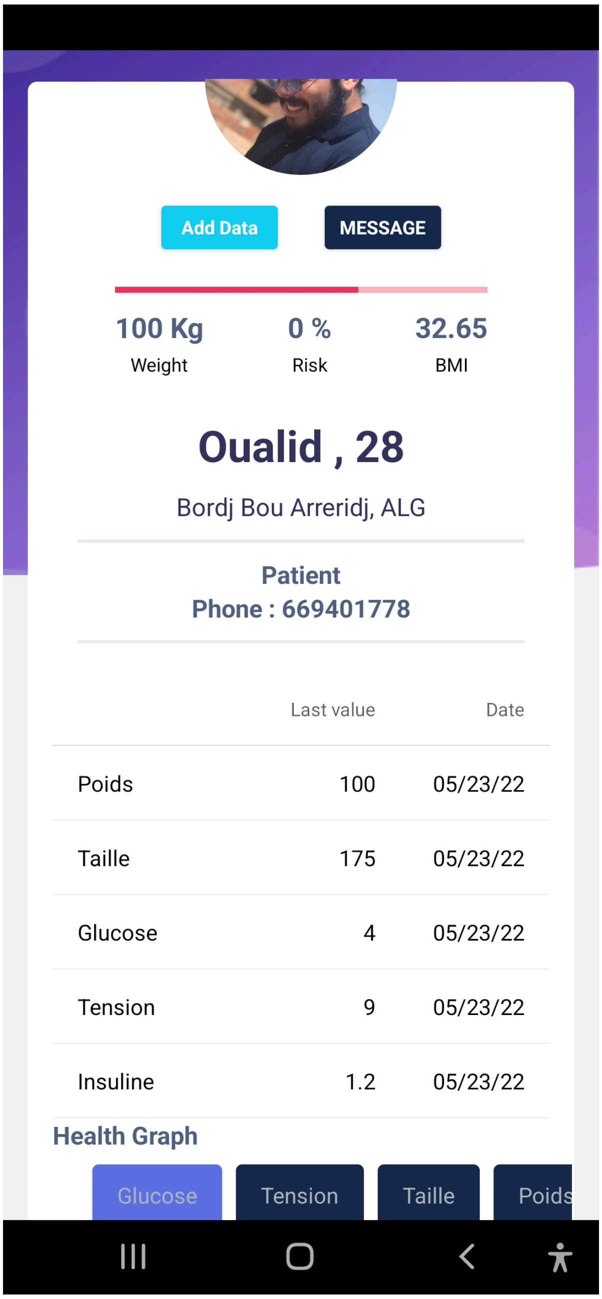
The welcome screen serves as an introduction to the app, featuring the message ”DIABETES We ARE With You.” It invites users to join the app’s community by entering their information, emphasizing inclusivity and support. The screen highlights the app’s target audience, including Patients, Doctors, Gymnists, and Nutritionists, ensuring that all stakeholders feel welcomed and valued.



become one of our family, enter your informations bellow

Patient Data Overview

The patient data screen provides a comprehensive overview of a user's health metrics. For example, it displays the name (Name, Age), location (City, Country), and contact information (Phone) of the user. Key health data includes weight, height, glucose levels, tension, and insulin levels. The screen also calculates and displays the patient's BMI and risk percentage, offering a quick snapshot of their health status.



