

# **Detecting Cardiac Arrhythmias with 1D Convolutional Neural Network**

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2024

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**CERTIFICATE OF RECOMMENDATION**

**To Whom It May Concern**

I hereby recommend that the project report entitled “**Detecting Cardiac Arrhythmias with 1D Convolutional Neural Network**” has been carried out by (Reg. No.: 163593 of 2022-23, Roll No.: 002210503001, Exam Roll: MCA244001), under my guidance and supervision and be accepted in partial fulfilment of the requirement for the degree of Master of COMPUTER APPLICATION in DEPARTMENT of COMPUTER SCIENCE and ENGINEERING, JADAVPUR UNIVERSITY during the academic year 2023-2024.

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This is to certify that the project report entitled “**Detecting Cardiac Arrhythmias with 1D Convolutional Neural Network**” is a bonafide record of work carried out by Sayan Bhowal, in fulfillment of the requirements for the award of the degree of Master of Computer Application in the Department of Computer Science and Engineering, Jadavpur University. It is understood that by this approval the undersigned do not necessarily endorse or approve any statement made, opinion expressed or conclusion drawn therein but approve the project report only for the purpose for which it has been submitted.

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**DECLARATION OF COMPLIANCE WITH  
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I hereby declare that this project report entitled "**Detecting Cardiac Arrhythmias with 1D Convolutional Neural Network**" is an outcome of my genuine and independent work, as part of my Master of Computer Application program.

All information in this document has been obtained and presented in accordance with academic rules and ethical conduct.

I also declare that, as required by these rules and conduct, all materials and results that are not original to this work have been fully cited and referenced.

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# *Abstract*

Arrhythmias, irregular heart rhythms, are a significant health concern, particularly among the elderly. The manual classification of electrocardiograms (ECGs), the standard method for detecting cardiac activity, is challenging due to the ECG signal's low amplitude, complexity, and non-linearity. Therefore, there is a pressing need for automated systems that can accurately identify abnormal heartbeats from large ECG datasets in healthcare. This study proposes a deep learning approach using Convolutional Neural Networks (CNNs) to automatically classify three types of ECG signals: normal (N), supraventricular ectopic beats (S), and ventricular ectopic beats (V). The proposed CNN model processes segments of ECG signals, each comprising 2000 samples, and their corresponding RR intervals from the MIT-BIH arrhythmia database using a multi-input structure. Through a five-fold cross-validation strategy, the model achieves an impressive accuracy of 99.28%. These results highlight the robust generalization performance of the proposed CNN model, indicating its potential as an effective tool to assist clinicians in diagnosing arrhythmias. The model's ability to accurately classify different types of arrhythmias from ECG signals demonstrates its potential for real-world clinical applications, paving the way for improved cardiac healthcare.

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# 1. Introduction

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Arrhythmias, or irregular heart rhythms, represent a significant health concern, particularly among the elderly population. Although most arrhythmias are not life-threatening, they can be symptomatic of underlying heart disease and can escalate into more severe conditions such as rapid atrial fibrillation, paroxysmal supraventricular tachycardia, and persistent ventricular tachycardia. These conditions can manifest in various ways, including palpitations, chest tightness, dizziness, low blood pressure, sweating, syncope, and, in extreme cases, sudden cardiac death.

The timely and accurate diagnosis of arrhythmias is crucial for effective treatment and management. However, the manual classification of electrocardiograms (ECGs)—the standard diagnostic tool for monitoring cardiac activity—poses significant challenges. The inherent characteristics of the ECG signal, including its non-linearity, low amplitude, and susceptibility to noise, make manual interpretation difficult. Additionally, traditional methods of ECG analysis are often subjective and time-consuming, requiring prolonged recordings and expert analysis. This underlines the necessity for automated systems to enhance the accuracy, objectivity, and efficiency of arrhythmia diagnosis.

Numerous computer-based methods have been developed to facilitate automatic ECG analysis. Despite their potential, these methods frequently encounter limitations, such as poor generalization performance on new data and a propensity for overfitting. Traditional approaches based on frequency analysis, wavelet transform, and decision trees have demonstrated commendable performance on established datasets but often lack robustness when confronted with new, unseen data. This shortfall underscores the need for more sophisticated techniques that can improve both the accuracy and generalization capabilities of automated ECG analysis systems.

