Electrocardiogram-based Heart Disease Classification with Machine Learning Techniques

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Abstract. Automatic extraction of relevant and reliable information from electrocardiogram (ECG) signals is essential for heart disease diagnosis and treatment. This study proposes deep learning model based on improved one-dimensional convolutional neural network (1D-CNN) architecture for classifying heart disease using ECG data. First, we collect ECG recordings from patients with and without heart disease. Then, the relevant features are extracted from the ECG data, which is a critical step as the features' quality directly impacts the predictive models' performance. Next, we apply the predictive models, encompassing 1D-CNN, Support Vector Machine (SVM), and Logistic Regression, combined with fine-tuned hyperparameters and StandardScaler, to improve heart disease prediction performance. The experimental results show that the proposed deep learning model using 1D-CNN combined with fine-tuning hyperparameters and StandardScaler can achieve better classification results on ECG-based heart disease classification tasks than previous studies.

Keywords: Electrocardiogram, Heart Disease, 1D-Convolutional Neural Network, Fine-tuned Hyperparameters

1 Introduction

Cardiovascular disease is one of the most common causes of death worldwide annually. Early detection of abnormal heart conditions can avoid sudden cardiac death and other dangerous illnesses caused by heart disease. In addition, the early heart disease diagnosis helps doctors know the patient's condition and offer reasonable and early treatment plans. ECG, a non-invasive diagnostic tool that records the heart's electrical activity through electrodes placed on the chest, arms, and legs, is widely used in diagnosing heart disease [1]. The ECG signals are the recordings of the cardiac system's bioelectrical activities, which can be used to identify abnormal heart rhythms, heart damage, and other conditions that may indicate an increased risk of heart disease.

Many researchers have recently applied deep learning architectures to analyze ECG data for predicting the likelihood of heart disease and identifying specific risk factors and characteristics associated with heart disease as well. This research proposes ECG-based heart disease prediction model using an improved

1D-CNN algorithm. First, the ECG recordings are obtained from many patients with and without heart disease. The data are preprocessed to remove noise and ensure signal quality. Then, the relevant features are extracted from the ECG data. Next, the predictive models based on deep learning frameworks, comprising 1D-CNN, SVM, and Logistic Regression, combined with fine-tuned hyperparameters and StandardScaler, are applied to classify heart disease. Finally, the performance of these predictive models is evaluated using various metrics, e.g., accuracy, precision, recall, and F1-score. We can see from the experimental results that the proposed deep learning model based on 1D-CNN combined with fine-tuned hyperparameters and StandardScaler can improve the performance in classifying ECG-based heart disease.

In the rest of this paper, the related work applied machine learning and statistical models for heart disease prediction are briefly presented in Section 2. Section 3 proposes deep learning model based on the improved 1D-CNN framework for classifying heart disease using ECG data. Section 4 evaluates the performance of the proposed improved 1D-CNN model and compares it to those of some state-of-the-art studies to evaluate the proposed approach's effectiveness. Finally, the conclusion is discussed in Section 5.

