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Deep Learning–Based Classification of ECG Heartbeats Using One–Dimensional Convolutional Neural Networks

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Abstract. Accurate classification of arrhythmic heartbeats is critical for effective clinical diagnosis and treatment. This study employs advanced deep learning techniques to enhance the automatic classification of arrhythmias using a one–dimensional convolutional neural network (1D–CNN). ECG data from the MIT–BIH Arrhythmia Database were analyzed, focusing on five heartbeat types: normal (N), LBBB, RBBB, PVC and APC. The process began by extracting ECG segments and identifying individual beats within those segments. The ECG segments were normalized and padded and then used to train a 1D–CNN model on 80058 heartbeats, with an additional 20004 beats used for testing and validation. The CNN architecture included five convolutional layers, five pooling layers, and a fully connected component with dense layers. The model achieved an accuracy of 99.65%, sensitivity of 99.13%, specificity of 99.78%, and AUC of 0.9996. Outperforming previous studies, this method highlights the efficacy of deep learning in arrhythmia detection, offering significant advances in clinical applications.
Keywords: Electrocardiogram, Heartbeat, 1D–CNN, Signal Processing, Classification.

1. **Introduction.** Arrhythmic heartbeats are closely linked to abnormal cardiac electrical activity and may result in severe clinical consequences, including sudden cardiac death [1]. Therefore, accurate detection of arrhythmias from ECG signals is essential for effective diagnosis and treatment. Traditional classification methods primarily depend on manual analysis and heuristic rules, which are often inefficient and vulnerable to classification errors [2].

Electrocardiography is a non–invasive method of recording cardiac electrical activity, and remains central to evaluating heartbeat behaviour and cardiac function. ECG signals can be used to detect a wide range of cardiac disorders, including arrhythmias, ischaemic heart disease and myocardial infarction [3, 4].Therefore, improving ECG-based analytical techniques is crucial for achieving more accurate and efficient arrhythmia classification, as well as mitigating the limitations associated with traditional methods [5]. A critical component of heartbeat analysis is the detection of R peaks in electrocardiogram (ECG) signals, as they provide essential data to assess heart rate variability, timing of the cardiac cycle, and diagnosis of arrhythmias [6]. The Pan–Tompkins algorithm, renowned for its precision, is commonly used for accurate R–peak detection [7]. In addition, the traditional adaptive thresholding approach used by the Pan–Tompkins algorithm can lead to incorrect threshold estimation when there is signal interference. It also relies on multiple preceding data points for accurate detection, which restricts its effectiveness in predicting arrhythmia in real time [8]. The conventional Pan and Tompkins method is also inadequate for reliably extracting features associated with premature ventricular contractions (PVCs), as these often exhibit highly variable and non-uniform morphologies in ECG signals. The algorithm is optimized primarily to identify QRS complexes with positive deflections, those with negative peaks are often missed [8]. Furthermore, the high computational complexity of the algorithm adds to its limitations. Its inability to capture precise ECG features increases the likelihood of misclassification, which is a critical concern in real–world clinical applications where diagnostic accuracy is paramount.

Recent advances in this area have led to the development of several computer–based systems that use various feature extraction and classification techniques to enhance the detection of ECG signal abnormalities. These systems significantly improve the automation of arrhythmia detection by employing sophisticated signal processing, feature extraction and machine learning algorithms. Feature extraction techniques include time–domain, frequency–domain, time–scale and time–frequency analyses [9, 10, 11, 12]. These methods are essential for extracting relevant information from ECG signals and for accurately discriminating between normal heartbeats and arrhythmia patterns. Ultimately, they improve both diagnostic accuracy and efficiency.

Previous studies have used traditional machine–learning methods to classify different types of arrhythmia based on heartbeat data. Algorithms such as Support Vector Machines (SVM) [13, 14], Random Forests (RF) [15], and Artificial Neural Networks (ANN) [16] have been applied to ECG signal analysis to successfully distinguish between different arrhythmic heartbeats. More recently, deep learning (DL) approaches, particularly convolutional neural networks (CNNs), have attracted considerable attention for ECG signal classification and arrhythmia beat detection [17, 18]. These advanced models can automatically learn features from raw ECG data, which significantly improves the precision and effectiveness with which various cardiac conditions can be identified. [19].

The following studies investigated the use of one-dimensional convolutional neural networks (1D–CNNs) for classifying ECG signals, with a specific focus on distinguishing between five types of heartbeat: normal, left bundle branch block (LBBB), right bundle branch block (RBBB), premature ventricular contractions (PVC), and atrial premature contractions (APC). Jeong–Hwan et al. developed a deep learning (DL) architecture for the classification of ECG signals using three fully connected (Fc) layers, although the number of convolutional layers was not specified. They achieved an accuracy of 95.5% on a dataset of 95,197 beats. However, Fengjuan *et al.* [20] and Shu Lih *et al.* [1] employed a CNN architecture of three convolutional layers for the classification of ECGs. In [20], the model processed 99863 heartbeats, achieving an accuracy of 99.11% and a sensitivity of 97.15%. In contrast, [1] processed 16499 heartbeats, with an accuracy of 98.10%, a sensitivity of 97.5%, and a specificity of 98.7%. Furthermore, other studies [21, 22, 23, 24] have used convolutional neural networks (CNN) with four convolutional layers for the classification of ECG arrhythmias. Fatma Murat *et al.* [21] processed 100022 heartbeats and achieved an accuracy of 99.16%. However, the best performance was achieved by the CNN–4 model, which contains four convolutional layers and outperformed models with two and three convolutional layers. Similarly, Mengze *et al. et al.* [22] processed 38396 heartbeats, achieving an accuracy of 97.41%, with sensitivity and specificity values of 97.05% and 99.35%, respectively. Saroj Kumar *et al.* [23] processed a dataset of 99,567 heartbeats and achieved a classification accuracy of 97.41% and a sensitivity of 98.78%. Zhenghao Shi *et al.* [25] proposed a deep learning framework using a deep architecture with two convolutional layers to effectively extract and classify the temporal features of ECG signals. Their method achieved remarkable performance with an accuracy of 99.49%, a sensitivity of 96.98% and a specificity of 99.63%. Furthermore, Nestor Alexander *et al.* [24] classified 28676 heartbeats and achieved an accuracy of 99.09%. Ozal Yildirim *et al.* used a convolutional autoencoder (CAE) with eight convolutional layers for non–linear compression of arrhythmic ECG signals. The model achieved an accuracy of 99.11% on a data set of 100022 heartbeats [26].

Convolutional neural networks (CNNs) are deep learning models that perform feature extraction and classification within a unified training framework, making them one of the most widely adopted architectures in contemporary deep learning research [27, 28, 29]. The number of convolutional layers is a critical hyperparameter that significantly affects the model's ability to extract and learn complex patterns from ECG signals [30, 26, 21]. Although increasing the number of layers can enhance a model's ability to capture hierarchical features, selecting an optimal depth of five layers in our study is crucial for achieving high classification accuracy while minimizing overfitting. Deeper networks, such as those with eight layers, can extract more complex features but are more susceptible to overfitting, particularly when the available dataset is limited. Moreover, choosing an optimal number of layers improves computational efficiency by reducing training time and resource requirements. As highlighted by Caleb Isaac *et al.* [31], deeper networks provide greater learning capacity but tend to overfit, becoming highly specialized on training data and performing poorly on unseen data. Networks with excessive layers not only increase model complexity but may also capture noisy patterns instead of meaningful features. The introduction of additional layers adds more parameters, enabling the model to memorize training data, detect irrelevant details, and treat noise as informative, thereby reducing its generalization ability. Furthermore, excessively deep networks demand higher computational resources, longer training times, and rely heavily on powerful hardware such as GPUs or TPUs. They are also prone to numerical instabilities, such as vanishing and exploding gradient problems, which complicate training further.

