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Master Thesis

AI-based predictive modelling to provide a comprehensive health status analysis using vital data

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Master-Thesis

for Ms. **Aashika Chakravarty**

KI-basierte prädiktive Modellierung für eine umfassende Analyse des Gesundheitszustands anhand von Vitaldaten

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Disposition

This research endeavors to develop a holistic health evaluation system by integrating deep learning models for various vital signs, including electrocardiogram (ECG), blood pressure, respiratory rate, and other relevant metrics. The study involves the creation of individual models for each vital sign, followed by the synthesis of these models into a unified framework for comprehensive health status evaluation.

While individual vital sign monitoring provides valuable insights into specific aspects of health, a comprehensive evaluation demands an integrated approach. This research aims to leverage deep learning, primarily using TensorFlow and Keras, to create specialized models for different vital signs and, subsequently, fuse these models to deliver a unified health assessment.

Method:

1. Data Collection and Organization
   - Diverse datasets are collected, including ECG, blood pressure, and respiratory rate data.
   - Patient data is structured into feature-rich dictionaries, encapsulating various vital sign attributes.
2. Individual Model Development
   - Specialized models are crafted for each vital sign, utilizing deep learning architectures tailored to the nature of the data.
   - TensorFlow and Keras are employed for model development and training.
3. Model Fusion for Comprehensive Evaluation
   - Individual models are combined into a single, integrated framework.
   - TensorFlow is used for seamless integration, accounting for the interplay of various vital signs.
4. Training and Evaluation
   - The entire framework is trained on a diverse dataset encompassing various health conditions.
   - TensorFlow and Keras are used for training, and evaluation metrics, such as accuracy and sensitivity, validate the performance of the comprehensive health evaluation model.

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The proposed approach is anticipated to offer a more thorough and nuanced evaluation of an individual's health status. By combining insights from multiple vital signs, the model aims to enhance diagnostic accuracy and provide a more comprehensive understanding of overall health.

This research contributes to the evolution of health monitoring by introducing a comprehensive evaluation system. The integration of deep learning models for various vital signs using TensorFlow and Keras acknowledges the interconnected nature of physiological parameters and seeks to provide a more holistic perspective on an individual's health

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Abstract

In recent years, advancements in Artificial Intelligence (AI) and Machine Learning (ML) techniques have demonstrated significant potential in enhancing healthcare applications. This master thesis explores the integration of AI in the medical field, specifically focusing on the analysis of vital sign data. The objective is to develop a reliable system capable of providing preliminary diagnoses based on vital signs, thereby assisting medical professionals by offering an initial assessment before a detailed clinical consultation.

The project aims to develop predictive models using AI techniques to monitor and forecast changes in vital signs, including heart rate, blood pressure, respiratory rate, body temperature, and oxygen saturation. By identifying deviations from normal patterns, the system can detect critical health conditions early. Separate models will be created for each vital sign, and these models will be integrated into a comprehensive AI-driven system that can analyze and interpret the data collectively.

The proposed system will offer a detailed analysis and evaluation of an individual's health status, providing personalized health recommendations and alerting healthcare providers to potential health issues. This integration of AI in vital sign analysis aims to improve the accuracy of diagnoses, enhance efficiency in healthcare delivery, and facilitate continuous monitoring and early detection of health conditions, ultimately contributing to better patient outcomes and more effective use of healthcare resources.

Kurzreferat

Diese Masterarbeit konzentriert sich auf die Entwicklung eines KI-basierten Vorhersagemodellierungsrahmens, der darauf abzielt, eine umfassende Analyse des Gesundheitszustands von Einzelpersonen anhand wichtiger Daten bereitzustellen. Durch den Einsatz von Techniken der künstlichen Intelligenz (KI) zielt das Framework darauf ab, Daten aus verschiedenen Quellen zu integrieren und zu analysieren, darunter Elektrokardiogramm (EKG), Blutdruck (BP), Sauerstoffsättigung (SpO2), Temperatur und Atemfrequenz. Dieser Ansatz ermöglicht eine ganzheitliche Beurteilung der Gesundheit und erleichtert die Früherkennung von Anomalien und personalisierte Interventionen.

Das Framework umfasst die Datenerfassung aus verifizierten medizinischen Datenbanken, die Merkmalsextraktion mithilfe von Signalverarbeitungstechniken und die prädiktive Modellierung mithilfe von Algorithmen für maschinelles Lernen. Jedes Vitalzeichen wird unabhängig verarbeitet, um relevante Merkmale zu extrahieren, die dann integriert werden, um eine umfassende Gesundheitsbewertung zu ermöglichen. Fortschrittliche KI-Techniken wie Deep Learning und Ensemble-Methoden werden genutzt, um Vorhersagemodelle zu entwickeln, die Gesundheitsergebnisse vorhersagen und potenzielle Gesundheitsrisiken identifizieren können.

Die Forschung hat erhebliche Auswirkungen auf die klinische Praxis und bietet Gesundheitsdienstleistern ein leistungsstarkes Instrument für proaktives Gesundheitsmanagement und Krankheitsprävention. Durch die Nutzung der Vorhersagefähigkeiten der KI ermöglicht das Framework die frühzeitige Erkennung von Gesundheitsverschlechterungen und personalisierte Interventionen, die auf die individuellen Bedürfnisse des Patienten zugeschnitten sind. Zu den künftigen Zielen gehören die Verfeinerung der Vorhersagemodelle, die Durchführung klinischer Validierungsstudien und die Integration zusätzlicher Datenquellen, um die Genauigkeit und Wirksamkeit des Rahmenwerks bei der Verbesserung der Gesundheitsergebnisse weiter zu verbessern.

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1. Introduction

1.1 Background and Context

Artificial Intelligence (AI) has begun to permeate every industry, revolutionizing traditional practices and introducing innovative solutions. From finance to transportation, AI's ability to process vast amounts of data and make intelligent decisions has paved the way for enhanced efficiency and performance. In healthcare, AI is particularly transformative, offering new avenues for patient care, diagnostics, and treatment planning through its capability to analyze complex medical data and provide actionable insights.

Vital signs, including electrocardiogram (ECG), blood pressure (BP), oxygen saturation (SpO2), body temperature, and respiratory rate, are fundamental indicators of an individual's health. Regular monitoring of these vital signs is crucial for early detection of medical conditions, ongoing health management, and timely interventions. Historically, such monitoring has been periodic and reliant on manual methods, which can delay the identification of critical changes in a patient's condition.

Integrating AI with continuous monitoring of vital signs offers a promising solution to this challenge. By leveraging AI's analytical power, we can transform raw vital data into a comprehensive health status analysis. This integration not only enhances the ability to detect anomalies and predict health risks but also paves the way for personalized healthcare, where interventions can be tailored to individual needs based on real-time data. This thesis explores the potential of AI-based predictive modeling to provide a comprehensive health status analysis using vital data.

1.2 Research Motivation and Objectives

The motivation behind this research is driven by the need to improve health outcomes through early detection and timely intervention. Traditional health monitoring methods often rely on periodic check-ups and manual analysis, which may fail to capture critical changes in a patient's condition in real-time. AI-based predictive modeling offers a solution by continuously analyzing vital data to identify patterns and anomalies indicative of health risks. The hope is to provide doctors and patients with a comprehensive analysis of the patient's health status, along with personalised recommendations. Using this preliminary diagnostic system, doctors can make a more informed decision on further tests and processes to treat the patient's condition and improve their overall health score.

The primary objective of this thesis is to develop a robust AI-based framework capable of providing a comprehensive analysis of an individual's health status using vital data. This involves integrating data from multiple sources, extracting meaningful features, and employing advanced machine learning algorithms to predict health outcomes and identify potential health issues. This research aims to demonstrate the potential of AI in revolutionizing health monitoring and management through continuous analysis of vital data. The final objective is to create a scalable and adaptable system capable of integrating individual patient data and generating personalized health insights and recommendations based on individually trained AI models.

The project utilizes a Python-based framework, leveraging libraries such as NumPy, pandas, and scikit-learn for data processing, analysis, and machine learning tasks. Flask, a lightweight web framework, serves as the backbone for developing the interactive web interface, facilitating seamless integration with backend functionalities. Additionally, the project employs various data visualization libraries such as Matplotlib and Plotly to generate informative visualizations for interpreting health insights and trends. The machine learning aspect involves training individualized models for each vital sign, utilizing algorithms like Random Forest, Support Vector Machines (SVM), and Gradient Boosting. Moreover, the project implements robust data preprocessing techniques and feature engineering methodologies to ensure the accuracy and reliability of the predictive models. Overall, the project encompasses a comprehensive blend of Python-based technologies and machine learning methodologies, orchestrated within a Flask-powered web interface, to deliver personalized health analyses and recommendations.

1.3 Scope and Structure of the Thesis

This thesis is structured to comprehensively cover the development and evaluation of the AI-based predictive modeling framework. The scope of the research includes data acquisition from wearable sensors or medical databases, signal processing for feature extraction, and the application of various machine learning techniques to build and evaluate predictive models. The structure of the thesis is as follows:

1. **Chapter 2: Literature Review**
   (a) An extensive review of relevant literature on AI applications in healthcare.
   (b) The role of vital signs in health monitoring.
   (c) Previous studies and existing models for health status analysis using AI.
2. **Chapter 3: Methodology**
   (a) Detailed description of data collection methods from wearable sensors.
   (b) Pre-processing steps and feature extraction techniques.
   (c) Development and training of predictive models using machine learning algorithms.
3. **Chapter 4: Results and Discussion**
   (a) Presentation of the results obtained from the predictive models.
   (b) Analysis of the performance metrics and comparison with existing methods.
   (c) Discussion on the implications of the findings for healthcare practice.
4. **Chapter 5: Conclusion and Future Work**
   (a) Summary of the key findings and contributions of the research.
   (b) Discussion on the limitations of the study.
   (c) Suggestions for future research directions in AI-based health monitoring.

This structured approach aims to demonstrate the potential of AI in enhancing health monitoring and management through the continuous analysis of vital data, ultimately contributing to better health outcomes and personalized patient care.

2. Literature Review

2.1 AI Applications in Healthcare

AI has become a key factor in advancing healthcare by leveraging its powerful data processing and predictive abilities. One of the most transformative applications of AI in this field is predictive analytics for patient outcomes. By utilizing ML models to analyze extensive electronic health records (EHRs), AI can forecast critical medical events, such as patient re-admissions, the onset of sepsis, and other severe complications [1, 2]. These models detect complex patterns and correlations within the data that precede adverse outcomes, enabling healthcare providers to implement preemptive interventions. This proactive approach can significantly enhance patient care by allowing timely and targeted responses to potential health crises [2].

Furthermore, AI-driven systems have played a crucial role in personalizing treatment plans. These advanced algorithms can optimize medication dosages by considering a patient's unique characteristics, such as age, weight, medical history, and even genetic information [3]. For example, pharmacogenomic data can be integrated to predict how a patient might respond to a particular drug, thereby minimizing adverse effects and maximizing therapeutic efficacy [3]. This personalized approach ensures that treatments are tailored to the individual needs of patients rather than relying on a one-size-fits-all strategy [3].

Additionally, AI models assist in identifying the most effective therapies by continuously learning from clinical outcomes and adjusting recommendations based on real-world data [3]. This dynamic and iterative process allows for continuous improvement in treatment protocols, ensuring that patients receive the best possible care based on the latest evidence [3]. Overall, the integration of AI in predictive analytics and personalized medicine holds the promise of enhancing the quality of healthcare, reducing costs, and improving patient outcomes by making healthcare more proactive, precise, and patient-centered [1, 2, 3].

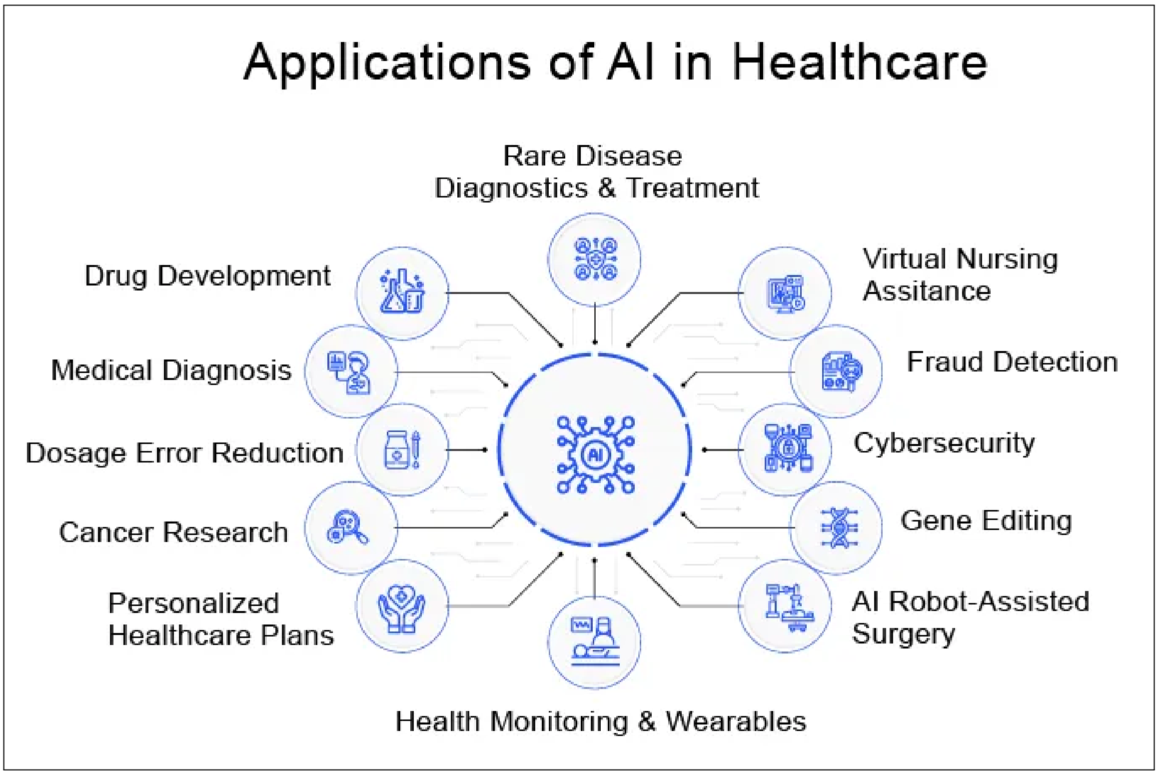


Figure 2.1: Applications of AI in Healthcare [4]

In the context of the applications of AI in healthcare, these developments are part of a broader trend encompassing various innovative uses, such as drug development, medical diagnosis, dosage error reduction, cancer research, personalized healthcare plans, rare disease diagnostics and treatment, virtual nursing assistance, fraud detection, cybersecurity, gene editing, health monitoring and wearables, and AI robot-assisted surgery (see Figure 2.1) [3]. These applications demonstrate the vast potential of AI to transform multiple facets of the healthcare industry [3].

AI's role in administrative tasks is pivotal in enhancing healthcare efficiency and reducing the burden on providers. Natural language processing (NLP) algorithms have revolutionized clinical documentation by automating the extraction and organization of relevant information from clinical notes [5]. This automation not only streamlines the coding process for insurance claims but also ensures the maintenance of accurate patient records, minimizing errors and discrepancies [5]. Consequently, healthcare providers are relieved from extensive paperwork, allowing them to dedicate more time to patient care [5]. Moreover, these AI-driven systems facilitate faster and more efficient administrative workflows, contributing to the overall improvement of healthcare delivery [5].

2.2 Role of Vital Signs in Health Monitoring

Vital signs are crucial indicators of a person's physiological state and are fundamental in assessing overall health. The primary vital signs—heart rate, blood pressure, respiratory rate, body temperature, and oxygen saturation—provide critical information about the body's basic functions. Vital signs are one of the first parameters evaluated by doctors and medical professionals, and they offer a window into a person's overall well-being and can help detect and diagnose possible health issues [6].

A shift from a person's baseline vitals can point to some kind of underlying problems, which can then be properly diagnosed with more specific tests. Continuous monitoring of these parameters is essential in various healthcare settings, from intensive care units to outpatient clinics, as they help in the early detection of medical conditions and monitoring of ongoing treatments [6].

Figure 2.2: Vital Signs [7]

Heart rate and blood pressure are key indicators of cardiovascular health. Abnormalities in these parameters can signal conditions such as hypertension, arrhythmias, and other cardiac disorders [8]. Respiratory rate and oxygen saturation are vital in assessing respiratory health, with deviations from the norm indicating potential issues like chronic obstructive pulmonary disease (COPD), asthma, or acute respiratory distress syndrome (ARDS) [9]. Body temperature is a primary marker for infections and inflammatory processes, where fever often indicates an underlying condition that requires medical attention [10].

The advent of wearable technology has significantly enhanced the ability to monitor vital signs continuously. Devices such as smartwatches and fitness trackers can measure heart rate, track activity levels, and even monitor sleep patterns [11]. More advanced medical wearables can also measure blood pressure and oxygen saturation [12]. These devices generate continuous streams of data, which, when analyzed effectively, can provide insights into long-term health trends and facilitate timely medical interventions [11].

