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Improving Accuracy Through Preprocessing and Data Augmentation Techniques with a Deep Learning-Based Approach for Arrhythmia Detection

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Abstract

Arrhythmia detection plays a critical role in the early diagnosis and management of cardiovascular diseases. In this study, we propose a deep learning-based model for arrhythmia classification using advanced preprocessing and data augmentation techniques. The proposed model is evaluated on the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Dataset and achieves 98% and 95% accuracy rates, respectively. These results demonstrate the strong ability of the model to classify complex heartbeat patterns, achieving higher accuracy, precision, sensitivity, and F1 score compared to existing methods. The model uses a convolutional neural network (CNN) architecture trained on pre-processed ECG signals with data segmented into individual heartbeats. Data augmentation techniques are applied to reduce data imbalances and improve the generalization ability of the model. Experimental results highlight that the model provides a significant increase in accuracy rates over traditional methods. The results of this study highlight the potential of deep learning architectures in biomedical signal analysis, especially for real-time arrhythmia detection. This approach offers promising potential for clinical applications by enabling higher diagnostic accuracy and timely intervention in cardiovascular healthcare.

1. Introduction

Heart rhythm analysis is a key component of cardiovascular health assessment and is essential for detecting irregular heart rhythms such as arrhythmias, tachycardia, bradycardia and atrial fibrillation. Arrhythmias are one of the leading causes of cardiovascular disease worldwide and significantly increase mortality rates. Regular monitoring of heart rhythm plays a critical role in early detection and intervention. Early detection of cardiovascular disease improves patients' quality of life and reduces mortality. Heart rhythm analysis is therefore an important tool for identifying cardiovascular risks. Biomedical signals such as electrocardiography (ECG) and photoplethysmography (PPG) are often used in these analyses. ECG directly measures the electrical activity of the heart by recording the electrical potential differences that occur with each heart contraction as a time series [1]. ECG signals are a highly effective method for identifying rhythm disturbances, while PPG provides an indirect measurement by optically monitoring blood flow in blood vessels. These two methods provide important data for the assessment of heart rhythm.

The heart rhythm is generated by regular electrical impulses from the sinus node, and this rhythm allows the heart muscle to pump blood throughout the body. However, cardiovascular and systemic factors can disrupt the heart rhythm, which can lead to heart disease [2]. For example, conditions such as arrhythmias, ventricular fibrillation, tachycardia, and bradycardia can affect heart rhythm and lead to serious health problems. Irregular rhythms, such as atrial fibrillation, can lead to serious risks including stroke, heart failure and sudden cardiac arrest. Early detection of these conditions is critical to improving patient survival and making treatment more effective. Regular monitoring of heart rhythm is essential for the successful management and treatment of cardiovascular disease. However, because heart rhythm signals are high-frequency and complex, their analysis can be susceptible to noise. Therefore, the use of reliable and efficient analysis methods is important to ensure accurate results.

The analysis of heart rhythm signals is limited by conventional methods. In particular, the analysis of components such as P wave, QRS complex, and T wave in the ECG signal provides information about the regularity of the heart rhythm, but it is difficult to evaluate the multidimensional structure of these components [3]. However, deep learning methods have revolutionized the field of heart rhythm analysis in recent years. Deep learning has the ability to learn and analyze complex patterns in large data sets, and is highly effective in analyzing biomedical data. The application of deep learning techniques provides more accurate and precise results than traditional methods, especially when processing time series data [4]. Deep learning models such as Convolutional Neural Networks (CNN) are particularly effective for heart rhythm analysis. CNN is very powerful in extracting features from visual data and time series signals. CNN can learn the features of each signal and rhythm and make classifications based on these features [5].

In these studies on heart rhythm analysis, only data obtained from heart sounds were analyzed using CNN [6]. In this analysis, more precise and accurate results were obtained by going beyond traditional methods. CNN uses specially designed filters to remove noise when processing signal data, and thus can accurately classify heart rhythm abnormalities [7]. This feature makes CNN-based systems highly effective in diagnosing cardiovascular diseases. Heart sounds are an important component of heart rhythm analysis and provide valuable information for detecting heart rhythm abnormalities [8]. CNN is highly successful in detecting differences in heart sounds and rhythm disturbances [9]. In addition, CNN-based models provide more accurate and reliable results due to their ability to learn from large data sets [10]. Deep learning-based approaches to cardiac rhythm analysis and cardiovascular disease diagnosis will play an important role in cardiology in the future, helping to achieve more effective outcomes in patient care.

As a result, the use of deep learning techniques has led to significant advances in the early detection of cardiovascular disease. CNN-based models have been particularly successful in heart rhythm analysis and abnormality detection. These analyses using data obtained from heart sounds provide more accurate results than traditional methods, and these approaches stand out as an innovative approach to early diagnosis and treatment of cardiovascular diseases.

This study makes a significant contribution by using Convolutional Neural Networks (CNN), a deep learning method, to detect heart rhythm abnormalities. The study is tested on the MIT-BIH Arrhythmia and PTB Diagnostic ECG datasets and demonstrates that the model performs arrhythmia detection with high accuracy and reliability. Furthermore, by applying data augmentation techniques, the generalization ability of the model is enhanced and overfitting problems are minimized. The results show that the proposed model performs better than traditional methods.

