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Classification of ECG Signals Using CNNs: An Improved Model for Cardiac Disease Diagnosis

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Abstract The analysis of ECG signals poses significant challenges as a result of the complex electrical patterns of the heart and issues related to the imbalanced data. Addressing such challenges requires having advanced methods and models for the purpose of ensuring accurate diagnoses and improving the results of the treatments. The combination of the ECG analysis with the approaches of artificial intelligence (AI) became a priority for the health-care improvement, especially as the prevalence of heart diseases keeps rising worldwide. In the present study, Convolutional Neural Networks (CNNs) have been used for creating a classification model for the ECG signals, tested across the balanced as well as the imbalanced data structures from MIT-BIH Arrhythmia data-sets. Results have shown consistently high accuracy of classification, which exceeds 98% in all of the cases. For example, the model has been able to achieve 98.36% accuracy with the unbalanced data after 20 cycles (epochs) of training with the use of the early stopping. When the number of the cycles has been increased to 104, with extended patience setting of 25, accuracy has been increased to 98.76%. Balanced data had produced outcomes that are slightly better, with the model reaching an accuracy level of 98.88% in 25 cycles and 98.45% in 20 cycles. These findings have highlighted the importance of the training cycle count as well as the data balance in increasing the accuracy of the model. Moreover, early stopping proved beneficial in maintaining high performance and training efficiency in ECG signal classification.

Keywords: Deep learning, ECG signal, Atrial fibrillation, Convolutional neural network, Heart rate variability.

1. Introduction

Heart disease is a serious illness that primarily affects people in their middle and later years of life. It damages the veins, heart, and arteries, leading to a significant number of fatalities globally. According to the World Health Organization (WHO), over 17.9 million people die yearly from cardiovascular diseases (CVD), accounting for about 32% of all deaths worldwide [1]. Human mortality is primarily caused by CVDs, which are common around the world. Hypertension, diabetes, smoking, dyslipidemia obesity and inactivity are examples of conventional risk factors. Furthermore, evolving and new risk factors include autoimmune diseases, depression, gestational diabetes mellitus, breast cancer treatments, premature delivery, and hypertensive pregnancy disorders [2], [3]. The heart is able to continuously pump blood throughout the body, delivering oxygen to organs and cells, thanks to the regular contractions of the ventricles and atria. The electrical activity of the muscles controls the heartbeat. Arrhythmias can result from heart disease which is often a natural consequence of aging. An electrocardiogram (ECG) captures the electrical activity of the heart [4], [5] Heart health can be tracked, and potential heart disease and arrhythmias can be detected by examining the ECG waveform. Therefore, patients with heart disease are advised to undergo regular (and sometimes continuous) clinical monitoring [8], [9].

Healthcare providers can utilize ECG data to remotely diagnose a variety of medical conditions and develop individualized treatment strategies, as it measures heart rates and rhythms. Early detection of diseases by machine and deep learning could lessen their effect as the globe changes, particularly throughout pandemics. [10], [11] ECG offers two primary types of data. Cardiologists can first determine if the activity is irregular or regular, slow or fast, by monitoring

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the time intervals required for electrical waves to pass through the heart's conduction system. Second, they can determine whether certain heart areas are enlarged or overworked by measuring electrical activity. Three important waves, which include ventricular depolarization (QRS complex), atrial depolarization (P-wave), and repolarization (T-wave), are essential segments of the normal ECG heartbeat, as depicted in Figure 1. The ECG signals are affected by arrhythmias, which are anomalies in the electrical activity of the heart. [6], [7].