2.2.1 Heart Rate and ECG

1. **Heart Rate**
   Heart rate (also known as pulse) is the number of times the heart beats within the span of one minute. It is an indication of the heart's rhythm and strength. Normal ranges for resting heart rate (RHR) vary for different ages and genders. Generally, a normal resting heart rate for adults ranges from 60 to 100 beats per minute (bpm). Children tend to have higher resting heart rates, which gradually decrease as they grow older. Factors such as fitness level, medication, and overall health also play significant roles in determining one's normal resting heart rate [13].

Age	Men (bpm)	Women (bpm)
18 - 25	62 - 73	64 - 80
26 - 35	62 - 73	64 - 81
36 - 45	63 - 75	65 - 82
46 - 55	64 - 76	66 - 83
56 - 65	62 - 75	64 - 82
Over 65	62 - 73	64 - 81

Table 2.1: Normal Heart Rates based on Age and Gender

Figure 2.3 shows how the average resting heart rate varies for adult men and women. Statistically, women tend to have higher resting heart rates compared to men. This difference can be attributed to factors such as body size, hormone levels, and metabolic rate [13]. As people age, the muscles of the heart, like the rest of the body, undergo changes. The heart muscle weakens, loses some of its elasticity, and its ability to pump efficiently can diminish. These changes result in a reduced maximum heart rate during physical activity and a general reduction in resting heart rate over time. An easy way to calculate maximum possible heart rate for an individual is to subtract one's age from 220. For example, a 50-year-old person would have an estimated maximum heart rate of 170 bpm (220 - 50) [13].

While heart rate alone cannot diagnose any underlying diseases, an abnormal heart rate is often the first indication that there is an underlying cardiovascular disease or cause for concern. For instance, consistently elevated heart rates (tachycardia) or unusually low heart rates (bradycardia) can be symptomatic of various cardiac conditions [8]. Fluctuations in heart rate can occur due to several reasons, including dehydration, which reduces blood volume and forces the heart to work harder; inactivity, which can lead to a lower overall cardiovascular fitness; chronic stress, which triggers the release of adrenaline and increases heart rate; smoking, which causes the heart to beat faster by constricting blood vessels; and caffeine, which stimulates the central nervous system and increases heart rate [10].

Tracking and maintaining a note of one's heart rate at rest and during various activities can help keep tabs on overall heart health. Regular monitoring can help detect early signs of heart disease and enable timely medical intervention. Wearable technology, such as fitness trackers and smartwatches, has

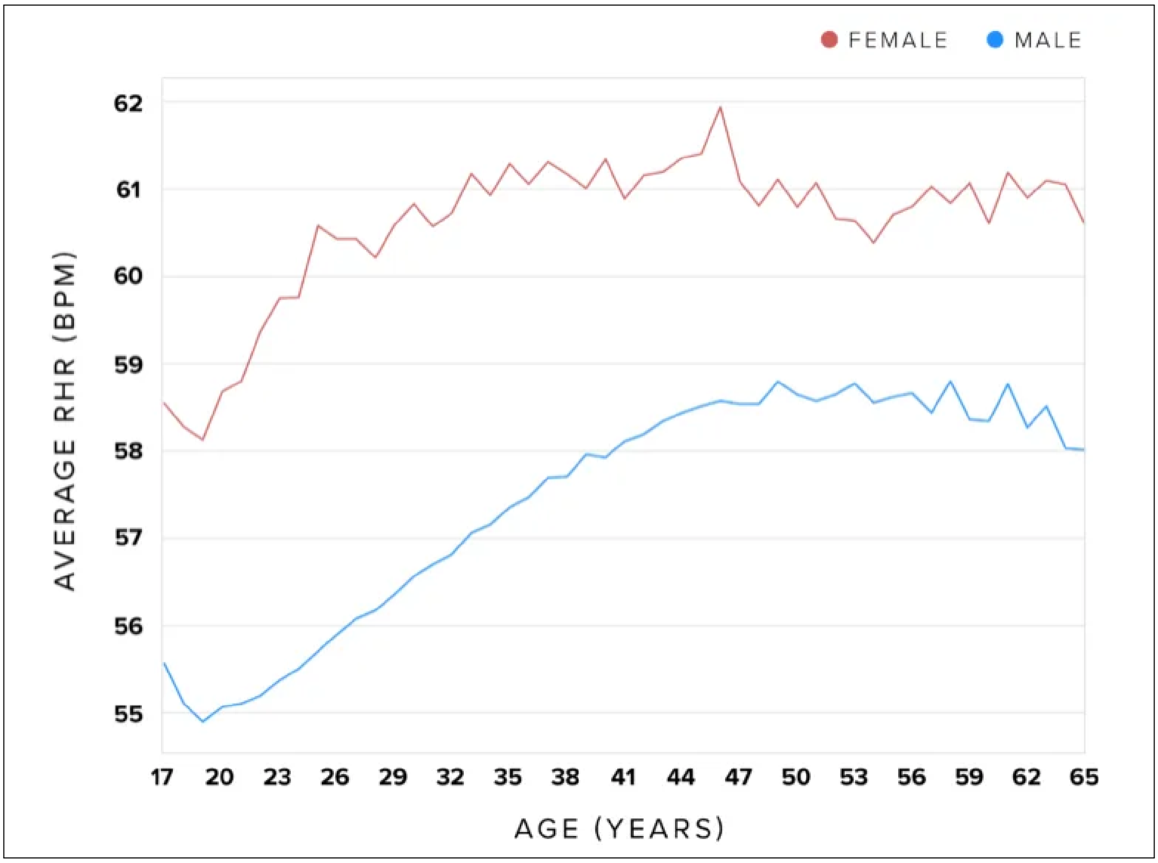


Figure 2.3: Average Resting Heart Rate with age for Men vs. Women [14]

made it easier for individuals to monitor their heart rate continuously and gather data that can be shared with healthcare providers. This continuous tracking provides valuable insights into how the heart responds to different activities, stress levels, and overall lifestyle, thus facilitating more personalized and effective healthcare management [11].

Common heart conditions related to heart rate include:

(a) **Bradycardia:** This condition is characterized by a slower than normal heart rate, typically below 60 beats per minute. While it can be normal in well-trained athletes, in others it may indicate problems with the heart's electrical system [8]. Symptoms of bradycardia can include fatigue, dizziness, confusion, and shortness of breath. In severe cases, it might require medical intervention such as the implantation of a pacemaker to maintain an adequate heart rate.

(b) **Tachycardia:** This is when the heart rate is faster than normal, generally above 100 beats per minute at rest. It can be caused by stress, anxiety, medications, or underlying health conditions such as anemia or hyperthyroidism [8]. Persistent tachycardia can lead to complications like heart failure, stroke, or sudden cardiac arrest. Treatment may involve lifestyle changes, medications, or procedures to control the rapid heart rate.

(c) **Atrial Fibrillation (AFib):** This is a common type of arrhythmia where the heart beats irregularly and often rapidly. It can lead to blood clots, stroke, heart failure, and other heart-related complications. Symptoms include palpitations, shortness of breath, and fatigue [9]. AFib often requires long-term management with medications to control heart rate and reduce the risk of stroke, as well as procedures like electrical cardioversion or catheter ablation.

(d) **Premature Ventricular Contractions (PVCs):** These are extra heartbeats that begin in one of the heart's two lower pumping chambers (ventricles). These extra beats disrupt the regular heart rhythm, sometimes causing a sensation of a skipped beat or palpitations. While PVCs are common and often benign, frequent PVCs or certain patterns may necessitate further evaluation and treatment to prevent more serious arrhythmias.

(e) **Supraventricular Tachycardia (SVT):** This is an abnormally fast heart rate originating above the heart's ventricles. It can cause palpitations, chest pain, and shortness of breath. SVT episodes can be sudden and may stop on their own or require medical intervention. Treatments include medications, vagal maneuvers (techniques to stimulate the vagus nerve), or procedures like catheter ablation to disrupt the abnormal electrical pathways causing SVT.

(f) **Heart Block:** This occurs when the electrical signals that control heartbeats are partially or completely blocked. It can lead to slower heart rates and sometimes requires the use of a pacemaker. Heart blocks can vary in severity, from first-degree (least severe) to third-degree (most severe), with third-degree blocks often requiring immediate medical intervention due to the risk of serious complications like heart failure or sudden cardiac death.

Monitoring heart rate and using electrocardiograms (ECGs or EKGs) can provide deeper insights into heart function. ECGs measure the electrical activity of the heart, providing detailed information about the timing and strength of heartbeats. This helps in diagnosing various heart conditions, assessing the effectiveness of treatments, and predicting potential cardiac events [15]. Regular monitoring through wearable technology and periodic medical check-ups can be crucial for early detection and management of heart diseases. ECGs can reveal conditions such as arrhythmias, myocardial infarction, and other cardiac abnormalities. By analyzing the patterns and intervals of the heart's electrical activity, healthcare providers can make informed decisions about treatment strategies and interventions, ultimately improving patient outcomes.

2. **ECG**

   Electrocardiogram (ECG or EKG) is a non-invasive medical test that records the electrical activity of the heart over a period of time. The resulting tracing, known as an electrocardiogram, shows the heart's rhythm and electrical conduction pathways. Understanding the significance of the waves and intervals in an ECG is essential for diagnosing various cardiac conditions. The typical waveform of an ECG consists of several distinct components, each reflecting different phases of the cardiac cycle (see Figure 2.4):

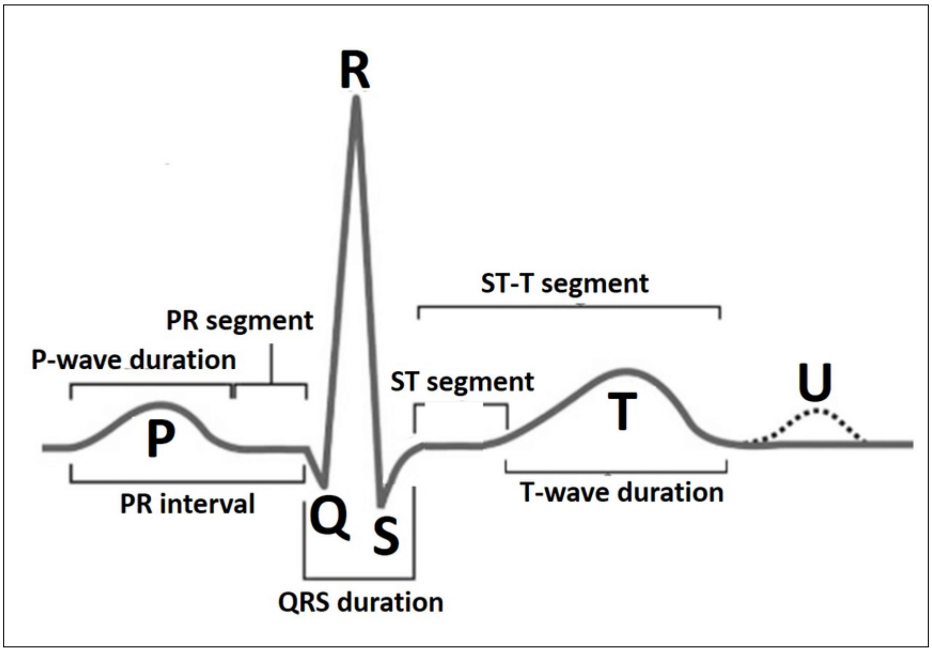


Figure 2.4: PQRST Wave [16]

- **P Wave:** The P wave represents atrial depolarization, the electrical impulse that triggers the contraction of the atria. It appears as a small upward deflection on the ECG tracing.
- **QRS Complex:** The QRS complex signifies ventricular depolarization, the electrical impulse that causes the contraction of the ventricles. It consists of three distinct waves: Q, R, and S. The Q wave is the first downward deflection, the R wave is the first upward deflection following the Q wave, and the S wave is the downward deflection that follows the R wave. The QRS complex is typically the largest waveform on the ECG tracing.
- **T Wave:** The T wave represents ventricular repolarization, the recovery of the ventricles following contraction. It appears as a smooth upward deflection on the ECG tracing.
- **PR Interval:** The PR interval measures the time from the beginning of the P wave to the beginning of the QRS complex. It reflects the time taken for the electrical impulse to travel from the atria to the ventricles through the atrioventricular (AV) node. Prolongation or shortening of the PR interval may indicate abnormalities in atrioventricular conduction.
- **QT Interval:** The QT interval represents the time from the beginning of the QRS complex to the end of the T wave. It reflects the total duration of ventricular depolarization and repolarization. Prolongation of the QT interval may predispose individuals to ventricular arrhythmias, including torsades de pointes.
- **ST Segment:** The ST segment is the portion of the ECG tracing between the end of the S wave and the beginning of the T wave. It represents the early part of ventricular repolarization. Deviations from the baseline level of the ST segment may indicate myocardial ischemia, injury, or infarction.

Interpretation of an ECG involves analyzing the morphology and timing of these waves and intervals to identify abnormalities suggestive of cardiac pathology. Common abnormalities include arrhythmias, conduction defects, myocardial ischemia, infarction, and electrolyte imbalances. Integration of clinical history, physical examination findings, and other diagnostic tests is crucial for accurate interpretation and appropriate management of patients with suspected cardiac conditions.

Understanding the significance of ECG waves and intervals enables healthcare providers to make informed decisions regarding patient care, including initiation of treatment, referral for further evaluation, and monitoring of disease progression and response to therapy.

2.2.2 Blood Pressure

Blood pressure, a fundamental physiological parameter, measures the force exerted by circulating blood against the walls of arteries as the heart pumps blood throughout the body. It is expressed as two numbers: systolic pressure, representing the pressure when the heart beats while pumping blood, and diastolic pressure, indicating the pressure when the heart is at rest between beats. Normal blood pressure typically falls below 120/80 mm Hg, where 120 represents the systolic pressure and 80 represents the diastolic pressure [17].

Blood Pressure Categories

American Heart Association.

BLOOD PRESSURE CATEGORY	SYSTOLIC mm Hg (upper number)		DIASTOLIC mm Hg (lower number)
NORMAL	LESS THAN 120	and	LESS THAN 80
ELEVATED	120 – 129	and	LESS THAN 80
HIGH BLOOD PRESSURE (HYPERTENSION) STAGE 1	130 – 139	or	80 – 89
HIGH BLOOD PRESSURE (HYPERTENSION) STAGE 2	140 OR HIGHER	or	90 OR HIGHER
HYPERTENSIVE CRISIS (consult your doctor immediately)	HIGHER THAN 180	and/or	HIGHER THAN 120

Figure 2.5: Ranges of Blood Pressure [18]

Figure 2.5 illustrates the categories of blood pressure readings, ranging from normal to hypertensive crisis. Regular monitoring of blood pressure is crucial for assessing cardiovascular health and identifying potential risks of heart disease, stroke, and other health conditions. Blood pressure can be measured using a sphygmomanometer (manual or digital), which consists of an inflatable cuff wrapped around the upper arm and a pressure gauge to measure the pressure in the arteries [19].

The American Heart Association defines blood pressure categories as follows:

1. **Low Blood Pressure:** Also known as hypotension, low blood pressure is characterized by readings below 90/60 mm Hg. While some individuals may naturally have low blood pressure without experiencing symptoms, severe hypotension can lead to dizziness, fainting, blurred vision, fatigue, and difficulty concentrating [20].

2. **Normal Blood Pressure:** Normal blood pressure ranges between 90/60 mm Hg and 120/80 mm Hg. Individuals with normal blood pressure levels are at a lower risk of cardiovascular complications and generally experience better overall health [21].

3. **Elevated Blood Pressure:** Elevated blood pressure is a systolic pressure ranging from 120 to 129 mm Hg and a diastolic pressure below 80 mm Hg. While not classified as hypertension, elevated blood pressure indicates an increased risk of developing hypertension in the future if not managed through lifestyle changes [22].

4. **Hypertension Stage 1:** Hypertension stage 1 is characterized by systolic blood pressure ranging from 130 to 139 mm Hg or diastolic blood pressure ranging from 80 to 89 mm Hg. Individuals with hypertension stage 1 may not experience noticeable symptoms but are at an increased risk of heart disease, stroke, and other health issues [23].

5. **Hypertension Stage 2:** Hypertension stage 2 is defined by systolic blood pressure of 140 mm Hg or higher or diastolic blood pressure of 90 mm Hg or higher. At this stage, individuals are at a significantly higher risk of cardiovascular complications and may require medication and lifestyle modifications to manage their blood pressure effectively [24].

6. **Hypertensive Crisis:** A hypertensive crisis occurs when blood pressure readings reach 180/120 mm Hg or higher, posing an immediate risk of organ damage, stroke, heart attack, or other life-threatening complications. Emergency medical attention is required to lower blood pressure rapidly and prevent serious health consequences [25].

