Deep Learning Based Classification of Cardiovascular Diseases Via ECG Signal Analysis

Khokhwan Weangoukost, Supanut Jantasiri, and Thaweesak Yingthawornsuk

***Abstract*— This research study focuses on developing a deep learning algorithm to analyze ECG signals for the early detection of cardiovascular diseases, particularly heart arrhythmias and heart failure. The proposed study aims to design and implement a deep learning model to classify and screen ECG signals for abnormalities. The dataset consists of ECG signals from various databases, including those representing normal heart rhythms, arrhythmias, and congestive heart failure. The algorithm's performance is evaluated by comparing it with existing computer programs. The results are expected to enhance the diagnostic accuracy of heart disease, reduce the burden on medical professionals, and provide a reliable tool for early detection of heart conditions. The implementation could potentially serve as a medical aid, improving initial diagnoses and supporting healthcare practitioners.**

***Keywords*—Deep Learning, ECG Signal, Power Spectral Density, Cardiovascular Disease.**

I. Introduction

Heart diseases, particularly cardiac arrhythmias, represent a significant global health issue. Cardiac arrhythmia is a condition characterized by abnormal heart rhythms, which can lead to inefficient blood circulation throughout the body. This condition poses a heightened risk of severe outcomes such as heart failure or stroke. The prevalence of heart failure, a state where the heart cannot pump blood effectively, is especially alarming among older populations, affecting 1-2% of the general population and over 10% of those aged 70 years and above [1]. With the growing number of elderly individuals in Thailand [2], heart diseases are expected to impose a considerable burden on the healthcare system [3].

The electrocardiogram (ECG) is widely used as a key tool for diagnosing heart conditions, as it records the heart's electrical activity and provides important insights into cardiac function. However, manual interpretation of ECG signals can be time-consuming, error-prone, and often requires expert knowledge. As a result, many studies have shown that traditional methods for classifying heart diseases based on ECG data may not always be effective.

To address these limitations, researchers have been exploring more advanced features and techniques to improve classification accuracy. Approaches such as Data Synthesis, Entropy Analysis, Power Spectral Density analysis, Fourier Decomposition, R-peak detection and Filtering, Feature Extraction from ECG signals, Feature Selection and Validation have shown strong potential in enhancing performance [4–12]. These methods support the growing shift toward more sophisticated computational models, particularly those based on deep learning.

This project aims to design and implement a deep learning algorithm, specifically using Convolutional Neural Networks (CNNs), to analyze ECG signals and screen for heart conditions. By leveraging deep learning techniques, the system can automatically identify abnormalities in ECG signals, reducing the diagnostic burden on medical professionals and enabling more precise and timely detection of heart diseases. The proposed algorithm will be evaluated for its effectiveness compared to existing diagnostic tools, with the goal of improving the accuracy and reliability of heart disease screening. In this work, the ECG signals of ninety patients from MIT-BIH Database are collected and implemented in deep-learning model training.

