ECG Arrhythmia Classification and Interpretation using Convolutional Networks for Intelligent IoT Healthcare System

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Abstract

In modern healthcare, timely and precise diagnosis of arrhythmias can significantly impact patient outcomes, as arrhythmias are indicative of various cardiac disorders that require immediate attention. The classification of these irregular heartbeats based on electrocardiogram (ECG) signals is essential for the development of intelligent healthcare systems that can provide real-time monitoring and diagnosis, integrating seamlessly into smart city infrastructures and IoT-enabled smart homes. In this paper, we propose novel methods to enhance the classification and interpretation of arrhythmia by ECG signals based on convolutional neural network (CNN). Leveraging the MIT-BIH Arrhythmia Database, which includes 48 recordings from 47 patients, the proposed approach involved preprocessing the ECG signals into fragments and enhancing the CNN architecture with Batch Normalization layers and an additional convolutional layer. The network was trained and validated using statistical metrics namely accuracy, precision, recall, and F_1-scores. The results demonstrated an overall classification accuracy of 99.43%, with particularly high precision and recall for Normal beats, Right bundle branch block beats, and Left bundle branch block beats, achieving F_1-scores close to 100%. The introduced CNN showed superior performance in distinguishing between nine types of arrhythmias. However, the study highlighted the limitation of relying on clinical features for decision justification, especially in cases of overlapping pathologies. Overall, the findings suggest that the proposed approach can serve as a reliable supporting tool for arrhythmia diagnosis, offering high accuracy and potential integration into real-time monitoring systems.

Keywords

ECG classification, ECG interpretation, arrhythmia detection, convolutional neural networks, IoT healthcare, intelligent systems

1. Introduction

Over a vast period, healthcare professionals have relied on a multitude of measurements presented as time series to diagnose the state of the human body. Among these, the electrocardiogram (ECG) is crucial for diagnosing heart diseases. In the current era, the proliferation of computing devices, including those belonging to the Internet of Things (IoT),

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has essentially facilitated the collection of such signals [1]. Wearable devices and other IoT technologies enable the recording and storage of large volumes of ECG data, facilitating its reuse for various research purposes and expanding the range of consumers of this information [2, 3]. This shift highlights the critical need for efficient processing and accurate decision-making based on these signals.

Within the domain of IoT systems, the ability to process and analyze vast amounts of data from connected devices is crucial. Deep learning (DL) models [4], particularly convolutional neural networks (CNNs) [5], have emerged as powerful tools for addressing tasks related to ECG signal analysis and arrhythmia classification [6]. The use of CNNs in this context allows for the automated and highly accurate interpretation of ECG signals, making them invaluable in IoT healthcare systems. These intelligent systems enhance the capability of IoT devices to not only monitor but also provide actionable insights in real-time, significantly improving health outcomes and preventive care.

However, the sensitivity of medical diagnoses necessitates not only high accuracy but also the ability to explain and interpret the decisions made by these AI models, a field known as explainable artificial intelligence (XAI) [7]. The integration of CNNs with XAI techniques ensures that healthcare professionals can trust and understand the AI-driven insights [8], thus, enhancing the reliability and acceptance of these advanced diagnostic tools in real-world applications [9]. In the context of IoT systems, this ensures that the data collected by smart devices is not only used effectively but also transparently [10], fostering trust and broader adoption of IoT-enabled healthcare solutions [11, 12].

In the field of ECG classification using DL models, several studies have made significant contributions, each with unique methodologies and insights. Xu and et al. [13] developed a neural network classifier that identifies five classes, including an “all other” class. However, the inclusion of the “all other” class can lower overall accuracy due to the broad range of signals it encompasses, potentially leading to less specificity for certain pathologies. Degirmenci et al. [14] achieved high accuracy using a 64x64 input data size for arrhythmic heartbeat classification. Despite this, the significant computational resources required pose challenges for real-time applications and use on devices with limited processing power. Abdelhafid et al. [15] focused on ECG arrhythmia classification using five classes without an “all other” class. This likely contributed to their high classification rates. However, the exclusion of a miscellaneous class may not reflect real-world accuracy, as it ignores signals that do not fit predefined categories.

In addition to the above, Zhang et al. [16] presented an interpretable DL model for diagnosing 12-lead ECGs. Their work stands out for its interpretability and comprehensive analysis of multiple leads, offering detailed insights into the diagnostic process. However, the complexity of their model may hinder its use in simpler or more resource-constrained settings, as high interpretability often comes at the cost of computational efficiency. Singh and Sharma [17] proposed a deep CNN for arrhythmia interpretation and classification, demonstrating high accuracy and efficiency. However, like other studies, they face challenges in real-time application due to computational demands. Additionally, their work does not address the classification of signals that do not fit predefined classes, which is crucial for practical deployment.