The limitations of the study are that it was tested on only two common datasets and the model used can only detect a limited number of arrhythmia types. Also, although the overall accuracy of the model is high, it appears that further testing on rarer types of arrhythmias is warranted. Future studies could focus on increasing the accuracy and generalization capacity of the model with different datasets and more diverse arrhythmia types.

2. Literature Review

Oyeleye et al. examined the role of IoT, AI and wearable devices in early detection of heart diseases caused by low heart rate. In the study, ARIMA, linear regression, SVR, KNN, decision tree, random forest and LSTM models were used for heart rate prediction with accelerometer data. The performance of the models was evaluated in different time periods and it was shown that ARIMA and linear regression models were particularly effective [11].

Sahoo et al. reviewed current ECG analysis methods for arrhythmia detection and summarized signal processing, feature extraction and classification techniques. The study emphasizes the importance of computer-aided systems in real-time arrhythmia detection [12]. Ahmed et al. pointed out the risk of misdiagnosis due to noise and randomness of traditional methods in ECG arrhythmia detection. In the study, a 1D-CNN-based deep learning model trained with noise-reduced real ECG data is presented [13]. Mohammed et al. examined the difficulties in predicting heart rate variability problems and its impact on diagnosis. In the study, a machine learning-based assessment is proposed to detect heart rate variability responses in children with autism spectrum disorder (ASD). They also focused on the risk of congenital heart holes and heart block in children with ASD [14].

Anand et al. presented a study on 109,446 samples in the MIT-BIH arrhythmia database using deep learning methods for cardiac arrhythmia detection. In the study, automatic arrhythmia predictions made with CNN and ResNet-18 architectures were compared, and ResNet-18 was found to give better results with an accuracy of

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98.14%. The study discusses the applicability of this model for cardiac arrhythmia detection on a global scale [15]. In a study of 100 patients, Kouz et al. used hierarchical clustering to identify six different endotypes of intraoperative hypotension: myocardial depression, bradycardia, vasodilation (with and without cardiac index increase), hypovolemia and mixed type. These endotypes may help target the treatment of hypotension [16]. Albaladejo-González et al. examined artificial intelligence models with heart rate data for stress detection. LOF and MLP models showed the highest performance on WESAD and SWELL-KW datasets. LOF performed better in transfer learning tests, while training in multiple contexts improved model performance. These findings suggest a new approach for stress management mobile applications [17]. Malakouti stated that analyzing ECG data is a critical step in the diagnosis of cardiovascular diseases. In this study, machine learning methods such as Gaussian NB, Random Forest, Logistic Regression, Linear Discriminant Analysis and Dummy Classifier were used, focusing on health and disease classification [18].

Al Ahdal et al. stated that heart disease is the most common cause of death worldwide. In this study, various machine learning methods were developed using the UCI dataset for early detection of heart disease. Random Forest classifier showed the highest performance with 96.72% accuracy and Extreme Gradient Boost with 95.08% accuracy [19]. Jothibasu et al. developed a system that combines facial features and heart rate monitoring to detect driver fatigue. It detects fatigue with 94% accuracy and minimizes false alarms by analyzing eye angle ratio and heart rate [20]. K M and Syed K. aimed at noise removal and feature extraction from ECG signals for arrhythmia detection. Using MIT-BIH database, classification was performed with machine learning and deep learning models by improving ECG quality with IIR filter [21]. Mamyrbayev et al. developed a method for automatic classification of dangerous arrhythmias using 2-second ECG segments. ECG signals were transformed into scalograms by continuous wavelet transform and classified by AlexNet neural network [22].

3. Material and Method

In this study, a Convolutional Neural Networks (CNN) based model is developed for the detection of heart rhythm disorders. Data augmentation techniques were applied to the dataset to improve the success of the model. Below, the materials used and the methodologies applied are described in detail.

3.1 Data Set

The dataset used in this study consists of heartbeat signals from two famous datasets widely used in the field of heartbeat classification: MIT-BIH Arrhythmia Dataset and PTB Diagnostic ECG Dataset. These datasets are widely used in the analysis and classification of electrocardiogram (ECG) signals and contain large enough samples for deep neural networks [23].

MIT-BIH Arrhythmia Dataset:
Number of Samples: 109.446
Number of Categories: 5
Sampling Frequency: 125Hz
Data Source: PhysioNet MIT-BIH Arrhythmia Data Set
Classes:

- ✓ 'N' (Normal): 0
- ✓ 'S' (Supraventricular ectopic beats): 1
- ✓ 'V' (premature ventricular contractions): 2
- ✓ 'F' (Fusion pulses): 3
- ✓ 'Q' (Unclassified pulses): 4

This dataset consists of labeled heartbeat signals including normal sinus rhythm and various abnormal heart rhythms. The signals were preprocessed and segmented so that each segment corresponds to one heartbeat.