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II. METHODS

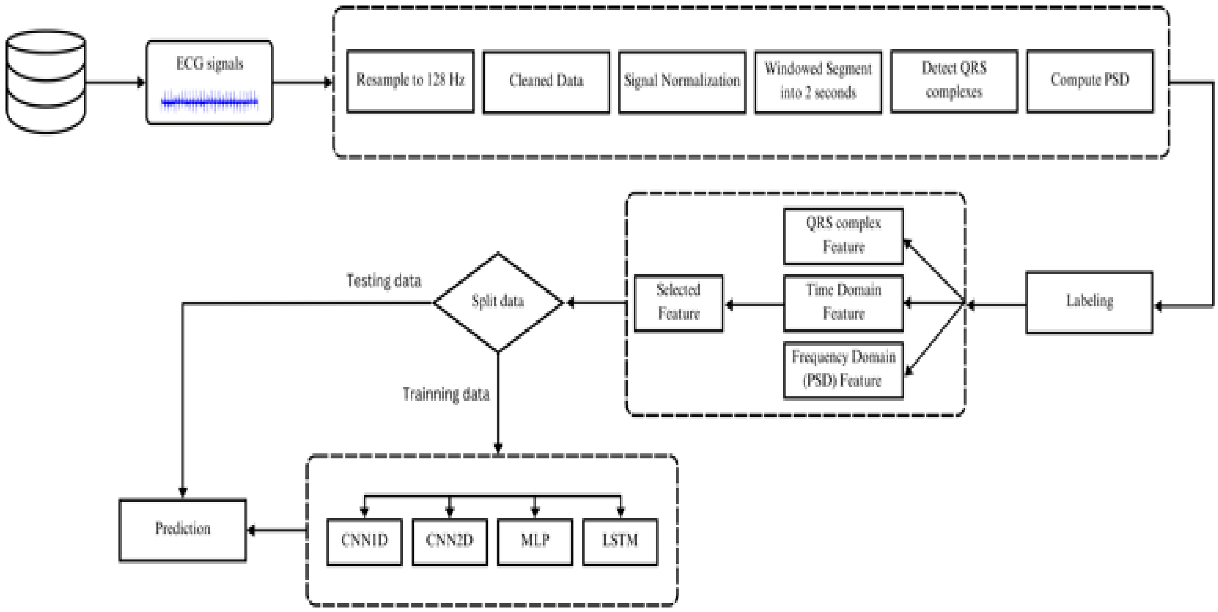

Fig. 1. Proposed heart disease identification system.

Figure 1 describes the key steps used in developing the deep learning algorithm for ECG signal analysis to screen for cardiovascular diseases. The process encompasses data preparation, feature extraction, and model training with a focus on Convolutional Neural Networks (CNNs).

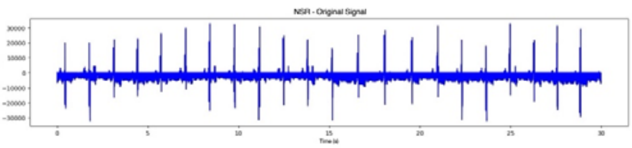

Fig. 2. Traditional ECG signs of a person with Normal ECG signal (NRS).

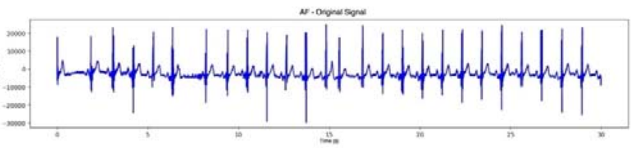

Fig. 3. Traditional ECG signals of a person with Atrial fibrillation (AF).

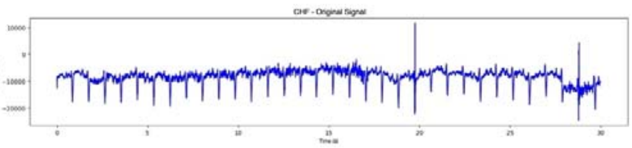

Fig. 4. Traditional ECG signals of a person with Congestive Heart Failure (CHF).

A. *Pre-Processing*

Pre-processing is a critical phase in ECG signal analysis aimed at enhancing data quality before it is fed into deep learning algorithms, and it involves several key steps. First, signal filtering is applied to eliminate noise from recording devices and artifacts caused by patient movement using a band-pass filter that retains essential frequency components in the range of 0 Hz to 9 Hz, preserving the important characteristics of the heart's electrical activity while removing extraneous interference. Next, normalization adjusts the amplitudes of the ECG signals to ensure they fall within a consistent range, reducing variability caused by differences in recording equipment or patient conditions, which allows the analysis to focus on intrinsic features and improves the model's learning and classification abilities. Finally, segmentation divides continuous ECG signals into manageable segments, typically lasting about 2 seconds each, facilitating a more detailed examination of the signal's characteristics and enabling the model to learn patterns effectively within these shorter time frames. By implementing these steps—filtering, normalization, and segmentation—the quality of ECG signals is significantly enhanced, laying a strong foundation for subsequent feature extraction and model training, ultimately leading to more accurate classifications and improved screening for cardiovascular diseases.