Monitoring blood pressure regularly and understanding the significance of different readings are essential for maintaining cardiovascular health and preventing adverse health outcomes. It allows individuals and healthcare providers to identify trends, assess the effectiveness of treatments, and make informed decisions to manage blood pressure effectively.

2.2.3 Body Temperature

Body temperature is a vital sign that reflects the balance between heat production and heat loss within the body. It is typically measured using a thermometer and is expressed in degrees Fahrenheit (°F) or Celsius (°C). Normal body temperature varies slightly among individuals but is generally considered to be around 98.6°F (37°C) when measured orally. However, body temperature can fluctuate throughout the day, influenced by factors such as time of day, physical activity, and hormonal changes [26, 27].

Various methods are used to measure body temperature, including oral, rectal, axillary (underarm), tympanic (ear), and temporal artery thermometers. Each method has its advantages and limitations, with rectal thermometers providing the most accurate measurement but being less convenient, especially for adults.

Body temperature is an essential indicator of health, with deviations from the normal range often indicating an underlying condition. For adults, a body temperature above 100.4°F (38°C) is generally considered a fever, signaling an immune response to infection or illness. Conversely, a body temperature below 95°F (35°C) may indicate hypothermia, a potentially life-threatening condition where the body loses heat faster than it can produce it [26, 27].

Monitoring body temperature is crucial in diagnosing and managing various medical conditions. Fever, for example, is a common symptom of infections such as influenza, COVID-19, and urinary tract infections. Hypothermia can occur in cold environments or as a result of certain medical conditions, such as sepsis or hypothyroidism [28, 29].

Additionally, body temperature can provide valuable insights into a person's overall health and physiological status. For instance, elevated body temperature during exercise or physical activity is normal due to increased metabolic activity and muscle exertion. However, persistent or unexplained changes in body temperature may warrant further evaluation by a healthcare professional to rule out underlying medical conditions [26, 27].

	Measurement site		
	Mouth / armpit	Ear / forehead	Rectum
Low temperature	< 35.8	< 35.7	< 36.2
Normal temperature	35.9 - 37.0	35.8 - 36.9	36.3 - 37.5
Increased temperature	37.1 - 37.5	37.0 - 37.5	37.6 - 38.0
Light fever	37.6 - 38.0	37.6 - 38.0	38.1 - 38.5
Moderate fever	38.1 - 38.5	38.1 - 38.5	38.6 - 39.0
High fever	38.6 - 39.5	38.6 - 39.4	39.1 - 39.9
Very high fever	39.6 - 42.0	39.5 - 42.0	40.0 - 42.5

Figure 2.6: Body Temperature Ranges [30]

Figure 2.6 illustrates the typical ranges of body temperature for different measurement methods, highlighting the normal range and thresholds for fever and hypothermia. Understanding these temperature ranges is essential for accurate interpretation and clinical decision-making.

2.2.4 Respiratory Rate

Respiratory rate is a critical vital sign that indicates the number of breaths a person takes per minute. It is a key indicator of pulmonary function and overall respiratory health. In adults, a normal resting respiratory rate ranges from 12 to 20 breaths per minute. This rate can vary with age, activity level, and overall health status [31, 32].

The respiratory rate is typically measured by counting the number of breaths for one full minute. This can be done manually by observing the rise and fall of the chest or abdomen or using electronic monitoring devices. Accurate measurement is essential, especially in clinical settings, as changes in respiratory rate can be among the earliest indicators of a developing health issue.

An elevated respiratory rate, known as tachypnoea, can indicate a variety of conditions, including respiratory infections, asthma, chronic obstructive pulmonary disease (COPD), heart failure, and anxiety. Conversely, a decreased respiratory rate, known as bradypnoea, may be seen in conditions such as opioid overdose, hypothyroidism, or brain injury [33, 34].

Monitoring respiratory rate is crucial in several clinical scenarios. For instance, in emergency and critical care settings, a sudden increase in respiratory rate can signal respiratory distress or failure, necessitating immediate medical intervention. In chronic conditions like COPD, regular monitoring of respiratory rate can help manage the disease and adjust treatment plans accordingly [35, 36].

AGE	BREATHS/MIN
1 Month	25 - 50
3 Months	25 - 45
6 – 12 Months	20 - 40
18 Months	20 - 35
2 – 7 years	20 - 30
8 – 11 years	15 - 25
>12 years	12 - 24

Figure 2.7: Normal Respiratory Rate Ranges by Age [37]

Figure 2.7 illustrates the normal ranges of respiratory rates across different age groups. Newborns and infants have higher respiratory rates, typically ranging from 30 to 60 breaths per minute, which gradually decrease as they grow older. Adults maintain a more stable respiratory rate, as previously mentioned.

Respiratory Rate Abnormalities:

1. **Tachypnea:** Defined as a respiratory rate exceeding the normal range, tachyp-

nea can result from conditions such as pneumonia, pulmonary embolism, or sepsis. Rapid breathing increases oxygen intake and carbon dioxide elimination, which is a compensatory mechanism in response to various physiological stresses [33].

2. **Bradypnea:** A slower than normal respiratory rate can occur due to factors like central nervous system depressants (e.g., opioids), metabolic disorders, or severe hypothyroidism. Bradypnea can reduce oxygen delivery to tissues, leading to hypoxia and subsequent complications [34].

Accurate assessment and continuous monitoring of respiratory rate provide critical insights into a patient's respiratory and overall health. Innovations in wearable technology and remote monitoring devices have significantly enhanced the ability to track respiratory rate in real-time, facilitating timely medical interventions and improving patient outcomes [38].

2.2.5 Blood Oxygen Saturation

Blood oxygen saturation, also known as SpO2, is a measure of the amount of oxygen carried by hemoglobin in the blood. It is a crucial indicator of respiratory and overall health, reflecting how effectively oxygen is being delivered to the body's tissues. Normal SpO2 values typically range from 95 to 100 percent in healthy individuals [39]. Values below this range may indicate hypoxemia, a condition characterized by low levels of oxygen in the blood, which can be a sign of various underlying health issues, including respiratory diseases, cardiovascular problems, and severe infections [40].

Blood oxygen saturation is commonly monitored using a non-invasive device called a pulse oximeter, which is typically placed on a thin part of the body, such as a fingertip or earlobe [42]. This device uses light-emitting diodes (LEDs) to measure the relative absorption of red and infrared light by oxygenated and deoxygenated hemoglobin, providing a quick and painless way to estimate blood oxygen levels [43].

Low Blood Oxygen Saturation: Levels below 95 percent may indicate hypoxemia, which can cause symptoms such as shortness of breath, rapid breathing, and confusion. Severe hypoxemia, with SpO2 levels below 90 percent, requires immediate medical attention as it can lead to organ dysfunction and is considered a medical emergency [44].

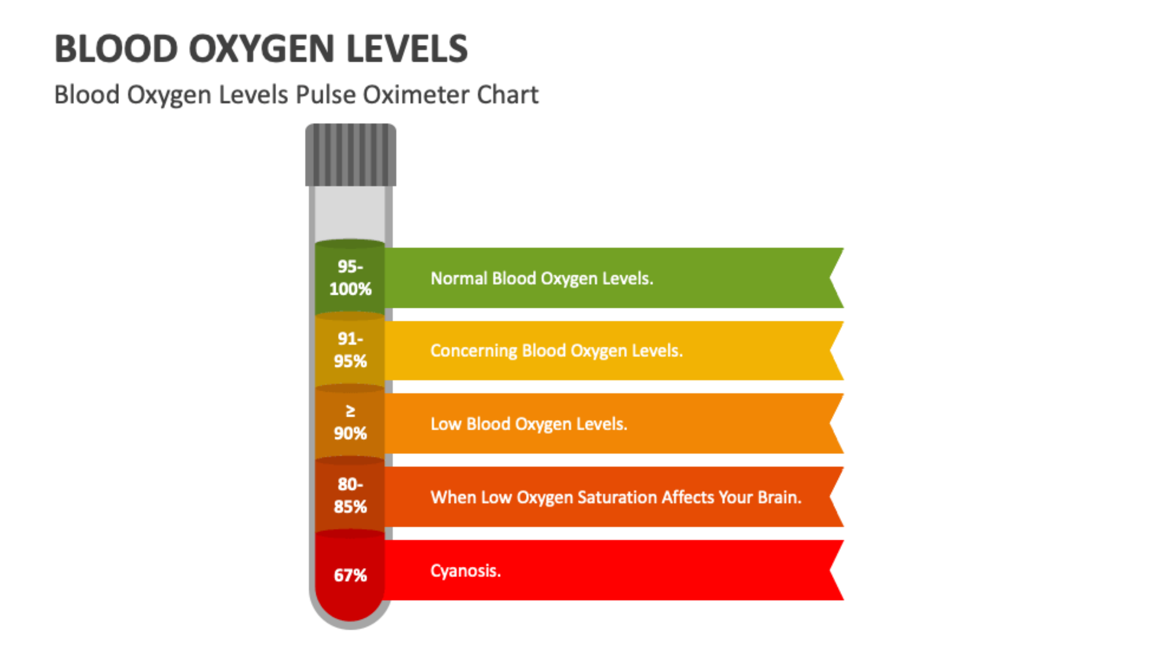


Figure 2.8: Ranges of Blood Oxygen Saturation [41]

Normal Blood Oxygen Saturation: A SpO2 range of 95 to 100 percent is considered normal for healthy individuals. It indicates that the blood is carrying sufficient oxygen to meet the body's needs [39].

Regular monitoring of blood oxygen saturation is particularly important for individuals with chronic respiratory conditions such as chronic obstructive pulmonary disease (COPD), asthma, and sleep apnea. It is also crucial during the management of acute conditions like pneumonia and during recovery from surgeries that affect respiratory function [45, 46].

The advent of wearable technology has greatly enhanced the ability to continuously monitor SpO2 levels. Modern smartwatches and fitness trackers are now equipped with pulse oximeters, allowing users to track their blood oxygen levels in real time. This continuous monitoring can provide valuable insights into trends and patterns, helping in the early detection of potential health issues and enabling timely medical interventions [47].

In conclusion, maintaining optimal blood oxygen saturation is vital for ensuring efficient oxygen delivery throughout the body. By utilizing both traditional and modern monitoring techniques, individuals and healthcare providers can keep a close watch on this critical parameter, ensuring prompt responses to deviations from the norm.

2.3 Previous Studies and Existing Models for Health Status Analysis Using AI

Several studies have explored the use of AI in analyzing health status using vital signs, focusing on developing predictive models for cardiovascular events. These models often utilize machine learning algorithms, particularly support vector machines (SVMs) and random forests, to predict the risk of heart attacks and strokes by analyzing ECG data, blood pressure readings, and other cardiovascular indicators. These predictive models have demonstrated promising results, identifying high-risk individuals and enabling the implementation of preventive measures. For instance, early identification of individuals at risk of heart attacks can prompt lifestyle changes or medical interventions that significantly reduce the likelihood of such events [48]. Figure 2.9 shows the projections of Artificial Intelligence in the healthcare industry from 2021 to 2030.

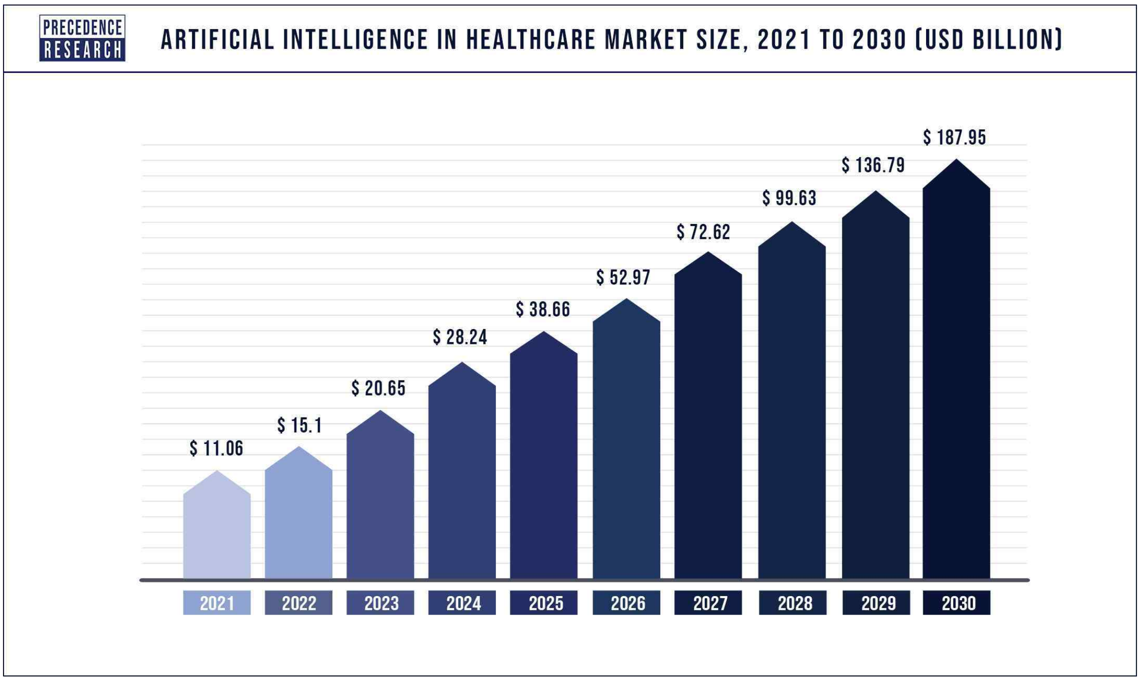


Figure 2.9: Current and Future Market Projections of AI in Healthcare [4]

In respiratory health, AI models have been applied to analyze respiratory rate and oxygen saturation data to predict exacerbations in patients with Chronic Obstructive Pulmonary Disease (COPD). Continuous monitoring of these vital signs allows the models to detect early signs of respiratory distress, facilitating timely interventions that can prevent hospitalizations. Similarly, AI algorithms have been developed to detect sepsis by analyzing trends in body temperature, heart rate, and blood pressure. Early detection of sepsis is crucial as it enables timely treatment, which can significantly improve patient outcomes and reduce mortality rates [49, 50].

Moreover, integrated AI systems that combine multiple vital signs have been developed to provide a comprehensive health status analysis. For instance, multi-parameter monitoring systems use data from ECG, blood pressure, SpO2 (oxygen saturation), and temperature sensors to predict adverse events in critical care settings. These systems employ advanced machine learning techniques, such as ensemble learning and deep learning, to enhance prediction accuracy and reliability. Previous research underscores the importance of feature extraction and data preprocessing in developing effective predictive models. Studies highlight that selecting relevant features, such as heart rate variability measures from ECG data or spectral analysis of respiratory signals, significantly impacts AI model performance. Additionally, techniques like data augmentation and synthetic data generation, including methods like Synthetic Minority Over-sampling Technique (SMOTE), are used to address class imbalances in training datasets, resulting in more robust and generalizable models [51, 52].

Beyond predictive models, AI has broader applications in health monitoring. For instance, AI is employed in continuous glucose monitoring systems for diabetes management, mental health assessment through speech and activity analysis, and sleep disorder diagnosis using wearable devices that track sleep stages and patterns [53]. AI's role in personalized medicine is also notable; algorithms predict individual responses to medications based on genetic, phenotypic, and lifestyle data, optimizing treatment plans for better outcomes [54].

AI's integration with Electronic Health Records (EHRs) enhances holistic health assessments by combining historical patient data with real-time monitoring to identify long-term health trends and risk factors [55]. Additionally, AI-powered applications engage patients in their health management by providing real-time feedback on vital signs and health metrics, encouraging healthier behaviors and better disease management [56].

Despite these advancements, challenges remain, including data privacy concerns, the need for high-quality data, and integrating AI systems into clinical workflows. Future research should focus on addressing these challenges and advancing AI technologies to further enhance health status analysis and patient care [57].

3. Methodology

3.1 Overview

This chapter outlines the methodological approach employed in this study to analyze health status using AI, focusing on vital signs such as heart rate, blood pressure, respiratory rate, body temperature, and blood oxygen saturation. The methodology is divided into several key stages: data collection, data pre-processing, feature extraction, model development, model training and evaluation, deployment, and the development of a Flask web interface for real-time health monitoring and diagnostics.

3.2 Data Collection

This study collected data from various sources to analyze vital signs such as heart rate, blood pressure, respiratory rate, body temperature, and blood oxygen saturation. The primary data sources include a large-scale ECG database from PhysioNet and a synthetic dataset created for other vital signs. The details of these sources are outlined below:

3.2.1 Heart Rate Data

For heart rate analysis, data was utilized from a database titled *A Large Scale 12-Lead Electrocardiogram Database for Arrhythmia Study* from PhysioNet. This newly inaugurated research database for 12-lead electrocardiogram (ECG) signals was created under the auspices of Chapman University, Shaoxing People's Hospital, and Ningbo First Hospital. It aims to enable the scientific community in conducting new studies on arrhythmia and other cardiovascular conditions.

