A NOVEL HYBRID MODELS FOR IDENTIFY CLASSIFICATION OF ECG ABNORMALITIES USING DYNAMIC MODAL DECOMPOSITION AND MACHINE LEARNING APPROACHES

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by

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

CVD	Cardiovascular disease
ECG	Electrocardiogram
STFT	Short-Time Fourier transform
PCA	Principal Component Analysis
DMD	Dynamic Mode Decomposition
DMDC	Dynamic Mode Decomposition-Classifier
HDMD	Hankel Dynamic Mode Decomposition
SVM	Support Vector Machine
BLSTM	Bidirectional Long Short-Term Memory
EEG	Electroencephalogram
EMG	Electromyography
SpO2	Peripheral Capillary Oxygen Saturation
ML	Machine Learning
AI	Artificial Intelligence
MAR	Multivariate Autoregressive
SAR	scalar Autoregressive
DFT	Discrete Fourier Transform
FFT	Fast Fourier Transform
MFCC	Mel Frequency Cepstral Coefficients
DCT	Discrete Cosine Transform
AR	Autoregressive
WVD	Wigner–Ville Distribution

GTR1DA	Generalized Tensor Rank one Discriminant Analysis
CKD	Cone-shaped Kernel
CWD	Choi–Williams Distribution
EMD	Empirical Mode Decomposition
WT	Wavelet Transform
SVD	Singular Value Decomposition
ITD	Intrinsic Time-Scale decomposition
MP	Matching pursuits
DL	Deep Learning
CNNs	Convolutional Neural Networks
RNNs	Recurrent Neural Networks
KNN	k-Nearest Neighbors
MLP	Multilayer Perceptron
LSTM	Long Short-Term Memory
CAD	Coronary Artery Disease
PAF	Paroxysmal Atrial Fibrillation
BPNN	Backpropagation Neural Network
EKFs	Extended Kalman Filters
UKFs	Unscented Kalman Filters
SSA	Singular Spectrum Analysis
NLSA	Nonlinear Laplace Spectrum Analysis
ERA	Eigensystem Realization Algorithm
PD	Parkinson’s disease
POD	Proper Orthogonal Decomposition
EDMD	Extended Dynamic Mode Decomposition

STLF	short-term load forecasting
DMs	Dynamic Modes
ECoG	Electrocorticography
ALS	Amyotrophic Lateral Sclerosis
BCI	Brain-Computer Interface
GAN	Generative Adversarial Network

MODEL HIBRID BAHARU UNTUK PENGELASAN KETIDAKNORMALAN ECG MENGGUNAKAN PENDEKATAN MODEL PENGURAIAN DINAMIK DAN PEMBELAJARAN MESIN

ABSTRAK

Klasifikasi isyarat ECG adalah penting untuk mendiagnosis penyakit kardiovaskular. Walau bagaimanapun, kaedah sedia ada menghadapi kesukaran dalam klasifikasi yang tepat disebabkan cabaran dalam mengekstrak mod tidak stabil, menangani ketidakpadanan rank matriks, dan memproses data siri masa. Kaedah dekomposisi mod tradisional gagal menangkap mod tidak stabil, menyebabkan kehilangan ciri-ciri penting. Kajian ini mencadangkan tiga model untuk klasifikasi keabnormalan ECG. Model DMDC menggabungkan dekomposisi mod dinamik (DMD) dengan 11 pengelas untuk mengekstrak mod tidak stabil. Model HDMD+SVM menggunakan pembinaan matriks Hankel dan dekomposisi nilai tunggal (90%) untuk mengesan keabnormalan. Model MDB-NET mengintegrasikan DMD dengan rangkaian LSTM dwihala (BLSTM) untuk mengoptimumkan pemprosesan data siri masa. Keputusan eksperimen menunjukkan bahawa DMDC meningkatkan ketepatan lebih daripada 10% pada pangkalan data PTB. HDMD+SVM meningkatkan pengesanan mod abnormal dan ketahanan. MDB-NET mencapai ketepatan 87.3% dan AUC sebanyak 0.9, mengatasi kaedah lain. Model-model ini menangani cabaran utama dalam klasifikasi ECG: DMDC memberi tumpuan kepada mod tidak stabil, HDMD menyelesaikan ketidakpadanan rank matriks, dan MDB-NET menangkap ciri-ciri temporal. Kerja masa depan akan mengoptimumkan parameter dan meneroka aplikasi pemantauan ECG masa nyata untuk pengesanan awal keabnormalan.

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ABSTRACT

ECG signal classification is vital for diagnosing cardiovascular diseases. However, existing methods struggle with accurate classification due to challenges in extracting unstable modes, handling matrix rank mismatches, and processing time-series data. Traditional modal decomposition methods fail to capture unstable modes, losing critical features. This study proposes three models for ECG abnormality classification. The DMDC model combines dynamic modal decomposition (DMD) with 11 classifiers to extract unstable modes. The HDMD+SVM model uses Hankel matrix construction and singular value decomposition (90%) to detect abnormalities. The MDB-NET model integrates DMD with bidirectional LSTM networks (BLSTM) for optimized time-series processing. Experimental results show that DMDC improves accuracy by over 10% on the PTB database. HDMD+SVM enhances abnormal mode detection and robustness. MDB-NET achieves 87.3% accuracy and an AUC of 0.9, outperforming other methods. These models address key challenges in ECG classification: DMDC focuses on unstable modes, HDMD resolves matrix rank mismatches, and MDB-NET captures temporal features. Future work will optimize parameters and explore real-time ECG monitoring applications for early abnormality detection.