B. *Extract Features*

Feature extraction is an important process that transforms raw ECG signals into useful inputs for the deep learning model. This process includes:

QRS Complexes

Extracting fundamental features of the QRS complex in ECG signals helps analyze heart function. It starts with detecting the R-peak with the highest amplitude, followed by identifying the onset and offset points to calculate QRS duration and measure the amplitudes of T, S, R, Q, P waves and R-R intervals to assess heart rate irregularities, such as arrhythmias, quickly and accurately.

Statistical features

Statistical features of ECG in the time domain helps analyze the signal in real-time to detect heart abnormalities. Key features include mean, variance, skewness and kurtosis. This method is ideal for preliminary diagnosis as it directly utilizes raw ECG data and is computationally simple, making it effective for early detection of heart issues.

Power Spectral Density (PSD)

A powerful technique for extracting frequency-domain characteristics from electrocardiogram (ECG) data, revealing critical information about heart functionality and autonomic nervous system behavior. This methodology converts ECG signals from their original time-domain representation into distinct frequency components. The analysis focuses on three key frequency ranges: 0-3, 3-6, and 6-9 Hz. The essential features derived from this analysis include both the absolute power within each frequency band and the various power ratios between these bands. This PSD-based feature extraction approach has emerged as a fundamental component in contemporary ECG signal analysis and cardiac diagnosis.

Selected Features

Helping reduce complexity, increase accuracy, and address the problem of overfitting by selecting the most important features to optimize the model.

C. *Model Training*

Convolutional Neural Networks (CNNs) is used for processing ECG data because it effectively detects spatial features of the signals. CNNs filter and extract important features from the data to differentiate between ECG signals in patients with Atrial fibrillation (AF) and Congestive heart failure (CHF) compared to those with Normal sinus rhythm (NSR).

Two-Dimension Convolutional Neural Networks (CNN2D) is a special version of CNNs designed to process two-dimensional data. It can effectively distinguish between CHF patients and those with normal heart rhythms (NSR) in the tested models.

Long Short-Term Memory (LSTM) is used for analyzing temporal features of ECG signals. LSTM can handle time-continuous data well, making it suitable for classifying complex signals that change over time, such as ECG signals.

Multilayer Perceptron (MLP) consists of multiple layers of neurons, including input, hidden, and output layers. Each layer processes and transforms the data, making it effective for complex classification tasks and prediction in ECG analysis.

III. RESULTS

The developed model is able to effectively classify the three distinct heart conditions - Normal Sinus Rhythm (NSR), Atrial fibrillation (AF), and Congestive heart failure (CHF) with a high degree of accuracy. This is achieved by carefully selecting the optimal features from both the time domain (Statistical ECG data and QRS complex characteristics) and the frequency domain (Power Spectral Density: PSD).

Incorporating the PSD features from the frequency domain was particularly impactful, as it significantly improved the overall classification performance compared to using time domain features alone. This suggests that spectral information captured by the PSD metric provides valuable discriminatory power in differentiating between the different heart conditions.

The focus on selecting the most informative features is an important strength of the model development approach. By carefully curating the input features, the model is able to efficiently capture the key physiological differences between the heart conditions, leading to the high classification accuracy reported.

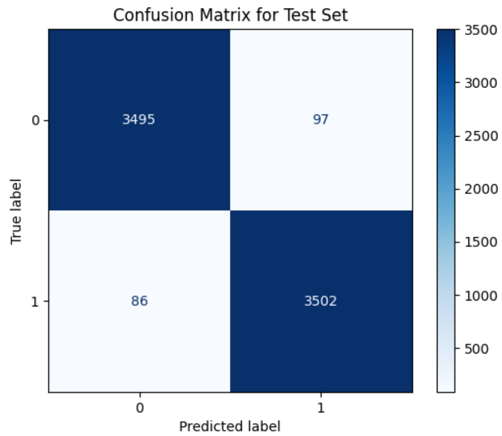

Fig. 5. Confusion Matrix For Test Set in NSR/CHF Pairwise Classification.