Certain types of arrhythmias, such as atrial fibrillation, have a pronounced negative impact on public health, quality of life, and medical expenditures. As a non-invasive test, ECG is a major and vital diagnostic tool for detecting these conditions. This practice, however, generates large amounts of data, the analysis of which requires considerable time and effort by human experts. Modern machine learning and statistical tools can be trained on high-quality, large data to achieve exceptional levels of automated diagnostic accuracy.

This novel database contains 12-lead ECGs of 45,152 patients with a 500Hz sampling rate that features multiple common rhythms and additional cardiovascular conditions, all labeled by professional experts. The dataset can be used to design, compare, and fine-tune new and classical statistical and machine learning techniques in studies focused on arrhythmia and other cardiovascular conditions.

The database consists of 45,152 patient ECGs. The number of volts per A/D bit is 4.88, and the A/D converter had a 32-bit resolution. The amplitude unit was microvolts (mV). The upper limit was 32,767, and the lower limit was −32,768. The institutional review board of Shaoxing People's Hospital and Ningbo First Hospital approved this study, granted the waiver application to obtain informed consent, and allowed the data to be shared publicly after de-identification. Each patient has a respective .mat file (containing the ECG information) and a .hea file (containing the patient data like age, sex, etc.) [58].

3.2.2 Synthetic Dataset for Other Vital Signs

Due to a lack of proper databases with a sufficient number of patients for other vital signs, a synthetic dataset was created with some variations and imperfections. The dataset was categorized into respective conditions to simulate real-world scenarios and ensure robustness in model training and evaluation. The synthetic dataset includes the following:

1. **Blood Pressure:** Data for 6,000 patients, categorized into normal, elevated, hypertension stage 1, hypertension stage 2, and hypertensive crisis conditions.

2. **Blood Oxygen Saturation (SpO2):** Data for 871 patients, covering a range of oxygen saturation levels.

3. **Respiratory Rate:** Data for 1,200 patients, including variations to represent normal and abnormal respiratory patterns(bradypnoea and tachypnoea).

4. **Body Temperature:** Data for 3,000 patients, categorized into low temperature, normal, and various fever conditions.

The synthetic dataset was generated using statistical methods and domain knowledge to create realistic variations and anomalies. This approach ensured that the models could learn from a diverse set of conditions, enhancing their ability to generalize to real-world data.

3.3 Data Pre-processing

3.3.1 Heart Rate Dataset

The pre-processing of the heart rate dataset from the large-scale 12-lead electrocardiogram (ECG) database involved several critical steps to ensure data quality and readiness for analysis.

Initially, the frequency of each diagnosis was checked, and patients with invalid disease codes and those with insufficient samples for a particular disease were removed. Subsequently, disease codes were mapped to their respective condition names, and the age, gender, and diagnosis information for each patient were extracted. This information was appended to a list, with each element containing comprehensive data about the respective patient, including the Patient ID derived from the file name without the extension.

Next, the ECG data was loaded from the .mat files, focusing on the ECG array containing the signal from the first lead only. The number of samples (length of the ECG array) and the time axis were calculated.

To process the ECG signal, a function was created that applied several signal processing steps. First, a notch filter was designed and applied to remove powerline interference. Then, baseline wander correction was implemented to eliminate imperfections caused by patient movement during ECG recording. Following this, a Savitzky-Golay (Savgol) filter was applied to smooth the corrected ECG signal, and finally, the filtered ECG signal was normalized. The processed ECG files for each patient were appended to a single list containing all the ECG files of the patients considered.

To verify the effectiveness of the signal processing, plots of the original unedited ECG signal and the filtered and normalized signal were generated for comparison (See Figure 3.1).

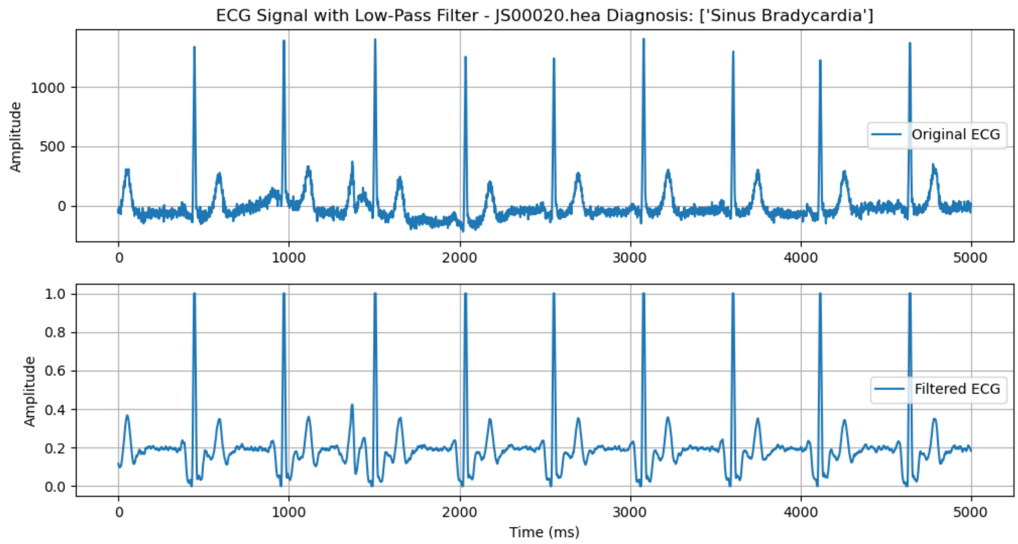


Figure 3.1: Raw vs. Filtered and Normalised ECG Signal Plot

3.3.2 Other Vitals Dataset

Pre-processing for the other vital signs data (blood pressure, respiratory rate, body temperature, and blood oxygen saturation) was deemed unnecessary since the data was synthetic and already formatted appropriately for analysis.

3.4 Feature Extraction

3.4.1 Features

These are features than can be extracted from the ECG signal and their relevance:
Heartrate metrics:

- Average Heart rate
- Max. Heart rate
- Min. Heart rate
- Heart rate variability (metrics like Standard deviation, Root mean square of successive differences (RMSSD), etc...)

ECG Waveform Analysis:

- PQRST Intervals (durations of the P and T waves, QRS complex)
- Amplitude characteristics (Amplitude analysis of the ECG signal)

- Peak analysis (Locations of various peaks of the ECG wave)

Frequency domain Features:

- Power Spectral Density (Compute frequency domain features like power in different frequency bands (very low frequency (VLF), low frequency (LF), and high frequency(HF)) using techniques like Fourier analysis)

Additional Clinical Variables:

- Age
- Sex

3.4.2 Feature Relevance

Amplitude Characteristics:

- Absolute amplitude: It is the absolute voltage values of each wave or complex. Specific thresholds of R-wave or depths of S-wave may lead to the diagnosis of conditions like myocardial infarction or ventricular hypertrophy.
- Relative Amplitude: The ratio of the amplitude of one wave or complex to another. Differences in relative amplitudes can indicate certain cardiac conditions or abnormalities. Eg. abnormally high R-P amplitude can suggest ventricular hypertrophy. Low R-T amplitude can indicate conduction abnormalities.
- Amplitude Variability: Variation in amplitude over time across different leads, or within the same lead. It quantifies the variation in amplitude across different waves, leads, or over time within the same lead. This can help assess stability and consistency of amplitude measurements.
- Statistical summaries (mean, median, etc...): These provide a summary of the distribution of amplitude values across multiple waves, offering insights into the variability and distribution of electrical activity. They help in quantifying the central tendency and dispersion of amplitude values

Frequency Domain Features:

- Frequency domain features are often obtained by performing Fourier Analysis. Parameters like power spectral density and frequency bands (VLF, LF, and HF components) can be determined.

  PSD can help calculate several parameters like:

  - Total Power: It represents the overall variability of heart rate across all frequency components and provides a measure of overall cardiac autonomic modulation and variability

  - Peak Frequency: It represents the dominant oscillatory component of the ECG signal and may vary under different conditions.
  - Frequency variability: These metrics capture the distribution of power across different frequency components and provide insights into the complexity of the cardiac dynamics.
  - Spectral entropy: It's a measure of the irregularity of the PSD. It quantifies the degree of spectral complexity and can indicate deviations from normal cardiac dynamics.

- Frequency domain analysis is a complex technique that shows how much of a signal lies within one or more frequency bands. Fast Fourier Transform (FFT) based Welch's Periodogram is used to transform the time series to frequency series data.
- HF Power: Frequency activity in the 0.15 - 0.40Hz range
  LF Power: Frequency activity in the 0.04 - 0.15Hz range
  VLF Power: Frequency activity in the 0.003 - 0.04Hz range
- Low LF/HF power ratio: Parasympathetic Nervous System (PSNS) Dominance.
- High LF/HF power ratio: Sympathetic Nervous System (SNS) Dominance
- The Autonomous Nervous System (ANS) consists of two subsystems: Sympathetic Nervous System (SNS) and Parasympathetic Nervous System (PSNS). A healthy balance between the two is vital, which is obtained by properly-functioning nerves and spinal cord.

  - SNS is responsible for the fight or flight response. When a threat is perceived, the SNS kicks into gear and brings out automatic and involuntary responses (like increased heart rate, elevated BP, heightened awareness, elevated respiration rate, and sweating). SNS also shuts down many parasympathetic responses in order to use more energy for the fight or flight response.

  - PSNS is responsible for "Rest and Digest". It works to slow down certain responses and bring about a state of calm to the body, allowing it to relax, rest, and repair. PSNS affects the same bodily functions as the SNS. Its primary function is to maintain longterm health and a healthy balance across all of the body's functions. PSNS responses include increasing digestive enzymes, decreasing heart rate, constricting bronchial tubes in lungs, relaxing the muscles, etc...

- For Frequency domain analysis of heart rate variability (HRV), a signal duration of:
  5 minutes: for VLF
  2 minutes: for LF
  1 minute: for HF
  is required, and the dataset used only has an ecg signal duration of 10 seconds. Therefore, another type of HRV analysis is required.

Time Domain Analysis:

- Time domain HRV analysis like SDNN (standard deviation of all normal RR (NN) intervals), RMSSD, and pNN50, can provide insights into overall HRV even with short duration recordings.

3.4.3 Feature Extraction Methodology

In a separate file, the filtered and normalized ECG data, along with age and sex information, were imported. The number of unique diagnoses was also calculated. The Python package NeuroKit2 was installed and imported for wave analysis.

Within a loop that iterated through the entire patient dataset, several steps were undertaken. First, the R-peaks locations and ECG signal delineation were identified using continuous wavelet transform and discrete wavelet transform, with the discrete wavelet transform yielding better results. The analysis focused on the location of the peaks of P, Q, R, S, T waves (i.e., timestamps), the onsets of P, Q, and R waves (start of the wave), and the offsets of P, Q, and R waves (end of the wave). Plots were obtained to ensure proper identification of the peaks and wave boundaries. Figure 3.2 and Figure 3.3 show the locations of the peaks and respective boundaries of the PQRST waves as detected by the neurokit2 Python package.

To handle the data effectively, various functions were created. A function was implemented to fill in missing peaks that may have been overlooked by the NeuroKit2 package. Additionally, a function was developed to calculate the amplitudes of the signal based on the location of the peak or onset/offset of the wave and to store these values in a list. To address any missing or NaN values in the amplitudes list, a function was created to fill in these gaps based on surrounding values. One was created used to determine the interval between two boundaries of a wave (i.e., wave

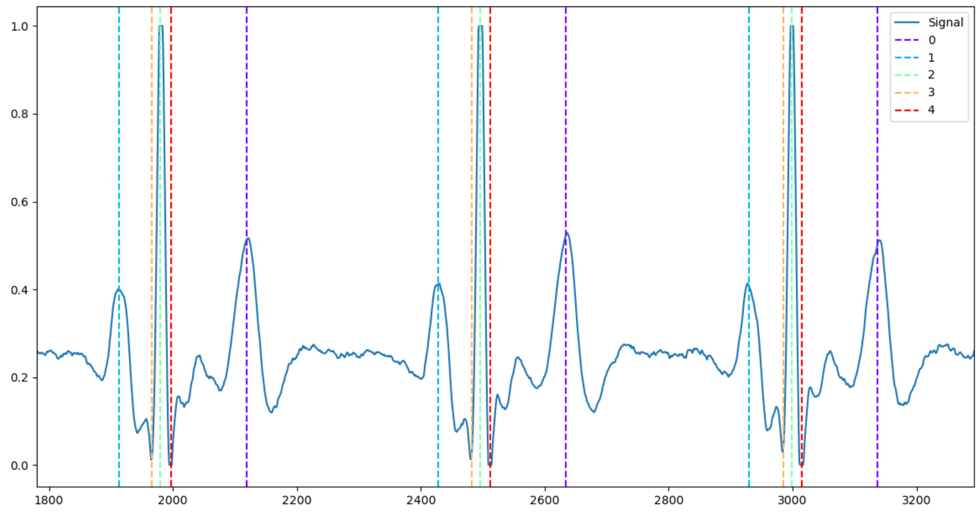


Figure 3.2: Detected Peaks of the PQRST waves

interval) and finally, a function to calculate statistical summaries for each wave was designed.

Through this process, several key values were calculated. These included the peaks of P, Q, R, S, T waves (with missing values filled), the amplitudes of P, Q, R, S, T waves (also filled), and the onsets and offsets of P, R, and T waves. Additionally, the intervals of the P, R, and T waves, as well as the QRS complex, were determined. Absolute amplitudes of P, Q, R, S, T waves were calculated, along with the relative amplitude of the R wave compared to the P wave and the R wave compared to the T wave. Statistical summaries such as the mean, median, coefficient of variation, standard deviation, and range were also computed for each wave.

Heart rate metrics were derived by converting the RR interval from milliseconds to seconds and calculating the average RR interval, shortest RR interval, longest RR interval, average heart rate, maximum heart rate, minimum heart rate, SDNN (standard deviation of NN intervals), RMSSD (root mean square of successive differences), and pNN50 (percentage of successive RR intervals that differ by more than 50 ms).

In the frequency domain, features were extracted by calculating the total power, peak frequency, frequencies, and power spectral density (PSD) of the ECG signal using Welch's method. Additional parameters such as peak frequency, spectral en-

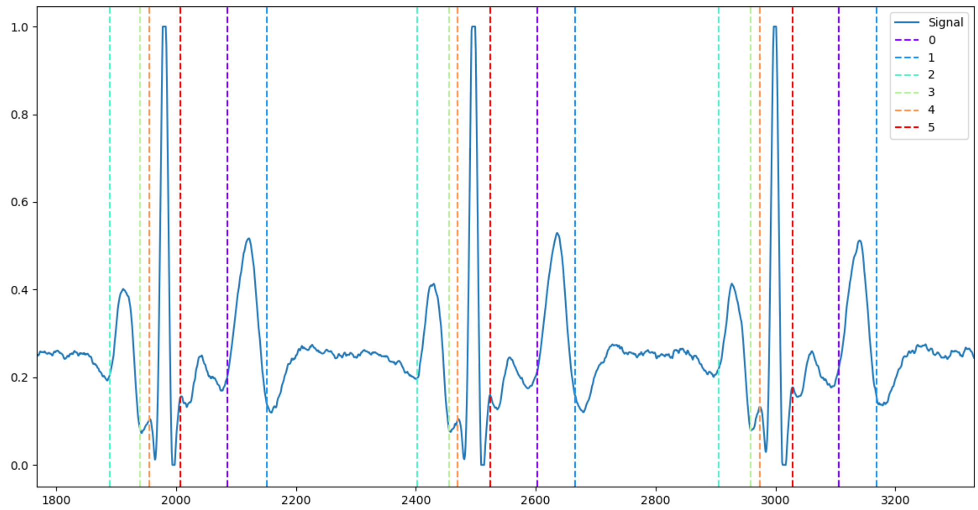


Figure 3.3: Detected Boundaries of the PQRST waves

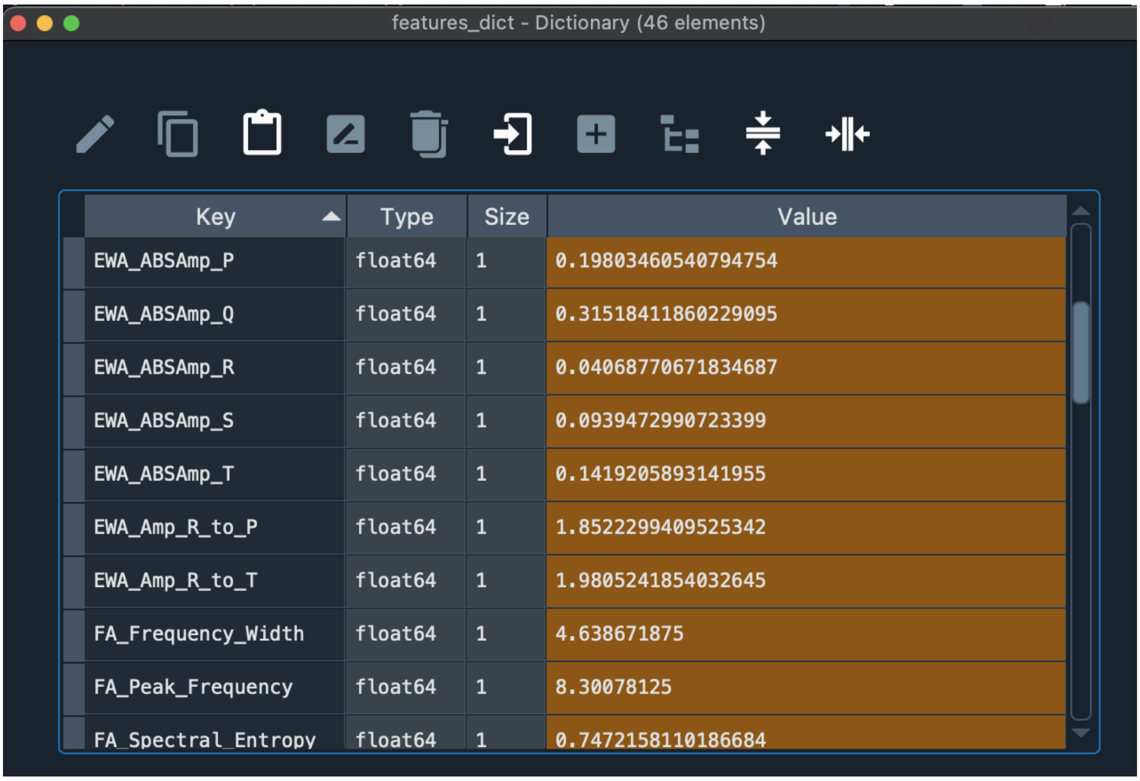
tropy, PSD threshold, and frequency width were also determined.