Deep learning algorithms, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools in the realm of medical image

analysis, including the analysis of ECG signals. CNNs are adept at extracting complex, high-dimensional features from ECG signals, which can significantly enhance classification accuracy and generalization. Recent studies have underscored the efficacy of CNNs in the automatic diagnosis of arrhythmias, showcasing their potential as a suitable choice for this study. By leveraging CNNs, we can potentially achieve a more reliable, efficient, and accurate system for arrhythmia detection, ultimately improving patient outcomes through timely and precise intervention.

## 2. Past Work

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In the field of automatic ECG arrhythmia recognition, various machine learning and deep learning models, including Support Vector Machines (SVM), Random Forest, Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), and Convolutional Neural Networks (CNN), have been studied.

Several studies have explored the application of these models for ECG signal analysis. For instance, Asl et al. (2008) used SVM to discriminate six different types of cardiac arrhythmias, applied to the HRV signals obtained from the MIT-BIH arrhythmia database with an accuracy of 98% [2]. Similarly, Wang et al. (2019) used a Random Forest Classifier to classify arrhythmias with an average accuracy of 95% [3]. Wu et al. (2020) worked with CNNs to classify 5 classes with an accuracy of 97.41% [4]. Chen et al. (2020) used LSTM and CNN with 5-second ECG signal segments as input and achieved an accuracy of 94.90% [5]. Hassan et al. (2022) also worked with Bi-LSTM and achieved an accuracy of 95.90% on the MIT-BIH database [6]. Ullah et al. (2021) experimented with 2D CNNs to classify 5 classes with accuracy rate 97.38% [7]. Hu et al. (2022) proposed a transformer based deep neural network for arrhythmia detection using continuous signal with 99.12% accuracy [8]. There have been many other research works on the MIT-BIH Arrhythmia Database.

While Convolutional Neural Networks (CNNs) have demonstrated promising results in ECG signal classification, other models such as Support Vector Machines (SVM), Random Forest, Long Short-Term Memory (LSTM), and Bidirectional LSTM (Bi-LSTM) have also shown significant effectiveness. SVM and Random Forest models are often favored for their interpretability and computational efficiency. They provide clear insights into the feature importance and decision-making process, which is crucial

for understanding and diagnosing arrhythmias. On the other hand, LSTM and Bi-LSTM models are preferred for their ability to capture long-term dependencies in sequential data, making them well-suited for time-series analysis like ECG signal processing.

The past work reviewed in this section provides valuable insights into the performance of different machine learning and deep learning models for arrhythmia detection. For instance, studies have highlighted the strength of SVM and Random Forest in handling high-dimensional data and their robustness in classification tasks. Meanwhile, LSTM and Bi-LSTM have been noted for their superior performance in capturing temporal patterns and handling variable-length sequences, which are inherent in ECG signals.

Our project aims to build upon this existing body of knowledge by conducting a comprehensive evaluation of SVM, Random Forest, LSTM, Bi-LSTM, and CNN models on a common dataset. Specifically, we will use the MIT-BIH arrhythmia ECG dataset from PhysioNet, a well-established benchmark in the field. The goal is to identify the most effective model for multi-class arrhythmia classification, considering both accuracy and computational efficiency. By comparing these diverse approaches under consistent conditions, we hope to provide clear recommendations for the most suitable model for arrhythmia detection in clinical and research settings.

### 3. Dataset Overview

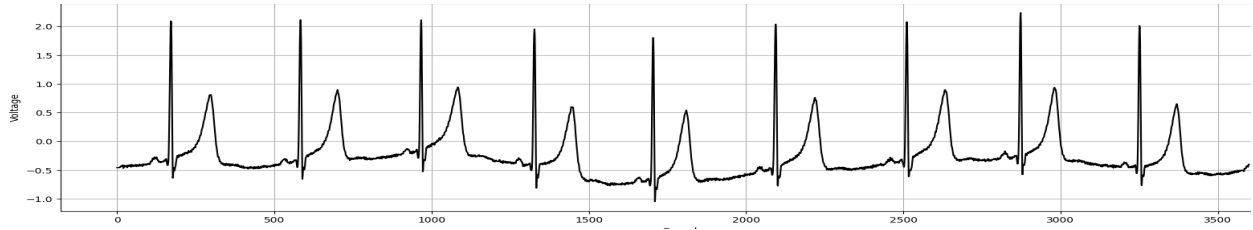
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In this study, the electrocardiogram (ECG) datasets and corresponding annotation files were obtained from the publicly available PhysioNet MIT-BIH Arrhythmia database. This database contains recordings from 47 subjects collected between 1975 and 1979. It comprises 48 records from Lead 2, V1, V2, V4, and V5. The recordings were sampled at 360 samples per second per channel. This database includes annotations for beat class and timing information, verified by an independent expert.