PTB Diagnostic ECG Data Set:
Number of Samples: 14.552
Category Number: 2
Sampling Frequency: 125Hz
Data Source: PhysioNet PTB Diagnostic Data Set

The PTB Diagnostic ECG Dataset offers a smaller but important collection of ECG signals. This dataset is used to diagnose normal and pathological heart disease, and specifically includes conditions such as myocardial infarction. The signals from this dataset are also preprocessed and segmented, with each segment corresponding to one heartbeat. The classes in this dataset are generally labeled as normal and abnormal.

3.2 Preprocessing and Segmentation

Both datasets undergo preprocessing steps such as noise filtering, normalization and segmentation of the ECG signals into individual heartbeats. Each heartbeat segment is processed as an independent input for the model. This preprocessing step plays a critical role in improving classification accuracy by enhancing signal quality. This combined dataset has been widely used in heartbeat classification tasks, with significant performances by deep neural networks. It has also been used to explore the impact of transfer learning techniques [24]. Transfer learning offers the potential to provide better model generalization through the use of pre-trained models. The large sample size of the dataset and the variety of cardiac states make it highly suitable for training robust deep learning models for automatic heartbeat classification.

3.3 Data Augmentation

Data augmentation is an important technique to increase the generalization capacity of deep learning models and reduce the risk of model overfitting. In this study, data augmentation is used for the heartbeat classification model and various strategies are applied to overcome class imbalances and data deficiencies. In particular, different data augmentation techniques were used on the signals obtained from the MIT-BIH Arrhythmia Dataset and PTB Diagnostic ECG Dataset, preserving the time series structure of the signal. These techniques include shifting the signals in time, adding noise, changing the amplitude of the signal and rotating the signals. In addition, in order to increase the size of the time series data, the diversity of the data set was increased by rescaling the signals horizontally or vertically, changing the segments and manipulating the time intervals. These data augmentation processes enabled the model to produce more robust and reliable results and prevented potential performance degradation due to class imbalances and data insufficiencies encountered during training. In this way, the model can run on a larger dataset, the learning process is accelerated and the generalization capacity of the model is increased.

3.4 Model Structure

The CNN-based model was used to classify heart rhythm disorders. The model has a multi-layered structure and different features are extracted in each layer. The first layers are used to extract basic features (edge, texture, etc.), while the deeper layers are designed to recognize more complex rhythm disturbance patterns. In the model, max-pooling was applied after each layer and the learned features were combined and classified in the final layerCNN structure is given in Figure 1.

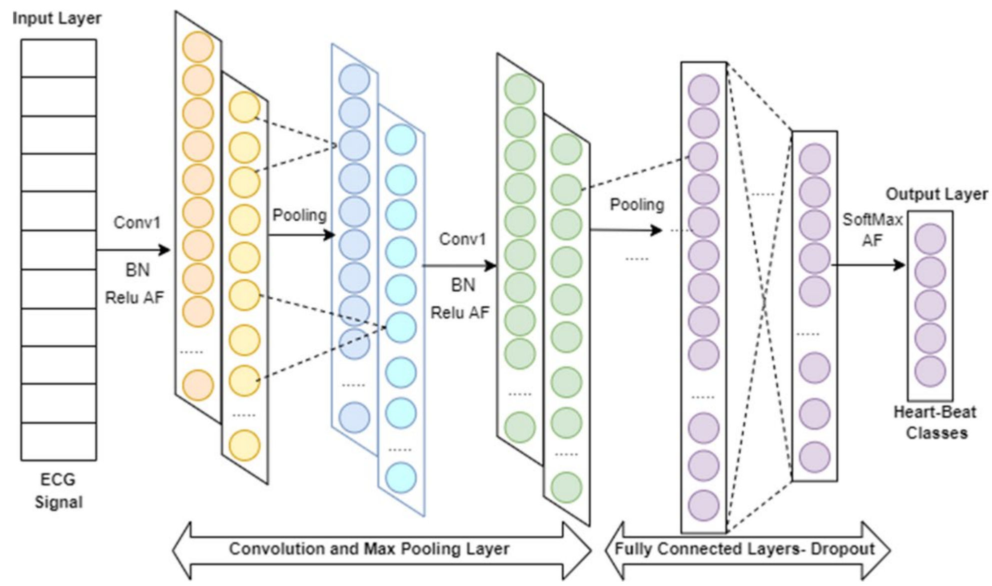

Fig. 1 *CNN architecture*

For the training of the model, the CNN model was optimized using the training data. The training process was optimized with the early stopping method by evaluating the accuracy and loss of the model after each epoch. Adam optimizer was preferred as the optimization algorithm used during training. The learning rate was carefully adjusted so that the model could achieve more efficient results during the learning process. In the training process, the dropout method (random resetting of weights) was also applied to improve the classification success.

The performance of the model was evaluated with metrics such as accuracy, sensitivity, specificity and F1 score. In addition, the confusion matrix was used to visualize the correct and incorrect classifications of the model [25]. To improve the performance, hyperparameter adjustments were made and the best model parameters were selected.

3.5 Adam Optimizer

Adam (Adaptive Moment Estimation) is a widely used algorithm for optimizing deep learning models. Considered as an improved version of traditional methods such as stochastic gradient descent (SGD), Adam determines adaptive learning rates for each parameter, allowing the model to learn faster and more stably. This optimization method performs parameter updates using first moment (mean) and second moment (variance) estimates for each parameter. In this way, it offers a more efficient and effective learning process.