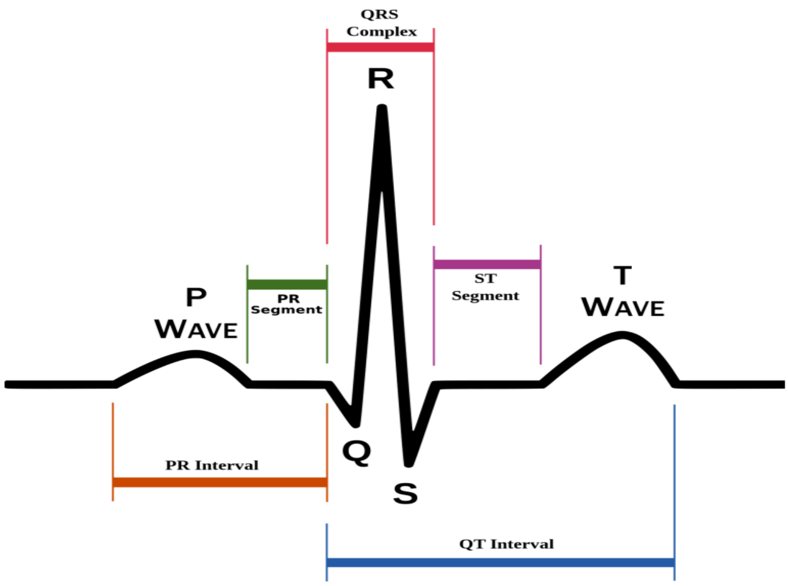

Figure 1. Illustration of a normal electrocardiogram (ECG) waveform highlighting its principal signal segments, including the P wave, QRS complex, and T wave, adapted from[8].

A wide range of computational approaches has been introduced in the literature to analyses electrocardiogram (ECG) data for disease detection, feature extraction, and signal classification. Existing ECG analysis methodologies can generally be categorized into three main groups: classical signal processing techniques machine learning-based approaches and deep learning models. Classical methods primarily depend on handcrafted feature extraction using time-domain statistics frequency-domain transformations and wavelet-based representations to capture the underlying characteristics of ECG signals. Machine learning methods usually use pre-defined classifiers such k-nearest neighbors (KNN), linear discriminant analysis (LDA), random forest (RF), hidden Markov models (HMM), principal component analysis (PCA), support vector machines (SVM), and independent component analysis (ICA). The quality of the hand-made features is crucial to the performance of these procedures. Over the last several years, researchers have increasingly turned to deep learning techniques, including RNNs, CNNs, and LSTM networks (long short-term memory). Unlike conventional approaches, these models can automatically learn hierarchical feature representations from raw or lightly treated ECG data. This helps them expand both dependence and independent patients situations. This is partly due to their capacity to automatically extract hierarchical feature representations and generalise between patient-specific and patient-independent ECG datasets.

ECG is commonly used to diagnose cardiac diseases since waveform changes can reveal several pathological conditions. That's because ECGs might reveal abnormal disorders. An automated technique for identifying atrial fibrillation (AF) from electrocardiogram (ECG) data was suggested [16]. This model was recommended for this specific spot. The technique used HRV and frequency-domain characteristics to evaluate signal patterns. The model was tested using a short-duration ECG dataset. The public may access this information, which contained arrhythmias, normal rhythm, and atrial fibrillation. The results showed that the Bagging Tree and Support Vector Machine classifiers could classify all three categories with 82% accuracy.

In the proposed Work ECG data is thoroughly analyzed with a deep learning algorithm to improve claassificaton accuracy [17]. The major areas of concern during the study were noise and aberrant transient patterns. It uses a CNN-GRU hybrid model with an autoencoder to generate compact feature representations. Electrocardiogram data can show potential geographical and temporal correlations. furthermore, Each person who participated in the study made that decision. Experimental evaluations on multi-class tasks for noise and arrhythmia detection resulted in an overall accuracy of 65.80% across all six target classes.

In this Study focuses data augmentation strategy proposed in [18] aimed to increase the variety of electrocardiogram (ECG) samples and improve class balance. Additionally,their method included segment replication, signal reshaping, and the combining of numerous signals to create a larger dataset. Nevertheless, the advantage of this method was tested on the 2017 Atrial Fibrillation (CinC) dataset utilising a two-layer LSTM model trained with ten-fold cross-validation, and it obtained an 82% detection accuracy for atrial fibrillation.

This research [19], investigates a hybrid real-time framework was successfully developed for atrial fibrillation detection, based on atrial activity (AA) and RR interval (RRI) time series extracted from electrocardiogram (ECG) recordings. Consequently, the system was evaluated using the MIT-BIH AF database, with features effectively extracted via the Random Subspace Method (RSM). Random Forest (RF), Linear Discriminant Analysis (LDA), and Bagging of Trees (BoT) are some of the learning techniques that were utilised in order to classify these characteristics. However, the goal of this endeavour was to apply these algorithms. The Random Forest model obtained the greatest performance among the classifiers, with sensitivity coming in at 98%, F1-score coming in at 97.10%, and accuracy coming in at 97.60%, respectively.

This study [20] the researcher used the MIT-BIH arrhythmia database to categorise heartbeats into five different types using a 12-layer 1D-CNN architecture. In the same way, their approach used an adaptive wavelet thresholding method to improve the quality of the ECG signals before classification by reducing noise. Furthermore, data interpretation on multi-lead ECG recordings was done using the SHAP approach. This allowed us to identify the most influential leads and evaluate the various components of the waveform, such as the P wave, QRS complex, and T wave.