Overall, as stated above, the field of ECG classification using DL models faces several challenges [18]. For effective arrhythmia detection, it is crucial to develop DL models that might balance accuracy, computational feasibility, and the ability to handle a wide range of signals, ensuring practicality and robustness in real-world applications. Thus, to overcome these issues, this study aims to enhance the classification and interpretation of arrhythmia based on ECG signals using deep CNN. The main contributions of this work include:

- The proposed method for classifying heart activity disorders (arrhythmias) based on ECG signals, which differs from known methods due to a modified neural network architecture, which is designed to identify nine types of arrhythmias, the volume of input data, and the expansion of the list of classes, resulting in improved classification quality.
- The proposed method for interpreting the classification results of arrhythmias obtained using a DL model, which allows presenting the classification results in a form understandable to the doctor.

The structure of this paper is organized as follows: The Methods section details the proposed method for classifying pathologies in the ECG signal and the proposed method for interpreting the classification results in a manner, understandable to medical professionals. The Results section presents the classification and interpretation results demonstrating the effectiveness of the proposed methods. Finally, the manuscript concludes with the Conclusions section summarizing the findings and discussing future research directions.

2. Methods

2.1. Method for classification of pathologies on the ECG signal

The proposed method for classifying pathologies in the ECG signal is schematically shown in Figure 1.

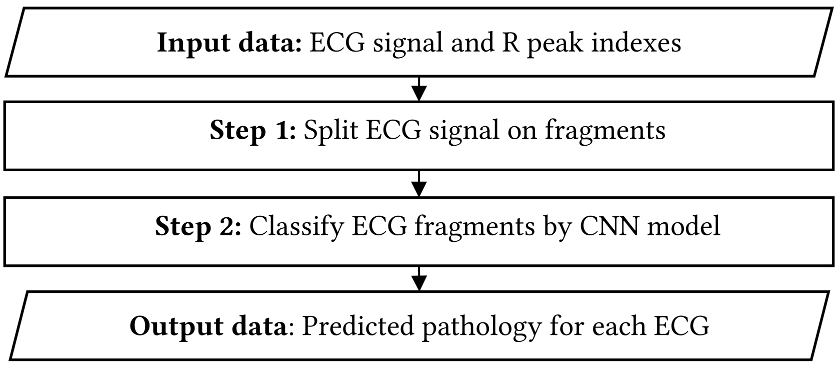


Figure 1: Schema of the ECG signal classification method for detecting arrhythmia pathologies, beginning with input data of the ECG signal and R peak indexes, followed by splitting the ECG signal into fragments (Step 1), classifying each fragment using a CNN model (Step 2), and resulting in output that reaffirms the initial input data for continuous analysis.

Input Data for the Method:

- ECG Signal: A one-dimensional array S that represents the amplitude of the electrical signal measured at specific moments in time for a given lead. The recordings were digitized at 360 samples per second with 11-bit resolution within the range of 10 mV.
- Indices of R-Peaks: A one-dimensional array P, where each element p_i matches the index i in the array S, where an R-peak occurs.

Output Data: The predicted pathology.

Below, we examine the main steps of the proposed method.

2.1.1. Splitting the ECG signal into fragments

The first step of the method is aimed at preprocessing the input data and forming a fragment suitable for classification. Based on domain knowledge from the medical field, it is necessary to consider not just the current cardiac cycle but also the preceding and succeeding cardiac cycles to make an accurate decision regarding a specific pathology [19]. Examples of input ECG signal fragments are shown in Figure 2.

Figure 2: Examples of the input fragments of the ECG signal: (a) ECG-signal with the normal beat, (b) ECG-signal, representing the right bundle branch block beat, (c) ECG-signal with the left bundle branch block beat, and (d) ECG-signal, which represent the paced beat.

As illustrated in Figure 2, the fragment of the signal should contain information on both the current cardiac cycle (the primary object of classification) and the preceding and subsequent cardiac cycles. Therefore, the fragment should be constructed to include three cardiac cycles, with the primary cardiac cycle located in the middle. Preliminary experimental studies [20] have shown that 700 signal samples are required to represent the three cardiac cycles (for this input signal format).

The formed ECG signal fragments are transferred to the second step of the method for further classification using the CNN model.

2.1.2. Classification of ECG fragments with the CNN model

In the current step of the proposed method, the classification of ECG signal fragments is carried out using a CNN. This work proposes an enhancement of the CNN architecture for a similar ECG signal classification task presented in [13], but with different input sample types. The authors claimed a numerical result with an overall accuracy of 99.43%. Note that the stated architecture was used for a limited number of classes. The proposed CNN architecture is shown in Figure 3.

