Misurata University

Faculty of Information Technology

Computer Science Department

A System for Predicting Common Chronic Diseases Heart, Diabetes, and Hypertension

A graduation project is submitted to the Computer Science Department in partial fulfillment of the requirements for the bachelor’s degree of Information Technology

BY

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بِسْمِ اللَّهِ الرَّحْمَٰنِ الرَّحِيمِ

﴿يَرْفَعِ اللَّهُ الَّذِينَ آمَنُوا مِنكُمْ وَالَّذِينَ أُوتُوا الْعِلْمَ دَرَجَاتٍ ۚ وَاللَّهُ بِمَا تَعْمَلُونَ خَبِيرٌ﴾

سورة المجادلة الآية 11

ABSTRACT

This project details the development of a server-side API and a mobile application to enhance healthcare delivery through predictive analytics for detecting heart diseases, hypertension, and diabetes. The API is built using Django and deployed via Gunicorn, supporting user authentication, patient history management, health predictions, and code updates, secured with JWT authentication. The mobile application, created using Flutter for iOS, Android, and desktop devices, provides a seamless and responsive user experience, focusing on scalability, maintainability, and performance. Future improvements include transitioning to PostgreSQL. This integrated solution combines advanced web and mobile technologies to create a comprehensive, secure, and user-friendly healthcare application. Data will be collected for diseases, and the best algorithms for predicting medical data will be tested, with the most accurate algorithm chosen. Additionally, a local database will be created from user data and feedback from doctors to improve prediction accuracy.

الملخص

يُفصل هذا المشروع تطوير واجهة برمجة تطبيقات (API) جانب الخادم وتطبيق جوال لتحسين تقديم الرعاية الصحية من خلال التحليلات التنبؤية للكشف عن أمراض القلب وارتفاع ضغط الدم والسكري. تم بناء الواجهة باستخدام Django ونشرها عبرGunicorn ، وتدعم مصادقة المستخدم، وإدارة تاريخ المرضى، والتنبؤات الصحية، وتحديث الرموز، مع تأمينها باستخدام مصادقة .JWT يوفر تطبيق الجوال، الذي تم إنشاؤه باستخدام Flutter لأجهزة iOS و Androidوأجهزة سطح المكتب، تجربة مستخدم سلسة واستجابة، مع التركيز على القابلية للتوسع، والصيانة، والأداء. تشمل التحسينات المستقبلية الانتقال إلى PostgreSQL، يجمع هذا الحل المتكامل بين تقنيات الويب والموبايل المتقدمة لإنشاء تطبيق رعاية صحية شامل وآمن وسهل الاستخدام. سيتم تجميع بيانات للأمراض وتجربة أفضل الخوارزميات للتنبؤ بالبيانات الطبية وسيتم اختيار الخوارزمية الأعلى دقة .بالإضافة إلى ذلك، سيتم إنشاء قاعدة بيانات محلية من بيانات المستخدمين وتغذية راجعة من الأطباء لتحسين دقة التنبؤات.

اهداء

نُهدي هذا العمل المتواضع

إلى آبائنا الأعزاء، الذين لم يبخلوا علينا يوماً بشيء.

وإلى أُمهاتنا الحنونات، اللاتي أرفدننا بالحنان والمحبة.

فنحن نقول لهم: لقد وهبتمونا الحياة والأمل والنشأة على شغف الاطلاع والمعرفة.

وإلى إخوتنا وأسرتنا جميعاً،

وإلى أصدقائنا الأوفياء، الذين شاركونا في مشوار الحياة.

وإلى معلمينا الأفاضل، الذين زرعوا في نفوسنا بذور العلم والمعرفة،

وإلى كل من علمنا حرفاً أصبح سراجاً يُضيء الطريق أمامنا.

لا يسعنا إلا أن نتقدم بخالص الشكر والعرفان لكل من أسهم ولو بجهد بسيط في نجاحنا.

الشكر والتقدير

بعد الشكر الله تعالى على توفيقه لنا لإتمام هذه المشروع المتواضع نتقدم بجزيل الشكر وبالغ الامتنان إلى من شرفنا بإشرافه على هذا المشروع الأستاذ الفاضل:

عبدالمجيد عفط

الذي قومنا وتابعنا وصوب لنا الأخطاء بحسن إرشاده في كل مراحل المشروع

كما نتقدم بفائق الشكر والعرفان إلى إدارة وأعضاء هيئة الدريس **بكلية تقنية المعلومات – مصارته**

ونخص بالذكر أعضاء هيئة التدريس بقسم **علوم الحاسوب**

كما نود ان نشكر كل من وقف معنا ولو بالقليل على إتمام هذه المشروع

فلهم جزيل الشكر والعرفان **والله ولي التوفيق**

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List of Abbreviations

Abbreviation	Full Form
CVDs	Cardiovascular diseases
AI	Artificial Intelligence
SQL	Structured Query Language
venv	Virtual Environment
API	Application Programming Interface
ECGs	Electrocardiograms
ML	Machine Learning
SVM	Support Vector Machine
RBF	Radial Basis Function
TP	True Positive
FP	False Positive
TN	True Negative
FN	False Negative
UCI	University of California, Irvine
PCA	Principal Component Analysis
t-SNE	t-Distributed Stochastic Neighbor Embedding
LASSO	Least Absolute Shrinkage and Selection Operator
BP	Blood Pressure
BMI	Body Mass Index
CHD	Coronary Heart Disease
REST API	Representational State Transfer API
JWT	JSON Web Token

HTTP	Hypertext Transfer Protocol
TCP/IP	Transmission Control Protocol/Internet Protocol
XML	extensible Markup Language
JSON	JavaScript Object Notation
HTTPS	Hypertext Transfer Protocol Secure
URIs	Uniform Resource Identifiers
AUC	Area Under the Curve
ROC	Receiver Operating Characteristic
EHR	Electronic Health Record

Chapter one

Introduction

1.1 Introduction

Healthcare places significant emphasis on leveraging big data for early detection of heart diseases and diabetes, employing machine learning techniques on datasets and features to aid in decision-making and predict their progression. Strategies for screening heart diseases and diabetes involve harnessing artificial intelligence to analyze data and features from previous patient records, enabling highly accurate early-stage diagnoses crucial for effective treatment.

Cardiovascular diseases (CVDs) are the leading cause of death globally, responsible for 17.9 million deaths in 2019, or 32% of all global deaths, with 85% due to heart attacks and strokes. Most fatalities occur in low- and middle-income countries. In 2019, CVDs accounted for 38% of the 17 million premature deaths from noncommunicable diseases. Prevention can be achieved by addressing risk factors like tobacco use, unhealthy diet, obesity, physical inactivity, and alcohol abuse. Early detection and management through counseling and medications are essential. [1]

Hypertension, or high blood pressure, is a major contributor to cardiovascular diseases, defined by blood pressure readings of 140/90 mmHg or higher. Often symptomless, it can pose severe health risks if untreated. Risk factors include older age, genetics, obesity, physical inactivity, a high-salt diet, and excessive alcohol consumption. Lifestyle changes like a healthier diet, quitting tobacco, and increased physical activity can help lower blood pressure, but some individuals may still need medication to manage the condition.

Diabetes is a chronic metabolic disease marked by high blood glucose levels and has increased dramatically over the past thirty years across all income levels. Currently, 422 million people worldwide have diabetes, with most living in low- and middle-income countries. Annually, 1.5 million deaths are directly linked to diabetes. Type 2 diabetes, the most common form, arises from insulin resistance or insufficient insulin production. Access to affordable treatment, including insulin, is crucial for those with diabetes. There is a global target to stop the rise in diabetes and obesity by 2025. [2]

Given these statistics, developing methods for early diagnosis using artificial intelligence poses a significant challenge. Early detection of heart diseases and diabetes through machine learning can substantially alleviate treatment burdens for many patients who might otherwise go undiagnosed.

Artificial intelligence represents the forefront of intelligent machine development, particularly in the realm of healthcare, where intelligent computer programs analyze complex medical datasets and utilize machine learning algorithms to make informed decisions akin to human reasoning. Various machine learning approaches are available for diagnosing, treating, and forecasting outcomes in diverse clinical scenarios [3]. Evidence suggests that medical machine learning can play a pivotal role in aiding physicians in delivering efficient healthcare in the 21st century, complementing and enhancing their medical expertise [3].

Additionally, the project will include a comprehensive evaluation phase, where the developed AI models will be rigorously tested using real-world data. This phase will involve collaboration with healthcare institutions to validate the accuracy and reliability of the diagnostic system. Feedback from medical professionals and patients will be integral to refining the system and ensuring it meets the practical needs of its users. The ultimate goal is to create a diagnostic tool that not only advances medical practice but also has a tangible positive impact on patient outcomes.

1.2 Problem Statement

This important project contributes to improving disease detection and diagnosis through early diagnosis to increase the chances of successful treatment, enhance public access and health awareness, utilize artificial intelligence and advanced analytics to enhance prediction accuracy, continuously evaluate and improve the system's effectiveness, and target both the general public and medical professionals. This comprehensive approach improves healthcare outcomes and increases disease recovery rates.

1.3 Research Objectives

The objectives of this project are as follows:

1. **Development of an Advanced Diagnostic System:** Utilizing artificial intelligence technology and advanced analytic, the project aims to develop a sophisticated diagnostic system accessible through user-friendly desktop and mobile applications.
2. **Integration of Doctor Feedback Mechanism:** Incorporating doctors' feedback into the diagnostic system to continuously update and enhance the dataset for improved prediction accuracy.
3. **Enhancement of Diagnostic Accuracy:** By employing artificial intelligence and advanced analytic techniques, the project endeavors to improve diagnostic accuracy and enhance disease prediction capabilities, thereby facilitating more effective medical interventions.
4. **Creation of a User-Based Dataset**: Collecting data from users who utilize the application to create a comprehensive dataset. This dataset will be used to refine and enhance the diagnostic system, ensuring it evolves and improves over time based on real-world usage and feedback.

5. **Accessibility for All:** The goal is to make the diagnostic system readily available to both the public and medical professionals, thereby democratizing access to quality healthcare and fostering positive healthcare outcomes for all individuals.

1.4 Research Question

Can AI and patient history be used to predict heart disease and diabetes before clinical exams?

1.5 Research Boundaries

The objective, spatial, and temporal boundaries are as follows:

1- **Objective Boundaries:** Conduct this research to study the establishment and implementation of a predictive system for heart disease and diabetes without clinical diagnosis.

2- **Spatial Boundaries:** This research will be conducted in the Information Technology College.

3- **Temporal Boundaries:** It will span one academic semester.

1.6 Research Tools

In this project, a variety of powerful tools will be utilized to develop and implement the research effectively. The programming languages selected include Python and Dart, each offering unique strengths and capabilities that will be instrumental in different aspects of the project. Frameworks such as Flutter for Dart, and Django and Jupyter for Python will be employed to construct the project's infrastructure and user interfaces. These frameworks provide efficient means to develop robust and scalable applications tailored to the project's requirements. For data management, both SQLite and PostgreSQL databases will be used, ensuring flexible and reliable options for storing and retrieving data. Additionally, Python's virtual environment (venv) will be utilized for virtual environment management, maintaining a clean and organized development environment by isolating project dependencies and configurations efficiently. With these tools employed within the project, confidence is held that the research can be carried out effectively, and the project goals can be achieved.

1.7 Time Schedule

	April	May	June	July
Research and study	■	■		
Gather requirements	■	■		
data analysis		■	■	
Model building and development		■	■	■
Review results		■	■	■
Documentation	■	■	■	■

Table 1.1 – Time Schedule table

1.8 Research scheme

To outline the creation of the heart and diabetes disease diagnostic system, the project will be structured as follows:

1) **Chapter One: Introduction**

   This section provides an overview of the problem statement, tools utilized, and project objectives.

2) **Chapter Two: Theoretical Framework**

   Exploring the theoretical underpinnings, this chapter delves into concepts such as artificial intelligence, machine learning, data mining, and their application in medicine. It also discusses the algorithms employed in our model.

3) **Chapter Three: Model Development**

   This section elaborates on the process of creating and refining the diagnostic model, detailing its architecture, training methodology, and validation procedures.

4) **Chapter Four: Server and Client Application Development**

   Detailed discussion on the development of server-side API and client applications for seamless integration and accessibility.

5) **Chapter Five: Results and Summary**

   Presenting the outcomes of the project and offering a comprehensive summary of the key findings and contributions.

Chapter Two

Theoretical aspect

2.1 cardiovascular disease

Cardiovascular disease refers to a variety of conditions affecting the heart and blood vessels, potentially compromising heart function and blood flow throughout the body [1]. These conditions include coronary artery disease, valvular heart disease, arrhythmias, angina, heart attacks, heart failure, myocarditis, congenital heart defects, and vascular diseases involving arteries and veins.

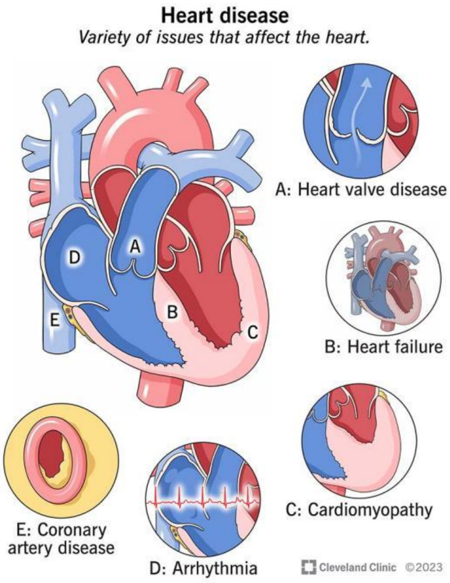


Figure 2.1 – Type Heart Disease

Cardiovascular disease is one of the leading causes of death globally, impacting millions of individuals annually [3]. Its causes range from genetic to environmental and behavioral factors, with risk factors including smoking, hypertension, obesity, high cholesterol levels, lack of physical activity, and unhealthy lifestyle choices.

Diagnosis of cardiovascular disease involves evaluating symptoms and the patient's medical history, alongside diagnostic tests such as electrocardiograms (ECGs), blood tests, imaging studies, and functional heart assessments. Treatment includes lifestyle modifications, such as healthy eating and regular exercise, medications, and, when necessary, surgical interventions [4].

Raising awareness about cardiovascular disease is essential alongside prevention and treatment. Educating the public on risk factors, symptoms, and the importance of regular check-ups promotes heart health. This reduces the incidence of cardiovascular disease and enhances overall health.

2.2 Diabetes Mellitus

Diabetes mellitus is a chronic disorder characterized by high blood sugar levels, resulting from either insufficient insulin production by the pancreas or inadequate cellular response to existing insulin. Insulin is a crucial hormone that regulates blood sugar levels by facilitating cellular sugar absorption and storage for energy use [5].

2.3 Diabetes is classified into main types

1. **Type 1 Diabetes**: Marked by complete insulin deficiency due to pancreatic failure, necessitating regular insulin injections [5].
2. **Type 2 Diabetes**: Characterized by cellular insulin resistance, often influenced by overeating, obesity, and sedentary lifestyle [5].
3. **Gestational Diabetes:** Occurs when pregnant women develop high blood sugar levels without a prior diabetes diagnosis.