The proposed approach offers several significant contributions, particularly in terms of training efficiency and classification performance.

- Improved Architecture of the CNN: The proposed model utilizes CNNs optimized for capturing essential ECG signal features effectively, thereby avoiding the overfitting or poor performance often observed in other models.
- Improved efficiency of training: due to the use of an early stopping algorithm as well as the reduced number of the training cycles, the model has been able to achieve a high level of accuracy at the same time as reducing training time, which makes it more efficient in comparison with other approaches requiring more training cycles for achieving similar results.
- Higher level of accuracy with a smaller number of epochs: Achieving an accuracy level of 98.88% with fewer epochs demonstrates the suggested model's efficiency.

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- Superior performance on balanced and imbalanced data: The model has demonstrated effectiveness in handling both balanced and imbalanced datasets, making it well-suited for practical applications involving non-ideal data.

The structure of the paper was presented as follows: The second section presented the techniques of the study, describing the dataset and preprocessing it, proposed model utilized to meet the study's goals. Results and Discussion: The results obtained from the experiments and analyses are presented in Section 3. They provide a detailed description of how well the proposed model performs compared to other approaches. The final section provides a summary of the research, outlining the key findings and their significance for enhancing the classification and diagnosis of heart diseases.

2. Materials and Methods

2.1. Dataset Description

The dataset consists of heartbeat signals extracted from the MIT-BIH Arrhythmia Database, one of the most well-known datasets for heartbeat classification. The dataset contains sufficient samples for training a deep neural network. Forty-eight half-hour excerpts of 2-channel ambulatory ECG recordings from 47 people examined in the institute's Arrhythmia Laboratory between 1975 and 1979 are included in the MIT-BIH Arrhythmia Database. We also demonstrate that inference models can be successfully trained on this data using the knowledge gained from the previous database. Lead II ECG signals resampled to a sampling frequency of 125Hz have been utilized as input in all of our studies [12], [15].The dataset was split into two different files, the first for training and the other for testing. Overall signals were 109,446, 80% for train and 20% for test. The ECG signal consists of a number of labels and classes, as shown in Table 1.

Table .1 A summary of ECG signal

Number of Samples	109446
Number of Categories	5
Sampling Frequency	125Hz
Data Source	Physionet's MIT-BIH Arrhythmia Dataset
Classes	['N': 0, 'S': 1, 'V': 2, 'F': 3, 'Q': 4]

Where:

N represents non-exotic beats (normal beat), *V* represents ventricular ectopic beats, *S* represents supraventricular ectopic beats, *Q* is unknown beats, and *F* represents fusion beats.

2.2. Data Preprocessing

A notable disparity in the quantity of records across various categories is indicative of an imbalanced dataset. The performance of statistical algorithms, machine learning, and deep learning algorithms may be adversely affected by datasets that are significantly imbalanced in reality. Table 2 and Figure 2 display the distribution of the dataset and sample recordings.

Table 2. The dataset class distribution

Class	No. of records	Proportion
Normal Beat	72471	82.8
Supraventricular Ectopic Beats	2223	2.5
Fusion Beats	641	0.7
Ventricular Ectopic Beats	5788	6.6
Unknown Beats	6431	7.4

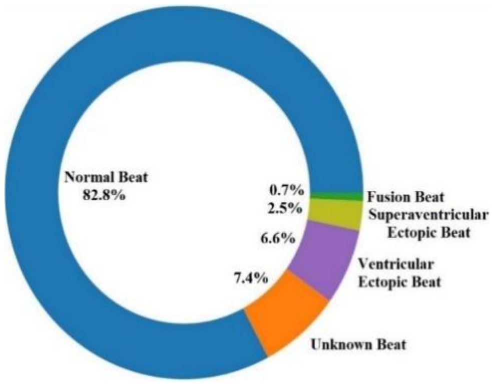

Figure 2. Proportion of each class before balancing the dataset.

Through properly setting tc, the number of samples between classes can be balanced. Assume that each class contains Nc samples, in which c stands for *N, S, V, F*, and Q. Assuming N_{max}-max (N_N, N_S, N_V, N_F, N_Q). The t_c for every class C recording could be computed as follows in order to balance the quantity of samples for the five classes:

$$t_c = \frac{N_{max}}{N_c} \tag{1}$$

Only the training dataset underwent data augmentation; the testing dataset did not. Figure 3 shows the percentage of each class from the dataset after resampling, assuming a target number of 20,000 samples for every class.