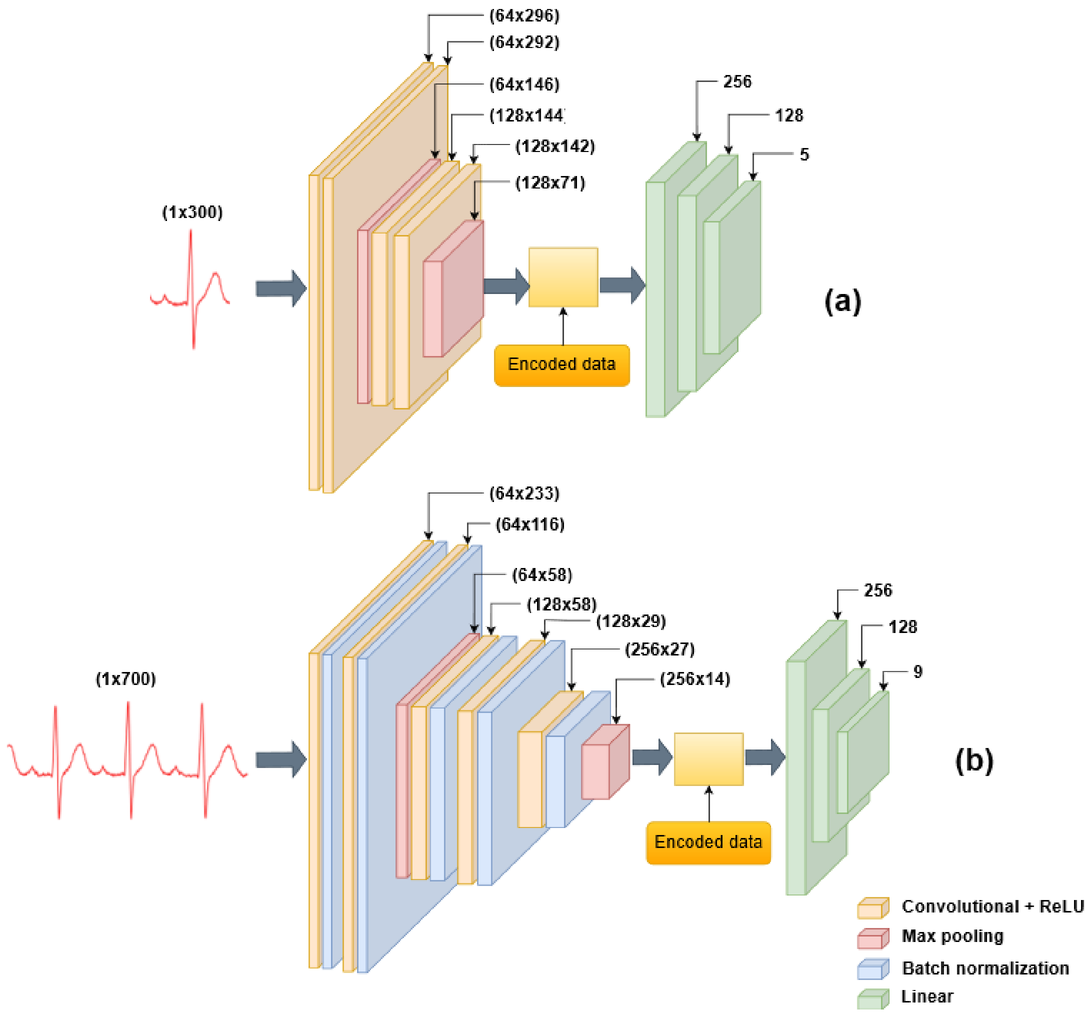


Figure 3: The CNN architecture for ECG classification, showing (a) the original model [12] and (b) the improved model, each detailing the input size, convolutional layers with ReLU activation, max pooling, batch normalization, encoded data, and linear layers for the classification output.

To achieve better results and extend the classes of pathologies, we propose the following improvements to the CNN architecture: (i) adding Batch Normalization layers after each convolutional layer, (ii) adding an additional convolutional layer, and (iii) optimizing hyperparameters for the main CNN layers.

The final version of the improved network architecture contains 1,147,081 trainable parameters. For comparison, the network proposed in [13] uses 1,045,213 parameters. The difference is 101,868 parameters. Considering the input data size increased from 300 to 700 and the number of classification classes increased (from 5 to 9), this increase in training parameters is negligible.

Additional work was conducted to find the optimal hyperparameters for the neural network layers for ECG signal pathology classification. Libraries PyTorch Lightning [21] and Optuna [22] were used for hyperparameter optimization.

The classification result obtained by the considered method is forwarded for the interpretation of the classification results by the method considered in the next section.

2.2. Method of interpretation of classification results

Given the sensitivity of decision-making in the medical field and the opacity of decisions made by proposed DL tools (decisions are made through an opaque "black box" mechanism), there is a need to explain the results in a form understandable to the doctor. The proposed interpretation method will be described as follows:

1. General concept of the proposed approach.
2. Criteria by which the doctor determines a specific pathology on the ECG signal.
3. Establishing the method of providing these criteria to the doctor in the parameters of the input ECG signal supplied to the DL model.