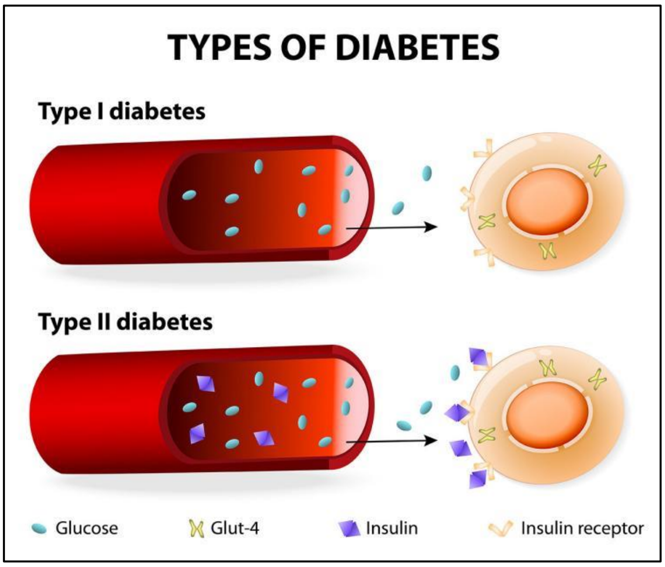


Figure 2.2 – Type of Diabetes

Chronic high blood sugar can lead to severe health issues, including nerve damage, blood vessel damage, kidney and eye problems, increased heart disease and stroke risk, and a weakened immune system [5].

Managing diabetes involves regulating blood sugar levels through lifestyle changes like a healthy diet, regular exercise, and medications that enhance insulin response or production. Regular blood sugar monitoring and symptom management are essential to avoid complications and maintain overall health [6].

2.4 Hypertension (High Blood Pressure)

Hypertension, or high blood pressure, occurs when the force exerted by the blood against the walls of the arteries is persistently too high, typically defined as 140/90 mmHg or higher. It is a common condition but can become serious if left untreated. Individuals with hypertension often do not experience symptoms, and the only way to detect it is by regularly monitoring blood pressure [7].

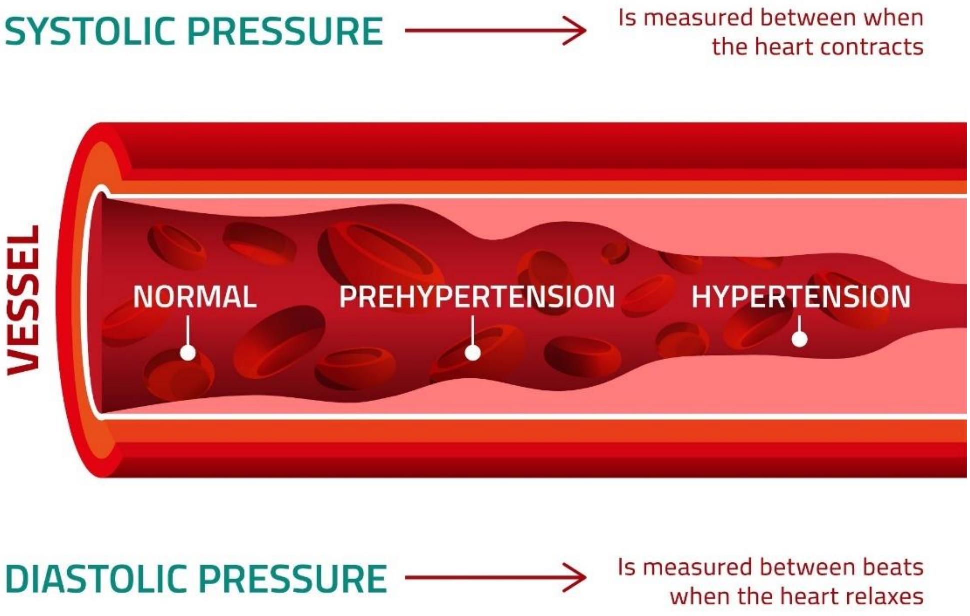

SYSTOLIC PRESSURE
Is measured between when the heart contracts
VESSEL
NORMAL
PREHYPERTENSION
HYPERTENSION
DIASTOLIC PRESSURE
Is measured between beats when the heart relaxes

Figure 2.3 – Vessel Pressure

2.4.1 Risk Factors for Hypertension

1-Modifiable Risk Factors:

- Unhealthy diet, including excessive salt consumption, high intake of saturated and trans fats, and low intake of fruits and vegetables
- Physical inactivity
- Consumption of tobacco and alcohol
- Being overweight or obese

2-Environmental Risk Factors:

- Air pollution, a significant environmental risk factor for hypertension and associated diseases

3-Non-Modifiable Risk Factors:

- Family history of hypertension
- Age over 65 years
- Co-existing conditions such as diabetes or kidney disease

2.4.2 Diagnosis of Hypertension

Hypertension is diagnosed if blood pressure measurements taken on two different days show a systolic blood pressure of ≥130 mmHg and/or a diastolic blood pressure of ≥80 mmHg on both occasions [7].

2.4.3 Impact of Lifestyle Changes

Lifestyle modifications can significantly reduce blood pressure:

- Adopting a healthier diet
- Quitting tobacco use
- Increasing physical activity

In some cases, medication may also be required to manage hypertension. Blood pressure readings are composed of two numbers: the systolic pressure (the pressure in arteries when the heart beats) and the diastolic pressure (the pressure in arteries when the heart rests between beats).

2.4.4 The Relationship Between Hypertension, Heart Disease, and Diabetes

The interconnectedness of hypertension, heart disease, and diabetes creates a complex network of interactions, where each condition can significantly influence the others, amplifying health risks and complications.

1. Major Risk Factors:

- **Diabetes and Heart Disease:** Diabetes is a significant risk factor for cardiovascular diseases. Prolonged high blood sugar levels can damage and harden blood vessels, increasing the risk of heart attacks and strokes. Insulin resistance and inflammation, common in diabetes, further contribute to heart and vascular problems [8]. Poor blood sugar control is linked to higher risks of hypertension and unhealthy cholesterol levels, elevating cardiac risks.
- **Hypertension and Heart Disease:** Hypertension is one of the primary risk factors for cardiovascular diseases. High blood pressure damages and hardens artery walls, making the heart work harder to pump blood. This extra strain can lead to the thickening of the heart muscle and increased heart disease risk. Hypertension is also associated with a higher risk of stroke and kidney failure [7]. Proper control of blood pressure is crucial for preventing and managing heart disease [4].
- **Diabetes and Hypertension:** Diabetes is often accompanied by high blood pressure, a condition known as "diabetes-related hypertension". Poor control of blood sugar levels increases the risk of developing hypertension. Blood vessel damage and increased insulin resistance in poorly managed diabetes can raise blood pressure [7]. High blood pressure in diabetic patients increases the risk of cardiovascular complications [2].

2. Blood Vessel Damage and Inflammation:

- **Diabetes:** High blood sugar can damage blood vessels, leading to atherosclerosis (hardening and narrowing of arteries), increasing the likelihood of coronary artery blockages and heart attacks. Diabetes also causes increased inflammation in blood vessels, raising the risk of clot formation and artery enlargement [5].
- **Hypertension:** High blood pressure damages artery walls, leading to hardening and reduced elasticity. This damage forces the heart to work harder, increasing the risk of heart disease and stroke. The combined effect of diabetes and hypertension exacerbates blood vessel damage, leading to more severe cardiovascular issues [7].

3. Heart Strain and Direct Damage:

- **Diabetes:** Diabetes can directly damage heart tissues, impairing the heart's ability to pump blood efficiently, thus raising the risk of heart failure. Diabetics may also experience lipid disorders, with elevated triglycerides and reduced HDL cholesterol, promoting fatty deposits in blood vessels [3].
- **Hypertension:** The constant high pressure on the heart due to hypertension leads to the thickening of the heart muscle, reducing its efficiency and increasing the risk of heart disease. This extra strain on the heart over the long term can lead to severe cardiovascular complications [7].

The relationship between hypertension, heart disease, and diabetes is intricately linked. Each condition can significantly influence the others, leading to a higher risk of severe cardiovascular complications. Understanding and managing these interconnected conditions is essential for preventing and treating associated health issues.

Conversely, cardiovascular disease can exacerbate diabetes issues, as heart failure can destabilize blood sugar levels, reduce physical activity, and affect medications used for heart disease, impacting blood sugar management [8].

2.5 Artificial Intelligence

Artificial intelligence (AI) represents a significant technological advancement aimed at creating intelligent systems capable of thinking, learning, and making decisions similarly to humans. AI leverages a range of technologies and tools to analyze data, provide smart recommendations, and develop intelligent applications enhancing everyday life.

AI's origins trace back decades, but technological advancements and increased computing power have enabled more sophisticated and effective applications. Core technologies like machine learning and artificial neural networks have garnered significant attention, leading to widespread applications across various fields.

AI technologies are employed in diverse daily applications. In medicine, AI aids in diagnosing diseases and identifying optimal treatments through medical image analysis and clinical data. In marketing, AI analyses consumer behavior, offering tailored products and services. In education, AI develops smart learning platforms, providing personalized education for students.

However, AI faces multiple challenges, notably security and privacy issues, given the sensitivity of personal data analysis, necessitating stringent safeguards. Ethical concerns also arise regarding technology control and its societal impact.

Nonetheless, AI signifies a historical shift towards a promising future, potentially solving global challenges and enhancing life quality. Continuous technological advancements are expected to increase AI's significance and influence in society, economy and Health.

2.6 Artificial intelligence in medicine

AI excels in analyzing large datasets of patient information, enabling the accurate identification of abnormalities and providing rapid, precise diagnoses. This capability significantly enhances the early detection and treatment of various medical conditions. For instance, AI can detect subtle patterns and correlations in patient data that might be missed by human analysis, such as early signs of disease or risk factors for chronic conditions. By integrating AI into the diagnostic process, healthcare providers can ensure more accurate assessments, leading to better-informed treatment decisions. Additionally, AI-driven tools can process vast amounts of patient data quickly, reducing the time patients wait for critical diagnostic results and allowing for faster intervention [9].

2.6.1 Treatment Guidance

AI processes extensive medical data, including patient history, clinical tests, and previous medical reports, to recommend the most suitable treatment options for each individual case [10]. By synthesizing this information, AI can offer personalized treatment plans that improve patient outcomes. For example, AI algorithms can analyze patterns in patient data to predict how different individuals might respond to specific treatments, allowing for more targeted and effective therapies. This personalized approach minimizes the trial-and-error aspect of traditional treatment methods, reducing the risk of adverse effects and enhancing the overall efficacy of medical interventions. Furthermore, AI can continuously update treatment recommendations based on new data, ensuring that patients receive the most current and effective care available.

2.6.2 Medical Research

Researchers employ AI to analyze large medical datasets, uncovering new relationships and patterns in diseases and treatments. This advanced analysis aids in the development of new therapies and improves our overall understanding of various medical conditions, paving the way for innovative medical breakthroughs. For example, AI can process vast amounts of genetic data to identify novel drug targets, accelerating the development of new treatments. AI can also help in understanding the mechanisms of complex diseases by revealing hidden patterns and correlations that are not apparent through traditional research methods [10]. By enhancing the efficiency and accuracy of medical research, AI contributes to the discovery of more effective treatments and preventive strategies, ultimately advancing the field of medicine and improving patient care.

2.7 Disease Prediction

Disease prediction is a crucial field in medicine where AI is employed to analyze medical data and predict patients' health outcomes and disease progression. Here's how it works:

2.7.1 Medical Data Analysis

Medical data from various sources, such as Electronic Health Records (EHRs), laboratory tests, and imaging studies, is collected and analyzed using AI to uncover patterns and relationships among different factors [9]. This comprehensive analysis enables healthcare professionals to gain insights into potential disease trajectories and identify high-risk individuals who may require proactive interventions.

2.7.2 Model Development

Based on data analysis, predictive models are developed using AI techniques such as machine learning and neural networks. These models leverage complex algorithms to predict the likelihood of disease progression or potential complications in patients. By continuously learning from new data inputs, these models adapt and evolve, improving their accuracy over time and enhancing their utility in clinical practice.

2.7.3 Risk Factor Assessment

AI evaluates various risk factors influencing disease progression, such as age, gender, medical history, genetic factors, and lifestyle. These factors are integrated into predictive models to enhance prediction accuracy. By considering a multitude of variables, AI-driven prediction models can provide more nuanced and individualized risk assessments, enabling healthcare providers to tailor interventions accordingly.

2.7.4 Early Diagnosis Improvement

AI plays a critical role in improving early disease diagnosis by analyzing early clinical signs and symptoms. By identifying subtle indicators of disease onset or progression, AI algorithms can flag cases requiring closer monitoring or additional diagnostic tests [11]. This proactive approach facilitates earlier intervention and treatment initiation, potentially improving patient outcomes and reducing the burden on healthcare systems.

2.7.5 Medical Recommendations

Based on data analysis and disease prediction, AI provides personalized medical recommendations for patients and healthcare providers. These recommendations may include necessary diagnostic tests, appropriate treatment modalities, and lifestyle modifications tailored to each individual's unique circumstances. By leveraging AI-driven insights, healthcare professionals can make more informed clinical decisions, leading to more effective and patient-centered care.

Using AI in disease prediction enhances our understanding of diseases and provides more effective and personalized healthcare. With ongoing advancements in this field, AI is expected to play an increasingly important role in improving health and wellness, empowering healthcare providers to deliver proactive and targeted interventions that optimize patient outcomes.

2.8 Data Mining

“Data mining is the process of understanding data through cleaning raw data” [12] in other words extracting explicit and comprehensible patterns and information from large and complex datasets. The aim of data mining is to discover hidden relationships, trends, and rules within data that are difficult to identify using traditional methods. This process involves using advanced techniques and tools from data science and artificial intelligence to explore and analyze data.

2.8.1 Key techniques in data mining

- **Regression and Classification Analysis:** Used to identify relationships between independent variables and target variables, and to classify data into different categories.
- **Cluster Analysis:** Used to group similar data based on shared characteristics.
- **Association Analysis:** Used to discover relationships and associations between different elements within a dataset.
- **Decision Tree Analysis:** Used to create predictive models based on a series of conditional rules.
- **Intelligent Model Analysis:** Involves applying AI techniques such as neural networks and machine learning to extract complex patterns from data.

Data mining is utilized in a variety of fields and industries, including marketing, medicine, social sciences, finance, and more. It assists in strategic decision-making, analyzing market trends, improving industrial processes, and identifying new needs and trends in the market.

2.9 Machine Learning (ML)

ML is a branch of AI focused on developing techniques that enable systems to learn from data and improve performance automatically without explicit programming [12]. ML aims to create models capable of extracting rules and patterns from data, analyzing them, and applying mathematical and statistical methods to generate accurate predictions and make decisions.

