POLITECNICO DI TORINO

Master Degree
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Master Thesis

Prediction of Cardiovascular Complications using Multi-modal Data

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Summary

This study aims to predict the risk of cardiovascular complications in elderly patients after open-heart surgery based on multimodal data. Single-lead Electrocardiogram (ECG) signals and tri-axial accelerometer data were collected from 80 patients using a chest-worn heart rate monitor during various physical tests, including the veloergometry test, six-minute walk test (6MWT), stair climbing test, time up and go (TUG) test, and gait analysis on a treadmill. To ensure data reliability and analytical accuracy, multi-level preprocessing was applied to the ECG and accelerometer data, including resampling, filtering, outlier detection and removal, and data segmentation.

In data analysis, Machine Learning (ML) algorithms, including decision trees, k-Nearest Neighbors (KNN), and random forests, were employed to classify the types of physical activities (e.g., stair climbing, walking, and cycling) performed by the patients. Subsequently, a random forest model was utilized to predict patients' heart function status under different activity contexts, adopting the New York Heart Association (NYHA) Functional Classification as an evaluation standard. For each prediction task, the results were compared using only clinical features (e.g., height, age, weight, postoperative days, type of surgery), only sensor features (ECG and accelerometer data), and a fusion of both in a multimodal approach. When using only clinical features, the model achieved an accuracy of 68.7% on the test set, with a precision of 69.05%, recall of 68.75%, and F1 score of 68.63%, highlighting its limited ability to generalize across datasets. The performance showed instability across multiple runs, with an average accuracy of 54.38% $\pm$ 7.82%. For sensor features, cycling and combined activities achieved higher accuracies of 66.67% and 68.75%, respectively. However, activities such as walking faced challenges, with precision as low as 25%, despite a perfect recall of 100%. This imbalance led to lower F1 scores, indicating misclassification issues. In contrast, the multimodal approach significantly improved model performance. After integrating clinical features and sensor features, combined activities achieved the highest accuracy of 87.5%, followed by cycling at 86.67%. Precision and recall improved across all activity types, with the combined activity and cycling achieving F1 scores of 85.71% and 83.33%, respectively. These results demonstrate that the integration of clinical and sensor data provides a more robust and reliable prediction model, significantly outperforming the single-modality approaches.

By analyzing the effectiveness of multimodal data in predicting cardiovascular complications, the varying impacts of different activities and features on the prediction outcomes were evaluated. For example, the veloergometry test was found

to be more predictive than stair climbing, and integrating results from multiple activities and features provided a more comprehensive risk assessment. Feature importance analysis identified key features with the greatest influence on prediction results, offering valuable clinical insights for early diagnosis and risk management of cardiovascular diseases. This study highlighted the advantages of integrating clinical data and sensor data with the NYHA classification system, emphasizing its role in improving the accuracy and robustness of heart function predictions. Compared to existing approaches, such as frailty-based indicators, the NYHA system combined with gait analysis provides a more dynamic evaluation of cardiac health under various activity contexts. However, some limitations were identified, including the reliance on publicly available datasets, which may introduce variability in data quality and consistency due to differences in data collection protocols across studies. Future work should focus on validating the model with larger and more diverse datasets, exploring more efficient feature selection and data preprocessing techniques, and integrating additional physiological indicators (e.g., blood oxygen saturation) to further improve model robustness and applicability.

In conclusion, this research demonstrates the potential of multimodal data fusion to enhance the prediction of cardiovascular complications. By integrating clinical and sensor features across diverse activity types, the proposed model offers a more comprehensive and reliable tool for assessing heart function, paving the way for improved early diagnosis and personalized risk management strategies in clinical practice.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

Cardiovascular disease (CVDs) is a general term that refers to all types of diseases affecting the circulatory system, including the heart and blood vessels, which are responsible for replacing and transporting blood [1]. CVDs is the leading cause of non-communicable deaths in Europe (accounting for about 50% of all deaths, and approximately 30% of all deaths globally) [2]. Despite significant advancements in modern medicine in prevention and treatment, early prediction and intervention of cardiovascular complications remain a pressing issue.

Cardiovascular complications include heart failure, atrial fibrillation (AF), chronic obstructive pulmonary disease (COPD), depression, musculoskeletal system diseases, oncological diseases, and others [3]. Typical symptoms include chest pain or discomfort, shortness of breath, dizziness, fainting, or palpitations, all of which impose a significant burden on patients and affect their quality of life. Diagnosing cardiovascular complications requires a comprehensive consideration of the patient's medical history, physical examination results, and various diagnostic tests. Traditional diagnostic methods include electrocardiograms, echocardiography, coronary angiography, stress tests, magnetic resonance imaging, and intravascular ultrasound [1]. However, few studies have reported that improved ML models can achieve early detection and diagnosis of heart disease compared to traditional methods [4]. This provides an opportunity for us to use multimodal data to predict cardiovascular complications.

Many studies have shown that there are differences in gait patterns between people with and without CVDs [4]. On the other hand, exercise-based cardiac rehabilitation has been proven to help improve the physical fitness and quality of life of patients with CVDs [5]. Exercise electrocardiogram testing is low-cost, reliable, and reproducible, and it can provide relevant disease interpretation. It plays an important role in predicting the risk of adverse cardiovascular events.

In the past decade, the effectiveness and prevalence of smart wearable devices have significantly increased. There is a wide variety of smart wearable devices used for the diagnosis, monitoring, and treatment of CVDs, including wristbands, patches, headbands, glasses, and necklaces [6]. Analysis of heart rate monitoring data from mainstream market brands of heart rate chest straps and smartwatches shows that chest straps remain the most accurate consumer-grade heart rate monitoring devices [7]. Theoretically, chest straps are closer to the heart, and their monitoring technology directly reads heartbeats rather than using optical sensors to monitor blood flow and then using software for conversion. This eliminates issues of accuracy affected by light and skin.

With the continuous development of digital technology, wearable technology and artificial intelligence (AI) have been deeply applied to cardiovascular complications and other diseases. Wearable technology offers lightweight, portable, easy-to-use, and affordable devices that can provide accurate body measurements [8]. The application of multimodal data in CVDs research has shown great potential, helping to improve disease management and accelerate the development of new therapies.

1.1 Incidence and Prevalence of Cardiovascular Complications

CVDs are the leading cause of morbidity and mortality worldwide. CVDs impose a significant health and economic burden globally [9].

Prevalence is the proportion of a population that has a specific disease or condition at a given point in time. Prevalence is typically presented in a standardized manner to allow for comparisons across different populations [10].

Gregory et al. [11] used estimates from the 2019 Global Burden of Disease (GBD) study to review the overall burden of CVDs. By utilizing all available population-level data sources on incidence, prevalence, case fatality, mortality, and health risks, they estimated the burden in 204 countries and regions from 1990 to 2019. The GBD is an ongoing multinational collaborative project aimed at providing comparable and consistent estimates of population health over time.

The study shows a certain relationship between CVDs incidence and age. As shown in Figure 1.1, the prevalence of CVDs has been steadily increasing, with the total number of cases rising from 271 million in 1990 to 523 million in 2019. The figure indicates that while the age-standardized prevalence is gradually decreasing, the total age-specific prevalence is steadily increasing, suggesting that aging is a major factor contributing to the overall increase in CVDs.

On the other hand, the occurrence of CVDs is also closely related to gender. In 2019, the total number of disability-adjusted life years (DALYs) due to CVDs was higher in males than in females before the age of 80 to 84 (Figure 1.2). After this age, the pattern reverses. The gender difference in DALYs is most pronounced

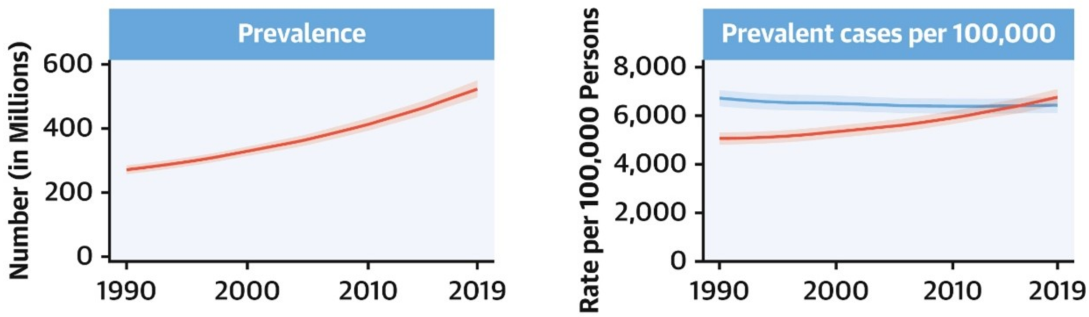

Figure 1.1. Total number and incidence of CVDs (Age-standardized prevalence (blue line) and all-age prevalence (red line) of CVDs from 1990 to 2019. The shaded areas represent the 95 % uncertainty intervals).

between the ages of 30 to 60 (higher in males) and over 80 (higher in females). Starting from the age of 80 to 84, the excess mortality from CVDs in females should focus attention on age-specific causes of death in the elderly and impact secondary prevention strategies.

Prevalence refers to the proportion of the general population affected by CVDs at a specific point in time, while incidence refers to the number of new diagnoses of CVDs within a certain time period.

Melanie Nichols et al. [2] stated in their article that population-based hospitalization rates for CVDs have been on the rise since the early 2000s (as shown in Table 1.1).

In 2012, the median number of discharges per 100,000 people for various countries was 2,097 for CVDs, 608 for coronary heart disease, and 298 for stroke, higher than the respective numbers in 2001, which were 1,829, 532, and 258. In recent years, more countries have seen an increase in CVDs discharge rates (34 countries) compared to those with a decrease (15 countries). Significant differences between countries are also evident in hospitalization rates.

1.2 Etiology and Risk Factors of Cardiovascular Complications

The main causes of cardiovascular complications can be categorized into four aspects: (1) vascular factors such as atherosclerosis, hypertensive arteriolosclerosis, and arteritis [12]; (2) hemodynamic factors like hypertension [13]; (3) hemorheological abnormalities such as hyperlipidemia and diabetes [14]; and (4) blood

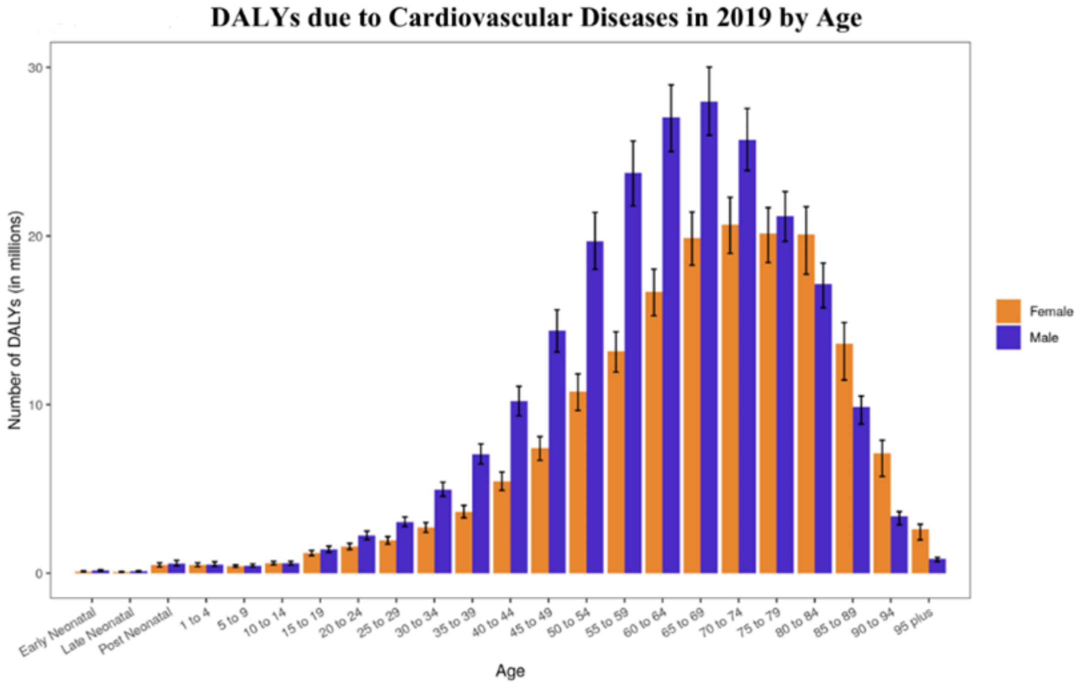

Figure 1.2. Number of DALYs due to CVDs by age and sex with 95 % uncertainty intervals, 2019.

component factors including leukemia, anemia, and thrombocytosis [15]. The related risk factors are as follows:

- Hypertension: Prolonged hypertension can cause the arterial walls to thicken or harden, leading to narrowed vessel lumens and impaired blood supply to the heart. Hypertension increases the workload of the heart, making left ventricular hypertrophy more likely, which can further lead to hypertensive heart disease and heart failure [12]. Additionally, hypertension accelerates the process of arteriosclerosis, causing damage to endothelial cells. This damage facilitates platelet aggregation at the injury site, increasing the risk of thrombosis and triggering myocardial infarction [16].

- Blood viscosity: The fast-paced nature of modern life, increasing pressures from work and family, and growing emotional instability contribute to higher blood viscosity [13]. Excessive alcohol consumption, high intake of dietary fats, lack of necessary exercise, and environmental pollution, along with a sharp decrease in the negative ion content in the air, lead to insufficient intake of negative ions. These factors directly cause a slowdown in metabolic

		2001	2012			2001	2012
Albania	(2001–2011)	520	776	Andorra	(2001–2012)	610	749
Armenia	(2001–2012)	599	1666	Austria	(2001–2009)	3615	3697
Azerbaijan	(2001–2012)	484	783	Belarus	(2001–2012)	4749	6401
Belgium	(2001–2008)	2347	2173	Bulgaria	(2001–2010)	2013	3617
Croatia	(2001–2010)	1692	1847	Cyprus	(2001–2008)	927	672
Czech Republic	(2001–2010)	3430	3086	Denmark	(2001–2010)	2546	2634
Estonia	(2001–2009)	3245	3327	Finland	(2001–2007)	3654	2913
France	(2001–2009)	2303	2282	Georgia	(2001–2012)	427	1116
Germany	(2001–2009)	3305	3500	Greece	(2001–2007)	2432	2786
Hungary	(2001–2010)	4039	3678	Iceland	(2001–2009)	1919	1440
Ireland	(2001–2010)	1492	1154	Israel	(2001–2008)	1925	1482
Italy	(2001–2009)	2572	2120	Kazakhstan	(2001–2012)	1389	2074
Kyrgyzstan	(2001–2011)	1036	1473	Latvia	(2001–2010)	3137	2884
Lithuania	(2001–2010)	3890	4490	Luxembourg	(2001–2007)	2364	2172
Malta	(2001–2010)	665	1341	Montenegro	(2001–2012)	1539	1732
Netherlands	(2001–2009)	1369	1694	Norway	(2001–2010)	2366	2368
Poland	(2003–2009)	2880	2885	Portugal	(2001–2010)	1156	1307
Republic of Moldova	(2001–2012)	1311	2532	Romania	(2001–2010)	2741	2982
Russian Federation	(2001–2012)	3020	3693	Serbia	(2001–2012)	1587	2199
Slovakia	(2001–2010)	2569	2689	Slovenia	(2001–2009)	1738	1976
Spain	(2001–2009)	1342	1295	Sweden	(2001–2009)	2556	2334
Switzerland	(2002–2009)	1699	1729	Tajikistan	(2001–2012)	561	1072
TFYR Macedonia	(2001–2007)	1398	1443	Turkey	(2001–2010)	1009	1502
Turkmenistan	(2001–2012)	1247	1933	Ukraine	(2001–2010)	2791	3854
UK	(2001–2010)	1405	1291	Uzbekistan	(2001–2012)	1059	1615

Table 1.1. Hospital discharges for CVDs per 100 000 population, by country, 2001–2012

rate, reduced blood flow velocity, and a rapid increase in blood viscosity [17]. This can result in inadequate blood supply to the heart. If not addressed promptly through prevention and adjustment, it can lead to coronary heart disease, hypertension, and other cardiovascular conditions.

- Smoking: Smokers have a significantly higher incidence of CVDs compared to non-smokers. Among those who smoke more than 20 cigarettes a day, the incidence of coronary heart disease is 2.8 times higher than that of non-smokers, and the mortality rates for coronary heart disease and cerebrovascular diseases are 5 times higher [18]. Smoking is the leading risk factor for cerebral infarction. Nicotine increases the levels of adrenaline in the plasma, promotes platelet aggregation, and causes endothelial cell contraction, leading to elevated blood viscosity factors [19].

- Abnormal metabolism of vascular smooth muscle cells: Like other tissues in the body, vascular tissue undergoes periodic metabolism. If new cell tissues fail to form properly during the metabolism of vascular smooth muscle cells, it can result in defects in the vascular wall, leading to impaired vasomotion. Blood vessels are crucial conduits for blood flow and are also regulated by the nervous system. Therefore, abnormalities in the nervous system can disrupt blood supply and contribute to cardiovascular disorders [20].

- Alcohol abuse: The amount of alcohol consumed has a direct dose-related effect on hemorrhagic stroke. Individuals who consume more than 66 grams of alcohol per day have an increased risk of myocardial infarction and cerebrovascular accidents [21]. Long-term heavy drinking can lead to increased platelet levels in the blood, resulting in poor blood flow regulation, arrhythmias, hypertension, and hyperlipidemia, which makes CVDs more likely to occur [22].

- Diabetes: Diabetes is an independent risk factor for heart disease and ischemic stroke. As the condition progresses, it gradually leads to various cardiovascular complications, such as coronary atherosclerosis, cerebral infarction, and the formation of atherosclerotic plaques in the lower limb arteries [14].

- Others: Factors such as obesity, insulin resistance, aging, gender (with a higher incidence in males compared to females), race, and genetics are also associated with an increased risk of CVDs [23].

1.3 Diagnosis of Cardiovascular Complications

Almost all diagnostic imaging methods for CVDs involve radiation. These methods can be categorized into invasive and non-invasive techniques.

Non-invasive tests do not require incisions or needle punctures, though they may involve blood draws or the insertion of a standard short intravenous (IV) catheter into the arm vein. These tests include:

- Computed Tomography (CT): A medical imaging technique that combines a series of X-ray images to create detailed cross-sectional images of internal structures such as the heart [24]. CT can detect structural abnormalities in the heart, pericardium (the sac surrounding the heart), major blood vessels, lungs, and supportive structures of the chest [25], Types of CT include multidetector CT, electron beam CT, and computed tomography angiography (CTA).

- ECG: A quick, simple, and painless medical test that measures the electrical impulses produced by the heart. During an ECG, these impulses are measured, amplified, and recorded. The resulting record, known as an ECG (or EKG), provides information such as the origin of each heartbeat (the pacemaker, known as the sinoatrial node), the heart's electrical conduction pathways, heart rate, and rhythm [26] [27] [28]. An ECG can sometimes reveal heart enlargement (e.g., possibly due to hypertension) or inadequate oxygen supply to the heart due to a blockage in a coronary artery [26] [28]. Conversely, arrhythmias and myocardial ischemia may be transient or unpredictable [28]. To detect these issues, doctors may use continuous ambulatory ECG, which records the heart's electrical activity continuously without interfering with the patient's daily activities [29].

- Magnetic Resonance Imaging (MRI): A medical imaging technique that uses strong magnetic fields and high-frequency radio waves to produce highly detailed images, including of the heart and chest. MRI is primarily used to diagnose complex congenital heart diseases and to differentiate between normal and abnormal tissues [30]. MRI has some drawbacks compared to CT or echocardiography. It takes longer to generate images, and because the heart is in motion, MRI images can be blurry. However, newer MRI techniques, such as ECG-gated MRI, can synchronize imaging with specific phases of the ECG, resulting in clearer images than traditional MRI scans [31].

- Positron Emission Tomography (PET): A type of medical imaging that falls under radioactive isotope scanning. PET creates images by detecting radiation from a radioactive substance administered to the patient, providing information related to myocardial function [32]. Radioactive isotopes emitting positrons (positively charged electrons) are used to label nutrients necessary for normal heart cell function, such as oxygen or glucose [32]. After injecting the labeled nutrient into a vein, it reaches the heart within minutes. Sensors detect the positrons and use them to create images of the examined body part.

- Radionuclide Imaging: A medical imaging technique that generates images by detecting radiation from a radioactive substance administered via IV injection [33]. Cardiac radionuclide imaging helps determine the cause of chest pain. A small amount of radioactive material (radionuclide) is used as a tracer and injected into the vein [34]. The patient receives a minimal amount of radiation from the radionuclide. The tracer emits gamma rays, which can be detected by a gamma camera. The computer automatically analyzes the received data and constructs images showing how much tracer is absorbed by the tissues [35].

- Stress Testing: Assesses heart function under stress conditions, such as exercise-induced or medication-induced stress, through an ECG [36]. If the heart's load is increased through exercise, patients typically walk on a treadmill or ride a stationary bike. If patients cannot perform the required exercise, medications are used to increase the heart's load (pharmacological stress test) [37].

- Tilt Table Test: A medical examination that measures the effects of different body positions on heart rate, rhythm, and blood pressure [38] [39]. The tilt table test is usually recommended for patients who experience unexplained fainting (syncope) without structural heart disease (e.g., aortic stenosis). It is also used to evaluate patients with unexplained lightheadedness, dizziness, or recurrent falls. Sometimes, the tilt table test is used to differentiate between types of syncope or syncope caused by certain types of epilepsy [38].

- Ultrasound (including Echocardiography): A medical imaging technique that uses high-frequency sound waves (ultrasound) to create dynamic images of internal organs and other tissues [40]. Echocardiography is used to assess whether the heart muscle moves normally and to measure the amount of blood pumped by the heart with each beat. This test can also detect structural abnormalities of the heart, such as valve defects, congenital defects (e.g., holes between heart chambers), as well as left ventricular hypertrophy or chamber enlargement (common in conditions like hypertension, heart failure, or cardiomyopathy). Additionally, it can identify pericardial effusion (fluid accumulation between the layers of the pericardium), restrictive pericarditis (scar tissue replacing the normal pericardium), and aortic dissection (tearing between the layers of the aortic wall) [41] [42].

- X-ray Examination: A type of medical imaging that uses very low doses of radiation to capture images of bones and soft tissues [33]. Chest X-rays are sometimes used for patients suspected of having heart disease. All patients suspected of heart disease undergo both frontal and lateral chest X-rays [43]. X-rays can reveal the shape and size of the heart, as well as the outlines of the lungs and major chest blood vessels. Abnormalities in heart shape or size, as well as other anomalies such as calcium deposits in the vessels, can be observed [44].

Minimally invasive procedures typically involve inserting a long, flexible catheter into a blood vessel in the wrist, neck, or thigh and advancing it to the heart [45]. These procedures include:

- Angiography: Involves injecting a radiopaque contrast agent (a visible liquid on X-rays) into the blood vessels and taking X-ray images to generate detailed images of the vessels [46]. Coronary angiography provides information about the coronary arteries, which supply oxygen-rich blood to the heart [47]. It is performed during left heart catheterization because the coronary arteries branch off from the aorta just after leaving the left heart [45]. These two procedures are often performed simultaneously [48].

- Cardiac Catheterization: A procedure that involves inserting a catheter into a vein or artery and guiding it into the heart to measure heart function [48] [49]. Coronary angiography can be performed during cardiac catheterization to produce images of the coronary arteries that supply blood to the heart using X-rays and contrast agents [48].
- Central Venous Catheterization: Used to measure the pressure in large veins that return blood from the upper body to the heart [50] [51]. A catheter is inserted into a large vein in the neck, upper chest, arm, or groin. This procedure is commonly used for IV fluids, medication administration, or when peripheral venous access (e.g., in the arm or leg) is not feasible [52].
- Electrophysiological Study (EPS): Measures the electrical activity of the heart by inserting electrode wires into all four heart chambers [53]. EPS is used to assess significant abnormalities in heart rhythm or electrical conduction [54] [55].

Most of these procedures carry minimal risk, but the risk increases with the complexity of the procedure, the severity of the heart disease, and any other medical conditions of the patient.

1.4 Symptoms of Cardiovascular Complications

The clinical and non-clinical symptoms of cardiovascular complications are diverse. While there is some overlap between different conditions, each disease also has its own distinct characteristics. Common clinical symptoms, such as chest pain, shortness of breath, palpitations, dizziness, and syncope, can serve as early indicators of cardiovascular problems [56]. However, non-clinical symptoms are often atypical and can easily be overlooked.

1.4.1 Clinical Symptoms

The clinical symptoms of cardiovascular complications primarily manifest as abnormalities in heart function or the vascular system, typically presenting in the following ways:

- Chest Pain: Common in conditions like coronary heart disease and myocardial infarction, patients experience a squeezing pain in the chest that may radiate to the shoulders, arms, or back [57].

- Shortness of Breath: Patients with heart failure or coronary artery disease may experience breathlessness during physical activity or while lying flat. In severe cases, it may lead to orthopnea (difficulty breathing when lying down) [58].

- Palpitations: Those with arrhythmias or coronary artery disease often feel rapid, irregular, or abnormal heartbeats [59].

- Fatigue and Weakness: Due to reduced heart pumping function, patients frequently feel physically weak and have a lower tolerance for activity [60].

- Syncope or Dizziness: Patients may experience sudden fainting or dizziness, sometimes with temporary loss of consciousness, due to arrhythmias, low blood pressure, or insufficient blood supply to the heart [36].

- Edema: Heart failure patients often exhibit swelling, particularly in the lower extremities, such as the ankles and calves [61].

- Shock: Severe myocardial infarction may lead to hypotension, confusion, and even shock [62].

1.4.2 Non-clinical Characteristics

Non-clinical symptoms of cardiovascular complications are often subtle, easily overlooked, or confused with other conditions. These include:

- Painless Heart Attack: Some elderly individuals or diabetic patients may not experience typical chest pain but may instead feel fatigue, shortness of breath, or indigestion [63].

- Gastrointestinal Symptoms: Patients with coronary heart disease or myocardial infarction may exhibit symptoms resembling gastrointestinal issues, such as upper abdominal discomfort, nausea, or vomiting [64].

- Sleep Disorders: Patients with heart failure may experience difficulty sleeping due to chest tightness or shortness of breath at night, often needing to sit up to alleviate symptoms.

- Emotional Changes: Some cardiovascular patients may experience anxiety, depression, or other emotional issues, particularly under the long-term impact of the disease affecting mental health [13].

- Abnormal Findings in Physical Exams: Some patients may not show obvious clinical symptoms but might have abnormalities detected through routine physical exams, such as elevated blood pressure, abnormal ECG results, or blood markers indicating conditions like hypertension, latent coronary heart disease, or early arterial sclerosis.

- Sudden Fatigue: During the latent period of arrhythmias or other CVDs, patients may experience sudden, unexplained fatigue that does not improve with rest.

In summary, clinical symptoms of cardiovascular complications are more overt and easily noticeable, while non-clinical symptoms are more subtle and may be confused with other systemic diseases. Special attention is needed for symptom changes in high-risk populations.

1.5 Clinical Assessment

Assessment of cardiac function is a critical step in evaluating a patient's heart health, especially in the diagnosis, treatment, and management of CVDs. It reflects the heart's efficiency and the patient's quality of life. Cardiac function assessment typically employs a range of clinical tools and standards to quantify the heart's performance under various load conditions.