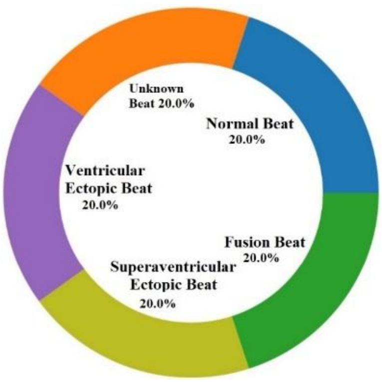

Figure 3. Proportion of every class after balancing the dataset

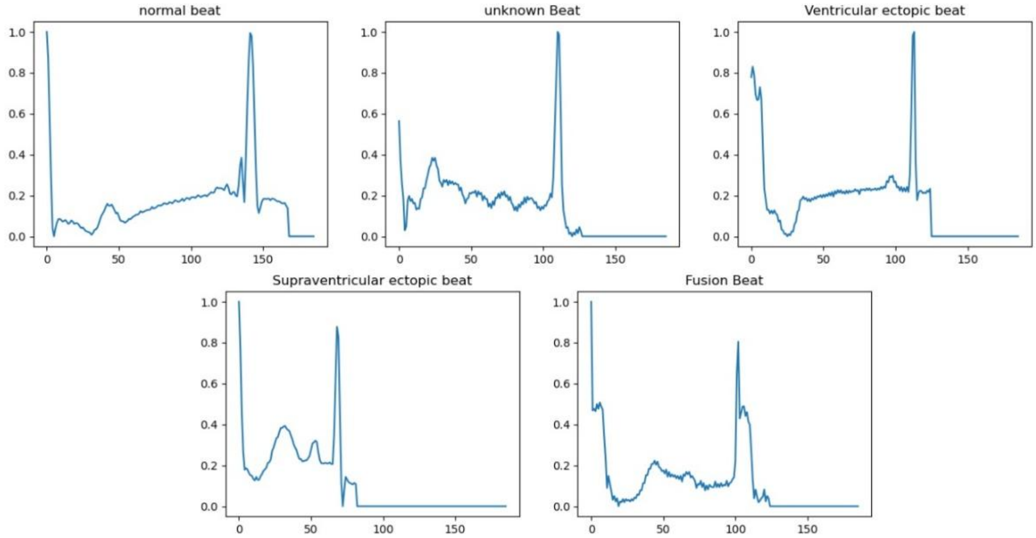

Figure 4**.** Proportion of each class after balancing the dataset

2.3. Proposed Model Architecture

Using ECG datasets, CNNs have demonstrated significant potential in classifying heart disease. This field has evolved as a result of their ability to extract hierarchical characteristics from raw data directly. Convolutional Neural Networks (CNNs) have proven to be highly effective in ECG-based applications, particularly in for instance, Figure 4 illustrates that various ECG signal classes exhibit distinct heartbeat characteristics and patterns.

The detection of arrhythmias and ischemic conditions, due to their strong ability to capture localized waveform characteristics. A typical CNN architecture is composed of two main stages: feature extraction and classification. During the feature extraction stage, discriminative representations are automatically learned from ECG signals without the need for manual feature design. These learned representations are subsequently passed to the classification stage where they are used to determine the corresponding cardiac class.

CNNs rely on a hierarchical structure that integrates convolutional and pooling layers to model spatial dependencies and local signal variations. The convolutional layers play a crucial role by applying multiple filters to different regions of the ECG signal, enabling the detection of salient waveform patterns. Pooling layers further enhance robustness by reducing dimensionality while preserving essential information. Finally, fully connected layers aggregate the extracted features and produce the final classification output.

The dimensionality of the filtered outputs is then decreased by pooling layers, which preserve important features. Typically, Max pooling is used to collect the greatest value in each region. Finally, the FCLs classify the input according to the learned features by using the flattened data from earlier stages.

$$Conv(x) = \sigma(\omega * x + b) \tag{2}$$
$$MaxPool(x) = Max(x) \tag{3}$$
$$FullyConnected(x) = \sigma(\omega * x + b) \tag{4}$$

Where:

x is input to the neuron of layer, w is the weight of kernel filters, and the weight of neuron in fully connected (Neural Network), σ is the activation function. A CNN is used to identify ECG signals in the provided model. Each block in its sequence consists of a convolutional layer, followed by layers for batch normalization and max pooling.

Model performance is improved through architecture design, training, and early stopping procedures. The model, organized into four blocks, includes four max-pooling, four convolutions, and FCLs. In addition, activation and normalization components are included in both convolutional and FCLs: ReLU activation and the normalization layer. To improve the convergence rate of the neural network and address the "gradient explosion" problem, the ECG signal batches are normalized during processing.