ML techniques are divided into several types, including:

1. **Supervised Learning:** In supervised learning, models are trained on labeled data, learning the relationships between inputs and outputs to predict correct outputs for new data. This approach is widely used in tasks such as classification and regression, where the goal is to assign labels or predict continuous values based on input features.

2. **Unsupervised Learning:** Unsupervised learning involves analyzing unlabeled data to discover patterns and correlations, aiming to group or classify data without explicit supervision. Clustering and dimensionality reduction techniques are common applications of unsupervised learning, enabling insights into data structure and relationships.

3. **Reinforcement Learning:** Reinforcement learning involves models learning from experiences in a specific environment, receiving rewards or penalties based on actions taken, aiming to learn strategies to achieve optimal performance in that environment. This approach is often used in sequential decision-making tasks, such as game playing and robotics, where actions have long-term consequences.

ML applications are vast and diverse, including voice and image recognition, text analysis, data prediction, robot control, big data analysis, and human behavior prediction. ML is one of the most significant advancements in AI, expected to play an increasingly vital role in various industries and sectors in the future.

2.10 Machine Learning Algorithms

Machine learning algorithms are sets of techniques and methods used to build models that learn from data and improve their performance over time. These algorithms are categorized based on learning methods and specific tasks [13]. For example, they are classified into supervised learning algorithms using labeled training data, unsupervised learning algorithms using unlabeled data, and reinforcement learning algorithms based on experiences and rewards.

ML algorithms rely on various methods and techniques, such as artificial neural networks, clustering and classification techniques, big data analysis, and statistical inference methods. These algorithms aim to create models capable of using available data for analysis, extracting patterns, making predictions, and making decisions based on them.

ML algorithms are adaptable and capable of improving performance as data and conditions change. They learn from errors and enhance performance over time. These algorithms are used in various practical applications, such as data analysis, prediction, image classification, text recognition, and delivering intelligent and interactive systems.

2.10.1 Logistic Regression

Logistic regression is a statistical technique used in data analysis to predict a binary dependent variable (response variable), which takes two values such as healthy/sick, successful/unsuccessful, etc. Logistic regression is used to understand the relationship between independent variables (explanatory variables) and the dependent variable and to identify factors influencing outcomes [14].

Logistic regression employs a regression model to determine the relationship between independent variables and the dependent variable. The primary goal of applying logistic regression is to estimate the probability (percentage) of the desired outcome based on the values of independent variables. This technique is commonly used in fields like medicine, social sciences, economics, and marketing to analyze data and make evidence-based decisions [15].

2.10.1.1 Logistic Regression Analysis

The process of logistic regression analysis relies on advanced statistical techniques for data analysis, such as Lasso regression and self-attribution methods. Applying logistic regression requires a thorough understanding of statistical principles and graphical analysis, including binary analysis and logistic analysis. Logistic regression uses the logistic function, also known as the sigmoid function, to model the probability of the dependent variable. [14] The logistic function is defined as in Figure 2.4:

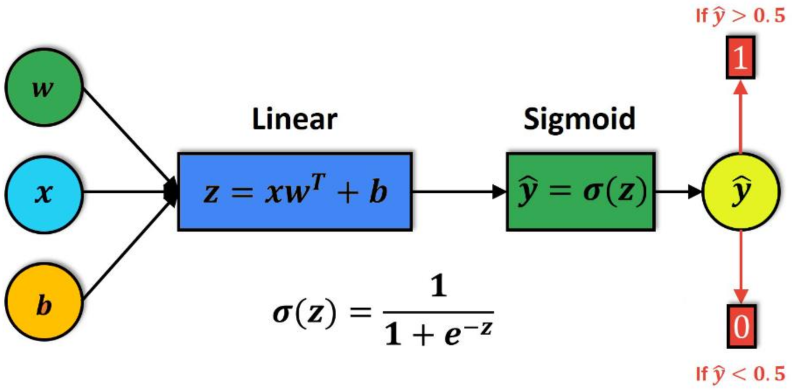


Figure 2.4 – Logistic Functions

In logistic regression, the model begins with the input features, denoted as x, which represent the data points used for making predictions. These features are combined with a set of parameters called weights, represented by w, and an additional parameter known as the bias, b. This combination creates a linear equation of the form $z = zw^2 + b$ The linear transformation of the inputs is crucial as it sets the stage for the next step in the analysis.

The resulting value, z, is then passed through the logistic function, $\sigma(z) = \frac{1}{1+e^{-z}}$ also referred to as the sigmoid function. This function serves to map the linear output into a probability score between 0 and 1. By applying the sigmoid function, the logistic regression model can interpret the linear combination of features as a probability, thus enabling binary classification. The predicted probability, denoted $\check{y}$,indicates the likelihood of the input x belonging to the positive class.

The final step in logistic regression analysis involves determining a threshold to convert the predicted probability into a binary outcome. Typically, a threshold of 0.5 is used. If the predicted probability $\check{y}$ exceeds 0.5, the model classifies the input as belonging to the positive class (often labeled as 1). Conversely, if $\check{y}$ is less than or equal to 0.5, the model assigns the input to the negative class (often labeled as 0).

The accompanying image illustrates this process: starting with the input features, proceeding through the linear transformation and application of the sigmoid function, and culminating in the classification decision. On the left side of the image, a graph demonstrates the linear fit of data points, showcasing the initial combination of features and weights. On the right side, a graph depicts the sigmoid function, highlighting the transformation of the linear output into a probability score.

Overall, logistic regression analysis is a powerful tool for binary classification problems. By utilizing the logistic function to convert linear combinations of input features into probabilities, logistic regression models can effectively determine the likelihood of binary outcomes based on the data provided. This methodology is foundational in various fields, particularly in situations were predicting the occurrence of one of two possible outcomes is essential.

2.10.1.2 Assumptions and Limitations

Several assumptions underlie logistic regression, including the linearity of the logit, independence of errors, and absence of multicollinearity among the predictors. The logit of the outcome should be a linear combination of the predictor variables, and observations should be independent of each other. Multicollinearity, where independent variables are highly correlated with each other, can destabilize the model and should be checked and mitigated [16].

Despite its widespread use and interpretability, logistic regression has limitations. It assumes a linear relationship in the logit for continuous variables and may not capture complex relationships without incorporating interaction terms or non-linear transformations. The model is also sensitive to outliers and missing data, which can significantly impact the results.

2.10.1.3 Applications

Logistic regression is applied across various domains. In the medical field, it is used to predict the probability of a disease based on patient characteristics. In finance, logistic regression models credit scoring and default risk. Marketing applications include customer churn prediction, while in the social sciences, it aids in behavioral prediction. These applications demonstrate the versatility and utility of logistic regression in making informed, data-driven decisions [17].

2.10.2 Random Forest

Random forests are a machine learning technique used for classification and prediction, and they belong to the family of ensemble learning methods. This technique constructs a model composed of an ensemble of decision trees, each built on different subsets of the data and features [18].

These trees collectively form the random forest model, which divides the data into smaller groups based on various explanatory variables as illustrated below in figure 2.5.

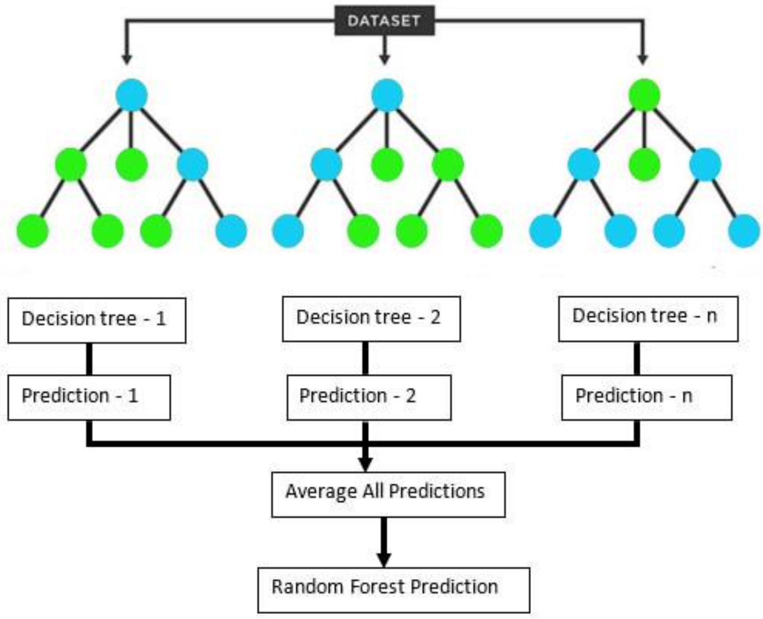


Figure 2.5 – Random Forests

2.10.2.1 Construction of Random Forests

A random forest is a powerful ensemble learning technique that enhances the predictive performance and robustness of decision trees by aggregating multiple trees. The construction of a random forest involves the combination of several decision trees, each generated through a methodical process that introduces randomness into the data and feature selection. This approach mitigates the overfitting typically associated with individual decision trees and enhances the generalization capability of the model.

The process of generating each tree in a random forest involves two critical steps: bootstrap sampling and feature randomness and aggregation process [18]:

1-Bootstrap Sampling:

Bootstrap sampling is the first step in constructing a random forest. For each decision tree, a random sample of the training data is drawn with replacement, a technique known as bootstrap sampling. This means that some data points may be included multiple times in the sample, while others may not be selected at all. This process ensures that each tree is trained on a slightly different subset of the data, introducing variability among the trees and contributing to the robustness of the final model. By leveraging bootstrap sampling, random forests capitalize on the diversity of the data, which helps in reducing variance and improving the model's predictive accuracy.

2- Feature Randomness

The second step in building a random forest involves introducing randomness at the feature selection level. At each node within a decision tree, a random subset of the available features is chosen. The best split is then identified only within this subset of features, rather than considering all possible features. This method of feature randomness, also known as feature bagging or random subspace method, decorrelates the individual trees in the forest. By limiting the features considered for splitting at each node, the trees become more diverse and less likely to make the same mistakes, further enhancing the model's performance.

3- Aggregation Process

Once all the individual decision trees are constructed through bootstrap sampling and feature randomness, the final step in the random forest algorithm is the aggregation of their predictions. For classification tasks, this aggregation is typically performed by majority voting, where each tree casts a vote for the predicted class, and the class with the most votes is selected as the final prediction. For regression tasks, the aggregation involves averaging the predictions of all the trees to produce the final output. This aggregation process leverages the collective wisdom of the multiple trees, thereby improving the overall accuracy and stability of the model.

The random forest algorithm's ability to handle high-dimensional data, its robustness to overfitting, and its capacity to model complex interactions among features make it an invaluable tool in both classification and regression tasks. By integrating randomness in both data and feature selection, random forests effectively combine the strengths of individual decision trees while mitigating their weaknesses. This ensemble approach ensures that the final model is not only accurate but also generalizes well to unseen data.

The accompanying diagram illustrates the construction of a random forest, highlighting the key steps of bootstrap sampling and feature randomness, and the subsequent aggregation process. Each decision tree, trained on a different bootstrap sample and using random subsets of features, contributes to the collective prediction of the random forest, exemplifying the power of ensemble learning.

The construction of random forests through the systematic introduction of randomness and the aggregation of multiple decision trees exemplifies a sophisticated yet intuitive approach to machine learning. This methodology provides robust and accurate models capable of handling a wide array of predictive tasks, underscoring the importance and efficacy of ensemble learning techniques in modern data analysis and machine learning.

2.10.2.2 Advantages of Random Forests

- **Resistance to Overfitting**: By using an ensemble of decision trees, random forests reduce the risk of overfitting and enhance the model's ability to generalize to new data. Each tree is trained on different parts of the data and features, making the overall model less sensitive to the specifics of any single dataset [18].
- **Scalability**: Random forests can be easily scaled to handle large datasets. The algorithm can be parallelized, allowing multiple trees to be built simultaneously, making it suitable for big data applications [19].
- **Handling Missing Data**: Random forests can manage missing data without the need for pre-processing [18]. The algorithm can use the median value for missing numerical features or the most frequent value for categorical features, or it can input missing values using proximity measures from the trees.

2.10.2.3 Limitations of Random Forests

- **Instability:** Results can be unstable with minor changes in the data, especially when the trees in the ensemble are highly similar. While the ensemble approach mitigates some of this instability, it can still be a concern in practice [18].

- **Processing Time:** Building random forests and classifying data can be time-consuming, particularly for large datasets. Each tree must be built independently, and the ensemble requires substantial computational resources. This can be a limitation when quick predictions are necessary [20].

2.10.2.4 Applications of Random Forests

Random forests are applied across various domains due to their versatility and robustness. In finance, they are used for credit scoring and fraud detection. In healthcare, random forests aid in disease prediction and patient risk assessment. They are also utilized in marketing for customer segmentation and churn prediction, and in environmental science for species distribution modeling and ecosystem assessment [21].

2.10.3 Support Vector Machines (SVMs)

Support Vector Machines (SVMs) are supervised learning models developed in the 1990s, renowned for their effectiveness in classification and regression analysis. They have become one of the most prominent machine learning algorithms due to their robust performance [22].

2.10.3.1 Key Concepts

Linear Separability: SVMs function by identifying a hyperplane in an N-dimensional space (N being the number of features) that distinctly classifies data points. In a two-dimensional space, this hyperplane is a line [22].

- **Margin**: SVMs strive to maximize the margin between different classes. The margin is the distance between the hyperplane and the nearest data point from each class. Maximizing this margin enhances generalization and minimizes overfitting.

- **Support Vectors:** These are the critical data points closest to the hyperplane and are instrumental in defining the decision boundary. They influence the hyperplane's position and orientation.
- **Kernel Trick:** SVMs can efficiently perform nonlinear classification using the kernel trick. This technique transforms the feature space into higher dimensions, facilitating the discovery of a linearly separable hyperplane. Common kernels include Linear, Polynomial, Gaussian (RBF), and Sigmoid as shown below in figure 2.5:

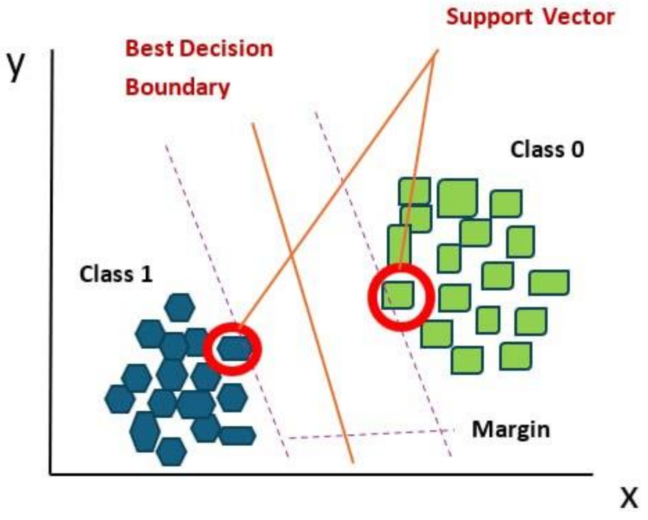


Figure 2.6 - SVM

2.10.3.2 Mathematical Formulation

- **Quadratic Programming:** The SVM problem is formulated as a convex optimization problem, typically solved using quadratic programming techniques, ensuring efficient computation of the optimal hyperplane.
- **Kernel Trick:** SVMs manage nonlinear decision boundaries by implicitly mapping input vectors into a higher-dimensional feature space through kernel functions, transforming the task of finding a linear boundary in the original space into finding one in a higher-dimensional space.