The MIT-BIH Arrhythmia database is a widely used resource in the field of cardiology and signal processing, providing valuable data for the development and evaluation of arrhythmia detection algorithms. The recordings in this database are of high quality and have been extensively annotated, making them suitable for training and testing machine learning models for arrhythmia classification.

The annotations in the MIT-BIH Arrhythmia database include beat annotations, which indicate the location and class of each beat (e.g., normal beat, ventricular ectopic beat, supraventricular ectopic beat, etc.), as well as rhythm annotations, which provide labels for entire segments of the recordings (e.g., normal rhythm, atrial fibrillation, etc.). These annotations are essential for training machine learning models to accurately classify different types of arrhythmias.

Overall, the MIT-BIH Arrhythmia database is a valuable resource for researchers and clinicians interested in arrhythmia detection and classification, providing a standardized dataset for benchmarking algorithms and comparing results across different studies.



**Fig. 1:** Sample of ECG signals

**Table 1:** Group details of ECG classes

| Groups | ECG classes                                                                                                                                                                                              |
|--------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| N      | Normal(N)<br>Left Bundle Branch Block(L)<br>Right Bundle Branch Block(R)<br>Change in signal quality(~)                                                                                                  |
| S      | Supraventricular premature(S)<br>Non-conducted P-wave (x)<br>Atrial premature(A)<br>Aberrated atrial premature(a)<br>Nodal (junctional) escape(j)<br>Nodal (junctional) premature(J)<br>Atrial escape(e) |
| V      | Premature ventricular contraction(V)<br>Ventricular escape(E)                                                                                                                                            |

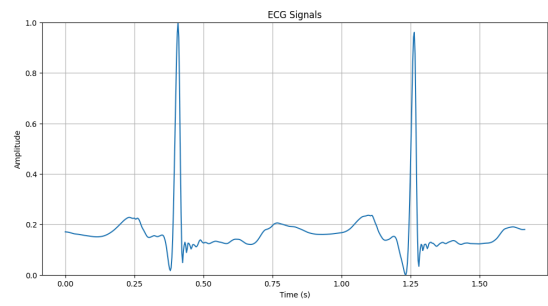
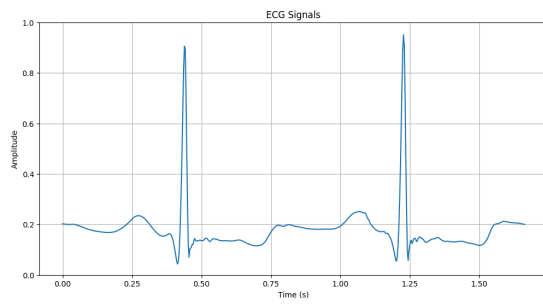
## 4. Methodology

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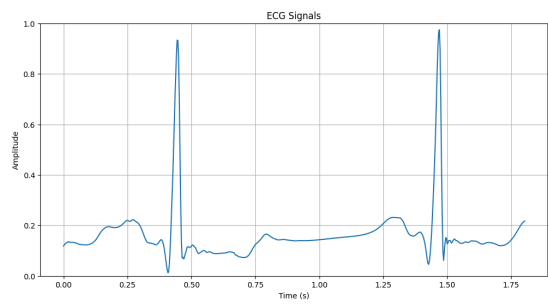
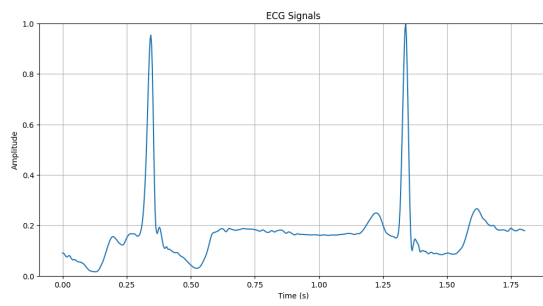
This study aims to develop a deep learning-based classification method for ECG signals to analyze and recognize three classes of ECG segments: normal (N), supraventricular ectopic beats (S), and ventricular ectopic beats (V). The proposed method will utilize CNNs to extract spatial information from ECG signals and RR intervals, improving the model's abstraction ability and generalization performance. The method will be validated using the MIT-BIH arrhythmia database to evaluate its effectiveness and applicability in real-world scenarios.