In this study, we optimize a CNN model by adjusting the number of convolutional layers to improve performance and achieve high–performance metrics, distinguishing it from related work. Using a 1D–CNN with five convolutional layers, we developed an advanced algorithm for heartbeat classification from ECG data. The developed model focuses on two main contributions:

(i) Development of a robust 1D–CNN model: We design a 7–layer deep 1D–CNN architecture, including five convolutional layers and two fully connected dense layers, specifically tailored to classify five types of heartbeat using the MIT–BIH Arrhythmia Database. This process involves extracting ECG segments, isolating and normalizing individual heartbeats, and training the 1D–CNN model on these sequences.

(ii) High classification accuracy: Using the deep learning capabilities of the 1D–CNN architecture, our study achieves high classification accuracy for different types of arrhythmia beats. The model is evaluated on a dataset of 100062 ECG beats from the MIT–BIH Arrhythmia Database, with a separate test set of 20004 ECG beats. Our approach effectively distinguishes between normal arrhythmias (N), left bundle branch block (LBBB), right bundle branch block (RBBB), premature ventricular contraction (PVC) and atrial premature contraction (APC), demonstrating the robustness and effectiveness of the model.

Complementing recent advances in 1D–CNN methods, our proposed model achieves an accuracy of 99.65% using a large dataset of 100062 ECG recordings for the detection of arrhythmias. This performance outperforms related studies that used smaller datasets.

2. **Materials and Methods.** In this study, we analyzed ECG data from the MIT-BIH Arrhythmia Database, focusing on five different types of arrhythmia beats [32]. The classification algorithm for ECG beats follows a systematic approach: first, we extract ECG segments from the database and then identify individual beats within these segments. The ECG segments are then normalized and padded. These processed segments are converted into sequences of ECG heartbeats, which are then used to train a 1D–CNN model. A schematic representation of the algorithm developed is shown in Figure 1.

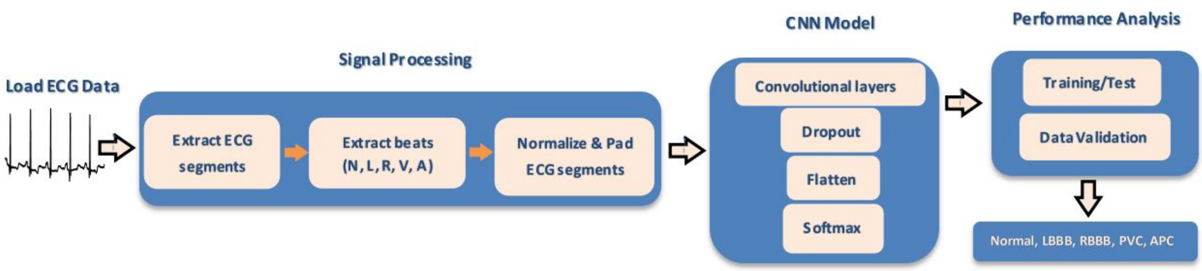

FIGURE 1. Block diagram of the proposed approach.

2.1. **Database.** We used ECG heartbeat data from the MIT–BIH Arrhythmia Database, collected at the MIT Biomedical Engineering Center and the BIH Biomedical Engineering Laboratory. [32].

2.1.1. *ECG Lead Configuration.* Electrodes were placed on the chest according to limb lead II (MLII) to record the ECG signals. Recordings were obtained from leads V1, V2 and V5, in accordance with the standard electrode configuration established by the BIH Arrhythmia Laboratory [32].

2.1.2. *ECG Signal Digitization.* The electrocardiograph signals from the MIT–BIH Arrhythmia Database were first processed using a bandpass filter with a frequency range of 0.1 to 100 Hz, followed by a 60 Hz notch filter to remove power line interference. The signals were digitized at a sampling rate of 360 Hz. Analog–to–digital conversion was performed in unipolar mode, with a voltage range of ±5 mV and 11 bit resolution. This configuration generated digital values ranging from 0 to 2047, with 1024 corresponding to zero volts [32].

2.1.3. *ECG Heartbeats in the MIT–BIH Arrhythmia Database.* The MIT–BIH Arrhythmia Database contains 48 half–hour excerpts from ambulatory dual–channel ECG recordings of 47 subjects. Several cardiologists annotated Each recording independently, resulting in approximately 110000 annotations [32].

Table 1 provides a summary of the distribution of beats across different arrhythmia types, along with their classifications for testing. The dataset contains beat types including Atrial Premature Contraction (APC), Left Bundle Branch Block (LBBB), Normal (N), Premature Ventricular Contraction (PVC), and Right Bundle Branch Block (RBBB). Each beat type is labeled with corresponding classes ('A', 'L', 'N', 'V', 'R'), including beat counts for both training and test phases.

TABLE 1. Distribution of ECG beats by type, classification, and annotation.

Beat Type	Classes	Annotation	Beat Count	Beat Test
Normal	Normal	N	75052	15017
Left Bundle Branch Block	LBBB	L	8075	1627
Right Bundle Branch Block	RBBB	R	7259	1480
Atrial premature contraction	APC	A	2546	444
Premature Ventricular Contraction	PVC	V	7130	1436

As shown in Table 1, the dataset exhibits a noticeable class imbalance among the different heartbeat categories. In this study, no explicit class balancing techniques were applied during training. The model was trained using the categorical cross–entropy loss function without class weighting, allowing the network to learn directly from the original data distribution. Despite this imbalance, the proposed 1D–CNN achieved high classification performance across all classes, indicating that the network was able to learn discriminative features even from minority classes.

Figure 2 shows the ECG signal for recording 100 from the MIT–BIH Arrhythmia Database, highlighting the R–peaks detected by the Pan-Tompkins algorithm [7]. The signal's morphology illustrates the heart's electrical activity over time, focusing on normal beats, which are essential for evaluating heart rate and rhythm. It also shows the RR intervals, the time between consecutive R–peaks measured in seconds [33]. These intervals are crucial for assessing heart rate variability, which is key to analyzing heart rhythm and diagnosing arrhythmias.