2 Related work

Recently there have been numerous studies in predicting heart disease based on ECG data, using various machine learning and statistical methods. Notably, Wang et al. [2] presented an improved CNN-based method to classify arrhythmia's heartbeat automatically. In a study [3], Xu and Liu developed a Holter data CNN heartbeat classifier based on coupled-convolution layer structure and adopted the dropout mechanism to classify ECG heartbeat. Another work [4] was introduced by Sahker et al. proposed an ECG classification model applying generative adversarial networks for restoring the balance of the dataset, then using two deep learning approaches-an end-to-end approach and a two-stage hierarchical approach-based on deep CNNs for eliminating hand-engineering features by combining feature extraction, feature reduction, and classification. In the study [5], the authors presented a prediction method based on six types of machine learning techniques, including linear discriminant analysis, linear and quadratic SVMs, decision tree, k-nearest neighbor, and artificial neural networks to identify the most significant parameters extracted from ECG signals for cardiovascular disease prediction. Wang et al. [6] proposed an ECG classification method using Continuous Wavelet Transform (CWT) and CNN. In the method, CWT was used for decomposing ECG signals to obtain different time-frequency components, and CNN was used for feature extraction from the 2D scalogram composed of the above time-frequency components. Hassan et al. [7] presented a cardiac arrhythmia classification model, which combined CNN and Bidirectional Long Short-Term Memory (BLSTM) using MIT-BIH and St-Petersburg datasets. In another work [8], the authors developed an ECG heartbeat classification model based on a CNN-BLSTM-based classifier to classify ECG heartbeats of MIT-BIH imbalanced dataset. Cui et al. [9] presented a deep learning-based multidimensional feature fusion method that combines traditional approaches and 1D-CNN to find the optimal feature set for ECG arrhythmia classification. In a study [10], Rafi and Akthar proposed an ECG classification method based on a hybrid deep-learning approach that incorporates both a revolution and a recurrent deep neural network for reliably identifying the cardiac beats. In work [11], Farag developed a tiny CNN classifier combined with the matched filter theory for inter-patient ECG classification and arrhythmia detection. Exciting work in [12] applied a cardiac disease detection model which used discrete wavelet transform for preprocessing to remove unwanted noise or artifacts and a nonlinear vector decomposed neural network to enhance heart disease prediction performance.

Numerous studies have explored the robustness of machine learning applied to medical data. However, the applications of such approaches are limited to ECG data on heart disease. In addition, heart disease is dangerous and must be detected early to deploy treatments as soon as possible. Therefore, our study aims to predict heart disease based on ECG data by leveraging the powers of machine learning algorithms.

3 Methods

In this section, the main steps are applied to solve the problem of predicting heart disease based on ECG data, as shown in Figure 1. These steps will be described in detail in the following sections.

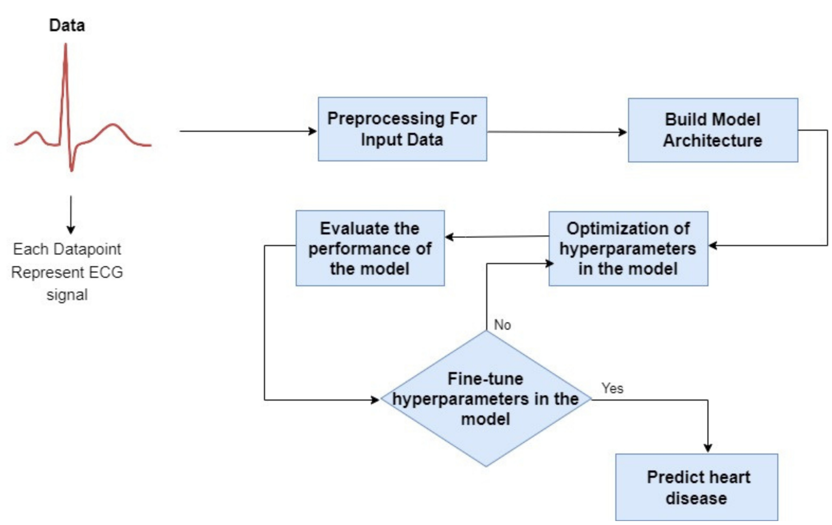


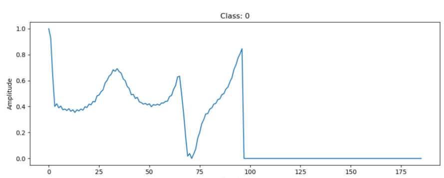
Fig. 1: Heart disease prediction based on ECG data

3.1 ECG data collection

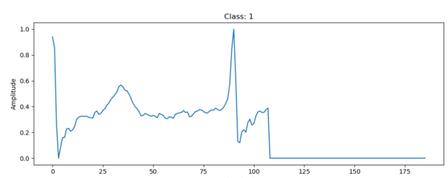
This study proposes the improved 1D-CNN model to classify heart rate types on the ECG dataset. The data used in this work are two collections of heartbeat signals derived from two famous datasets in heartbeat classification, MIT-BIH Arrhythmia dataset [13] and PTB Diagnostic ECG dataset [14]. Both datasets provide enough samples to support deep neural network training. Furthermore, the normal and different arrhythmias cases and myocardial infarctions on the ECG can correlate to the signals. These signals have been preprocessed and segmented, and each segment corresponds to a pulse.