1.5.1 NYHA Functional Classification System

NYHA functional classification system is one of the most commonly used tools for assessing heart function, particularly in patients with chronic heart failure [65]. It evaluates heart function based on the patient's ability to perform daily activities and the severity of symptoms triggered by these activities. It has long served as a foundational tool for risk stratification of HF and determines clinical trial eligibility and candidacy for drugs and devices. Whereas it is widely acknowledged that NYHA classification is subjective and has low reproducibility, its use is ingrained in both guidelines and contemporary practice, and it serves as a cornerstone of clinical documentation, trial enrollment, and candidacy for therapeutics [65]. The NYHA classification includes four stages [66]:

- Class I: No physical activity limitations. Daily activities do not cause fatigue, shortness of breath, or palpitations.

- Class II: Slight physical activity limitations. Symptoms such as fatigue, shortness of breath, or palpitations occur with normal activities but not at rest.

- Class III: Marked physical activity limitations. Symptoms occur with less than ordinary activities, but the patient is asymptomatic at rest.

- Class IV: Inability to perform any physical activity without discomfort. Symptoms occur even at rest, and any activity increases discomfort.

The NYHA classification is straightforward and widely used to evaluate the severity of heart failure and monitor treatment effectiveness. It helps physicians adjust treatment strategies, such as modifying medication dosages or recommending cardiac rehabilitation programs, based on the severity of the patient's symptoms.

1.5.2 Left Ventricular Ejection Fraction

Left ventricular ejection fraction (LVEF) is the central measure of left ventricular systolic function. Kosaraju et al. [67] gave the definition and range in their paper titled LVEF: It measures the percentage of blood ejected from the left ventricle with each heartbeat. LVEF is typically assessed using echocardiography or nuclear cardiovascular imaging and is crucial for determining the heart's pumping ability. Normal ranges for two-dimensional echocardiography obtained LVEF as per the American Society of Echocardiography and the European Association of Cardiovascular Imaging are: LVEF (%) among the male population: 50% to 70%, and LVEF (%) among the female population: 54% to 74% normal range. Values below this range can indicate heart dysfunction or heart failure.

- Mildly Reduced: 40%–49%, suggesting mild left ventricular dysfunction.
- Moderately Reduced: 30%–39%, indicating moderate left ventricular dysfunction.
- Severely Reduced: Less than 30%, suggesting severe left ventricular dysfunction or end-stage heart failure.

LVEF is valuable for evaluating the prognosis of heart failure patients and selecting appropriate treatments, such as cardiac resynchronization therapy (CRT) or implantable cardioverter-defibrillator (ICD) therapy.

1.5.3 Six-Minute Walk Test

The American Thoracic Society has issued guidelines for the 6MWT. The 6MWT is safer, easier to administer, better tolerated, and better reflects activities of daily living than other walk tests (such as the shuttle walk test) [68]. In this test, patients are asked to walk as far as possible within six minutes. The distance walked is closely related to the patient's cardiac function, with those having poorer cardiac function typically walking shorter distances.

The 6MWT is useful for:

- Initial Assessment: Determining the baseline functional capacity of heart failure patients.

- Evaluating Treatment Effects: Assessing how treatments are impacting the patient's exercise capacity.

- Monitoring Disease Progression: Tracking changes in the patient's walking distance over time to gauge disease progression or improvement.

This test provides valuable information on functional status and can help guide treatment decisions and monitor patient outcomes.

1.5.4 Other Methods

Cardiac Magnetic Resonance (CMR) [69] is an advanced imaging technique that provides high-resolution information on cardiac anatomy and function. CMR is highly precise in evaluating myocardial function, myocardial fibrosis, and myocardial perfusion, making it particularly suitable for complex cases of heart failure. By assessing indicators such as myocardial wall thickness, chamber size, and myocardial fibrosis, CMR allows for a comprehensive understanding of structural and functional changes in the heart.

NT-proBNP and BNP [70]: B-type Natriuretic Peptide (BNP) and its N-terminal propeptide (NT-proBNP) are important biomarkers in the blood of heart failure patients and are commonly used to assess the severity of heart failure. Levels of BNP and NT-proBNP are typically elevated in heart failure patients because, when the heart is under excessive load, ventricular wall tension increases, leading to the release of BNP and NT-proBNP. These biomarkers not only assist in diagnosing heart failure but also help monitor treatment efficacy and determine prognosis. Higher levels of BNP or NT-proBNP indicate more severe cardiac dysfunction and a poorer prognosis.

Cardiopulmonary Exercise Testing (CPET) [71]: Cardiopulmonary Exercise Testing (CPET) is a more complex tool for assessing cardiac function. It measures oxygen uptake, carbon dioxide output, and ventilation during exercise to comprehensively evaluate cardiac and pulmonary function under exertion. CPET assesses parameters such as maximal oxygen consumption (VO2 max) and the ventilatory equivalent for carbon dioxide (VE/VCO2), providing an accurate reflection of cardiopulmonary function. A lower VO2 max indicates worse cardiopulmonary function and a poorer prognosis, making CPET particularly useful for risk assessment and exercise capacity evaluation in heart failure patients.

Hemodynamic Assessment [72]: Hemodynamic monitoring, typically performed via right heart catheterization, is a direct method for assessing cardiac pressure load and hemodynamic status. This approach is mainly used to evaluate parameters such as cardiac output, pulmonary artery wedge pressure (PAWP), and systemic vascular resistance (SVR) in patients with severe heart failure. These data are crucial for determining the severity of heart failure, formulating treatment strategies, and assessing treatment effectiveness.

Through these various methods of heart function assessment, clinicians can gain a comprehensive understanding of a patient's cardiac status and develop appropriate treatment strategies. Each assessment method has its advantages, and doctors can choose the most suitable tool based on the patient's specific condition to ensure accurate diagnosis and optimized treatment plans.

1.6 Treatment Methods

The treatment of cardiovascular complications primarily includes both pharmacological and non-pharmacological approaches. By integrating these two types of treatment, it is possible to effectively control disease progression, alleviate symptoms, and improve patient outcomes.

1.6.1 Pharmacological Treatment

Pharmacological treatment [73] is fundamental in managing cardiovascular complications. By regulating blood pressure, heart rate, lipid levels, and hemodynamic status, medication can effectively control disease progression. Commonly used drugs include antihypertensives, diuretics, anticoagulants, lipid-lowering agents, and other medications targeting specific symptoms. The specifics of these drugs and their mechanisms of action are as follows:

- Diuretics: By reducing blood volume, diuretics lower blood pressure and relieve edema, commonly used in heart failure and hypertension patients.

- Antihypertensives: These include ACE inhibitors, ARBs, β-blockers, and calcium channel blockers. They primarily work to lower blood pressure and reduce the cardiac workload.

- Anticoagulants and Antiplatelet Drugs: These are used to prevent thrombosis and reduce the risk of stroke and myocardial infarction.

- Lipid-Lowering Agents [74]: Statins, for example, lower LDL cholesterol and reduce the risk of atherosclerosis.

- Other Medications: Such as cardiac glycosides to improve heart function, and nitrates to relieve angina.

1.6.2 Non-pharmacological Treatment

Non-pharmacological treatments are essential complements to pharmacological therapy. By incorporating lifestyle changes, surgical interventions, and the use of medical devices, these approaches help manage symptoms and improve cardiovascular health. Common non-pharmacological treatments include [75]:

- Lifestyle Modifications: Such as dietary management, increased physical activity, weight control, smoking cessation, and limiting alcohol intake, which help reduce the risk of CVDs.

- Surgical Interventions: Procedures like coronary artery bypass grafting (CABG) and percutaneous coronary interventions (PCI) are used to improve myocardial blood supply or repair damaged heart structures.

- CRT and Implantable ICDs: These are employed to treat heart failure and prevent life-threatening arrhythmias.

- Cardiac Rehabilitation: This includes exercise, psychological support, and education to help patients recover health and reduce the risk of recurrence.

By combining pharmacological and non-pharmacological treatments, the survival rate and quality of life for patients with cardiovascular complications can be significantly improved.

1.7 Importance of Predicting Cardiovascular Complications

Predicting cardiovascular complications is an important and highly focused area of research in modern medicine due to its profound impact on improving patient outcomes, optimizing medical interventions, and enhancing the efficiency of healthcare resource utilization. Advanced prediction techniques allow for more accurate risk assessment, enabling personalized interventions that not only save lives but also significantly reduce long-term healthcare costs and societal burden.

First, predicting cardiovascular complications facilitates personalized treatment and precision medicine. Each patient has different risk factors for cardiovascular complications, involving a variety of biological, genetic, and environmental factors. Therefore, traditional "one-size-fits-all" treatment approaches are inadequate for meeting the complex and variable clinical needs. Research in cardiovascular complication prediction focuses on quantifying individual risk by analyzing key parameters such as blood pressure, blood glucose, cholesterol levels, and lifestyle habits, along with family history and medical history. This enables clinicians to identify high-risk patients earlier, allowing for more intensive monitoring and proactive interventions. Personalized treatment strategies can help reduce the incidence of cardiovascular events, improve therapeutic outcomes, and mitigate the long-term damage caused by complications.

Secondly, utilizing multimodal data for predicting cardiovascular complications represents a cutting-edge research direction, providing new opportunities to improve the accuracy and effectiveness of prediction. Multimodal data refers to the integration of various types of health data from multiple sources, including clinical data, imaging data, behavioral data (e.g., physical activity, diet, sleep), and environmental factors (e.g., air quality, socioeconomic status). Compared to traditional prediction methods relying on a single data source, multimodal data offers the advantage of providing a more comprehensive assessment of a patient's health status. For instance, combining imaging data (such as cardiac MRI or CT) with genomic information can reveal the underlying biological mechanisms and disease progression trends, while behavioral and lifestyle data help dynamically track changes in risk factors.

The integration of multimodal data not only enhances the understanding of disease progression but also aids in identifying potential risks that traditional clinical indicators may not capture. For example, integrating genomics and proteomics data can potentially uncover new biomarkers associated with cardiovascular complications, leading to early prediction and prevention. Additionally, algorithms based on big data and AI can efficiently process and analyze data from different modalities, revealing complex interaction patterns. ML models, for instance, can be trained on vast amounts of patient data to detect subtle correlations between seemingly unrelated factors, thus predicting the timing and severity of cardiovascular complications more accurately.

Another crucial significance of predicting cardiovascular complications lies in its ability to significantly enhance the efficiency of healthcare resource allocation. By identifying high-risk patients in advance, healthcare systems can allocate resources more effectively, reduce unnecessary tests and treatments, and optimize medical processes. For low-risk patients, predictive models can help avoid overtreatment, thus lowering healthcare costs. For high-risk patients, early intervention can reduce the occurrence of acute events, lowering hospitalization rates and mortality. This resource allocation approach, based on precise prediction, not only alleviates the burden on healthcare systems but also ensures more timely and effective medical services for patients.

Lastly, multimodal prediction technology also contributes to the formulation and improvement of public health policies. By analyzing large-scale population health data, it becomes easier to understand the epidemiological trends and risk factors associated with cardiovascular complications, helping public health authorities design targeted preventive measures. Furthermore, predictive data can be used to assess the effectiveness of existing interventions, driving the optimization of public health resource allocation and ultimately leading to improved societal health outcomes.

In conclusion, predicting cardiovascular complications is a critical research direction, not only for enabling personalized precision treatments and improving patient outcomes but also for the immense potential that multimodal data holds in enhancing the accuracy and effectiveness of predictive models. Advances in this field will significantly improve the management of CVDs, reduce the incidence of complications, and have a profound impact on global healthcare systems.

Chapter 2

Digital Technologies in CVDs Management

2.1 Digital Health Technologies

Digital health technology refers to a range of tools and platforms that collect, analyze, store, and transmit health data through digital means, enhancing health management efficiency, improving disease prediction, and treatment outcomes. With the rapid advancement of information technology, digital health applications in the medical field have become increasingly widespread, particularly playing a significant role in the prevention, diagnosis, and management of CVDs. In practice, digital technology has shown improvements in morbidity and mortality outcomes for CVDs patients. For researchers, studies on the use of digital technology in cardiovascular care are relatively new, making it essential to understand the historical context of digital health technology in cardiovascular research [76].

2.1.1 Overview of Digital Health Technologies

Digital innovation and connectivity are essential components of a modern and accessible healthcare system. Digital health is an umbrella term that describes a variety of technologies, including mobile health and apps, electronic medical records (eMR), telemedicine and telehealth, wearable devices, robotics, and AI [77]. These technologies serve multiple purposes, including disease detection, assisting in patient treatment, ensuring continuity of care, and managing personal health information. With the continuous advancement of sensor technology, wireless communication, big data, and AI, digital health technology is progressively expanding to encompass more complex tasks in health monitoring and disease prediction [76].

Digital health technology today spans several key areas:

- Wearable Devices and Sensors: Such as smartwatches, fitness bands, wearable ECG sensors, and accelerometers, which can monitor vital signs and activity levels in real time.
- Mobile Health Platforms: Including various health management apps that help patients track their health, offer health advice, and enable remote medical consultations through smartphones or other mobile devices.
- Remote Monitoring [77]: Using wireless sensors and communication technology, doctors can monitor patients' health remotely and adjust treatment plans promptly.

Additionally, with the recent deployment of innovative medical devices, healthcare services increasingly extend beyond clinical settings to community and home environments, further driving mobile care services [78]. Digital health technology plays a vital role in CVDs prevention, diagnosis, and treatment, particularly in early risk prediction, disease monitoring, and personalized care.

- Cardiovascular Risk Assessment: Through various digital health technologies, such as wearables that monitor heart rate, blood pressure, and ECG parameters, potential cardiovascular risks can be detected early, helping doctors develop personalized prevention plans for patients.
- Real-Time Health Monitoring: Wearable sensors and mobile health apps enable patients to monitor their cardiovascular health in real time, receive alerts promptly, and prevent sudden cardiovascular events.
- Remote Diagnosis and Treatment: Digital health technology facilitates easier communication between patients and doctors, offering new treatment options, especially for those living in remote areas through telemedicine and real-time data transmission.

Through these technologies, digital health not only improves treatment outcomes for cardiovascular patients but also enhances the efficiency of early diagnosis and health management.

2.1.2 Role of Multimodal Data

In CVDs prediction, the application of multimodal data offers a more comprehensive and precise perspective for risk assessment. Multimodal data refers to information spanning different types and contexts (such as imaging, text, or genomics).

Methods for integrating multimodal data fundamentally aim to combine data with varying scales and distributions into a unified feature space (i.e., database), where the information can be represented in a more consistent manner [79] .

Multimodal data typically includes clinical data, sensor data, and imaging data. Clinical data covers the patient's basic information, such as age, gender, height, weight, and detailed medical records like prior medical history and type of surgery. Sensor data is collected via wearable devices and includes real-time physiological parameters, such as heart rate, gait, and activity level. Imaging data provides insights into the structure and function of the heart, such as echocardiography and CT scan results. By integrating information from diverse data sources, multimodal data presents a more complete picture of the patient's health status.

The application of multimodal data in CVDs risk prediction offers significant advantages [80]. Firstly, combining multiple data types overcomes the limitations of single data sources, enabling predictive models to assess from more perspectives and thus improving the accuracy of disease risk prediction. Secondly, clinical data and sensor data provide distinct health information—clinical data focuses on the patient's medical history and treatment records, while sensor data reflects the patient's real-time physiological status. Integrating these data types can substantially enhance prediction precision, allowing the model to capture the patient's health status from multiple dimensions. Multimodal data also supports personalized risk prediction by adjusting model weights according to individual patient circumstances, helping physicians design tailored health management plans.

Despite its great potential, there are challenges in the practical application of multimodal data in cardiovascular risk prediction [80]. Sensor data, for instance, may be affected by noise or device accuracy, impacting the reliability of predictions. Data privacy and security are also critical in multimodal data applications, as safeguarding patient privacy and data security is essential. Despite these challenges, with advancements in data processing and ML, the use of multimodal data in CVDs risk prediction will become increasingly refined and reliable, offering robust support for health management and disease prevention.

2.2 Multimodal Data Integration

In multimodal approaches for predicting cardiovascular complications, different types of data sources complement each other, providing a more comprehensive perspective for the model. Clinical data and sensor data are the core components of multimodal data. Clinical data includes the patient's basic physiological information, medical history, and surgical details, reflecting long-term health trends and potential cardiovascular risk factors. Sensor data (such as ECG and accelerometer data) captures real-time physiological states and activity patterns during the postoperative recovery period, offering dynamic health indicators.

The integration of such multimodal data is especially important in predicting cardiovascular complication risks [80]. Clinical data is often characterized by high quality and reliability, but its static nature makes it difficult to reflect the patient's instantaneous changes during recovery. Sensor data, on the other hand, addresses this limitation by enabling the model to track the patient's physiological status and activity levels in real time. In the following sections, the characteristics of these data sources and their applications in CVDs prediction will be discussed.

2.2.1 Clinical Data in CVDs Prediction

In CVDs prediction, clinical data plays a critical role. This data includes fundamental patient information such as age, gender, height, and weight, along with more crucial elements such as medical history, surgical records, and laboratory results. Particularly in cardiovascular risk assessment, details like surgery type, hospitalization duration, and recovery progress provide personalized insights for doctors. These clinical details are typically reliable and stable, forming an essential part of disease prediction models.

Clinical data not only helps in understanding an individual's health status but also provides the background for cardiovascular risk assessment based on long-term trends and specific physiological characteristics. For example, basic attributes like age, gender, height, and weight are often used to assess the initial cardiovascular health risk. These foundational data can reveal the risk of potential metabolic diseases (e.g., obesity and diabetes) or genetic conditions, while medical history helps identify other factors that may increase cardiovascular burden. By tracking these variables over time, doctors can monitor the health trends of patients, enabling timely intervention.

Moreover, details such as surgery type, surgery duration, and recovery progress provide unique clinical insights. These data not only help evaluate the impact of the surgery on the cardiovascular system but also reflect potential complications or treatment responses during the post-surgery recovery process. For example, certain types of surgeries, like CABG or heart valve replacement, may increase the risk of cardiovascular issues post-operatively, while hospitalization duration and recovery speed provide insight into the patient's recovery process, indicating possible post-surgical complications. Therefore, these clinical characteristics significantly enhance the accuracy of prediction models, aiding doctors in making more personalized clinical decisions.

Despite the high reliability of clinical data, its limitations should not be overlooked. Clinical data is typically static, collected at regular intervals, and lacks real-time feedback, making it difficult to reflect the patient's immediate health status.

2.2.2 Sensor Data in CVDs Prediction

Sensor data plays a critical role in the real-time monitoring of cardiovascular health [81]. Common types of sensor data include ECG, accelerometer data, gait data, and heart rate, which are continuously collected through wearable devices to dynamically monitor the patient's physiological status. For example, ECG can detect changes in heart rhythms, identifying potential issues like arrhythmias, while accelerometer data reflects a patient's activity level and movement patterns, providing insights into the impact of physical activity on cardiovascular health. Real-time tracking of heart rate allows for the detection of potential cardiovascular abnormalities, such as excessively fast or slow heart rates, helping assess the patient's cardiovascular health. Gait data reveals the patient's mobility and physical condition, which, especially for elderly or postoperative patients, may indicate early signs of CVDs or other complications.

The advantage of sensor data in CVDs prediction lies in its high-frequency, continuous data flow, allowing the model to capture subtle changes in the patient's physiological state [82]. Traditional clinical data is often collected at regular intervals and lacks real-time capabilities, whereas sensor data provides a continuous stream of information that reflects fluctuations in the patient's physiology. For instance, accelerometer-based gait and movement data can offer dynamic insights into the patient's activity levels, helping predict the effects of insufficient or excessive physical activity on cardiovascular health. Additionally, real-time monitoring of physiological signals like heart rate and blood oxygen saturation provides rich time-series data for predicting CVDs risk, aiding in the early detection of potential problems [81] [82]. By tracking this data over extended periods, trends and patterns related to changes in health conditions can be identified, offering valuable data for personalized treatment.

The advantage of real-time data lies in its ability to enable early disease detection and help doctors assess the effectiveness of treatment plans through daily monitoring [83]. Obtaining timely physiological changes in patients not only aids in spotting early signs of disease but also allows real-time evaluation of treatment effectiveness. For instance, after surgery, monitoring changes in ECG and activity levels can help doctors assess the recovery progress and adjust the treatment plan based on the patient's physiological response. The continuity and real-time nature of sensor data, especially in elderly or postoperative patients, offer a unique advantage in identifying the risk of cardiovascular complications at an early stage.

However, sensor data is often limited by noise and device accuracy. Therefore, data cleaning and feature extraction are essential to ensure the reliability of the information [84]. Since sensor data is usually collected in dynamic environments, it can be subject to interference from movement, sensor instability, and external factors. To improve data quality, noise filtering and outlier detection are necessary to ensure that only high-quality data is used for further analysis. Additionally, sensor data typically contains a large amount of information, requiring feature extraction to highlight key features that aid in disease prediction, such as heart rate variability (HRV), exercise intensity, and frequency. These cleaned and extracted features effectively reflect the patient's health status, providing a solid data foundation for subsequent CVDs prediction.

By combining sensor data with clinical data, the advantages of different data sources can be leveraged to provide more comprehensive support for CVDs risk prediction. While sensor data can capture real-time changes in the patient's physiological state, clinical data provides a broader context for the patient's health. Integrating both types of data not only enhances the accuracy of prediction models but also helps doctors make more personalized and timely medical decisions.

2.3 ML in Cardiovascular Prediction

In recent years, AI has experienced explosive growth and has been widely applied in the healthcare field. ML, as a typical AI technology, holds immense potential in predicting CVDs by leveraging large amounts of medical data for training and optimization. It is expected to play a key role in reducing the incidence and mortality of CVDs [80]. By utilizing multimodal data, such as clinical data, sensor data, and patient histories, ML can uncover underlying patterns and build efficient predictive models, helping clinicians identify the risks of CVDs at an early stage.

In CVDs prediction tasks, ML algorithms are widely used in areas such as feature selection, pattern recognition, and risk assessment. Compared to traditional statistical methods, ML models can handle complex data relationships and provide more accurate predictions. This is particularly advantageous when dealing with multidimensional data fusion, which allows for better performance in capturing intricate interactions between various data types.

2.3.1 Overview of ML in Cardiovascular Risk Prediction

ML involves endowing computers with the ability to simulate or replicate human learning behaviors, enabling them to acquire new knowledge or skills, reorganize existing knowledge structures, and continuously improve their performance. As a critical subset of artificial AI, it has emerged in recent years as a highly promising field of research. ML's capacity for data-driven learning and decision-making has broadened its applications across diverse areas, from healthcare to finance and beyond, allowing computers to effectively tackle complex tasks without explicit programming for each specific scenario. This transformative potential has positioned ML at the forefront of technological advancement and innovation [85].

Significant progress has been made in applying ML to CVDs prediction. Traditionally, cardiovascular risk assessments relied heavily on physicians' expertise and conventional statistical models, which often struggled with complex, nonlinear relationships and numerous variables. ML models, however, allow for a more sophisticated handling of existing variables, such as nonlinearity and time dynamics, and can also incorporate novel variables like ECG results, medical imaging, and even genomics data [86]. This enhanced ability to process and integrate a wide range of data sources has positioned ML as a powerful tool for more precise and comprehensive cardiovascular risk assessment.ML algorithms, particularly supervised learning methods, can automatically identify patterns related to cardiovascular risk through large volumes of historical data and improve prediction accuracy through continuous learning and optimization.

ML is a method that enables machines to learn without explicit programming. It is a branch of AI aimed at enabling machines to perform tasks proficiently through intelligent software [87]. ML algorithms use various statistical, probabilistic, and optimization techniques to learn from past experiences and detect useful patterns from large, unstructured, and complex datasets [88]. In cardiovascular risk prediction, ML primarily includes methods such as supervised learning, unsupervised learning, and reinforcement learning. Supervised learning algorithms, such as Support Vector Machines (SVM), Decision Trees, KNN, and Random Forest, have become the mainstream methods for predicting cardiovascular risk. These algorithms construct models that predict disease risk by taking clinical and sensor data as input. On the other hand, unsupervised learning methods are mainly used for data exploration and clustering, helping to identify potential subgroups of patients, while reinforcement learning has shown promise in optimizing personalized treatment plans [89]. This project will focus on using supervised learning algorithms.

ML's advantages in CVDs prediction are not only reflected in its ability to model complex data relationships but also in its capacity to continuously improve prediction accuracy through ongoing training, adapting to individual differences among patients. By combining clinical data with sensor data, ML provides strong support for early detection and risk assessment of CVDs. This integration allows for more personalized and accurate predictions, helping clinicians identify high-risk patients early and tailor interventions accordingly.

2.3.2 Supervised Learning for Activity Prediction

Activity prediction is a crucial aspect of CVDs prediction, especially for elderly or postoperative patients, as physical activity levels are closely related to cardiovascular health. Physical activity not only affects heart function but also serves as an effective indicator of a patient's overall health status and recovery progress.

For postoperative patients, assessing their activity levels helps determine recovery progress and identify potential complications. By accurately predicting activity using ML, personalized treatment plans and rehabilitation programs can be developed for patients. Therefore, activity prediction not only helps doctors better understand the patient's condition but also provides important insights for predicting cardiovascular health risks.

In supervised learning, the concept of "acquiring expertise from experience" is applied to "experience" as training data, which contains important information missing in the unseen "test examples," and the acquired expertise is applied to these missing pieces of information. In this case, the acquired expertise is aimed at predicting the missing information in the test data [89]. Examples of supervised algorithms include KNN classifier, decision tree classifier, and so on. To date, ML has become more efficient and useful in collaboration with the medical field [84]. For instance, Random Forest can handle noise and uncertainty in accelerometer data by integrating multiple decision trees, thereby providing more robust activity prediction results. By predicting a patient's daily activities, doctors can assess the impact of their physical activity on cardiovascular health and make personalized treatment and intervention decisions based on their activity levels.

However, the accuracy of activity prediction is limited by data quality and feature selection. Sensor data is often influenced by noise, environmental factors, and device limitations. Therefore, data preprocessing and feature extraction are particularly important when applying supervised learning for activity prediction [89]. Data cleaning is a key step in removing outliers and noise, which significantly improves the quality of the data and the accuracy of the model. Feature extraction helps to identify meaningful patterns from complex raw data, allowing ML models to learn more effectively. Effective feature extraction can include time-domain features (such as mean, standard deviation), frequency-domain features (such as power spectral density), and other relevant statistical metrics. By using these methods, the accuracy of activity prediction can be improved, further optimizing CVDs risk prediction and providing more reliable support for clinical decision-making.

2.3.3 Random Forest for Cardiovascular Risk Prediction

Random Forest is a ML method that constructs multiple decision trees on a training dataset to generate a classification model. The algorithm makes decisions based on the majority vote, providing high accuracy when handling large datasets. By integrating multiple decision trees for classification and regression, it can handle high-dimensional data and offer strong robustness [90]. The Random Forest algorithm combines two feature selection strategies, namely bagging and random selection, to generate a more effective ensemble model. By using multiple decision trees, the Random Forest method reduces the risk of overfitting and training time. It also provides estimates for key classification variables and missing data, all of which contribute to improved accuracy. Bagging, or Bootstrap Aggregating, helps reduce variance by training each tree on a random subset of the data and then averaging the predictions. Random selection of features at each split point within the trees further ensures diversity among the trees, allowing the ensemble model to capture more complex patterns in the data. These mechanisms together make Random Forest robust, capable of handling large, high-dimensional datasets, and providing reliable predictions in tasks like CVDs risk assessment.