### 4.1. Preprocessing

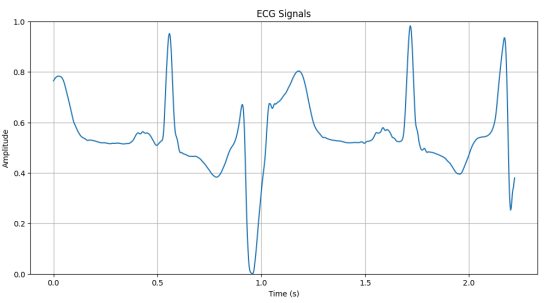
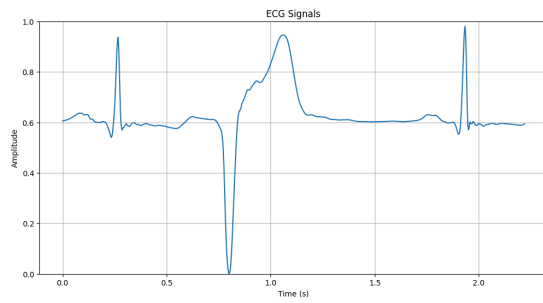
In this study, only Lead 2 data of ECG signals was considered and ECG classes were grouped into 3 classes mentioned in [Table 1](#). Out of the 48 records, 4 records were removed: records 102, 104, 107, and 217. Records 102 and 104 were excluded because they lacked Lead 2 data. The remaining two records were removed because their annotations did not belong to the considered 3 classes: normal (N), supraventricular ectopic beats (S), and ventricular ectopic beats (V). The ECG signals were denoised using Wavelet Transform and the R peaks were subsequently extracted. Signals were segmented into 2000-sample segments, each corresponding to an RR interval. In cases where the difference between RR intervals was less than 2000, the remaining half was taken from the previous RR intervals, and the other half from the subsequent RR intervals. If the RR interval difference exceeded 2000, the extra half was removed from the beginning, and the other extra half from the end of the RR interval. In the MIT-BIH Arrhythmia Database (MITDB), ECG rhythm labels are provided as annotations. Each segment of ECG data corresponds to one label. The segments were labeled based on the nearest annotation sample of the second R peak of each RR interval. Subsequently, Z-score normalization was applied to each segment to address amplitude scaling issues.



**Fig. 2:** Example of Normal Beats(N)



**Fig. 3:** Example of Supraventricular Ectopic Beats (S)



**Fig. 4:** Ventricular Ectopic Beats (V)

**Table 2:** Number of ECG segments

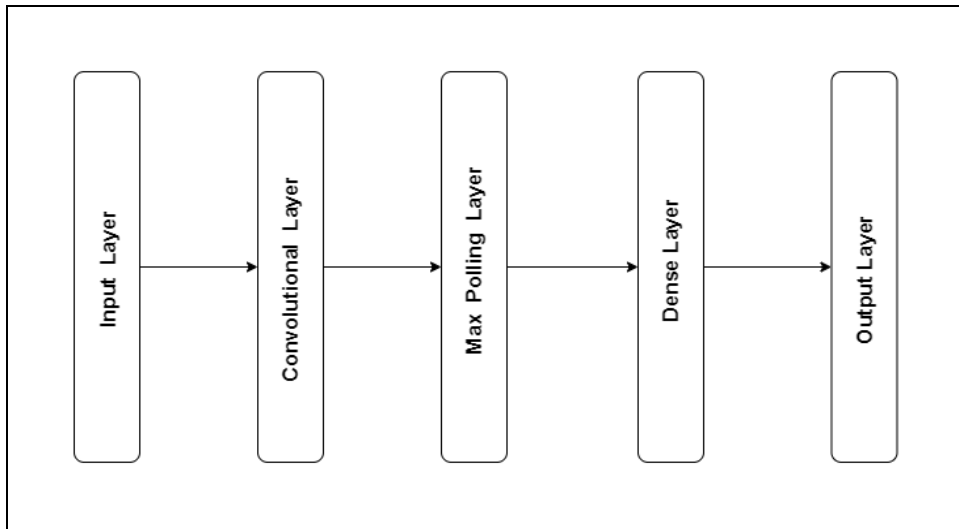
| <b>Class</b>                       | <b>Number of segments</b> |
|------------------------------------|---------------------------|
| Normal Beats (N)                   | 89062                     |
| Supraventricular Ectopic Beats (S) | 2909                      |
| Ventricular Ectopic Beats (V)      | 5867                      |