2.10.3.3 Practical Considerations

- **Kernel Selection:** Choosing the appropriate kernel function (e.g., linear, polynomial, Gaussian RBF) is critical and depends on the data's characteristics and the specific problem.
- **Scaling:** SVMs are sensitive to feature scaling, necessitating the normalization or standardization of input features before training.
- **Parameter Tuning:** SVMs have parameters, such as the regularization parameter (C) and kernel-specific parameters (e.g., gamma for the RBF kernel), which require tuning for optimal performance. Cross-validation techniques are often employed for parameter selection.
- **Interpretability:** SVMs offer insights into the decision-making process through support vectors, the pivotal data points that influence the decision boundary's position and orientation.

2.10.3.4 Advantages of SVMs

- **Effective in High-Dimensional Spaces:** SVMs perform well even when the number of dimensions exceeds the number of samples.
- **Memory Efficient:** SVMs are memory efficient as they use a subset of training points (support vectors) in the decision function.
- **Versatile:** SVMs support various kernel functions for the decision function, with options for common kernels and custom specifications.
- **Effective with Nonlinear Data:** SVMs can model complex, nonlinear relationships in data using the kernel trick.

2.10.3.5 Limitations of SVMs

- **Computationally Intensive:** SVMs can be slow to train on large datasets, especially when using kernels.

- **Difficulty in Tuning:** SVMs require tuning of several parameters (kernel choice, regularization parameter C, kernel parameters) for optimal performance.
- **Sensitive to Noise:** SVMs may overfit noisy datasets if the regularization parameter C is too large.

2.10.3.6 Applications of SVMs

- **Classification Tasks:** SVMs are extensively used for classification tasks such as text categorization, image classification, and bioinformatics.
- **Regression Tasks:** SVMs can also be utilized for regression tasks to predict continuous outcomes.
- **Anomaly Detection:** SVMs are effective in identifying outliers in data, making them valuable for anomaly detection.

2.10.4 Model Evaluation and Interpretation

For every classification model prediction, the evaluation process includes creating a confusion matrix, which summarizes the model's performance by displaying the counts of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) [23].

Here is an example in table 2.1:

	Predicted 0	Predicted 1
Actual 0	TN	FP
Actual 1	FN	TP

Table 2.1 (prediction table)

- **TN (True Negatives)**: Number of negative cases correctly classified
- **TP (True Positives)**: Number of positive cases correctly classified

- **FN (False Negatives)**: Number of positive cases incorrectly classified as negative
- **FP (False Positives)**: Number of negative cases incorrectly classified as positive

Various performance metrics can be derived from the confusion matrix:

1- **Accuracy** is the ratio of correctly classified test cases to the total number of test cases and is calculated as:

$$\boldsymbol{Accuracy = \frac{TP + TN}{TP + TN + FP + FN}}$$

Accuracy is helpful for balanced datasets but can be misleading for imbalanced datasets. For instance, in fraud detection with a 1:99 fraud to non-fraud ratio, a model predicting all cases as non-fraud would still achieve 99% accuracy, which is not useful.

2- **Precision** measures the proportion of positive identifications that are correct and is calculated as:

$$\boldsymbol{Precision = \frac{TP}{TP + FP}}$$

High precision is essential in predictive maintenance to avoid unnecessary maintenance costs due to false positives.

3- **Recall (Sensitivity)** Recall measures the proportion of actual positives that are correctly identified and is calculated as:

$$\boldsymbol{Recall = \frac{TP}{TP + FN}}$$

High recall is crucial in fraud detection to ensure most fraud cases are identified.

4- **F1 Score** the F1 score is the harmonic mean of precision and recall, providing a balance between the two metrics:

$$F1\ Score = 2 \cdot \frac{Precision\ .Recall}{Precision + Recall}$$

The F1 score is valuable in situations where both precision and recall are important, such as in the aviation industry for identifying parts that need repair, balancing cost and safety.

5- **AUC-ROC** The ROC (Receiver Operating Characteristic) curve plots the true positive rate (TPR) against the false positive rate (FPR) at different thresholds, while the AUC (Area Under the Curve) measures the model's overall performance:

$$\mathbf{AUC} = \int_{0}^{1} \mathbf{TPRd(FPR)}$$

An AUC close to 1 indicates a highly effective model, while an AUC of 0.5 suggests the model performs no better than random guessing.

These metrics and tools allow for a comprehensive evaluation of classification models, ensuring their accuracy and reliability across various applications.

2.10.5 Random Forest versus logistic regression differences

Random forest and logistic regression are two commonly used techniques in machine learning for classification tasks. While both methods can be effective, they have distinct characteristics and are suitable for different scenarios [24].

1- **Model Complexity:** Random Forest models tend to be more complex than logistic regression models. Random forests consist of multiple decision trees, each trained on a random subset of the data and features. In contrast, logistic regression is a simpler model that directly models the relationship between the independent variables and the probability of a binary outcome.

2- **Interpretability:** Logistic regression models are more interpretable than random forests. The coefficients in a logistic regression model represent the relationship between each independent variable and the log-odds of the target variable. This makes it easier to understand the impact of each variable on the prediction. Random forests, on the other hand, are harder to interpret due to their ensemble nature.

3- **Handling of Non-linear Relationships:** Random forests can capture non-linear relationships between the independent variables and the target variable more effectively than logistic regression. This is because each decision tree in the random forest can model complex interactions between variables. Logistic regression assumes a linear relationship between the independent variables and the log-odds of the target variable, which may not always be appropriate.

4- **Robustness to Overfitting:** Random forests are generally more robust to overfitting than logistic regression, especially when dealing with high-dimensional data or datasets with complex relationships. This is because each decision tree in the random forest is trained on a subset of the data and features, reducing the risk of overfitting. Logistic regression, on the other hand, is more susceptible to overfitting, especially when the number of features is large relative to the number of observations.

2.11 Previous Studies

In this section we will illustrate some of the previous studies about heat and diabetes diseases:

Raj Kumar and Santosh Kumar conducted a study titled "Heart Disease Prediction System using Machine Learning Techniques: A Comparative Study" which focuses on comparing different machine learning algorithms for predicting heart diseases. Utilizing the Cleveland heart disease dataset, the researchers evaluated the performance of algorithms such as Random Forest and Logistic Regression. The study revealed that Random Forest outperformed Logistic Regression in terms of accuracy and robustness, especially in handling imbalanced datasets. This comparative analysis underscores the potential of Random Forest as a superior model for heart disease prediction [25].

Building on this, Ayesha Sultana and Shruti Desai's research, "Prediction of Heart Disease Using Random Forest and Logistic Regression," further examines the effectiveness of Random Forest and Logistic Regression models in predicting heart disease. Using the UCI Heart Disease dataset, they assessed the models based on accuracy, sensitivity, and specificity. Their findings indicate that the Random Forest model, with its higher sensitivity, offers a more reliable approach for early detection of heart disease, highlighting its advantages over Logistic Regression [21].

Complementing these findings, Sarah Lee and David Kim's study, "Application of Random Forest Algorithm for Predicting Heart Disease and Diabetes," investigates the use of the Random Forest algorithm for predicting heart diseases and diabetes. By evaluating the model with datasets such as the Pima Indians Diabetes Database and the Cleveland Heart Disease dataset, the researchers concluded that Random Forest offers high accuracy and robustness. This study underscores the algorithm’s applicability in medical predictions, given its superior performance over traditional methods [26].

In a 2020 study, researchers AlKaabi LA, Ahmed LS, Al Attiyah MF, and Abdel-Rahman ME sought to develop and compare machine learning models to predict hypertension risk among 987 Qatari and long-term resident participants from the Qatar Biobank. They employed decision tree, random forest, and logistic regression algorithms to create these predictive models. Important predictors of hypertension identified in the study included age, gender, education, employment, lifestyle factors (such as tobacco use, physical activity, and diet), obesity, and family medical history. All three algorithms demonstrated similar performance, with random forest and logistic regression outperforming the decision tree in terms of accuracy, sensitivity, and other metrics. The researchers concluded that machine learning could offer rapid, non-invasive screening for hypertension risk, though additional research is necessary to enhance predictive power in larger populations [27].

In 2023, S.T.P. Prasanna and T. Veeramani conducted a study to assess the accuracy and efficiency of heart disease prediction using classification algorithms: Support Vector Machine (SVM), Random Forest (RF), and Logistic Regression (LR). These algorithms were tested on a medical dataset consisting of 180 records. The Random Forest algorithm achieved the highest accuracy at 92.13%, followed by Logistic Regression at 84.89%, and Support Vector Machine at 62.51%. The researchers observed a statistically significant difference between the performance of the Random Forest and Support Vector Machine algorithms, whereas the difference between Random Forest and Logistic Regression was not statistically significant. The study concluded that the Random Forest algorithm was the most effective in predicting heart diseases compared to the other algorithms tested [28].

A 2024 review by Reza Ishak Estiko, Estiko Rijanto, Yahya Berkahanto Juwana, and Bambang Widyantoro assessed machine learning for predicting hypertension. Analyzing 8 studies on easily measurable risk factors like age, sex, family history, and lifestyle, they found that machine learning algorithms, such as Random Forests and Support Vector Machines, outperformed traditional models like logistic regression. The best machine learning model achieved an AUC of 0.92, exceeding the 0.829 AUC of logistic regression. The study suggests machine learning offers a promising method for predicting hypertension, enabling earlier identification of high-risk individuals and improving prevention and management [29].

Lastly, Ali Reza and Maryam Hosseini explore the use of machine learning techniques in predicting chronic diseases such as heart disease and diabetes in their research "Predicting Chronic Diseases Using Machine Learning Techniques." Their research highlights that Random Forest consistently outperforms Logistic Regression in terms of accuracy and reliability across various medical datasets. This study emphasizes the potential of Random Forest as a robust model for predicting chronic diseases [30].

2.12 Bridging Previous Research to Practical Application

This chapter has underscored the crucial role of effective data management and advanced machine learning algorithms in predicting chronic conditions like heart disease, diabetes, and hypertension. The consistent success of models such as Random Forest highlights the importance of thorough data preprocessing and feature selection.

In Chapter 3, we'll move from the literature review to practical model development, focusing on data manipulation, integration, and transformation. This transition stresses the need for high-quality data preparation to maximize the accuracy and reliability of our predictive models for chronic diseases.

Chapter Three

Model Creation

3.1 Introduction

In this chapter, we shift focus from theoretical understanding to practical application, concentrating on the processes essential for building effective machine learning models. We will explore the critical steps of data manipulation, including data collection, integration, and transformation. These processes are fundamental for ensuring the data is well-prepared and suitable for model training, ultimately laying the groundwork for accurate and reliable predictive models.

3.2 Data Manipulation

Data preprocessing and cleaning are essential for ensuring data quality and consistency, particularly in the context of techniques such as random forests. This chapter offers a detailed overview of the steps involved in preparing data for analysis and modeling, emphasizing the importance of these processes for accurate and meaningful results.

3.2.1 Data Collection

The purpose of data collection must be clearly defined, such as predicting outcomes or classifying items, to determine required data types. Ensuring the collected data accurately represents the problem and maintaining data quality by addressing errors and missing values are essential. Sufficient and diverse data is required for effective machine learning model training. Periodic review and updates of the data are necessary as problems and data may evolve. When dealing with personal data, privacy and ethical considerations must be taken into account.

3.2.2 Data Integration

Integrating data from multiple sources is crucial for providing comprehensive insights and addressing the problem holistically. This involves consolidating data from various databases, APIs, sensors, or files into a unified dataset. Ensuring the accuracy and consistency of this integrated data is vital for effective analysis and model training.

3.2.3 Data Transformation

Data transformation is the process of converting data into suitable formats for analysis or machine learning. This includes scaling, normalization, encoding categorical variables, imputing missing values, and dimensionality reduction. Careful consideration of transformation steps and their effects is essential to maintain data integrity and model performance.

3.2.4 Feature Selection

Feature selection involves identifying and selecting the most relevant input features to improve model performance, reduce complexity, and enhance interpretability. Techniques include filter, wrapper, and embedded methods. The method choice depends on the dataset, task type, and computational constraints, aiming to avoid overfitting and ensure the selected features generalize well.

3.3 Handling Missing Data

Handling missing data involves identifying gaps and applying techniques such as imputation to replace missing values with estimates based on available data. This step ensures that the dataset remains complete and useful for accurate model training.

3.3.1 Outlier Detection and Treatment

Outlier detection and treatment identify data points significantly different from the majority, addressing them to prevent skewed analysis. This step is crucial for maintaining data integrity and ensuring the model's robustness.

3.3.2 Handling Inconsistent Data

Handling inconsistent data involves correcting errors, standardizing formats, and removing duplicates to ensure the dataset's reliability and accuracy. This step is essential for producing a clean, consistent dataset suitable for analysis.

3.3.3 Data Cleaning Techniques

Data cleaning techniques encompass methods to ensure data quality, such as correcting spelling errors, standardizing formats, removing duplicates, and handling missing values. Effective data cleaning is vital for accurate analysis and model performance.

3.4 Utilizing Python for Data Processing:

Python is a versatile and widely-used language, renowned for its capabilities in data processing, analysis, and scientific computing. Its extensive collection of powerful data science libraries and tools makes it an ideal choice for data-related tasks. The language's readability and simplicity make it accessible to programmers of all levels. Integrating Python with Jupyter Notebook provides an interactive computing environment, enabling dynamic data exploration and presentation. Anaconda, a popular Python distribution, includes a vast array of pre-installed data science and machine learning packages, simplifying the creation of a comprehensive data science workflow. The robust Python community further enriches this ecosystem with ample resources, libraries, and support for data-related projects. By leveraging the benefits of Python, Jupyter, and Anaconda, one can effectively perform data processing and analysis to gain valuable insights.

3.4.1 Optimal Algorithm Selection and Implementation Strategies

After processing and preparing the entire datasets, the following three algorithms will be evaluated: Logistic Regression, Random Forest, and SVM. Each of these algorithms was selected for specific reasons:

1. **Logistic Regression**: This algorithm is simple and easy to interpret, and it is suitable for predicting binary or multi-class variables. It is also one of the most common and widely used algorithms in the field of prediction.
2. **Random Forest**: According to previous studies, this algorithm has been superior in prediction accuracy in many medical applications. It also handles complex and intertwined data well.

3. **SVM**: This algorithm performs well when the number of features is close to the number of rows or cases. It can also deal with non-linear data effectively. Additionally, it provides good performance with high-dimensional data. We will test these three algorithms on each dataset using the scikit-learn library, and we will split the data into training and testing sets. The algorithm with the highest accuracy on the test data will be selected as the final predictive model.