100 Kg	0 %	32.65
Weight	Risk	BMI

Oualid , 28

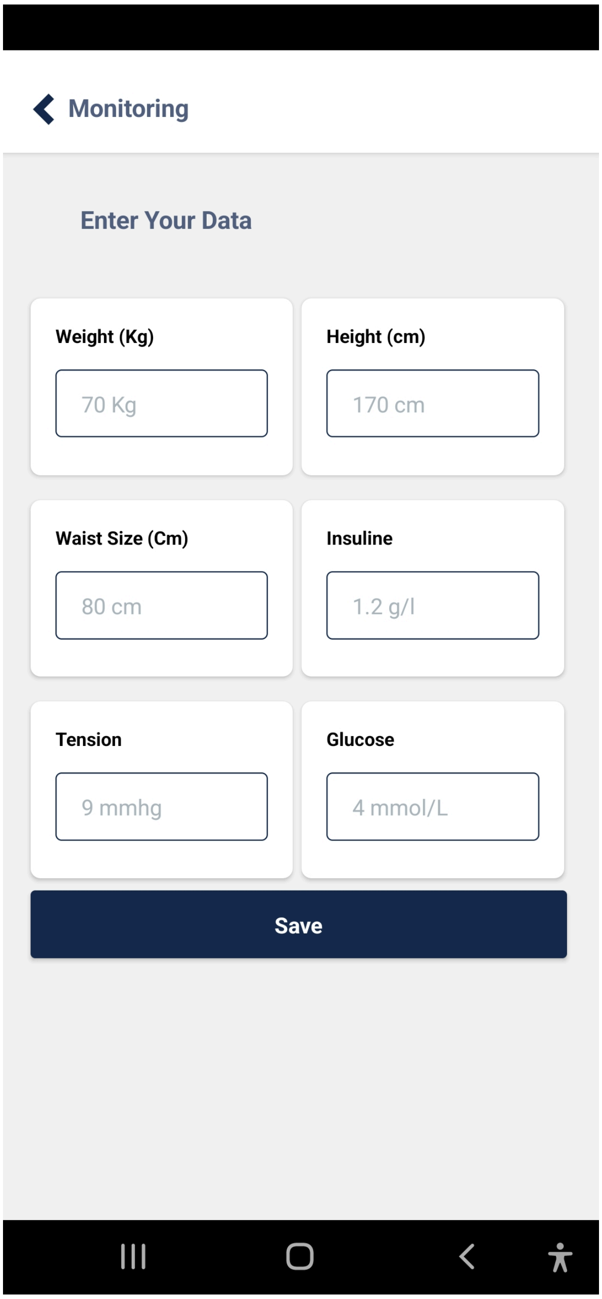
Bordj Bou Arreridj, ALG

Patient
Phone : 669401778

	Last value	Date
Poids	100	05/23/22
Taille	175	05/23/22
Glucose	4	05/23/22
Tension	9	05/23/22
Insuline	1.2	05/23/22

Data Monitoring Screen

The data monitoring screen allows users to input and track their health metrics. Users can enter details. A ”Save” button is prominently displayed, enabling users to store their data for future reference. This feature is essential for maintaining accurate and up-to-date health records.



Enter Your Data

Weight (Kg): 70 Kg

Height (cm): 170 cm

Waist Size (Cm): 80 cm

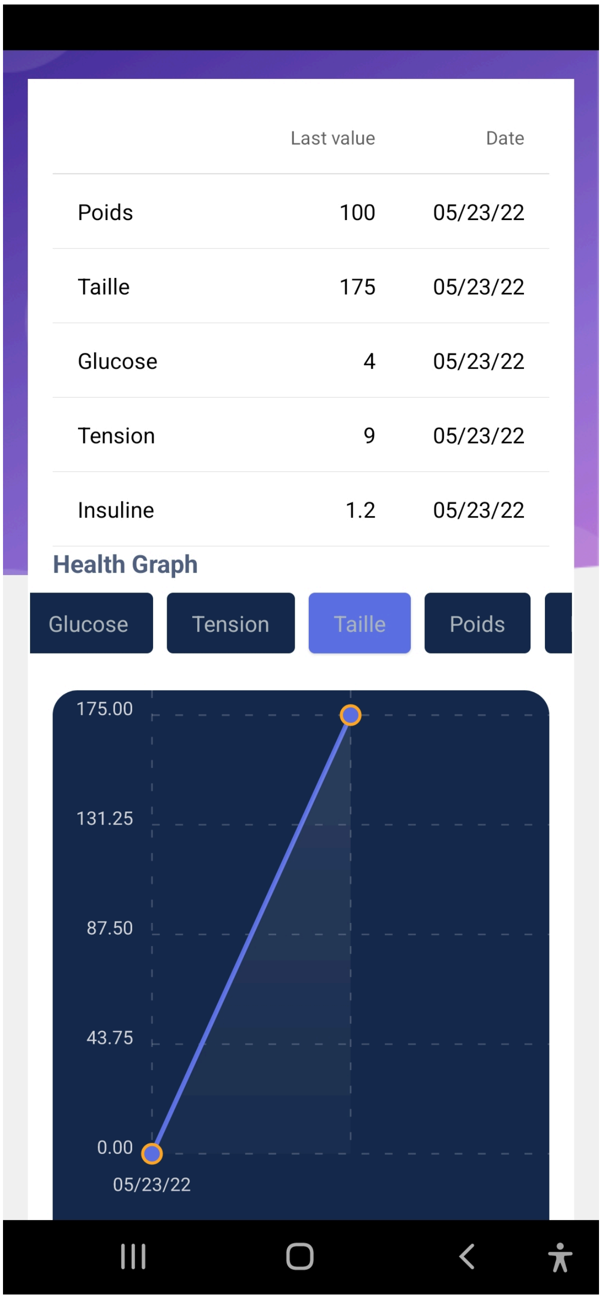
Insuline: 1.2 g/l

Tension: 9 mmhg

Glucose: 4 mmol/L

Health Graph

The health graph screen visualizes the patient's health data over time, making it easier to identify trends and patterns. For instance, it displays historical data for on every time entered. The graph plots these metrics, providing a clear visual representation of the patient's progress and helping users and healthcare providers make informed decisions.



