Examining Interpretability of Machine Learning-based Models for Diabetes Prediction using LIME Explainable AI Technique

Tayyeba Sadaq

100611584

Supervised by Dr. Oluwarotimi Samuel

Discipline of Computing and Mathematics

School of Computing and Engineering

University of Derby

Submitted May 2025, in partial fulfilment of the conditions for the award of the degree of **BSc Computer Science**

# Abstract

Diabetes is a chronic disease characterised by the pancreas producing insufficient insulin or the body’s inability to utilise produced insulin effectively. The imbalance, as a result, causes a disruption in the blood sugar’s regulation – potentially leading to severe complications affecting the nervous systems and blood vessels. The prevalence of pre-diabetes (hyperglycaemia) is rising, the latest National Diabetes Audit reporting 3,615,330 individuals registered with a GP as having pre-diabetes in 2023 – an 18% increase from 2022 [1].

This study seeks to bridge the gap between traditional diagnostic methods and modern artificial intelligence (AI) techniques by developing a web and mobile application that integrates Explainable AI (XAI) frameworks with machine learning (ML) models. Specifically, it evaluates the performance of three models – Logistic Regression (LR), Random Forest (RF), and Gradient Boosting (GBM)– in conjunction with the LIME XAI framework.

The aim is to identify the most effective ML-XAI combination for delivering accurate, interpretable, and actionable diabetes diagnosis predictions. By fostering transparency and trust in AI driven healthcare solutions, the findings contribute to improving the usability and readability of AI assisted diabetes diagnosis.

**Keywords:** Machine Learning, Explainable AI, Diabetes, Hyperglycaemia, logistic regression, random forest, gradient boosting, LIME

# Acknowledgements

Table of Contents

[Abstract 2](#_Toc192602075)

[Acknowledgements 3](#_Toc192602076)

[Chapter 1: Introduction 8](#_Toc192602077)

[1.1 Introduction 8](#_Toc192602078)

[1.2 Motivation 8](#_Toc192602079)

[1.3 Research Aims and Objectives 8](#_Toc192602080)

[Chapter 2: Background and Literature Review 9](#_Toc192602081)

[2.1 Background of Diabetes and Diagnosis 9](#_Toc192602082)

[2.1.1 Traditional Diagnosis Methods 9](#_Toc192602083)

[2.1.2 Machine Learning and Diabetes Diagnosis 9](#_Toc192602084)

[2.2 Literature Review 9](#_Toc192602085)

[Chapter 3: Research Methodology 10](#_Toc192602086)

[3.1 Research Method 10](#_Toc192602087)

[3.2 Data Collection 10](#_Toc192602088)

[3.3 Data Analysis 10](#_Toc192602089)

[3.4 Ethics 10](#_Toc192602090)

[3.5 Limitations 10](#_Toc192602091)

[3.6 Conclusions 10](#_Toc192602092)

[Chapter 4: Design and Implementation 11](#_Toc192602093)

[4.1 Logistic Regression 11](#_Toc192602094)

[4.1.1 How LR works and Implementation 11](#_Toc192602095)

[4.2 Random Forest 11](#_Toc192602096)

[4.2.1 How RF works and Implementation 11](#_Toc192602097)

[4.3 Gradient Boosting Model 11](#_Toc192602098)

[4.3.1 How GBM works and Implementation 11](#_Toc192602099)

[Chapter 5: Results and Analysis 12](#_Toc192602100)

[5.1 Datasets 12](#_Toc192602101)

[5.2 Evaluation Metrics 12](#_Toc192602102)

[5.3 Experimental Setup 12](#_Toc192602103)

[5.4 Results and Analysis 12](#_Toc192602104)

[5.5 Evaluation Comparison 12](#_Toc192602105)

[Chapter 6: Conclusion 13](#_Toc192602106)

[6.1 Conclusion 13](#_Toc192602107)

[6.2 Limitations 13](#_Toc192602108)

[6.3 Future Work 13](#_Toc192602109)

[References 14](#_Toc192602110)

Table of Figures

[Figure 1 - Global death rate from diabetes mellitus per 100,000 population (1980-2021) demonstrating a consistent upward trend in mortality over 4 decades [3] 10](#_Toc192758151)