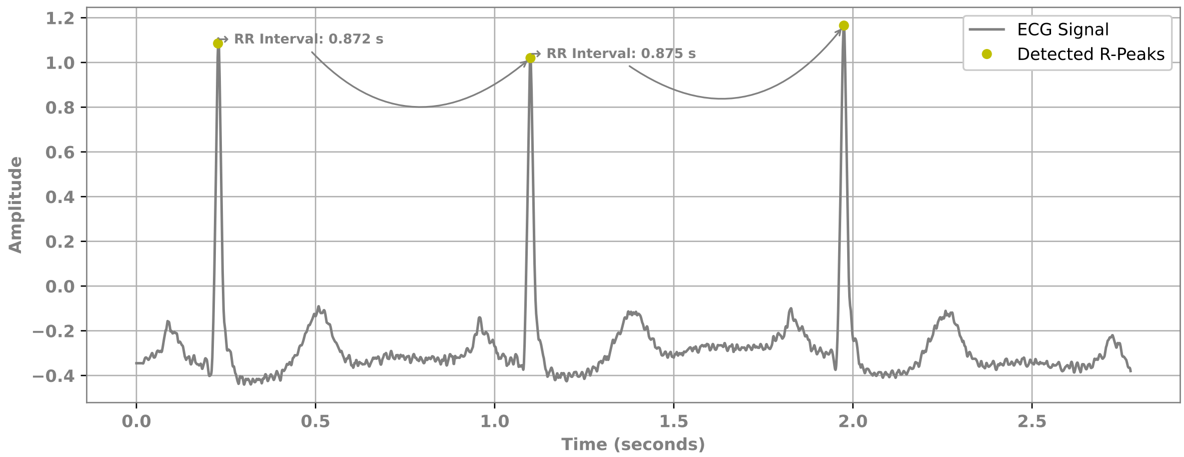

FIGURE 2. ECG signal segment: MIT–BIH Arrhythmia Database, record 101.

2.2. **Computational Setup for ECG Heartbeat Classification.** In this arrhythmia classification study, we used a high–performance computing system designed for intensive computational tasks. This system efficiently processed data and trained models, using advanced hardware for precision and reliability. Python served as our primary programming language, complemented by TensorFlow and Keras libraries. This setup played a critical role in meeting the computational needs of our research (see Table 2).

TABLE 2. System configuration and training parameters for the model.

	Parameters	Values
Hardware	Operating System	Windows 10 x64
	CPU	Intel Core i7–8750H
	GPU	NVIDIA GeForce GTX 1070
	Memory (RAM)	16 GB
Software	Version	Anaconda3 (64-bit)
	Programming Language	Python
	Libraries	TensorFlow, Keras
Training Cycle	Epoch	50
	Iteration	62500
	Iterations per epoch	1250
	Batch Size	64
	Learning Rate	0.00001
	Optimizer	Adam
	Loss	Categorical Cross–Entropy
	Regulation/Validation	Early Stopping
Training Time	Epoch Time	130 sec
	Elapsed Time	1 h, 47 min, 24 sec, 150 ms

2.3. **Overview of Convolutional Neural Network (CNN) Architecture.** A convolutional neural network (CNN) is an advanced form of artificial neural network, rooted in deep learning techniques. While traditional machine learning models typically include an input layer, a hidden layer, and an output layer, CNNs have a more complex architecture with multiple hidden layers [34].

The architecture of CNNs is inspired by the neural networks of the human brain, which consist of multiple hidden layers (see Figure 3). Each layer, containing numerous neurons, processes the input data and transforms it to facilitate interpretation by the output layer. Neurons within these layers are specialized in detecting features from the input data, as described by equation (1).

$$y_j = f_j(x) = \phi(w_j \cdot x + b_j) \tag{1}$$

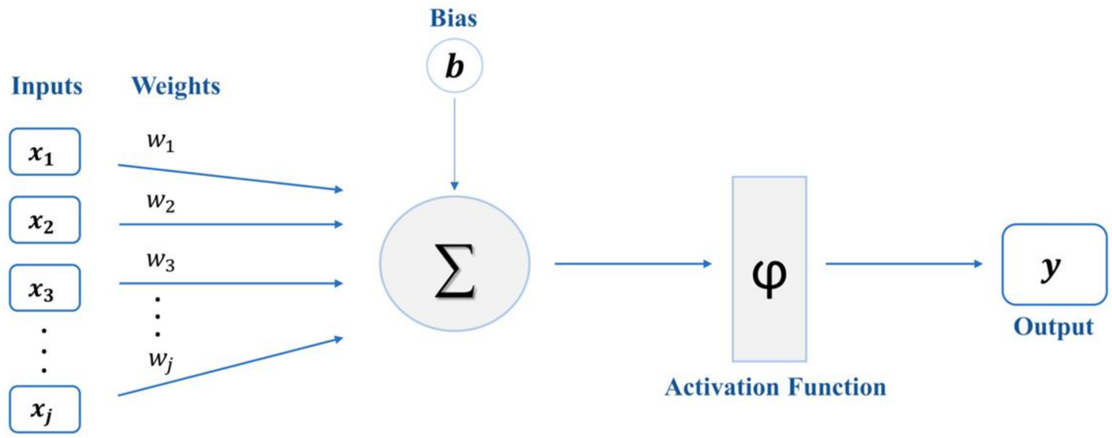

FIGURE 3. Architecture of artificial neural networks.

Where f_j is a function applied to the input x, modulated by the connection weights w_j, adjusted by a neuron bias b_j, and transformed by the activation function ϕ.

Unlike traditional machine learning approaches, CNNs can automatically learn significant patterns from the data without requiring manual feature extraction [35]. They employ convolutional layers to identify these patterns, pooling layers to reduce dimensionality, and fully connected layers to perform the final classification. In the convolutional layer, one-dimensional input data is processed using a specific kernel that extracts multiple features as it slides across the input. The discrete convolution operation is defined by equation (2).

$$(f * g)(x) = \sum_t f(t) \cdot g(x+t) \tag{2}$$

Where $f(t)$ denotes the input signal, and $g(x+t)$ represents the kernel function.

In this study, we proposed a new CNN model consisting of five convolutional layers, five pooling layers, and a fully connected component with two dense layers and a softmax activation function.

2.3.1. *Convolution layer.* In this study, a one–dimensional convolutional kernel is employed to process ECG signals, enabling independent operations on the feature maps generated by the preceding layer. The convolution kernel slides over the input, producing outputs that are subsequently transformed by a non–linear activation function [19]. The mathematical expression of the output is presented in equation (3).

$$h_i^{l,k} = f\left(b_i^{l,k} + \sum_{n=1}^{N} W_{n,i}^{l.k} \cdot x_{i+n-1}^{l-1,k}\right) \tag{3}$$

where:

- $h_i^{l,k}$ is the output of the i-th neuron in layer l,
- $f()$ is the activation function,
- $b_i^{l,k}$ is the bias (offset) of the neuron in layer l,
- $x_{i+n-1}^{l-1,k}$ is the output of the neuron in layer $l-1$,
- $W_{n,i}^{l.k}$ is the k-th convolutional kernel in layer l.

2.3.2. *Pooling layer.* The convolutional layer is typically succeeded by a pooling layer, which reduces the dimensionality of the convolutional output. This reduction decreases network complexity and mitigates the risk of overfitting, thereby enhancing the network's robustness [19]. The pooling layer performs either averaging or maximization of the convolutional features, referred to as Average Pooling and Max Pooling, respectively. The output of this operation is expressed by the following equation;

$$o_i^{l,k} = f\left(\alpha_i^{l,k} \cdot \text{pool}\left(x_i^{l-1,k} + b_i^{l,k}\right)\right) \tag{4}$$

2.3.3. *Fully–connected layer.* Features extracted through multiple convolution and pooling layers are then combined by the fully connected layer. Classification is performed by the SoftMax layer using logistic regression [19]. The fully connected layer calculates the weighted sum of the outputs from preceding layers and applies an activation function [19]. The resulting output is expressed by equation 5.

$$o_i^{l,k} = f\left(w_i^{l,k} \cdot x_i^{l-1,k} + b_i^{l,k}\right) \tag{5}$$

Where $o_i^{l,k}$ is the output of the l-th layer of the i-th neuron, $f()$ is the activation function, $b_i^{l,k}$ is the bias of the l-th layer for the neuron, $x_i^{l-1,k}$ is the output from the $(l-1)$-th layer for the i-th neuron, and $i^{l,k}$ represents the weight of the network.