The Random Forest algorithm is widely applied in CVDs risk prediction. In CVDs prediction tasks, Random Forest can utilize patients' clinical and sensor data by building multiple decision trees and integrating their predictions, thus improving the accuracy and stability of the model.

Random Forest demonstrates strong robustness in handling data with noise and missing values, making it particularly valuable in medical data applications [91]. CVDs prediction involves various types of data, such as clinical data (e.g., age, gender, height, weight, medical history) and sensor data (e.g., ECG, accelerometer), which are characterized by high dimensionality, non-linearity, and missing values. Traditional models, such as single decision trees or linear models, may struggle to fully capture the complex relationships in the data. Random Forest, by training multiple decision trees, effectively models these complex, multidimensional datasets and provides accurate prediction results.

In CVDs prediction, Random Forest not only handles different data sources (e.g., clinical features and sensor data) but also performs feature selection, identifying the most valuable variables for disease risk prediction. With Random Forest models, researchers can analyze which factors (e.g., surgery type, weight, ECG features) have the greatest impact on CVDs risk, helping doctors formulate more targeted treatment plans. Additionally, Random Forest can provide importance scores for the model's features, aiding clinicians in better understanding the decision-making process and improving the model's interpretability.

The strength of Random Forest lies in its ability to model non-linear relationships and adapt to large-scale data, making it highly applicable in multi-modal data fusion and CVDs risk assessment. By combining clinical data and sensor data, Random Forest provides strong support for the early diagnosis and personalized treatment of CVDs.

2.4 Challenges and Future Directionse

With continuous technological advancements, the field of CVDs prediction is moving towards greater precision, personalization, and intelligence. Digital health technologies, AI, and big data analytics offer new possibilities for the early prevention and personalized treatment of CVDs. These innovations enable the integration of diverse data sources, such as clinical records, sensor data, and genetic information, which can be leveraged to develop highly accurate models for risk prediction and tailor treatment strategies to individual patients. As a result, these technologies hold the potential to revolutionize cardiovascular healthcare, improving patient outcomes and reducing the overall burden of heart diseases.

2.4.1 Emerging Trends in Digital Health

In recent decades, emerging fields like telemedicine and remote monitoring have been widely adopted, with the COVID-19 pandemic driving healthcare services to adapt and evolve faster than ever. Remote monitoring is now expected to transform over the coming years into a mainstream approach for managing cardiovascular care. This shift aims to provide continuous, accessible care for patients, offering proactive monitoring and timely interventions to enhance disease management and improve patient outcomes in cardiovascular health [76].Advancements in digital health technologies for cardiovascular care have provided solutions to many medical and public health challenges faced on a daily basis. With new technologies becoming increasingly accessible and more patients engaging in remote healthcare monitoring, there is a growing need for further evaluation and research on digital health technologies, particularly regarding their long-term effectiveness. This ongoing assessment will help ensure that digital health solutions are reliable, beneficial, and capable of addressing the complexities of CVDs management.

Digital health technologies are playing an increasingly critical role in CVDs prediction, especially with the development of wearable devices and remote monitoring platforms, enabling doctors and patients to access health data anytime, anywhere. Sensor technologies, such as ECG monitoring, blood pressure, and heart rate tracking, combined with IoT devices, allow physicians to monitor patients' physiological status in real time and promptly detect abnormal trends. This continuous data collection and analysis provides ongoing support for patient disease management, helping doctors to more accurately assess cardiovascular health and develop personalized treatment plans.

Moreover, the application of AI and ML technologies has made the processing and analysis of digital health data more intelligent. For instance, by analyzing daily activity data, ML algorithms can predict CVDs risks and health trends.

These data-driven models can quickly respond to changes in patient status, providing doctors with scientifically based decision support. However, further development in digital health still faces many technical challenges, including enhancing device monitoring accuracy, improving device interoperability, and ensuring real-time data transmission and analysis. Addressing these issues will be essential to fully realizing the potential of digital health in cardiovascular care.

2.4.2 Future Challenges in CVDs Prediction

Despite the great potential shown by digital health and AI technologies in CVDs prediction, significant challenges lie ahead. Firstly, issues related to data quality and diversity represent a critical hurdle. CVDs prediction relies on vast amounts of data; however, clinical and sensor data can vary significantly due to differences in collection devices, environments, and data sources. Poor-quality input data can bias ML models, and even minor errors or biases in training data can lead to unforeseen consequences in model predictions [80]. The diversity of data also impacts the generalizability and accuracy of predictive models, posing difficulties for real-world application. Therefore, ensuring data standardization, consistency in quality, and accuracy in multi-source data integration is one of the primary challenges for CVDs prediction.

Moreover, data privacy and security are challenges that cannot be overlooked. CVDs prediction requires integrating large amounts of sensitive personal health data, including patient demographics, medical history, and daily activity data. As the volume of data increases, protecting data privacy and preventing data breaches become even more critical. Future developments will need to strike a balance between data sharing and privacy protection, ensuring that patient privacy is not compromised while enabling effective data utilization.

In conclusion, the future challenges of CVDs prediction not only involve data and technical issues but also require comprehensive consideration of factors such as algorithm interpretability, real-time data processing capabilities, and privacy protection. Addressing these challenges will help build more reliable, interpretable, and ethically sound CVDs prediction systems, providing patients with personalized and intelligent health management solutions.

Chapter 3

Materials and Methods

3.1 Study Population and Data Collection

3.1.1 Patient Demographics

The data for this study was collected from 80 elderly frail patients who entered a cardiac rehabilitation program after undergoing heart surgery. Frailty is a common phenomenon in the elderly population, typically accompanied by a reduction in physiological reserves, leading to increased vulnerability to physical stressors and heightened susceptibility to CVDs [92]. Frail patients often face higher risks of mortality, hospitalization, and loss of mobility. Therefore, this study focuses on this group, aiming to analyze the cardiovascular responses and gait characteristics of frail patients using kinematic and cardiac activity signals collected from wearable devices.

The inclusion criteria for these patients were as follows:

- Age $\geq$ 65 years;
- A frailty score of $\geq$ 4, as assessed by the Edmonton Frailty Scale (EFS), meeting the definition of frail patients;
- A walking distance of $\geq$ 150 meters in the 6MWT;
- Patient consent to participate in the study.

Among the 337 patients initially screened, 99 met the inclusion criteria. However, due to technical issues, data from 19 patients were lost, resulting in data from 80 patients being included in the final analysis. All patients were frail individuals in post-cardiac surgery rehabilitation and underwent routine clinical evaluations at the start of the study. Each patient's basic information and clinical data were verified and recorded by a physician to ensure data accuracy and completeness.In this study, the basic information of the patients includes the following aspects:

In this study, all participants were aged 65 years and above, with an age range from 66 to 85 years and a mean age of 72.6 ± 5.3 years. Regarding gender distribution, 65% of the patients were male, while 35% were female. Additionally, the patients' weight and height were recorded to calculate their body mass index (BMI), which ranged from 19.84 to 41.78 kg/m². Among the patients, 24 had a normal weight, 35 were overweight, and 20 were classified as obese, indicating a wide range of body types within the study cohort, from normal weight to obesity. As shown in the figure 3.1 below:

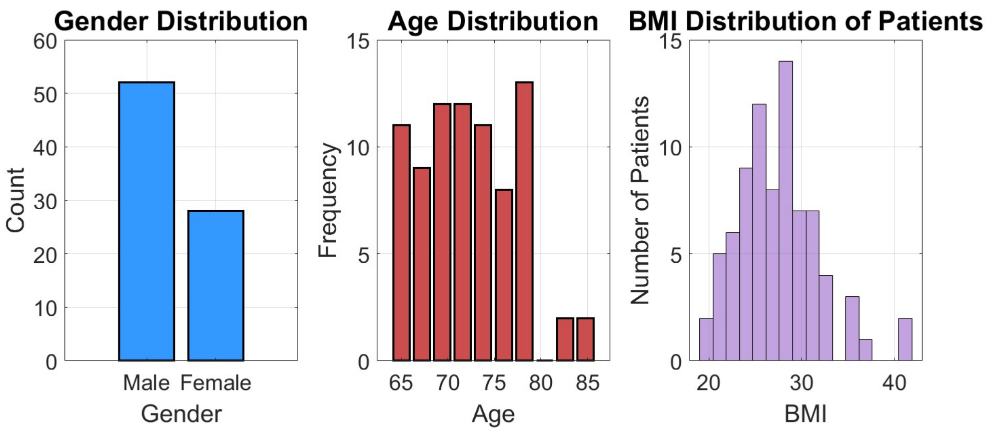

Figure 3.1. Demographic and Clinical Characteristics: Age, Gender, and BMI Distribution

Some patients in this study were diagnosed with various chronic conditions, including AF, COPD, Depression, Musculoskeletal Diseases, and Oncological Diseases. Figure 3.2 illustrates the distribution of chronic diseases among the participants in this study, specifically showing the prevalence of several common chronic conditions in the patient cohort.

AF was relatively common in this study, with patients categorized into four types based on the severity of their condition: 0 (no AF), 1 (persistent AF), 2 (paroxysmal AF), and 3 (temporary AF), as shown in Figure 3.3. The majority of patients (54 individuals), representing 68% of the total sample, exhibited no AF, suggesting that although AF is prevalent among elderly populations, the heart rhythm in most patients in this study remained normal. Approximately 32.5% of the patients had AF, with distribution across the types, where temporary AF was the most common form.

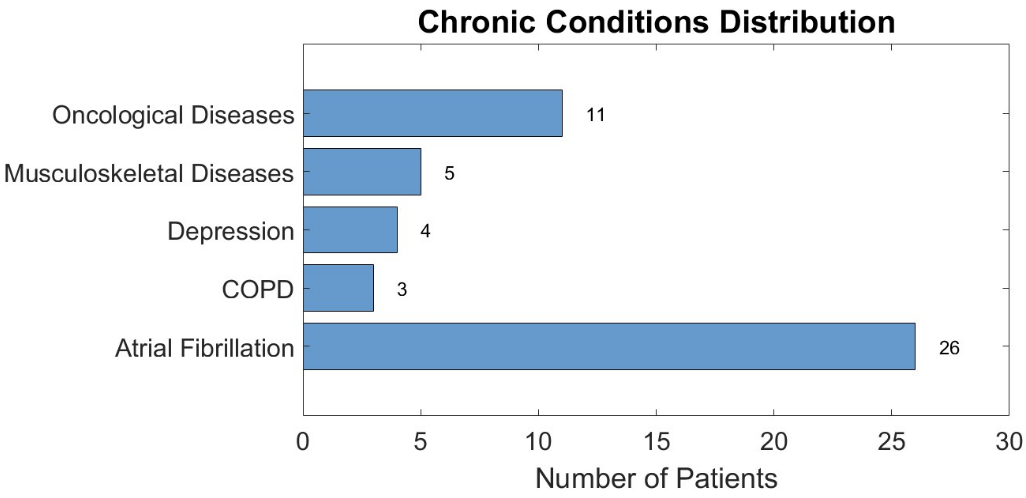

Figure 3.2. Distribution of Chronic Conditions in Study Participants

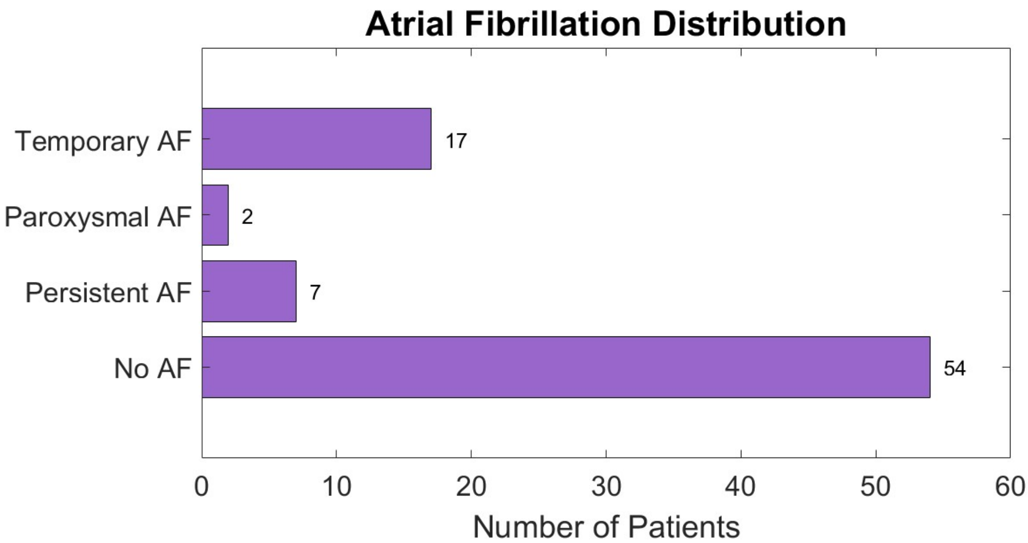

Figure 3.3. Distribution of AF Subtypes Among Patients

Several patients presented with multiple chronic conditions, significantly impacting their overall health status and quality of life. COPD patients frequently experience symptoms such as dyspnea and chronic cough, which impair daily activities and physical endurance. Patients diagnosed with depression often exhibit low mood and diminished interest in activities, further influencing their overall health. Musculoskeletal diseases, including osteoarthritis and rheumatoid arthritis, are typically associated with aging and adversely affect mobility and quality of life; although relatively few patients were diagnosed with musculoskeletal disorders, these conditions substantially influence both functional status and emotional well-being. Additionally, 11 patients (approximately 13.75%) were diagnosed with oncological diseases. Cancer is relatively common in elderly populations and often coexists with other chronic conditions, compounding health challenges.

All patients participating in this study received cardiac rehabilitation interventions in addition to medication therapy. The medications primarily fall into the following categories (see Figure 3.4, Distribution of Medication Usage):

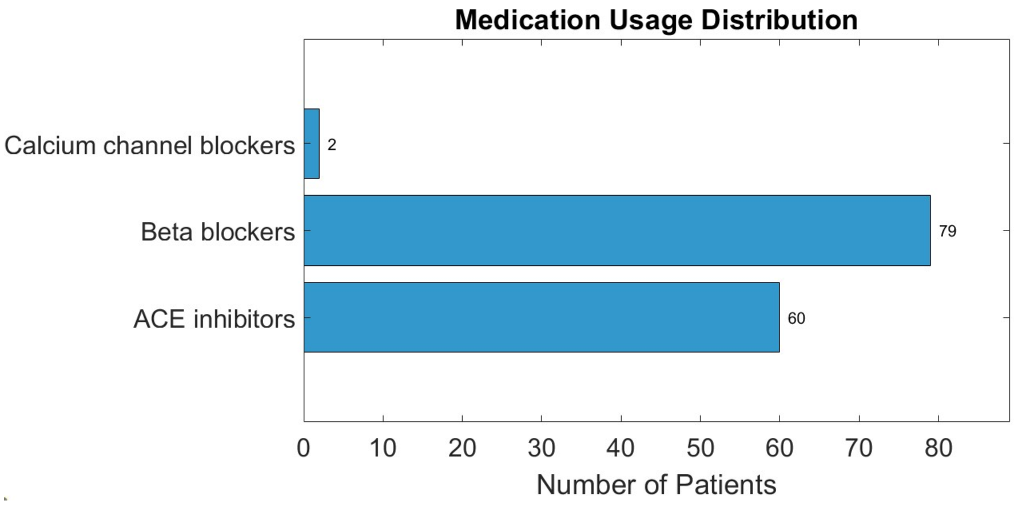

Figure 3.4. Distribution of Medication Usage

- ACE Inhibitors: These are used to control hypertension and reduce the cardiac workload in heart failure patients. Despite the effectiveness of ACE inhibitors in managing cardiac load, only 2 patients (about 2.5%) received this treatment.
- Beta Blockers: Beta blockers are commonly prescribed for heart failure to reduce cardiac workload and alleviate symptoms. In this study, 79 patients (approximately 98.75%) received beta blockers, underscoring the widespread clinical application of these drugs.
- Calcium Channel Blockers: Primarily used to treat hypertension and arrhythmia, calcium channel blockers are suitable for some heart failure patients. A

total of 60 patients (around 75%) received calcium channel blockers, aiding in blood pressure control and reducing cardiac stress.

The use of these medications not only effectively helps in managing heart failure symptoms but also contributes to improving overall cardiac function. However, the long-term use of beta blockers and calcium channel blockers may lead to side effects such as hypotension and fatigue, potentially affecting patients' physical strength and daily activity levels. These potential adverse effects should be carefully monitored during cardiac rehabilitation to ensure that medication use aligns with the rehabilitation process.

The frailty status of the patients was assessed using the EFS, which includes nine dimensions: cognitive function, general health status, social support, medication use, nutrition, mood, functional performance, incontinence, and others [93]. The EFS scores range from 0 to 9, with higher scores indicating greater severity of frailty. In this study, the EFS scores ranged from 4 to 9, with higher scores indicating greater frailty. Figure 3.5 illustrates the distribution of EFS scores. The EFS scores of all patients were concentrated in the moderate to high range, indicating that a significant proportion of frail elderly patients were included in this sample. Frailty has a significant impact on the health and prognosis of elderly patients, particularly in those with heart failure, where frailty is a major risk factor for adverse health events such as hospitalization and death.

Based on the distribution of EFS scores, the most common score was 4, with 16 patients (25% of the total). The second most common scores were 5 and 6, with 19 and 16 patients, respectively, indicating that the majority of patients experienced a moderate level of frailty. There were 12 patients with a score of 7, 6 patients with a score of 8, and 11 patients with a score of 9, indicating that fewer patients were in the moderate-to-severe or extremely frail states. Overall, the distribution of frail patients was relatively balanced, with a larger proportion of patients experiencing moderate frailty and a smaller number in extremely frail states.

In addition, all participants underwent heart failure assessment based on NYHA classification. The NYHA classification divides heart failure patients into four classes, from Class I (asymptomatic) to Class IV (unable to perform any physical activity) [94] [65]. This assessment helps determine the patient's cardiac function status and provides a reference for further treatment decisions [65].

From the distribution in Figure 3.6, it can be observed that the NYHA classification of the participants was mainly concentrated in classes II and III. The data show that the majority of patients (approximately 75%) were classified as NYHA class II, indicating moderate heart dysfunction with some activity limitations. The second largest group was class III, accounting for 20%, with patients exhibiting severe heart dysfunction and significant activity limitations. There were fewer patients in class I and class IV, with only 3 and 1 patient, respectively, which

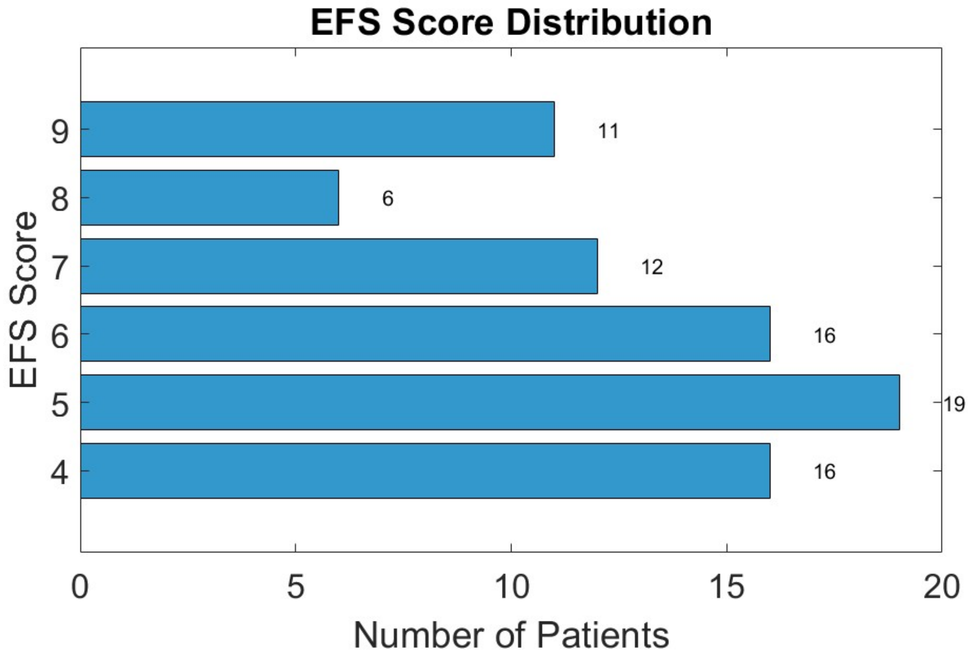

Figure 3.5. Distribution of EFS Score

represents a small proportion. Class I indicates mild heart function, while class IV indicates severe heart function. Due to the small sample sizes in classes I and IV, and the extreme clinical conditions of these patients, including them in the training of ML models could lead to imbalance and instability. This also highlights that these patients experience moderate to severe heart dysfunction, necessitating special attention to their cardiovascular response and activity levels. Therefore, in this study, class I and class II were combined into class II, and class III and class IV were combined into class III to improve data balance and the stability of model training.

3.1.2 Data Acquisition Process

The data in this study were collected using the Polar H10 wearable device (Polar Electro OY, Finland). This device records the patient's ECG signals and three-axis accelerometer signals, with a sampling frequency of 130 Hz for the ECG signals and 200 Hz for the accelerometer signals. All signals are transmitted in real-time via Bluetooth to a smartphone carried by the patient, which serves as both the receiver and storage unit for the data, ensuring real-time transmission and accuracy. The device uses a chest strap sensor, and no additional actions are required from

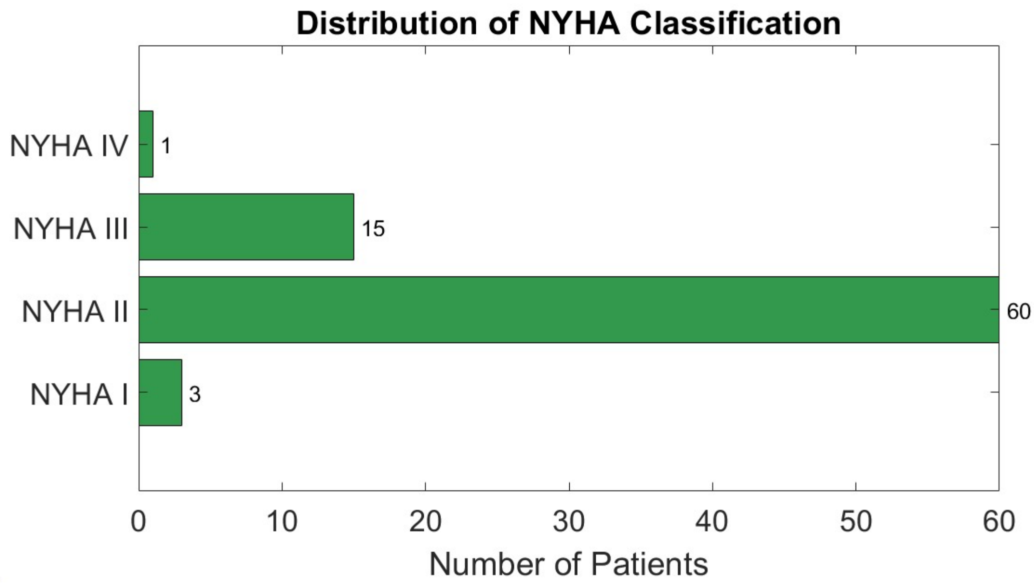

Figure 3.6. Distribution of NYHA Classification

the patient during the test. The simple and interference-resistant design makes it suitable for long-term use. When the device is worn on the chest, the X-axis of the three-axis accelerometer represents acceleration in the forward-backward direction, the Y-axis represents acceleration in the left-right direction, and the Z-axis represents acceleration in the up-down direction. This layout ensures comprehensive monitoring of the patient's daily activities and allows for accurate capture of the accelerometer signals across all dimensions.

The physical performance tests for the patients included five standardized assessments: the TUG test, the 6MWT, the stair climbing test, the gait analysis, and the timed speed test. These tests were selected based on their ability to reflect changes in cardiac and motor function in frail patients, and they have been widely used for frailty assessment. The specific testing procedures are as follows:

- Veloergometry: Veloergometry is primarily used to assess the cardiovascular system's response to increasing physical exertion. The patient is required to cycle on the Viasprint 150P ergometer (Ergoline GmbH, Bitz, Germany), starting with a load of 25 W, which is increased by 12.5 W per minute until the patient reaches subjective fatigue or certain termination criteria, such as shortness of breath, chest pain, or leg fatigue. The clinical parameters measured during this test include the maximum load, maximum heart rate, and test duration.

- 6MWT: The 6MWT is a well-established and commonly used exercise test method to assess a patient's functional capacity. The patient is required to walk for 6 minutes on a flat surface. The key metric of the test is the total distance walked, which reflects the patient's cardiopulmonary endurance and physical mobility.

- Stair Climbing Test: In this test, the patient is required to climb a set of 12 stairs. The purpose of this test is to assess the patient's gait and balance abilities, as stair climbing demands greater physical exertion and coordination than walking on flat ground. No clinical parameters were recorded during the test.

- TUG Test: The TUG test is an important tool for assessing the patient's balance and fall risk. During the test, the patient stands up from a chair, walks 3 meters, turns around, and then returns to the chair and sits down. The key parameter of the test is the time required to complete this task, which reflects the patient's balance ability and mobility speed. The time taken to perform the TUG test is recorded as a clinical parameter.

- Gait Analysis: Gait analysis was performed using a gait analysis system with a treadmill (Zebris FDM-T, Zebris Medical GmbH, Germany). The patient was asked to walk on the treadmill for 30 seconds, during which the system dynamically analyzed the gait and generated various gait parameters such as stride length, stride frequency, step length, double-leg support phase, and swing phase. This test helps assess the patient's gait response to frailty and further reveals changes in physical coordination and stability.

Before and after each physical test, patients were required to rest for at least 3 minutes in a resting state to avoid interference with the data from the exercise. Prior to and after each exercise test, patients were allowed to pause or terminate the test according to their condition. All data collection adhered to ethical guidelines, and patients signed an informed consent form before participating in the tests.

During data collection, ECG and accelerometer signals were recorded at different sampling frequencies, and each patient's data was stored in a separate Waveform Database (WFDB) compatible format. To ensure data synchronization and integrity, the signal recordings for each patient were strictly aligned based on timestamps. Each patient's dataset typically consists of a pair of signals recorded during a single session. In certain cases, due to the extended duration of data collection or technical issues, a patient's data might span two or more days, resulting in multiple pairs of ECG and accelerometer signal recordings for each patient. This approach ensures data diversity and comprehensive coverage.