## 4.2. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) play a crucial role in the realm of artificial neural networks, particularly in the analysis of visual data. Originating from the early 1990s and pioneered by LeCun, CNNs have emerged as a powerful tool for feature extraction and time-series data classification.

A CNN architecture comprises several fundamental layers that collectively enable its functionality. These include an input layer, convolutional layers, pooling layers, and fully connected layers. The input layer serves as the entry point for data, while the convolutional layers apply filters to extract pertinent features. Pooling layers then downsample the data, reducing computational complexity. Finally, fully connected layers leverage these extracted features to make the ultimate prediction.

At the heart of a CNN, the convolutional layer is pivotal. It applies filters to input data, extracting features by computing the dot product between the filter and the region of the input data it is currently analyzing. This process generates activation maps that highlight specific features within the data. These filters are not pre-defined but are learned during the network's training phase, allowing the CNN to adapt to various tasks and datasets.



**Fig. 4:** Simple CNN architecture

Accompanying the convolutional layers are activation functions, such as ReLU (Rectified Linear Unit), which introduce non-linearity to the network, enabling it to learn complex patterns within the data. Additionally, pooling layers, such as Max Pooling, help reduce the spatial dimensions of the data, retaining essential information while reducing computational load.

Ultimately, the fully connected layers utilize the features extracted by the convolutional and pooling layers to make a final prediction. These layers are characterized by their dense interconnections, with each neuron connected to every neuron in the previous layer. This dense connectivity enables the network to learn intricate patterns and relationships within the data, crucial for accurate classification tasks. Throughout the training process, the network learns optimal filters through techniques like backpropagation and gradient descent. This iterative process adjusts the filter values to minimize the disparity between predicted and actual outputs, progressively improving the network's performance and ability to discern complex patterns within the data.

In this study, the ECG signal is processed through a sub-CNN architecture comprising 19 layers, consisting of alternating 1D convolutional layers and 1D maximum pooling layers and dropout layers. The input layer (layer 0) is convolved with a kernel size of 151 to generate layer 1. Subsequently, a max-pooling operation with a size of 2 is applied to each feature map (layer 2). This process continues, with feature maps from each layer being convolved with varying kernel sizes and followed by max-pooling. The flatten layer(layer 16) is used to convert a multidimensional vector into one-dimensional vector. The final layer (layer 19) is the output layer with the softmax function.

Rectified Linear Units (ReLU) were utilized as activation functions for all 1D convolutional layers, while a softmax function was applied to the last layer for classification. To prevent overfitting, a dropout layer with a dropout rate of 0.2 was included, randomly removing connections within the network during training.

**Table 3:** Details of the proposed network structure

| Layer | Type         | Output Shape | Kernel Size/ Pool Size | Strides |
|-------|--------------|--------------|------------------------|---------|
| 0     | ECG Input    | (2000, 1)    | -                      | -       |
| 1     | Conv1D       | (1850, 5)    | 151                    | 1       |
| 2     | MaxPooling1D | (925, 5)     | 2                      | 2       |
| 3     | Conv1D       | (826,5)      | 100                    | 1       |
| 4     | MaxPooling1D | (413, 5)     | 2                      | 2       |
| 5     | Conv1D       | (333, 10)    | 81                     | 1       |
| 6     | MaxPooling1D | (166, 10)    | 2                      | 2       |
| 7     | Conv1D       | (136, 20)    | 31                     | 1       |
| 8     | MaxPooling1D | (68, 20)     | 2                      | 2       |
| 9     | Conv1D       | (55, 20)     | 14                     | 1       |
| 10    | MaxPooling1D | (27, 20)     | 2                      | 2       |
| 11    | Dropout      | (27, 20)     | -                      | -       |
| 12    | Flatten      | 540          | -                      | -       |
| 13    | Dense        | 5            | -                      | -       |
| 14    | Dense        | 3            | -                      | -       |

### 4.3. Evaluation Strategy

For model evaluation, a five-fold cross-validation approach was utilized. The preprocessed ECG segments were randomly shuffled and divided into training (80%) and testing (20%) sets. This process was repeated five times, ensuring that each segment was used for testing exactly once. The model was trained and tested five times, and the average performance across the five runs was used as the final evaluation metric. This study employs a variety of metrics for evaluation, including the confusion matrix, overall accuracy (Acc) as well as precision and recall for each class. These metrics serve different purposes: accuracy assesses the model's overall performance in correctly identifying samples.