2.4. **1D–CNN–Based Approach for Accurate Heartbeat Recognition.** In this study, we used ECG data from the MIT–BIH Arrhythmia Database [36]. To pre–process the data, we first detected the R–peaks in the ECG signals, which allowed us to segment the recordings into intervals representing different heartbeats, including normal beats and different arrhythmias, such as left bundle branch block (L), right bundle branch block (R), premature ventricular contraction (V) and Atrial premature contraction (APC). After segmentation, we applied length normalization by padding to ensure that all segments were standardized for input into our convolutional neural network (CNN) model. Figure 4 illustrates the architecture of our convolutional neural network (CNN), which is designed to process one–dimensional ECG signals. The model incorporates convolutional layers that capture temporal patterns in the data, supported by regularisation and batch normalization to improve generalization and stability [37, 38]. Pooling layers are used to reduce dimensionality while preserving important features, and dropout layers are used to mitigate overfitting. The fully connected layer processes the flattened features extracted by the convolutional layers, with specific configurations in the dense layers to facilitate effective classification.

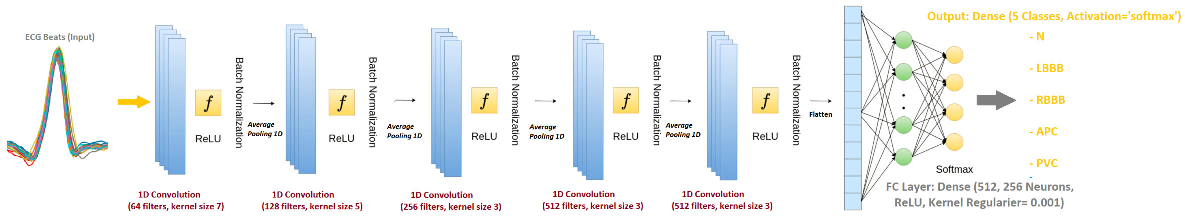

FIGURE 4. Schematic of the proposed convolutional neural network (CNN) Model.

Adaptive learning rates were integrated with regularisation techniques, including early stopping and learning rate reduction on the plateau, to improve model training. These methods successfully reduced overfitting and optimized model performance on the validation dataset. The model was rigorously evaluated on a specialized test set, with results confirming its accuracy in classifying different types of heartbeats. This thorough approach was essential for the accurate analysis and interpretation of ECG data, providing a solid foundation for clinical applications in the diagnosis and management of arrhythmic heartbeats.

In this study, a convolutional neural network (CNN) model was developed to efficiently process one–dimensional (1D) input sequences (see Figure 3). The architecture starts with a convolutional layer consisting of 64 filters with a kernel size of 7 and padding to preserve the input length, enabling the model to capture features from the entire sequence. The second convolutional layer employs 128 filters with a kernel size 5 and an appropriate padding for consistent feature extraction. The third convolutional layer further refines the features with 256 filters and a kernel size 3. The model is extended with a fourth convolutional layer using 512 filters and a kernel size of 3, followed by a fifth and final convolutional layer also with 512 filters and a kernel size of 3.

Each convolutional layer is followed by batch normalization to enhance training stability and convergence, and the ReLU activation function to introduce non–linearity. Average pooling with a pool size of 2 is applied to reduce the dimensionality of the feature maps while preserving essential information.

Following the convolutional layers, the network's output is flattened into a one–dimensional (1D) vector and then processed through two fully connected dense layers. The first dense layer comprises 512 neurons and employs the ReLU activation function, with L2 regularization applied to mitigate overfitting. Additionally, a dropout rate of 50% is used to further reduce overfitting. The second dense layer, featuring 256 neurons with similar activation, regularization, and dropout settings, enhances the model's generalization ability. The architecture culminates with an output layer, where the number of units corresponds to the number of classes, and the softmax activation function is applied to generate probabilistic class predictions, thereby facilitating multi–class classification.

2.4.1. *Data Splitting and Model Training.* The ECG dataset was preprocessed by segmenting the signals, padding them to equal lengths, and encoding the annotations. The resulting data (X and Y) were split into training and test sets using an 80/20 split (`train_test_split` with `random_state=42`). During model training, the test set (X_{test}, y_{test}) was used as validation data via the `validation_data` parameter in `model.fit()`, with **callbacks** applied for learning rate adjustment (`ReduceLROnPlateau`), model checkpointing (`ModelCheckpoint`), and early stopping (`EarlyStopping`).

In this study, no separate validation set was created and validation was performed on the test set. Furthermore, the data were split at the heartbeat level rather than patient–wise, meaning that heartbeats from the same patient could appear in both the training and test sets.

2.5. **Performances Evaluation.** The performance of the classifier was assessed by calculating Sensitivity (S_e), Specificity (S_p), and Accuracy (Acc). Sensitivity represents the true positive rate, as defined in equation (6);

$$S_e = \frac{TP}{TP + FN} \tag{6}$$

Table 3. Summary of CNN Model with Layer Details: Kernel Size, Activation Function, Number of Filters, and Scheme

No	Layer Name	Kernel Size	Activation Function	Number of Filters	Scheme
1	Convolutional Layer 1	7×1	ReLU	64	–
2	Average Pooling 1	2×1	–	64	–
3	Convolutional Layer 2	5×1	ReLU	128	–
4	Average Pooling 2	2×1	–	128	–
5	Convolutional Layer 3	3×1	ReLU	256	–
6	Average Pooling 3	2×1	–	256	–
7	Convolutional Layer 4	3×1	ReLU	512	–
8	Average Pooling 4	2×1	–	512	–
9	Convolutional Layer 5	3×1	ReLU	512	–
10	Average Pooling 5	2×1	–	512	–
11	Flatten	–	–	–	–
12	Dense Layer 1	–	ReLU	–	512 Neurons
13	Dropout 1	–	–	–	50%
14	Dense Layer 2	–	ReLU	–	256 Neurons
15	Dropout 2	–	–	–	50%
16	Output Layer	–	Softmax	–	–

Specificity represents the true negative rate, as defined in equation (7);

$$S_p = \frac{TN}{FP + TN} \tag{7}$$

Accuracy is defined as the ratio of correct predictions to the total number of predictions, as given in equation (8);

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

TP: True positive: correctly classified as positive.
FP: False positive: falsely classified as positive.
TN: True negative: correctly classified as negative.
FN: False negative: falsely classified as negative.

3. **Results.** Accurate identification of arrhythmic ECG heartbeats is important for effective clinical assessment. This study investigates an automated heartbeat classification approach using the MIT–BIH Arrhythmia Database. By employing advanced deep learning techniques, specifically a one–dimensional convolutional neural network (1D–CNN), the objective is to achieve high performance in the identification and classification of various arrhythmia types. It has been demonstrated that the proposed approach markedly improves the accuracy and reliability of arrhythmia detection, thereby representing a significant advancement in clinical practice and patient outcomes.