3.2 Data prepropcessing

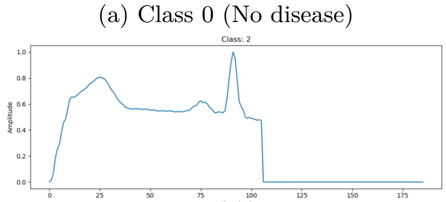
Although ECG data obtained from the MIT-BIH database is expected not to contain as much disruptive noise as ECG data obtained directly from a patient, it still contains some noise that requires attention to improve the subsequent steps of the system. Therefore, the signal preprocessing step is focused on removing noise from ECG recordings. Below is an illustration (Figure 2) of the samples of the MIT-BIH Arrhythmia dataset.



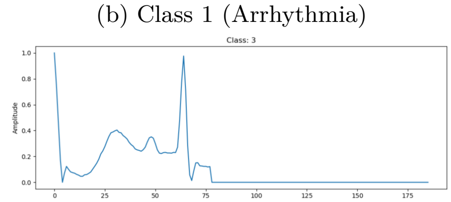
(a) Class 0 (No disease)



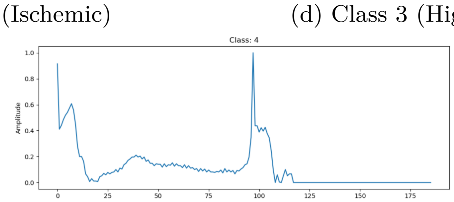
(b) Class 1 (Arrhythmia)



(c) Class 2 (Ischemic)



(d) Class 3 (High blood pressure)



(e) Class 4 (Valve disease)

Fig. 2: Some samples of various heartbeat types

As a first step, mean removal is applied to remove the noise in the ECG signals. Next, the unwanted component is removed by subtracting the mean of the ECG recording from every sample point, and the signal baseline amplitude is pulled back to level zero. However, nearly all ECG recordings also have high and low-frequency noise present, which is brought on by various causes, including muscular contraction, breathing movements, inadequate electrode contact, and the presence of other external equipment. Therefore, the next step is to eliminate the low-frequency noise components once the high-frequency noise has been removed. This low-frequency noise manifests as baseline wandering, mainly brought on by the patient's breathing. Finally, all ECG recordings are subjected to a derivative-based (high pass) filter to eliminate this low-frequency noise, which passes high frequencies but attenuates low frequencies.

3.3 Convolutional Neural Network on 1D data (1D-CNN)

CNN has become one of the most popular artificial intelligence techniques because of its excellent ability to recognize traits automatically. Moreover, 1D-CNN can be ideal for real-time applications because of its low processing demands on 1D data. The proposed CNN model consists of two 1D convolution layers and two fully connected layers enabled by the ReLU activation function—feature map for the related input [15].

Firstly, we divided the dataset into training and testing sets and performed preliminary steps such as segmenting each ECG signal into small segments and normalizing signal values. Subsequently, we construct a simple CNN model with two 1D convolution layers and two fully connected layers[7]. The model is trained on the training dataset for 100 epochs with a learning rate of 0.001. The results obtained indicate that the model is capable of accurately classifying different types of heart rhythms from ECG signals with high accuracy. We also utilize data augmentation techniques such as rotation and flipping to increase the diversity of the training dataset and reduce model overfitting. Finally, based on the outcomes of experiments, we predict cardiac diseases, precisely five types represented in the ECG data.

4 Experimental results

In this section, we evaluate the performance of the proposed improved 1D-CNN model. These results are compared to the results of some state-of-the-art studies to evaluate the effectiveness of the proposed approach.