The main advantages of the Adam algorithm include fast convergence, adaptive learning rate utilization and low memory consumption. First, it allows the model to learn more efficiently by adjusting the learning rates to each parameter. This is an important advantage, especially when working with large data sets and complex models. Furthermore, by updating the learning rate for each parameter, it can improve the overall performance of the model and allow it to generalize better [26,27]. Adam uses memory efficiently by storing previous gradient information, optimizing memory usage when working with large data sets. This is especially important when training deep learning models. As a result, the Adam algorithm speeds up the learning process by increasing stability, which allows the model to be trained in less time. Therefore, it is one of the preferred optimizers, especially in large-scale projects and time-limited studies.

4. Experimental Results

Figure 2 shows the distribution of classes in the dataset in bar chart format, revealing a clear imbalance in the dataset. The Y-axis represents the number of samples belonging to each class and the X-axis represents the class categories. The results show that class 0 (normal heartbeat) contains the vast majority of samples in the dataset. In contrast, classes 1, 2, 3 and 4 contain a considerably lower number of samples compared to class 0. In particular, class 3 is the least represented category in the dataset.

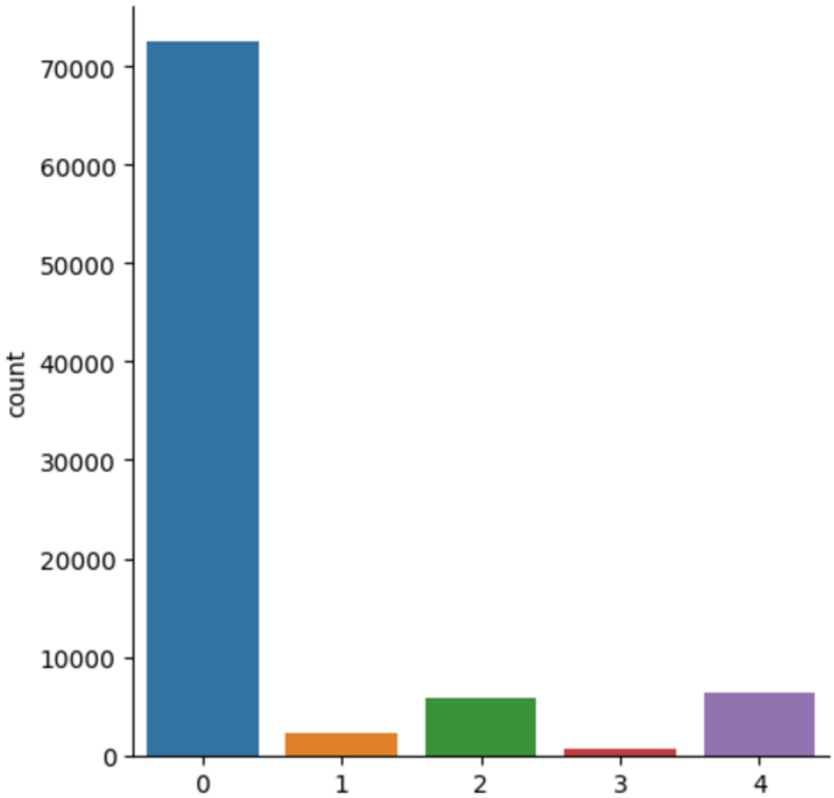

Fig. 2 *Unbalanced class distribution in heart rhythm*

This unbalanced class distribution is an important factor that can directly affect the performance of classification models. Underrepresented classes can make it difficult for the model to accurately learn and predict data in these categories. This can lead to higher error rates, especially for unbalanced classes. In such datasets, data augmentation techniques (e.g., methods such as SMOTE) or sampling strategies can be used to improve model performance and ensure accurate classification of minority classes. Furthermore, the integration of weighted loss functions can alleviate the imbalance problem by allowing the model to give more importance to minority classes. In this context, analyzing the class imbalance in the dataset and applying appropriate methods is critical to improve the accuracy and generalizability of the models to be developed for heart rhythm analysis. For this reason, the data was increased and a situation as shown in Figure 3 was obtained and re-analyzed.