3.1. **Characterization and Representation of QRS Complexes in ECG–Heartbeat Datasets.** This paper employed a comprehensive dataset comprising 100062 electrocardiogram (ECG) heartbeats, including a meticulously curated subset of 20004 beats for rigorous testing and validation. The dataset encompasses a range of heartbeat types, including atrial premature contractions (PAC), premature ventricular contractions (PVC), left and right bundle branch blocks (LBBB and RBBB), and normal sinus rhythms (N).

Figure 5illustrates the QRS complexes of five distinct types of heartbeats, with multiple examples provided for each. The QRS complexes, which are integral to the electrocardiogram (ECG), display considerable variability in shape, amplitude, and symmetry. The variations in shape, amplitude, and symmetry of these QRS complexes provide crucial information for the identification and classification of different heartbeat types. Such detailed visualization facilitates comprehension of the diverse electrical conduction patterns within the heart, thereby enabling accurate diagnosis and treatment.

The box plots in Figure 6 illustrate the distribution of amplitude (mV) and duration (Seconds) for five heartbeat types: Normal (N), left bundle branch block (LBBB), right bundle branch block (RBBB), premature ventricular contraction (PVC), and atrial premature contraction (APC). These plots were derived from an analysis of 100,062 heartbeats obtained from the MIT–BIH Arrhythmia Database.

The table 4 presents the main statistical measures of amplitude and duration for five types of heartbeats, calculated from the box plot shown in Figure 6. These statistics, including the mean, median, and interquartile range (Q25–Q75), offer valuable insight into the variability and distribution of these

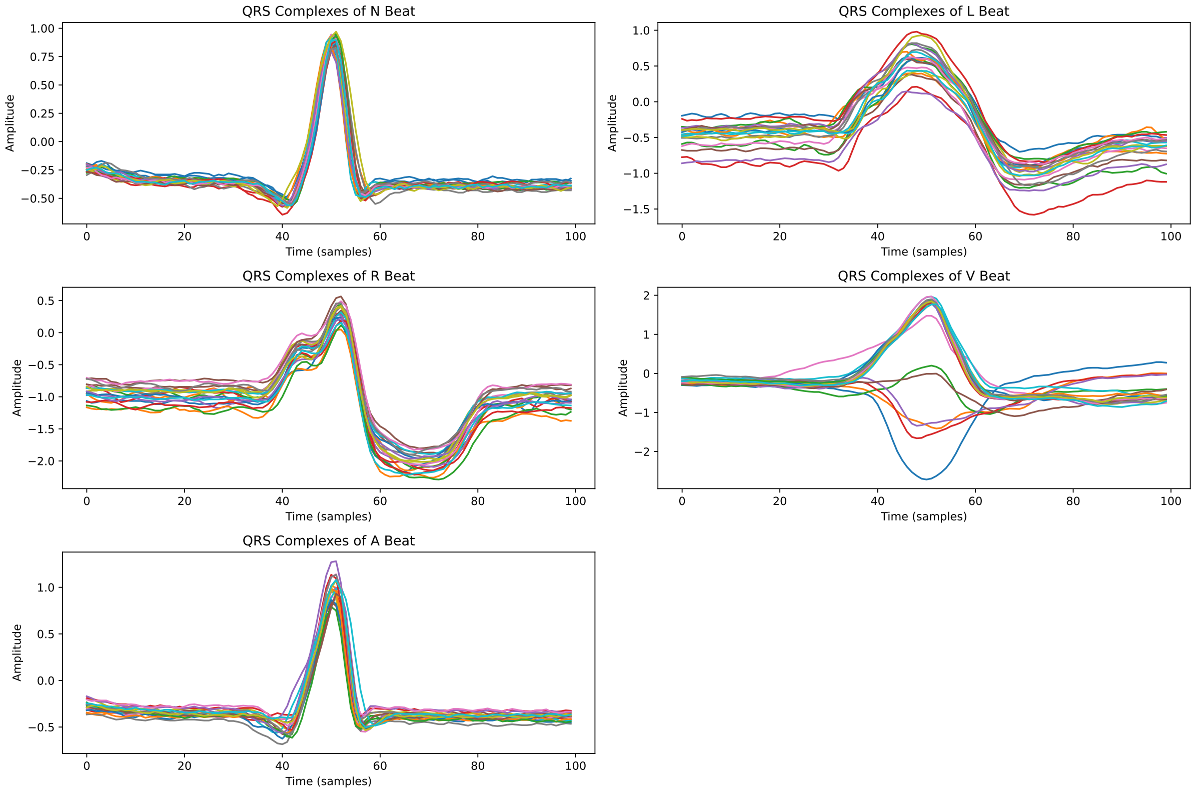

FIGURE 5. Twenty examples of QRS complexes per beat type.

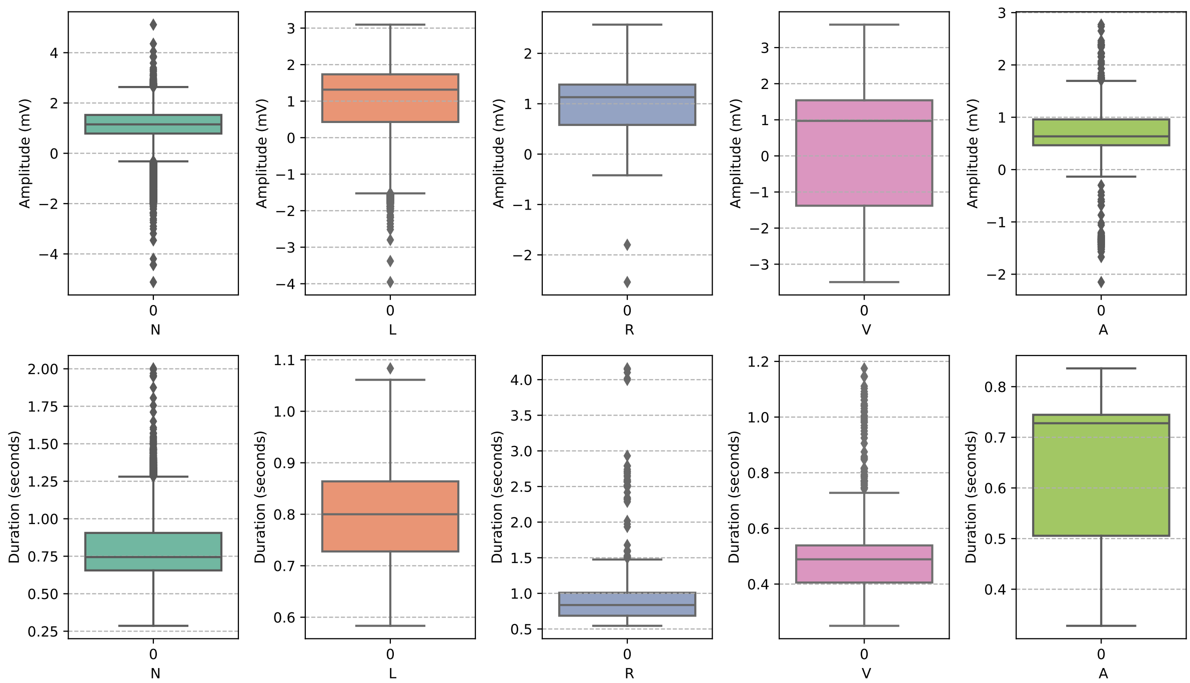

FIGURE 6. Box Plot of Amplitude and Duration for Different Heartbeat Types.