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Cardiovascular disease (CVD) remains the leading cause of death globally. According to recent predictions, the annual number of CVD-related deaths is projected to exceed 20 million, accounting for more than 30% of all global deaths (Gaidai et al., 2023). Heart disease is a general term for diseases or conditions affecting the heart and its function. They may involve different parts of the heart, including the myocardium (heart muscle), coronary arteries (blood vessels that supply the heart), heart valves (valves that control blood flow), the heart's electrical conduction system (the electrical signals that regulate the heartbeat), and more. It can be seen that cardiovascular disease is one of the biggest threats to the health of world residents. Common heart diseases include coronary artery disease (coronary artery disease), heart failure, cardiomyopathy, arrhythmias, valvular disease, congenital heart disease, and pericardial disease.

Heart disease is extremely harmful to health and may lead to serious complications such as heart failure, stroke, and organ damage, significantly reducing the quality of life and bringing heavy psychological and economic burdens. In addition, heart disease increases the risk of sudden death, especially if it is not treated promptly. Therefore, the detection of heart disease is crucial. Through early screening and diagnosis, potential heart diseases can be effectively identified, so that timely intervention measures can be formulated to prevent the progression of the disease and the occurrence of related complications. Scientific and systematic testing can not only reduce the risk of acute events such as myocardial infarction and cardiac arrest, but also optimize the long-term prognosis of patients and reduce the occupation of medical resources. Heart disease detection plays an irreplaceable role in clinical management.

Electrocardiogram (ECG) is a medical testing tool used to record and analyze the heart's electrical activity (Al-Zaiti et al., 2023; Kim et al., 2023; Shi et al., 2024). As

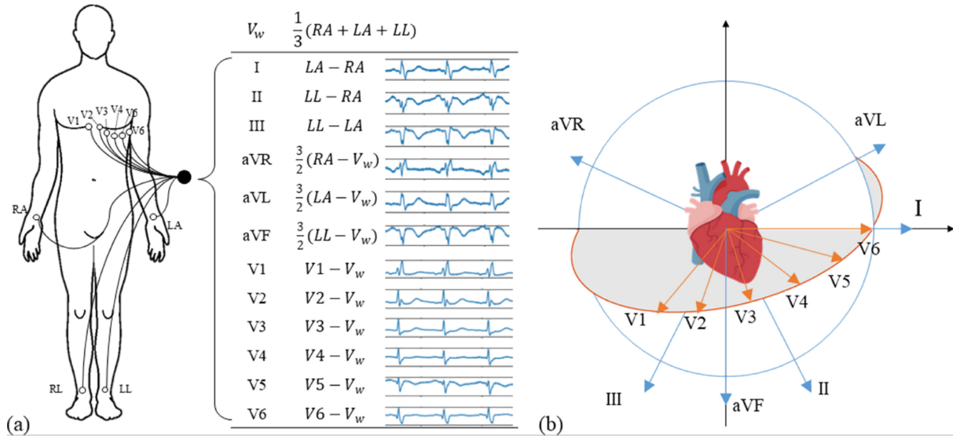
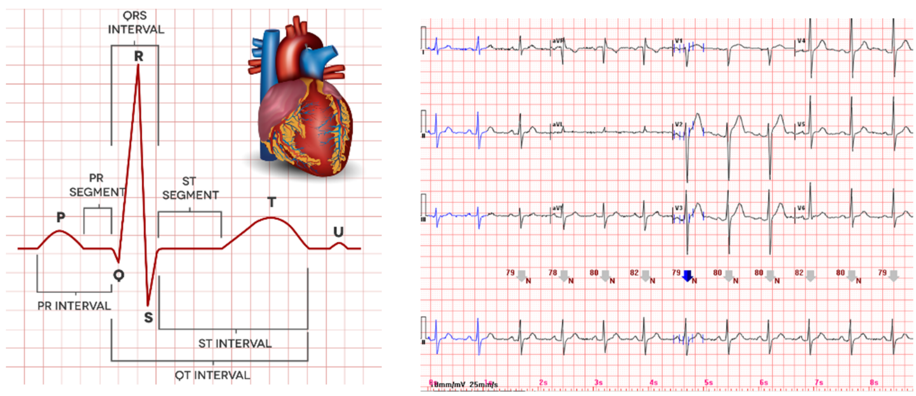


Figure 1.1: Schematic diagram of standard 12-lead ECG electrode placement and signal calculation (Shi et al., 2024)

shown in Figure 1.1, by placing electrodes on the surface of the skin, ECG captures the electrical signals generated by the heart with each heartbeat and converts these signals into graphic records for doctors to analyze the function and health of the heart. Every time the heart beats, the electrical conduction system (including the sinus node, atrioventricular node, bundle of His, and Purkinje fibres) generates electrical signals that trigger depolarization and repolarization of the atria and ventricles, driving the heart's Contraction and relaxation. Electrodes are placed on the patient's skin, usually on the chest, wrists and ankles, and wires transmit signals to the ECG device. The device amplifies, filters, and digitizes these electrical signals to generate an electrocardiogram. As shown in Figure 1.2 (a), an electrocardiogram (ECG) consists of several



(a) Basic components of an ECG (b) Normal standard 12-lead ECG

Figure 1.2: ECG components and normal 12-lead ECG (Kim et al., 2023)

key components. The P wave represents the depolarization of the atria and marks the beginning of atrial contraction; the QRS complex consists of Q wave, R wave and S wave, reflecting the depolarization of the ventricles and is the most significant part of the electrocardiogram; the T wave is Represents repolarization of the ventricles, demonstrating the process by which the ventricles return to their resting state. Additionally, the PR interval measures the time from atrial depolarization to ventricular depolarization, the QT interval shows the total time from ventricular depolarization to repolarization, and the ST segment is between the QRS complex and the T wave, Reflects the plateau after ventricular depolarization. The shape, spacing and amplitude of these waveforms help doctors assess the health of the heart (Hampton and Hampton, 2019).