Figures 3.7 and 3.8 show partial ECG signals and accelerometer signals from a specific patient, respectively. A total of 196 recordings were collected for this study,

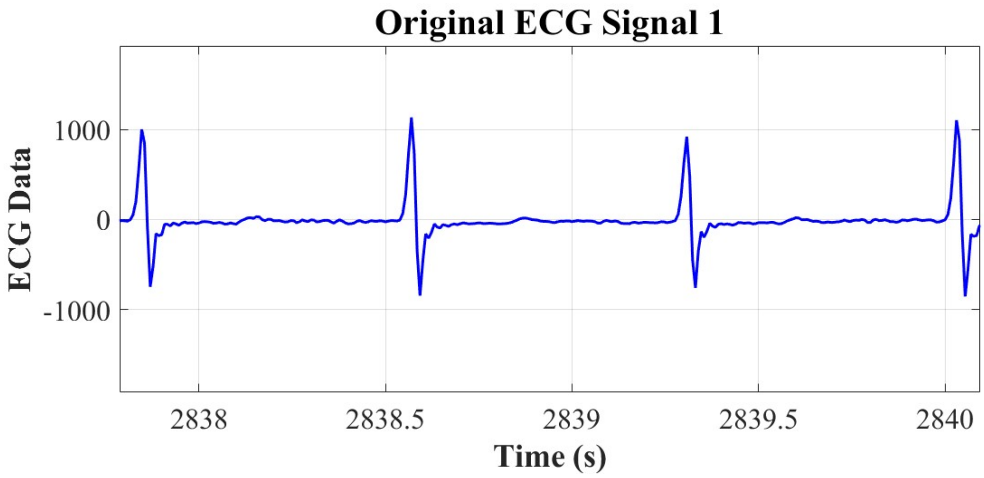

Figure 3.7. Segment of ECG Signal from a Patient

divided into two main categories: ECG recordings and accelerometer recordings. All data files were rigorously classified by signal type to ensure standardization and analyzability.

3.2 Multimodal Data Processing

Multiple preprocessing operations were applied to the collected multimodal data (ECG signals and accelerometer signals) to ensure accuracy and validity. The processing steps primarily involved resampling, filtering, outlier handling, and data segmentation. A detailed explanation of each step, along with the corresponding analysis results, is provided below.

3.2.1 ECG Signal Preprocessing

In this study, due to the different sampling frequencies of the ECG signals and accelerometer signals (130 Hz and 200 Hz, respectively), resampling was required to ensure temporal synchronization between the two signals. By adjusting the sampling frequency, temporal consistency between the two datasets was achieved, allowing each ECG signal sample to correspond to the respective accelerometer signal sample. This step was critical for enabling accurate feature extraction and analysis across modalities.

The purpose of resampling was to reduce the dimensionality of the signals and computational load without losing critical information. Two primary factors were

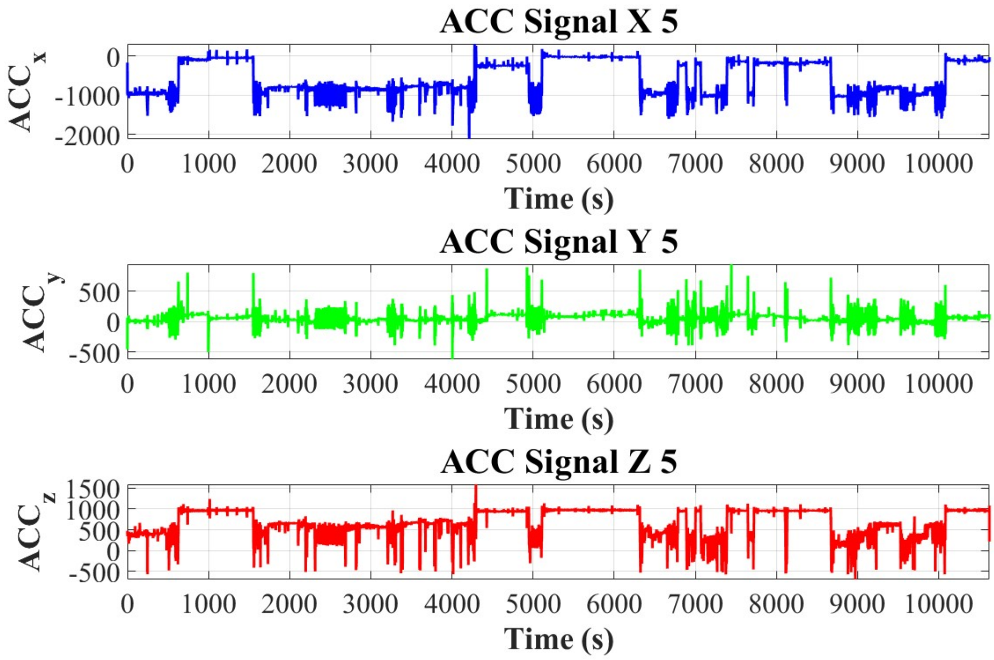

Figure 3.8. Segment of Accelerometer Signal from a Patient

considered when selecting the resampling frequency:

- Signal Fidelity: To preserve essential features of the ECG signals, such as the P-wave, QRS complex, and T-wave, which generally occur in the low-frequency range.
- Data Processing Efficiency: To ensure that the reduced data volume would not compromise computational efficiency or analytical accuracy.

Based on these considerations, resampling frequencies of 100 Hz and 50 Hz were chosen. These frequencies effectively retained the main components of the signals while avoiding data redundancy associated with higher sampling rates. For ECG signals, a frequency of 100 Hz is sufficient to capture the critical waveforms, as studies have shown that most clinical ECG features are contained within this range. Similarly, accelerometer signals at 50 Hz accurately capture motion patterns such as gait and walking, ensuring no significant motion characteristics are lost.

The Figure 3.9 and Figure 3.10 resampling to the ECG signals at 100 Hz and

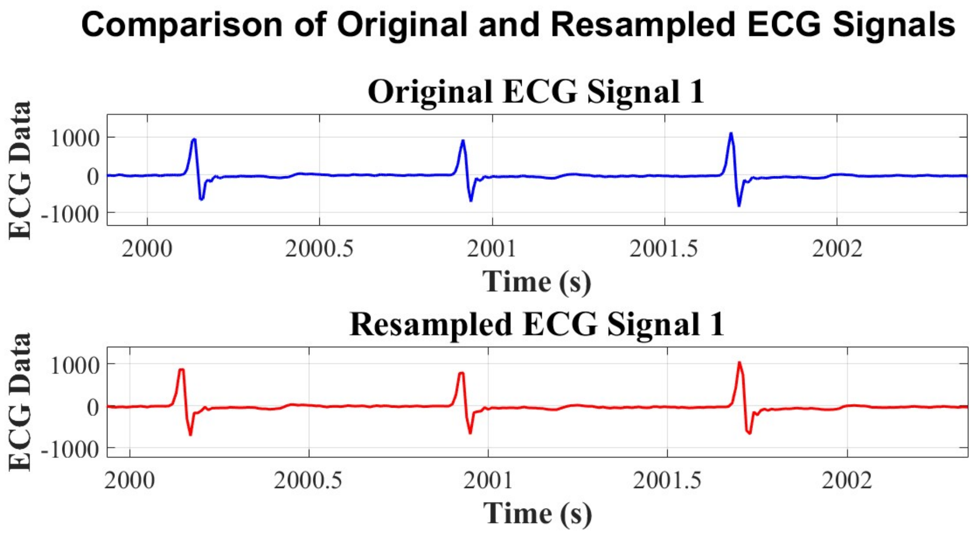

Figure 3.9. Comparison of ECG Signal Before and After Resampling (resampling frequency=100Hz)

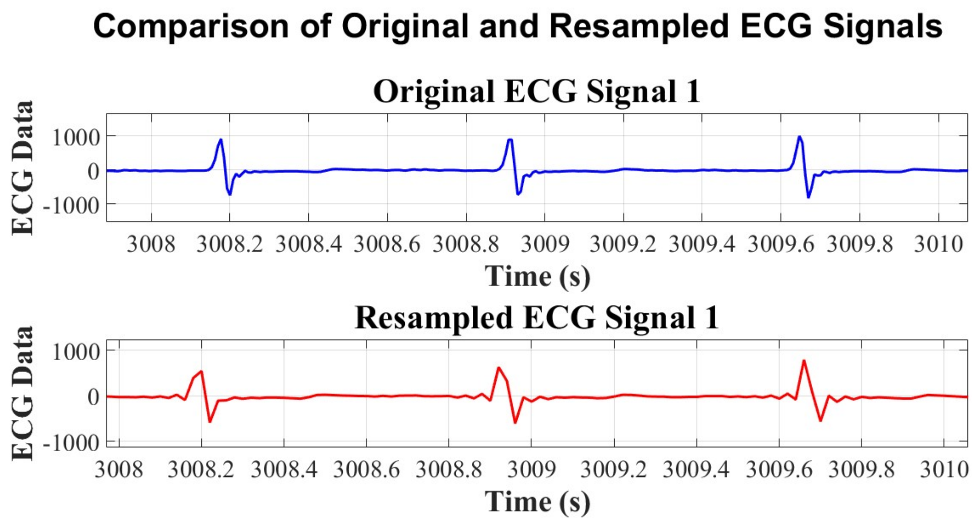

Figure 3.10. Comparison of ECG Signal Before and After Resampling (resampling frequency=50Hz)

50 Hz are analyzed the effects of these frequencies on the signal quality and computational performance. From the figures, it can be observed that at a sampling

frequency of 50 Hz, the main waveforms of the ECG signal, particularly the T-wave, are more distinct. Additionally, the 50 Hz frequency enhances the efficiency of accelerometer data processing. Further analysis confirms that the chosen frequency strikes a balance between signal fidelity and computational efficiency, making it well-suited for multimodal analysis in this study.

In the process of processing ECG signals, filtering is a crucial step to ensure signal quality, remove noise, and preserve physiologically relevant features. Signals in different frequency bands are typically associated with different physiological activities. For example, lower frequency components (such as 0.05–0.15 Hz) are often linked to slow-changing physiological processes like respiration, while higher frequency components (above tens of Hz) may reflect subtle electrical activity during cardiac muscle contraction. The most prominent parts of the ECG typically lie within the mid-frequency range (a few Hz to tens of Hz), which corresponds to key features of the cardiac cycle, such as the P-wave, QRS complex, and T-wave.

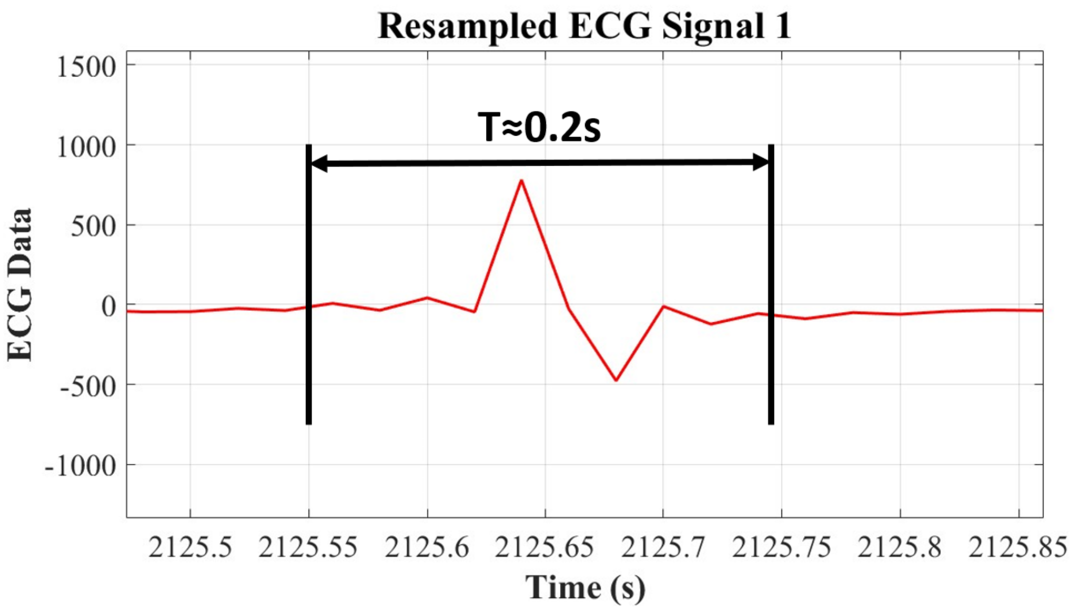

Figure 3.11. ECG Signal with Marked Main Feature Wave Period ($T \approx 0.2s$)

In this study, the primary focus is on the main feature waves of the ECG, thus targeting the mid-frequency range for filtering. Given that the period of the main feature waves in the Figure 3.11 is approximately 0.2 seconds (corresponding to a frequency of about 5 Hz), it is necessary to remove low-frequency noise (such as baseline drift, which typically has a frequency below 0.5 Hz) and high-frequency noise (such as electromyographic noise and electromagnetic interference, which typically has a frequency above 50 Hz) in order to preserve these physiologically important components. Therefore, a Butterworth bandpass filter with cutoff frequencies of 0.5 Hz to 50 Hz and 1 Hz to 50 Hz was applied for comparative analysis.

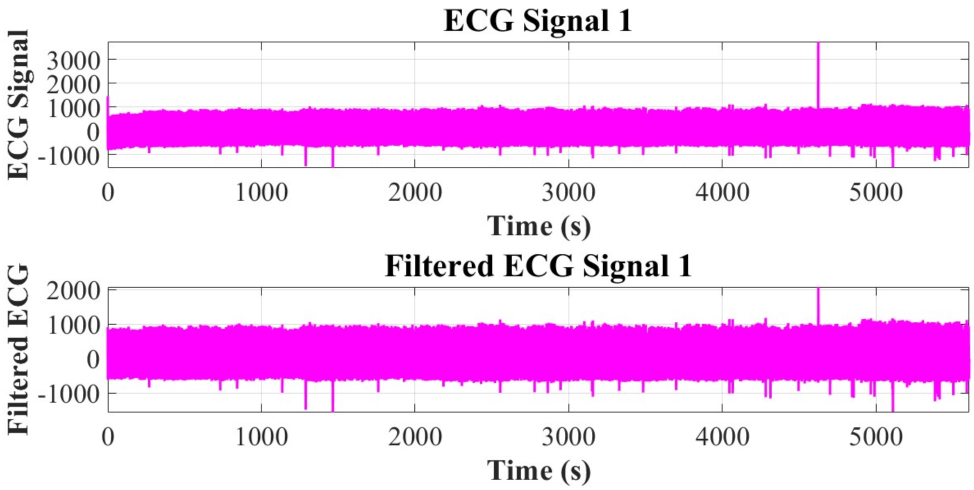

Figure 3.12. ECG Signal Before and After 1 Hz to 50 Hz Bandpass Filtering (Overall View)

Figures 3.12 and 3.13 illustrate the filtering effects of a second-order Butterworth bandpass filter with a frequency range of 1 Hz to 50 Hz on ECG signals. From Figure 3.12, it is evident that the filter effectively eliminates baseline drift at the initial stage of the signal, resulting in a more stable signal and it can be further observed that the filter successfully suppresses some extreme outlier values. In the magnified details shown in Figure 3.13, the main characteristic waveforms of the ECG, such as the P wave, QRS complex, and T wave, are preserved. In summary, the second-order Butterworth bandpass filter with a frequency range of 1 Hz to 50 Hz achieves a good balance between noise reduction and signal fidelity, providing a reliable foundation for subsequent analysis.

Figures 3.14 and Figure 3.15 illustrate the filtering effects of a second-order Butterworth bandpass filter with a frequency range of 0.5 Hz to 50 Hz on ECG signals. From Figure 3.14, it can be observed that the filter effectively eliminates baseline drift during the initial stage of the signal, resulting in a more stable signal. However, further analysis reveals that its performance in suppressing extreme outliers is not as effective as the 1 Hz to 50 Hz filter. In the magnified details

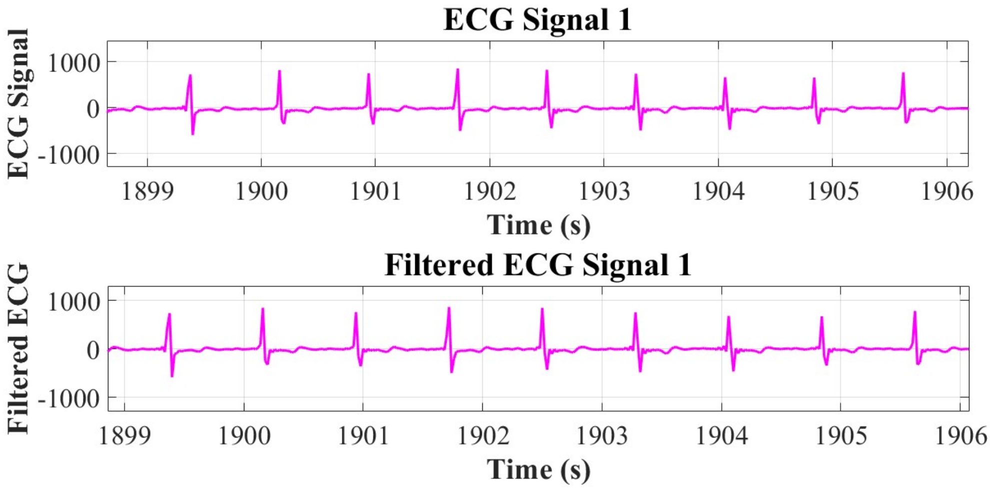

Figure 3.13. ECG Signal Before and After 1 Hz to 50 Hz Bandpass Filtering (Zoomed-in View)

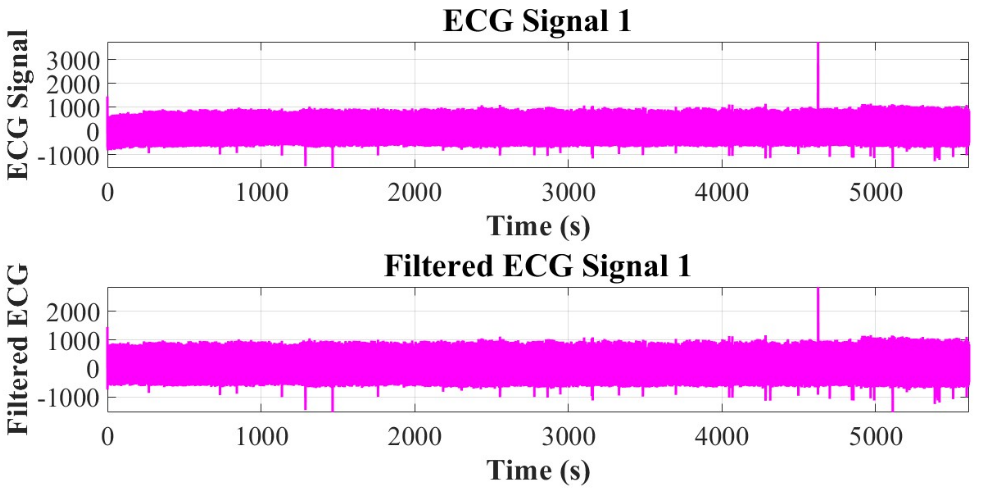

Figure 3.14. ECG Signal Before and After 0.5 Hz to 50 Hz Bandpass Filtering (Overall View)

shown in Figure 3.15 , it is evident that the filter performs similarly to the 1 Hz to 50 Hz filter in preserving the main characteristic waveforms of the ECG.

In conclusion, the second-order Butterworth bandpass filter with a frequency

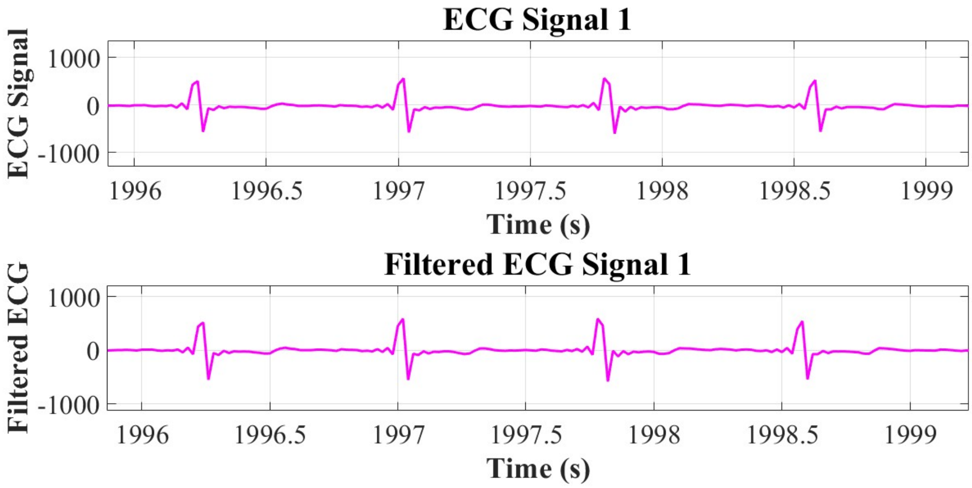

Figure 3.15. ECG Signal Before and After 0.5 Hz to 50 Hz Bandpass Filtering (Zoomed-in View)

range of 1 Hz to 50 Hz achieves a better balance between noise reduction and signal fidelity, providing a more reliable foundation for subsequent analysis.

There are still some outliers and extreme values in the filtered data, which may adversely affect the subsequent ML process. Therefore, it is necessary to handle these outliers. Figure 3.16 and Figure 3.17 show the comparison of the ECG data before and after outlier handling. Figure 3.16 presents the comparison of the overall signal, while Figure 3.17 shows the amplified details.

First, the median and standard deviation of the signal are calculated to establish a threshold based on the standard deviation for identifying outliers that deviate beyond a certain range from the median. Then, the positions of these outliers are identified based on the threshold, and the outliers are replaced with an appropriate value from the preceding major feature waveform of the ECG signal, thereby smoothing the signal and reducing the impact of outliers on subsequent analysis.

By comparing the figures, it is evident that after outlier handling, the signal is smoother and more stable, providing more reliable input data for subsequent analysis and modeling.

3.2.2 Accelerometer Data Preprocessing

In general, sampling frequencies of 100 Hz and 50 Hz are sufficient to capture the essential features of movements such as gait and walking in everyday activities,

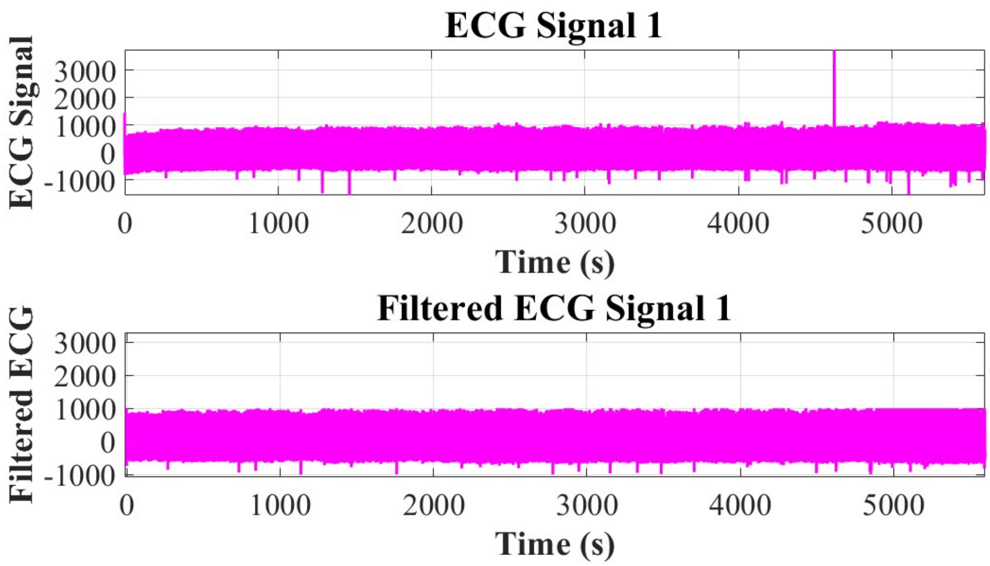

Figure 3.16. ECG Signal Before and After Outlier Removal (Overall View)

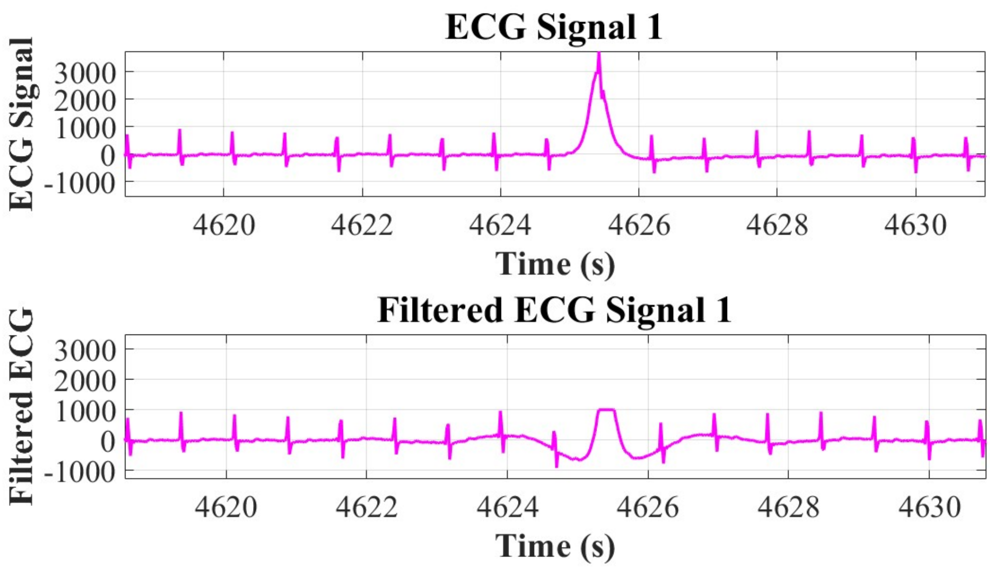

Figure 3.17. ECG Signal Before and After Outlier Removal (Zoomed-In View)

without causing significant loss of key motion characteristics. Specifically, these frequencies are well-suited for accelerometer signal acquisition, meeting the accuracy requirements for analyzing daily activities. As shown in Figure 3.19 and Figure 3.18, comparing signals at different frequencies reveals that, at 50 Hz, the main motion features of the signal are effectively preserved, while also improving computational efficiency.

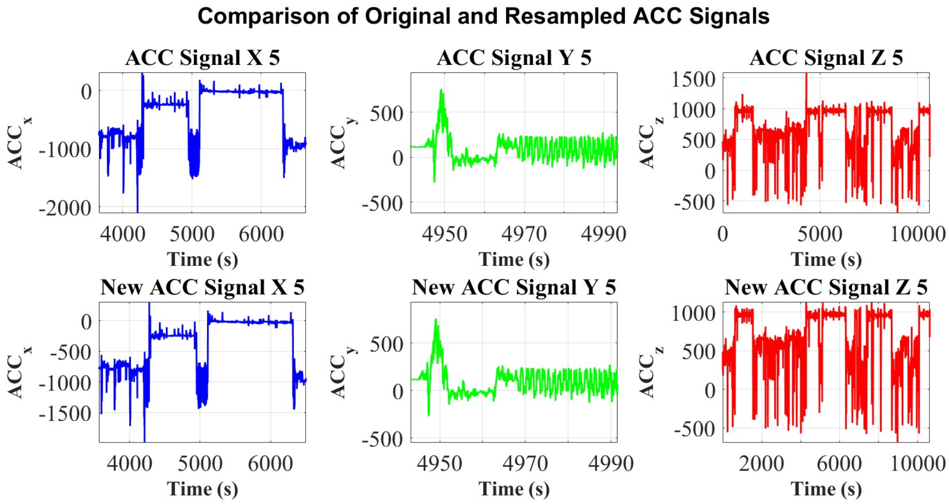

Figure 3.18. Comparison of Accelerometer Signal Before and After Resampling (resampling frequency=50Hz)

It can be seen that choosing 50 Hz as the resampling frequency is perfectly adequate for the accelerometer. To ensure temporal consistency between the ECG and accelerometer signals, 50 Hz was selected as the final sampling frequency for the accelerometer data. This decision not only preserves the fidelity of the signals but also optimizes data processing efficiency, making it more suitable for further analysis.