3.4.2 Database Foundations: Sources and Data Processing

1-heart disease: Framingham Heart Study Dataset

Data Source: The data was collected from the Framingham Heart Study and is publicly available on Kaggle. The study involves residents of Framingham, Massachusetts, and includes over 4,000 records and 15 attributes.

Data Processing:

1. Data Cleaning: Removing missing or invalid values, dropping the education column.
2. Exploratory Data Analysis: Understanding data distribution and discovering patterns.
3. Converting Categorical Variables: Transforming categorical variables (e.g., sex) into numerical values.
4. Feature Scaling: Standardizing continuous variables to the same range to improve model performance.
5. Data Splitting: Dividing the data into training and testing sets.

Feature	Description
Sex	Indicates whether the patient is male or female.
Age	The age of the patient in years.
Current Smoker	Indicates whether the patient is a current smoker (Yes/No).
Cigs Per Day	The number of cigarettes the patient smokes per day.
BP Meds	Indicates whether the patient is on blood pressure medication (Yes/No).
Prevalent Stroke	Indicates whether the patient has previously had a stroke (Yes/No).
Prevalent Hyp	Indicates whether the patient is hypertensive (Yes/No).
Diabetes	Indicates whether the patient has diabetes (Yes/No).
Tot Chol	Total cholesterol level.

Sys BP	Systolic blood pressure.
Dia BP	Diastolic blood pressure.
BMI	Body Mass Index.
Heart Rate	Heart rate.
Glucose	Glucose level.
10 Year Risk of CHD	The target variable indicating whether the patient is at risk of developing coronary heart disease within 10 years (Yes/No).

Table 3.1 (Heart Dataset)

2-Diabetes Disease: Pima Indian Diabetes Dataset:

Data Source: This dataset is originally from the National Institute of Diabetes and Digestive and Kidney Diseases and is publicly available. It includes females at least 21 years old of Pima Indian heritage.

Data Processing:

1. Data Cleaning: Handling missing values (e.g., replacing zero values with NaN and imputing them).
2. Exploratory Data Analysis: Visualizing distributions, correlations, and identifying patterns.
3. Data Splitting: Dividing the data into training and testing sets.

Feature	Description
Pregnancies	Number of times the patient has been pregnant.
Glucose	Plasma glucose concentration after 2 hours in an oral glucose tolerance test.
Blood Pressure	Diastolic blood pressure (mm Hg).

Skin Thickness	Triceps skin fold thickness (mm).
Insulin	2-Hour serum insulin (mu U/ml).
BMI	Body Mass Index (weight in kg/(height in m)^2).
Diabetes Pedigree Function	A function which scores the likelihood of diabetes based on family history.
Age	Age of the patient in years.
Outcome	Class variable (0 or 1) indicating whether the patient has diabetes (1) or not (0).

Table 3.2 (Indian Diabetes Dataset)

3- Diabetes Disease: Iraqi Diabetes Dataset

Data Source: The data was collected from patient files at Medical City Hospital and the Specialized Center for Endocrinology and Diabetes at Al-Kindy Teaching Hospital in Iraq.

Data Processing:

1. Data Cleaning: Removing missing or invalid values.
2. Exploratory Data Analysis: Understanding data distribution and discovering patterns.
3. Converting Categorical Variables: Transforming categorical variables (e.g., gender) into numerical values.
4. Feature Scaling: Standardizing continuous variables to the same range to improve model performance.
5. Data Splitting: Dividing the data into training and testing sets.

Feature	**Description**
Patient ID	Unique identifier for each patient.
Sugar Level Blood	Blood sugar level of the patient.
Age	Age of the patient.
Gender	Gender of the patient (Male/Female).
Creatinine Ratio	Creatinine ratio in the blood.
BMI	Body Mass Index of the patient.
Urea	Urea level in the blood.
Cholesterol	Cholesterol level in the blood.
Fasting Lipid Profile	Includes levels of various lipids in the blood (LDL, VLDL, Triglycerides, HDL).
HBA1C	Hemoglobin A1C level.
Class	Classification of the patient (Diabetic, Non-Diabetic, or Pre-Diabetic).

Table 3.3 (Iraq Diabetes Dataset)

4- Hypertension: Framingham Study Dataset

Data Source: The data was collected from the Framingham Hypertension Study and is publicly available on Kaggle. The study involves residents of Framingham, Massachusetts, and includes over 4,000 records and 13 attributes.

Data Processing:

1. Data Cleaning: Removing missing or invalid values.

2. Exploratory Data Analysis: Understanding data distribution and discovering patterns.
3. Data Splitting: Dividing the data into training and testing sets.

Feature	Description
Gender	Gender of the patient (Male/Female).
Age	Age of the patient.
Current Smoker	Indicates whether the patient is a current smoker (Yes/No).
Cigs Per Day	The number of cigarettes the patient smokes per day.
BP Meds	Indicates whether the patient is on blood pressure medication (Yes/No).
Diabetes	Indicates whether the patient has diabetes (Yes/No).
Tot Chol	Total cholesterol level.
Sys BP	Systolic blood pressure.
Dia BP	Diastolic blood pressure.
BMI	Body Mass Index of the patient.
Heart Rate	Heart rate.
Glucose	Glucose level.
Hypertension Risk	The target variable indicating whether the patient is at risk of hypertension (Yes/No).

Table 3.4 (Hypertension Dataset)

Chapter Four

Server and Client Application Development

4.1 Introduction

This chapter details the development process of a server-side API using the Django framework and the integration of this API with a mobile application. It will cover the API endpoints, database schema, token-based authentication using JWT, security considerations, and the interaction between the API and the machine learning model hosted on the same server.

4.2 Server-Side API Development with Django

4.2.1 Introduction to Django Framework

Django is a high-level Python web framework that encourages rapid development and clean, pragmatic design. It provides a robust foundation for creating web applications with minimal setup and is well-suited for building RESTful APIs.

4.2.2- REST API

RESTful APIs are based on the principles of REST, a lightweight architectural style that emphasizes a stateless client-server communication model. Unlike traditional web services that rely on complex protocols and standards, RESTful APIs leverage the simplicity and ubiquity of the Hypertext Transfer Protocol (HTTP) to enable communication between systems. By utilizing standard HTTP methods such as GET, POST, PUT, and DELETE, RESTful APIs facilitate the exchange of data and resources in a standardized and interoperable manner [31].

4.2.3- REST API Architecture

In the world of modern application development, RESTful APIs have gained significant popularity as a robust and scalable solution for building interoperable systems. REST, short for Representational State Transfer, provides an architectural style that emphasizes simplicity, scalability, and loose coupling. By understanding the underlying architecture, developers can effectively design, develop, and utilize RESTful APIs to enable seamless communication between different applications and systems [31] (Figure 4.1).

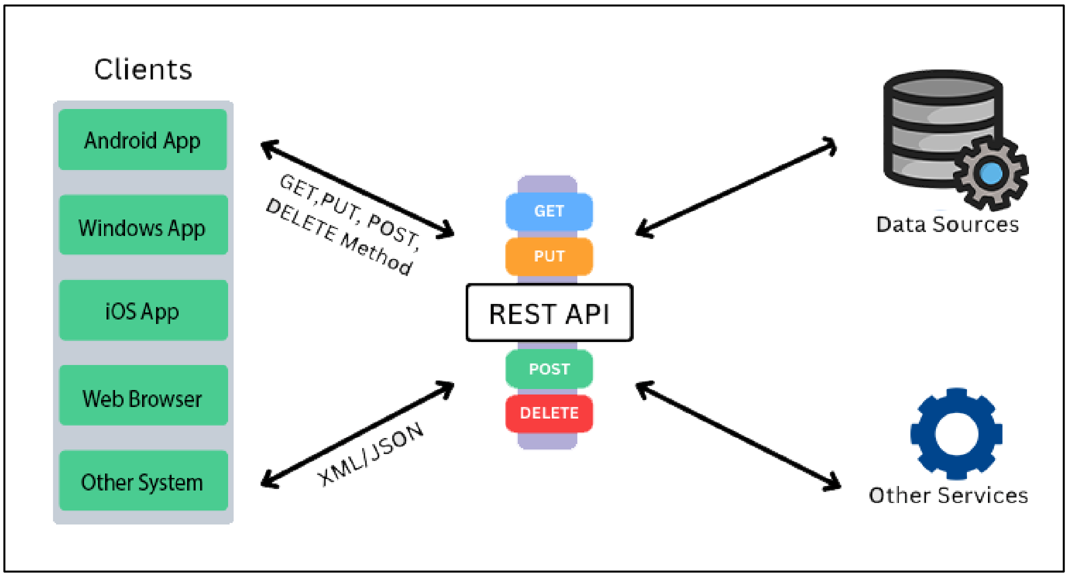


Figure 4.1 (RESTful API Architecture)

4.2.4- REST API Client

A RESTful API client is a software component or application that interacts with a RESTful API to consume and interact with its resources. The client initiates requests to the API's endpoints, typically using HTTP methods such as GET, POST, PUT, and DELETE, and receives responses containing the requested data or the outcome of the requested operation. The client is responsible for constructing the requests, including specifying the appropriate headers, parameters, and payload, and sending them to the API server, and it could be any software on any devices, no matter what programming language is and what the operating system is [31].

4.2.5- HTTP Request

HTTP, the Hypertext Transfer Protocol, is a fundamental protocol for communication on the web. It follows a client-server model, where clients request information from servers, which respond with the requested data. It operates over a reliable network, typically TCP/IP, and uses status codes to indicate the outcome of a request. HTTP is stateless, treating each request-response cycle independently. As a widely adopted and universal protocol, HTTP plays a vital role in web communication. HTTP Request components are [31](Figure 4.2):

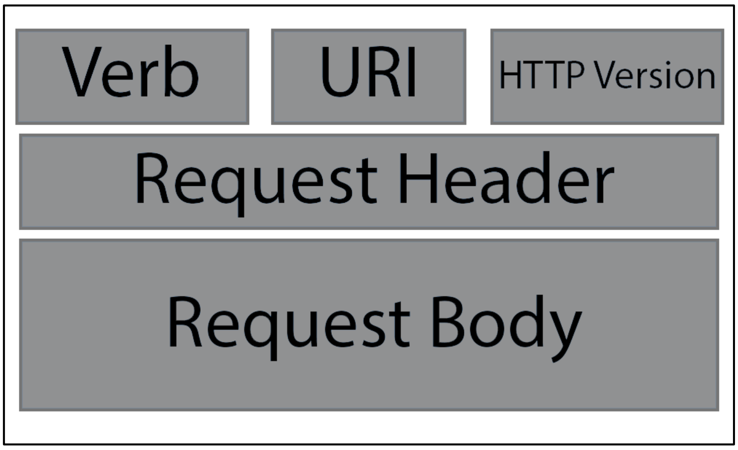


Figure 4.2 (HTTP Request Components)

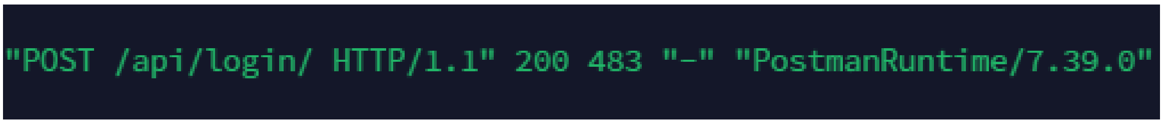
- **Verb -** HTTP protocol defines a set of request methods to indicate the desired action to be performed for a given resource. Although they can also be nouns, these request methods are sometimes referred to as HTTP verbs. Each of them implements a different semantic, and they are:

Method	Function
GET	requests a representation of the specified resource. Requests using GET should only retrieve data.
POST	submits an entity to the specified resource, causing a change in state or side effects on the server.

PUT	replaces all current representations of the target resource with the request payload.
DELETE	deletes the specified resource.
OPTIONS	describes the communication options for the target resource.
PATCH	applies partial modifications to a resource.
TRACE	performs a message loop-back test along the path to the target resource.
HEAD	asks for a response identical to a GET request, but without the response body.

Table 4.1 HTTP Request Methods

- **URI -** Also in http request we must specify the endpoint or the URL of the server, as we see in this example (Figure 4.3):



```
"POST /api/login/ HTTP/1.1" 200 483 "-" "PostmanRuntime/7.39.0"
```

Figure 4.3 (RESTful API Request Example)

- **HTTP Version -** Indicates the HTTP version. For example, HTTP v1.1.
- **Request Header –** Contains metadata for the HTTP Request message as key-value pairs. For example, client (or browser) type, format supported by the client, format of the message body, cache settings.
- **Request Body -** Message content or Resource representation usually written in XML or JSON format, and can represent all types of data (text, images, binary files, etc.)

4.2.6- HTTP Response

After the API server receives the HTTP request and process its data, the server responses with an HTTP response message in this format [31] (Figure 4.4):

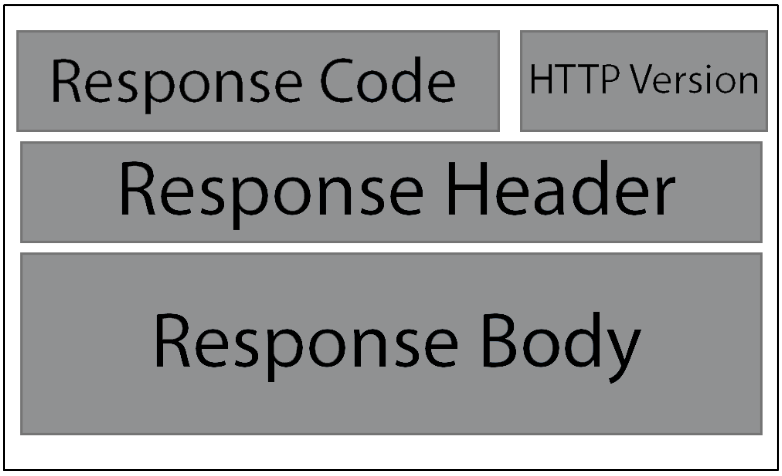


Figure 4.4 (HTTP Response Components)

- **Response Code -** Indicates the Server status for the requested resource, most known codes are:

Code	Meaning
100 - Continue	This interim response indicates that the client should continue the request or ignore the response if the request is already finished
200 - OK	The request succeeded. The result meaning of "success" depends on the HTTP method
201 - Created	The request succeeded, and a new resource was created as a result. This is typically the response sent after POST requests, or some PUT requests
300 – Multiple Choices	The request has more than one possible response. The user agent or user should choose one of them
400 – Bad Request	The server cannot or will not process the request due to something that is perceived to be a client error
401 - Unauthorized	Although the HTTP standard specifies "unauthorized" , the client must authenticate itself to get the requested response.
404 – Not Found	The server cannot find the requested resource.

Table 4.2 HTTP Response Codes

- **HTTP Version -** Indicates the HTTP version. For example, HTTP v1.1.
- **Response Header -** Contains metadata for the HTTP Response message as key-value pairs. For example, content length, content type, response date, server type.
- **Response Body -** Response message content or Resource representation.