All relevant extracted features were compiled into a dictionary for each patient, including attributes like Patient ID, Age, Sex, Average heart rate, and others. In total, the dictionary for a single patient contains 46 elements. The extracted features dictionary for each patient was then appended into a comprehensive file containing data for all patients. Feature extraction is a critical step in transforming raw data into meaningful inputs for machine learning models. Figure 3.4 shows snippet of the dictionary for a patient.

3.5 Model Development and Training

3.5.1 Heart Rate Model

Various machine learning algorithms were explored for heart rate prediction, including Support Vector Machines (SVM), Neural Networks, Random Forest, and ensemble methods. After experimentation, the RandomForestClassifier was selected due to its robust performance and ability to handle high-dimensional data.The dataset was split into training, validation, and test sets. Cross-validation techniques, such as k-fold cross-validation, were used to ensure the model's generalizability.


features_dict - Dictionary (46 elements)

Key	Type	Size	Value
EWA_ABSAmp_P	float64	1	0.19803460540794754
EWA_ABSAmp_Q	float64	1	0.31518411860229095
EWA_ABSAmp_R	float64	1	0.04068770671834687
EWA_ABSAmp_S	float64	1	0.0939472990723399
EWA_ABSAmp_T	float64	1	0.1419205893141955
EWA_Amp_R_to_P	float64	1	1.8522299409525342
EWA_Amp_R_to_T	float64	1	1.9805241854032645
FA_Frequency_Width	float64	1	4.638671875
FA_Peak_Frequency	float64	1	8.30078125
FA_Spectral_Entropy	float64	1	0.7472158110186684

Figure 3.4: Feature Dictionary of a random patient

Ensemble learning techniques, such as bagging and boosting, were considered to improve model performance by combining multiple base classifiers. However, the RandomForestClassifier, which inherently employs ensemble learning, provided satisfactory results without the need for additional ensemble techniques.

Hyperparameter tuning was conducted for the RandomForestClassifier using techniques like GridSearchCV to optimize model parameters such as maximum tree depth, minimum samples split, and leaf size. This fine-tuning process aimed to enhance the model's predictive accuracy and generalization capabilities.

Evaluation metrics such as accuracy, precision, recall, and F1-score were utilized to assess the performance of the heart rate model across various heart conditions. These metrics provided insights into the model's ability to accurately classify different heart rate categories.

3.5.2 Blood Pressure, Respiratory Rate, SpO2, and Body Temperature Models

Similar to the heart rate model, multiple machine learning algorithms were explored for predicting blood pressure, respiratory rate, SpO2, and body temperature. SVM, Neural Networks, Random Forest, and ensemble methods were considered during the model development phase.
After thorough experimentation with Logistic regression and other models, the RandomForestClassifier was chosen for its consistent performance and ease of implementation across all vital signs. The model's ability to handle class imbalances and nonlinear relationships in the data contributed to its selection.
Hyperparameter tuning was performed for each vital sign model to optimize model parameters and improve predictive accuracy. GridSearchCV was utilized to search for the best combination of hyperparameters, ensuring optimal model performance.
Evaluation metrics, including accuracy scores and classification reports, were used to evaluate the performance of each vital sign model. These metrics provided valuable insights into the models' effectiveness in accurately classifying vital sign categories and guiding further model refinement efforts.
The training models for blood pressure (BP), body temperature, respiratory rate (RR), and blood oxygen saturation (SpO2) share similarities due to their common characteristics in terms of data structure and classification tasks:

1. **Classification Task:** All four models are tasked with classifying different categories or ranges within their respective vital signs. For example, blood pressure might classify into categories like normal, elevated, or hypertensive, while body temperature might classify into normal, fever, or hypothermia. This similarity in classification tasks leads to the utilization of similar classification algorithms and techniques.

2. **Dataset Structure:** The datasets for BP, temperature, RR, and SpO2 likely have similar structures, with features representing the vital sign values and labels indicating the corresponding categories. This uniformity in dataset structure facilitates the application of similar preprocessing steps, feature extraction methods, and model training procedures.

3. **Model Selection:** The RandomForestClassifier was chosen for its effectiveness in handling high-dimensional data, nonlinear relationships, and multiclass classification tasks. Its flexibility and robustness make it suitable for diverse datasets, including those related to vital sign classification.

4. **Imbalanced Data Handling:** Class imbalance is a common issue in medical datasets, including those related to vital signs. Techniques like class weights adjustment and oversampling (e.g., SMOTE) are often employed to address this imbalance. The similarity in dealing with imbalanced data contributes to the resemblance in model training approaches.

5. **Hyperparameter Tuning:** The process of hyperparameter tuning, such as using GridSearchCV, aims to optimize model performance by selecting the best combination of hyperparameters. This process is essential for enhancing model accuracy and generalization across different vital signs.

In summary, the similarities in training models for BP, body temperature, RR, and SpO2 stem from their shared characteristics in classification tasks, dataset structures, model selection, imbalanced data handling, and hyperparameter tuning strategies. These similarities allow for a streamlined approach to model development while ensuring effective classification of vital sign categories.

3.6 Flask Web Interface Development

The development of the Flask web interface aims to provide a unified platform that integrates all the trained models, enabling users to input their health data and receive comprehensive diagnostic results, an overall health score, and personalized health recommendations. The process involved several key steps and components.

3.6.1 Interface Design

Key features of the interface include:

1. **Input Fields:** Users can enter their vital signs such as heart rate, blood pressure, respiratory rate, body temperature, and blood oxygen saturation.

2. **Real-Time Analysis:** Upon submission, the interface processes the input data using the trained AI models and provides immediate feedback.

3. **Diagnostic Results:** The interface displays relevant diagnoses for each parameter, highlighting any abnormalities and potential health concerns.

4. **Overall Health Score:** An aggregate health score is calculated based on the inputted vital signs, providing a comprehensive overview of the user's health status.

5. **Personalized Recommendations:** Tailored health recommendations are generated, including lifestyle changes, medical advice, and alerts for necessary medical consultations.

3.6.2 Backend Integration

The backend of the Flask application integrates with the trained AI models to facilitate real-time processing and analysis. This integration involves:

1. **Model Loading:** Loading the pre-trained machine learning models into the Flask application for on-demand predictions.

2. **Data Handling:** Processing and normalizing the input data to match the format required by the models.

3. **Prediction Generation:** Running the input data through the models to generate predictions and health scores.

4. **Result Interpretation:** Translating the model outputs into meaningful diagnostic results and recommendations for the user.

3.6.3 Heart Rate Model Integration

The initial step was to integrate the heart rate model into the Flask application. The application was designed to accept user-uploaded '.hea' and '.mat' files. These files contain the necessary ECG data and patient information, respectively. The steps involved were:

1. **File Upload and Data Extraction:** The '.hea' file provided age and sex information, while the '.mat' file contained the ECG signal data. The application extracted the ECG signal from the first lead of the '.mat' file.

2. **ECG Signal Pre-processing:** The extracted ECG signal underwent pre-processing, including filtering to remove noise and normalization.

3. **Feature Extraction:** Key features were extracted from the pre-processed ECG signal, such as R-peak locations and various wave amplitudes and intervals.

4. **Model Prediction:** The processed data was fed into the trained heart rate model to predict the diagnosis. Additionally, the application calculated the average heart rate and other relevant metrics.

5. **Visualization:** The filtered and normalized ECG signal was plotted, and the predicted diagnosis along with the calculated average heart rate was displayed.

3.6.4 HTML Interface Development

The web interface consists of two main HTML files:

1. **index.html:** This file served as the input form for the users, allowing them to upload their '.hea' and '.mat' files and enter other necessary vital sign details.

2. **results.html:** After processing the inputs, this file displayed the results, including the ECG plot, the diagnosis, and relevant heart rate metrics.

3.6.5 Integration of Other Vital Signs

Similar processes were followed for integrating models for other vital signs, such as blood pressure, respiration rate, SpO2, and body temperature. These are the steps included:

1. **Data Input:** Users could input relevant data for each vital sign directly through the web interface.

2. **Model Prediction:** Each input was processed by the respective pre-trained model to predict the diagnosis or category (e.g., normal, elevated, high).

3. **Results Display:** The results for each vital sign were displayed on the results.html page, providing users with a comprehensive overview of their health status.

To facilitate real-time health monitoring and diagnostics, a Flask web interface was developed. This interface allows users to input vital signs and receive relevant diagnoses, an overall health score, and personalized recommendations. Figure 3.5 shows the web interface where the user can input the patient details.

3.7 Health Score Calculation

In this section, we present a detailed methodology for evaluating an individual's health using various vital parameters. This methodology includes the identification of key vital parameters, establishment of normal ranges and weightings, scoring system development, and calculation of an overall health score. The health score is

Figure 3.5: Flask Web Interface - User input

designed to provide a clear, quantitative measure of health status, facilitating risk assessment and decision-making regarding the necessity of seeking healthcare.

3.7.1 Identification of Vital Parameters

The following vital parameters were selected for the health score evaluation based on their common use and significance in medical assessments:

- Blood Pressure (BP): Systolic and diastolic measurements
- Heart Rate (HR)
- Respiratory Rate (RR)
- Body Temperature (BT)
- Oxygen Saturation (SpO2)

3.7.2 Establishment of Normal Ranges and Weightings

For each parameter, normal ranges were defined according to standard medical guidelines. Weightings were assigned based on the relative importance of each parameter to overall health, as follows:

- **Blood Pressure:**
  Normal range 90/60 mmHg to 120/80 mmHg, weighting 20
- **Heart Rate:**
  Normal range 60-100 beats per minute, weighting 15
- **Respiratory Rate:**
  Normal range 12-20 breaths per minute, weighting 10
- **Body Temperature:**
  Normal range 36.1°C to 37.2°C (97°F to 99°F), weighting 10
- **Oxygen Saturation:**
  Normal range 95-100 percent, weighting 15

3.7.3 Scoring System Development

A scoring system was developed to quantify each parameter on a scale of 0 to 100, with scores reflecting the degree to which a given measurement falls within or deviates from the normal range.

- **Blood Pressure:**
  - 90/60 mmHg to 120/80 mmHg: 100 points
  - 121/81 mmHg to 140/90 mmHg: 75 points
  - 141/91 mmHg to 160/100 mmHg: 50 points
  - >160/100 mmHg or <90/60 mmHg: 25 points

- **Heart Rate:**
  - 60-100 bpm: 100 points
  - 101-110 bpm or 50-59 bpm: 75 points
  - 111-120 bpm or 40-49 bpm: 50 points
  - >120 bpm or <40 bpm: 25 points

- **Respiratory Rate:**
  - 12-20 breaths per minute: 100 points
  - 21-24 breaths per minute or 10-11 breaths per minute: 75 points
  - 25-30 breaths per minute or 8-9 breaths per minute: 50 points
  - >30 or <8 breaths per minute: 25 points

- **Body Temperature:**
  - 36.1°C to 37.2°C: 100 points
  - 37.3°C to 38.0°C or 35.5°C to 36.0°C: 75 points
  - 38.1°C to 39.0°C or 34.5°C to 35.4°C: 50 points
  - >39.0°C or <34.5°C: 25 points

- **Oxygen Saturation:**
  - 95-100 percent: 100 points
  - 93-94 percent: 75 points
  - 90-92 percent: 50 points
  - <90 percent: 25 points

3.7.4 Calculation of the Comprehensive Health Score

The comprehensive health score is calculated by multiplying the score for each parameter by its weighting and summing the results. This sum is then divided by the total of the weightings to produce a normalized health score on a scale from 0 to 100. The formula used is:

$$\text{Health Score} = \frac{\sum(\text{Parameter Score} \times \text{Weighting})}{\sum(\text{Weighting})}$$

3.7.5 Interpretation and Risk Assessment

The resulting health score is interpreted to assess overall health and risk:

- 90-100: Excellent health
- 80-89: Good health
- 70-79: Moderate health
- 60-69: Below average health
- <60: Poor health

3.7.6 Example Calculation

To illustrate, consider an individual with the following parameter values:

- Blood Pressure: 130/85 mmHg (75 points) - Heart Rate: 85 bpm (100 points) - Respiratory Rate: 18 breaths/min (100 points) - Body Temperature: 37°C (100 points) - Oxygen Saturation: 98 percent (100 points)

Using the assigned weightings:

$$\text{Health Score} = \frac{(100 \times 20) + (100 \times 20) + (100 \times 20) + (75 \times 25) + (100 \times 15)}{20 + 20 + 20 + 25 + 15}$$

$$\text{Health Score} = \frac{2000 + 2000 + 2000 + 1875 + 1500}{100} = \frac{9375}{100} = 93.75$$

The health score gets rounded to the nearest whole number. This individual has a health score of 94, falling within the "Very Good health" category. While the probability of health risks is low, maintaining regular check-ups and a healthy lifestyle is advisable.

3.7.7 Conclusion

This methodology offers a structured, quantitative approach to evaluating an individual's health using multiple vital parameters. The comprehensive health score facilitates clear health status interpretation and supports informed decision-making regarding healthcare needs. Adjustments can be made to the model based on specific clinical requirements or additional parameters. The integration of these components into a single Flask application provided a seamless and user-friendly interface for health monitoring and diagnostics, enabling users to get detailed insights into their health and take informed actions.

3.8 Security and Privacy

3.8.1 Data Privacy and De-identification

Ensuring patient privacy and confidentiality is paramount in any healthcare application. In this web interface development, several measures were taken to de-identify patient data and protect personal information.

3.8.2 De-identification of Patient Data

The patient data used for the development and training of the models was thoroughly de-identified. This process involved:

1. **Removal of Personal Identifiers:** All personal identifiers such as patient names, addresses, and contact information were removed from the datasets. This ensured that no individual could be directly identified from the data.

2. **Anonymization Techniques:** Advanced anonymization techniques were applied to ensure that even indirect identifiers could not be traced back to an individual. This included data masking and generalization of certain data fields.

3.8.3 Limited Display of Personal Information

The web interface was designed to display only minimal personal information, which is essential for the diagnostic models:

1. **Age and Sex:** The interface only displays the patient's age and sex. These parameters are necessary for the models to make accurate predictions but are not sufficient to identify an individual.

2. **No Names or Identifiers:** The interface does not display any patient names, identification numbers, or other personal identifiers. This minimizes the risk of compromising patient privacy.

3. **Secure Data Handling:** All data inputs and outputs are handled securely within the application. Uploaded files and diagnostic results are processed in a secure environment to protect patient confidentiality.

By adhering to these principles, the web interface ensures that patient privacy is maintained while providing essential health diagnostics. This balance of privacy and functionality is critical in healthcare applications, where sensitive information must be protected without compromising the quality of care.

3.9 Installation guide

Installation guide to run the Flask application locally:

1. Install Anaconda Navigator, and install the newest version of the Spyder application to view and edit the code as necessary.

2. Navigate to the project directory (Folder name: Interface):

```
cd path\to\your\project
```

3. Set up the virtual environment:
   - On MAC systems:

     ```
     python -m venv venv
     source venv/bin/activate
     ```

   - On Windows systems:

     ```
     python -m venv venv
     venv\Scripts\activate
     ```

4. Open the terminal and install the following libraries: numpy, scipy.io, matplotlib, base64, sys, pickle, logging, joblib, flask, pandas, neurokit2

```
pip install scipy.io
```

5. Run the Flask app "interface.py":

```
python app.py
```

6. You should see output indicating that your Flask app is running, and you can view it in your web browser at `http://127.0.0.1:5000`.