Similar to ECG signals, accelerometer signals can also be affected by various types of noise, including mechanical noise from the device itself, motion artifacts, and external environmental factors. As a result, filtering is a crucial step in the processing of accelerometer signals to reduce interference and extract key information. This study aims to detect human motion patterns, including gait analysis and activity monitoring. Gait analysis and activity monitoring typically focus on signal components within the frequency range of 0.5 Hz to 20 Hz. Among these, gait characteristics are primarily concentrated in the 1 Hz to 3 Hz range, while rapid movements of the arms and head typically correspond to the 10 Hz to 20 Hz frequency range.

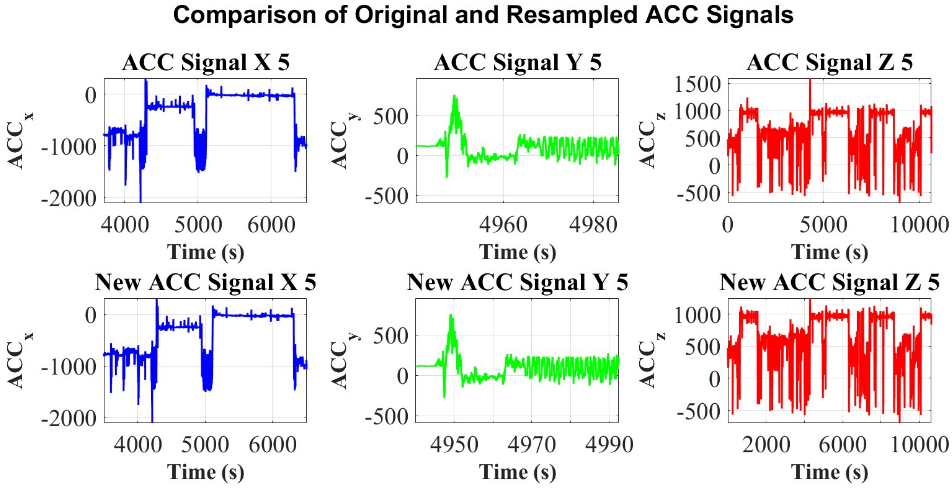

Figure 3.19. Comparison of Accelerometer Signal Before and After Resampling (resampling frequency=100Hz)

To ensure the capture of these motion characteristics while effectively removing high-frequency noise, this study applies a low-pass filter to process the accelerometer signals, with a cutoff frequency set at 20 Hz. The filtered results are shown in the accompanying Figure 3.20 and Figure 3.21.

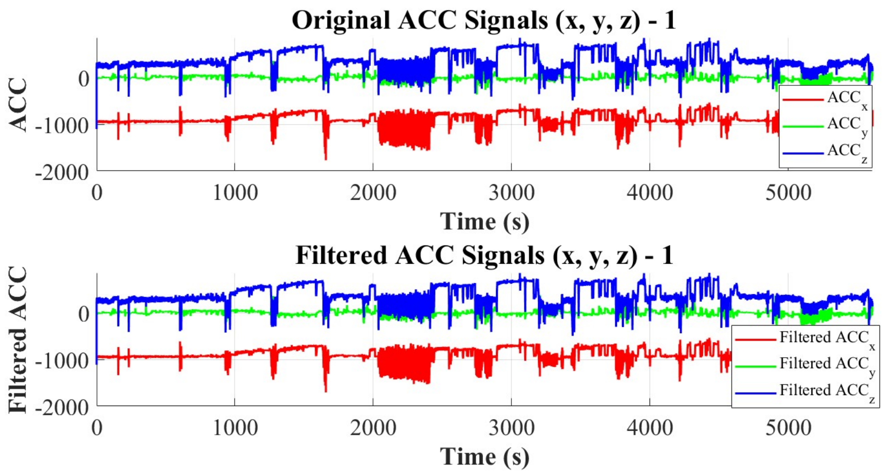

Figure 3.20. Accelerometer Signal Before and After 20 Hz lowpass Filtering (Overall View)

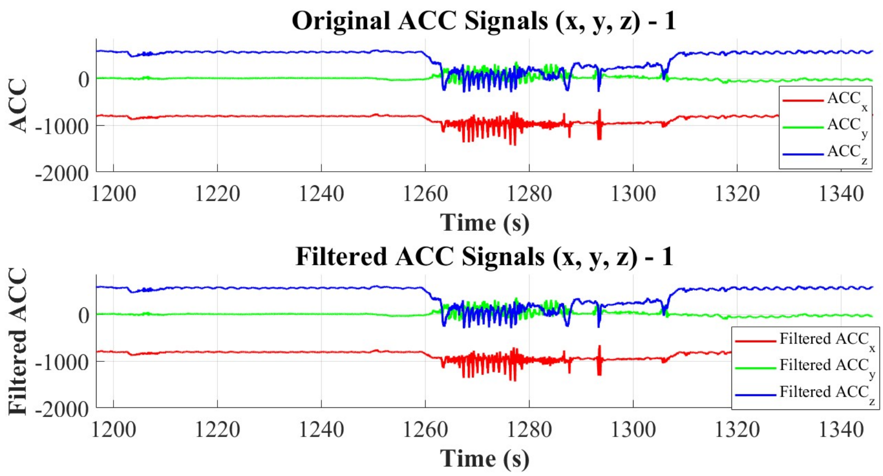

Figure 3.21. Accelerometer Signal Before and After 20 Hz lowpass Filtering (Zoomed-in View)

Figure 3.20 shows a comparison of the accelerometer signal before and after low-pass filtering, while Figure 3.21 displays the amplified signal details. As can be seen from the figures, the differences between the pre- and post-filtered signals are not significant, indicating that the raw accelerometer data already effectively reflects the patient's gait and activity information. Further analysis reveals that the application of the low-pass filter has minimal impact in this study, suggesting that the raw data could be used directly to reduce unnecessary preprocessing steps while preserving the integrity of the signal.

When processing accelerometer data, it is essential to segment the signal based on the start time and duration of each activity to extract valid data for each activity phase. For some activities, the start time and duration are explicitly indicated in the raw data or metadata table. However, for activities where the duration cannot be directly obtained, it is necessary to extract and determine these parameters based on signal characteristics.

The start time of stair-climbing activities is marked in the raw data, but the end time needs to be calculated based on signal characteristics. This study employs the following segmentation method:

- Use the known activity start time as a reference and begin calculations from the 2-second mark.
- Calculate the standard deviation of all peak values within every 3-second time window.

- If the standard deviation of peak values in a time window is less than 10, stop extraction, and this time point is designated as the end time of the activity.

The core of this method lies in leveraging the regularity of changes in activity signal intensity. When the standard deviation decreases significantly, it indicates that the activity has essentially ceased or stabilized. Figure 3.22 illustrates the overall signal of the stair-climbing activity after segmentation.

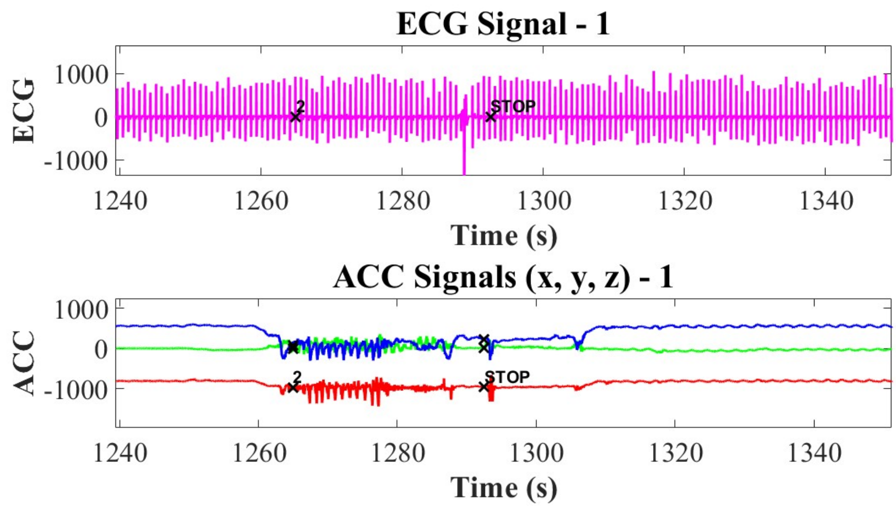

Figure 3.22. Data Segmentation of STAIR

The duration of the 6MWT is 300 seconds, during which the accelerometer signal corresponds to walking activity. Based on the start time provided in the basic information table, a 300-second segment of the signal is extracted starting from the indicated time. Figure 3.23 shows the overall signal after segmentation.

The duration of the TUG test is explicitly recorded in the basic information table. Using the start and end times provided in the table, the signal is directly extracted without further calculations. Figure 3.24 illustrates the segmented signal results

Similarly, the duration of the veloergometry can also be found in the basic information table. The accelerometer signal is segmented according to the time range specified in the table. Figure 3.25 presents the segmented signal for the speed test.

The duration of the gait analysis activity is 30 seconds. Using the start time provided in the basic information table as a reference, a 30-second segment of the signal is extracted as the segmentation result. Figure 3.26 displays the segmented signal for the gait analysis activity.

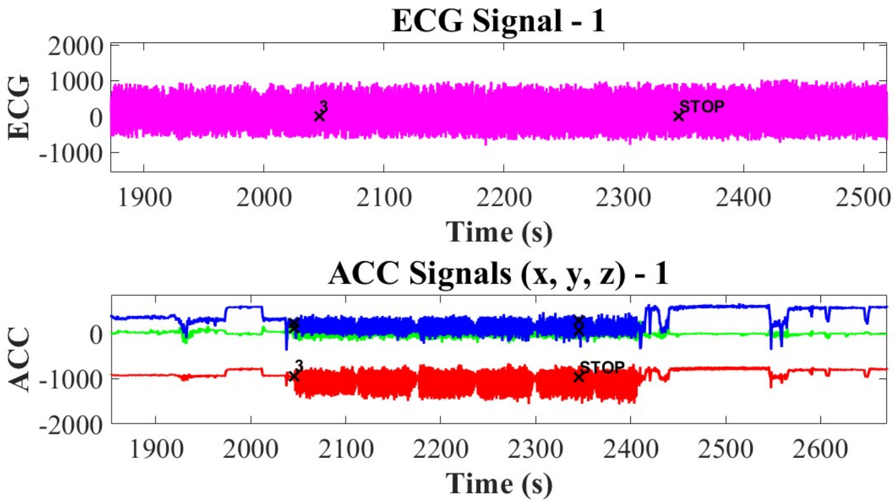

Figure 3.23. Data Segmentation of 6MWT

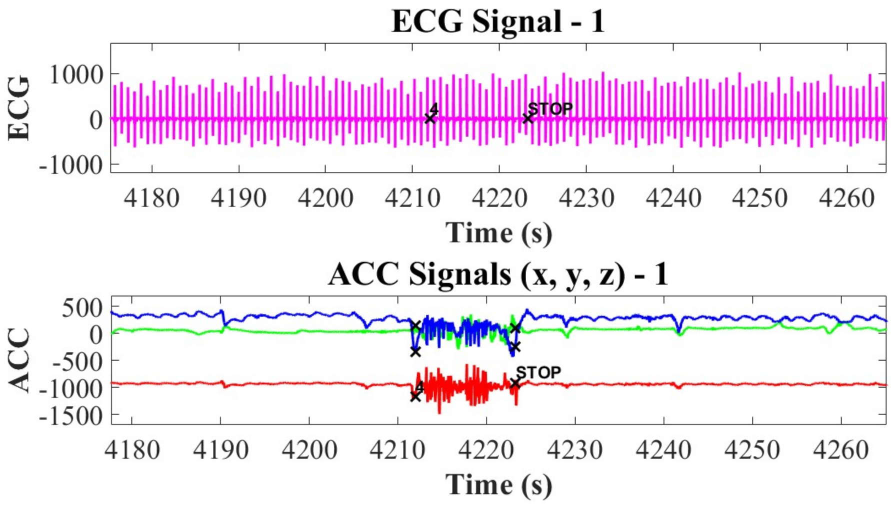

Figure 3.24. Data Segmentation of TUG

Using the segmentation methods described above, effective signals from each activity phase were successfully extracted. This provides a solid foundation for subsequent feature extraction and multimodal analysis, ensuring that the signals from each activity phase are representative and reliable.

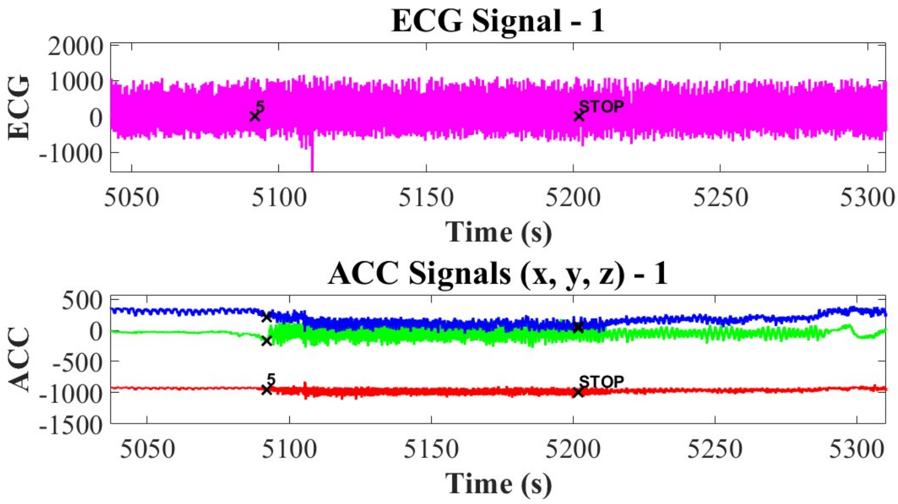

Figure 3.25. Data Segmentation of VELO

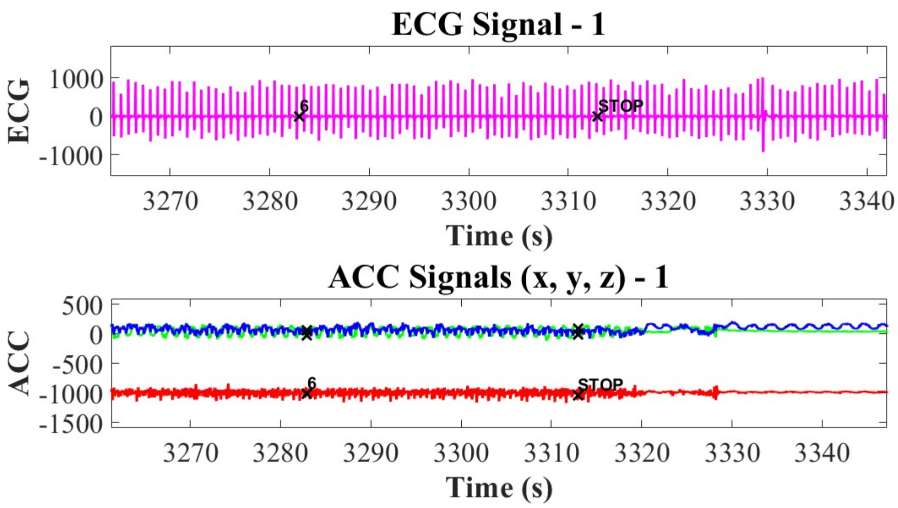

Figure 3.26. Data Segmentation of Gait Analysis

3.3 Feature Extraction and Selection

3.3.1 Clinical Features

In the study of predicting cardiovascular complications, clinical features are an important data source for assessing CVDs risk. These features can directly reflect the patient's underlying health status, medical history, and post-surgery recovery, making them highly valuable for reference. This study selected the following key clinical features based on their potential association with the risk of CVDs occurrence, as show in 3.1.

Feature	**Description**
Age	Age of the patient in years
Gender	Gender of the patient (e.g., 0 - Male, 1 - Female)
Height	Height of the patient in cm
Weight	Weight of the patient in kg
Days after surgery	Number of days since the surgery
Surgery type	Type of surgery (0 - Coronary artery bypass graft, 1 - Isolated valve, 2 - Combined surgery)
COPD	Presence of chronic obstructive pulmonary disease (0 - No, 1 - Yes)
Depression	Presence of depression (0 - No, 1 - Yes)
Musculoskeletal system diseases	Presence of musculoskeletal system diseases (0 - No, 1 - Yes)
Oncological diseases	Presence of oncological diseases (0 - No, 1 - Yes)

Table 3.1. Clinical Features

These features provide important information closely related to cardiovascular health, helping us understand the overall health status of patients and predict the occurrence and progression of diseases.

- Age: The patient's age is one of the common clinical features. As age increases, there is often a decline in bodily functions, which may be associated with an increased risk of CVDs, respiratory diseases, and others.

- Gender: Gender is an important factor influencing cardiovascular health. Men and women may have different risks, disease manifestations, and responses to treatment.

- Height and Weight: These indices are typically used to assess the relationship between obesity and cardiovascular health. Obesity is a significant risk factor for CVDs.

- Surgery Type: There are three types of surgery in this study: CABG, isolated valve surgery, and combined surgery. The type of surgery directly impacts the patient's post-operative recovery and the restoration of cardiovascular function.

- Days after Surgery: The number of days after surgery reflects the patient's recovery time and is an important indicator for assessing the rehabilitation process.

- COPD, Depression, Musculoskeletal System Diseases, and Oncological Diseases: These chronic conditions may exacerbate the patient's overall health burden, affect the recovery of cardiovascular function, and increase the risk of post-operative complications.

These clinical features provide rich health information about the patient and are helpful for predicting the patient's recovery process after surgery, the likelihood of complications, and long-term health outcomes.

3.3.2 Sensor Features

In this study, the extraction of sensor features was performed separately from the accelerometer data and ECG data. By extracting these features, meaningful information from both the motion and cardiac signals can be obtained to help predict the occurrence and progression of CVDs.

To effectively extract sensor features, this study adopted the sliding window method. First, the window size was set to 250 data points, approximately 5 seconds, which is effective for capturing the periodic variations in both cardiac and motion signals, ensuring the timeliness and representativeness of the feature extraction. The step size between windows was set to 25 data points, ensuring a 90% overlap between adjacent windows. As shown in Figure 3.27, this approach improves the accuracy of feature extraction while ensuring that more dynamic changes in the time series are captured.

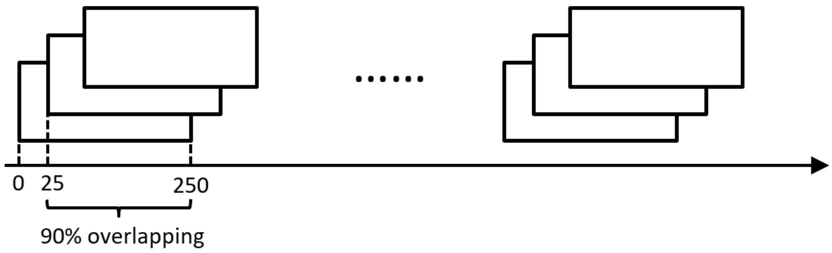

Figure 3.27. Sliding Window Method for Feature Extraction in Time-Series Data

Accelerometer features are mainly used to describe the patient's movement status, particularly information related to gait, physical activity, and activity type. These features are essential for evaluating the patient's daily activity level, functional status, and mobility. The accelerometer features are categorized into two types: time-domain features and frequency-domain features, as shown in the Table 3.2 below.

Time-domain features directly describe the trend of the signal's variation over time, reflecting the basic statistical properties of the signal. Common time-domain features include:

- RMS: Root Mean Square, which represents the magnitude of the signal's

Table 3.2. Accelerometer Features

Time-domain Features	Frequency-domain Features
RMS	Total Power Magnitude
Mean	Mean Power Magnitude
Std	Std Power Magnitude
Correlation Coefficients	Total Power Components
	Mean Power Components
	Std Power Components
	Max Power Components
	Dominant Frequency
	Mean Frequency
	Median Frequency
	Peak Frequency
	Skewness Frequency

energy. It is used to measure the intensity and amount of the patient's physical activity.

- Mean: The mean value of the signal, reflecting the average level of the signal, which helps understand the overall trend of the activity.
- Standard Deviation: The standard deviation of the signal, representing the variability of the signal, reflecting the stability of the patient's activity.
- Correlation Coefficients: The correlation coefficient of the signal, used to describe the correlation between different dimensions of the signal. This feature helps assess the coordination of movement.

Frequency-domain features provide information on the distribution of the signal across different frequencies, typically used to reveal periodicity and energy distribution within the signal. The accelerometer's frequency-domain features generally involve the following:

- Total power magnitude: The total power of the signal, representing the overall energy level of the signal, which reflects the intensity of the patient's activity.
- Mean power magnitude: The mean power, reflecting the balance of the signal's energy.
- Standard deviation power magnitude: The standard deviation of the power, indicating the degree of fluctuation in the signal's energy, which can assess the stability of the activity.

- Dominant frequency: The dominant frequency, which indicates the frequency component with the highest energy concentration, helping to identify the type of activity the patient is performing.

- Mean frequency, median frequency, peak frequency: These represent the mean frequency, median frequency, and peak frequency, respectively, and help analyze the frequency distribution characteristics during the activity.

- Skewness frequency: The skewness of the frequency, which describes the asymmetry of the frequency distribution and helps uncover any asymmetry in the signal during movement.

ECG signals reflect the electrical activity of the heart and play a crucial role in assessing heart health and function. In this study, five main types of features from the ECG signals were extracted: HRV features, QRS waveform features, QT waveform features, time-domain ECG features, and heart rate information. Each type of feature represents different physiological processes and health conditions of the heart, as shown in the Table 3.3.

Table 3.3. ECG Features

HRV Features	**QRS Features**
HRV Mean HRV Std HRV RMS Std HRV PNN 50ms	Mean QRS Durations Mean QRS Widths Mean QRS Amplitudes
QT Wave Features	**Time-domain Features**
Q Wave Amplitudes Q Wave Durations T Wave Amplitudes T Wave Durations	Mean ECG Std ECG Max ECG Min ECG Range ECG
Other Feature: Heart Rate	

HRV features are used to assess the autonomic nervous regulation of the heart and reflect the heart's health status. It refers to the variation in the time intervals (RR intervals) between successive heartbeats. HRV reflects the autonomic nervous system's ability to regulate the heart and is widely used to evaluate heart health. The main HRV features include the following:

- **Mean HRV (HRV_mean):** The mean HRV represents the average value of RR intervals and reflects the stability of heart rhythms. The formula is:

$$\mathrm{HRV}_{\mathrm{mean}} = \frac{1}{N}\sum_{i=1}^{N} RR_i$$

where RR_i is the i-th RR interval, and N is the total number of RR intervals.

- **Standard Deviation of HRV (HRV_std):** The standard deviation of HRV indicates the amplitude of RR interval fluctuations, representing the variability of heart rhythms. The formula is:

  $$\mathrm{HRV}_{\mathrm{std}} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RR_i - \mathrm{mean}(RR))^2}$$

  where RR_i is the i-th RR interval, $\mathrm{mean}(RR)$ is the mean of RR intervals, and N is the total number of RR intervals.

- **Root Mean Square of Successive Differences (HRV_rmssd):** The root mean square of successive differences (RMSSD) reflects the short-term variations in RR intervals and is commonly used to assess the function of the autonomic nervous system. The formula is:

  $$\mathrm{HRV}_{\mathrm{rmssd}} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1} - RR_i)^2}$$

  where $RR_{i+1} - RR_i$ represents the difference between two consecutive RR intervals.

- **PNN50 (HRV_pnn50):** The PNN50 index of HRV represents the proportion of adjacent RR intervals with differences greater than 50 milliseconds. It is often used to measure the magnitude of short-term heart rate fluctuations. The formula is:

  $$\mathrm{HRV}_{\mathrm{pnn50}} = \frac{\sum_{i=1}^{N-1} I\left(|RR_{i+1} - RR_i| > 0.05\right)}{N-1} \times 100$$

  where I is an indicator function, which equals 1 when the difference between two consecutive RR intervals exceeds 50 milliseconds, and 0 otherwise.

The QRS complex is a crucial component of the ECG, reflecting ventricular electrical activity, particularly the process of ventricular contraction. QRS waveform features can be used to assess the conduction speed and overall health of the heart. The related features include:

- QRS durations: The average duration of the QRS complex, indicating the propagation speed of cardiac electrical activity. Prolonged QRS duration may suggest abnormalities in the heart's conduction system.
- QRS widths: The average width of the QRS complex, describing the morphological characteristics of the QRS waveform. Abnormal QRS widths may be associated with pathological changes in the heart.
- QRS amplitudes: The average amplitude of the QRS complex, reflecting the intensity of the ECG signal. Reduced amplitude may indicate potential cardiac dysfunction.

QT waveform features are used to analyze the heart's repolarization process and are critical indicators of cardiac health. Specific features include:

- Q wave amplitudes: The amplitude of the Q wave, reflecting the strength of the electrical signal during the heart's repolarization process. Reduced amplitude may indicate cardiac dysfunction.
- Q wave durations: The duration of the Q wave, representing its persistence. Prolonged duration may suggest delayed or abnormal cardiac electrical activity.
- T wave amplitudes: The amplitude of the T wave, reflecting the strength of the heart's repolarization. Reduced amplitude may indicate cardiac functional issues.
- T wave durations: The duration of the T wave, representing its persistence. Prolonged T wave duration may be a marker of abnormal cardiac repolarization.

Time-domain ECG features directly capture changes in ECG signals, providing insights into the amplitude and variability of cardiac electrical activity. The extracted time-domain features include:

- ECG mean: The mean value of the ECG signal, representing the overall level of the ECG. A higher mean value may reflect stronger cardiac activity.
- ECG std: The standard deviation of the ECG signal, indicating the variability of the signal. A larger standard deviation suggests instability in cardiac activity.
- ECG max, ECG min, ECG range: Represent the maximum, minimum, and range of the ECG signal, respectively. These features reflect the amplitude variations in cardiac electrical activity, with a larger range potentially indicating greater fluctuations in cardiac function.

In addition, heart rate features were extracted. These features are derived from the positions of R waves in the ECG signal, reflecting the instantaneous HRV across different time windows.

By extracting these features, we can conduct a comprehensive analysis of the patient's cardiac health, providing a foundation for further disease prediction and risk assessment.

3.4 ML Models for Activity Classification

In this study, to analyze patient activities and identify specific activity types, we compared several commonly used ML algorithms. The patients' activities were categorized into three types: stair climbing, walking, and cycling. For simplicity, the activities "gait analysis," "TUG," and "6MWT" were grouped under the "walking" category. These ML models were employed to classify the activities, and their performance was evaluated using five-fold cross-validation.

3.4.1 Algorithm comparison

When selecting ML algorithms, we primarily considered their representativeness, applicability, and suitability for the research data. In this study, we chose KNN, decision trees and random forests as the classification algorithms.

- KNN: KNN is an intuitive classification algorithm based on the concept of nearest neighbors. It predicts the category by calculating the distance between samples. KNN is simple and easy to use, requiring no complex assumptions about the data, and directly classifies based on distance relationships between samples. It is suitable for small datasets, and the dataset size in this study is relatively moderate, making KNN's computational efficiency acceptable. Additionally, KNN can effectively handle multi-class problems, such as the multi-class activity classification in this study. However, KNN performance may fluctuate due to variations in data distribution. Therefore, it is necessary to compare it with other algorithms to evaluate its performance.