The proposed method is schematically depicted in Figure 4.

Next, we will examine the stages of the interpretation method in detail. The main concept of the developed method is aimed at explaining the classification results in an accessible form using features that the doctor uses to diagnose pathologies on the ECG signal. These are specific features that the doctor can see on the input signal (cardiac cycle) and which, in a certain way, allow the doctor to agree or disagree with the decision made by the DL model.

In the process of determining a specific pathology on the ECG signal, the doctor considers various features that indicate possible pathologies. These features are predefined for each type of pathology and may all be present together or only some of them, based on which the doctor makes the final decision.

The input information of the interpretation method is the cardiac cycle signal in the form in which it was supplied to the input of the neural network classifier (Figure 4) and the class of pathology determined by the same classifier.

Step 1: Empirically determine the fragment of the input signal (attention zone) that may contain information about the feature.

Step 2: The goal is to choose a means by which the doctor will be informed about the presence or absence of a feature on the signal fragment. The selection of the means is carried out by sequentially analyzing the information according to the criteria presented below.

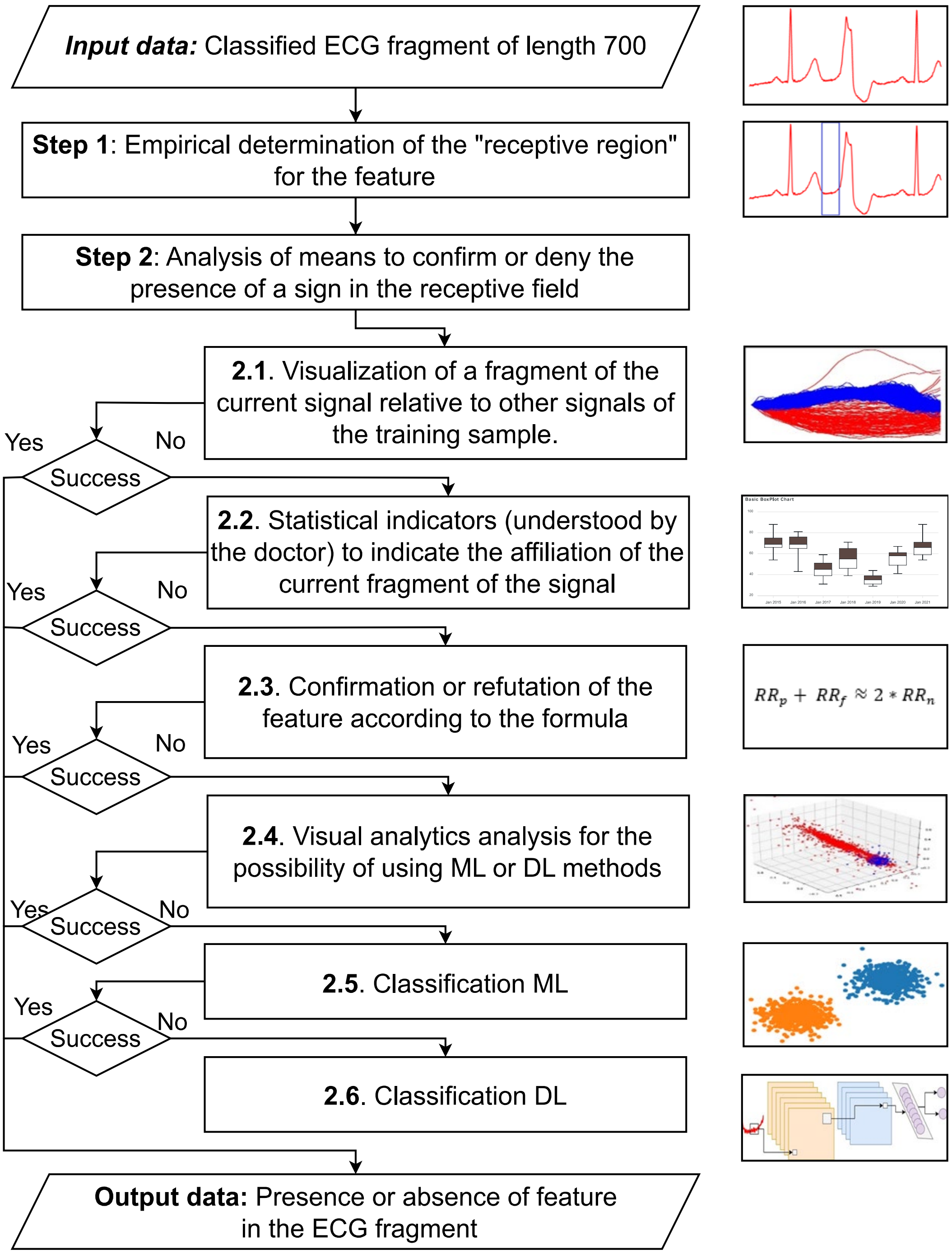


Figure 4: The proposed interpretation method for ECG fragments involves empirically determining the receptive region for the feature (Step 1), followed by analyzing means to confirm or deny the presence of a sign in the receptive field (Step 2), ultimately determining the presence or absence of the feature in the ECG fragment.