4.1 Dataset description

In this study, we use the MIT-BIH dataset, which contains 48 half-hour segments of two-channel ambulatory ECG recordings from 47 subjects participating in BIH Arrhythmia Laboratory research between 1975 and 1979. Then, 23 recordings were randomly selected from a pool of 4000 24-hour ambulatory ECG recordings taken by a mixed group of inpatients (approximately 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital. To include less common but clinically relevant arrhythmias that would not be well represented in a small random sample, the remaining 25 recordings from the same set were chosen [16].

Table 1 briefly reviews all classes referred to in the dataset, where N stands for normal and no arrhythmia, S stands for Supra-ventricular premature, V stands for Ventricular escape, and F stands for Fusion of ventricular and normal, and Q stands for Fusion of paced and normal unclassifiable. In the study, they are trained on a set of 109446 samples shown in Figure 3 and a test set of 21892 samples, where N is 72471 samples, S is 2223 samples, V is 5788 samples, F is 641 samples, and finally Q is 6431 samples.

Table 1: Summary for each category in dataset

Category	**Label**	**Annotations**	**Type of disease**
N	0	Normal	No disease
S	1	Supraventricular ectopic	Arrhythmia
V	2	Ventricular ectopic	Ischemic
F	3	Fusion	High blood pressure
Q	4	Unknown	Valve disease

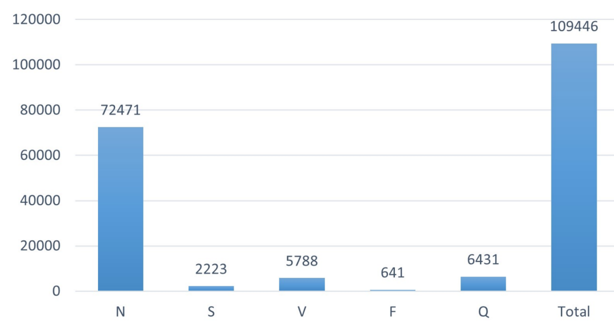


Fig. 3: The number of samples of each class

4.2 Environmental settings

All the above processes are coded and applied on the Jupyter Notebook environment. These notebooks provide users an interactive environment to analyze data and train machine learning models. It is run on a PC with Intel(R) i5-6500

CPU 3.20 GHz and 8 GB RAM. The trained model was created with 100 epochs and a batch size 256.

To evaluate the performance of the proposed model, this study uses several evaluation matrices such as accuracy, recall, precision, and F1-score.

4.3 Experimental results

Scenario 1: Comparison between using default hyperparameters and fine-tuned hyperparameters This section compares three popular machine learning algorithms, including 1D-CNN, SVM, and Logistic Regression, with default values of hyperparameters and fine-tuned hyperparameters (Table 2).

Table 2: Classification report between using default hyperparameters and fine-tuned hyperparameters

	Default hyperparameters			**Fine-tuned hyperparameters**		
	1D-CNN	**SVM**	**LR**	**1D-CNN**	**SVM**	**LR**
N	0.99	0.98	0.95	0.99	0.96	0.95
S	0.84	0.71	0.46	0.83	0.61	0.51
V	0.96	0.91	0.45	0.95	0.42	0.44
F	0.79	0.59	0.38	0.81	0.45	0.40
Q	0.99	0.95	0.91	0.99	0.92	0.91
Accuracy	0.98	0.97	0.91	0.98	0.92	0.91
Macro avg	0.91	0.83	0.63	0.92	0.67	0.64
Weighted avg	0.98	0.97	0.90	0.98	0.91	0.90

This study has leveraged the RandomizedSearchCV method [17] to seek optimal hyperparameters. RandomizedSearchCV selects random values for hyperparameters with 3-fold cross-validation on the training set. For the comparison, we use the default value of hyperparameters for the considered algorithms.