- Decision Tree: A decision tree is a rule-based classification algorithm that constructs a tree-like structure to make decisions based on feature values. It can automatically select the most important features for splitting, making it suitable for datasets with complex features. Additionally, decision trees can naturally handle nonlinear relationships between features. Although decision trees may suffer from overfitting, their simplicity and efficiency make them a commonly used baseline model for the initial evaluation of the complexity of a classification task.

- Random Forest: Random Forest is an ensemble-based classification algorithm that trains multiple decision trees and combines their outputs through a voting mechanism to make predictions. It is highly robust, suitable for high-dimensional data, and capable of providing feature importance scores, which help in understanding the impact of various features. Moreover, by incorporating randomness and aggregating multiple tree models, it effectively reduces the risk of overfitting associated with individual models. Due to its excellent overall performance, Random Forest is a widely used mainstream algorithm for classification tasks. Comparing it with other algorithms can validate its advantages in this study.

These algorithms encompass various classification paradigms, including instance-based (KNN), rule-based (Decision Tree) and ensemble-based (Random Forest), demonstrating strong representativeness. Moreover, these algorithms are widely applied in medical data analysis and activity classification studies, providing a comprehensive performance evaluation for the research.

To enhance the model's accuracy, the algorithm was optimized to align with practical scenarios. Given that patients are unlikely to engage in multiple activities within a short time frame (e.g., 2 seconds), a data correction measure was implemented during training to address significant changes in activity data detected over consecutive seconds. Specifically, outlier data points were replaced with the most common values observed within the time period, minimizing the impact of these fluctuations on the training process and resulting in a more robust and accurate model.

3.4.2 Model Training and Validation

To evaluate the performance of each classification algorithm, 5-fold cross-validation was employed. 5-fold cross-validation is a widely used model validation technique that randomly divides the dataset into five subsets. Four subsets are used for training, and the remaining one is used for testing. This process is repeated five times, with each subset serving as the test set once, and the final results are averaged. The main advantage of 5-fold cross-validation is that it maximizes the use of the dataset, avoids bias caused by uneven splits between the training and testing sets, and provides a better evaluation of the model's performance on different data. This method effectively reduces the bias in model selection, leading to more reliable evaluation results.

During model training, the default parameter settings have been used for each algorithm, the models have been trained, and their performance have been compared on the test set. To evaluate the classification effectiveness of the models, we calculated the confusion matrix and common evaluation metrics such as accuracy, precision, recall, and F1 score. Accuracy reflects the model's overall prediction correctness, precision measures the accuracy of positive class predictions, recall reflects the model's ability to identify positive cases, and the F1 score is the harmonic mean of precision and recall, providing a comprehensive view of the model's performance.

3.5 Feature Importance Analysis

In this section, to further explore the impact of different types of features on heart function prediction based on NYHA classification, the SHapley Additive exPlanations (SHAP) method was employed to analyze feature importance. SHAP is a technique for explaining ML model outputs, capable of quantifying the contribution of each feature to the prediction results, thereby providing greater transparency in model interpretation. Feature importance analysis was conducted for the following three scenarios: (1) using only clinical features; (2) using only sensor features; and (3) using multimodal fused data that combines clinical and sensor features.

In the feature importance analysis, the mean absolute SHAP values (mean |SHAP Value|) were used as an indicator of feature importance, with the analysis conducted on the top 100 samples. Additionally, the top 10 features with the highest importance in each experiment were identified, revealing the key factors that contributed the most to the prediction results. These high-importance features not only provide insights into the model's decision-making logic but also offer valuable guidance for optimizing data selection in future research and practical applications.

Chapter 4

Results

This chapter compares different ML models and presents the results of cardiovascular function prediction models based on the NYHA classification using different types of features, including clinical feature models, sensor feature models, and the final combined model that integrates both. In the analysis, the clinical feature model predicts based on the characteristics of each patient's data. The sensor feature model, on the other hand, analyzes data from different activity types (stair climbing, walking, and cycling) and selects the most frequent prediction outcome across these activities as the patient's final NYHA classification. The final model combines clinical and sensor features by aggregating the results from the three activities to predict the patient's cardiovascular function level. Furthermore, each section provides an in-depth discussion of the model's prediction performance and the importance of the top ten features.

4.1 ML Model Comparison

In this study, the model selection was based on the results of five-fold cross-validation, with the performance on the validation set first evaluated. Figure 4.1 shows the performance of different models on the validation dataset.

The KNN model achieved an accuracy of 79.29%, a precision of 77.30%, a recall of 76.49%, and an F1 score of 77.89% on the validation set. Although the KNN model performed well in terms of accuracy and precision, it showed some shortcomings in recall, indicating its weaker ability to identify minority class samples. This is because the KNN model relies heavily on the labels of nearby samples, and when the data is imbalanced, the model may favor the majority class, thereby affecting its performance in recognizing the minority class.

In comparison to KNN, the decision tree model showed a slight improvement on the validation set. It achieved an accuracy of 77.07%, precision of 82.09%, recall

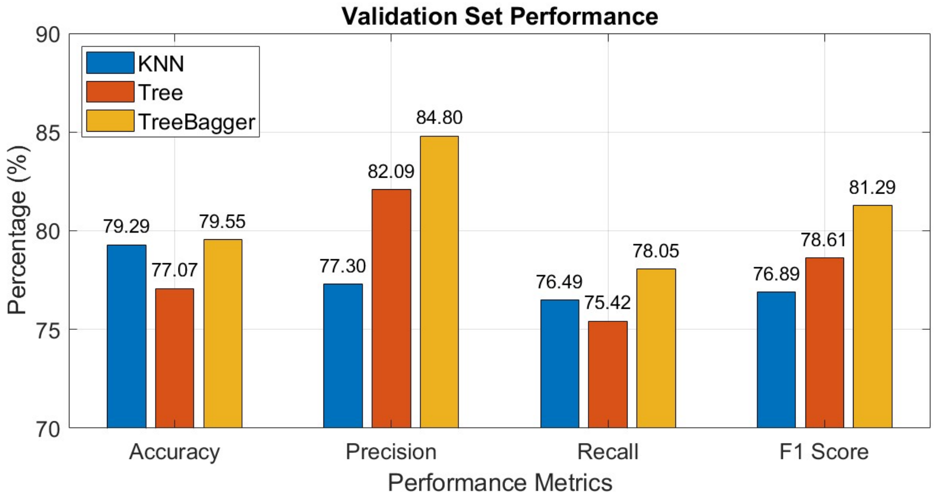

Figure 4.1. Comparison of Classification Models on Validation data Sets

of 75.42%, and an F1 score of 78.05%. The decision tree model demonstrated an increase in precision, meaning it was more accurate when predicting the positive class. However, it still faced issues with the recognition of the minority class. Decision trees may overfit the training data by relying too much on individual features, leading to overfitting problems. Nonetheless, the decision tree was able to capture certain patterns in the data, especially when strong decision boundaries existed between features.

The random forest model performed the best on the validation set. It achieved an accuracy of 79.55%, precision of 84.80%, recall of 78.05%, and an F1 score of 81.31%. These metrics were significantly higher than those of the other two models, particularly showing a notable advantage in precision and F1 score. By integrating multiple decision trees and using voting or averaging, the random forest significantly improved the model's robustness to the data, reduced the risk of overfitting, and better handled the class imbalance issue. It demonstrated strong performance in identifying minority class samples and maintained high performance when dealing with imbalanced data.

Therefore, based on the performance on the validation set, the random forest is the best-performing model in this study. Its accuracy, recall, and F1 score all outperform those of KNN and decision trees, with a clear advantage in handling class imbalance.

After analyzing the validation set and selecting the best model, the performance on the test set was then evaluated to verify the model's generalization ability, with the results shown in Figure 4.2. The performance of the KNN model decreased on

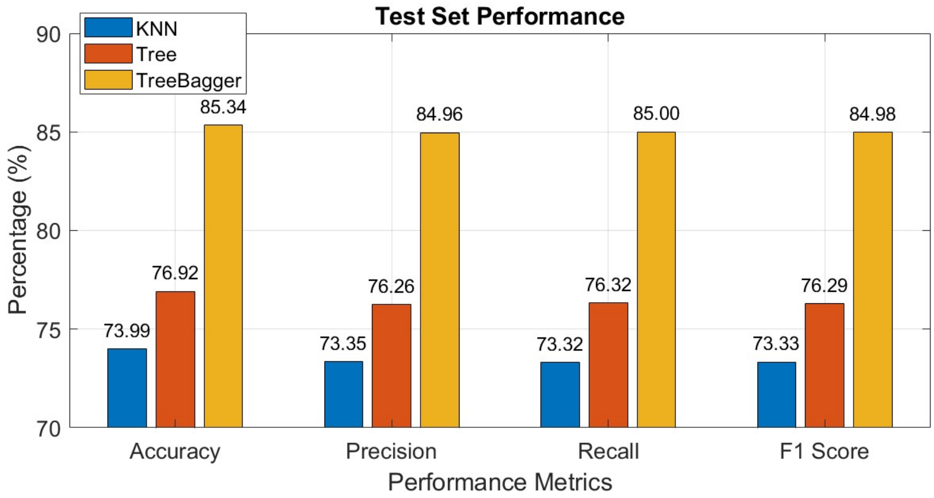

Figure 4.2. Comparison of Classification Models on Testing data Sets

the test set, with an accuracy of 73.99%, precision of 73.35%, recall of 73.32%, and F1 score of 73.33%. These results suggest that while the KNN model performed well on the validation set, its stability in real-world applications is weaker, especially when handling more complex and imbalanced data, as its performance on the test set is worse than on the validation set.

The decision tree showed some improvement on the test set, with an accuracy of 76.92%, precision of 76.26%, recall of 76.32%, and an F1 score of 76.29%. Although the decision tree performed better on the test set than on the validation set, it still could not match the random forest model. The decision tree model may have overfitted on the training set, leading to insufficient generalization ability when faced with unseen data.

The random forest model undoubtedly performed the best on the test set, with an accuracy of 85.34%, precision of 84.96%, recall of 85.00%, and F1 score of 85.00%. These results demonstrate that the random forest not only performed excellently on the validation set but also has strong generalization ability, maintaining high accuracy and stability on the test set. By integrating multiple decision trees, the random forest effectively reduces the risk of overfitting and performs particularly well in recognizing minority class samples, which gives it a clear advantage in handling class imbalance compared to the other models.

Considering the results from both the validation and test sets, the random forest model stands out for its exceptional performance on the validation set and its strong generalization ability. It outperforms the KNN and decision tree models on multiple evaluation metrics (accuracy, precision, recall, and F1 score) and shows significant advantages in handling class imbalance. The ensemble learning mechanism of the random forest makes it highly robust and generalizable when dealing with complex datasets, effectively avoiding overfitting and excelling in minority class recognition. Therefore, the random forest is selected as the best model in this study, demonstrating high reliability and adaptability in practical applications.

4.2 Clinical Model

First, the NYHA classification was predicted using the patients' clinical features. These clinical features include height, weight, type of surgery, and length of hospital stay. The Random Forest model was used for training. The model training was conducted using five-fold cross-validation to ensure the robustness and generalizability of the results. The evaluation metrics for validation and testing included Accuracy, Precision, Recall, and F1 Score.

The training results when we use only clinical features are shown in Figure 4.3, while Table 4.1 presents the evaluation metrics of training and testing results.

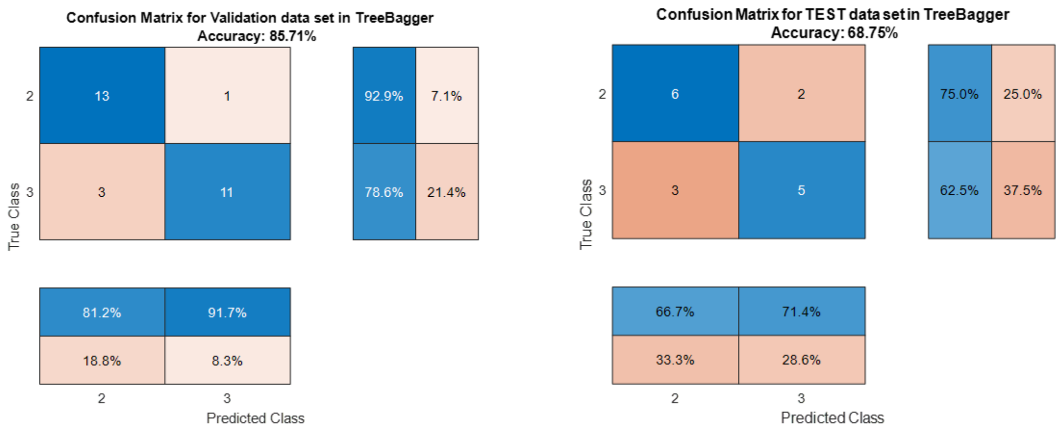

Figure 4.3. Comparison of Classification Models on Validation and Test Sets based on Clinical Features

The performance results of the model on the validation and test sets show a clear discrepancy between the two. Specifically, the accuracy on the validation set (78.94%) is significantly higher than that on the test set (68.75%). Similar trends are observed for Precision (80.99% vs. 69.05%), Recall (80.34% vs. 68.75%), and F1 Score (79.63% vs. 68.63%). This suggests that the model performs relatively well on the validation set, likely because the data distribution of the validation set

Metric	Validation Set	Test Set
Accuracy (%)	78.94	68.75
Precision (%)	80.99	69.05
Recall (%)	80.34	68.75
F1 Score (%)	79.63	68.63

Table 4.1. Performance Metrics on Validation and Test Sets for Clinical Features

is similar to that of the training data, or the validation set samples are easier to classify. In contrast, the performance on the test set is poorer, possibly because the test set contains more challenging or complex samples, making it harder for the model to accurately capture their features, resulting in a decline in accuracy and other metrics. The model's underperformance on the test set, especially the larger differences in Precision and Recall, indicates some degree of overfitting, meaning the model may have been over-optimized for the validation set and failed to generalize effectively to the test data.

In order to evaluate the stability and performance of the model, it was run ten times, and the results showed an accuracy of 54.38 ± 7.82 %. This indicates that the model's performance shows some variability and has not consistently achieved high accuracy. The lowest accuracy of 43.75% suggests that, in some tests, the model's prediction performance was poor.

The clinical feature model's results are directly based on each patient's feature data to predict their NYHA classification, with an analysis of the contribution of the top five most important features.

Patient ID	36	61	108	139	144	146	155	159	163
Pred.	II	II	III	III	III	III	II	II	II
Orig.	III	II	III	III	II	III	II	II	III

Patient ID	188	208	249	269	282	295	319
Pred.	II	II	III	III	III	II	II
Orig.	III	II	II	III	III	II	II

Table 4.2. Predicted vs Original NYHA Classification Result based on clinical features

Table 4.2 shows a comparison between each patient's predicted results and actual outcomes. In this prediction analysis, we compared the predicted NYHA classification (Pred.) with the patients' actual NYHA classification (Orig.). The model's predictions were categorized into NYHA II and NYHA III, where NYHA II represents mild heart dysfunction and NYHA III represents moderate heart dysfunction. Based on the analysis of the test set, the model achieved an accuracy of 62.5% for the 16 patients, meaning the prediction results for 10 patients matched their actual classifications, while 6 patients were misclassified.

Specifically, the model was able to predict the patients' heart function classifications accurately in most cases. However, among the misclassified patients, some NYHA II patients were incorrectly predicted as NYHA III, and some NYHA III patients were incorrectly predicted as NYHA II. For example, patient 108 (actual NYHA III) was predicted as NYHA II, and patient 188 (actual NYHA II) was predicted as NYHA III. This misclassification indicates that the model faces some challenges in distinguishing between NYHA II and NYHA III patients.

In conclusion, although the model was able to accurately predict the NYHA classification for some patients, its overall prediction accuracy was relatively low. In particular, the model's performance in distinguishing between NYHA II and III patients was not ideal, suggesting that further optimization of the boundary between these two categories is needed to improve the model's overall performance.

In addition, the importance of certain features was also analyzed in detail. As shown in Figure 4.4, the importance of the features is ranked, with the figure displaying not only the absolute SHAP values of each feature but also highlighting which features have the greatest impact on the prediction of NYHA classification.

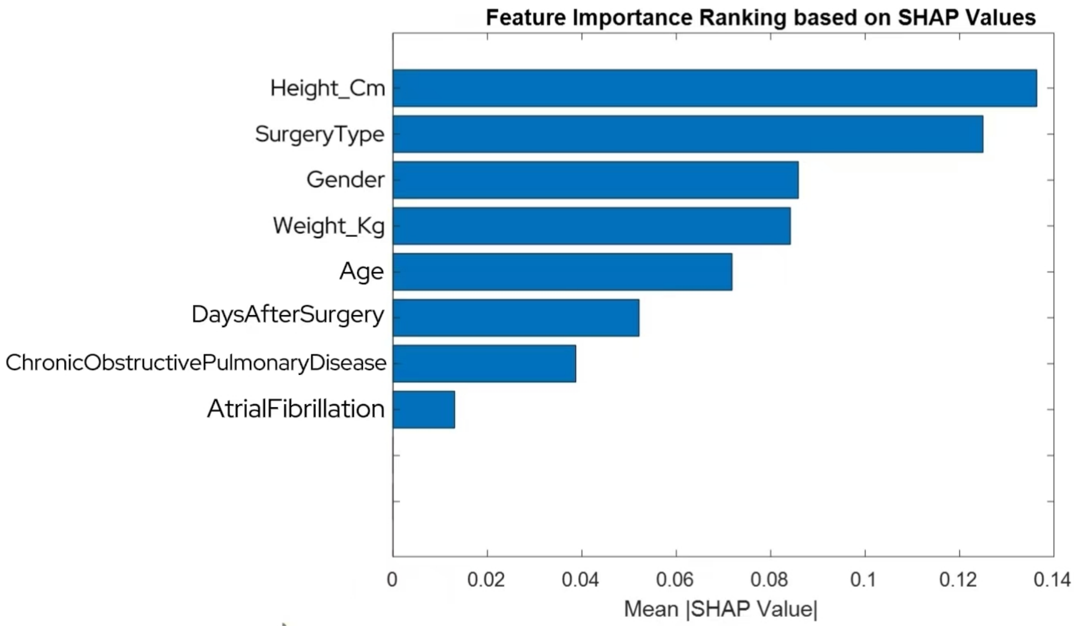

Figure 4.4. Feature Importance Ranking based on SHAP Values using Clinical features

When predicting using only clinical features, the feature importance analysis revealed that the top-ranking features were Height, Surgery Type, Gender, Weight and Age. Height, as one of the most important features, may be associated with the patient's body size and overall health, which could indirectly affect heart function or recovery after surgery. Surgery Type ranked second, indicating that different types of surgeries might significantly influence the NYHA classification. For example, high-risk or invasive procedures like Combined Surgery and Coronary Artery Bypass Graft are more likely to result in NYHA Class III, whereas isolated valve surgeries are typically associated with NYHA Class II. Gender ranked third, potentially reflecting differences in susceptibility to heart diseases and recovery rates between males and females. Weight, as the fourth most important feature, likely indicates the direct impact of increased body weight on cardiac load, which can lead to a decline in heart function. Age ranked fifth, aligning with the clinical fact that CVD risk increases with age.

These rankings highlight the model's effectiveness in capturing the relationships between clinical features and NYHA classification. Fundamental physiological characteristics such as height, weight, and age are closely linked to heart function, while surgery type and gender further reveal the potential impact of specific interventions or demographic factors. These findings not only validate the scientific rationale of the model but also provide valuable insights for optimizing prediction models and designing more targeted, personalized treatment plans.

4.3 Sensor Model

Based solely on the sensor data features, we performed classification prediction of the patients' cardiac function. The sensor data was collected from the patients' activity records under specific conditions, including standing, walking, and climbing stairs—three daily activities.

4.3.1 Stair Climbing Activity Analysis

Metric	Validation Set	Test Set
Accuracy (%)	95.74	59.67
Precision (%)	95.67	60.66
Recall (%)	95.66	58.47
F1 Score (%)	95.66	56.86

Table 4.3. Performance Metrics on Validation and Test Sets based on Sensors Features (Task: Stair climbing)

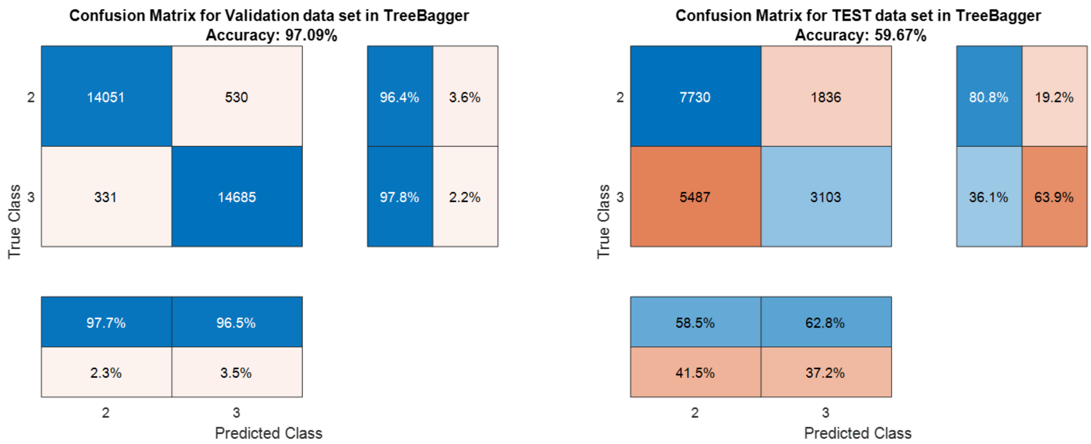

Figure 4.5. Comparison of Classification Models on Validation and Test Sets based on Sensors Features (Task: Stair climbing)

Figure 4.5 illustrates the NYHA classification prediction during stair climbing, while Table 4.3 presents the evaluation metrics for this activity, including accuracy, precision, recall, and F1 score.

The results of ten test runs show that the model's accuracy is 60.75 ± 5.30 %. The results of the stair climbing activity are shown in Table 4.4.

Patient ID	36	61	108	139	144	146	155	159	163
Pred.	III	II	II	III	II	II	II	II	II
Orig.	III	II	III	III	II	III	II	II	III

Patient ID	188	208	249	269	282	295	319
Pred.	II	II	III	III	III	II	II
Orig.	III	II	II	III	III	II	II

Table 4.4. Predicted vs Original NYHA Classification Result based on sensor features for stair climbing

When predicting heart function classification for the stair climbing task using only sensor data, the model's performance shows some variation. By comparing the predicted results with the original NYHA classification, it was found that the model performs relatively accurately when predicting Class II heart function status. Specifically, for patients with IDs 36, 61, 155, 159, 295, and 319, the model's predictions were consistent with the original labels, indicating accurate predictions. However, the model showed bias when predicting Class III heart function status. For example, the original labels for patients with IDs 108, 249, 269, and 282 were Class III, but the model predicted Class II, indicating that the model faces challenges in distinguishing more severe heart failure (Class III).

This bias may arise from the noise in the sensor data itself or limitations in the feature extraction methods, especially when some critical clinical information is missing. In such cases, sensor data may struggle to accurately differentiate between Class II and Class III heart function status. Moreover, while the model demonstrates high accuracy in predicting Class II heart function status, its accuracy in predicting Class III status is lower, suggesting that the model may need further optimization for more complex heart function classification tasks.

In conclusion, while sensor data provides useful information for heart function classification, it still has limitations when predicting more severe heart function statuses. To improve the model's accuracy, especially in predicting Class III heart function status, it is recommended to combine more multimodal data, integrating sensor data with clinical data, to enhance the model's classification ability and robustness.

In addition, the importance of certain features was also analyzed in detail. As shown in Figure 4.6, the importance of the features is ranked, with the figure displaying not only the absolute SHAP values of each feature but also highlighting which features have the greatest impact on the prediction of NYHA classification.

When analyzing the stair climbing activity using only sensor data, the top ten most important features mainly include ECG and accelerometer (ACC) signals. The features of the ECG signal, particularly the mean of the ECG and the duration of the T-wave, hold prominent positions in the model, indicating that the overall level of heart activity and recovery period plays a crucial role in influencing the activity. Additionally, the standard deviation of the ECG and the amplitude of the T-wave reflect the variability and intensity of the heart signal, which aids in a more detailed distinction of heart function status.

The features of the accelerometer signal exhibit important motion pattern information, especially the maximum power component and standard deviation on the Z-axis, indicating that vertical acceleration fluctuations and energy output during stair climbing play a key role in assessing the intensity of the activity. Other accelerometer features, such as the root mean square on the X-axis and the total power of the accelerometer data, also reflect the intensity and overall level of physical movement, further enhancing the model's accuracy in identifying activity types.

Moreover, frequency-domain features, such as the skewness of the Y-axis and Z-axis frequency domains, provide details of the gait pattern, helping to distinguish different exercise intensities. Overall, these features work together to reveal the close relationship between heart function and physical movement, offering important insights for the analysis of stair climbing activities and disease prediction.

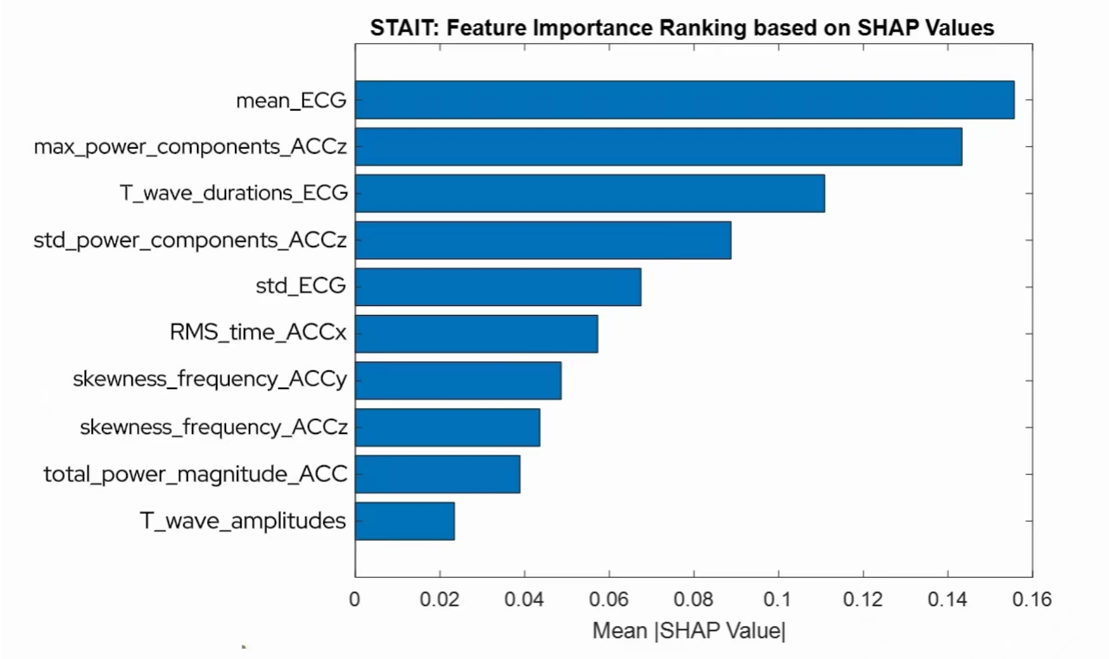

Figure 4.6. Feature Importance Ranking based on SHAP Values using Sensor features for stair climbing

In summary, the ranking of these features indicates that during stair climbing activities, sensor data has an impact on the model's predictions. The ECG signal reflects the physiological state of the heart, while the accelerometer (ACC) signal describes the body's motion patterns. Together, they interact to determine the activity intensity and the heart function status. The importance of these features highlights the close relationship between the physiological response of the heart and physical movement, playing a significant role in disease prediction and activity recognition.