A normal ECG should show regular P waves, QRS complexes, and T waves. As shown in the Figure 1.2 (b), the normal PR interval is between 0.12 and 0.20 seconds, the QT interval is between 0.36 and 0.44 seconds, and the ST segment should be stable without significant elevation or depression. However, ECG abnormalities may indicate a variety of heart diseases. For example, ST-segment elevation is common in acute myocardial infarction, while ST-segment depression may indicate myocardial ischemia. Increased QRS wave width can be seen in bundle branch block or premature ventricular beats; P wave abnormalities such as atrial fibrillation are manifested as absent P waves and atrial flutter is serrated. T wave abnormalities such as inverted T waves may indicate myocardial ischemia, while height changes in T waves may be related to electrolyte imbalances. In addition, a prolonged QT interval is associated with long QT syndrome, which may lead to arrhythmias; a shortened QT interval may be associated with short QT syndrome or hypercalcemia. These ECG abnormalities provide key evidence for clinical diagnosis and treatment by revealing underlying heart problems.

ECG can be divided into single-lead, dual-lead, three-lead, twelve-lead, and fifteen-lead types according to the number of leads (Francis, 2016). Single-lead ECG uses one electrode to record the basic electrical activity of the heart and is suitable for preliminary screening; dual-lead ECG provides more detailed heart rhythm information through two electrodes; three-lead ECG uses three electrodes to generate three different ECG views, which are suitable for more comprehensive heart monitoring. The twelve-lead ECG uses ten electrodes to generate twelve leads, providing a full view of the heart's electrical activity. It is the most commonly used standard method for detailed diagnosis of heart diseases. The extended fifteen-lead ECG adds three frank leads, VX, VY, and VZ, to the twelve-lead ECG, which can provide a detailed analysis of the right ventricle and the back of the heart.

Although all leads record the overall process of cardiac electrical activity, including P waves, QRS complexes (including Q, R, and S waves), and T waves, the specific waveform characteristics displayed by each lead will be different. This is because different leads view the heart's electrical activity from different angles, so certain waveforms may be more apparent in some leads and less apparent or even missing in other leads. These different types of ECG provide a variety of basic to detailed information on the heart's electrical activity, depending on the number and configuration of their leads, which helps in accurate diagnosis and treatment in clinical practice.

Therefore, ECG has a crucial role in the detection of heart diseases. By recording the electrical activity of the heart, ECG provides detailed information about the heart rhythm, electrical axis, ventricular and atrial electrical activity. Normal ECG help assess the health of the heart, while abnormal ECG can reveal a wide range of cardiac problems. In particular, the multi-lead configuration of ECG can comprehensively capture the electrical activity of the heart at different angles, helping doctors to accurately diagnose complex cardiac diseases. As a result, ECG has an irreplaceable place in the detection and management of heart disease as a non-invasive, quick and effective diagnostic tool.

Classification is a core task in machine learning and data analysis, and its main purpose is to assign data samples to predefined categories or labels. This process predicts or determines the category to which a sample belongs by analyzing data features, and plays an important role in various fields. For example, in email systems, classification is used for spam filtering (Youn and McLeod, 2007); in computer vision, classification is used for image recognition (Javidi, 2002); in the field of natural language processing, it is used for sentiment analysis (Mouthami et al., 2013); in financial services, it is used to detect and prevent fraud (Ngai et al., 2011); and in marketing, classification helps in customer segmentation (Cooil et al., 2008). In particular, classification technology is of particular importance in the field of medicine, where it can help accurately diagnose various diseases by analyzing patients' symptoms or diagnostic test results (Association, 2018; Gadaras and Mikhailov, 2009; Yadav and Jadhav, 2019).

In medical applications, ECG classification is particularly important. It can identify and distinguish different heart diseases or abnormal states by analyzing and classifying ECG signals (Houssein et al., 2017). ECG classification involves extracting key features in the electrocardiogram signal, such as waveform shape, intervals, and amplitude, and applying classification algorithms to map the signal into predefined disease categories. This process includes feature extraction, model training, and classification prediction. Through these steps, ECG classification not only improves the efficiency and accuracy of heart disease diagnosis but also significantly enhances the reliability of detection. Effective ECG classification enables early diagnosis and timely intervention, supporting clinicians to make faster and more accurate decisions, thereby significantly improving patient prognosis and quality of life.

Feature extraction methods include a variety of techniques, each method has its applicable scenarios and characteristics. The time domain feature extraction method (Sattari et al., 2021) directly extracts basic statistics and heart rate variability from time series data and is mainly used to describe the basic statistical characteristics of the signal. Frequency domain feature extraction methods such as Fourier transform and power spectral density convert the signal into the frequency domain and analyze its frequency components, which are suitable for the analysis of periodic signals. Time-frequency domain feature extraction methods such as wavelet transform and Short-Time Fourier transform (STFT) (Beeraka et al., 2022) provide both time and frequency information and are suitable for processing non-stationary signals. Model-driven feature extraction methods such as autoencoders and Principal Component Analysis (PCA) use machine learning technology to automatically extract and reduce dimensionality and are suitable for high-dimensional data processing. Dynamic Mode Decomposition (DMD) decomposes the signal into dynamic modes by analyzing the time evolution of the signal, which can effectively capture complex dynamic characteristics and nonlinear behaviour. These methods have their characteristics and provide rich options for feature extraction of ECG signals.

Among them, DMD is a method for analyzing and decomposing complex dynamic systems. DMD extracts the dynamic modes of the system from time series data and determines its stability by calculating the eigenvalues of the modes (Ingabire et al., 2021). Specifically, if the absolute value of the eigenvalue is less than 1, the modes are considered to be stable modes, that is, their amplitudes remain unchanged or gradually decrease over time; if the absolute value of the eigenvalue is greater than 1, the modes are unstable modes, and their amplitudes increase over time, usually corresponding to abnormal conditions or instability in the system. Unstable modes are very important in practical applications because they often reveal potential anomalies, faults, or other critical dynamic changes in the system. This makes DMD a powerful tool for monitoring and analyzing abnormal conditions in complex systems, and it has been widely used in fields such as fluid dynamics, structural health monitoring, and signal processing.