The selected values of hyperparameters in Table 2 include Logistic Regression algorithms (penalty='l2', C=1.0, solver='lbfgs', max-iter=100), SVM (kernel='linear', C=1.0) and 1D-CNN (epochs=100, batch-size=64). For the Logistic Regression algorithm, the accuracy shows that with fine-tuned hyperparameters, a value of 0.91 is obtained, and with default hyperparameters, it is also 0.91. For the SVM algorithm, the accuracy is not improved, with the fine-tuned hyperparameters achieving a value of 0.92 compared to 0.97 of the default hyperparameters. For the 1D-CNN algorithm, the accuracy shows no improvement, with the fine-tuned hyperparameters achieving value of 0.98 compared with 0.98 of the default hyperparameters.

Scenario 2: Comparison between using a scaler and without scaler While training a machine learning model, a scaling method such as StandardScaler can help improve the model's performance by bringing the data values to the same range. This makes it easier for the model to learn relationships and avoid problems like a boom or vanishing gradients and can improve the performance as shown in [18]. This study compares the performance of three machine learning algorithms, comprising 1D-CNN, SVM, and Logistic Regression when combining with StandardScaler and without StandardScaler.

As can be seen from Table 3, for the Logistic Regression algorithm, when we run the experiment with default hyperparameters, the accuracy, Macro-average accuracy (Macro avg), and Weighted average accuracy (Weighted avg) without using the scaler are 0.91, 0.58, and 0.89, respectively, and those of using the scaler are 0.91, 0.64, 0.90, respectively, which shows that the results are not much difference. For SVM, the accuracy, Macro avg, and Weighted avg without the scaler are 0.92, 0.67, and 0.91, respectively, while the performance with the scaler are 0.97, 0.84, 0.97, which shows an improvement when using the scaler. For the 1D-CNN, using the scaler, we can reach the accuracy performance, Macro avg, and Weighted avg are 0.98, 0.90, and 0.98, respectively, whereas those of without using the scaler are 0.98, 0.91, and 0.98, respectively, which shows that there are not much difference between two approaches.

The experimental results show that all three machine learning architectures can be improved effectively by using StandardScaler. However, there are some factors which we need to pay attention, e.g., the amount of data, network structure, selected hyperparameters, etc., to ensure that the training takes place effectively and precisely.

Table 3: Classification report with default hyperparameters for using the scaler and without using the scaler

	Without StandardScaler			**Using StandardScaler**		
	1D-CNN	**SVM**	**LR**	**1D-CNN**	**SVM**	**LR**
N	0.99	0.96	0.95	0.99	0.98	0.95
S	0.83	0.61	0.33	0.81	0.71	0.53
V	0.96	0.42	0.43	0.95	0.91	0.43
F	0.80	0.45	0.25	0.77	0.62	0.39
Q	0.99	0.92	0.92	0.99	0.95	0.92
Accuracy	0.98	0.92	0.91	0.98	0.97	0.91
Macro avg	0.91	0.67	0.58	0.90	0.84	0.64
Weighted avg	0.98	0.91	0.89	0.98	0.97	0.90

Scenario 3: The performance of using a scaler combined with fine-tuned hyperparameters We can see from Table 4, for the Logistic Regression algorithm, when we run the experiment using the scaler combined with fine-tuned hyperparameters, the accuracy, Macro avg, and Weighted avg are 0.91, 0.65, 0.90, while without using the scaler and running with default hyperparameters, those values obtain 0.91, 0.63 and 0.90 (Table 2), which shows that the

results are not much difference. For the SVM algorithm, with fine-tuned hyperparameters and using the scaler, the accuracy, Macro avg, and Weighted avg are 0.98, 0.87, and 0.98, respectively, whereas those of without using the scaler and running with default hyperparameters are 0.97, 0.83, and 0.97, respectively, which shows an improvement when using the scaler and running with fine-tuned hyperparameters. Similar to the 1D-CNN algorithm, using the scaler combined with fine-tuned hyperparameters, the accuracy, Macro avg, and Weighted avg are 0.99, 0.94, and 0.99, respectively. When not using the scaler combined with default hyperparameters, those values are 0.98, 0.91, and 0.98, which shows a significant improvement when using the scaler and running with fine-tuned hyperparameters. In summary, using the scaler combined with fine-tuned hyperparameters can improve the models' performance on heart disease classification.