	Last value	Date
Poids	100	05/23/22
Taille	175	05/23/22
Glucose	4	05/23/22
Tension	9	05/23/22
Insuline	1.2	05/23/22

Summary of Features

The app is designed to support diabetes management through a combination of data tracking, visualization, and community engagement. Key features include:

- **Role-Based Access**: Patients, Doctors, Gymnists, and Nutritionists can use the app, ensuring it meets the needs of a diverse user base.

- **Health Data Tracking**: Users can input and save critical health metrics such as weight, height, glucose levels, and insulin levels.
- **Data Visualization**: Health data is presented in graphs, making it easier to track progress and identify trends.
- **Risk Assessment**: The app calculates BMI and risk percentages, providing users with valuable insights into their health.
- **Community Focus**: The app fosters a sense of community and support, encouraging users to engage with healthcare professionals and each other.

6.4 Conclusion

This platform harnesses modern web and mobile technologies, supported by Firebase and machine learning, to provide predictive insights in real time for diabetes management. The use of React.js, React Native, and Firebase creates a seamless and secure experience across devices, empowering users to take control of their health. Offering a wide range of features designed to educate, support, and empower users. By providing detailed information about diabetes types, personalized user profiles, and tools for tracking health metrics, the platform addresses the diverse needs of individuals managing diabetes. Key highlights of the website include:

- **Educational Resources**: Clear and concise information about Type 1, Type 2, and Gestational Diabetes, helping users understand their condition better.
- **Personalized Tracking**: User profiles and medical information pages allow individuals to monitor their health metrics, such as glucose levels, insulin, weight, and tension, in real-time.
- **Data Visualization**: Graphs and tables provide an intuitive way to track progress and identify trends over time.
- **Community Support**: Motivational messages and statistics create a sense of community, encouraging users to stay committed to their health goals.

Ultimately, diabetes is a long-term condition that necessitates continuous oversight and self-regulation via medication, dietary adjustments, and physical activity. Individuals diagnosed with diabetes frequently encounter difficulties in integrating these components into their everyday lives. The emergence of mobile technologies has made diabetes management apps widely accessible, showing great promise in improving diabetes prediction and self-management.

However, many current apps fail to meet patient needs due to a lack of personalized feedback and usability challenges, especially for older users

For a diabetes prediction and self-management application to be effectively adopted, patients must feel secure and confident in its use, supported by their healthcare providers. Recent studies emphasize that the lack of clearly defined core features can profoundly affect the clinical results associated with particular application functionalities.

The increasing incidence of chronic (non-communicable) diseases is mainly linked to an aging demographic alongside ongoing risk factors. Numerous risk factors can be alleviated through health interventions and educational initiatives. Communication tools could play a crucial role in promoting healthy lifestyles and behavior changes. Over 100,000 health-focused applications are currently accessible in the market, allowing users to document, monitor, and evaluate vital signs and physical health information over extended periods. These applications also provide feedback and reminders for medication adherence and blood glucose monitoring, significantly enhancing disease management for patients.

This study introduces the architecture of a system capable of predicting, diagnosing, and monitoring diabetes, while also supporting self-management through a user-friendly UI/UX suitable for all users. Future work will focus on evaluating the clinical efficacy of the system and implementing a social networking component to collect adequate data for continuous research.

Chapter 7

General Conclusion

Machine learning (ML) and deep learning (DL) techniques have garnered significant attention in medical diagnosis and healthcare due to their ability to analyze complex datasets, such as medical images, clinical records, and genetic information. These approaches are particularly effective in supporting healthcare professionals in the diagnosis and management of chronic diseases like diabetes, where ML and DL can detect subtle patterns in medical imaging and other data sources that may be challenging for humans to discern.

Diabetes presents unique challenges for healthcare systems due to the complexity of its diagnosis, progression monitoring, and individualized management requirements. Traditionally, diabetes diagnosis and monitoring rely on blood tests to measure glucose levels, HbA1c, and other biomarkers. However, these methods are invasive, may require lab facilities, and can be cumbersome for continuous monitoring. Therefore, there is a growing need for accurate, non-invasive, and readily accessible diagnostic methods, particularly for early detection and risk assessment. ML and DL techniques show promise in addressing these challenges by leveraging data from imaging modalities such as retinal fundus photography, MRI, and CT scans to build reliable diagnostic models.