Precision measures the accuracy of the positive predictions. It is the ratio of correctly predicted positive observations to the total predicted positives.

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

Recall measures the ability of the classifier to find all the positive instances. It is the ratio of correctly predicted positive observations to all observations in the actual class.

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

Here, a general formulation for any class label A:

TP\_A = Number of instances correctly classified as A

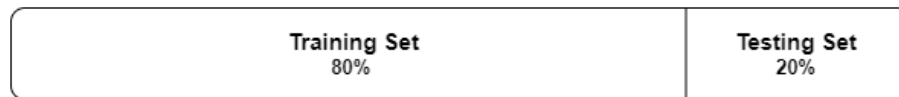
FP\_A = Number of instances not A but classified as A

FN\_A = Number of instances A but not classified as A

## 5. Result and Discussion

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The study used a five-fold cross-validation approach where the dataset was evenly divided into five portions. In each validation cycle, 80% of the data was allocated for training the model, while the remaining 20% was reserved for testing. This procedure was iterated five times, ensuring all data were eventually used for testing. To monitor the training progression and mitigate the risk of overfitting, test set was utilized to assess model performance at the conclusion of every training epoch. Total number of epochs was 10. Throughout each training epoch, model performance metric



**Fig. 5:** Details of Training and Test Data set

such as Accuracy was calculated. The average performance metrics from the five-fold cross-validation were used to assess the overall effectiveness of the system. Testing of our algorithm was carried out on a personal laptop equipped with an AMD Ryzen 7 5800H at 3.2GHz and 16GB RAM, utilizing the Keras framework with TensorFlow backend for development and assessment. The average training time for the model was recorded at approximately 4200 seconds.

**Table 4:** Confusion matrix of the classified ECG segments

|   | N     | S   | V    |
|---|-------|-----|------|
| N | 17769 | 23  | 21   |
| S | 52    | 529 | 1    |
| V | 23    | 10  | 1140 |

**Table 5:** Average Precision and Recall details for each class

| Class | Precision | Recall |
|-------|-----------|--------|
| N     | 99.75%    | 99.93% |
| S     | 98.30%    | 94.52% |
| V     | 99.64%    | 98.73% |

In [Table 4](#), a confusion matrix is presented for 3 classes. The results show that, after k-fold cross-validation, the average accuracy rate of the proposed CNN algorithm is 99.28%. It was noted that 99.93% of the instances from the N class, 94.52% from S class and 98.73% from the V class were correctly identified from [Table 5](#).

**Table 5:** Comparison with the proposed method with previous works

| Authors              | Methods      | Number of classes | Accuracy |
|----------------------|--------------|-------------------|----------|
| Wu et al. [3]        | 1D-CNN       | 5                 | 97.20%   |
| Murawwat et al. [14] | MEMD and ANN | 3                 | 89.8%    |
|                      | Proposed     | 3                 | 99.28%   |

## 6. Conclusion

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The early detection of arrhythmia is crucial for minimizing the risks associated with heart disease. In response to this need, our study introduces a robust automatic computer-aided diagnosis system employing Convolutional Neural Networks, based on deep learning techniques. This system is capable of classifying six distinct types of ECG fragments. It achieves a remarkable recognition rate of 99.28% on the MIT-BIH arrhythmia database. The outcomes achieved by our diagnostic model align closely with the initial goals of the research, providing a tool that assists healthcare professionals in rapidly and accurately identifying ECG types or confirming their diagnoses in clinical settings. This is accomplished with high accuracy and at a reduced cost. Future enhancements to the system's performance could be realized by training the model on a more extensive array of arrhythmia databases.