- Is it possible to obtain a solution through the visual representation (in various ways) of the signal fragment against similar fragments of the training set (labeled by two classes: i) the considered pathology or ii) norm and all other pathologies)?
- Is it possible to obtain a solution through statistical indicators understandable to the doctor?
- Is it possible to obtain a solution through the formulas?
- Is it possible to obtain a solution through visual analytics tools like Principal Component Analysis (PCA) [23], Multidimensional Scaling (MDS) [24], t-Distributed Stochastic Neighbor Embedding (t-SNE) [25], etc.)?
- Is it possible to obtain a solution through classifiers built for such cases using machine learning (ML) models?
- Is it possible to obtain a solution through classifiers built for such cases using DL models?

The result and output information of the proposed interpretation method is the presence (or absence) of a feature in the current fragment of the ECG signal.

2.3. Dataset

In this work, we use an ECG signal sample based on the MIT-BIH Arrhythmia Database. The MIT-BIH Arrhythmia Database was created for research in the field of automatic arrhythmia recognition. It was developed at the Laboratory for Computer Science and Artificial Intelligence at the Massachusetts Institute of Technology in conjunction with the Beth Israel Hospital Medical Center (now Beth Israel Deaconess Medical Center). The database includes 48 records, each 30 minutes long, taken from 47 different patients. At the same time, experts (cardiologists) commented on each cardiac cycle, thus forming an annotation that allows assessing and validating the results of arrhythmia detection approaches.

In this work, all signals from the database were divided into smaller segments with a length of 8000. The resulting sample of signals was divided into training and test samples in a ratio of 80% to 20%. Table 1 shows the quantitative distribution of each class of pathologies in the training and test samples.

In Table 1, the class names correspond to the annotation of the MIT-BIH Arrhythmia database, and have the following interpretation:

- Class 1: N – Normal beat.
- Class 2: R – Right bundle branch block beat.
- Class 3: L – Left bundle branch block beat.
- Class 4: / – Paced beat.
- Class 5: V – Premature ventricular contraction.
- Class 6: F – Fusion of ventricular and normal beat.
- Class 7: f – Fusion of paced and normal beat.
- Class 8: A – Atrial premature beat.
- Class 9: NA – Others.

Table 1
Quantitative distribution of classes in the training and testing samples of the MIT-BIH Arrhythmia Database

Class name / Dataset	N	R	L	/	V	F	f	A	NA
Training samples	36,971	3,458	3,469	3,148	2,937	389	444	1,175	189
Testing samples	12,784	1,657	959	1,224	1,097	168	141	476	89

2.4. Evaluation criteria

In this section, we provide evaluation criteria that were used to assess the performance of the proposed multi-class classification CNN model using several standard metrics: accuracy, precision, recall, and F_1-score that are computed based on the concepts of true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN) for each class.

Accuracy measures the overall correctness of the model. It is the ratio of the correctly predicted instances to the total instances.

$$\text{Accuracy} = \frac{\sum_{i=1}^{K} \text{TP}_i}{\sum_{i=1}^{K} (\text{TP}_i + \text{FP}_i + FN_i)}, \tag{1}$$

where K is the number of classes, i stands for the index of each class.

Precision, also known as Positive Predictive Value, is the ratio of correctly predicted positive instances to the total predicted positives.

$$\text{Precision}_i = \frac{\text{TP}_i}{\text{TP}_i + \text{FP}_i}, \tag{2}$$

Recall, or Sensitivity, is the ratio of correctly predicted positive instances to all actual positives. It measures the model's ability to identify positive instances.

$$\text{Recall}_i = \frac{\text{TP}_i}{\text{TP}_i + \text{FN}_i}, \tag{3}$$

The F_1-score is the harmonic mean of precision and recall, providing a balance between the two metrics.

$$F_1 - score_i = 2 \times \frac{\text{Precision}_i \times \text{Recall}_i}{\text{Precision}_i + \text{Recall}_i}. \tag{4}$$