4.3.2 Walking Activity Analysis

Figure 4.7 illustrates the NYHA classification prediction during walking, while Table 4.5 presents the evaluation metrics for this activity, including accuracy, precision, recall, and F1 score.

The results of ten test runs show that the model's accuracy is 54.35 ± 5.08 %. The lowest accuracy was 47.09%, indicating that there are still limitations in certain cases.

The results of the walking activity are shown in Table 4.6.

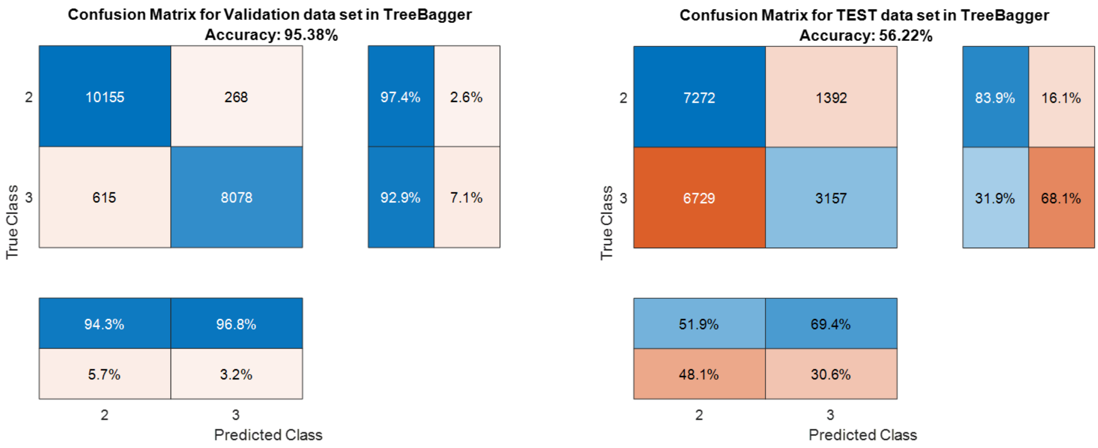

Figure 4.7. Comparison of Classification Models on Validation and Test Sets based on Sensors Features (Task: Walking)

Metric	Validation Set	Test Set
Accuracy (%)	93.70	56.22
Precision (%)	93.82	60.67
Recall (%)	93.72	57.93
F1 Score (%)	93.74	53.96

Table 4.5. Performance Metrics on Validation and Test Sets based on Sensors Features (Task: Walking)

Patient ID	36	61	108	139	144	146	155	159	163
Pred.	II	II	III	II	II	II	II	II	II
Orig.	III	II	III	III	II	III	II	II	III

Patient ID	188	208	249	269	282	295	319
Pred.	II	II	II	III	III	II	II
Orig.	III	II	II	III	III	II	II

Table 4.6. Predicted vs Original NYHA Classification Result based on sensor features for walking

Based on the prediction results ("Pred.") and the original NYHA classification ("Orig.") in the table, the model's prediction performance can be analyzed as follows. Overall, the model's predictions align with the original classification for most patients, particularly for Class II patients. However, there are some discrepancies, especially for Class III patients. For example, patients with IDs 36, 108, and 269 were originally classified as Class III, but the model predicted them as Class II, indicating errors in the model's classification for these patients.

In the cases where the predictions were accurate, such as for patients 61, 144, and 155, the model's predictions closely matched the original classification, showing that the model has a certain level of recognition ability for some samples. However, for some Class III patients (e.g., patients 36, 108, and 269), the model predicted Class II, highlighting discrepancies in its performance for these samples. These results suggest that while the model performs well for most Class II patients, its prediction accuracy for Class III patients needs improvement. Overall, the model demonstrates high prediction accuracy for Class II patients but exhibits errors in predicting some Class III patients.

In addition, the Figure 4.4 shows the importance ranking of the features.

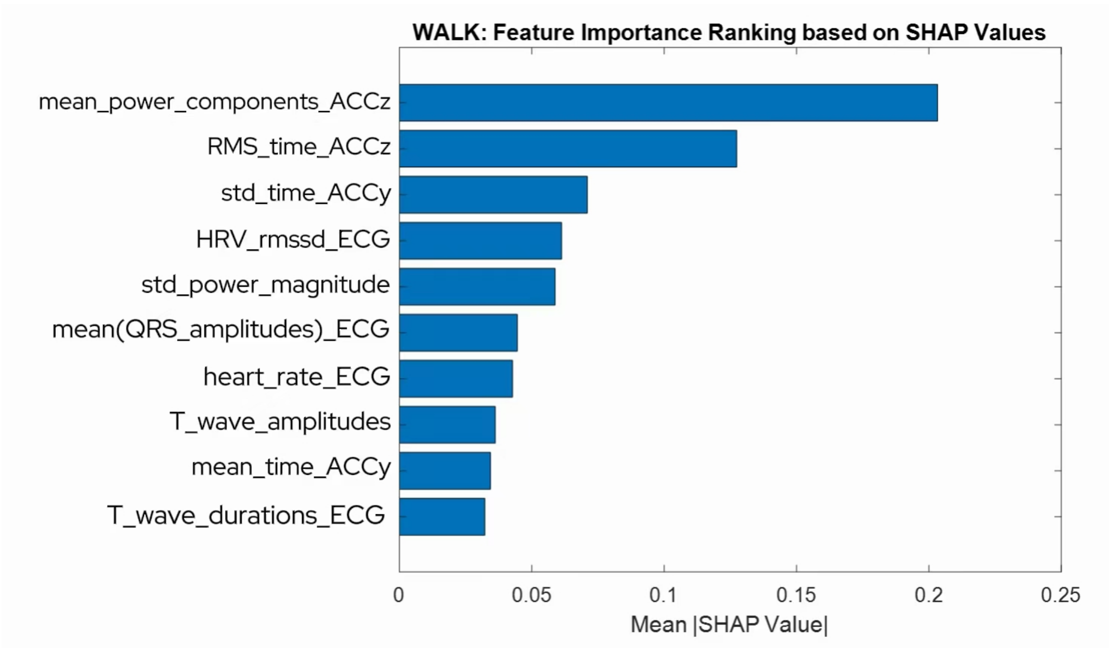

Figure 4.8. Feature Importance Ranking based on SHAP Values using Sensor features for walking

In the walking classification using only sensor features, the top ten ranked features reveal key physiological and motion signals important for gait prediction. First, the average power of the Z-axis acceleration and the root mean square (RMS) value of the Z-axis acceleration rank the highest, indicating that the intensity of vertical movement during gait activity has a significant impact on the model's prediction. Secondly, the standard deviation of the Y-axis acceleration also ranks in the top three, reflecting the variability in the forward-backward movement direction, which is crucial for classifying gait patterns.

Among the features related to heart health, the standard deviation of HRV RMS ranks fourth, suggesting that variations in heart rhythm have a significant impact on gait activity prediction, especially in individuals with poor cardiovascular health. The average amplitude of the QRS complex and heart rate follow closely behind, reflecting the intensity of cardiac electrical activity and the physical load during gait activity. These high-ranking ECG features indicate that gait activity prediction is not only influenced by motion intensity but also closely related to heart health.

Additionally, the amplitude of the T-wave and the average time of the Y-axis acceleration are also in the top ten. The former helps to reveal heart health status, while the latter reflects the temporal characteristics of gait activity. Finally, the duration of the T-wave ranks tenth, providing relevant information about the heart's recovery period and having a certain impact on gait activity classification.

In summary, these features emphasize the importance of variations in acceleration signals (especially along different axes) as well as ECG signals (such as heart rate, HRV, and T-wave characteristics) in gait activity classification. This suggests that gait prediction involves not only movement patterns but is also closely related to cardiovascular health status.

4.3.3 Veloergometry Activity Analysis

Figure 4.9 illustrates the NYHA classification prediction during cycling, while Table 4.7 presents the evaluation metrics for this activity, including accuracy, precision, recall, and F1 score.

Metric	**Validation Set**	**Test Set**
Accuracy (%)	94.48	77.29
Precision (%)	94.54	79.57
Recall (%)	94.57	77.61
F1 Score (%)	94.55	76.97

Table 4.7. Performance Metrics on Validation and Test Sets based on Sensors Features (Task: Velo)

After running ten times, the results showed an accuracy of 68.86 ± 5.41 %.

The results of the walking activity are shown in Table 4.8.

In the classification results using sensor features for the cycling test, the model

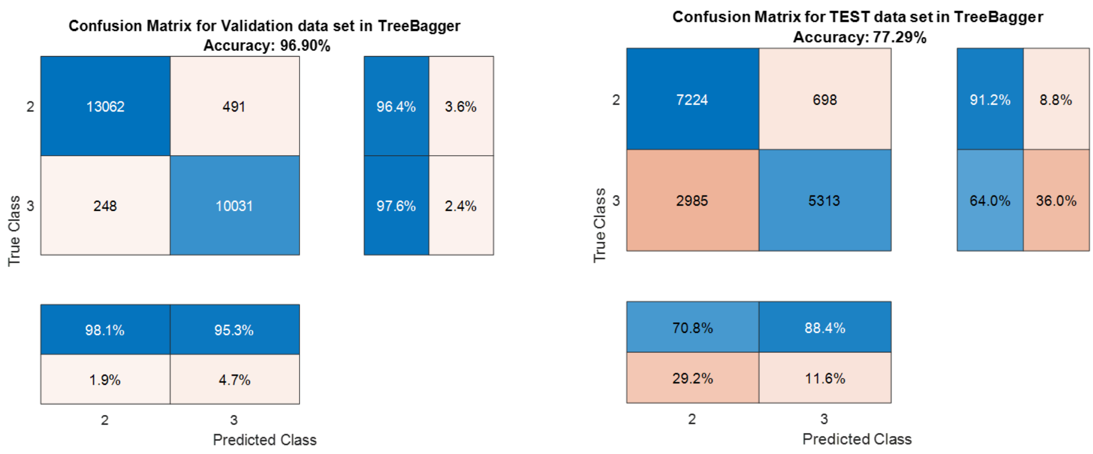

Figure 4.9. Comparison of Classification Models on Validation and Test Sets based on Sensors Features (Task: Velo)

Patient ID	36	61	108	139	144	146	155	159	163
Pred.	III	II	III	II	II	II	II	II	II
Orig.	III	II	III	III	II	III	II	II	III

Patient ID	188	208	249	269	282	295	319
Pred.	III	II	II	-	II	II	III
Orig.	III	II	II	-	III	II	II

Table 4.8. Predicted vs Original NYHA Classification Result based on sensor features for cycling

performs well for most samples, with a high overall prediction accuracy. Specifically, the predicted categories align with the actual categories for the majority of samples, especially for Class II samples, where 13 samples have predicted results that match the original labels perfectly. However, there are some discrepancies in predictions, such as for samples with IDs 139, 188, and 249, where the predicted and actual categories differ. Specifically, for IDs 139 and 188, the predicted category is II, while the original category is III; for ID 249, the predicted category is III, but the original category is II. In summary, while the model exhibits high prediction accuracy in the cycling test classification task, there is still room for improvement, particularly in handling Class III samples.

Based on the feature importance ranking, the top-ranking features make significant contributions to the classification task in the cycling test. These features

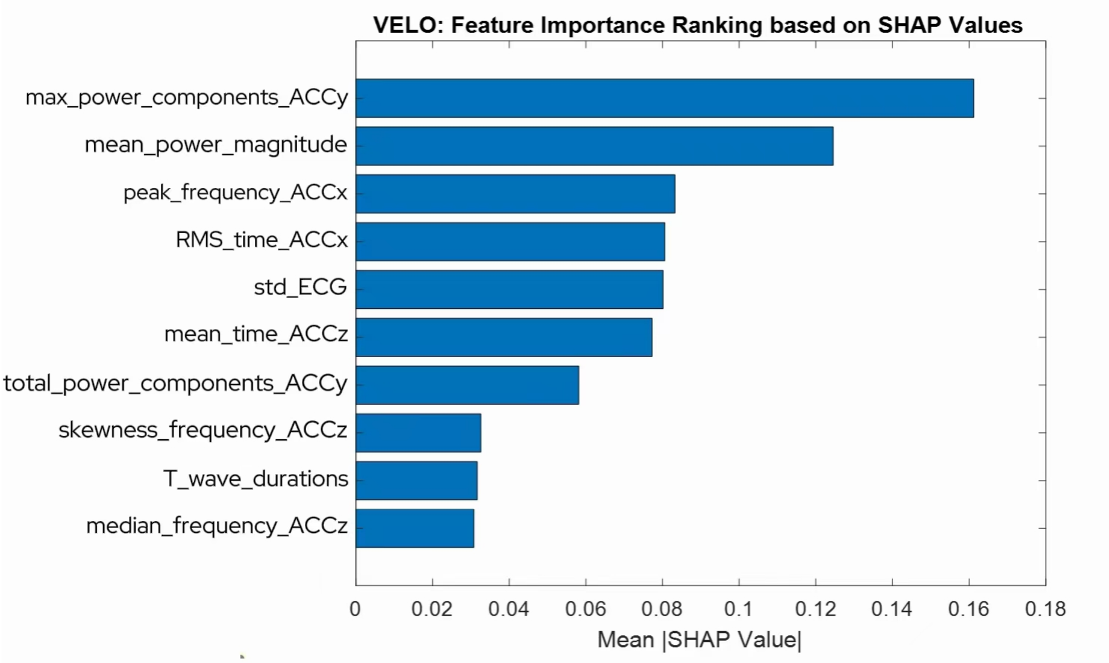

Figure 4.10. Feature Importance Ranking based on SHAP Values using Sensor features for cycling

primarily include the power, frequency, and time-domain characteristics of the accelerometer signal. For example, the maximum power and total power features of the accelerometer signal in the vertical direction, as well as the root mean square (RMS) power, effectively capture the energy information of the signal, which helps differentiate between various activity categories. Additionally, frequency features such as peak frequency and spectral skewness reveal the frequency components within the signal, which are crucial for identifying rapidly changing motion patterns.

Time-domain features, such as the root mean square (RMS) value and the time characteristics of the accelerometer signal, help capture the intensity and dynamic changes of movement, thus improving classification performance. At the same time, while ECG signal features, such as the standard deviation and T-wave duration, contribute less in an accelerometer-dominated classification task, they still provide additional information regarding heart health for the model.

In summary, the prediction of cardiovascular complications in this cycling activity task relies on both clinical and sensor features. While sensor-derived features, such as accelerometer power, frequency, and time-domain characteristics, play a dominant role in distinguishing activity patterns, clinical features, such as

ECG signal metrics, still provide valuable supplementary information about heart health. This combined approach highlights the importance of integrating both sensor and clinical data for more accurate and comprehensive cardiovascular risk prediction.

4.3.4 Multiactivity Sensor-Based Analysis

Table 4.9 and Figure 4.11 present the predicted NYHA classifications for multiple activities (Stair, Walk, Cycle) and their combined results (Comb.) compared to the original classifications (Orig.).

Patient ID	36	61	108	139	144	146	155	159	163	188	208	249	269	282	295	319
Stair	III	II	II	III	II	II	II	II	II	II	II	III	III	II	II	II
Walk	II	II	III	II	II	II	II	II	II	II	II	II	III	II	II	II
Cycle	III	II	III	II	II	II	II	II	II	III	II	II	-	II	II	III
Comb.	III	II	III	II	II	II	II	II	II	II	II	II	-	II	II	II
Orig.	III	II	III	III	II	III	II	II	III	III	II	II	-	III	II	II

Table 4.9. Predicted vs Original NYHA Classification for Multiple Activities based on Sensor Features

Table 4.9 shows that the model generally demonstrates high consistency and accuracy across different activities, with the Walk activity showing the most stable predictions. However, certain misclassifications are observed, particularly for Stair and Cycle activities. For instance, Patient 108 was consistently misclassified as Class II instead of the actual Class III in both Stair and Comb., indicating potential sensitivity issues in the extracted features for higher class predictions. Similarly, Patient 188 was misclassified during Stair and Comb., suggesting possible noise or data quality challenges.

Notably, the combined predictions (Comb.) align closely with the original classifications, reflecting the advantage of integrating features from multiple activities. However, there are exceptions, such as Patient 319, whose accurate classification in Cycle as Class III was downgraded to Class II in the combined results, potentially due to feature dilution across activities. Furthermore, a recurring trend of misclassifying Class III patients as Class II suggests that the model may struggle with distinguishing between these two categories, likely due to imbalanced data distribution or insufficiently sensitive features for Class III.

In Figure 4.11, the classification performance of the four models is analyzed based on four key evaluation metrics. The results show that the combined activity and cycling performed relatively better across multiple evaluation metrics. Specifically, the combined activity achieved the highest accuracy of 68.75%, indicating that the model performs well in handling data from multiple activities. Cycling also had a high accuracy of 66.67%. However, in terms of precision, all models

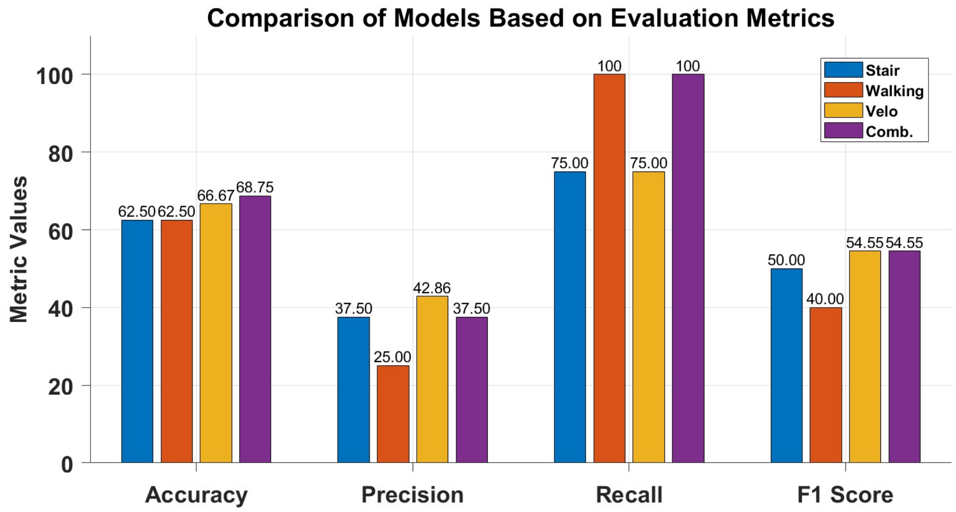

Figure 4.11. Comparison of Models Based on Evaluation Metrics using Sensor Features

performed poorly. Walking had the lowest precision, at only 25%, indicating that the prediction of the positive class for this activity is unstable, although there is still room for improvement. In terms of recall, walking and combined activities both achieved 100% recall, indicating that these activities were able to perfectly capture all positive samples. In contrast, the recall for stairs and cycling was 75%, which, although still good, is not as comprehensive as that of walking and combined activities. The F1 score, which combines precision and recall, was highest for cycling and combined activities, both with an F1 score of 54.55%, indicating a good balance between precision and recall for these two activities.

In summary, the combined activity and cycling performed well in terms of accuracy, precision, recall, and F1 score, while walking faced challenges with lower precision and F1 score, suggesting issues with misclassification in the model.

Overall, the model performs well across activities and offers reliable predictions when integrating features. However, specific instances of misclassification highlight the need for further refinement, such as optimizing feature selection, balancing data distribution, and considering additional modalities to enhance sensitivity, particularly for distinguishing higher NYHA classifications.

4.4 Final model

o further improve the classification accuracy, clinical features and sensor features were ultimately fused for multimodal prediction of the patient's heart function. The data fusion was performed at the feature level by concatenating the two feature sets and inputting them into the random forest model. The fused feature set not only retains the robustness of the clinical features but also fully leverages the sensor features' ability to finely capture activity behaviors. This multimodal fusion approach leverages the complementary advantages of static clinical features and dynamic activity features, significantly enhancing the overall predictive performance of the model.

4.4.1 Stair Climbing Activity Analysis in Combined Model

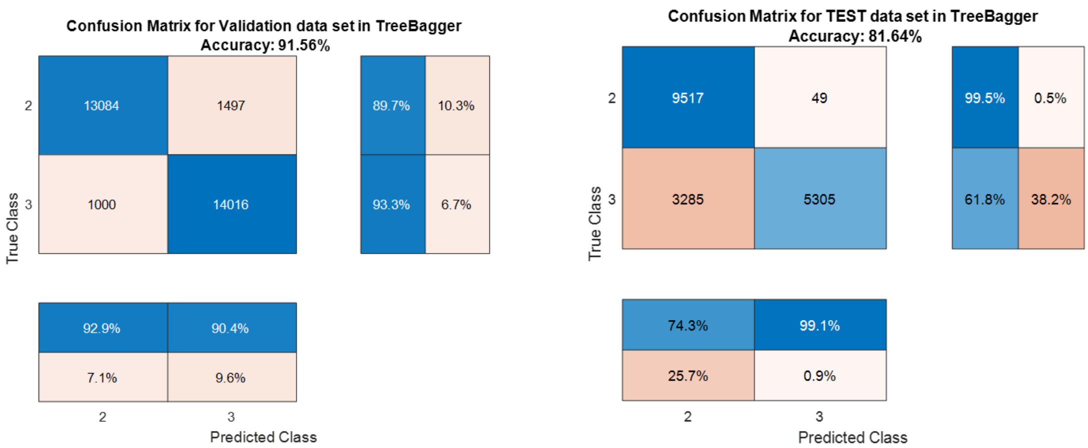

Figure 4.12. Comparison of Classification Models on Validation and Test Sets based on All Features (Task: Stair climbing)

Figure 4.12 illustrates the NYHA classification prediction during stair climbing, while Table 4.10 presents the evaluation metrics for this activity, including accuracy, precision, recall, and F1 score.

In order to evaluate the stability and performance of the model, it was run ten times, and the results showed an accuracy of 80.54 ± 5.85 %.

For stair climbing, the validation set accuracy was 89.77%, with an F1 score of 90.06%, indicating good predictive performance on training data. However, on the test set, accuracy dropped to 81.64%, and the F1 score decreased to 80.59%. A deeper analysis of ten test iterations showed accuracy ranging from 71.31% to

Metric	Validation Set	Test Set
Accuracy (%)	89.77	81.64
Precision (%)	90.05	86.71
Recall (%)	90.08	80.62
F1 Score (%)	90.06	80.59

Table 4.10. Performance Metrics on Validation and Test Sets based on All Features (Task: Stair climbing)

88.87%, highlighting some instability in performance across different test datasets, though accuracy remained relatively high.

The prediction results for stair climbing activity are further optimized after incorporating clinical features. The results for stair climbing activity are shown in Table 4.11.

Patient ID	36	61	108	139	144	146	155	159	163
Pred.	III	II	III	II	II	II	II	II	II
Orig.	III	II	III	III	II	III	II	II	III

Patient ID	188	208	249	269	282	295	319
Pred.	II	II	II	III	III	II	II
Orig.	III	II	II	III	III	II	II

Table 4.11. Predicted vs Original NYHA Classification Result based on All Features for Stair Climbing

In the heart function level prediction results for stair climbing activity based on fused features, overall, the model is able to accurately predict the patient's NYHA heart function level. For most patients, the predicted results align with the actual classification, such as for patients with IDs 36, 61, 144, 146, 159, 163, 188, 208, 249, 282, 295, and 319, whose predictions match the original classification. This indicates that the features used perform well in predicting the heart function levels of patients. However, there are a few cases where the predicted results do not align with the actual classification. For example, patients with IDs 108 and 269 were predicted to be "III" and "II" respectively, while the actual classification was "III," suggesting that the model may over-predict for patients with lower functional levels in some cases. Despite this, the overall prediction accuracy is high, indicating that the model has good applicability in the analysis of this activity.

As shown in Figure 4.13, ECG features, motion sensor features, and basic clinical indicators play key roles in predicting the NYHA heart function classification

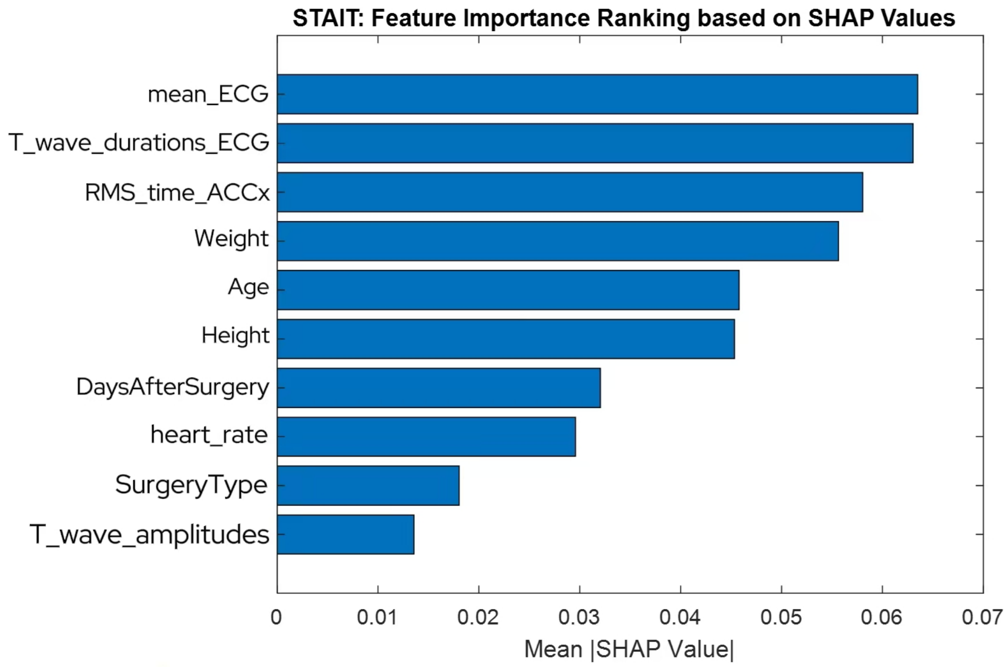

Figure 4.13. Feature Importance Ranking based on SHAP Values using All features for Stair Climbing

of patients. According to the feature importance ranking results, the model relies on both clinical and sensor features for heart function level prediction. This demonstrates that combining clinical information with sensor data helps improve prediction accuracy and provides a more comprehensive reflection of the patient's health status.

Among the top-ranking features, ECG-related characteristics (such as mean ECG, T wave durations ECG, and T wave amplitudes) hold a prominent position in the model. These features, obtained through sensor measurements, reflect the electrical activity of the heart and are crucial for assessing cardiac function. In particular, T-wave duration and T-wave amplitude, which are often associated with cardiac health and abnormalities, stand out in their contribution to heart function prediction. Among motion sensor features, the root mean square (RMS time ACCx) of acceleration signals ranks third, indicating its significance in capturing information about the patient's physical coordination and motor abilities.

Additionally, clinical features such as weight, age, height, postoperative days, and surgery type also rank high in importance. These features provide insights into the patient's baseline health, recovery status, and individual differences, all of which are critical for evaluating heart function. For instance, weight and height contribute to the calculation of BMI, which may be directly related to cardiac health. Meanwhile, age, surgery type, and postoperative days reflect the patient's recovery trajectory and influence prediction outcomes.

Finally, heart rate, as a direct physiological indicator of cardiac function, also proves to be important. Variations in heart rate are often closely linked to cardiac health, further emphasizing its impact on heart function prediction.