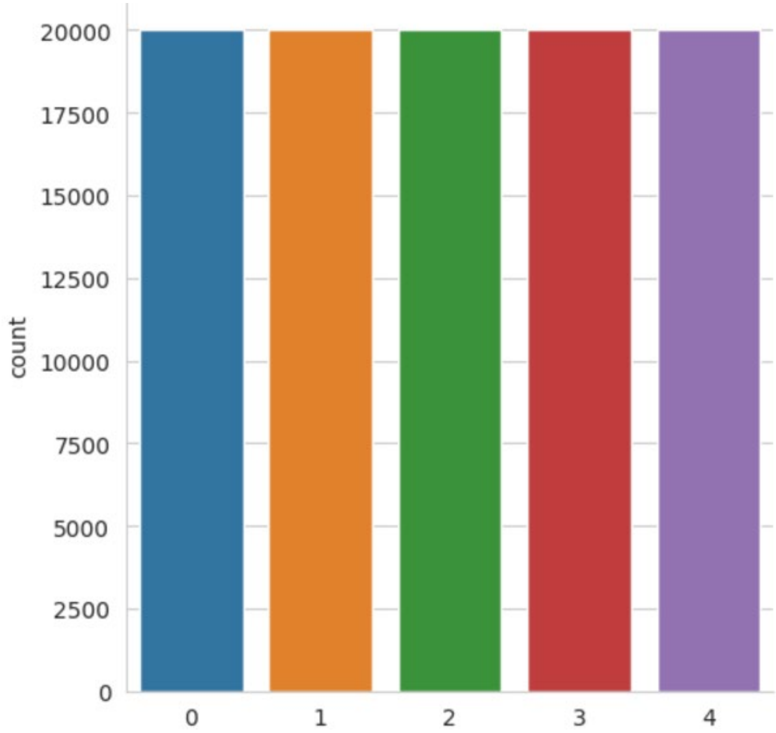

Fig. 3 *Distribution obtained with data augmentation*

Figure 4 shows the time and amplitude differences between normal heartbeats and supraventricular ectopic beats. The horizontal axis represents the time dimension of the heartbeats in milliseconds (ms), while the vertical axis reflects the normalized amplitude of the heartbeats. In the graph, the red color represents normal heartbeats, which are regular and physiologically stable. These beats show a regular fluctuation around low amplitude values (~0.2). In contrast, supraventricular ectopic beats, shown in blue, are characterized by a much higher amplitude, especially in the 0-25 ms range, and contain marked irregularities. These differences in peaks and fluctuations clearly demonstrate the abnormalities in electrical conductivity of supraventricular ectopic beats.

Such distinctive signals provide discriminative features that can improve the classification performance of deep learning-based convolutional neural network (CNN) models. In particular, the high amplitude values and irregular wave patterns of supraventricular ectopic beats provide a powerful learning resource for the model to detect these abnormalities. These results suggest that CNN-based approaches can be an effective tool for early detection and classification of rhythm disorders.

Figure 5 visualizes the time and amplitude differences between normal heartbeats and ventricular ectopic beats. The horizontal axis represents the time dimension in milliseconds (ms), while the vertical axis shows the normalized amplitude values of the heartbeats. Normal heartbeats, shown in red, reflect physiological normality, exhibiting a steady and regular fluctuation of approximately 0.2 amplitude. In contrast, ventricular ectopic beats, shown in blue, have markedly higher amplitudes and distinct patterns, especially in the 0-25 ms and 75-100 ms intervals. The wave patterns of ventricular ectopic beats are characterized by a higher amplitude (range approximately 0.6-1.0) and irregularity compared to normal beats. This suggests that ventricular ectopic beats reflect abnormalities in cardiac electrical activity and potential pathological processes. These pattern differences play a critical role for deep learning-based CNN models to recognize discriminative features. In particular, the high amplitude and fluctuation irregularities characteristic of ventricular ectopic beats provide an effective learning resource for the model to successfully detect such rhythm disturbances. These findings support the ability of CNN to detect and classify ventricular ectopic beats with high accuracy.

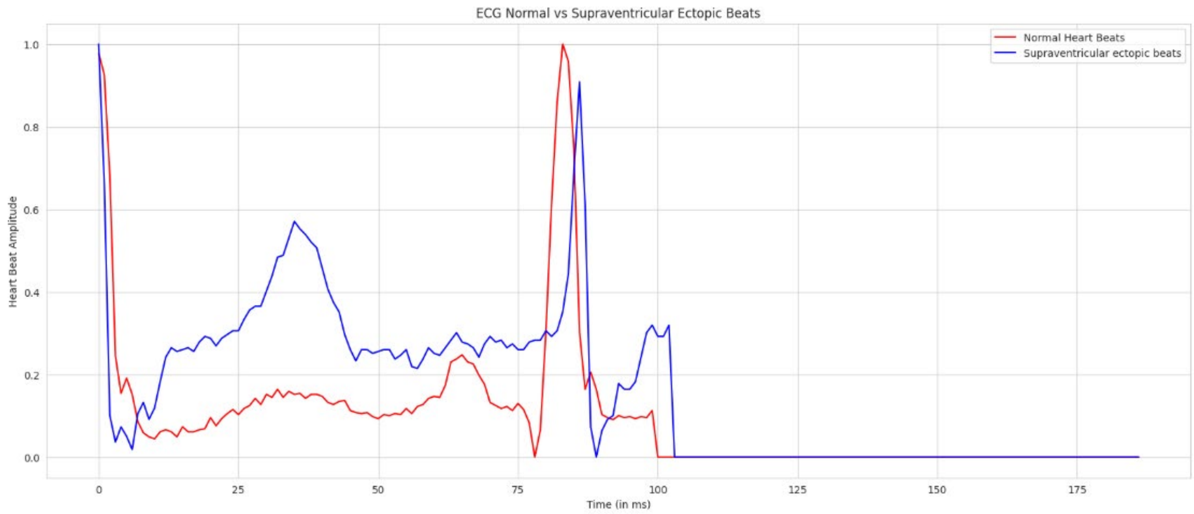

Fig. 4 *Time and amplitude differences between normal heartbeats and supraventricular ectopic beats*