features, which are crucial for heartbeat classification. The amplitude characteristics of different heartbeat types display distinct patterns, reflecting variations in their electrophysiological properties. Normal (N) beats show relatively stable amplitude values, with a mean amplitude of 1.23, a median of 1.22 and an interquartile range (Q25–Q75) of 0.86–1.56. LBBB beats show slightly higher amplitude values, with a mean of 1.37, a median of 1.46, and a broader IQR of 0.80–1.88, suggesting greater variability in amplitude patterns compared to normal beats. In contrast, RBBB beats display lower amplitude characteristics, with a mean of 1.01 and a narrower IQR of 0.58–1.38, reflecting less variability compared to normal beats. PVC beats show significant amplitude variability, with a mean of 1.35 and a wide IQR of 0.96–1.92, indicating irregular amplitude dynamics, as shown in Figure 5. APC beats have the lowest amplitude values, with a mean of 0.76 mV, a median of 0.76 and a narrow interquartile range of 0.48–0.98, indicating minimal amplitude variation compared to other beat types.

Regarding duration, Normal (N) beats show consistent patterns in the time domain, with a mean duration of 0.79 seconds and an IQR of 0.66-0.91. LBBB beats are temporally similar to normal beats, with a mean duration of 0.80 seconds and an IQR of 0.73-0.86, highlighting their low variability. RBBB beats display a longer mean duration of 0.87 seconds and a wider IQR of 0.69–1.01, indicating increased variability in temporal characteristics compared to normal beats. PVC beats are characterized by the shortest duration, with a mean of 0.51 and an IQR of 0.41–0.54, reflecting their rapid occurrence and short duration. However, APC beats exhibit intermediate temporal characteristics, with a mean duration of 0.65 and an IQR of 0.51–0.74, representing slightly longer patterns compared to VPCs.

TABLE 4. Amplitude and Duration Statistics for Different Beat Classes

Classes	Amplitude (mV)				Duration (s)			
	Mean	Median	Q25 (%)	Q75 (%)	Mean	Median	Q25 (%)	Q75 (%)
N	1.23	1.22	0.86	1.56	0.79	0.74	0.66	0.91
L	1.37	1.46	0.80	1.88	0.80	0.80	0.73	0.86
R	1.01	1.14	0.58	1.38	0.87	0.84	0.69	1.01
V	1.35	1.28	0.96	1.92	0.51	0.49	0.41	0.54
A	0.76	0.66	0.48	0.98	0.65	0.73	0.51	0.74

These findings highlight the importance of the morphology of the QRS–complex, particularly amplitude and duration, as key discriminative parameters for heartbeat classification, enabling accurate differentiation between normal and abnormal beats and increasing the effectiveness of automated arrhythmia detection systems.

3.2. **In–Depth Performance Evaluation and Optimization of 1D–CNN.** To thoroughly evaluate the effectiveness of our 1D–CNN model, we conducted a detailed analysis using multiple performance metrics and visualizations of the model's behavior throughout training. This subsection presents a comprehensive assessment, including the evolution of accuracy and loss curves, receiver operating characteristic (ROC) curves, and the confusion matrix. Additionally, performance metrics were analyzed for each heartbeat type, providing insights into the model's classification accuracy and robustness across all categories.

Figure 7 illustrates the evolution of accuracy and loss for our model's training and validation phases over epochs. Configured with the parameters detailed in Table 2, the training cycle consisted of 50 epochs for 62500 iterations, with 1250 iterations per epoch, a batch size of 64, and a learning rate of 0.00001. These graphs show the evolution of the model's performance during training and validation, allowing an assessment of the convergence and generalization of the results obtained. The left plot in Figure 7 shows the accuracy evolution for the training and validation datasets over 50 epochs. Initially, the model shows a steep increase in accuracy, reaching over 97% within the first few epochs. This rapid improvement indicates that the model is learning efficiently from the data. As training progresses, both training and validation accuracies converge and stabilize around 99%, suggesting that the model maintains high performance without overfitting. The small fluctuations observed in the validation accuracy are minimal, indicating the robustness of the model in dealing with unseen data. The right plot in Figure 7 illustrates the changes in training and validation loss over the epochs. There is a significant reduction in loss during the early epochs, indicating effective learning and optimization of the model parameters. Both losses continue to decrease and converge to low values, reinforcing the model's ability to minimize error and improve prediction accuracy. The close alignment of the training and validation loss curves further supports the generalizability of the model.

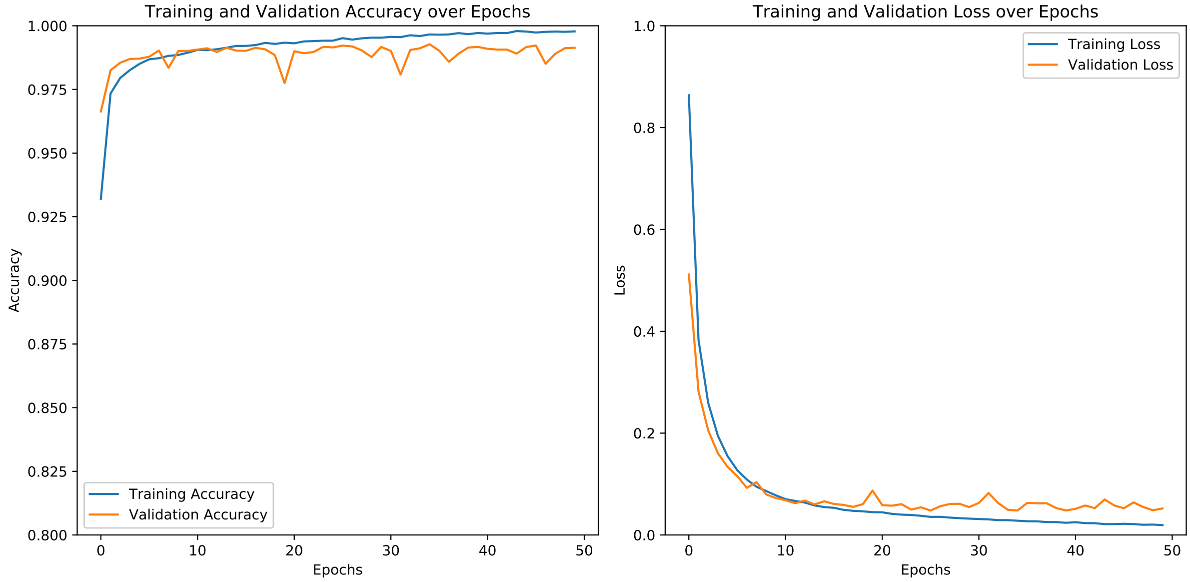

FIGURE 7. Accuracy and loss curves for training and validation across epochs

In this study, we evaluated the efficacy of our approach through rigorous training and parameter optimization to ensure convergence and robust generalization. The evaluation comprised an analysis of several metrics and receiver operating characteristic (ROC) curves, which illustrate the model's capacity to accurately distinguish between different types of arrhythmia. The results demonstrate that the model exhibits robust performance in terms of accurate discrimination and sensitivity.