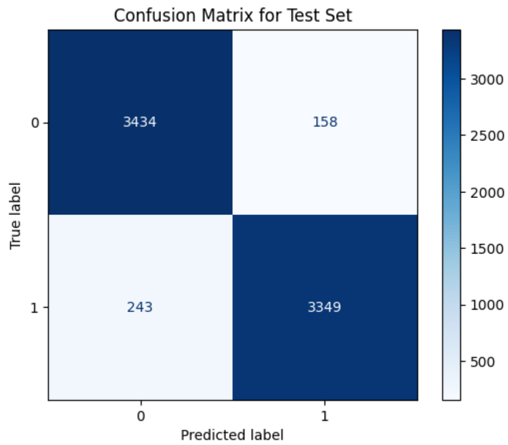

Fig. 6. Confusion Matrix for Test Set in NSR/Abnormal Pairwise Classification.

TABLE I: PERFORMANCE OF DIFFERENT MODELS IN NSR/CHF PAIRWISE CLASSIFICATION

Model	NSR/CHF		
	Accuracy (%)	Recall (%)	F1-Score (%)
CNN1D	97.32	97.32	97.32
CNN2D	97.26	97.66	97.66
LSTM	96.98	96.98	96.98
MLP	97.99	97.99	97.99

TABLE II: PERFORMANCE OF DIFFERENT MODELS IN NSR/ABNORMAL PAIRWISE CLASSIFICATION

Model	NSR/Abnormal		
	Accuracy (%)	Recall (%)	F1-Score (%)
CNN1D	95.62	94.62	94.62
CNN2D	94.53	94.53	94.53
LSTM	93.72	93.27	93.27
MLP	95.38	95.40	95.40

The deep learning models demonstrated exceptional classification results in distinguishing heart conditions. When discriminating between Normal Sinus Rhythm (NSR) and Congestive Heart Failure (CHF), accuracy rates were remarkably high, with the Multi-Layer Perceptron (MLP) model achieving the best performance at nearly 98% across accuracy, recall, and F1-score metrics. For the more complex task of classifying NSR versus abnormal rhythms (including both AF and CHF), the CNN1D model emerged as the top performer with approximately 96% accuracy, though the performance differences between models were minimal.

All tested deep learning architectures, including the Convolutional Neural Networks (CNNs), showed strong capabilities in binary classification tasks. The MLP model maintained strong performance when distinguishing NSR from abnormal rhythms collectively, though the margin between models remained small. The consistent success across these classification pairs likely stems from the clear physiological differences between normal and abnormal heart conditions.

In terms of computational efficiency, there were notable differences between models. The MLP was the quickest to train, while the Long Short-Term Memory (LSTM) model showed lower accuracy despite requiring similar training time to the CNNs models.

IV. CONCLUSIONS

In conclusion, it is clear that not all models are equally effective for heart disease ECG classification. For instance, although the LSTM model required a similar amount of training time as the CNNs, its accuracy was lower. This can be attributed to several factors. Firstly, LSTM models tend to have more trainable parameters compared to simpler models like CNNs and MLP, making them more susceptible to overfitting and less capable of generalizing effectively. Secondly, the task of classifying heart diseases based on ECG signals may not be the most suitable for an LSTM, as LSTMs perform best with tasks that involve long-term dependencies and sequential patterns, which may not be as prevalent in ECG data. Thirdly, the performance of the LSTM model is highly sensitive to the proper tuning of hyperparameters, such as the number of layers, units, and dropout rates. Without careful optimization, the model's performance may not be as effective as the other models. Finally, the nature and quality of the ECG data may not align well with the strengths of the LSTM architecture. Factors such as signal length, noise, and the distribution of target classes may have limited the LSTM's ability to learn meaningful representations. Given these considerations, the MLP model emerges as the most suitable for further development into a program or web application. It offers higher accuracy, faster training, and better overall performance, making it ideal for efficient and convenient disease diagnosis.

By incorporating the MLP model into a real-time heart screening system, not only can the speed and accuracy of ECG analysis be enhanced, but it can also reduce the workload of healthcare professionals. This system holds the potential for early detection of heart diseases, even in patients who show no obvious symptoms. Moreover, the algorithm can be expanded to address other heart conditions and adapted to more diverse datasets, further increasing its accuracy and utility. When integrated into healthcare systems, this approach could significantly improve both the speed and precision of cardiac diagnoses, ultimately benefiting both patients and healthcare providers.

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