In summary, sensor and clinical features complement each other in heart function level prediction. By integrating information from both, the model gains a multidimensional perspective, enhancing its predictive capability.

4.4.2 Walking Activity in Combined Model

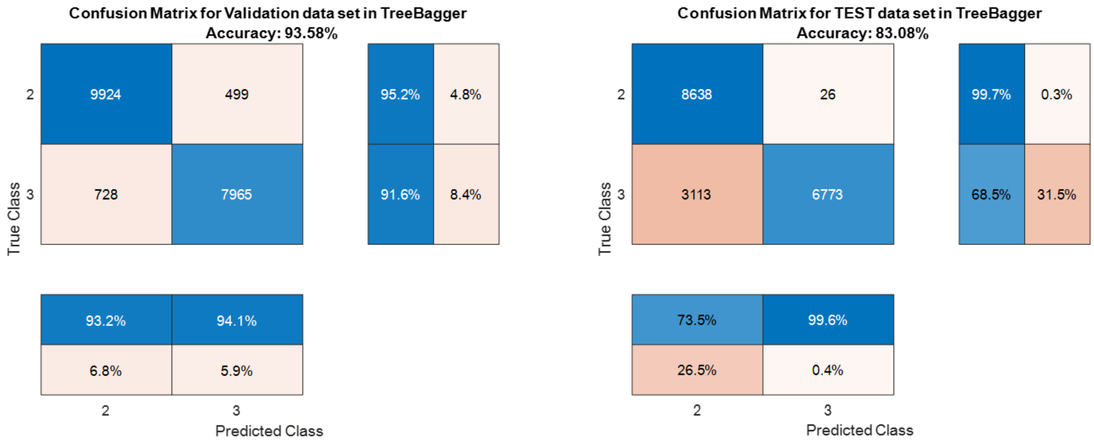

Figure 4.14. Comparison of Classification Models on Validation and Test Sets based on All Features (Task: Walking)

Metric	Validation Set	Test Set
Accuracy (%)	90.07	83.08
Precision (%)	89.76	86.56
Recall (%)	89.78	84.11
F1 Score (%)	89.74	82.91

Table 4.12. Performance Metrics on Validation and Test Sets based on All Features (Task: Walking)

Figure 4.14 illustrates the NYHA classification prediction during walking, while Table 4.12 presents the evaluation metrics for this activity, including accuracy, precision, recall, and F1 score.

The results after running the model ten times showed an accuracy of 81.11 ± 2.84 %.

For walking, the model's predictive performance was comparatively stable. The validation set achieved an accuracy of 90.07% and an F1 score of 89.74%. On the test set, accuracy was 83.08%, and the F1 score was 82.91%. Over ten tests, accuracy ranged from 76.06% to 83.64%, with less variation, indicating that walking data distribution was more uniform and its features were easier for the model to identify. Although test set performance was slightly lower than that of the validation set, the model demonstrated good stability.

The prediction results for walking activity are further optimized after incorporating clinical features. The results for walking activity are shown in Table 4.13.

Patient ID	36	61	108	139	144	146	155	159	163
Pred.	III	II	III	II	II	III	II	II	III
Orig.	III	II	III	III	II	III	II	II	III

Patient ID	188	208	249	269	282	295	319
Pred.	II	II	II	III	II	II	II
Orig.	III	II	II	III	III	II	II

Table 4.13. Predicted vs Original NYHA Classification Result based on All Features for Walking

Overall, the prediction results are highly aligned with the actual classifications, although there are some minor mismatches in the classification of certain patients. For example, for patient ID 139, the predicted classification is II, while the original classification is III, indicating a certain error in the classification prediction for this patient. Similarly, for patient ID 269, the prediction is III, and the original classification is also III, meaning the prediction matches the actual result. In general, the results shown in the table suggest that after combining clinical features and sensor features, the prediction performance for walking activities has been optimized. Although there are errors in a few individuals, the majority of the prediction results are highly consistent with the actual classifications. This indicates that the multimodal data fusion approach plays a positive role in the NYHA classification prediction for walking activities, helping to improve the accuracy of the model.

Figure 4.15 shows the feature importance ranking for walking activity.

In the classification task for walking activity, both clinical and sensor features

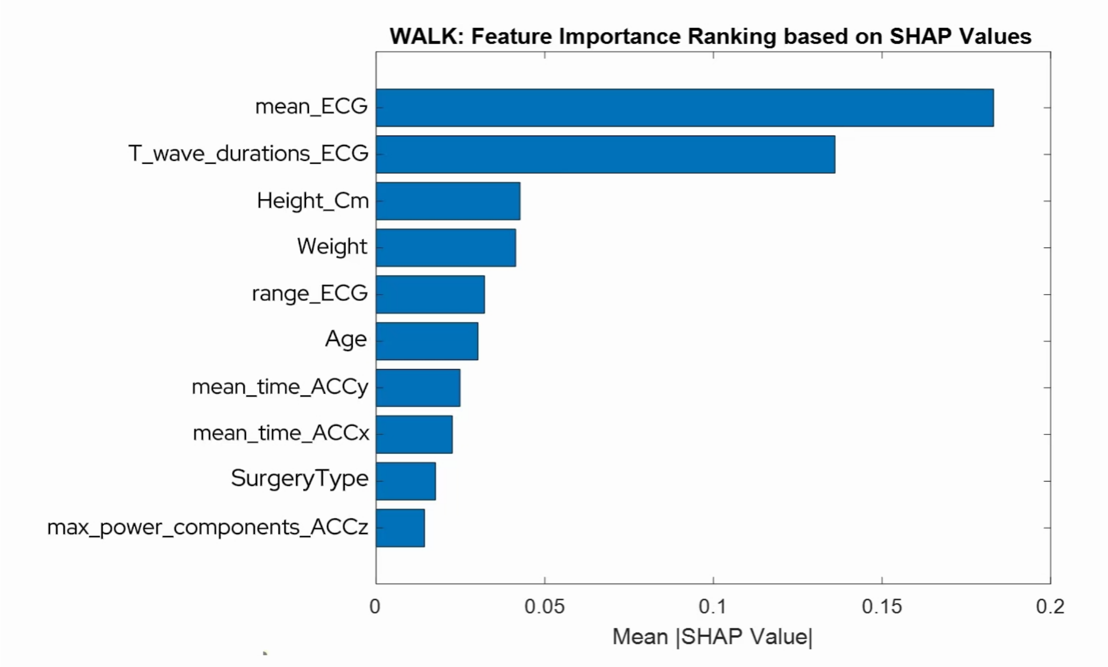

Figure 4.15. Feature Importance Ranking based on SHAP Values using All features for Walking

remain significant. ECG features, such as the mean ECG signal value and T-wave duration, rank highly, suggesting that the modulation of ECG signals during walking may provide crucial information for classification. Additionally, clinical features such as height and weight also rank highly, highlighting the impact of individual body characteristics on movement patterns and associated physiological signals. Among the sensor features, time-domain characteristics of the accelerometer (e.g., mean value in each window of ACC) and frequency-domain characteristics (e.g., the maximum power component in the Z-axis) hold prominent positions in the feature rankings. These features capture the distribution of accelerations and dynamic traits across different dimensions of the body during walking, contributing positively to the classification model.

4.4.3 Veloergometry Activity Analysis in Combined Model

Figure 4.16 illustrates the NYHA classification prediction during cycling, while Table 4.14 presents the evaluation metrics for this activity, including accuracy, precision, recall, and F1 score.

the results after running ten times showed an accuracy of 90.04 ± 4.84 %.

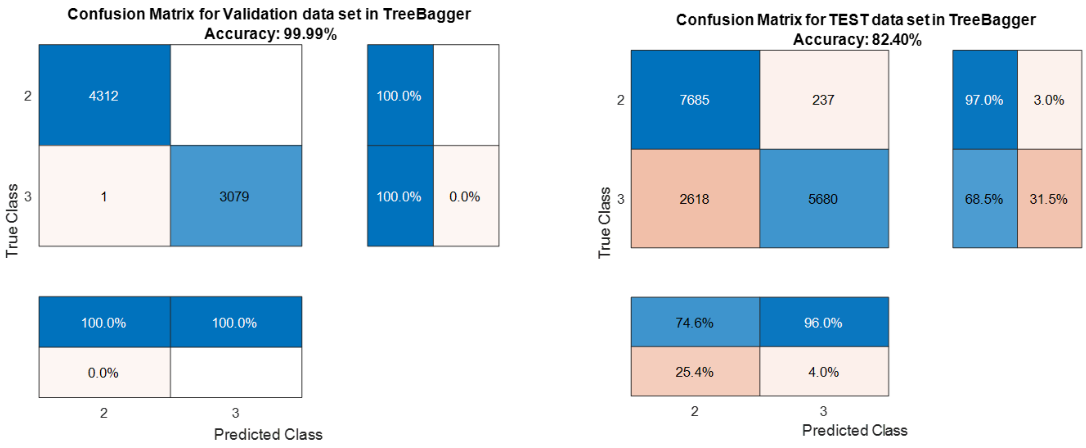

Figure 4.16. Comparison of Classification Models on Validation and Test Sets based on All Features (Task: Velo)

Metric	Validation Set	Test Set
Accuracy (%)	99.40	82.40
Precision (%)	99.43	85.29
Recall (%)	99.42	82.73
F1 Score (%)	99.42	82.13

Table 4.14. Performance Metrics on Validation and Test Sets based on All Features (Task: Velo)

Cycling showed the best predictive performance. The validation set achieved an impressive accuracy of 99.40% and an F1 score of 99.42%, indicating near-perfect recognition of cycling features. On the test set, accuracy decreased to 82.40%, and the F1 score was 82.13%, but these results still surpassed those of the other activities. Accuracy across ten tests ranged from 80.57% to 94.58%, suggesting the model had strong recognition capability for cycling activities, though some test datasets might have distributions inconsistent with the training data.

The prediction results for cycling activity are further optimized after incorporating clinical features. The results for cycling activity are shown in Table 4.15.

This result demonstrates the optimization of the cycling activity prediction after incorporating clinical features. For most patients, the predicted results align with the actual classifications, such as for patient IDs 108, 144, 146, 155, 159, 163, etc., where the predicted values are identical to the actual values. However, some patients' predictions differ from the actual results. For instance, for patient ID 139,

Patient ID	36	61	108	139	144	146	155	159	163
Pred.	III	II	III	II	II	III	II	II	III
Orig.	III	II	III	III	II	III	II	II	III

Patient ID	188	208	249	269	282	295	319
Pred.	II	II	II	-	III	II	II
Orig.	III	II	II	-	III	II	II

Table 4.15. Predicted vs Original NYHA Classification Result based on All Features for Cycling

the predicted classification is II, while the actual classification is III, indicating a certain prediction error. Similarly, for patient ID 269, the predicted classification is missing (-), indicating that the data is unavailable and a prediction cannot be made.

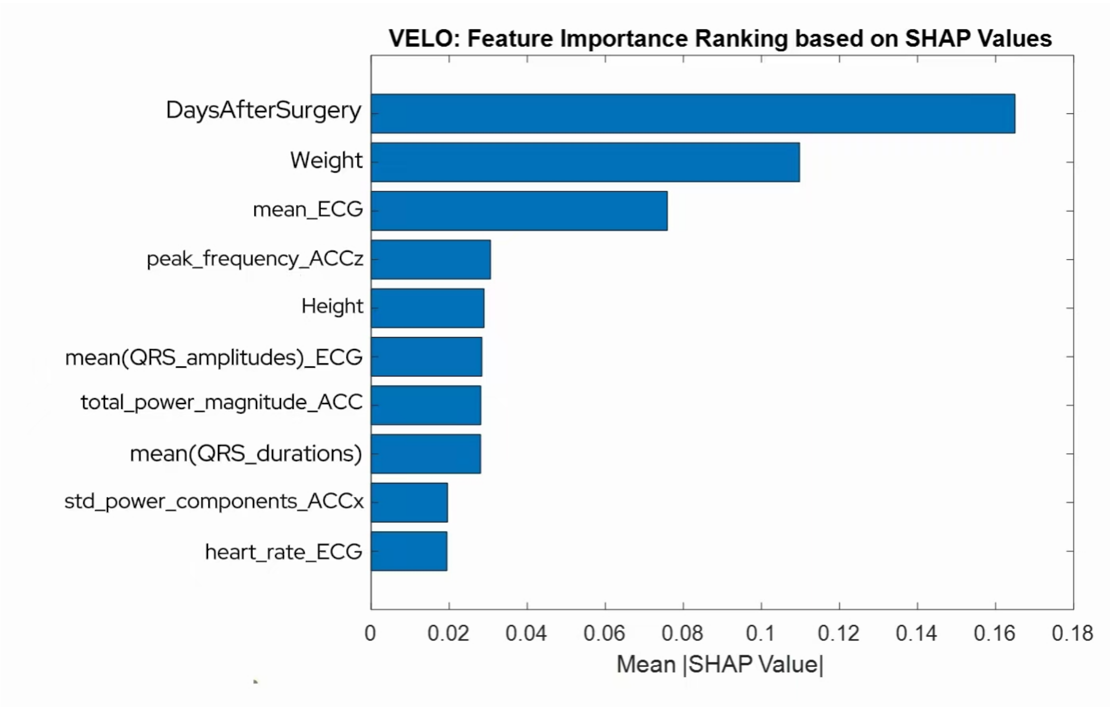

Figure 4.17. Feature Importance Ranking based on SHAP Values using All features for Cycling

According to the importance ranking shown in Figure 4.17, both clinical features and sensor features play significant roles. Among the clinical features, postoperative days and weight are the most important, which may reflect the substantial impact of the patient's postoperative recovery phase on their cycling ability. The recovery time may affect the patient's heart-lung function and exercise tolerance, influencing their physiological performance during cycling. Similarly, weight is a key feature, directly related to energy expenditure and dynamics during exercise.

Additionally, ECG features (such as the mean ECG signal value within the window, QRS wave amplitude, and heart rate) perform prominently in the ranking, highlighting the importance of cardiac physiological signals in distinguishing different activity patterns. Meanwhile, accelerometer sensor features (such as peak frequency of the z-axis acceleration and total acceleration power) rank highly as well, with these dynamic features effectively representing the complex movement patterns and power output during exercise.

Overall, it shows a noticeable optimization in the NYHA classification prediction for cycling activities after combining multimodal features. Although there are errors or missing predictions for a few patients, the majority of the predicted values match the actual classifications, indicating an improvement in the prediction accuracy after integrating clinical features. This also demonstrates that multimodal data fusion plays a positive role in enhancing the model's predictive power for the NYHA functional classification of cycling activities.

4.4.4 Multiactivity Sensor-Based Analysis in Combined Model

Table 4.16 and Figure 4.18 present the predicted NYHA classifications based on all features for multiple activities (Stair, Walk, Cycle) and their combined results (Comb.) compared to the original classifications (Orig.).

Patient ID	36	61	108	139	144	146	155	159	163	188	208	249	269	282	295	319
stair	III	II	III	II	II	II	II	II	II	II	II	II	III	III	II	II
walk	III	II	III	II	II	III	II	II	III	II	II	II	III	II	II	II
velo	III	II	III	II	II	III	II	II	III	II	II	II	-	III	II	II
Comb.	III	II	III	II	II	III	II	II	III	II	II	II	III	III	II	II
Orig.	III	II	III	III	II	III	II	II	III	III	II	II	III	III	II	II

Table 4.16. Predicted vs Original NYHA Classification for Multiple Activities based on All Features

Table 4.16 presents a comparison between the predicted NYHA functional classifications based on all features (including clinical and sensor features) and the actual classifications. These results involve three different activities: stair climbing (stair), walking (walk), and cycling (velo), as well as their combined (Comb.) results. By comparing the predicted (Pred.) and original (Orig.) classifications, we can assess the model's prediction accuracy after multimodal data fusion for different activities. The prediction results for each activity are analyzed as follows:

- Stair Climbing (Stair): Comparing the results in the table, the prediction for the stair climbing activity is generally consistent with the original values, with most patients' predictions matching the actual classifications. For example, patients with IDs 36, 61, and 108 have predictions that perfectly align with the actual classifications. However, there are a few patients with classification errors (e.g., patient ID 139, where the actual classification is III and the predicted classification is II). From the data, it can be seen that the classification accuracy for stair climbing is relatively high, with predictions for 4 patients not matching the original values, resulting in an error rate of 25%.

- Walking (Walk): The prediction results for the walking activity show a relatively consistent match with the actual classifications. For instance, patients with IDs 36, 61, and 108 have matching predictions and actual classifications. However, some patients (e.g., patient ID 163) experienced misclassification during walking, indicating that the model's prediction accuracy for this activity is somewhat limited. There were 3 misclassified patients, with an error rate of 18.75%.

- Cycling (Velo): In the cycling activity prediction results, while most patients' predictions match the actual classifications, there are a few instances of incorrect predictions (e.g., patient ID 269). Additionally, patient ID 249 was predicted as III, while the actual classification was II, indicating that the model's prediction accuracy for cycling is relatively lower. There were 2 misclassified patients, with an error rate of 13.33%.

The table also presents the combined (Comb.) results for the three activities, which involves integrating the prediction results of stair climbing, walking, and cycling into a unified classification. The results after multimodal data fusion show that combining the predictions from different activities can further improve overall accuracy, although some misclassifications still occur. For the combined results, 2 patients were misclassified, resulting in an error rate of 12.5%.

As shown in Figure 4.18, the performance of the four metrics (accuracy, precision, recall, and F1 score) across different activity types has significantly improved. Specifically, the accuracy of the combined activity reached 87.5%, the highest among all activities. The accuracy of cycling was 86.67%, also performing excellently. Compared to the results before data fusion, these activities saw a substantial improvement in accuracy, indicating that the model's overall performance in recognizing activity types has improved.

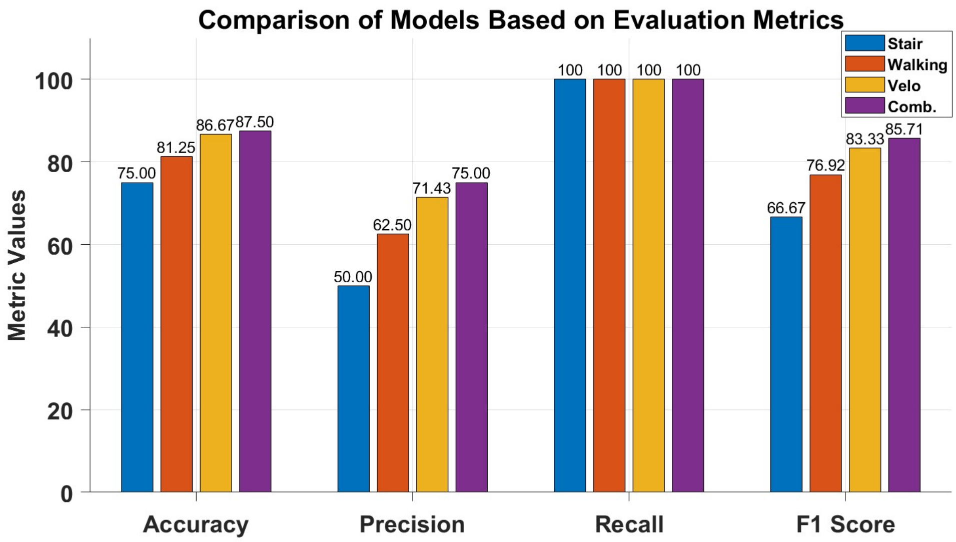

Figure 4.18. Comparison of Models Based on Evaluation Metrics using Multimodal Data

In terms of precision, the combined activity and cycling had precision values of 81.25% and 75%, respectively, which are much better than the previous results. The precision for the stairs activity also saw a significant improvement, reaching 86.67%. This indicates that the model's prediction of positive samples has become more stable. The precision for walking was 71.43%, still lower than the other activities but a significant improvement compared to the previous.

For recall, all activities achieved 100% recall, meaning the model perfectly identified all positive samples. In terms of F1 score, the combined activity and cycling achieved 85.71% and 83.33%, respectively, the highest among all activities, indicating that they have found a good balance between precision and recall. The F1 score for the stairs activity also improved, reaching 83.33%, while walking achieved an F1 score of 76.92%. Although lower than other activities, it represents a significant improvement compared to previous results.

Overall, these results show that the performance of all activities has significantly improved, especially in terms of precision, accuracy, and F1 score. The combined activity and cycling still perform the best, while the stairs activity has also made significant progress. The walking activity, though relatively weaker, has shown noticeable improvement, indicating that the model's misclassification issues have been partially addressed.

From the above analysis, it is evident that after integrating multimodal data (clinical features and sensor features), the prediction accuracy for each individual activity has improved to some extent. Cycling activity performed the best, followed by stair climbing and walking. The combined results (Comb.) show that by integrating predictions from different activities, the overall classification accuracy remains at a high level, especially for cycling, where the fusion yielded highly ideal prediction results. This indicates that multimodal data fusion not only effectively enhances the stability of the model but also improves its applicability across different activities, validating the advantages of this method in practical applications.

Chapter 5

Discussion

This study combines clinical data and sensor data to propose a heart function prediction model based on the NYHA classification system, aiming to predict the risk of cardiovascular complications in elderly patients after surgery. First, the effectiveness of using clinical data and sensor data individually was analyzed, and then the potential of combining both was explored. Through this approach, the accuracy and robustness of heart function prediction are aimed to be improved. In analyzing the results, comparisons were made with existing literature, and the innovative aspects of this study were also discussed the innovative aspects of this study, particularly the distinction between using the NYHA classification for heart function assessment and other studies based on frailty status.

Existing studies on the relationship between frailty and cardiovascular complications generally indicate that frailty is an important warning sign of CVDs risk. For example, N. Veronese et al. [95] pointed out through a meta-analysis that frail elderly individuals have a significantly higher mortality and morbidity rate when experiencing cardiovascular events. Frailty is considered a multi-factorial syndrome, characterized by physical decline, limited activity, and changes in gait, all of which are related to heart dysfunction. N. Veronese et al.'s research mainly explores frailty as a risk factor for cardiovascular complications. Although this study reveals a significant association between frailty and CVDs, it also highlights the complexity of causality, as there may be a bidirectional relationship between frailty and CVDs. Similarly, N. Veronese et al. [96] in another article also emphasized the close relationship between frailty and cardiovascular events, particularly in the elderly population.

Unlike these studies, this research does not directly use frailty as an indicator for predicting cardiovascular complications but focuses on the NYHA classification system, a traditional standard for evaluating heart function in patients with chronic heart failure. The NYHA classification system divides patients into Class I, II, III, and IV based on their physical activity capacity and symptoms, and it is widely used in clinical diagnosis and management. This approach avoids the potential bidirectional relationship between frailty and CVDs. We adopt the NYHA classification as the evaluation standard for heart function and integrate gait data with clinical data to enhance the accuracy of the prediction model. Unlike frailty assessments, which emphasize the overall decline in physiological function, the NYHA classification evaluates cardiac health based on a patient's endurance during various activities. Therefore, one of the core innovations of this study lies in supplementing and refining the dynamic aspects of the NYHA assessment through gait analysis, particularly by examining gait changes across different activities.

In the study of the relationship between gait and health, K. Wang et al. [97] explored the connection between gait variations and fall risk, suggesting that gait changes in different activities (such as climbing stairs) are highly correlated with fall risk. Although this study utilized wearable sensors to monitor gait, it primarily focused on predicting fall risk rather than evaluating heart function. While the relationship between gait variations and fall risk has been validated, this study proposes a new framework by integrating gait data with the NYHA classification system. This framework not only emphasizes gait variations but also incorporates dynamic performance under different levels of physical activity, providing a more comprehensive perspective for heart function evaluation. By innovatively combining dynamic gait analysis with the NYHA classification, this study offers a more accurate insight into patients' cardiac health during their daily activities.

Compared to the study by J. Lin et al. [81], our research offers a different perspective. Lin's study explored the relationship between multimodal data and CVDs, focusing on identifying which types of multimodal data (including pulse wave, PCG, ECG, and other signals) should be selected to improve prediction accuracy. While Lee et al.'s research also integrated multimodal data, it lacked an in-depth analysis of data integration or a comprehensive evaluation. In contrast, JD Huang et al. [98] combined ECG signals and accelerometer data, analyzing various AI algorithms, models, and their clinical applications. However, their study primarily focused on comparing different AI algorithms and models for various CVDs and did not thoroughly investigate how to integrate clinical data with gait data from different activity types for comprehensive CVD risk prediction.

Although numerous studies have investigated gait analysis, frailty, and CVDs prediction, research combining these elements with the NYHA classification system remains relatively scarce. The NYHA classification system, a validated standard for assessing heart function, can be further enhanced when integrated with gait variations and clinical data, providing robust support for the early warning and management of CVDs.

Our multimodal data integration approach not only improves the predictive power of the NYHA classification system but also offers a new perspective for heart function evaluation. This study conducts an in-depth analysis of gait data from various activities (e.g., walking and stair climbing) and integrates clinical data to enhance the accuracy and personalization of heart function predictions. This provides clinicians with more detailed diagnostic insights.

In addition, another innovation of this study lies in the approach to processing gait data. Unlike K. Wang et al., who focused on gait changes during stair descent, this study conducted a comprehensive analysis of patients' gait data during various daily activities, including walking on flat ground, stair climbing, and cycling. This consideration of activity type differences reveals that different types of activities have varying impacts on cardiac function, thereby enhancing the accuracy and applicability of this study in heart function prediction.

While this study has achieved preliminary results in data integration and gait analysis, some limitations were identified, including the reliance on publicly available datasets, which may introduce variability in data quality and consistency due to differences in data collection protocols across studies. Future work should focus on validating the model with larger and more diverse datasets, exploring more efficient feature selection and data preprocessing techniques, and integrating additional physiological indicators (e.g., blood oxygen saturation and heart rate) to further improve model robustness and applicability.

In summary, this study proposes a novel heart function prediction model by combining the NYHA classification system with multimodal data. A comparison with existing literature confirms the innovation and practicality of this approach in predicting cardiac health. Unlike studies that use frailty as an indicator of cardiovascular complications, this study integrates gait analysis with the NYHA system, providing new methods and perspectives for clinical heart function assessment.

Chapter 6

Conclusion and future work

In conclusion, this study demonstrates the tremendous potential of multimodal data fusion in predicting cardiac function. By combining clinical features and sensor data (including ECG and accelerometer data), and considering the impact of different activities (stair climbing, walking, and cycling), the model's predictive performance is significantly improved. Although there are some differences in the prediction results for different activities, the overall performance of the model is good, particularly for cycling, where it shows high stability and accuracy. Compared to using any single data type alone, combining all data sources provides a more comprehensive reflection of the patient's health status, thereby improving prediction accuracy.

Future work will focus on the following aspects: first, expanding the sample size and increasing patient diversity to further validate the model's generalizability and stability; second, exploring more efficient feature selection and data preprocessing methods to improve the model's performance on complex data; additionally, the plan is to incorporate more physiological sensor data (such as blood pressure, blood oxygen levels, etc.) to further enrich the model's input and improve prediction accuracy.; lastly, enhancing the model's interpretability to make it more transparent and understandable, thereby helping clinicians better apply this prediction tool.

By continuously optimizing and expanding this multimodal data fusion approach, it is expected that in the future, this method will provide a powerful tool for clinical use, helping doctors more accurately assess and manage heart failure patients' conditions, and providing data support for the development of personalized treatment plans.

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