This method reduces the model's dependence on initial weights while increasing training rates and accuracy. The features of the convolutional layer are first extracted and feeding to the flat layer to start the classification process. With dropout layers in between, there are three classification layers: the first has 128 neurons, the second has 64 neurons, and the third has 32 neurons. Dropout is a regularization approach that reduces the risk of overfitting in artificial neural networks (ANNs) by preventing the formation of overly complex co-adaptations on training data. Some correlations may become more predictive than others when all weights are trained simultaneously. The signal classification model utilizes a dense layer with five neurons and the SoftMax activation function to handle this task. According to Figure 5, it recognizes various heart disease classes, including Supraventricular Ectopic Beats, Normal Beats, Fusion Beats, Ventricular Ectopic Beats, and Unknown Beats. A proposed model used for both training and testing, after complete the training stage and the model has obtained the best weight. The test stage began with unseen data for performance evaluation. Table 3 provides a summary of the suggested CNN model architecture, which includes 1.1 million trainable parameters.

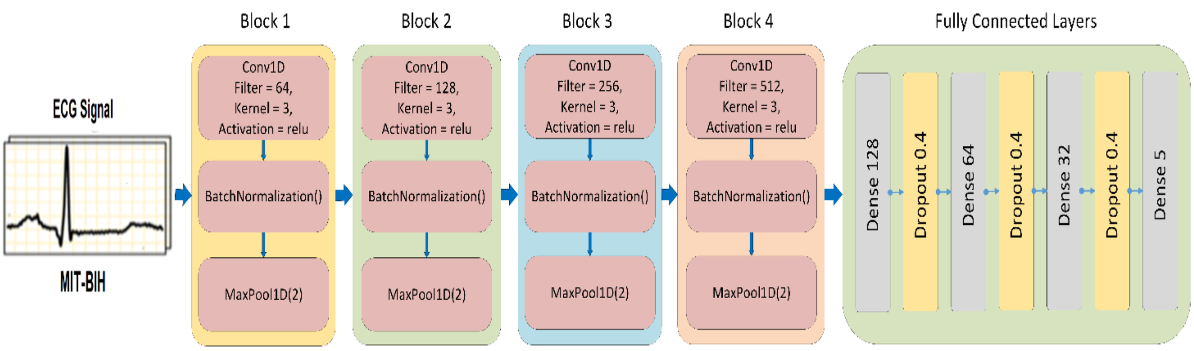

Figure 5. The suggested ECG signal classification model architecture

Table 3. Presents a general summary of the proposed CNN architecture

Layer (type)	Output Shape	Param #
inputs_cnn (InputLayer)	(None, 186, 1)	0
conv1d_1 (Conv1D)	(None, 181, 64)	448
batch_normalization_1 (Batch)	(None, 181, 64)	256
max_pooling1d_1 (MaxPooling1)	(None, 91, 64)	0
conv1d_2 (Conv1D)	(None, 89, 128)	24704
batch_normalization_2 (Batch)	(None, 89, 128)	512
max_pooling1d_2 (MaxPooling1)	(None, 45, 128)	0
conv1d_3 (Conv1D)	(None, 43, 256)	98560
batch_normalization_3 (Batch)	(None, 43, 256)	1024
max_pooling1d_3 (MaxPooling1)	(None, 22, 256)	0
conv1d_4 (Conv1D)	(None, 20, 512)	393728
batch_normalization_4 (Batch)	(None, 20, 512)	2048
max_pooling1d_4 (MaxPooling1)	(None, 10, 512)	0
flatten_1 (Flatten)	(None, 5120)	0
dense_1 (Dense)	(None, 128)	655488
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 64)	8256
dense_3 (Dense)	(None, 32)	2080
dropout_2 (Dropout)	(None, 32)	0
main_output (Dense)	(None, 5)	165
Total params: 1,187,269		
Trainable params: 1,185,349		
Non-trainable params: 1,920		

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2.4 Hyperparameters in Deep Learning Model Training

Training the proposed model involves tuning several hyperparameters that affect the model's ability to accurately fit the data. Unlike internal model parameters, hyperparameters are set before training and have a significant impact on performance. Hyperparameter optimization plays a critical role in improving the effectiveness and stability of deep learning models by selecting parameter values that lead to optimal performance for a given task. Among these parameters the learning rate is one of the most influential as it directly controls the speed and quality of convergence. An excessively large learning rate may result in unstable training and divergence, whereas an overly small value can significantly slow down the learning process.