Table 4 also shows that the 1D-CNN algorithm gives better results than other algorithms, followed by SVM, which is slightly better than the Logistic Regression algorithm. Moreover, from Figure 4a, the 1D-CNN algorithm shows high accuracy in all classes. The results are much higher than the other algorithms. Therefore, we choose the 1D-CNN algorithm for our proposed model.

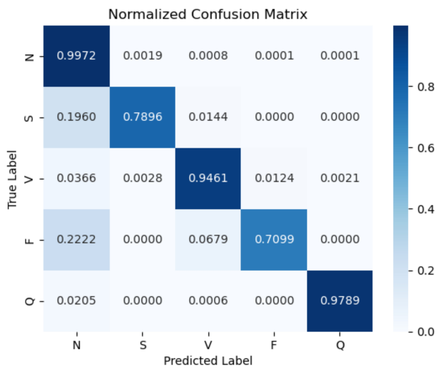
Table 4: Classification results of the improved algorithms by using StandardScaler combined with fine-tuned hyperparameters with RandomizedSearchCV

	1D-CNN	**SVM**	**LogisticRegression**
N	0.99	0.99	0.95
S	0.88	0.75	0.55
V	0.97	0.94	0.44
F	0.84	0.68	0.40
Q	1.00	0.98	0.92
Accuracy	0.99	0.98	0.91
Macro avg	0.94	0.87	0.65
Weighted avg	0.99	0.98	0.90

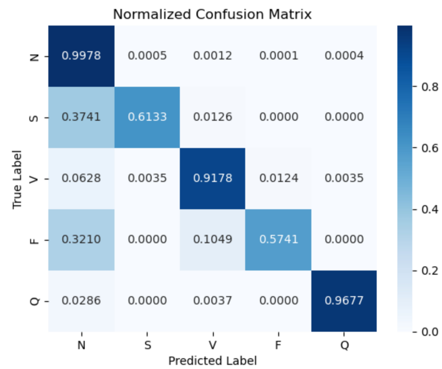
The classification accuracy results for the MIT-BIH data set were approximately 95.70% with a relatively flat curve after 100 training epochs. Whereas the validation datasets had an accuracy of between 96.70% and 99.30%, the curve was stable as revealed in Figure 5a. Therefore, the loss curve of the training set from 0.26 to 0.16 is pretty flat. Meanwhile, the validation loss is reduced to 0.11 to 0.03 across epochs (Figure 5b). The results show that the loss is significantly reduced, and the accuracy is relatively high. All are presented in Figure 5.

4.4 Comparison with previous studies and discussion

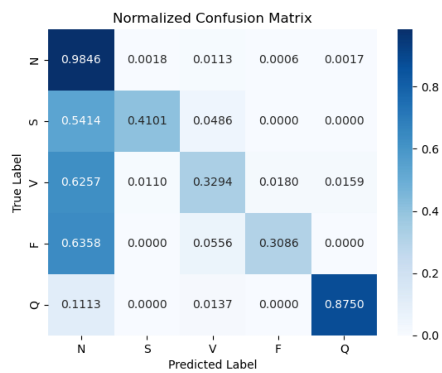
Table 5 shows that the proposed method outperforms the others. Furthermore, the best hyperparameter retrieved by the method was picked and was among the hyperparameters' learning rates. Therefore, it can be said that the suggested