1.2 Problem Statement

Most current studies on ECG classification focus on the abnormalities analysis of stable modes, while relatively little attention is paid to unstable modes. Although ECG signals have obvious periodic and regular characteristics, such as P waves, QRS complexes and T waves, their high dimensionality and susceptibility to noise interference increase the complexity of data processing, especially under noise interference, the nonlinear and unstable modes of the signal are often masked. Unstable modes play an important role in electrocardiograms. They may reveal early abnormal cardiac signals, such as early warning of potential diseases such as myocardial infarction, coronary heart disease or heart failure. However, although existing studies have involved both stable and unstable modes of ECG signals (Ingabire et al., 2021), most studies lack sufficient attention to unstable modes. This lack may limit the accurate capture and classification of abnormal changes, resulting in a decrease in the accuracy of detecting abnormalities, thereby limiting the ability to diagnose and prevent heart diseases in the early stage.

ECG signal classification faces the problem of data matrix rank mismatch, i.e., the rank of the matrix is not sufficient to effectively express all the important information in the signal. When processing ECG signals, matrix decomposition is usually required to extract dynamic features. However, in some cases, the constructed matrix dimensions are not able to effectively capture all the dynamic features in the signal, and the lack of critical information is especially significant when dealing with high-dimensional and complex signals. This affects the accuracy of modal extraction and thus constrains the performance of the classification model. The missing key information significantly reduces the classification accuracy of the model, especially for subtle differences such as arrhythmia.

ECG signals have significant temporal dependence, but existing classification methods fail to adequately take this into account. Temporal features in ECG signals incorporate dependencies on long-time scales. However, many conventional methods fail to model these temporal features effectively, especially when dealing with complex and non-linear ECG signals, and are unable to adequately capture the long-term dependencies involved. This limitation makes the models underperform in coping with the temporal complexity, which affects the accurate capture of details and hence the accuracy of the classification results.

The practical effectiveness of ECG signal classification methods still requires further validation and comparison. Preliminary results of existing methods are usually based on specific datasets and experimental conditions, but their combined effects have not been systematically evaluated across different datasets and arrhythmia types. Different datasets may have different characteristics and noise levels, and the complexity and variability of arrhythmia types may also affect model performance. Therefore, extensive experiments on diverse datasets are needed to validate their effectiveness in real-world applications. In addition, in order to further optimise the model, systematic comparative studies must be conducted to assess its performance against other state-of-the-art techniques, and adjustments and improvements must be made based on the results.

1.3 Objectives of the Study

The Objectives of this study are:

1. To analyze ECG signals with DMD, identifying and extracting unstable modes that have the highest absolute variance of eigenvalues, to improve classification accuracy.
2. To implement HDMD analysis of multi-lead ECG data, using the number of modes with a singular value ratio of 90% to determine the optimal delay parameter of the HDMD model to optimize the accuracy of modal extraction
3. To propose a novel classification method for ECG signals, namely the MDB-NET model, which combines an improved dynamic modal decomposition (DMD) and a bidirectional long short-term memory network (BLSTM).
4. To design Hybrid Models and compare with existing model, evaluating their accuracy in ECG signal classification and discussing the effectiveness of these models in practical applications

1.4 Scope and Limitation

This study aims to improve the classification of electrocardiogram (ECG) signals, especially in unstable mode extraction, data matrix rank matching and time series data processing. Three innovative models,Dynamic Mode Decomposition-Classifier (DMDC), Hankel Dynamic Mode Decomposition (HDMD)+Support Vector Machine (SVM) and MDB-NET, are proposed to improve the classification accuracy, especially in data matrix rank matching and time series processing. These models enhance the capture of unstable modes through improved DMD and Hankel matrix expansion, and improve the identification of modal features and timing information by combining SVM with Bidirectional Long Short-Term Memory (BLSTM) networks. The study was validated using the PTB Diagnostic ECG and CPSC 2018 datasets, and the performance of the model was evaluated on metrics such as accuracy, precision, recall, and F1 score. However, there are several limitations of this study. Firstly, the performance of the DMDC model under different datasets or arrhythmia patterns needs further validation, and the modality extraction strategy may need to be optimised when dealing with noise or data variability. Second, the HDMD+SVM model uses 90% singular value energy to extract modalities, but this threshold setting is subjective and may need to be adjusted in different noise environments. Finally, the MDB-NET (DMD+BLSTM) model, although excellent in terms of classification metrics, has a high computational complexity and needs to be further optimised for efficiency in practical applications. In addition, the PTB Diagnostic ECG and CPSC 2018 datasets used, while providing valuable validation data, may not be fully representative of clinical diversity due to the difficulty of obtaining real medical data, limiting the generalisation ability of the model. Future research could validate models on real medical datasets to improve their applicability and robustness. This study assumes that the selected dataset is representative of typical arrhythmia patterns, that the evaluation metrics used can comprehensively measure the classification effect, and that the model can maintain good performance on other datasets with similar characteristics. Specifically, the unstable mode extraction capability can be enhanced by the improved DMD and multiple classifiers (DMDC model); the HDMD method optimises the data matrix expansion and improves the classification robustness; and the MDB-NET combines the DMD and the BLSTM network, which significantly improves the temporal feature capturing capability. Overall, the three models perform well on the studied dataset and have good generalisation ability, providing an effective solution for arrhythmia diagnosis.

1.5 Significance of the study

Abnormal detection of ECG signals plays a crucial role in the early diagnosis and treatment of heart diseases. Although existing ECG analysis technologies have made significant progress, challenges in the accuracy and efficiency of traditional methods remain as data complexity and dimensionality increase. This study is committed to improving the ability of abnormality detection in electrocardiogram signals by introducing improved DMD and HDMD technology, combined with SVM and BLSTM. , which is of great significance for the early identification and accurate diagnosis of heart disease.