The number of training epochs represents how many times the model iteratively processes the entire training dataset, while the batch size defines how many samples are used to update the model parameters in each iteration. Larger batch sizes allow efficient use of parallel computation but demand higher memory resources, whereas smaller batch sizes introduce greater variability in gradient updates, which can sometimes improve generalization Proper tuning of these hyperparameters is essential to achieve robust model performance. In addition, Early Stopping is employed as a regularization strategy to mitigate overfitting by monitoring validation performance during training. When no further improvement is observed over a predefined number of epochs, the training process is halted, and the model parameters corresponding to the best validation results are restored. The selected hyperparameter configurations used in this study are summarized in Table 4.

Table 4. Hyperparameters of the proposed model

Hyperparameters	Value
Batch size	32
Epochs	150
Optimizer	Adam
Early Stopping	Patience = 20 and 30
Dropout	(0.4) at the end of each layer in the fully connected layers
Classifier	Softmax
Loss function	categorical_crossentropy

3. Results

The proposed model, which was developed and trained on a large-scale ECG dataset, can reliably diagnose a wide range of cardiac abnormalities. To ensure reliable and reproducible results, the model's performance was rigorously evaluated using widely accepted standard measurements. Each experiment was conducted using a computer system configuration that included an Intel Core i7-8600U CPU running at 2.60 GHz, 16 GB of system memory, and an NVIDIA GeForce GTX 2060 GPU with 4 GB of VRAM. Popular machine learning and experimental libraries such as Seaborn, Scikit-learn, Pandas, Matplotlib, and NumPy were integrated into the execution framework, which was built on Anaconda Python 3.7. Furthermore, using the MIT-BIH database, the classifiers had to assign electrocardiogram (ECG) signals to one of five medically relevant buckets: Normal Beats, Ventricular Ectopic Beats, Supraventricular Ectopic Beats, Fusion Beats, or Unidentified Beats. In contrast, two different experimental setups were utilised to investigate how data distribution influences model performance. Under the first experimental scenario, the dataset showed a clear class imbalance, with certain pulse categories appearing significantly more frequently than others. In addition, the model's predictive power improved for classes with a large number of samples, as evidenced by the confusion matrix, but it considerably decreased for minority classes. This behaviour reveals a tendency to retain patterns associated with more frequent types of heartbeats. The following time we did the research, this study utilised a class rebalancing strategy to balance out the dataset distribution. Consequently, results for classifying all kinds of heartbeats were enhanced.

The modified the matrix of confusion showed higher-quality and consistent accuracy values and improved class recognition. Figure 6 shows how data balance reduces classifying bias and improves ECG-based cardiovascular disease reliability and robustness.