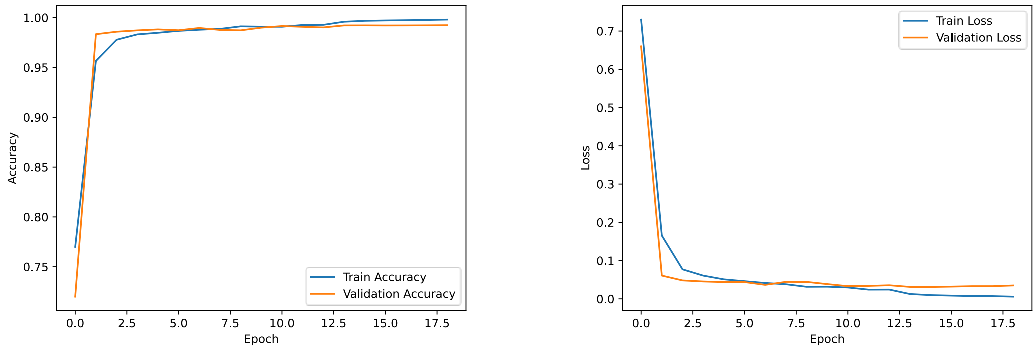
Metrics (1)–(4) allow us to comprehensively evaluate the performance of our multi-class classification model, providing insights into its strengths and weaknesses.

3. Results

3.1. Classification results

The classification results of the proposed deep convolutional network (CNN) for arrhythmia interpretation are visually represented below. These results highlight the model's performance across different classes of ECG signals, demonstrating its effectiveness and accuracy.

Figure 5 illustrates the training and validation accuracy and loss curves during the training process of the CNN model.



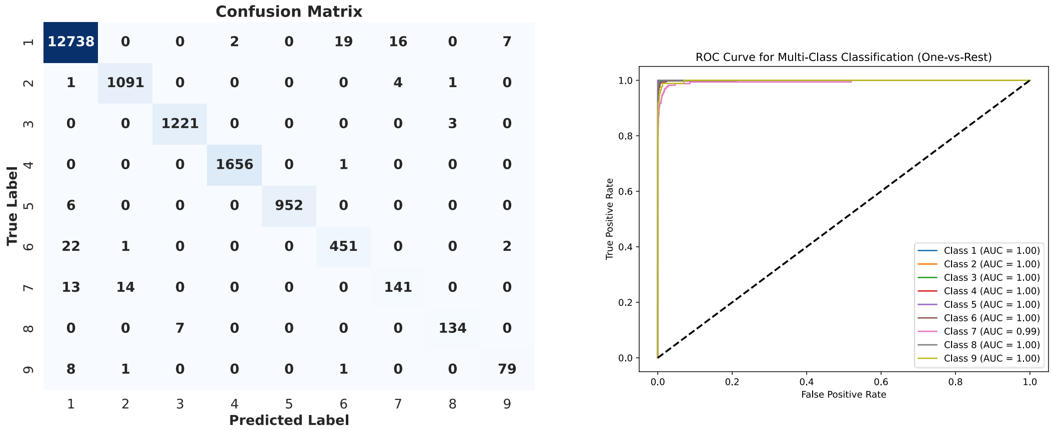
(a) **(b)**

Figure 5: Accuracy and loss curves that represent (a) training and validation accuracy and (b) training and validation loss while training the CNN model.

In Figure 5(a), the training and validation accuracy show a steady increase, reaching a high plateau as the epochs progress. This indicates that the model is learning effectively and achieving high accuracy on both the training and validation datasets. Figure 5(b) complements this by showing a consistent decrease in both training and validation loss, suggesting that the model is not only learning but also generalizing well to unseen data. The minimal overfitting observed here is crucial for the model's reliability in real-world applications.

The confusion matrix and ROC-curved presented in Figure 6 provide a detailed view of the model's performance across different classes of ECG signals.

Figure 6(a) presents a confusion matrix that provides a detailed overview of the proposed CNN performance in classifying nine classes of ECG signals. The high true positive rates along the diagonal indicate the model's ability to accurately classify the majority of ECG signal types, demonstrating its effectiveness in distinguishing between different arrhythmias. The minimal off-diagonal elements reflect a low rate of misclassification, underscoring the robustness and precision of the CNN model. Complementing this, Figure 6(b) showcases the ROC curves for multi-class ECG classification, illustrating the model's discriminative capability across different classes. The ROC curves, which plot the true positive rate against the false positive rate, exhibit high area under the curve (AUC) values, indicating the model's strong performance in achieving high sensitivity and specificity. Together, these figures validate the proposed CNN model's efficiency in accurately classifying arrhythmias, highlighting its potential for reliable real-world applications in medical diagnostics.



(a) **(b)**

Figure 6: Classification results: (a) confusion matrix obtained by the proposed CNN model based on the testing dataset; (b) ROC-curves for multi-class ECG classification.

Furthermore, Table 2 details the precision (2), recall (3), and F_1-score (4) for each class in the testing dataset, along with the number of elements per class.