Imaging data, especially retinal images, are widely used in diabetic diagnosis and monitoring because of their ability to reveal microvascular changes related to diabetic retinopathy, one of the most common diabetes-related complications. ML and DL models trained on these images can offer significant diagnostic support by detecting early indicators of diabetes and related complications, reducing the dependency on invasive testing. This thesis seeks to develop a quick, accurate, and accessible diagnostic approach for diabetes by leveraging ML and DL techniques with a focus on image-based analysis.

In line with these goals, a platforms was developed as part of this research to support the seamless monitoring and management of diabetes. The platform integrate ML and DL diagnostic models into intuitive user interfaces, enabling healthcare professionals to upload and analyze patient imaging data in real time. They include features for continuous monitoring, automated risk stratification, and alert generation for critical findings. Designed with a focus on clinical applicability, the platform support secure data handling, and role-based access for healthcare staff. A mobile-compatible module was also implemented to enable remote screening and monitoring, especially in resource-limited settings. These tools not only enhance diagnostic efficiency but also facilitate timely interventions and follow-up by providing actionable insights at the point of care.

The research questions guiding this thesis focus on (1) the feasibility of using ML-based diagnostic systems to match or complement the performance of traditional glucose-monitoring methods, (2) the necessity of DL methods in developing a robust diabetes diagnosis system based on imaging data, (3) strategies for addressing class imbalance issues in available diabetes datasets, particularly in large imaging datasets such as retinal images from diabetic and non-diabetic patients, and (4) the development of platforms for deploying ML/DL models in clinical settings with monitoring and decision-making capabilities. Specific objectives were set to provide a thorough theoretical background in ML, DL, dimensionality reduction, and data augmentation, followed by a detailed literature review of diabetes detection studies. A total of 40 studies were categorized into ML-based, DL-based, and comparative analyses. This analysis spanned approaches from ML to DL, feature extraction and selection techniques, and data augmentation and class-balancing strategies. Key limitations identified in the review included the need for high-quality, well-annotated imaging data, the lack of sufficient diabetic samples in some datasets, and the limited use of sensitivity metrics, often overlooked in existing studies, with values ranging from 73% to 81.2%.

Machine learning (ML) and deep learning (DL) are increasingly being used for diabetes diagnosis, particularly through analyzing imaging data. These technologies can identify complex patterns in medical images, such as retinal scans, that may be subtle or challenging for human clinicians to discern. This capability enhances the accuracy of early diagnosis, supports disease progression monitoring, and aids in predicting potential complications associated with diabetes. For instance, retinal fundus photography is commonly used to detect diabetic retinopathy, while MRIs, CT scans, and foot thermography are employed to identify other complications like neuropathy and cardiovascular risks.

In ML/DL applications for diabetes imaging, convolutional neural networks (CNNs) are widely used due to their strength in feature extraction. These models are trained to recognize visual cues such as microaneurysms or hemorrhages in retinal images, which signal diabetic retinopathy. The accuracy of these models can be high, often rivaling the diagnostic capabilities of trained professionals. However, the effectiveness of ML and DL models is heavily influenced by the quality of the data, the specific model architecture, and the type of complication being addressed. Real-world validation is essential to ensure these models perform well in diverse clinical environments.

While ML and DL present innovative tools for diabetes diagnosis, they are best viewed as complements to traditional methods, not replacements. These models can help streamline diagnosis and identify at-risk patients, but confirmation through standard tests, like blood glucose measurements, remains crucial. There are challenges in developing these models, including the need for high-quality, annotated images, handling class imbalances (where non-diabetic cases often outnumber diabetic cases), and ensuring data privacy and security. Ethical considerations, such as mitigating model bias and maintaining transparency in predictions, are also paramount, especially in clinical settings.

Data privacy in ML/DL diabetes research is maintained through methods like data anonymization and differential privacy, which help protect sensitive medical information. Looking ahead, future advancements in data augmentation techniques could address class imbalance issues, while hybrid models that integrate imaging data with clinical and genetic information may enhance diagnostic precision. Explainability methods, which clarify how models reach their conclusions, can build clinician trust. Real-time monitoring through remote imaging devices and wearables could further transform diabetes care by enabling continuous, proactive management.

These advancements hold great promise for enhancing diabetes diagnosis and management, contributing to more personalized and timely healthcare interventions.

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