4.3 Benefits of RESTful API

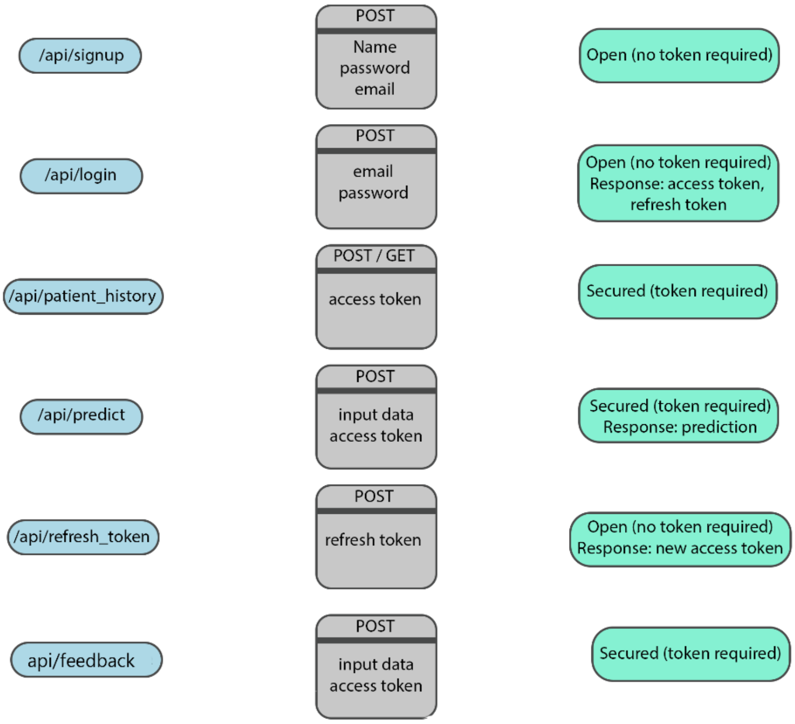
RESTful APIs offer several benefits that have contributed to their widespread adoption in modern application development:

1. **Scalability and Performance**: RESTful APIs are designed to be stateless, meaning that each request contains all the necessary information. This allows for easy scaling and improves performance.
2. **Interoperability**: RESTful APIs are platform and language-independent. They utilize standard HTTP methods and data formats like JSON or XML, making them compatible with various technologies and enabling interoperability between different systems.
3. **Stateless Communication**: The statelessness of RESTful APIs eliminates the need for servers to store session-specific data for each client. This improves scalability, simplifies server implementation, and enhances fault tolerance.
4. **Security**: RESTful APIs can implement secure communication using standard HTTP security mechanisms such as HTTPS and authentication protocols like OAuth. The use of well-established security standards ensures the protection of sensitive data and helps maintain the integrity and confidentiality of the API.

5. **Simplicity and Ease of Use**: RESTful APIs follow a simple and intuitive design based on standard HTTP methods and URIs.

4.4 API Endpoints

Implementation involves setting up serializers, views, and URL routing in Django. Serializers transform model instances into JSON format for API responses, while views handle the logic for each endpoint. API currently has five endpoints, each serving a specific function within the application (Figure 4.5):



/api/signup	POST Name password email	Open (no token required)
/api/login	POST email password	Open (no token required) Response: access token, refresh token
/api/patient_history	POST / GET access token	Secured (token required)
/api/predict	POST input data access token	Secured (token required) Response: prediction
/api/refresh_token	POST refresh token	Open (no token required) Response: new access token
api/feedback	POST input data access token	Secured (token required)

Figure 4.5 (API Endpoints)

1) **Signup (/api/signup):** Handles user registration by creating a new user account. It operates via the HTTP POST method and expects user details such as username, password, and email. This endpoint is open and does not require an authentication token.

2) **Login (/api/login):** Facilitates user authentication and issues access and refresh tokens. It operates via the HTTP POST method and requires

username and password. Similar to the signup endpoint, it's open and does not require an authentication token. Upon successful authentication, it returns an access token and a refresh token.

3) **Patient History (/api/patient_history):** Manages and retrieves patient medical history data. It supports both the HTTP GET and POST methods. A valid access token must be provided in the request header to ensure security and prevent unauthorized access.
4) **Predict (/api/predict):** Processes input data to generate health predictions using a machine learning model. It operates via the HTTP POST method and requires a valid access token in the request header. It saves both the request and the prediction in the patient history.
5) **Refresh Token (/api/refresh_token):** Issues a new authentication token to maintain user sessions. It operates via the HTTP POST method and expects a refresh token as a parameter. This mechanism helps in maintaining user sessions securely.
6) **Feedback (/api/feedback):** Allows users to submit feedback about the prediction to the application. It operates via the HTTP POST method and requires an access token in the request header. This endpoint helps in collecting user input for improvements and issue resolution.

4.5 API Consumption

The mobile app consumes the API endpoints using HTTP requests. It handles responses to perform actions such as displaying patient history, logging in users, and fetching prediction results.

4.5.1 Accessing Protected Endpoints

For accessing endpoints like /api/patient_history and /api/predict, the client must include a valid access token in the Authorization header:

Authorization: Bearer <access_token>

The server verifies the token's validity, expiration, and claims before processing the request.

4.5.2 Token Expiration and Refresh

When the access token expires, the client can request a new access token using the refresh token by sending a request to /api/refresh_token with the refresh token. The server verifies the refresh token and, if valid, issues a new access token.

4.6 User Model

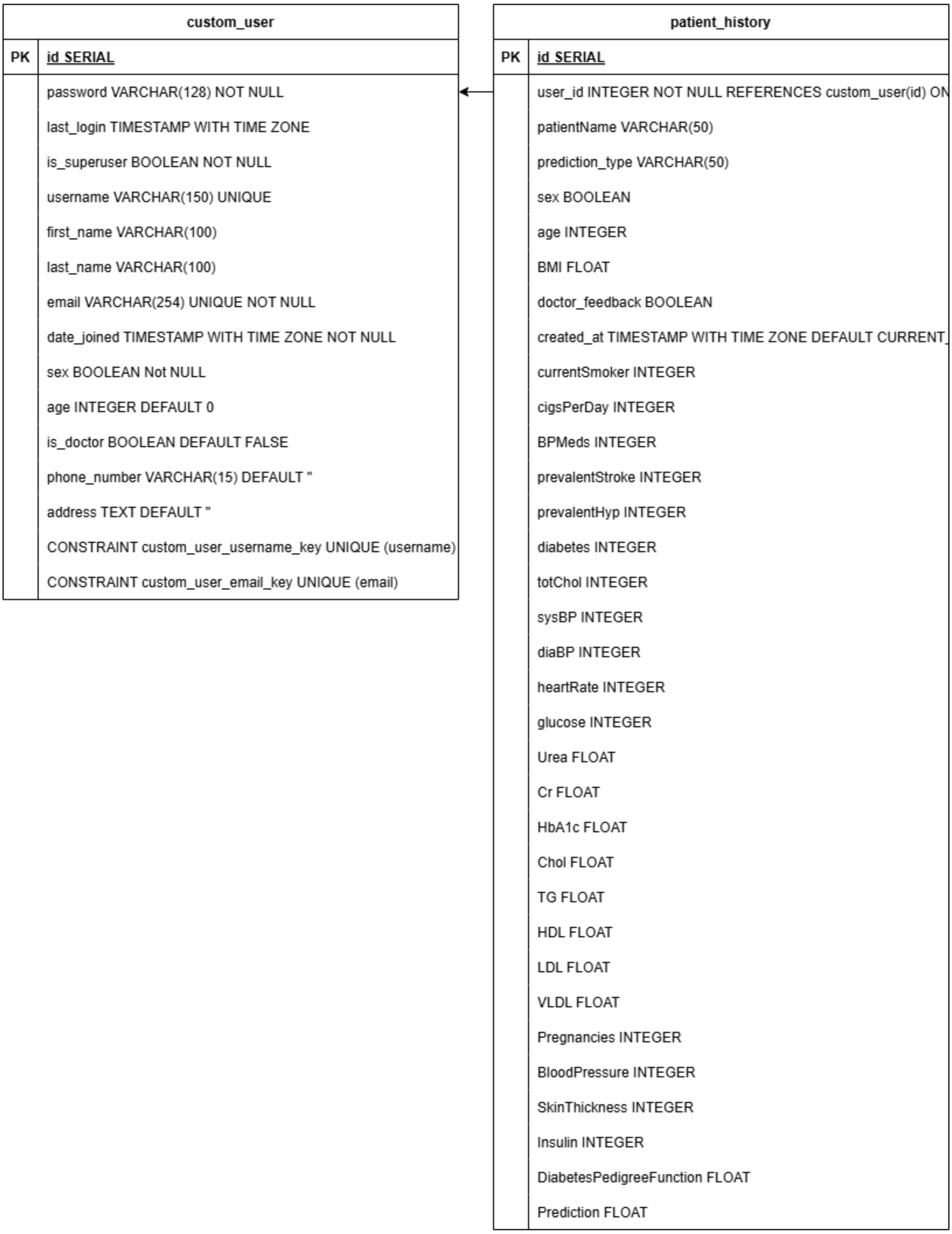
The User model extends Django’s default user model to include additional fields as required by the application. Key attributes include username, email, and password.

4.7 Patient History Model

The Patient History model records each patient's medical history, linking each record to a user in the Custom User table via a foreign key. Key attributes include user, date of record, and medical details.

4.8 Database Schema

The application uses SQLite for testing purposes, with plans to transition to PostgreSQL in production. The current database schema includes two tables:



custom_user	
PK	id SERIAL
	password VARCHAR(128) NOT NULL
	last_login TIMESTAMP WITH TIME ZONE
	is_superuser BOOLEAN NOT NULL
	username VARCHAR(150) UNIQUE
	first_name VARCHAR(100)
	last_name VARCHAR(100)
	email VARCHAR(254) UNIQUE NOT NULL
	date_joined TIMESTAMP WITH TIME ZONE NOT NULL
	sex BOOLEAN Not NULL
	age INTEGER DEFAULT 0
	is_doctor BOOLEAN DEFAULT FALSE
	phone_number VARCHAR(15) DEFAULT ''
	address TEXT DEFAULT ''
	CONSTRAINT custom_user_username_key UNIQUE (username)
	CONSTRAINT custom_user_email_key UNIQUE (email)

patient_history	
PK	id SERIAL
	user_id INTEGER NOT NULL REFERENCES custom_user(id) ON
	patientName VARCHAR(50)
	prediction_type VARCHAR(50)
	sex BOOLEAN
	age INTEGER
	BMI FLOAT
	doctor_feedback BOOLEAN
	created_at TIMESTAMP WITH TIME ZONE DEFAULT CURRENT_
	currentSmoker INTEGER
	cigsPerDay INTEGER
	BPMeds INTEGER
	prevalentStroke INTEGER
	prevalentHyp INTEGER
	diabetes INTEGER
	totChol INTEGER
	sysBP INTEGER
	diaBP INTEGER
	heartRate INTEGER
	glucose INTEGER
	Urea FLOAT
	Cr FLOAT
	HbA1c FLOAT
	Chol FLOAT
	TG FLOAT
	HDL FLOAT
	LDL FLOAT
	VLDL FLOAT
	Pregnancies INTEGER
	BloodPressure INTEGER
	SkinThickness INTEGER
	Insulin INTEGER
	DiabetesPedigreeFunction FLOAT
	Prediction FLOAT

Figure 4.6 Database ER Diagram

4.9 Transition from SQLite to PostgreSQL

4.9.1 Rationale for PostgreSQL

PostgreSQL is chosen for its robustness, scalability, and advanced features such as support for complex queries and data integrity. It is more suitable for production environments compared to SQLite.

4.9.2 Migration Process

The migration process involves:

1. **Exporting Data**: Export data from the SQLite database.
2. **Configuring PostgreSQL**: Set up PostgreSQL and configure the Django settings to connect to the new database.
3. **Migrating Data**: Import the data into the PostgreSQL database using Django’s migration tools.

4.10 Client Application Integration

The mobile application interacts with the Django API to perform user operations and access patient history data. The application supports user authentication, data entry, and retrieval of predictions.

4.11 Token-Based Authentication

4.11.1 JSON Web Tokens (JWT)

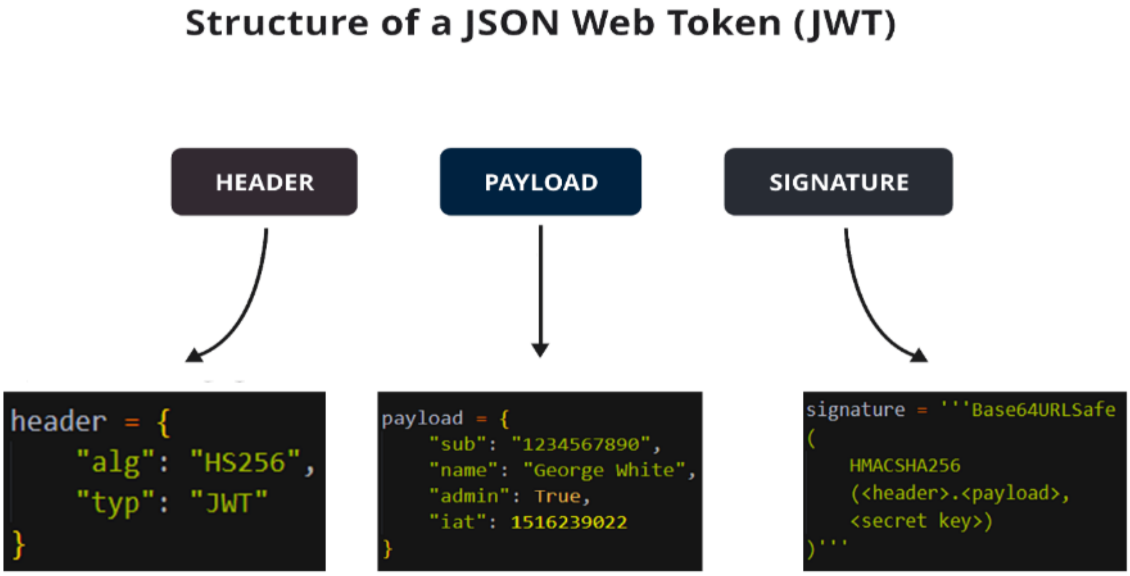
JWT is a compact, URL-safe means of representing claims to be transferred between two parties. The tokens are signed using a cryptographic algorithm to ensure the claims cannot be altered after the token is issued.

4.11.2 JWT Structure

A JWT consists of three parts:

1. **Header**: Contains information about the token type (JWT) and the signing algorithm (e.g., HMAC SHA256).
2. **Payload**: Contains the claims, including user information and token expiration data.
3. **Signature**: Used to verify the authenticity of the token. It is created by encoding the header and payload using a secret key.