List of Abbreviations

AI Artificial Intelligence

ML Machine Learning

XAI Explainable Artificial Intelligence

LR Logistic Regression

RF Random Forest

GBM Gradient Boosting Model

LIME Local Interpretable Model-Agnostic Explanations

FPG Fasting plasma glucose

WHO World Health Organisation

ADA American Diabetes Association

# Chapter 1: Introduction

## 1.1 Introduction

The World Health Organisation describes diabetes as a chronic disease where the pancreas does not produce enough insulin, or the body is unable to effectively use any insulin that is being produced. As insulin regulates the body’s blood sugar levels, when not controlled, it can lead to serious damage to various bodily systems including the nervous and blood vessels [2]. For both Type 1 and Type 2 diabetes, the condition’s long-term implications means that the condition’s risks can often be significantly mitigated. While there is no real methods of prevention, there are ways in which to adjust and manage one’s lifestyle in order to prevent and avoid premature death.

Despite advances in medical science, diabetes remains undiagnosed and undertreated. According to the World Health Organisation, around 830 million people have diabetes – with over half not receiving treatment or diagnosis [2]. This highlights a critical gap in global healthcare systems, especially in low-resource settings where [access to healthcare is more limited and the impacts of missed diagnosis an limited access to healthcare is more fatal to those affected]

## 1.2 Motivation

Diabetes alone is a prevalent condition most people face, however only a small percentage of the population is often aware of their underlying condition and fewer still manage to live a less detrimental lifestyle as a result. This lack of knowledge and understanding of your own health conditions is prevalent in less developed countries and can often be a leading cause of death [back up with figures]. A condition that can often be managed through small shifts and changes in one’s lifestyle, diet and environment is something that ought to have accessible diagnosis available to patients. Creating an application that allows for people input their medical data safely and securely to provide several predictions in which to help them understand further steps is a useful and somewhat mandatory tool to help bridge the current gap in global healthcare systems. Especially those which are less developed and thereby offer less support and treatment.

## 1.3 Research Aims and Objectives

This study aims to bridge the gap between traditional diagnostic approaches and modern AI techniques by implementing a web and mobile application that leverages XAI frameworks alongside ML modes. By doing so, it seeks to improve the accessibility, interpretability and effectiveness of diabetes diagnosis to contribute to better health outcomes and a more proactive approach to[something]. fostering awareness to the diabetes and teaching ways in which people can proactively manage their health. Furthermore, addressing the strengths and limitations of XAI frameworks, the study contributes towards the development of more transparent, patient-centred and accessible healthcare.

# Chapter 2: Background and Literature Review

## 2.1 Background of Diabetes and Diagnosis

The rapid increase in the prevalence of diabetes has made early detection, diagnosis and management crucial to benefit the lives of individuals affected by the condition. As a leading cause of morbidity and mortality (Figure 1) due to the association with serious complications. The ability to provide early, accessible diagnosis is a further step taken to improve millions of lives worldwide.

A graph showing the number of patients with diabetes

Description automatically generated

Figure 1 - Global death rate from diabetes mellitus per 100,000 population (1980-2021) demonstrating a consistent upward trend in mortality over 4 decades [3]

### 2.1.1 Traditional Diagnosis Methods

Traditionally, diabetes diagnosis involves clinical testing, requiring blood to be drawn by doctors, from patients, and tested in a medical lab. Fasting plasma glucose (FPG) is a preferred method by doctors, given it’s easy, convenient and minimal costs compared to other tests [4].Working by measuring the levels of glucose in the blood after fasting for 8 hours, WHO defines that 7.0 mmol/L or less is normal and a level of 7 mmol/L or higher on two separate FPG tests as indicative of diabetes [2].

While effective in the diagnosis of diabetes, the traditional methods are not without their limitations. With a lack of consensus on the consistent standards and criteria for diagnosis - for example WHO and ADA offering different glucose thresholds, the need to fast, reliance on laboratory infrastructure, the possibility of delayed results and false diagnosis. There are clear areas for improvement to help provide more accessible diagnosis for patients and allow professionals to aid people more effectively. Recent advancements in technology and data science have opened new pathways for diabetes diagnosis and prediction.

### 2.1.2 Machine Learning and Diabetes Diagnosis

ML techniques enable the analysis of larger datasets to identify patterns and correlations that may not be immediately apparent. Predictive models can assess an individual’s risk based on factors such as age, weight, blood pressure and family history/genetics. This allows for an earlier intervention to be staged and therefore better management of the condition to avoid possible reliance on heavy medication to handle their condition.