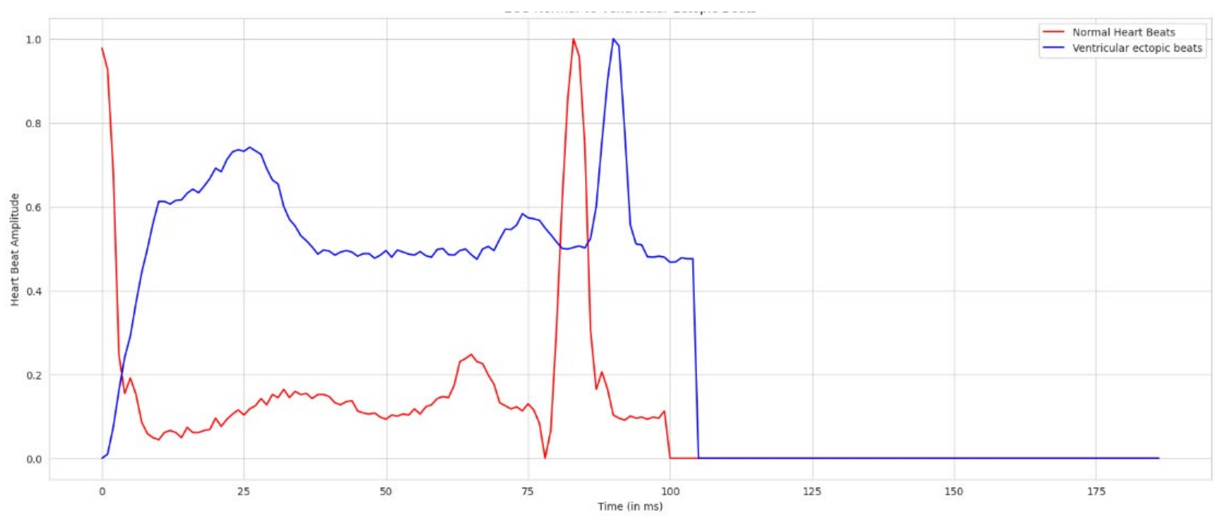

Fig. 5 *Time and amplitude differences between normal heartbeats and ventricular ectopic beats*

The presented 1D convolutional neural network (CNN) architecture uses Conv1D, BatchNormalization, MaxPooling1D, Flatten and Dense layers to classify time series data such as heart rhythm disturbances. Conv1D layers extract meaningful features while reducing the data size and have a total of 62,048 parameters. BatchNormalization layers increase the learning speed, while MaxPooling1D layers reduce the data size. The Dense layers perform the classification and have a total of 28,825 parameters. The model offers a lightweight and efficient structure with 92,069 total parameters (91,621 learnable). This architecture is effective and computationally efficient for diagnosing heart rhythm disorders. Details of the model are given in Table 1.

Table 1 *Details of the proposed model*

Layer (Type)	Output Shape	Number of Parameters (Param #)	Description
Conv1D	(None, 187, 64)	448	1D convolution layer with 64 filters
BatchNormalization	(None, 187, 64)	256	Normalizes the data for faster learning
MaxPooling1D	(None, 94, 64)	0	Reduces data size through pooling
Conv1D	(None, 94, 64)	24,640	1D convolution layer with 64 filters
BatchNormalization	(None, 94, 64)	256	Normalizes the data for faster learning
MaxPooling1D	(None, 47, 64)	0	Reduces data size through pooling
Conv1D	(None, 47, 64)	24,640	1D convolution layer with 64 filters
BatchNormalization	(None, 47, 64)	256	Normalizes the data for faster learning
MaxPooling1D	(None, 24, 64)	0	Reduces data size through pooling
Conv1D	(None, 24, 32)	12,320	1D convolution layer with 32 filters
BatchNormalization	(None, 24, 32)	128	Normalizes the data for faster learning
MaxPooling1D	(None, 12, 32)	0	Reduces data size through pooling
Flatten	(None, 384)	0	Flattens the data into a 1D array
Dense	(None, 64)	24,640	Fully connected layer with 64 neurons
Dense	(None, 5)	325	Fully connected output layer for 5 classes

In this study, the performance of a machine learning model for heart rhythm classification is analyzed with a complexity matrix. The matrix examines whether the model correctly or incorrectly classifies different rhythm classes. Class 0 showed the highest success with 17912 correct predictions. However, the accuracy rate decreases significantly in other classes. For example, in class 1 and class 4, the correct classification rates are limited to 484 and 1590, respectively. Mispredictions are often shifted to neighboring classes, suggesting that the model has difficulty discriminating between some classes. These results suggest that the model could be improved by using additional data processing methods or more complex algorithms to increase its overall accuracy. Figure 6 shows the confusion matrix.