In the study, the improved DMD method was used for preliminary analysis of electrocardiogram signals, which can effectively extract unstable modes in the signal and screen out modes with significant characteristics. This improved method provides higher accuracy than traditional DMD, especially showing better performance when processing high-dimensional and complex signals. At the same time, HDMD technology has been applied to binary classification problems of a variety of heart diseases. By combining with the SVM model, it can further improve the accuracy and reliability of classification and provide clinicians with more accurate diagnostic tools. The advantage of HDMD lies in its better capture of dynamic features and ability to process high-dimensional data, making the classification of various heart diseases more effective.

To address the problem of arrhythmia abnormality detection, this study adopts a model that combines DMD and BLSTM. BLSTM is able to effectively capture long-term dependencies in signals when dealing with time-series data, which is particularly important for possible temporal variations in ECG signals. Combined with the dynamic feature extraction capability of DMD, the model significantly enhances the detection of arrhythmia signals. This approach helps to identify and differentiate abnormalities more accurately, advances the development of ECG signal analysis techniques, and provides a more effective tool for clinical applications, helping physicians to detect and manage potential cardiac abnormalities earlier, thereby reducing health risks and medical costs.

Overall, the technological innovation and methodological improvements of this study are of great significance in improving the accuracy and practicality of electrocardiogram signal analysis. By optimizing DMD, HDMD, and the combination of SVM and BLSTM, this study not only provides a new solution for anomaly detection in ECG signals, but also provides strong support for the development of anomaly detection methods for other complex data. These research results will promote technological innovation and application expansion in related fields, laying a solid foundation for future medical research and clinical applications.

This study proposes three novel models for classifying CVD from ECG signals. The DMDC improves the extraction of unstable modes by combining enhanced DMD with multiple classifiers, enhancing abnormality detection. The HDMD+SVM model uses Hankel matrix construction and singular value decomposition for robust feature extraction, while the MDB-NET (DMD-BLSTM) integrates bidirectional long short-term memory networks for optimized time-series analysis. These models outperform traditional methods, addressing key challenges in CVD classification, such as mode instability, matrix rank mismatches, and temporal complexity in ECG data.

1.6 Thesis Framework

This paper is organized around the relevant issues of ECG signal classification and is divided into five chapters. The structure of this study is as follows: Chapter 1 introduces the current status of ECG signal research and classification issues in different fields, focusing on the characteristics of ECG signals and the need for feature extraction. The research problems, corresponding research objectives, research scope, limitations and significance of the research are explained. Chapter 2 discusses the analysis methods for feature extraction of ECG signals, related research on classification models, and literature review, summarizing the characteristics of existing methods and the problems they face. Chapter 3 proposes three models for feature extraction and classification of ECG signals, namely DMDC, HDMD-SVM and MDB-NET. The proposed models provide new solutions for ECG signal analysis and promote research and applications in related fields. The experimental part of Chapter 4 introduces the experimental results of the model in ECG signal feature extraction and classification, verifying the effectiveness of the model on public datasets. Chapter 5 includes conclusions, contributions, limitations of the research and future work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter will provide a detailed review of ECG signal analysis and related techniques to provide background knowledge for the selection and application of methods in research. Section 2.2 will introduce the analysis methods of ECG signals, covering feature extraction and classification techniques, and focus on how to effectively process and understand ECG data. Section 2.3 will focus on the analysis of unstable modes, explaining their importance in dynamic systems and how to judge unstable modes through eigenvalues. Section 2.4 will introduce the selection of delay parameters and analyze how to improve the accuracy of analysis through parameter optimization in methods such as DMD. Section 2.5 will explore the application of DMD and its variants and evaluate their performance in processing complex signals. Section 2.6 will discuss the multi-classification problem of arrhythmias in detail, introduce the current classification standards and their challenges in practical applications. Finally, Section 2.7 will review the application of hybrid models in ECG signal analysis, compare the advantages of different models, and analyze their potential in future research. Sections 2.8 and 2.9 will systematically review and summarize the literature in these areas. This chapter will provide a comprehensive theoretical background for various methods in ECG signal analysis, reveal the progress and challenges of existing technologies, and provide references for subsequent research.

2.2 Analysis of ECG signal

Signal analysis is a complex field consisting of multiple processes that work together to form a powerful process for automated data analysis. The main processes of signal analysis include data acquisition, data preprocessing, feature extraction and selection, model training and classification, and performance evaluation. In the medical field, the analysis of biomedical signals is crucial, such as ECG, Electroencephalogram

(EEG), Electromyography (EMG), Peripheral Capillary Oxygen Saturation (SpO2), and respiratory signals.

ECG signal analysis is an important technology for studying cardiac electrical activity and is widely used in the detection, diagnosis and long-term monitoring of heart diseases. By analyzing ECG signals, doctors can identify a variety of diseases such as arrhythmias and myocardial infarction, and thus develop targeted treatment plans. With the increasing demand for health monitoring, ECG signal analysis has also been widely used in wearable devices and telemedicine systems, achieving real-time monitoring and early warning of heart health. Therefore, this article will pay special attention to ECG signals and review the feature extraction and classification techniques commonly used in the industry. As shown in Figure 2.1, the ECG signal analysis framework summarizes the main steps and common methods of this process, including data preprocessing, feature extraction, feature selection/optimization, signal classification, and post-processing and decision-making.

Therefore, this section will focus on ECG signals and review the feature extraction and classification techniques commonly used in the industry. Table 2.1 summarizes the application of different methods in ECG feature extraction, covering time domain analysis, frequency domain analysis, time-frequency domain analysis, decomposition domain analysis, deep feature extraction, and DMD techniques.