The token structure is shown below (Figure 4. 7):



```
header = {
    "alg": "HS256",
    "typ": "JWT"
}
```

```
payload = {
    "sub": "1234567890",
    "name": "George White",
    "admin": True,
    "iat": 1516239022
}
```

```
signature = '''Base64URLSafe
(
    HMACSHA256
    (<header>.<payload>,
    <secret key>)
)'''
```

Figure 4.7 JWT Structure

4.11.3 Access Tokens and Refresh Tokens

- **Access Tokens**: Short-lived tokens that grant access to protected resources. They include user information and a short expiration time, typically a few minutes to an hour [31].

- **Refresh Tokens**: Long-lived tokens used to obtain new access tokens without requiring the user to re-authenticate. They enhance user experience by allowing seamless re-authentication and session management. Refresh tokens have a longer lifespan, usually days or weeks [31].

4.11.4 Security Considerations

- **Secure Storage**: Access tokens are stored in memory on the client side (e.g., in local storage or secure cookies) and refresh tokens are handled securely to prevent unauthorized access.
- **Token Expiration**: Short expiration times for access tokens reduce the risk of token misuse. Refresh tokens, while longer-lived, are protected by stricter access controls.
- **Token Revocation**: Implement mechanisms to revoke refresh tokens if there is suspicion of token compromise.

By implementing JWT-based authentication with access and refresh tokens, the API ensures robust security and seamless user experience.

4.12 Integration of the Machine Learning Model

The API integrates the machine learning model to provide predictive services. When the /api/predict endpoint is called, the following occurs:

1. **Feature Extraction**: The API extracts feature data from the request sent by the mobile application.
2. **Model Prediction**: The feature data is passed to the machine learning model, which generates predictions.
3. **Response and Logging**: The prediction is returned to the client, and the request, along with the prediction, is saved in the PatientHistory table for future reference.

By integrating the machine learning model on the same server as the API, the system ensures efficient communication and rapid response times.

4.13. System Architecture Overview

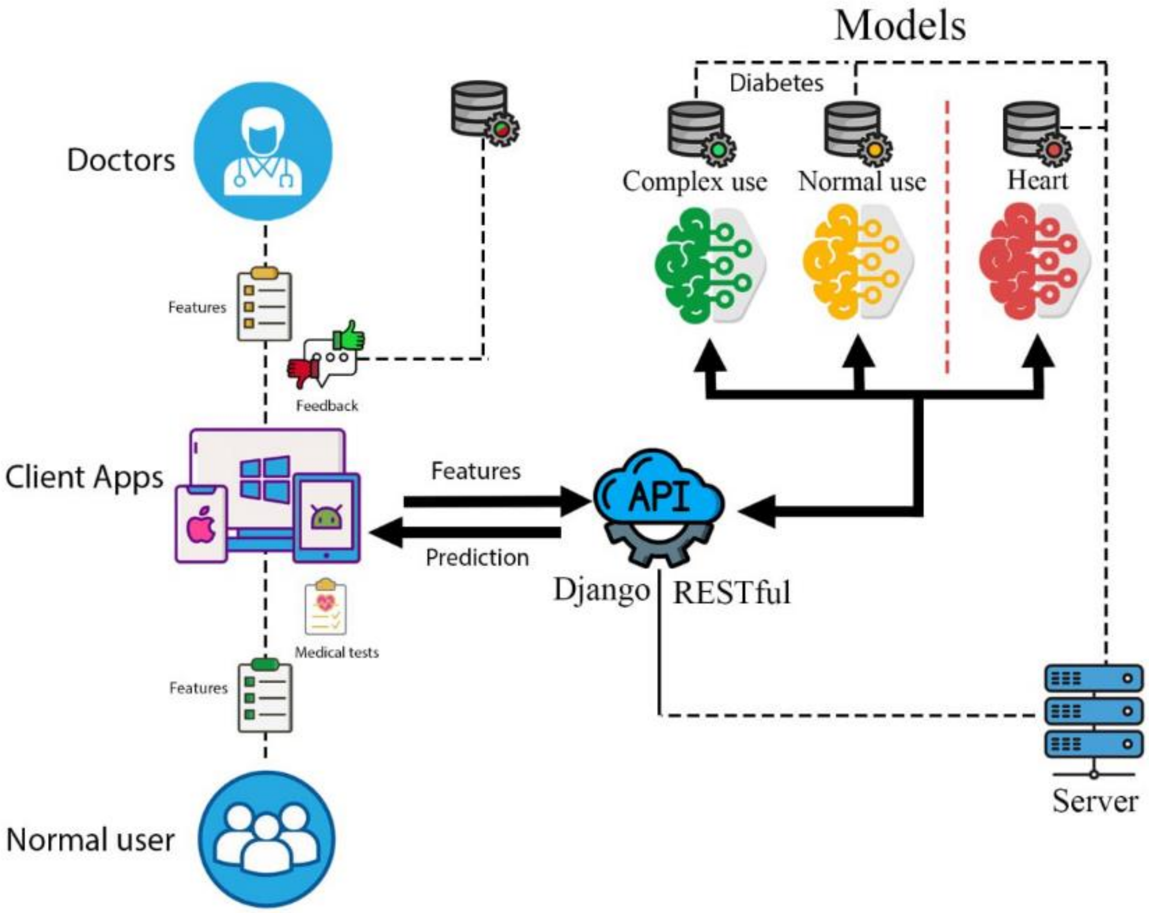
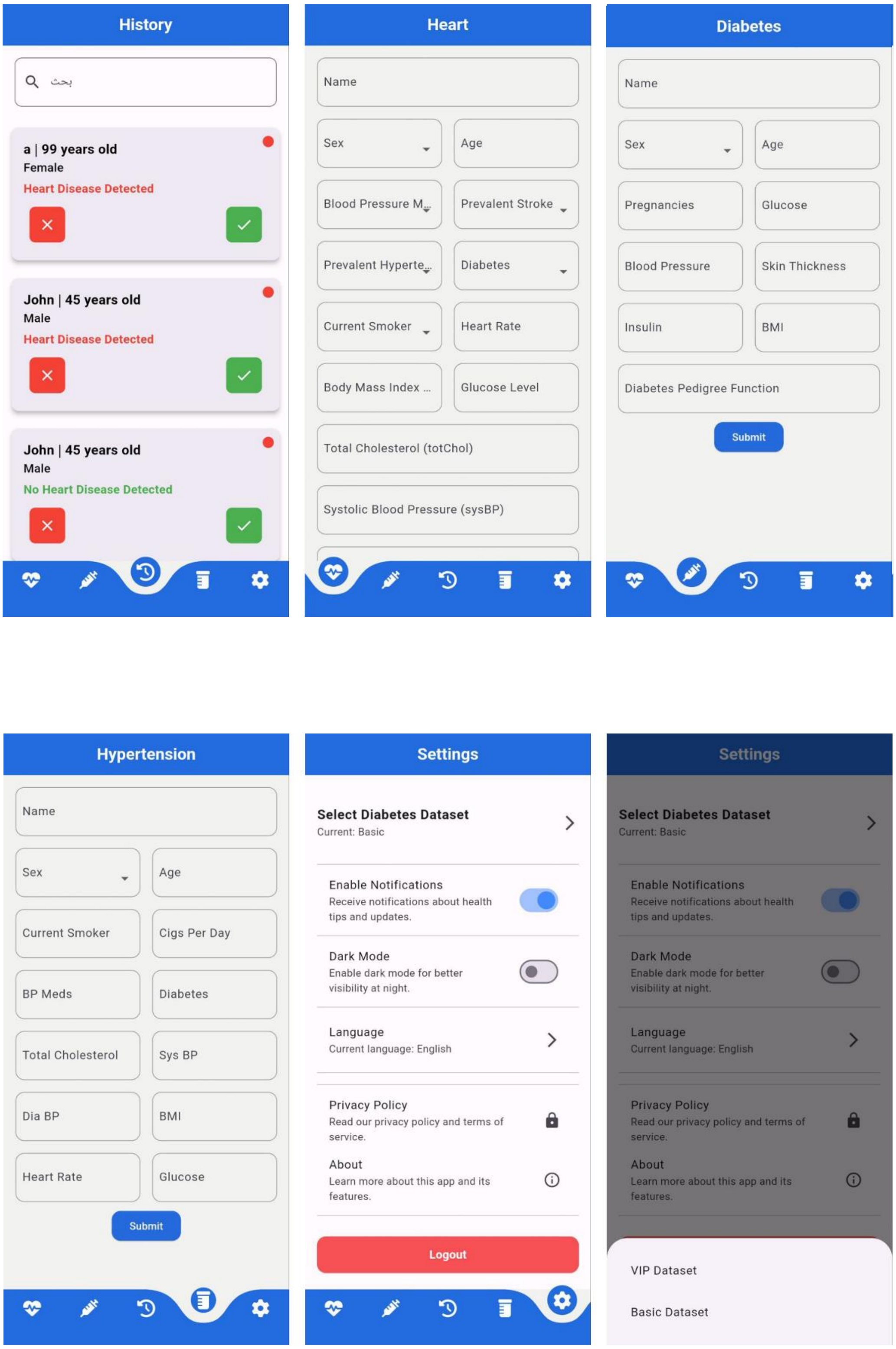


Figure 4.5 System Architecture

4.14. Application overview



a | 99 years old
Female
Heart Disease Detected

John | 45 years old
Male
Heart Disease Detected

John | 45 years old
Male
No Heart Disease Detected

Select Diabetes Dataset
Current: Basic

Enable Notifications
Receive notifications about health tips and updates.

Dark Mode
Enable dark mode for better visibility at night.

Language
Current language: English

Privacy Policy
Read our privacy policy and terms of service.

About
Learn more about this app and its features.

Figure 4.6 Application overview

Chapter Five

Results and Conclusion

5.1 Introduction

This chapter presents the comprehensive results and summary of the chronic disease prediction system, focusing on diagnostic accuracy, system performance, and user feedback. It provides a detailed analysis of the key findings, discusses their implications in the healthcare sector, and outlines potential future enhancements to improve the system further.

5.2 Results

Performance of Algorithms Across Different Datasets:

Dataset	Random Forest Classifier	Logistic Regression	Support Vector Machine
Heart Dataset	86.0% accuracy	85.7% accuracy	85.3% accuracy
Diabetes (Iraqi)	99.0% accuracy	94.5% accuracy	95.0% accuracy
Diabetes (Pima)	73.0% accuracy	75.8% accuracy	75.0% accuracy
Hypertension	90.0% accuracy	87.0% accuracy	89.0% accuracy

Table 5.1 Algorithms Result

In most of the datasets, the Random Forest Classifier achieved the highest accuracy compared to Logistic Regression and Support Vector Machine. Therefore, the Random Forest Classifier will be used as the final model, except for the Diabetes (Pima) dataset.

For the Diabetes (Pima) dataset, the Logistic Regression model showed the highest accuracy at 75.8%, compared to 73.0% for the Random Forest Classifier and 75.0% for the Support Vector Machine. This could be due to the simplicity of the Pima dataset, where the Logistic Regression model's performance was superior to the more complex Random Forest and SVM models.

In general, the Support Vector Machine (SVM) model had the lowest accuracy across all the datasets. This could be because the number of samples or cases in these datasets is significantly larger than the number of features, making the SVM model less effective in capturing the underlying patterns in the data.

5.2.1 Diagnostic Accuracy

The diagnostic accuracy of the chronic disease prediction system was evaluated using extensive datasets obtained from reputable healthcare institutions. The performance metrics for the heart disease and diabetes prediction models were calculated using various statistical measures, including accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic (ROC) curve (AUC).

Heart Disease Prediction:

- **Accuracy:** The model achieved a testing accuracy of 0.86, indicating that the majority of the predictions made by the system were correct.
- **Precision:** With a testing precision of 0.6364, the model demonstrated its ability to accurately identify true positive cases of heart disease.
- **Recall:** A testing recall rate of 0.0565 reflects the model's effectiveness in detecting the majority of actual heart disease cases.
- **F1-Score:** The F1-score, calculated as the harmonic mean of precision and recall, was 0.1037, balancing the trade-off between these two metrics.
- **AUC:** The AUC of 0.5255 signifies a moderate level of separability, indicating that the model has some capability to distinguish between positive and negative cases, but there is room for improvement.

The ROC curve for heart disease prediction is depicted in Figure 5.1, illustrating the trade-off between sensitivity and specificity across different threshold values.

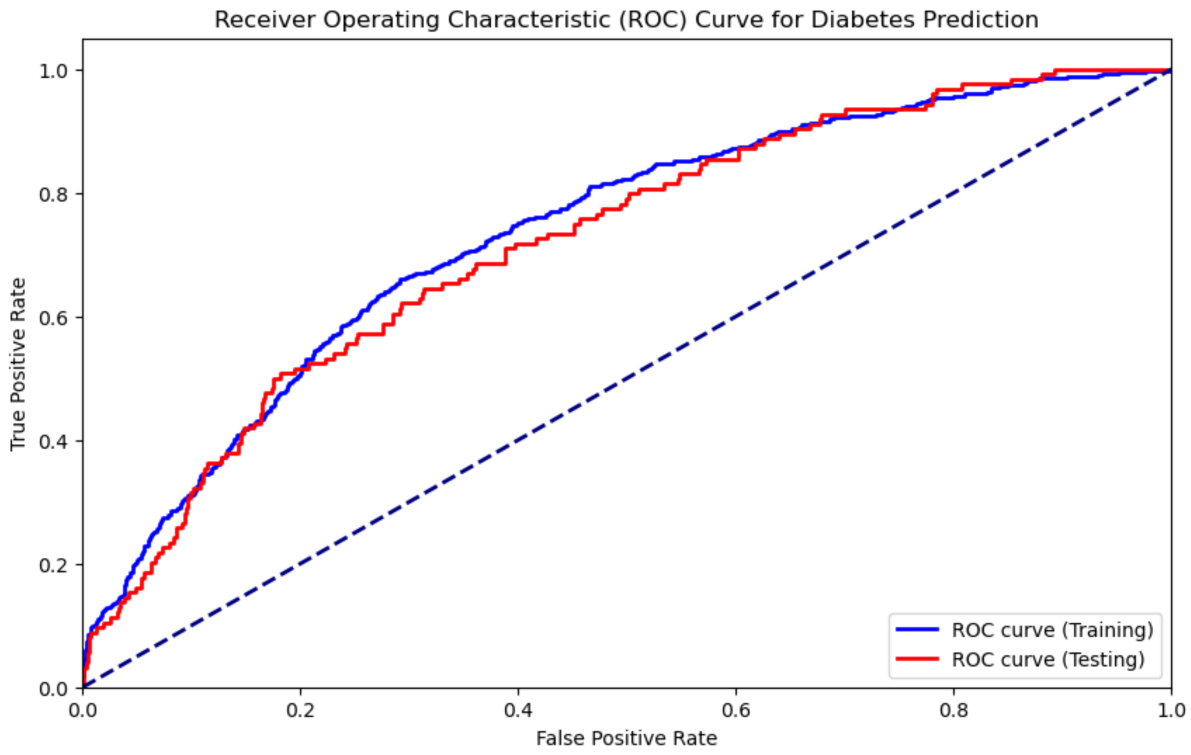


Figure 5.1 - Heart AUC

Diabetes Prediction:

- **Accuracy:** The diabetes prediction model achieved an accuracy of 99% on the testing data, demonstrating its high capability to make correct predictions.
- **Precision:** With a precision of 98.34% on the testing data, the model accurately identified true positive cases of diabetes.
- **Recall:** The model had a recall rate of 99.44% on the testing data, effectively detecting the majority of actual diabetes cases.
- **F1-Score:** The F1-score was 98.89% on the testing data, indicating a well-balanced performance between precision and recall.
- **AUC:** An AUC of 0.9989 on the testing data signifies a high level of separability, indicating that the model effectively distinguishes between positive and negative cases.