4. Results

This chapter presents the outcomes of the trained models for heart rate, blood pressure, respiration rate, SpO2, and body temperature. It evaluates the performance metrics of each model, discusses the results from the web interface development, and provides insights into the overall health score calculation.

4.1 Model Results

4.1.1 Heart Rate

The heart rate model demonstrated strong performance with an accuracy of 89.6%. It effectively classified various cardiac rhythm abnormalities, including Sinus Rhythm, Atrial Flutter, Atrial Fibrillation, Sinus Bradycardia, and Sinus Tachycardia. The model's precision and recall were particularly high for Sinus Rhythm and Sinus Bradycardia, indicating its effectiveness in identifying normal and bradycardic heart rhythms.

```
Accuracy: 0.896457765667575
Best Parameters for Each Label:
Label 1: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 200}
Label 2: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 50}
Label 3: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 300}
Label 4: {'max_depth': None, 'min_samples_leaf': 2, 'min_samples_split': 5, 'n_estimators': 300}
Label 5: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 200}
Classification Report:
                      precision    recall  f1-score   support

       Sinus Rhythm       0.99      0.96      0.98       164
     Atrial Flutter       0.00      0.00      0.00        21
Atrial Fibrillation       0.87      0.71      0.78       112
  Sinus Bradycardia       0.98      0.99      0.98       331
  Sinus Tachycardia       0.94      0.92      0.93       106

          micro avg       0.96      0.90      0.93       734
          macro avg       0.76      0.72      0.73       734
       weighted avg       0.93      0.90      0.91       734
        samples avg       0.96      0.90      0.90       734
```

Figure 4.1: Heart Rate Training report

4.1.2 Blood Pressure

The blood pressure model exhibited exceptional accuracy, achieving a perfect accuracy score of 100% on the independent test set. It accurately classified different blood pressure categories, including Elevated, Hypertension Stage 1, Hypertension Stage 2, Hypertensive Crisis, Hypotension, and Normal. The model's robust performance underscores its reliability in predicting blood pressure levels with high precision and recall across all categories.

```
Accuracy on independent test set: 1.0
Classification Report on independent test set:
                       precision    recall  f1-score   support

            elevated       1.00      1.00      1.00      1000
hypertension_stage_1       1.00      1.00      1.00      1000
hypertension_stage_2       1.00      1.00      1.00      1000
 hypertensive_crisis       1.00      1.00      1.00      1000
         hypotension       1.00      1.00      1.00      1000
              normal       1.00      1.00      1.00      1000

            accuracy                           1.00      6000
           macro avg       1.00      1.00      1.00      6000
        weighted avg       1.00      1.00      1.00      6000

Predictions:
Input 1: Systolic - 120, Diastolic - 80 - Predicted class: normal
Input 2: Systolic - 140, Diastolic - 90 - Predicted class: hypertension_stage_1
Input 3: Systolic - 150, Diastolic - 120 - Predicted class: hypertension_stage_2
```

Figure 4.2: Blood Pressure Training report

4.1.3 Respiration Rate

The respiration rate model achieved outstanding accuracy, with a perfect score of 100%. It effectively categorized respiration rates into different categories, demonstrating precision, recall, and F1-scores of 1.00 for all categories. The model's flawless performance highlights its ability to accurately assess respiratory health based on input data.

```
Best Hyperparameters: {'max_depth': 5, 'min_samples_leaf': 1, 'min_samples_split': 2}
Accuracy: 1.0
Classification Report:
               precision    recall  f1-score   support

  Bradypnoea       1.00      1.00      1.00        63
      Normal       1.00      1.00      1.00       144
  Tachypnoea       1.00      1.00      1.00        33

    accuracy                           1.00       240
   macro avg       1.00      1.00      1.00       240
weighted avg       1.00      1.00      1.00       240
```

Figure 4.3: Respiration Rate Training report

4.1.4 SpO2 Results

The SpO2 model achieved an impressive accuracy of 99.4%. It accurately classified SpO2 levels into various categories, including normal and abnormal oxygen saturation levels. The model demonstrated high precision and recall across all categories, indicating its effectiveness in identifying oxygen saturation abnormalities with high confidence.

Accuracy: 0.9942528735632183
Classification Report:

	precision	recall	f1-score	support
Concerning Blood Oxygen levels	0.97	1.00	0.98	29
Cyanosis	1.00	1.00	1.00	22
Low Blood Oxygen levels	1.00	1.00	1.00	57
Low Blood Oxygen levels that can affect your brain	1.00	1.00	1.00	42
Normal Blood Oxygen levels	1.00	0.96	0.98	24
accuracy			0.99	174
macro avg	0.99	0.99	0.99	174
weighted avg	0.99	0.99	0.99	174

Figure 4.4: SpO2 Training report

4.1.5 Body Temperature Results

The body temperature model demonstrated exceptional accuracy, achieving a perfect score of 100%. It effectively categorized body temperature into different levels, including elevated temperature, high fever, low temperature, moderate fever, normal temperature, and very high fever. The model exhibited high precision, recall, and F1-scores across all temperature categories, demonstrating its robust performance in accurately assessing body temperature levels.

Accuracy: 1.0
Classification Report:

	precision	recall	f1-score	support
Elevated temperature	1.00	1.00	1.00	100
High fever	1.00	1.00	1.00	100
Low temperature	1.00	1.00	1.00	100
Moderate fever	1.00	1.00	1.00	100
Normal	1.00	1.00	1.00	100
Very high fever	1.00	1.00	1.00	100
accuracy			1.00	600
macro avg	1.00	1.00	1.00	600
weighted avg	1.00	1.00	1.00	600

Figure 4.5: Body Temperature Training report

4.1.6 Overall Model Evaluation

Overall, the results showcase the effectiveness and reliability of the developed models in accurately predicting vital signs and health conditions. The high accuracy, precision, and recall scores across all models indicate their potential for clinical use and health monitoring applications. The integration of these models into a user-friendly web interface enhances accessibility and usability, providing individuals with valuable insights into their health status and personalized recommendations for proactive health management.

4.2 Integrated Web Interface Results

4.2.1 Flask Development

The Flask web interface development aimed to provide users with a user-friendly platform for accessing the trained models and receiving personalized health insights. The interface was designed to be intuitive and easy to navigate, with separate sections for inputting user data and displaying results.

- **Input Section:**The input section of the web interface allowed users to upload their data files, including ECG signals, blood pressure measurements, respiratory rate, SpO2 levels, and body temperature. Additionally, users provide demographic information such as age and sex.
- **Results Section:** Upon submitting the data, the web interface processed the input through the respective trained models and generated personalized health insights. The results section displayed the diagnosis and analysis for each vital sign, including heart rate rhythm, blood pressure category, respiratory rate status, oxygen saturation level, and body temperature classification.

4.2.2 Health Score Calculation

In addition to providing individual vital sign assessments, the web interface incorporated a health score calculation system to offer users a comprehensive overview of their overall health status. The health score was calculated based on the weighted contributions of each vital sign assessment, considering their respective importance in determining overall health.

- **Weighted Contributions:** Each vital sign assessment was assigned a weight based on its significance in assessing overall health. For example, heart rate rhythm and blood pressure measurements were assigned higher weights due to their critical role in cardiovascular health, while other vital signs such as body temperature had lower weights.

- **Calculation Process:** The health score calculation involved aggregating the weighted contributions of individual vital sign assessments to generate an overall health score. The score provided users with an indication of their overall health status, with higher scores indicating better health and lower scores suggesting potential areas for improvement.

4.2.3 Personalized Recommendations

In addition to the health score, the web interface provided users with personalized recommendations based on their individual health assessments. These recommendations were tailored to address specific health concerns identified through the analysis of vital signs.

- **Targeted Interventions:** The recommendations encompassed lifestyle modifications, preventive measures, and healthcare interventions aimed at improving overall health and mitigating potential health risks. For example, individuals identified with abnormal blood pressure levels may receive recommendations for dietary changes, exercise regimens, or medical consultations.
- **Educational Resources:** The web interface also offered access to educational resources and informational materials related to each vital sign assessment. These resources empowered users with knowledge and insights into their health conditions, enabling them to make informed decisions about their health and well-being.

4.2.4 Interface Conclusion

The Flask web interface development and health score calculation system provided users with a powerful tool for monitoring and managing their health. By integrating trained models, personalized health assessments, and actionable recommendations, the interface facilitated proactive health management and empowered users to take control of their well-being. Figure 4.6, Figure 4.7, Figure 4.8, and Figure 4.9 show the results of different user vitals' details.