# References

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- [1] PhysioNet. (2005). MIT-BIH Arrhythmia Database, version 1.0.0.
- [2] B M Asl, S K Setarehdan, M Mohebbi, "Support vector machine-based arrhythmia classification using reduced features of heart rate variability signal", *Artificial Intelligence in Medicine*, vol. 44, 2008.
- [3] Zhizhong Wang, Hongyi Li, Chuang Han, Songwei Wang, Li Shi, "Arrhythmia Classification Based on Multiple Features Fusion and Random Forest Using ECG", *Journal of Medical Imaging and Health Informatics*, vol.9, 2019.
- [4] M Wu, Y Lu, W Yang, S Y Wong, "A Study on Arrhythmia via ECG Signal Classification Using the Convolutional Neural Network", *Front. Comput. Neurosci.*, vol. 14, 2020.
- [5] C Chen, Z Hua, R Zhang, G Liu, W Wen, "Automated arrhythmia classification based on a combination network of CNN and LSTM", *Biomedical Signal Processing and Control*, vol. 57, 2020.
- [6] Shahab Ul Hassan, Mohd S Mohd Zahid, Talal AA Abdullah, Khaleel Husain, "Classification of cardiac arrhythmia using a convolutional neural network and bi-directional long short-term memory", *Digital Health*, vol. 8, 2022.
- [7] Amin Ullah, Sadaqat ur Rehman, Shanshan Tu, Raja Majid Mehmood, Fawad, Muhammad Ehatisham-ul-haq, "A Hybrid Deep CNN Model for Abnormal Arrhythmia Detection Based on Cardiac ECG Signal", *Sensors*, vol. 21, 2021.
- [8] Rui Hu, Jie Chen, Li Zhou, "A transformer-based deep neural network for arrhythmia detection using continuous ECG signals", *Computers in Biology and Medicine*, vol. 144, 2022.

- [9] T F Romdhane, H Alhichri, R Ouni, M Atri, "Electrocardiogram heartbeat classification based on a deep convolutional neural network and focal loss", *Computers in Biology and Medicine*, vol. 123, 2020.
- [10] Xue Xu, S Jeong, Jianqiang Li, "Interpretation of Electrocardiogram (ECG) Rhythm by Combined CNN and BiLSTM", *IEEE Access*, vol. 8, 2020.
- [11] Fatma Murat, Ozal Yildirim, Muhammed Talo, Ulas Baran Baloglu, Yakup Demir, U Rajendra Acharya, "Application of deep learning techniques for heartbeats detection using ECG signals-analysis and review", *Computers in Biology and Medicine*, vol. 120, 2000.
- [12] Krzysztof Gajowniczek, Iga Grzegorzczak, Tomasz Ząbkowski, Chandrajit Bajaj, "Weighted Random Forests to Improve Arrhythmia Classification", *Electronics*, vol. 9, 2020.
- [13] Ehab Essa, Xianghua Xie, "An Ensemble of Deep Learning-Based Multi-Model for ECG Heartbeats Arrhythmia Classification", *IEEE Access*, vol. 9, 2001.
- [14] Sadia Murawwat, Hafiz M. Asif, Sana Ijaz, Muhammad Imran Malik, Kaamran Raahemifar, "Denoising and classification of Arrhythmia using MEMD and ANN", *Alexandria Engineering Journal*, vol. 61, 2022.
- [15] Ali Isin, Selen Ozdalili, "Cardiac arrhythmia detection using deep learning", vol. 120, 2017.
- [16] Dingfei Ge, Narayanan Srinivasan, Shankar M Krishnan, "Cardiac arrhythmia classification using autoregressive modeling", *BioMedical Engineering OnLine*, vol. 1, 2002.
- [17] L B Marinho, Nascimento, Souza, Gurgel, Filho, Albuquerque, "A novel electrocardiogram feature extraction approach for cardiac arrhythmia classification", *Future Generation Computer Systems*, vol. 97, 2019.

[18] N Kohli, NK Verma, “Arrhythmia classification using SVM with selected features”, International Journal of Engineering, Science and Technology, vol. 3, 2011.

[19] Getu Tadele Taye, Han-Jeong Hwang, Ki Moo Lim, “Application of a convolutional neural network for predicting the occurrence of ventricular tachyarrhythmia using heart rate variability features”, Scientific Reports, vol. 10, 2020.

[20] Jinkwon Kim, Hang Sik Shin, Kwangsoo Shin & Myoungho Lee, “Robust algorithm for arrhythmia classification in ECG using extreme learning machine”, BioMedical Engineering OnLine, vol. 8, 2009.