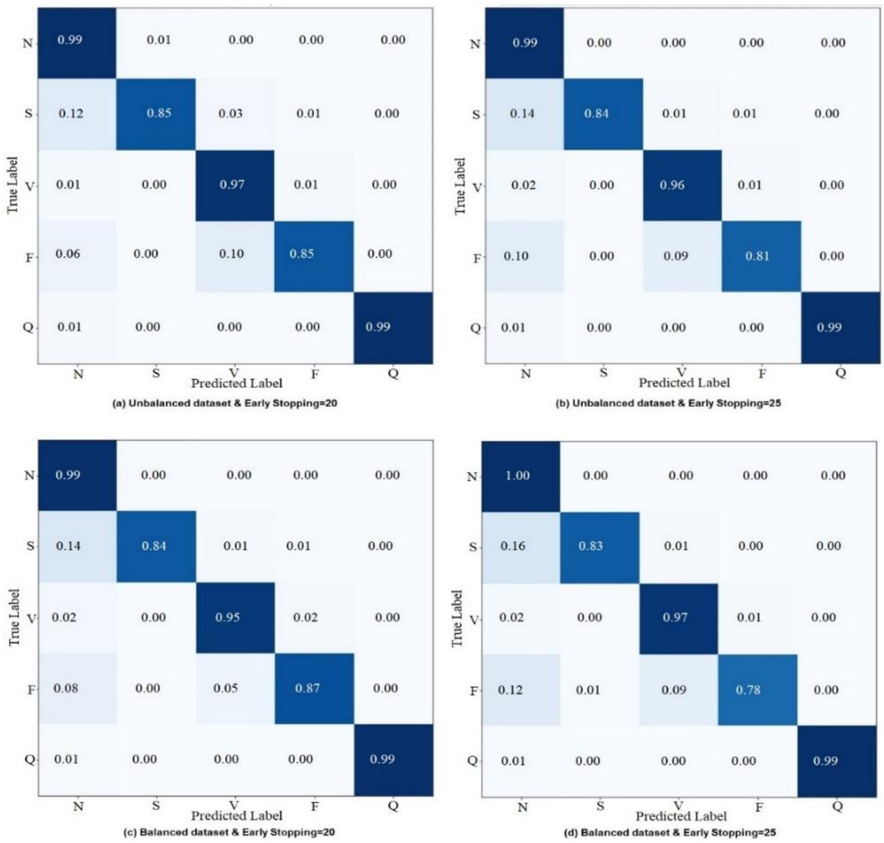

Figure 6. Confusion matrix for both balanced and unbalanced datasets (Early Stopping at 20 and 25).

1. To enhance training efficiency and avoid overfitting, an early stopping strategy was used during model optimisation. Two patience setups were tested with 150 epochs as the maximum. To test how patience values 20 and 25 affected training behaviour and performance stability, the model was examined. Patience = 20: The training procedure ended after 20 epochs of no validation accuracy increase. Early termination might lead the model to end training before attaining its optimal performance, especially with imbalanced data.
2. Patience = 25: In this configuration, the model was permitted to continue training for a longer duration before the early stopping criterion was triggered. This approach allowed the network to capture gradual yet consistent improvements in validation accuracy. As a result, a modest enhancement in overall accuracy was achieved compared to the patience-20 setting, indicating that extending the patience value can be advantageous, especially when training on unbalanced datasets. Plotting of the training and validation accuracy curves showed that the model reached saturation more rapidly on the training set, while

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exhibiting less stable behaviour on the validation set. This divergence emphasizes the impact of class imbalance as the model tends to favour dominant categories, which can lead to overfitting and limited generalization to unseen data. In contrast the use of balanced datasets resulted in a closer alignment between training and validation accuracy curves, reflecting improved stability and more uniform performance across different classes. As shown in Figure 7, combining balanced data with early stopping configurations of 20 and 25 epochs enabled the model to learn more class-independent feature representations, thereby reducing bias toward specific.

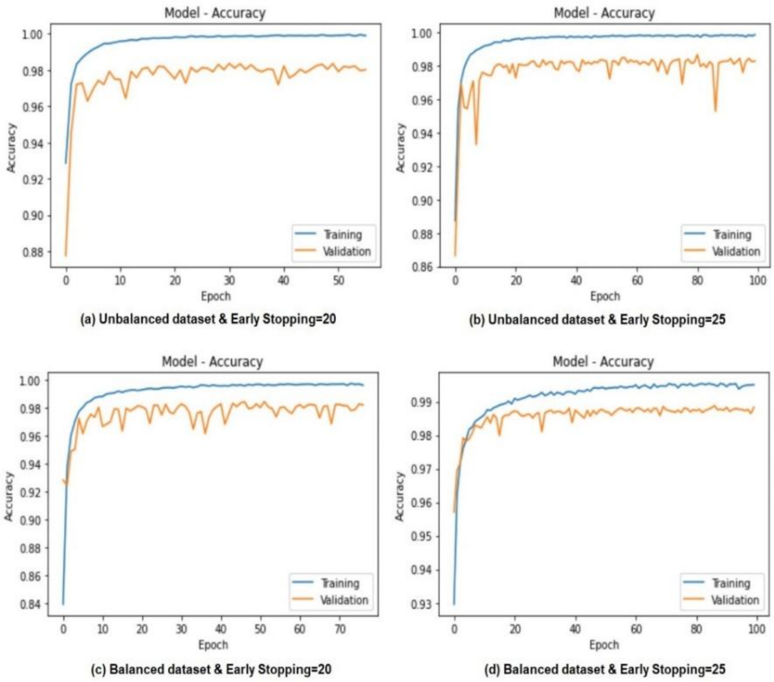

Figure 7. A comparison of the accuracy performance of the training phase with that of the validation phase for both balanced and unbalanced datasets, with early stopping configurations of 20 and 25 epochs.

Using a balanced dataset and an early ending patient factor of 25 improved the model's performance.This training design enhanced prediction accuracy and classification stability across all ECG signal classes. Class balance is essential for accurate and generalisable ECG classification models, as trials on the imbalanced dataset yielded poorer accuracy. Table5 shows that balanced data and careful tweaking of training parameters, including early stopping patience, enhance ECG signal classification.