Figure 8 presents the receiver operating characteristic (ROC) curve, which serves as a graphical representation of the model's diagnostic ability across different threshold levels. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1–specificity). The area under the ROC curve (AUC) is a crucial metric, with a value of 0.9996 indicating near–perfect classification performance. This high AUC value signifies the model's excellent discriminative power, effectively distinguishing between different classes of heartbeats with minimal misclassification. Furthermore, the proximity of the ROC curve to the top–left corner emphasizes the model's high sensitivity and specificity.

Table 5 presents the confusion matrix, which provides a detailed account of the classification performance for the five distinct types of heartbeats. The categories are as follows: Normal, LBBB, RBBB, PVC, and APC. It provides an overview of the model's predictive accuracy compared to the actual classes.

TABLE 5. Confusion Matrix

Actual/Predicted	APC	LBBB	Normal	RBBB	PVC
APC	373	0	65	5	1
LBBB	0	1616	8	1	2
Normal	21	2	14980	0	14
RBBB	3	0	5	1472	0
PVC	2	3	38	3	1390

Table 6 provides the performance metrics for classifying five types of heartbeats: APC, LBBB, Normal, PVC, and RBBB. These metrics, including Precision, F1–Score, Sensitivity, Specificity, and Accuracy, are derived from the confusion matrix presented in Table 5. APC beats to achieve a Precision of 93.48%, an F1–Score of 88.49%, a Sensitivity of 84.00%, a Specificity of 99.86%, and an Accuracy of 99.51%. LBBB beats show a Precision of 99.69%, an F1–Score of 99.51%, a Sensitivity of 99.32%, a Specificity of 99.97%, and an Accuracy of 99.92%. Normal beats have a Precision of 99.23%, an F1–Score of 99.49%, a

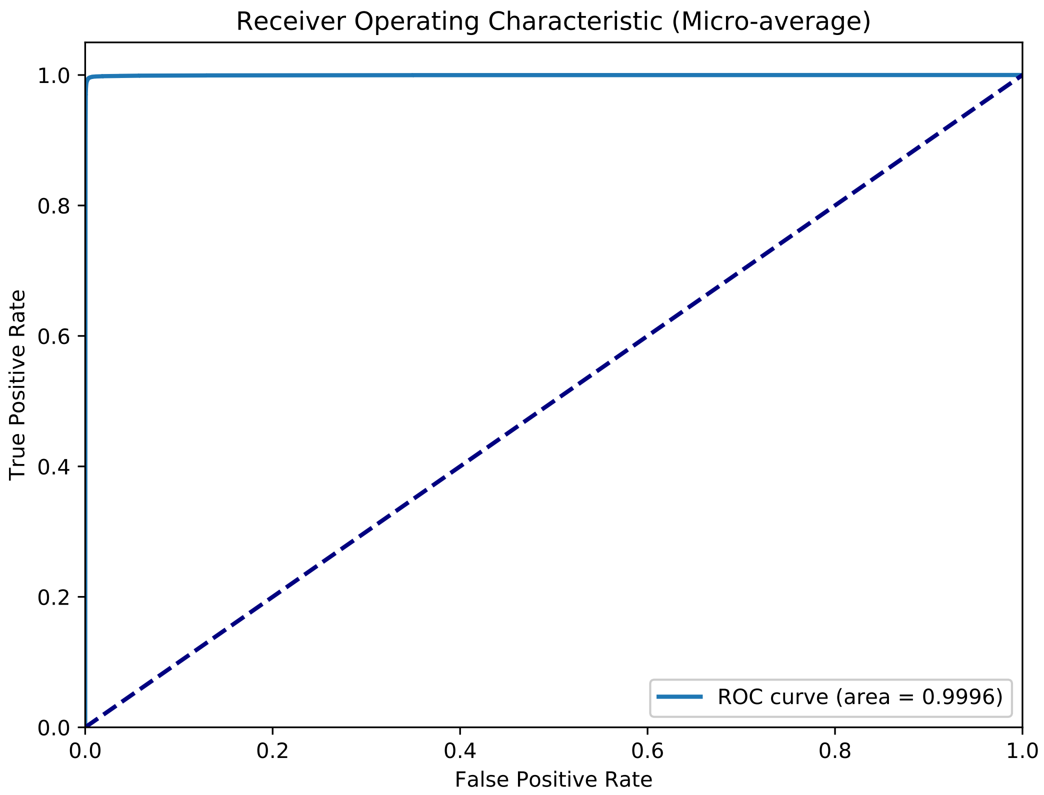

FIGURE 8. Receiver operating characteristic (ROC) curve with micro–average evaluation of our model.

TABLE 6. Classification metrics for heartbeats: APC, LBBB, Normal, PVC, and RBBB.

Classes	Metrics Performance				
	Precision (%)	F1–Score (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
APC	93.48	88.49	84.00	99.86	99.51
LBBB	99.69	99.51	99.32	99.97	99.92
Normal	99.23	99.49	99.75	97.67	99.23
PVC	98.79	97.78	96.79	99.90	99.68
RBBB	99.39	99.43	99.45	99.95	99.91
Overall (%)			99.13	99.78	99.65

Sensitivity of 99.75%, a Specificity of 97.67%, and an Accuracy of 99.23%. PVC beats achieve a Precision of 98.79%, an F1–Score of 97.78%, a Sensitivity of 96.79%, a Specificity of 99.90%, and an Accuracy of 99.68%. RBBB beats to reach a Precision of 99.39%, an F1–Score of 99.43%, a Sensitivity of 99.45%, a Specificity of 99.95%, and an Accuracy of 99.91%. The overall performance metrics indicate high efficacy, with a sensitivity of 99.13%, a specificity of 99.78%, and an accuracy of 99.65%. These metrics reflect the model's high–performance in accurately classifying various types of heartbeats.

4. **Discussion.** Heartbeat classification has progressed considerably, benefiting from both traditional machine learning methods and modern deep learning approaches. In this study, we analyzed ECG recordings from the MIT–BIH Arrhythmia Database and developed a one–dimensional convolutional

neural network (1D–CNN) for accurate heartbeat classification. The 1D–CNN effectively captures temporal features from ECG signals, improving classification performance and highlighting the benefits of deep learning for arrhythmia detection.