Explainable AI is a further advancement on predictive models. Given ML models are “black box” in nature, their ambiguity makes it challenging to gain insight into the internal mechanisms of the model, providing a lack of full trust in a system that would be responsible for critical and sensitive decision making [5]. XAI techniques and frameworks allow for an interpretability component to be integrated with ML model predictions, meaning end-users can comprehend and interpret outputs and predictions made by AI models [6].Transparency is the baseline needed to foster trust in AI-driven diagnosis and support for a more informed decision making. [add something on making AI more mainstream for healthcare]

## 2.2 Literature Review

The prediction of diabetes has been extensively studied. While traditional medical approaches remaining as the cornerstone for clinical practices, advancements in ML and AI have introduced more innovative methods. Promising improved accuracy, scalability and the promise of earlier detection capabilities. Not only improvements to what the clinical tests provide but a further enhancement and deeper understanding that can change how diabetes is managed and approached – even in pre-diabetic stages.

### 2.2.1 Importance of Explainable AI in Healthcare

### 2.2.2 Applications of XAI in Diabetes Prediction

### 2.2.3 XAI4Diabetes: A mobile Application for Diabetes Risk Prediction

# Chapter 3: Research Methodology

## 3.1 Research Method

## 3.2 Data Collection

Data collection is a critical step in building reliable ML models – as the quality and relevance of the data has a direct influence on the accuracy and interpretability of predictions being made. For this study, the Pima Indians Diabates Dataset was taken from Kaggle. This is a publicly available dataset whose objective is to diagnostically predict whether a patient has diabetes, meaning it aligns strongly with the purpose and needs of this study. Originally from the National Institute of Diabetes and Digestive Kidney Diseases, the dataset explores the medical history and status of an indigenous community living in the southwest region of the United States [7]. The origin of the data and the people which it involves is an important factor to consider and can be considered a limitation of this study which will be explored later. It’s a widely used benchmark dataset for diabetes research as it focusses on populations with high prevalence of diabetes, highlighting critical risk factors and concise feature sets that provide an ideal foundation in understanding the relationship between clinical metrics and diabetes risk.

## 3.3 Data Analysis

## 3.4 Ethics

## 3.5 Limitations

## 3.6 Conclusions

# Chapter 4: Design and Implementation

## 4.1 Logistic Regression

### 4.1.1 How LR works and Implementation

## 4.2 Random Forest

### 4.2.1 How RF works and Implementation

## 4.3 Gradient Boosting Model

### 4.3.1 How GBM works and Implementation

# Chapter 5: Results and Analysis

## 5.1 Datasets

## 5.2 Evaluation Metrics

## 5.3 Experimental Setup

## 5.4 Results and Analysis

## 5.5 Evaluation Comparison

# Chapter 6: Conclusion

## 6.1 Conclusion

## 6.2 Limitations

## 6.3 Future Work

# References

|  |  |
| --- | --- |
| [1] | England NHS, “NHS identifies over half a million more people at risk of type 2 diabetes in a year,” 12 June 2024. [Online]. Available: https://www.england.nhs.uk/2024/06/nhs-identifies-over-half-a-million-more-people-at-risk-of-type-2-diabetes-in-a-year/. [Accessed 9 December 2024]. |
| [2] | W. H. Organisation, “Diabetes,” 14 November 2024. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/diabetes. [Accessed 2024 December 2024]. |
| [3] | Network, Global Burden of Disease Collaborative, “Global Burden of Disease Study 2021 (GBD 2021) Results,” Institute for Health Metrics and Evaluation (IHME), 2022. [Online]. Available: https://vizhub.healthdata.org/gbd-results. [Accessed 8 January 2025]. |
| [4] | E. Mahoney, Diabetes: diagnosis and management, New York: Lucent Press, 2018. |
| [5] | S. A. Tanim, A. R. Aurnob, T. E. Shrestha, F. Mridha, R. I. Emon and S. U. Miah, “Explainable deep learning for diabetes diagnosis with DeepNetX2,” *Biomedical Signal Processing and Control,* vol. 99, p. 106902, 2025. |
| [6] | Z. Sadeghi, R. Alizadehsani, M. Akif, S. Kausar, R. Rehman, P. Mahanta, P. K. Bora, A. Almasri, A. Rami, S. Hussain, B. Alatas, A. Shoeibi, H. Moosaei, M. Hladík and Nahavandi, “A review of Explainable Artificial Intelligence in healthcare,” *Computers and Electrical Engineering,* vol. 118, p. 109370, 2024. |