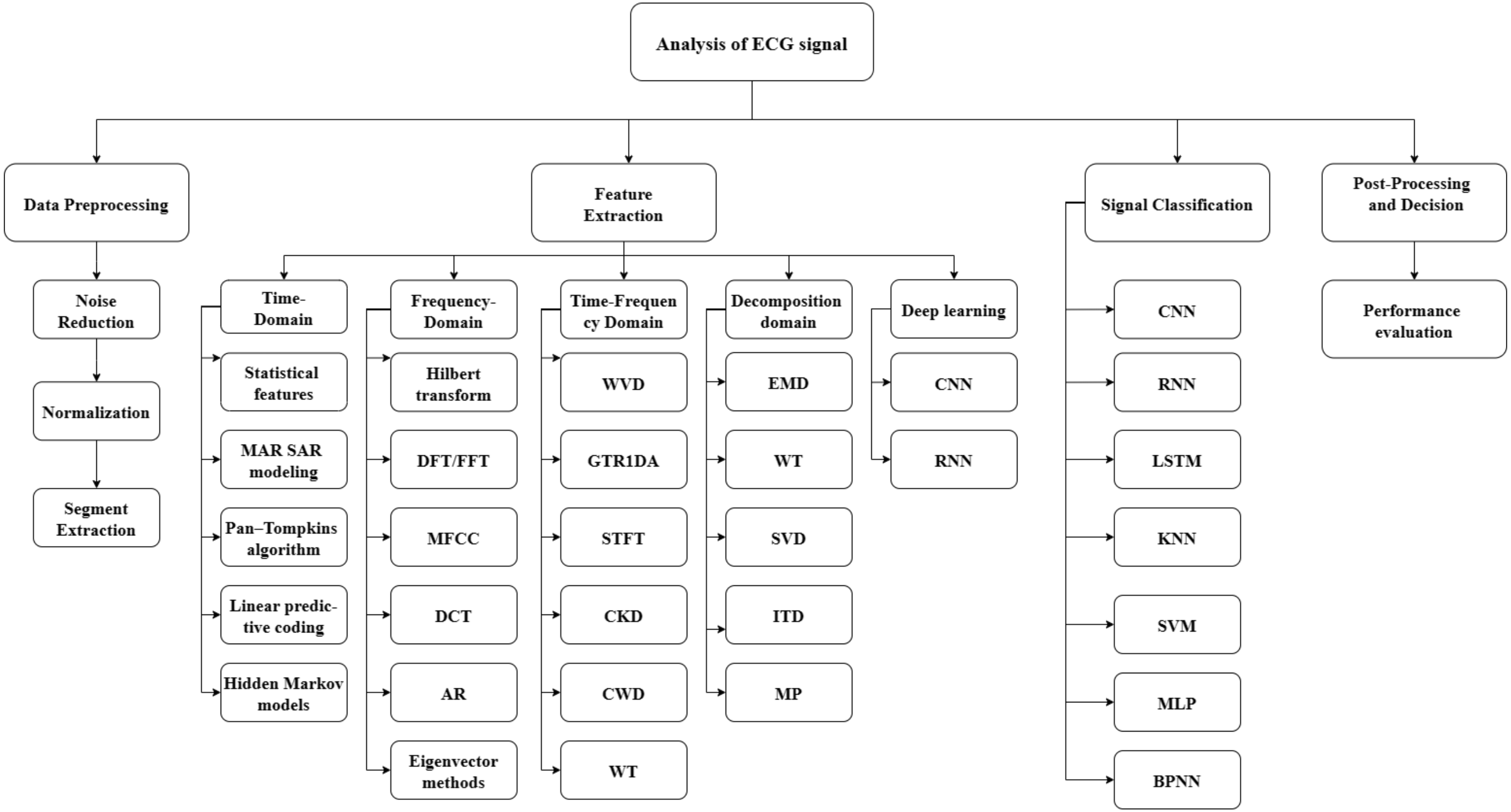


Figure 2.1: ECG signal analysis framework diagram

2.2.1 Feature extraction of ECG

The core goal of feature extraction is dimensionality reduction and data compression. In short, it is to represent data with fewer features, which enables these features to be more effectively applied in Machine Learning (ML) and Artificial Intelligence (AI) models, such as classification and diagnosis. The extracted features should accurately reflect the specific patterns and behaviors in the signal. Through this process, only representative information is extracted, and the redundant parts of the data are filtered out, which helps to better understand and analyze the potential characteristics and patterns of the signal. This not only simplifies the data processing process, but also improves the analysis efficiency, providing important support for subsequent model training and decision making.

The analysis process of ECG signals is complex and challenging, mainly due to the difficulties in signal acquisition and data characteristics. The acquisition of ECG signals typically takes several hours, which in itself poses a significant challenge (Subasi, 2019). A deep understanding of the fundamental properties of ECG signals is critical to effectively analyzing these signals. ECG signals usually have several key characteristics: non-stationarity (the statistical characteristics of the signal change with time), non-linearity (the relationship in the signal cannot be described by a simple linear model), non-Gaussianity (the distribution of the signal does not conform to the assumption of Gaussian distribution) and non-short form (the dynamic process of the signal is complex and difficult to represent with a simple model) (Krishnan, 2021). These characteristics make feature extraction and signal analysis more complex, requiring more advanced methods and technologies for accurate analysis and processing.

The methods for ECG signal feature extraction have undergone gradual development, as shown in Figure 2.1, including Time-Domain, Frequency-Domain, Time-Frequency Domain, Decomposition Domain analysis and deep features extraction (Singh and Krishnan, 2023).

Among them, the first generation of feature extraction methods mainly focused on time domain analysis, quantifying ECG signals by analyzing the temporal changes of biomedical signals. This usually involves windowing and segmenting the signal to extract time domain features in each window (Khan et al., 2015). Time domain analysis covers statistical features (Alotaiby et al., 2019; Saxena and Shinghal, 2015), Multivariate Autoregressive (MAR) and scalar Autoregressive (SAR) modeling (Vaneghi et al., 2012), Pan-Tompkins algorithm (Elgendi, 2013; Pan and Tompkins, 1985), linear predictive coding (Lin and Chang, 1989) and hidden Markov models (Coast et al., 1990).