Table 2
Classification metrics for the testing dataset

Class	Precision	Recall	F_1-score	Number of elements
1	1.00	1.00	1.00	1,2782
2	0.99	0.99	0.99	1,097
3	0.99	1.00	1.00	1,224
4	1.00	1.00	1.00	1,657
5	1.00	0.99	1.00	958
6	0.96	0.95	0.95	476
7	0.88	0.84	0.86	168
8	0.97	0.95	0.96	141
9	0.90	0.89	0.89	89

The model achieves nearly perfect precision, recall, and F_1-scores for most arrhythmia classes, particularly for Normal beat (N), Right bundle branch block beat (R), and Left bundle branch block beat (L), all with F_1-scores close to 1.00. The Premature ventricular contraction (V) class also shows excellent precision and recall, with an F_1-score of 1.00. While the Fusion of paced and normal beat (f) and Atrial premature beat (A) classes perform slightly lower, they still demonstrate strong classification metrics with F_1-scores of 0.86 and 0.96, respectively. The 'Others' (NA) class, though showing the lowest performance with an F_1-score of 0.89, still indicates a relatively high level of accuracy, suggesting some room for improvement.

Overall, the proposed deep CNN model demonstrates superior performance in classifying various arrhythmias from ECG signals. The high accuracy, precision, recall, and F_1-scores across most classes underscore the model's potential for real-world applications in medical diagnostics. The consistent performance across training and validation sets indicates that the model does not overfit and maintains its effectiveness on unseen data. The improvements in the CNN architecture, such as adding Batch Normalization layers and additional convolutional layers, have significantly contributed to the model's robust performance.

3.2. Interpretation results

3.2.1. Sample of applying the proposed approach

Let us consider an example of applying the proposed interpretation method to explain classification results for the pathology “Premature Ventricular Contraction” (PVC), also known as “Ventricular Extrasystole.” The following features are characteristic of this pathology:

- Absence of P-peak.
- Widened QRS complex.
- Deformed QRS complex; deformation implies a change in the shape of the QRS complex – right ventricular extrasystole if it resembles left bundle branch block in lead V1 and left ventricular extrasystole if it resembles right bundle branch block.
- Presence of a full compensatory pause, which is the interval between two consecutive ventricular complexes of sinus rhythm, with an extrasystole in between, equal to twice the RR interval of sinus rhythm.

The interpretation for each pathology will be discussed further.

3.2.2. No P-peak

Let us plot all ECG signals from the training set for the classes “Normal” and “Premature Ventricular Contraction” (Figure 7).

As seen in Figure 7, the attention zone for the feature was determined empirically (Figure 7(a). Simple visual representation does not work in this case. The red and blue areas completely overlap.

When reproducing fragments from a single point (Figure 7(b), the picture improves, but not for all cases (only for signals with a clearly defined presence and absence of the peak).

Since it was not possible to visually determine the presence or absence of the P-peak, it is proposed to use a peak detection function integrated into the Neurokit2 package [26].

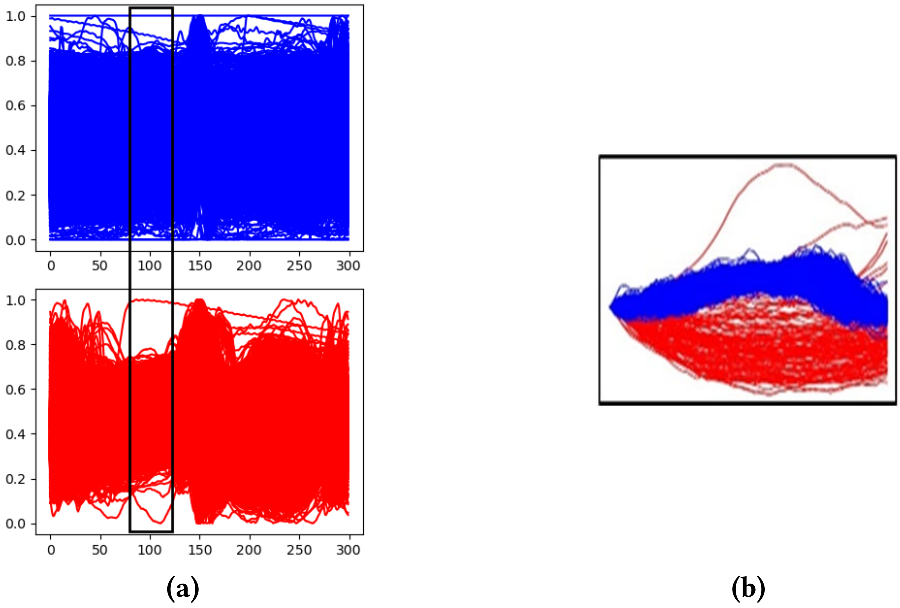


Figure 7: The interpretation results for an ECG-sample: (a) attention zone for the feature "Absence of P-peak" and (b) all fragments from a single point.