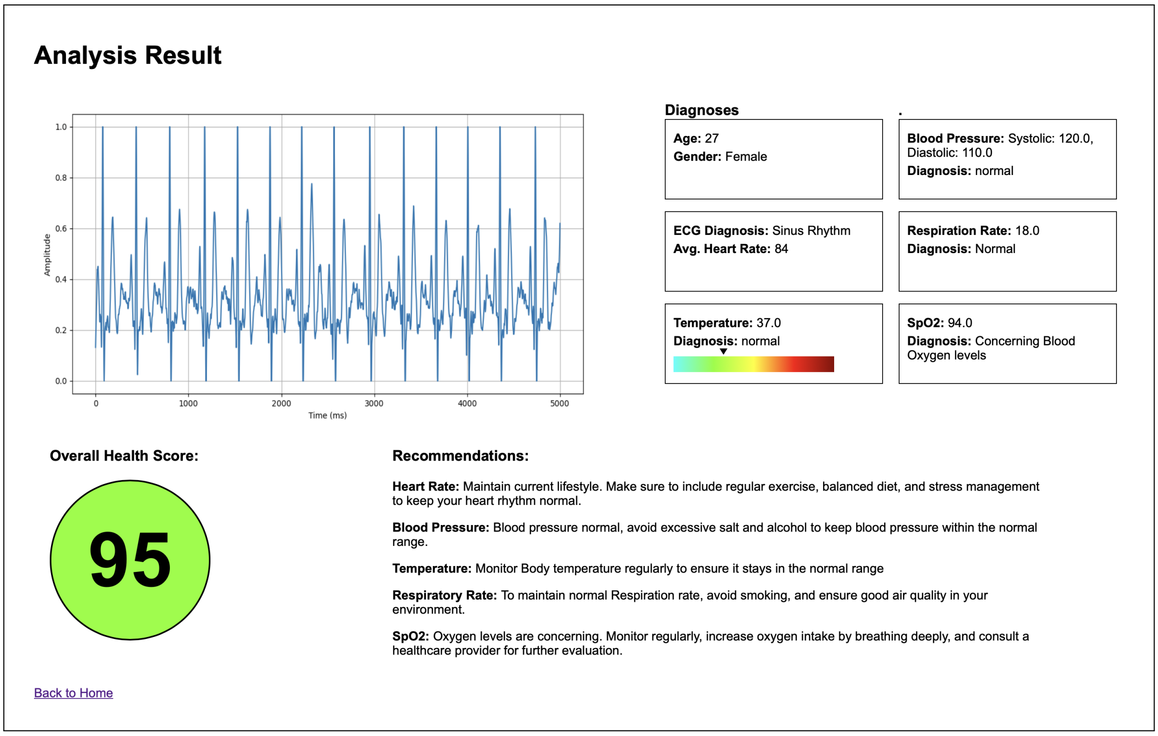


Figure 4.6: Interface Result: Excellent Health

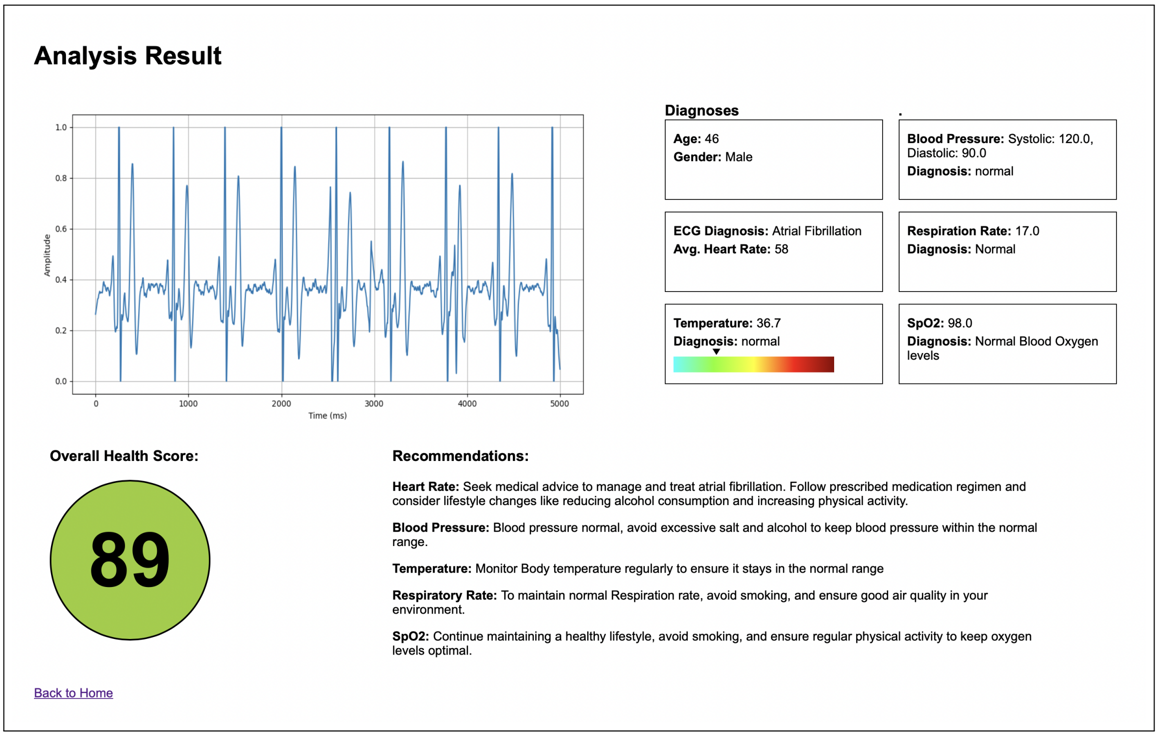


Figure 4.7: Interface Result: Good Health

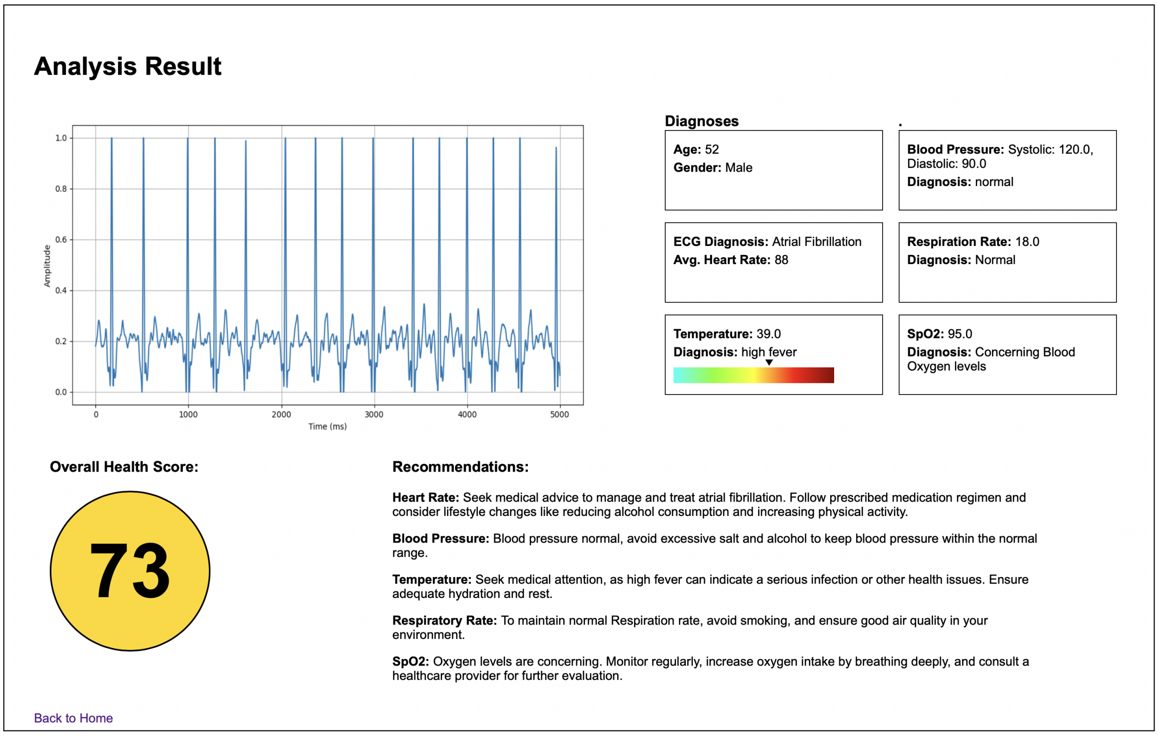


Figure 4.8: Interface Result: Moderate Health

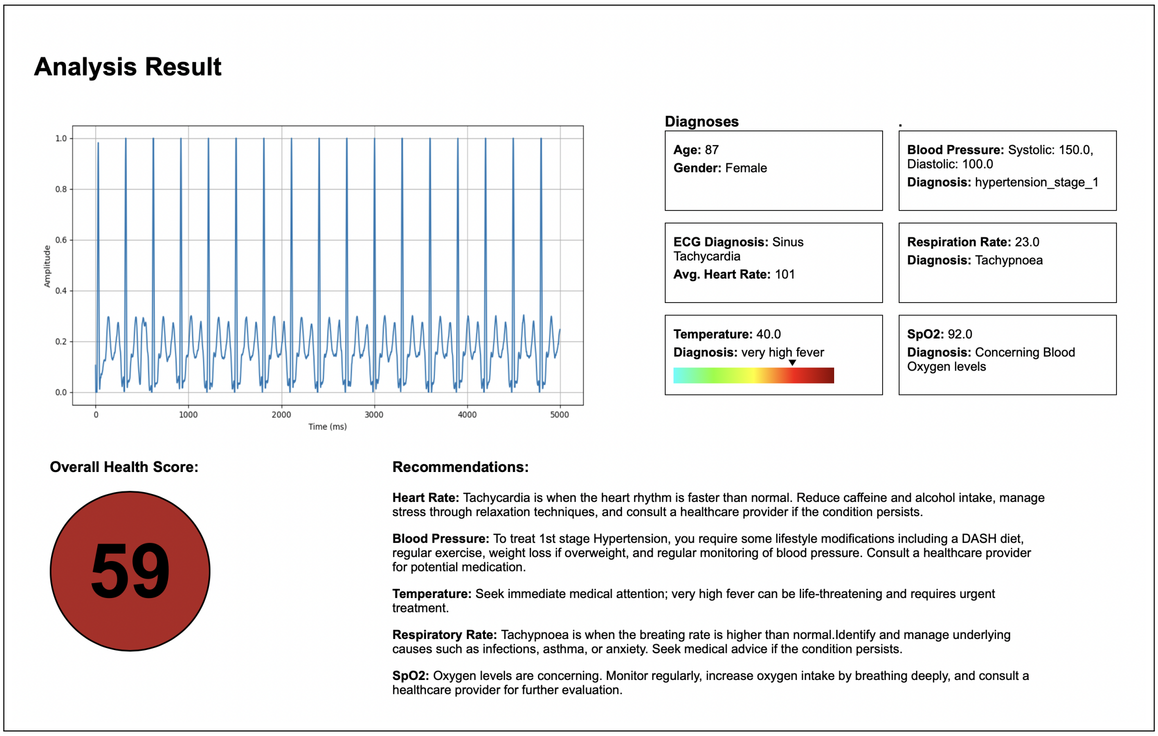


Figure 4.9: Interface Result: Poor Health

5. Conclusion

5.1 Summary and Contributions to the Field

This research contributes significantly to the healthcare industry by introducing a novel approach to diagnostic modeling and patient care through the development of a comprehensive web interface. By integrating machine learning algorithms with patient data inputs, the interface enables rapid and accurate diagnosis of various medical conditions based on vital signs analysis. This innovation has the potential to streamline clinical decision-making processes, enhance diagnostic accuracy, and improve patient outcomes.

Moreover, the development of the web interface facilitates the seamless integration of diagnostic models into existing healthcare systems, allowing for easy accessibility and utilization by healthcare providers. This accessibility ensures that the benefits of advanced diagnostic technologies are readily available to clinicians, empowering them to make informed decisions and provide personalized care to their patients.

Furthermore, by incorporating personalized health recommendations and overall health scoring features, the interface promotes patient engagement and empowerment. Patients can gain valuable insights into their health status, receive tailored recommendations for improving their well-being, and actively participate in their healthcare journey. This patient-centric approach fosters a collaborative relationship between patients and healthcare providers, ultimately leading to better health outcomes and increased patient satisfaction.

In summary, this research represents a significant contribution to the field by leveraging technology to revolutionize diagnostic processes and patient care delivery. By harnessing the power of machine learning and web-based interfaces, this innovative approach has the potential to transform the healthcare industry, improving efficiency, accuracy, and patient outcomes in clinical practice.

5.2 Limitations

Despite the advancements made in this thesis, there are several limitations to consider. Firstly, the accuracy of the machine learning models may vary depending on the quality and quantity of the input data. Moreover, the models may not perform optimally for individuals with rare or complex medical conditions.

Furthermore, the web interface developed in this thesis has certain limitations in terms of scalability and real-time data processing. As the user base grows, there may be challenges in managing the computational resources required to support a large number of simultaneous requests.

While these limitations are more general in nature, there were a few additional difficulties encountered while trying to implement the desired code. These will be discussed in more detail.

Indeed, one of the limitations encountered in this research was the presence of patients with multiple diagnoses. While the diagnostic models developed in this thesis were designed to classify patients into distinct categories based on their vital signs, the presence of comorbidities presented a challenge in accurately predicting multiple diseases for individual patients.

Additionally, the dataset used in this research may have been limited in terms of its size and diversity. Although efforts were made to collect a comprehensive dataset covering a wide range of medical conditions, the number of unique disease combinations observed in real-world clinical settings is vast. As a result, the predictive accuracy of the models may have been constrained by the limited representation of certain disease patterns in the dataset.

The process of training the heart rate model highlighted the issue of computational power. Handling very large databases required considerable computational resources, leading to prolonged training times and delayed result generation. This limitation underscores the need for more efficient algorithms and better computational infrastructure to manage extensive datasets effectively.

Another significant limitation was the scarcity of sufficient and diverse datasets for other vital signs such as SpO2, temperature, blood pressure, and respiration rate.

Most available medical databases included data from a maximum of about 50 patients, which is insufficient for training robust and generalizable models. This data insufficiency restricts the models' accuracy and applicability in broader clinical settings.

Addressing these limitations will require further research and development efforts. Future studies could explore the development of more sophisticated machine learning models capable of handling complex disease profiles and predicting multiple diagnoses simultaneously. Additionally, efforts to expand the dataset to include a broader range of patient populations and medical conditions may improve the generalizability and robustness of the diagnostic models.

Overall, while these limitations pose challenges to the current state of the research, they also highlight opportunities for future advancements in healthcare technology and data analysis. By addressing these challenges and building upon the foundations laid in this research, it may be possible to develop more effective and comprehensive diagnostic tools for improving patient care and outcomes.

5.3 Future Scope and Research Directions

Future research and development efforts can significantly enhance the capabilities and impact of the diagnostic system developed in this thesis. Several key areas present opportunities for further advancement:

- **Integration with Hospital Systems:**
  Integrating the web interface into hospital information systems to enable real-time data input from patient monitoring devices, allowing continuous analysis and immediate diagnostic feedback. This integration could improve patient outcomes by providing timely interventions based on real-time data.
- **Handling Complex Conditions:**
  Expanding the models to handle more complex medical conditions by collecting and utilizing larger and more diverse datasets that encompass a wide range of disease combinations and patient demographics. This will help the models recognize and accurately diagnose a wider variety of health conditions.
- **Enhanced Computational Efficiency:**
  Addressing computational limitations by developing more efficient algorithms and leveraging advanced computational infrastructure to reduce training times

and improve system responsiveness. Techniques such as parallel processing and optimization algorithms can be explored to enhance performance.

- **Advanced Machine Learning Techniques:**
  Incorporating advanced machine learning techniques, such as deep learning and natural language processing (NLP), to further improve diagnostic accuracy. Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), can be explored for more nuanced analysis of physiological data, and NLP can enhance the system by processing and analyzing unstructured clinical notes and patient histories.
- **Multimodal Data Integration:**
  Integrating additional sources of health data, such as genetic information, lifestyle factors, and environmental data, to provide a more comprehensive assessment of a patient's health. This multimodal approach could lead to more personalized and precise medical recommendations.
- **Patient-Centric Features:**
  Enhancing the user interface with more patient-centric features, such as personalized health plans, educational resources, and interactive tools for monitoring progress, to increase patient engagement and adherence to medical advice. Features that allow patients to track their health metrics over time and receive alerts for abnormal readings can further improve the system's utility.
- **Regulatory Compliance and Data Security:**
  Ensuring regulatory compliance and robust data security measures to protect patient data. Future work should focus on meeting healthcare regulations, such as HIPAA and GDPR, and implementing advanced security protocols.
- **Clinical Validation and Trials:**
  Conducting extensive clinical validation and trials to establish the diagnostic system's reliability and efficacy in real-world settings. Collaboration with healthcare institutions for pilot studies and clinical trials can provide valuable insights and help refine the system based on practical feedback.

By addressing these areas, future research can build on the foundations laid in this thesis, leading to the development of more sophisticated, efficient, and comprehensive diagnostic tools. Such advancements have the potential to revolutionize healthcare delivery, improve patient outcomes, and contribute to the broader field of medical technology.

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A. Appendix

A.1 Code Listings

Listing A.1: Heart Rate Training Code

```
from sklearn.model_selection import train_test_split,
    GridSearchCV, StratifiedKFold
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score,
    classification_report
import updatedstuff
import numpy as np
import pickle
from imblearn.over_sampling import SMOTE

# Extract features and labels from all_dict
features = []
labels = []

all_dict = updatedstuff.all_dict
diagnosis_list = updatedstuff.unique_diagnoses

# Extract features and binary labels for each disease
for patient_data in all_dict:
    feature_vector = [
        patient_data['Age'],
        patient_data['EWA_ABSAmp_P'],
        patient_data['EWA_ABSAmp_Q'],
        patient_data['EWA_ABSAmp_R'],
        patient_data['EWA_ABSAmp_S'],
        patient_data['EWA_ABSAmp_T'],
```

```
patient_data['EWA_Amp_R_to_P'],
patient_data['EWA_Amp_R_to_T'],
patient_data['FA_Frequency_Width'],
patient_data['FA_Peak_Frequency'],
patient_data['FA_Spectral_Entropy'],
patient_data['FA_Total_Power'],
patient_data['HRM_Average_HR'],
patient_data['HRM_Max_HR'],
patient_data['HRM_Min_HR'],
patient_data['HRM_PNN50'],
patient_data['HRM_RMSSD'],
patient_data['HRM_Sdnn_RR'],
patient_data['Mean_P'],
patient_data['Mean_Q'],
patient_data['Mean_R'],
patient_data['Mean_S'],
patient_data['Mean_T'],

patient_data['Median_P'],
patient_data['Median_Q'],
patient_data['Median_R'],
patient_data['Median_S'],
patient_data['Median_T'],

patient_data['cv_P'],
patient_data['cv_Q'],
patient_data['cv_R'],
patient_data['cv_S'],
patient_data['cv_T'],

patient_data['Std_Dev_P'],
patient_data['Std_Dev_Q'],
patient_data['Std_Dev_R'],
patient_data['Std_Dev_S'],
patient_data['Std_Dev_T'],

patient_data['Range_P'],
patient_data['Range_Q'],
patient_data['Range_R'],
patient_data['Range_S'],
```

```
            patient_data['Range_T'],

            # Add other features as needed
        ]
        features.append(feature_vector)
        binary_label = np.zeros(len(diagnosis_list))
        for i, diagnosis in enumerate(diagnosis_list):
            if diagnosis in patient_data['Diagnosis']:
                binary_label[i] = 1
        labels.append(binary_label)

# Convert lists to numpy arrays
X = np.array(features)
y = np.array(labels)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
    test_size=0.2, random_state=42)

# Apply SMOTE oversampling to the training data
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(
    X_train, y_train)

# Define the parameter grid
param_grid = {
    'n_estimators': [50, 100, 200, 300],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Train a separate classifier for each label
classifiers = []
best_params = []
for i in range(y_train_resampled.shape[1]):
    clf = RandomForestClassifier(random_state=42,
        class_weight='balanced')
```

```python
        grid_search = GridSearchCV(estimator=clf, param_grid=param_grid, cv=StratifiedKFold(3), scoring='accuracy')
        grid_search.fit(X_train_resampled, y_train_resampled[:, i])
        classifiers.append(grid_search.best_estimator_)
        best_params.append(grid_search.best_params_)

# Predict the probabilities for each label
y_proba = np.hstack([clf.predict_proba(X_test)[:, 1].reshape(-1, 1) for clf in classifiers])

# Make predictions on the test set using the best model
y_pred = (y_proba > 0.5).astype(int)

# Filter out classes with 0 support
non_zero_classes = [class_label for class_label, support in zip(range(len(y_test[0])), y_test.sum(axis=0)) if support > 0]
filtered_y_test = y_test[:, non_zero_classes]
filtered_y_pred = y_pred[:, non_zero_classes]

diagnosis_list= list(diagnosis_list)

# Evaluate the model
accuracy = accuracy_score(filtered_y_test, filtered_y_pred)
print("Accuracy:", accuracy)
print("Best Parameters for Each Label:")
for i, params in enumerate(best_params):
    print(f"Label {i + 1}: {params}")
print("Classification Report:")
print(classification_report(filtered_y_test, filtered_y_pred, target_names=[diagnosis_list[i] for i in non_zero_classes], zero_division=1))

# Serialize the trained model to a file
with open('HR_trained_modelz.pkl', 'wb') as f:
    pickle.dump(classifiers, f)
```

Listing A.2: BP Training Code

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report,
    accuracy_score
from sklearn.preprocessing import LabelEncoder
import joblib

# Load the generated blood pressure dataset
df = pd.read_csv("blood_pressure_dataset.csv")

# Extract blood pressure values and categories
X = df[['Systolic', 'Diastolic']]
y = df['Category']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
    test_size=0.2, random_state=42, stratify=y)

# Encode categorical labels into numerical representations
label_encoder = LabelEncoder()
y_train_encoded = label_encoder.fit_transform(y_train)
y_test_encoded = label_encoder.transform(y_test)

# Calculate class weights
class_weights = {label: 1 / count for label, count in zip(
    np.unique(y_train_encoded), np.bincount(y_train_encoded
    ))}

# Create and train the Random Forest classifier with class
    weights
clf = RandomForestClassifier(class_weight=class_weights,
    random_state=42)
clf.fit(X_train, y_train_encoded)

# Make predictions on the test set
y_pred = clf.predict(X_test)
```

```
# Decode predictions back to original labels if needed
y_pred_decoded = label_encoder.inverse_transform(y_pred)

# # Evaluate the model
# print("Accuracy:", accuracy_score(y_test_encoded, y_pred
    ))
# print("Classification Report:\n", classification_report(
    y_test_encoded, y_pred, zero_division=1))

# Make predictions on the independent test set
X_test_independent = df[['Systolic', 'Diastolic']]
y_test_independent = df['Category']
y_pred_independent = clf.predict(X_test_independent)
y_pred_decoded_independent = label_encoder.
    inverse_transform(y_pred_independent)

# Evaluate the model on the independent test set
accuracy_independent = accuracy_score(y_test_independent,
    y_pred_decoded_independent)
classification_report_independent = classification_report(
    y_test_independent, y_pred_decoded_independent)

print("Accuracy␣on␣independent␣test␣set:",
    accuracy_independent)
print("Classification␣Report␣on␣independent␣test␣set:\n",
    classification_report_independent)

# Example input data (systolic and diastolic blood
    pressure values)
input_data = [[120, 80], [140, 90], [150, 120]]  # Example
     input: [systolic, diastolic]

# Make predictions using the model
predictions = clf.predict(input_data)

# Display the predictions
print("Predictions:")
for i, pred in enumerate(predictions):
    systolic, diastolic = input_data[i]
```

```
    print(f"Input␣{i+1}:␣Systolic␣—␣{systolic},␣Diastolic␣
       —␣{diastolic}␣—␣Predicted␣class:␣{label_encoder.
       inverse_transform([pred])[0]}")

# Save the trained model
joblib.dump(clf, 'blood_pressure_model.pkl')
np.save('bp_label_classes.npy', label_encoder.classes_)
```

Listing A.3: Flask Code

```
from flask import Flask, render_template, request
import scipy.io
from io import BytesIO
import numpy as np
from matplotlib import pyplot as plt
import base64
import sys
import pickle
import logging
import joblib

sys.path.append('/Users/aashika/Desktop/Classes/Semester
   -3/Thesis/PythonFiles/Heartrate')
from Functions_HR import pre_processing, get_features

app = Flask(__name__)

# Set up logging
logging.basicConfig(level=logging.DEBUG)

def flatten_features(features_dict):
    feature_list = []
    for key in sorted(features_dict.keys()):  # Sort keys
       to preserve order
        value = features_dict[key]
        if isinstance(value, (list, np.ndarray)):
```

```
                feature_list.extend(np.ravel(value))  # Flatten any nested lists or arrays
            else:
                feature_list.append(value)
    return np.array(feature_list)