Frequency domain feature extraction is a method of analyzing the characteristics of a signal in the frequency domain, which is used to reveal the hidden frequency components and periodic patterns in the signal. The following are some common frequency domain feature extraction methods: Hilbert transform (Benitez et al., 2001), Discrete Fourier Transform (DFT) and Fast Fourier Transform (FFT) (Haque et al., 2009), Mel Frequency Cepstral Coefficients (MFCC) analysis (Jen, Hwang, et al., 2008), Discrete Cosine Transform (DCT) (Cherifi et al., 2017), Autoregressive (AR) models (Sassi et al., 2005), Eigenvector methods (Saxena and Shinghal, 2015).

Due to the non-stationary nature of ECG signals, time-frequency domain analysis can effectively capture the time and frequency characteristics of the signal at the same time. Mapping the signal to the two-dimensional time-frequency domain can better reveal its dynamic changes. Existing methods include Wigner–Ville Distribution (WVD) (Abeysekera and Boashash, 1989), Generalized Tensor Rank one Discriminant Analysis (GTR1DA) (K. Huang and Zhang, 2014), STFT (Afonso and Tompkins, 1995), Cone-shaped Kernel (CKD) (Afonso and Tompkins, 1995; Akansu and Haddad, 2001), Choi–Williams Distribution (CWD), and wavelet transform (Dhaka and Khetarpal, 2019; Hu et al., 2020).

Decomposition domain feature extraction of ECG signals extracts useful features by decomposing ECG signals into multiple components while excluding unnecessary components, thereby achieving data compression. Although sparse representation is not commonly used in traditional ECG feature extraction, it plays an important role in signal transmission and storage, especially in the application of the Internet of Things and telemedicine, where sparse representation can enhance the effect of related algorithms. Commonly used methods include Empirical Mode Decomposition (EMD), The Wavelet Transform (WT), Singular Value Decomposition (SVD), Intrinsic Time-Scale decomposition (ITD), and Matching pursuits (MP).

Deep Learning (DL) is an advanced branch of ML that aims to simulate complex pattern recognition capabilities by building multi-layer neural networks. In DL, multiple network layers are used to automatically learn and extract high-level features from data, thereby improving the model's ability to handle complex tasks. Unlike traditional machine learning methods, DL does not require tedious data preprocessing steps when processing unstructured data, which enables it to perform well in various application scenarios, especially in image and speech processing. The key advantage of DL is that it can autonomously identify and optimize the most useful features, reducing dependence on human intervention, thereby improving the automation and adaptability of the model (LeCun et al., 2015).

There are many types of neural networks in deep learning, among which Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are two common architectures. CNNs are commonly used for image processing tasks by automatically extracting local features and classifying them, such as identifying lesion areas in medical image analysis (Diker and Engin, 2019). RNNs are good at processing sequential data, such as time series or natural language. Their advantage is that they can capture the temporal dependencies in the data and perform well in applications such as speech recognition and text generation. The choice of network depends on the specific application requirements and data characteristics.

Feature selection is crucial after feature extraction, as it directly affects the performance of the model. Selecting application-relevant features ensures that the model better reflects the key patterns and behaviors of the signal, while inappropriate features may reduce the model effect. Effective feature selection can not only reduce computing resources and time, but also simplify the model and improve its application effect in healthcare and telemedicine. It should be noted that the number and combination of features should be reasonable to avoid overfitting or underfitting problems.

As shown in table 2.1, In the field of ECG feature extraction, only one study has used the DMD method to date (Ingabire et al., 2021). This study showed that DMD can effectively decompose the dynamic features in ECG signals, thereby improving the accuracy and efficiency of analysis. Although it has been less widely used, the potential of DMD in extracting dynamic patterns of signals suggests that more related research may be carried out in the future.

2.2.2 Classification of ECG

Classification refers to the process of categorizing data or signals into predetermined categories or labels. Signal classification plays a vital role in the medical field, especially in the diagnosis of cardiovascular diseases.ECG signal classification mainly involves classifying ECG signals into two or more categories, such as normal or abnormal heartbeats and various types of arrhythmias. The purpose of classification is to extract useful information from these signals for accurate diagnosis. Effective ECG signal classification can not only help doctors identify cardiac abnormalities, but also improve the overall understanding of the patient's health status. With the development of technology, new classification methods and algorithms are constantly being introduced, which not only improve the accuracy of classification, but also improve the efficiency of processing large amounts of data, making early detection and real-time monitoring of heart disease possible.

In the study of ECG signal classification, with the development of technology, more and more advanced methods have been proposed to improve the accuracy and efficiency of classification (Fikri et al., 2021). These methods include not only traditional machine learning algorithms such as SVM, k-Nearest Neighbors (KNN) and Multilayer Perceptron (MLP), but also deep learning techniques such as CNNs and Long Short-Term Memory (LSTM).

Traditional machine learning algorithms perform well in feature extraction and classification tasks, but with the increase of data complexity, deep learning methods show stronger adaptability and accuracy by automatically learning and extracting features. In addition, recent studies have also explored combination methods and optimized model structures to further improve classification performance and reliability in practical applications. The continuous advancement of these methods has provided strong support for the early detection and diagnosis of cardiovascular diseases such as arrhythmias and promoted the development of intelligent medical care.

CNN are a deep learning architecture widely used in image and signal processing that is particularly good at automatically extracting and classifying features from data. In ECG signal classification, CNN is used to identify various arrhythmia types, significantly improving the accuracy of automatic diagnosis (Rajkumar et al., 2019). Through the operation of convolutional layers, CNN can effectively process ECG data in the time domain and frequency domain and automatically extract features related to arrhythmia without the need for traditional manual feature extraction steps (Savalia and Emamian, 2018).