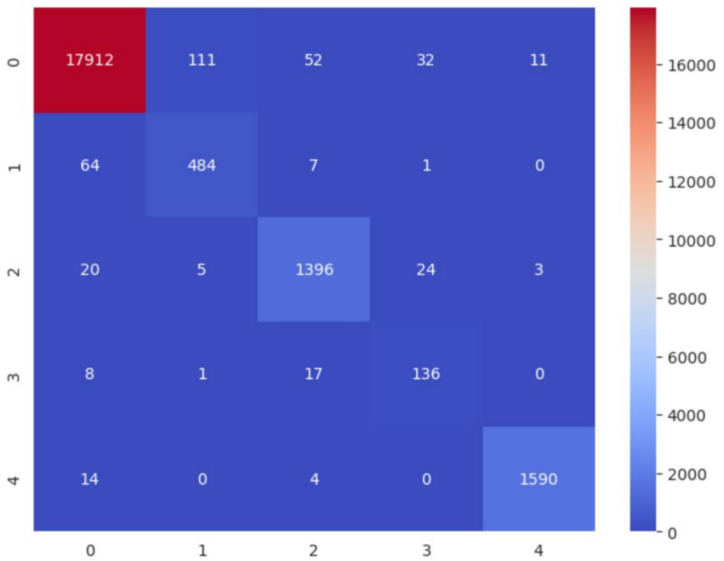

Fig. 6 *Confusion matrix*

The graphs obtained provide a comprehensive evaluation of the model's performance during the training process. The training accuracy increased rapidly from the first epochs and reached almost 100% after 50 epochs. This shows that the model performs quite well on the training data. However, when compared to the validation accuracy, it is observed that the model is at risk of overfitting. The validation accuracy, although generally increasing, followed a more fluctuating trend compared to the training accuracy. These fluctuations indicate that the model performs erratically on the validation data and has generalization problems on some data subsets. The relatively small difference between training accuracy and validation accuracy suggests that the generalization capacity of the model is acceptable. However, the fluctuations in the validation accuracy and the fact that it does not reach full stability indicate that the performance of the model should be optimized by using regularization methods or more data.

Another evaluation focuses on the loss and validation loss values of the training process. The training loss decreases rapidly from the first epochs and reaches almost zero after 50 epochs. This shows that the model can effectively minimize the error rate on the training data. However, although the validation loss initially decreased, it fluctuated after a certain point and tended to increase as the epochs progressed. The significant difference between the training loss and the validation loss indicates that the model overlearns and exhibits poor generalization performance on the validation data. These results suggest the application of regularization methods or early stopping strategy to improve the performance of the model on the validation set. Furthermore, strategies such as increasing the diversity of the dataset or reducing the complexity of the model may also be effective to control the increasing trend in validation loss.