(a) 1D-Convolutional Neural Network



(b) SVM

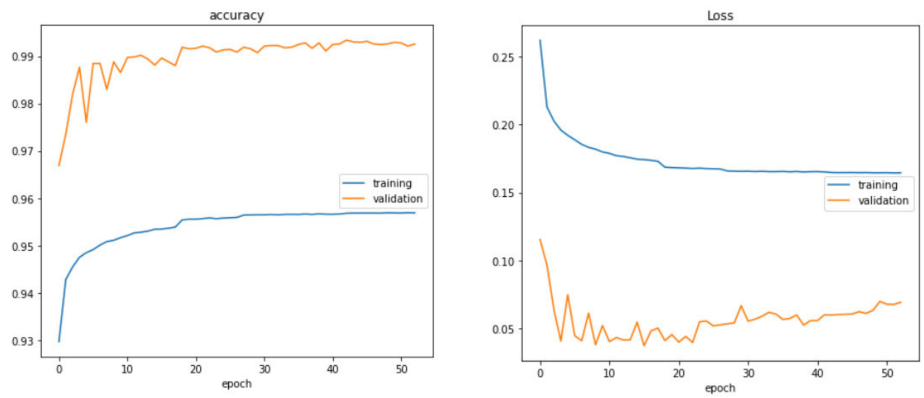


(c) Logistic Regression

Fig. 4: Confusion matrices of various algorithms

model has been improved using the 1D-CNN combined with the scaler and fine-tuned hyperparameters, which worked in the manner mentioned above.

The proposed improved 1D-CNN model using the scaler combined with fine-tuned hyperparameters plays an important role in improving the model's accuracy. Therefore, the model can scrutinize these layers more effectively than in the learning process. Table 5 compares the results of different approaches. Nazrul Anuar [5] achieved a 90.0% accuracy in identifying four arrhythmia classes by applying ANN. At the same time, MM Farag [11] designed a CNN model capable of automatically classifying five distinct types of heartbeats in ECG readings achieving an accuracy of 97.13%. Amin Shoughi [8] reported 98.71% accuracy for categorizing five classes by using the CNN with the Bi-LSTM model. SK Mohammad Rafi [10] designed a CNN model with RNN capable of automatically classifying five types of heartbeat in ECG datasets, which achieves an accuracy of 98.0%, while Abdelrahman M. Shaker [4] with CNN and GAN models achieves



(a) Accuracy (b) Loss

Fig. 5: An illustration of training and testing performance of 1D-CNN during epochs.

Table 5: Classification performance of the proposed improved 1D-CNN model compared to some state-of-the-art studies

Studies	Architecture	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Proposed Model	**CNN on 1D data**	**99.30**	**95.30**	**93.30**	**94.40**
Nayan Nazrul Anuar [5]	ANN	90.0	-	-	-
Tao Wang [6]	CNN with CWT	98.74	-	-	68.76
M. Mohamed Suhail [12]	CNN with DWT	90.67	-	-	-
Abdelrahman M. Shaker [4]	CNN with GAN	98.30	90.0	97.70	-
Mohammad Rafi [10]	CNN and RNN	98.0	90.80	84.40	97.40
Amin Shoughi [8]	CNN with BI-LSTM	98.71	92.50	94.40	-
MM Farag [11]	CNN	97.13	-	91.00	88.30

an accuracy of 98.30%. We achieve promising results which overcome the state-of-the-art studies by improving the 1D-CNN model using the scaler combined with fine-tuned hyperparameters. Our refined model yielded an impressive accuracy of 99.30%, which we consider a highly favorable outcome.

5 Conclusion

Machine learning has emerged as a critical tool in medicine and automatic diagnosis owing to its ability to achieve high accuracy in medical data analysis. This study proposes a novel approach to improve machine learning's performance in electrocardiogram-based heart disease prediction by using the scaler combined with fine-tuned hyperparameters. As shown from the experiments, the results of the proposed approach, which improved the 1D-CNN model by using the scaler combined with fine-tuned hyperparameters, can get better results than previous studies, with 99.30%, 95.30%, 93.30%, and 94.40% in accuracy, precision, recall, and F1-score, respectively. However, independently fine-tuned hyperparameters did not significantly improve the performance. In addition, classic machine learning algorithms such as SVM and Logistic Regression can benefit from scaler rather than fine-tuned hyperparameters.

Further studies can explore 2D convolutional networks to leverage deep learning advancements on images. Moreover, patterns of abnormalities in electrocardiograms should be further analyzed to detect heart diseases early.

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