In related research, scholars have used CNN to directly learn and classify arrhythmia types from ECG signals in databases such as PhysioBank and CPSC 2018, achieving high accuracy and sensitivity (Rajkumar et al., 2019; Savalia and Emamian, 2018). In addition, some studies have combined the LSTM network and CNN to process the temporal dependence of ECG signals, further improving the classification effect (Liu et al., 2019; Xu et al., 2020). In addition, J. Huang et al also used a two-dimensional CNN to convert the ECG signal into a time-frequency spectrum diagram and used this as input for classification, verifying the potential of CNN to achieve efficient classification without manual intervention (J. Huang et al., 2019). These studies demonstrate the powerful capabilities of CNN in ECG signal analysis and arrhythmia detection.

RNN, especially LSTM, have demonstrated powerful capabilities in ECG signal analysis, especially in processing physiological data with time dependence. As a variant of RNN, LSTM is capable of capturing and processing long-term dependencies in sequence data, making it excellent in ECG signal classification tasks. Saadatnejad et al proposed a lightweight LSTM-based ECG classification algorithm designed for wearable devices with limited resources. This method combines wavelet transform and LSTM architecture to achieve the goal of continuous and real-time monitoring of ECG signals on wearable devices, demonstrating high efficiency and real-time performance on the hardware platform (Saadatnejad et al., 2019).

Furthermore, Xu et al., combined a CNN and a BLSTM network to enhance the classification performance of ECG signals. By integrating the residual block and SENet structure, the combined network achieved significant performance improvements in arrhythmia detection, showing high recognition sensitivity and specificity (Xu et al., 2020). Rana and Kim proposed a single-layer LSTM model for heartbeat classification, which can accurately distinguish between normal and abnormal heartbeats. When evaluated using the MIT-BIH dataset, the method achieved a classification accuracy of 95%, showing higher accuracy compared to other CNN and RNN models (Rana and Kim, 2019).

Banerjee et al., introduced an innovative hybrid CNN-LSTM architecture for detecting Coronary Artery Disease (CAD). This model combines CNN-extracted ECG waveform features with LSTM-based HRV measurements, demonstrating high classification accuracy on MIMIC II and in-house datasets of 93% and 88%, respectively, indicating its utility in early CAD screening. effectiveness (Banerjee et al., 2020). These studies demonstrate the importance of LSTM and its variants in real-time ECG monitoring and heart disease diagnosis, especially in tasks that require processing of long time series data.

In the field of ECG signal classification, DL methods, such as CNN, have demonstrated strong performance. Recent research has demonstrated the advantages of using CNNs in conjunction with other traditional machine learning classifiers, such as KNN, SVM, and MLP. When dealing with Paroxysmal Atrial Fibrillation (PAF) patient screening problems, CNN is able to automatically learn representative features from raw ECG time series data, thereby simplifying the traditional manual feature extraction process.

By combining it with classifiers such as KNN, linear SVM, Gaussian kernel SVM, and MLP, research by Pourbabaee et al. shows that the integration of CNN as a feature extractor with these traditional classification methods significantly improves classification performance. Specifically, KNN classifies by calculating the distance between samples, which is suitable for processing features with obvious similarities; SVM uses boundaries in high-dimensional feature space for classification, and can effectively handle complex data distribution; MLP uses its multi-layer Structure captures non-linear relationships in data, enhancing the robustness of classification (Pourbabaee et al., 2017).

Al-Masri introduced an arrhythmia detection method based on a feedforward Backpropagation Neural Network (BPNN) (Al-Masri, 2018). This approach aims to reduce the set of features required during analysis and simplify the processing of ECG data. Specifically, the study included the RR intervals of two heartbeats before and after the current heartbeat in the feature set to capture potentially useful information. The results show that the system achieves an average accuracy of 98.70% in arrhythmia classification and has comparable performance compared to other methods using the same data source. The study also found that adding the features of two heartbeats before and after significantly improved the classification accuracy of the system. This high-performance BPNN system lays the foundation for future real-time detection and classification of ECG signals on portable devices.

Although these methods have achieved remarkable results in ECG signal classification, there are relatively few studies on the combination of modal decomposition techniques, such as DMD, with these classification methods. As an effective signal processing tool, DMD can extract dynamic features from data, but its application research in ECG signal classification is still limited. Combining DMD with existing deep learning methods, such as CNN, RNN, and LSTM, may bring new research breakthroughs and improve classification accuracy and model robustness. Therefore, future research should focus on how to integrate DMD technology with existing classification methods to fully tap its potential in ECG signal analysis and promote further development in this field.

Table 2.1: Studies on the feature extraction of ECG

Authour(s) Year(s)	Method						Remark
	Time-Domain	Frequency-Domain	Time-Frequency Domain	Decomposition Domain	Deep Features	DMD	
Pan & Tompkins (1985)	√	-	-	-	-	-	Real-time QRS detection algorithm successful
Lin & Chang (1989)	√	-	-	-	-	-	Linear prediction extracts QRS features
Coast et al. (1990)	√	-	-	-	-	-	HMM used for arrhythmia analysis
Afonso & Tompkins (1995)	-	-	√	-	-	-	Effective method for detecting ventricular fibrillation
Benitez et al. (2001)	-	√	-	-	-	-	Hilbert transform aids ECG analysis
Akansu & Haddad (2001)	-	-	√	-	-	-	Multiresolution time-frequency analysis techniques
Wei et al. (2001)	-	-	-	√	-	-	SVD compresses ECG data
Abeysekera & Boashash (2003)	-	-	√	-	-	-	Time-frequency features for P-wave detection
Jen & Hwang (2008)	-	√	-	-	-	-	Cepstrum and neural networks classify ECG
Haque et al. (2009)	-	√	-	-	-	-	FFT achieves automatic feature extraction