TABLE 7. Comparative summary of beat classification: Previous studies vs. our work

Authors (year)	**Database**	**Beat Types**	**Number of Classes**	Total Beats	**No. of Convolutional Layer**	**Performance**
Jeong-Hwan et al. (2018)	MIT–BIH Arrhythmia	Normal, LBBB, RBBB , APC, PVC	5	95197	–	Acc: 95.5%
Shu Lih *et al.* (2018)	MIT–BIH Arrhythmia	Normal, LBBB, RBBB , APC, PVC	5	16499	3	Acc: 98.10% Se: 97.50% Sp: 98.70%
Ozal Yildirim *et al.* (2019)	MIT–BIH Arrhythmia	Normal, LBBB, RBBB, APC, PVC	5	100022	8	Acc: 99.11%
Fengjuan *et al.* (2020)	MIT–BIH Arrhythmia	Normal, LBBB, RBBB, APC, PVC	5	99863	3	Acc: 99.32% Se: 97.15%
Fatma Murat *et al.* (2020)	MIT–BIH Arrhythmia	Normal, LBBB, RBBB, APC, PVC	5	100022	4	Acc: 99.16%
Zhenghao Shi *et al.* (2021)	MIT–BIH Arrhythmia	Normal, LBBB, RBBB, APC, PVC	5	–	2	Acc: 99.49% Se: 96.98% Sp: 99.63%
Mengze Wu *et al.* (2021)	MIT–BIH Arrhythmia	Normal, LBBB, RBBB, APC, PVC	5	38396	4	Acc: 97.41% Se: 97.05% Sp: 99.35%
Nestor Alexander *et al.* (2022)	MIT–BIH Arrhythmia	Normal, LBBB, RBBB, APC, PVC	5	28676	4	Acc: 99.09%
Saroj Kumar *et al.* (2023)	MIT–BIH Arrhythmia	Normal, LBBB, RBBB, APC, PVC	5	99567	4	Acc: 99.40% Se: 98.78%
Yaaqoub Kahlessenane *et al.* (2025)	MIT–BIH Arrhythmia	Normal, LBBB, RBBB, APC, PVC	5	–	4	Acc: 99.59% Se: 98.02% Sp: 99.73%
Our Work	MIT–BIH Arrhythmia	Normal, LBBB, RBBB, APC, PVC	5	**100062**	**5**	**Acc: 99.65%** **Se: 99.13%** **Sp: 99.78%** **AUC: 0.9996**

Table 7 provides a detailed comparison of the performance metrics achieved by different studies in the field of heartbeat classification using convolutional neural network. The studies compared use the MIT–BIH Arrhythmia Database, a standard in electrocardiography, to classify different types of heartbeats, including Normal, left Bundle branch block (LBBB), Right bundle branch block (RBBB), Atrial premature contraction (APC) and Premature ventricular contraction (PVC). This table highlights the chronological improvement in performance metrics from different studies over the years.

Jeong–Hwan *et al.* [39] used a dataset of 95197 beats and achieved an accuracy of 95.5%. However, the number of convolutional layers used in their model was not specified. Shu Lih *et al.* [1], Fengjuan *et al.* [20] and Fatma Murat *et al.* [21] developed models incorporating three convolutional layers. Shu Lih *et al.* [1] achieved a classification accuracy of 98.10% using a dataset of 16499 beats, with a sensitivity of 97.50% and a specificity of 98.70%. Fengjuan *et al.*[20] used a dataset of 99,863 annotated heartbeats and achieved a classification accuracy of 99.32% and a sensitivity of 97.15%. Fatma Murat *et al.*[21] processed 100022 annotated beats and reported a classification accuracy of 99.16%. In contrast, Nestor Alexander [24], Mengze Wu *et al.* [22] and Saroj Kumar emphet al. [23] implemented models with 4 convolutional layers. Nestor Alexander [24] used 28676 ECG beats and achieved an accuracy of 99.09%. Mengze Wu *et al.* [22] processed 38396 beats and achieved an accuracy of 97.41%, with sensitivity and specificity values of 97.05% and 99.35% respectively. Saroj Kumar *et al.* [23] analyzed 99567 beats, achieving an accuracy of 99.40% and a sensitivity of 98.78%. Zhenghao Shi *et al.* [25] implemented a model with 2 convolutional layers, although the exact number of beats used was not specified. Nevertheless, their model achieved an accuracy of 99.49%, with sensitivity and specificity values of 96.98% and 99.63%, respectively. In contrast, Ozal Yildirim et al (2019) used 8 convolutional layers, used 100022 ECG beats and achieved an accuracy of 99.23%. Yaaqoub Kahlessenane *et al.* [40] developed a two–dimensional deep learning approach for ECG heartbeat classification, employing a convolutional neural network (CNN) with four convolutional layers. This method achieved an accuracy of 99.59%, a sensitivity of 98.02% and a specificity of 99.73%.

Our study significantly advances heartbeat classification by implementing a one–dimensional convolutional neural network (1D–CNN) model, which uses the latest technological advances to improve the accuracy and efficiency of classification algorithms. Using five convolutional layers and a dataset of 100062 beats, our model achieved high-performance metrics, including an accuracy of 99.65%, sensitivity of 99.13%, specificity of 99.78%, and an area under the curve (AUC) of 0.9996.

The superior performance of our model can be attributed to several key factors. Firstly, using a one–dimensional convolutional neural network (1D–CNN) enables efficient processing of ECG signals by effectively capturing temporal features crucial for accurate heartbeat classification. Furthermore, the pre–processing techniques employed in this study, including ECG heartbeat segmentation, normalization, and padding of heartbeat segments, ensure optimal data preparation for effective model training. These steps enhance the model's ability to distinguish between different types of heartbeats, including normal beats (N) and abnormal beats such as LBBB, RBBB, PVC and APC, thereby improving classification accuracy.

Compared to previous studies, our model shows higher accuracy, Sensitivity, and specificity, indicating its exceptional ability to discriminate between different heartbeats. The high sensitivity achieved in our study also highlights the model's effectiveness in correctly identifying abnormal heartbeats, which is crucial for clinical applications in arrhythmia detection. These results establish our model as a highly effective solution for clinical and remote cardiovascular function monitoring, particularly in patients with arrhythmias.

4.1. **Limitations of the Proposed 1D–CNN Approach.** The limitations of the proposed 1D–CNN approach are as follows: First, no explicit class balancing strategies were applied during training; incorporating techniques such as weighted loss functions or synthetic oversampling could improve sensitivity for underrepresented arrhythmic heartbeat classes. Second, the study primarily relies on the MIT–BIH Arrhythmia Database, and the inclusion of additional datasets could increase heartbeat variability and enhance the model's generalizability. Third, employing advanced time–frequency representations with a 2D–CNN could potentially further enhance both the richness of the extracted features and the overall classification performance.

5. **Conclusion.** In this study, we presented a one–dimensional convolutional neural network (1D–CNN) for robust arrhythmia heartbeat classification using a large–scale ECG dataset. A total of 100062 ECG heartbeats were employed for training, while 20004 beats were reserved for thorough testing and validation. The proposed architecture consists of five convolutional layers followed by five pooling layers

and fully connected layers incorporating batch normalization, ReLU activation, and dropout regularization. Experimental results demonstrate high performance, achieving an accuracy of 99.65%, sensitivity of 99.13%, specificity of 99.78%, and an AUC of 0.9996. The model effectively distinguishes multiple arrhythmic heartbeat types, including left bundle branch block (LBBB), right bundle branch block (RBBB), premature ventricular contraction (PVC), and atrial premature contraction (APC), as well as normal beats (N). These findings confirm the reliability and efficiency of the proposed 1D–CNN framework for accurate arrhythmia heartbeat classification, which is essential for timely cardiovascular disease diagnosis and clinical decision making. Furthermore, the superior performance achieved compared with recent studies highlights the strong potential of the proposed approach for clinical applications. Future work will focus on further optimizing the model and exploring its deployment in real–time monitoring and diagnostic systems.

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