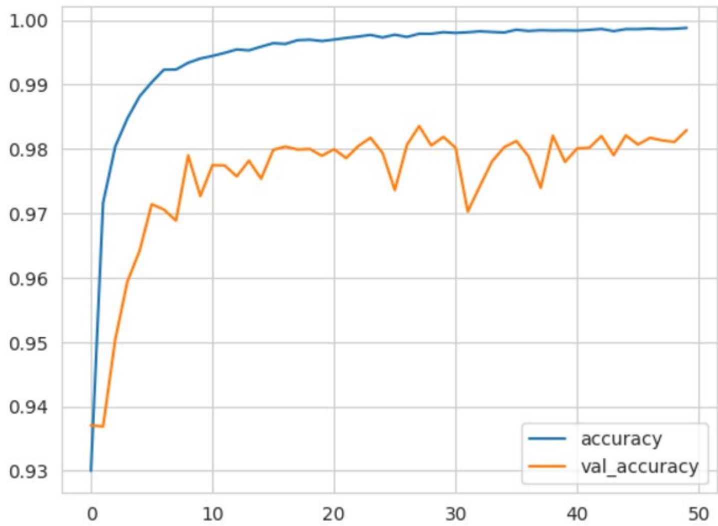

Fig. 7 *Accuracy graph of the model*

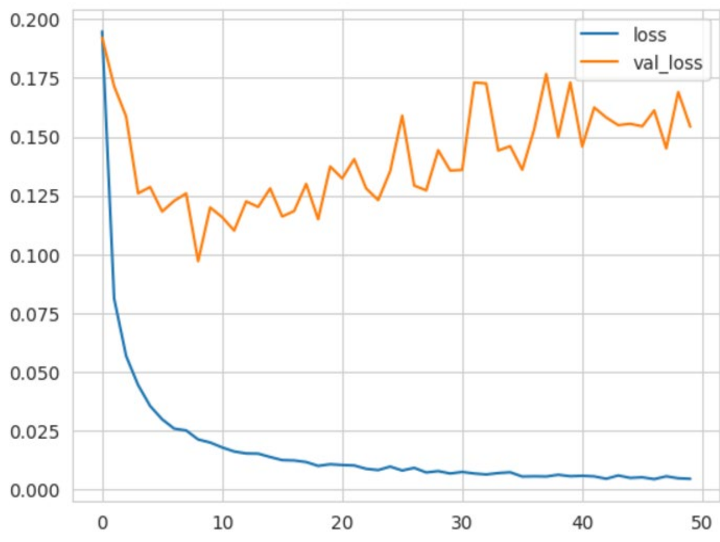

Fig. 8 *Loss graph of the model*

The main metrics used to evaluate the classification performance of the model are presented in Table 2. It is seen that the model has a high performance with an overall accuracy rate of 98%. In the class-based analysis, Precision, Recall and F1-Score values were calculated as 0.99 in the "Normal" class (Class 0) and this class was the class with the highest performance. This shows that the model is quite successful in distinguishing normal cases. Similarly, the same high performance values were obtained for "Other Abnormalities" (Class 4) (Precision, Recall and F1-Score: 0.99). However, it was observed that the model performance was lower in the "Low Frequency Anomalies" (Class 1) and "High Frequency Anomalies" (Class 3) classes compared to the other classes. Especially in Class 3, Precision was calculated as 0.70 and F1-Score was calculated as 0.77, revealing the effect of unbalanced distribution in the dataset.

Table 2 *Metrics used to evaluate the classification performance of the model*

	Precision	Recall	Fr-score	Support
0	0.99	0.99	0.99	18118
1	0.81	0.87	0.84	556
2	0.95	0.96	0.95	1448
3	0.7	0.84	0.77	162
4	0.99	0.99	0.99	1608
Accuracy			0.98	21892
Macro avg	0.89	0.93	0.91	21892
Weighted avg	0.98	0.98	0.98	21892

The Macro Average results show that the Precision, Recall and F1-Score values of the model are 0.89, 0.93 and 0.91 respectively when each class is given equal weight. However, the Weighted Average results are 0.98 for each of Precision, Recall and F1-Score. This implies that the classes that are heavily represented in the dataset contribute significantly to the overall performance. It is recommended that data imbalance should be eliminated and data augmentation methods should be applied to improve performance, especially in underrepresented categories such as Class 3. The results show that the model has a strong performance in general, but needs improvement for underrepresented classes. Table 3 presents the performance of the proposed model in comparison with various contemporary methods. The table includes an evaluation of the methods used for arrhythmia detection using key performance metrics such as accuracy (Accuracy, Acc), precision (Precision, Prec), recall (Recall, Rec) and F1 score (F1).

Table 3 *Performance comparison of arrhythmia detection techniques*

Methods	Acc	Prec	Rec	F1
Sharma et al. [24]	0.95	0.99	0.92	0.95
Acharaya et al. [25]	0.82	0.77	0.93	0.85
Bhagyalakshmi et al. [26]	0.84	0.82	0.88	0.86
Proposed Model	0.98	0.99	0.98	0.98

The proposed model outperformed the other methods in all metrics. In particular, the accuracy (0.98), precision (0.99), sensitivity (0.98) and F1 score (0.98) achieved the highest values, indicating that the proposed model provides a more reliable and effective solution for arrhythmia detection than other methods. Table 4 presents an analysis comparing the performance of different arrhythmia detection methods using four key evaluation metrics (accuracy, precision, sensitivity and F1 score). The results show that the Proposed Model performs the best on all metrics. The Proposed Model performs best on critical metrics such as accuracy (0.98), precision (0.99), sensitivity (0.98) and F1 score (0.98), making it the most efficient and reliable solution for arrhythmia detection. Sharma et al. (0.95 accuracy, 0.99 precision, 0.92 sensitivity, 0.95 F1 score) shows high performance, but slightly lower in terms of sensitivity. Bhagyalakshmi et al. (0.84 accuracy, 0.82 precision, 0.88

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sensitivity, 0.86 F1 score) and Acharaya et al. (0.82 accuracy, 0.77 precision, 0.93 sensitivity, 0.85 F1 score) have lower accuracy and precision, but still show strong performance.

These results emphasize that the proposed model offers a more reliable, sensitive and superior overall performance approach for arrhythmia detection. It demonstrates the contribution of innovative machine learning-based architectures to accurate classification and overall diagnostic processes.

5. Conclusion

In this paper, we propose a novel deep learning-based model for arrhythmia detection and demonstrate its superior performance compared to existing techniques. Experiments on standard datasets such as the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Dataset show that the proposed model achieves superior results in terms of accuracy, precision, sensitivity and F1 score. The integration of data augmentation and powerful preprocessing methods enables the model to effectively handle variations in the input data, while its architecture successfully captures complex patterns in ECG signals. The obtained results emphasize the robustness and reliability of the proposed model, making it a valuable tool for clinical applications. By providing accurate and timely arrhythmia detection, this approach has the potential to offer healthcare professionals important support in the diagnosis and management of cardiovascular diseases. Furthermore, the findings reveal the importance of using advanced machine learning algorithms and deep learning architectures to improve diagnostic accuracy and patient outcomes in the biomedical field. Future work could aim to extend the applicability of the model to other cardiovascular diseases, increase its generalizability to different populations, and integrate it into real-time diagnostic systems. This study provides a solid foundation for the development of AI-based solutions in cardiovascular healthcare.

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Conflict of Interest

Authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Author 1, Author 2;* ***data collection:*** *Author 1;* ***analysis and interpretation of results:*** *Author 2.*

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