# Load models and label encoders
def load_model_and_labels(model_path, label_path):
    try:
        clf = joblib.load(model_path)
        label_classes = np.load(label_path, allow_pickle=True)
        return clf, label_classes
    except Exception as e:
        logging.exception(f'Failed to load model or label classes from {model_path} or {label_path}')
        return None, None

temp_clf, temp_label_classes = load_model_and_labels('temp_random_forest_model.pkl', 'temp_label_classes.npy')
bp_clf, bp_label_classes = load_model_and_labels('blood_pressure_model.pkl', 'bp_label_classes.npy')
rr_clf, rr_label_classes = load_model_and_labels('RR_RandomForest_model.pkl', 'rr_label_classes.npy')
spo2_clf, spo2_label_classes = load_model_and_labels('spo2_random_forest_model.pkl', 'spo2_label_classes.npy')

def get_diagnosis(clf, label_classes, input_data):
    prediction_encoded = clf.predict(input_data)
    prediction_decoded = label_classes[prediction_encoded]
    return prediction_decoded[0]

# Define dictionaries
weights = {
    'heart_rate': 15,
    'blood_pressure': 20,
    'body_temperature': 10,
    'respiratory_rate': 10,
```

```
    'spo2': 15
}

scores = {
    'heart_rate': {
        'Sinus␣Rhythm': 100,
        'Sinus␣Bradycardia': 75,
        'Sinus␣Tachycardia': 75,
        'Atrial␣Fibrillation': 50
    },
    'blood_pressure': {
        'hypotension': 75,
        'normal': 100,
        'elevated': 75,
        'hypertension_stage_1': 50,
        'hypertension_stage_2': 25,
        'hypertensive_crisis': 10
    },
    'body_temperature': {
        'low␣temperature': 50,
        'normal': 100,
        'elevated␣temperature': 75,
        'moderate␣fever': 50,
        'high␣fever': 25,
        'very␣high␣fever': 10
    },
    'respiratory_rate': {
        'Normal': 100,
        'Bradypnoea': 75,
        'Tachypnoea': 75
    },
    'spo2': {
        'Normal␣Blood␣Oxygen␣levels': 100,
        'Concerning␣Blood␣Oxygen␣levels': 75,
        'Low␣Blood␣Oxygen␣levels': 50,
        'Low␣Blood␣Oxygen␣levels␣that␣can␣affect␣your␣
           brain': 25,
        'Cyanosis': 10
    }
}
```

```
recommendations = {
    'heart_rate': {
        'Sinus␣Rhythm': 'Maintain␣current␣lifestyle.␣Make␣
            sure␣to␣include␣regular␣exercise,␣balanced␣diet
            ,␣and␣stress␣management␣to␣keep␣your␣heart␣
            rhythm␣normal.',
        'Sinus␣Bradycardia': 'Bradycardia␣is␣when␣the␣
            heart␣rhythm␣is␣slower␣than␣normal.␣If␣
            asymptomatic,␣monitor␣regularly.␣If␣
            experiencing␣symptoms␣like␣dizziness␣or␣fatigue
            ,␣consult␣a␣healthcare␣provider␣for␣further␣
            evaluation.',
        'Sinus␣Tachycardia': 'Tachycardia␣is␣when␣the␣
            heart␣rhythm␣is␣faster␣than␣normal.␣Reduce␣
            caffeine␣and␣alcohol␣intake,␣manage␣stress␣
            through␣relaxation␣techniques,␣and␣consult␣a␣
            healthcare␣provider␣if␣the␣condition␣persists.'
            ,
        'Atrial␣Fibrillation': 'Seek␣medical␣advice␣to␣
            manage␣and␣treat␣atrial␣fibrillation.␣Follow␣
            prescribed␣medication␣regimen␣and␣consider␣
            lifestyle␣changes␣like␣reducing␣alcohol␣
            consumption␣and␣increasing␣physical␣activity.'
    },
    'blood_pressure': {
        'hypotension': 'For␣Hypotension,␣increase␣fluid␣
            and␣salt␣intake␣under␣medical␣supervision,␣
            avoid␣sudden␣position␣changes,␣and␣consult␣a␣
            healthcare␣provider␣if␣symptoms␣persist.',
        'normal': 'Blood␣pressure␣normal,␣avoid␣excessive␣
            salt␣and␣alcohol␣to␣keep␣blood␣pressure␣within␣
            the␣normal␣range.',
        'elevated': 'Elevated␣BP␣can␣put␣you␣at␣risk.␣
            Adopt␣a␣heart-healthy␣diet,␣reduce␣sodium␣
            intake,␣increase␣physical␣activity,␣and␣monitor
            ␣blood␣pressure␣regularly.',
        'hypertension_stage_1': 'To␣treat␣1st␣stage␣
            Hypertension,␣you␣require␣some␣lifestyle␣
            modifications␣including␣a␣DASH␣diet,␣regular␣
```

```
        exercise,␣weight␣loss␣if␣overweight,␣and␣
        regular␣monitoring␣of␣blood␣pressure.␣Consult␣a
        ␣healthcare␣provider␣for␣potential␣medication.'
        ,
    'hypertension_stage_2': 'To␣treat␣2nd␣stage␣
        Hypertension,␣you␣will␣need␣to␣follow␣a␣strict␣
        regimen␣of␣prescribed␣antihypertensive␣
        medication,␣make␣significant␣lifestyle␣changes,
        ␣and␣schedule␣regular␣follow-ups␣with␣a␣
        healthcare␣provider.',
    'hypertensive_crisis': 'Seek␣immediate␣medical␣
        attention␣to␣treat␣Hypertensive␣Crisis.␣This␣
        condition␣requires␣urgent␣treatment␣to␣prevent␣
        serious␣complications..'
},
'body_temperature': {
    'low␣temperature': 'Stay␣warm␣and␣hydrated,␣avoid␣
        exposure␣to␣cold,␣and␣seek␣medical␣advice␣if␣
        body␣temperature␣remains␣low.',
    'normal': 'Monitor␣Body␣temperature␣regularly␣to␣
        ensure␣it␣stays␣in␣the␣normal␣range',
    'elevated␣temperature': 'For␣elevated␣temperature,
        ␣take␣rest,␣stay␣hydrated,␣and␣monitor␣for␣
        other␣symptoms.␣Seek␣medical␣advice␣if␣the␣
        temperature␣persists␣or␣other␣symptoms␣develop.
        ',
    'moderate␣fever': 'For␣a␣moderate␣fever,␣take␣rest
        ,␣stay␣hydrated,␣take␣antipyretics␣like␣
        acetaminophen␣or␣ibuprofen␣as␣needed,␣and␣
        consult␣a␣healthcare␣provider␣if␣the␣fever␣
        persists.',
    'high␣fever': 'Seek␣medical␣attention,␣as␣high␣
        fever␣can␣indicate␣a␣serious␣infection␣or␣other
        ␣health␣issues.␣Ensure␣adequate␣hydration␣and␣
        rest.',
    'very␣high␣fever': 'Seek␣immediate␣medical␣
        attention;␣very␣high␣fever␣can␣be␣life-
        threatening␣and␣requires␣urgent␣treatment.'
},
'respiratory_rate': {
```

```
        'Normal': 'To maintain normal Respiration rate, avoid smoking, and ensure good air quality in your environment.',
        'Bradypnoea': 'Bradypnoea is when the breathing rate is lower than normal. Seek medical evaluation to determine the underlying cause. Avoid medications that can depress respiration and monitor for symptoms like dizziness or fatigue.',
        'Tachypnoea': 'Tachypnoea is when the breating rate is higher than normal.Identify and manage underlying causes such as infections, asthma, or anxiety. Seek medical advice if the condition persists.'
    },
    'spo2': {
        'Normal Blood Oxygen levels': 'Continue maintaining a healthy lifestyle, avoid smoking, and ensure regular physical activity to keep oxygen levels optimal.',
        'Concerning Blood Oxygen levels': 'Oxygen levels are concerning. Monitor regularly, increase oxygen intake by breathing deeply, and consult a healthcare provider for further evaluation.',
        'Low Blood Oxygen levels': 'Seek medical attention to identify and treat the underlying cause of low blood oxygen. Use supplemental oxygen if prescribed by a healthcare provider.',
        'Low Blood Oxygen levels that can affect your brain': 'Seek immediate medical attention, as severely low oxygen levels can lead to serious complications. Follow prescribed oxygen therapy and treatment plans.',
        'Cyanosis': 'Seek urgent medical attention, as cyanosis indicates critically low oxygen levels in the blood. Immediate intervention is necessary.'
    }
}
```

```python
def calculate_health_score(diagnoses):
    total_score = 0
    total_weight = 0
    detailed_recommendations = {}

    for parameter, diagnosis in diagnoses.items():
        score = scores[parameter][diagnosis]
        weight = weights[parameter]
        total_score += score * weight
        total_weight += weight
        detailed_recommendations[parameter] =
            recommendations[parameter][diagnosis]

    health_score = total_score / total_weight if
        total_weight > 0 else 0

    return health_score, detailed_recommendations

@app.route('/', methods=['GET', 'POST'])
def upload_file():
    if request.method == 'POST':
        try:
            # Handle file uploads
            if 'files' not in request.files:
                return render_template('index.html',
                    message='Please upload both .hea and .
                    mat files for ECG analysis.')

            files = request.files.getlist('files')

            if len(files) != 2:
                return render_template('index.html',
                    message='Please upload exactly two
                    files: one .hea and one .mat file.')

            file_hea, file_mat = None, None
            for file in files:
                if file.filename.endswith('.hea'):
                    file_hea = file
                elif file.filename.endswith('.mat'):
```

```
            file_mat = file

    if file_hea is None or file_mat is None:
        return render_template('index.html',
            message='Please upload both .hea and .
            mat files.')

    header_contents = file_hea.read().decode('utf
      -8').splitlines()
    age, gender = None, None
    for line in header_contents:
        if line.startswith('#Age'):
            age = int(line.strip().split(': ')
                [-1])
        if line.startswith('#Sex'):
            gender_value = line.strip().split(': '
                )[-1]
            gender = "Male" if gender_value == '
                Male' else "Female"

    if age is None or gender is None:
        return render_template('index.html',
            message='Missing age or gender
            information in .hea file')

    mat_content = file_mat.read()
    mat = scipy.io.loadmat(BytesIO(mat_content))

    if 'val' in mat:
        numpy_array = mat['val']
        first_row = numpy_array[0]
        pre_processed_row = pre_processing(
            first_row, notch_frequency=60,
            notch_bandwidth=2, baseline_window_size
            =100, fs=500)

        num_samples = len(first_row)
        time = np.linspace(0, num_samples - 1,
            num_samples)
        plt.figure(figsize=(12, 6))
```

```
plt.plot(time, pre_processed_row)
plt.xlabel('Time (ms)')
plt.ylabel('Amplitude')
plt.grid()

img_bytes = BytesIO()
plt.savefig(img_bytes, format='png')
img_bytes.seek(0)
plt.close()

encoded_img = base64.b64encode(img_bytes.
    getvalue()).decode('utf-8')

features_dict = get_features(
    pre_processed_row, age)
logging.debug(f"Features dictionary: {
    features_dict}")
heart_rate = features_dict['HRM_Average_HR
    ']

X_new = flatten_features(features_dict).
    reshape(1, -1)

logging.debug(f"Shape of X_new: {X_new.
    shape}")
logging.debug(f"Flattened features: {X_new
    }")

with open('HR_trained_model.pkl', 'rb') as
     f:
     trained_models = pickle.load(f)

y_pred_list = []
for i, model in enumerate(trained_models):

     y_pred_proba = model.predict_proba(
         X_new)
     logging.debug(f"Model {i} predicted 
         probabilities: {y_pred_proba}")
     y_pred_list.append(y_pred_proba[0][1])
```

```
        logging.debug(f"Predicted␣probabilities␣
            list:␣{y_pred_list}")

        y_pred = np.array(y_pred_list)
        logging.debug(f"Prediction␣array:␣{y_pred}
            ")

        HR_labels = ['Atrial␣Fibrillation', 'Sinus
            ␣Rhythm', 'Sinus␣Bradycardia', 'Sinus␣
            Tachycardia']
        max_pred_index = np.argmax(y_pred)
        final_diagnosis = HR_labels[max_pred_index
            ]
    else:
        return render_template('index.html',
            message='Invalid␣.mat␣file␣format')

    # Handle Temperature input
    temperature = None
    if 'temperature' in request.form:
        temperature = float(request.form['
            temperature'])
        temperature_diagnosis = get_diagnosis(
            temp_clf, temp_label_classes, np.array
            ([[temperature]]))
        min_temp = 35.0  # Minimum temperature for
             color bar
        max_temp = 42.0  # Maximum temperature for
             color bar
        arrowPosition = (temperature - min_temp) /
             (max_temp - min_temp)
    else:
        temperature_diagnosis = 'Temperature␣input
            ␣missing.'

    # Handle Blood Pressure input
    systolic, diastolic = None, None
    if 'bp_values' in request.form:
        bp_values = request.form['bp_values']
```

```python
    if '/' in bp_values:
        systolic, diastolic = map(float, bp_values.split('/'))
        bp_diagnosis = get_diagnosis(bp_clf, bp_label_classes, np.array([[systolic, diastolic]]))
    else:
        bp_diagnosis = 'Invalid input format for blood pressure. Please use "systolic/diastolic" format.'
else:
    bp_diagnosis = 'Blood pressure input missing.'

# Handle Respiration Rate input
respiration_rate = None
if 'respiration_rate' in request.form:
    respiration_rate = float(request.form['respiration_rate'])
    rr_diagnosis = get_diagnosis(rr_clf, rr_label_classes, np.array([[respiration_rate]]))
else:
    rr_diagnosis = 'Respiration rate input missing.'

# Handle SpO2 input
spo2 = None
if 'spo2' in request.form:
    spo2 = float(request.form['spo2'])
    spo2_diagnosis = get_diagnosis(spo2_clf, spo2_label_classes, np.array([[spo2]]))
else:
    spo2_diagnosis = 'SpO2 input missing.'

# Calculate health score and recommendations
diagnoses = {
    'heart_rate': final_diagnosis,
    'blood_pressure': bp_diagnosis,
    'body_temperature': temperature_diagnosis,
```

```
        'respiratory_rate': rr_diagnosis,
        'spo2': spo2_diagnosis
    }

    health_score, recommendations =
        calculate_health_score(diagnoses)
    heart_rate_recommendation = recommendations['
        heart_rate']
    bp_recommendation = recommendations['
        blood_pressure']
    temperature_recommendation = recommendations['
        body_temperature']
    respiratory_rate_recommendation =
        recommendations['respiratory_rate']
    spo2_recommendation = recommendations['spo2']

    return render_template('result.html',
                           message='Vitals␣
                               analysis␣complete',
                           plot=encoded_img,
                           age=age,
                           gender=gender,
                           heart_rate=round(
                               heart_rate),
                           ecg_prediction=
                               final_diagnosis,
                           temperature=temperature
                               ,
                           temperature_diagnosis=
                               temperature_diagnosis
                               ,
                           arrowPosition=
                               arrowPosition,
                           systolic=systolic,
                           diastolic=diastolic,
                           bp_diagnosis=
                               bp_diagnosis,
                           respiration_rate=
                               respiration_rate,
                           rr_diagnosis=
```

```
                                    rr_diagnosis,
                                spo2=spo2,
                                spo2_diagnosis=
                                    spo2_diagnosis,
                                health_score=round(
                                    health_score),
                                heart_rate_recommendation
                                    =
                                    heart_rate_recommendation
                                    ,
                                bp_recommendation=
                                    bp_recommendation,
                                temperature_recommendation
                                    =
                                    temperature_recommendation
                                    ,
                                respiratory_rate_recommendation
                                    =
                                    respiratory_rate_recommendation
                                    ,
                                spo2_recommendation=
                                    spo2_recommendation)

        except Exception as e:
            logging.exception('An error occurred during
                processing')
            return render_template('index.html', message=f
                'An error occurred during processing: {str(
                e)}')
    return render_template('index.html')


if __name__ == '__main__':
    app.run(debug=True)
```

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Thesen

Master-Thesis

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- A health evaluation system is developed, to provide a comprehensive health status analysis using vital sign data.
- AI-based predictive modelling using Python has been used for each vital sign, creating individual models for each, and then synthesizing these models into a unified framework.
- A flask application has been created to provide an interface where users can enter vital sign details and obtain the comprehensive health analysis, an overall health score, and personalised recommendations to improve their health.

Declaration

I hereby declare that I have completed this work independently and have used only the sources and aids referenced.
All parts of this work that include phrases or points taken from other sources are clearly marked with their origins. This includes diagrams, sketches, visual representations, and online sources.
I also declare that I have not submitted this work in any other examination process and will not do so in the future.
The submitted written work corresponds exactly to the electronic version. I consent to an electronic copy being made and stored for the purpose of verification by anti-plagiarism software.

Place, Date Signature