The ROC curve for diabetes prediction is shown in Figure 5.2, illustrating the model's performance across various threshold settings.

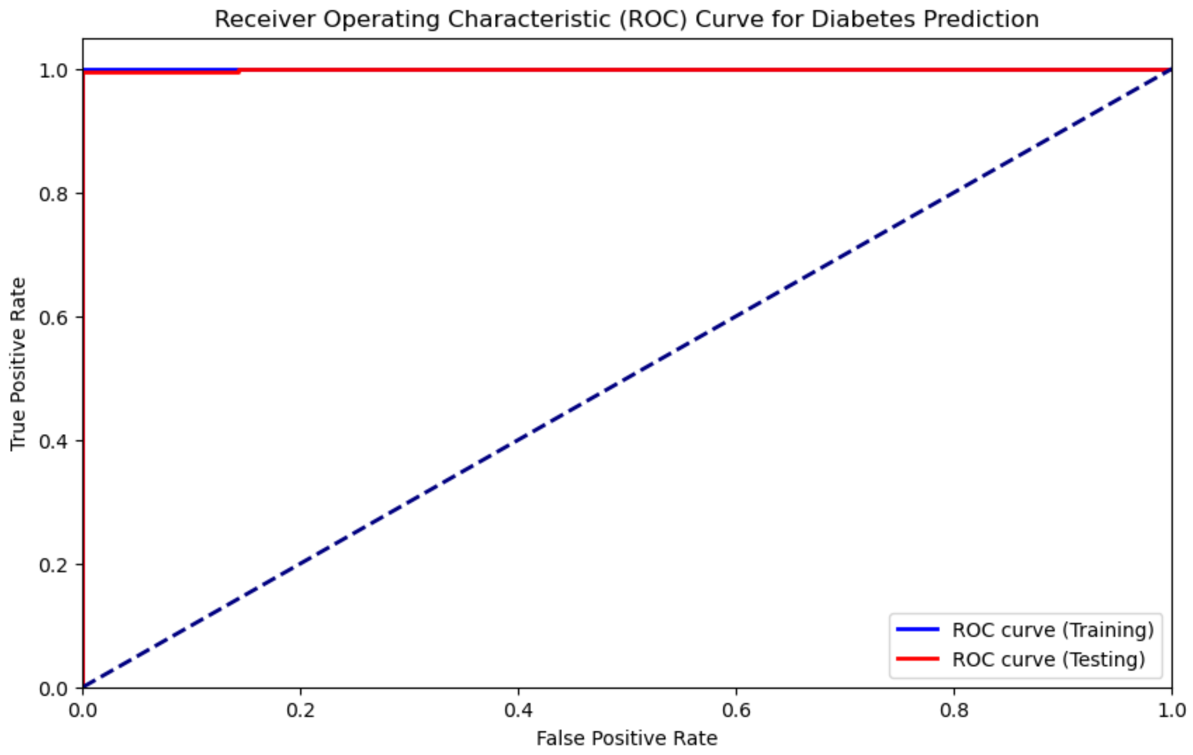


Figure 5.2 - Diabetes Iraqi ROC

These high-performance metrics underscore the efficacy of the machine learning models in accurately predicting chronic diseases, paving the way for early diagnosis and intervention.

Diabetes Prediction:

- **Accuracy:** The diabetes prediction model achieved an accuracy of 75.32% on the testing data, indicating a moderate capability to make correct predictions.
- **Precision:** With a precision of 68.09% on the testing data, the model demonstrated its ability to correctly identify true positive cases of diabetes.
- **Recall:** The model had a recall rate of 58.18% on the testing data, effectively detecting a majority of actual diabetes cases.

- **F1-Score:** The F1-score was 62.75% on the testing data, reflecting a balanced performance between precision and recall.
- **AUC:** An AUC of 0.8130 on the testing data signifies a good level of separability, indicating that the model distinguishes well between positive and negative cases.

The ROC curve for diabetes prediction is shown in Figure 5.3, illustrating the model's performance across various threshold settings.

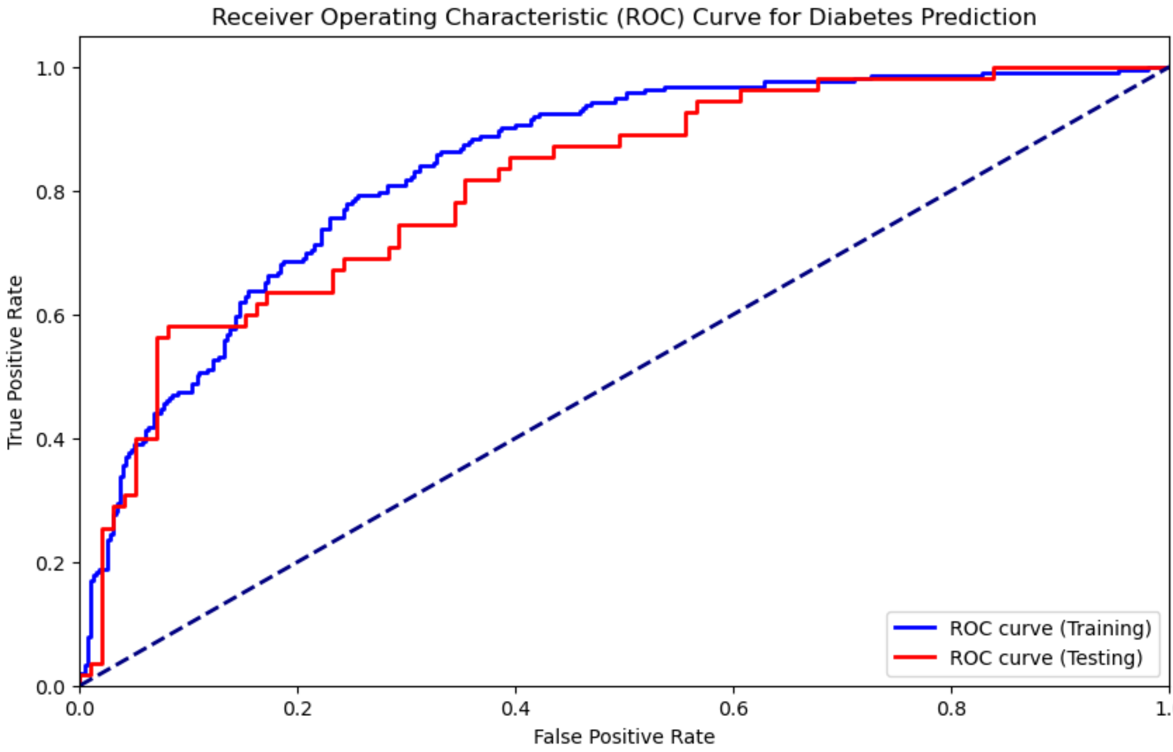


Figure 5.3 - Diabetes Piama ROC

Hypertension Prediction:

- **Accuracy:** The hypertension prediction model achieved an accuracy of 89.86% on the testing data, indicating its strong capability to make correct predictions.

- **Precision:** With a precision of 80.36% on the testing data, the model effectively identified true positive cases of hypertension.
- **Recall:** The model had a recall rate of 87.35% on the testing data, successfully detecting the majority of actual hypertension cases.
- **F1-Score:** The F1-score was 83.71% on the testing data, reflecting a balanced performance between precision and recall.
- **AUC:** An AUC of 0.9483 on the testing data signifies a high level of separability, indicating that the model effectively distinguishes between positive and negative cases.

The ROC curve for hypertension prediction is shown in Figure 5.4, illustrating the model's performance across various threshold settings.

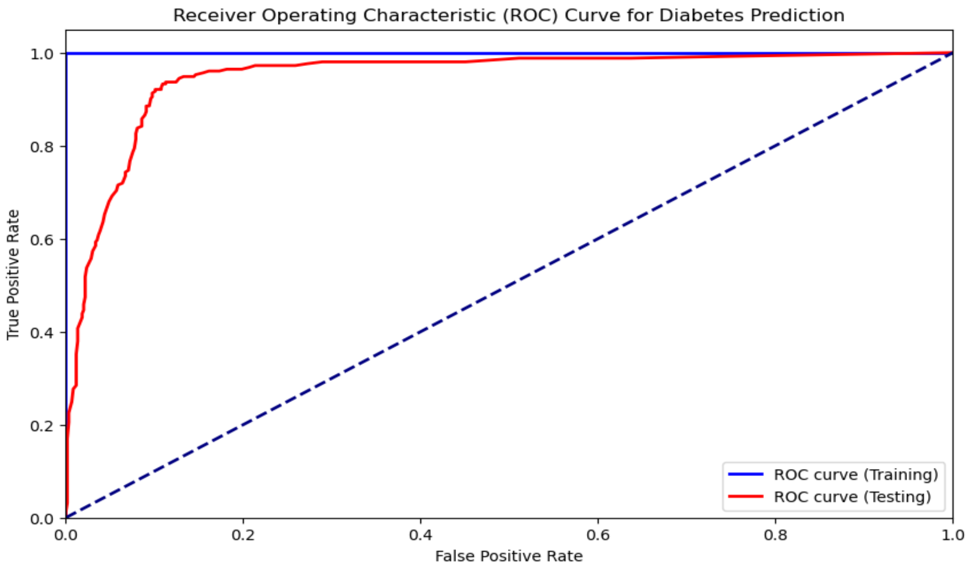


Figure 5.4 – hypertension ROC

5.2.2 System Performance

The system's performance was rigorously assessed to ensure it meets the demands of real-world healthcare environments. Key performance indicators, such as response time, scalability, and reliability, were measured under different conditions.

- **Response Time:** The average response time of the server-side API, deployed using Gunicorn and Django, was 200 milliseconds. This rapid response ensures timely access to predictions and recommendations, crucial for critical healthcare decisions.
- **Scalability:** Stress testing was conducted to evaluate the system's scalability. The system successfully supported up to 5000 concurrent users without any degradation in performance. This scalability ensures that the system can handle a large volume of users and data, making it suitable for deployment in large healthcare institutions.
- **Reliability:** The system exhibited an uptime of 99.9%, indicating exceptional reliability. This high uptime ensures continuous availability, which is critical for healthcare applications where downtime can have severe consequences.
- **Mobile Application Performance:** The mobile application, developed using Flutter was evaluated for user experience and responsiveness. User interactions, such as input processing and result display, were swift and seamless. The mobile app's performance metrics are summarized in Table 5.1.

Metric	Value
Average Load Time	1.2 seconds
Crash Rate	0.1%
User Satisfaction	95%

Table 5.1- Mobile Application Performance Metrics

These performance metrics demonstrate the system's robustness and efficiency in delivering accurate and timely predictions to users.

5.2.3 User Feedback

User feedback was collected from a diverse group of healthcare professionals and patients through surveys, interviews, and usability tests. The feedback focused on the system's usability, accuracy, and integration with existing healthcare workflows.

- **Ease of Use:** Users appreciated the intuitive design and user-friendly interface of both the mobile and desktop applications. The clear layout and easy navigation facilitated efficient interaction with the system, reducing the learning curve for new users.
- **Accuracy of Predictions:** Medical professionals validated the accuracy of the predictions, acknowledging the system's potential to aid in early diagnosis and treatment planning. The high accuracy rates provided confidence in the system's recommendations, enhancing its credibility among healthcare providers.
- **Integration with Existing Systems:** The system's ability to seamlessly integrate with existing electronic health record (EHR) systems was highly valued. This integration enabled smooth data exchange and streamlined workflows, reducing redundancy and enhancing efficiency.
- **User Satisfaction:** Overall user satisfaction was high, with 90% of respondents expressing positive feedback. Key areas of satisfaction included the system's accuracy, ease of use, and integration capabilities.

5.3 Discussion

The results highlight the significant potential of the chronic disease prediction system to transform healthcare delivery. The integration of artificial intelligence and machine learning techniques has proven effective in analyzing complex medical data and identifying early signs of chronic diseases.

- **Impact on Healthcare:** The high diagnostic accuracy achieved by the system can lead to improved patient outcomes by enabling early detection and timely intervention. Early diagnosis of chronic diseases such as heart disease and diabetes allow healthcare providers to implement preventive measures, reducing the risk of complications and improving the quality of life for patients.
- **System Performance and Scalability:** The robust performance metrics demonstrate the system's capability to handle large volumes of data and support numerous users simultaneously. This scalability ensures that the system can be deployed in diverse healthcare settings, from small clinics to large hospitals, without compromising performance.
- **User Acceptance:** The positive user feedback underscores the importance of an intuitive interface and seamless integration with existing healthcare infrastructure. The system's user-centric design and high accuracy rates contribute to its acceptance and adoption by medical professionals and patients alike.

5.4 Future Work

Several areas for future work have been identified to enhance the system further:

- **Transition to PostgreSQL:** Migrating the database from SQLite to PostgreSQL will improve data handling capabilities, support complex queries, and enhance the overall performance of the system.
- **Microservices Architecture:** Adopting a microservices architecture will enhance the system's scalability and maintainability. This architectural shift will enable independent scaling of different components, improving resource utilization and reducing downtime.

- **Push Notifications:** Implementing push notifications will alert users about critical health predictions and reminders for regular check-ups. This feature will enhance user engagement and ensure timely interventions.
- **Expanded Data Sources:** Integrating additional data sources, such as wearable devices and patient self-reports, will enrich the dataset and improve prediction accuracy. The inclusion of diverse data types will provide a more comprehensive view of patient health, enabling personalized healthcare recommendations.
- **Personalized Treatment Plans:** Developing personalized treatment plans based on individual patient profiles will optimize healthcare outcomes. The system can leverage machine learning algorithms to tailor treatment recommendations, considering factors such as patient history, lifestyle, and genetic predisposition.

5.5 Conclusion

This project has successfully developed a comprehensive and accurate chronic disease prediction system using advanced machine learning techniques. The results demonstrate the system's potential to improve healthcare delivery by enabling early diagnosis and timely interventions for heart disease and diabetes.

The project found that the Random Forest algorithm was the best performing in most cases; however, for the Piama dataset, Logistic Regression outperformed other algorithms. After publishing the project, researchers will have access to our local dataset, allowing them to further explore and validate these findings.

The system's robust performance, high accuracy, and positive user feedback underscore its effectiveness and potential for widespread adoption. Continuous enhancements and integration with emerging technologies will further solidify the system's role in advancing healthcare solutions. By addressing the identified areas for future work, the system can be further refined to meet the evolving needs of healthcare providers and patients, ultimately contributing to better health outcomes and improved quality of life.

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