3.2.3. The QRS complex is widened with deformation

On the graph with all ECG signals for the classes "Normal" and "Premature Ventricular Contraction," the attention zone for the current feature was empirically determined (Figure 8). The identified attention zone should fully cover the QRS complex.

As with the previous feature, simple visual comparison does not work due to significant overlap between signals. Applying PCA to the data from the attention zone in the ECG signal shows that the data does not have substantial dispersion, but instead exhibits some grouping. However, the formed groups do not have clear separation.

In such conditions, classification methods using ML models will perform worse than those using DL models. Therefore, identifying the QRS complex that corresponds to "normal" and "widened with deformation," according to the pathology of ventricular extrasystole, will be done using neural network methods.

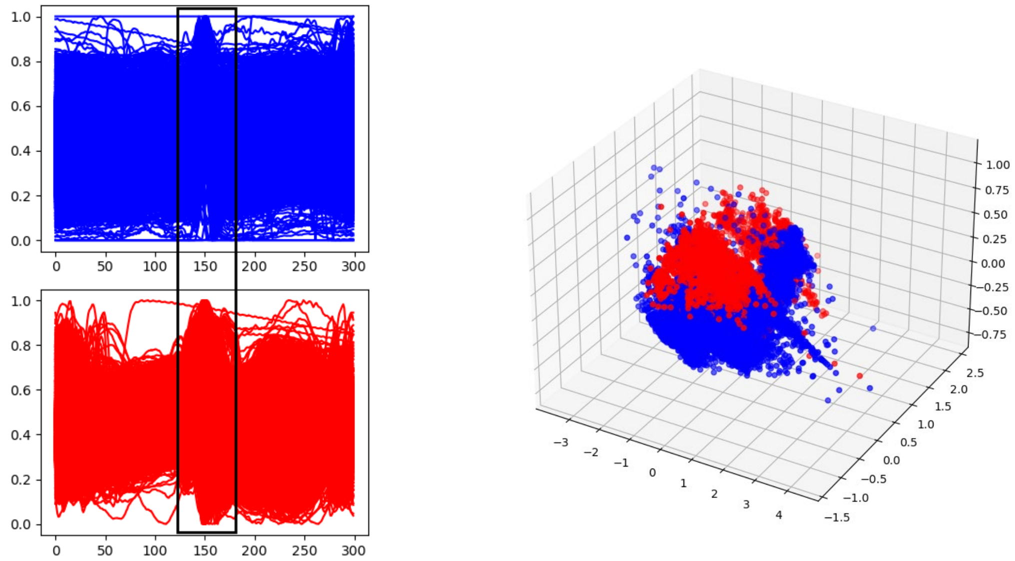
3.2.4. Presence of a full compensatory pause

A compensatory pause is the time that elapses after an extrasystole until the occurrence of a normal contraction. Therefore, when an extrasystole is situated between other extrasystoles, this calculation does not occur, and the check for the presence of the feature is only performed for the last instance of the extrasystole in the sequence.

A complete compensatory pause means that the heart rhythm fully returns to its normal cycle after an extrasystole. This happens when the sum of the intervals before and after the extrasystole equals two normal R-R intervals.

$$RR_p + RR_f \approx 2 * RR_n, \tag{5}$$

where RR_p is the R-R interval before the extrasystole, RR_f – R-R interval after the extrasystole, and RR_n – R-R interval between cardiac cycles in the norm.



(a) **(b)**

Figure 8: The interpretation results for an ECG-sample: (a) attention zone for the feature "Absence of P-peak" and (b) all fragments from a single point.

4. Conclusions

In this research paper, we proposed and implemented new methods for classifying and interpreting arrhythmias based on deep CNN applied to ECG signals. The method involved splitting ECG signals into fragments and classifying these fragments using an enhanced CNN architecture, which included the addition of Batch Normalization layers and an extra convolutional layer. The dataset used for training and testing was the MIT-BIH Arrhythmia Database, ensuring a robust evaluation of our approach. The obtained results demonstrated high accuracy, precision, recall, and F_1-scores, with particularly strong performance for Normal beats, Right bundle branch block beats, and Left bundle branch block beats, achieving F_1-scores close to 100%. The model's overall accuracy reached 99.43%, showcasing its effectiveness in distinguishing between different arrhythmias. Nevertheless, the main limitation of our proposed interpretation approach is the reliance on a limited number of clinical features to justify the decisions made by a DL model. This limitation is evident when multiple pathologies overlap within the same heart rhythm, necessitating the introduction of additional features to ensure accurate diagnosis.

Future work will focus on validating the proposed methods through clinical trials using real cases and cardiograms, aiming to enhance the model's reliability and applicability in real-world medical diagnostics.

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