Table 5. Evaluating how effectively the proposed model classifies ECG signals

Datasets structure	Early stopping	Number of epochs	Accuracy %
Unbalanced datasets	20	56	98.36
	25	104	98.67
Balanced datasets	20	77	98.45
	25	100	98.88

4. Discussion

The table (6) shows A comparison between the two versions of different models used to classify ECG signals. It focuses on the datasets used, the number of categories classified, the methods utilised, and the accuracy levels presented. This comparison is meant to place the model suggested in the context of other research and to show how it is better than previous investigations. It is worth noting that the MIT-BIH Arrhythmia database, which is considered one of the m21ost established and widely adopted benchmarks for ECG classification, has been consistently used across most of the reviewed studies including the present work. It should be noted that some studies, like [16], [18]employed the Computing in Cardiology Challenge (Cin C) 2017 database as well. In terms of the categories of classification, the majority of studies classify 3 to 6 classes, which may also vary. The proposed model operates within 5 categories, striking a balance between encompassing various classifications and maintaining the model's manageability. It had achieved very good efficiency of training, attaining a high level of accuracy with a smaller number of epochs, and shows more generalizability when compared to some of the other models, like the ones in [12], [19], as it effectively handles 5 classes. In contrast to other models, like the model that has been by [12], requiring 500 epochs to reach a 99% level of accuracy; the suggested model achieved a 98.88% accuracy level with considerably fewer epochs. The enhanced CNN architecture improves classification performance while reducing training risk, resulting in efficiency. Compared to that, several earlier research used support vector machines or hybrid frameworks integrating signal processing approaches with deep learning models, such as Wavelet-based CNNs Compared with these approaches, the proposed model distinguishes itself through its fully optimized CNN structure offering more stable, reliable, and consistent performance.

Table 6. Summarizes a comparative analysis between the proposed model and several existing studies

Study	Datasets	Number of classes	Approach	Accuracy (%)	Remarks
[16]	Computing in Cardiology Challenge (CinC) 2017	Three classes	support vector machines and bagging trees	82	Limited diseases Poor performance
[17]	MIT-BIH Arrhythmia	Six classes	CNN	65.8	Poor performance with 600 Epoch
[18]	Computing in Cardiology (CinC) Challenge 2017	Four classes	2-layer LSTM	82.9	Poor performance
[19]	MIT-BIH Arrhythmia	Three classes	Random Forest	97.4	Limited diseases
[20]	MIT-BIH Arrhythmia	Five classes	Wavelet + CNN	97.2	Poor performance
[12]	MIT-BIH Arrhythmia	Four classes	CNN	99	Limited classes with 500 Epoch
[15]	MIT-BIH Arrhythmia	Three classes	LightGBM	98.39	Limited diseases
Proposed model	MIT-BIH Arrhythmia	Five classes	CNN	98.88	Less Epoch and high accuracy

5. Conclusion

Cardiovascular disease (CVD) represents one of the leading causes of death globally, and that makes the early detection and diagnosis crucial for the potential saving of lives. ECG signals represent one of the essential tools for the identification of a variety of heart issues. However, the diagnosis of heart diseases through the ECG isn’t always straightforward and comes with a great number of challenges that could lead to exacerbate the issue. ECGs provide very important information about the electrical activity of the heart, which is helpful in detecting some conditions like heart attacks, arrhythmias, and heart enlargement. The early diagnosis through the ECG analyses provides the ability for timely medical intervention, which lowers the risks of death or severe complications. A highly important obstacle in the ECG-based diagnosis of heart diseases is dealing with the imbalanced data, in which some certain conditions appear in a more frequent manner compared to others in the datasets. Such imbalance could cause the models to favor the commonly seen conditions, typically overlooking the rarer yet more critical ones. The suggested model has been effective in addressing this issue, where it achieved a high accuracy in the classification of the ECG signals, thus leading to the improvement of the precision of diagnostic. This accuracy marks a significant improvement compared to the traditional methods, leading to the reduction of the risks that are related to human errors in the interpretation of the ECG signals. In addition to that, the proposed model had demonstrated efficiency, reaching a 98.88% accuracy with a smaller number of training cycles (epochs), which has resulted in saving time as well as computational resources. This outcome had underscored how important it is to balance the accuracy with the training efficiency in models of medical classification. Through the addressing of some challenges like data imbalance and enhancing the training efficiency, the model has a potential for improving health-care quality and lightening workload for the medical professionals. Further research is recommended to enhance the model's clinical applicability and generalizability by using other types of arrhythmias. Work should also be done to utilize the model in embedded systems for real-time applications.

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