Research Article

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Conception and realization of an IoT-enabled deep CNN decision support system for automated arrhythmia classification

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Abstract: Arrhythmias are irregular heartbeats that may be life-threatening. Proper monitoring and the right care at the right time are necessary to keep the heart healthy. Monitoring electrocardiogram (ECG) patterns on continuous monitoring devices is time-consuming. An intense manual inspection by caregivers is not an option. In addition, such an inspection could result in errors and inter-variability. This article proposes an automated ECG beat classification method based on deep neural networks (DNN) to aid in the detection of cardiac arrhythmias. The data collected by an Internet of Things enabled ECG monitoring device are transferred to a server. They are analysed by a deep learning model, and the results are shared with the primary caregiver. The proposed model is trained using the MIT-BIH ECG arrhythmia database to classify into four classes: normal beat (N), left bundle branch block beat (L), right bundle branch block beat (R), and premature ventricular contraction (V). The received data are sampled with an overlapping sliding window and divided into an 80:20 ratio for training and testing, with tenfold cross-validation. The proposed method achieves higher accuracy with a simple model without any preprocessing when compared with previous works. For the train and test sets, we achieved accuracy rates of 99.09 and 99.03%, respectively. A precision, recall, and $F1$ scores of 0.99 is obtained. The proposed model achieves its goal of developing a simple and accurate ECG monitoring system with improved performance. This simple and efficient deep learning approach for heartbeat classification could be applied in real-time telehealth monitoring systems.

Keywords: MIT-BIH, IoT, arrhythmia beat, ECG

MSC 2020: 68T07

1 Introduction

Heart rhythm problem (heart arrhythmia) refers to heartbeats that are too fast, too slow, or irregular. It might feel like a fluttering or racing heart and may be completely harmless. Some, however, may be life-threatening, necessitating immediate medical attention. According to the World Health Organization, the prevalence of cardiovascular diseases (CVD) is increasing and is the leading cause of death from non-communicable diseases worldwide [1,2]. High-level medical care is scarce in rural areas, which may result in death or other complications. In such cases, an automated neural network trained model can aid a primary caregiver in making an informed decision whether the arrhythmia is dangerous or not. The prompt intervention allows a patient to receive proper care and encourages him to live a healthier lifestyle.

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Electrocardiogram (ECG) is a non-invasive heart monitoring system that is widely adopted. Due to the availability of small, easy-to-use, low-cost, lead-free wearable cardiac monitors, continuous monitoring of heart condition is now possible [3]. ECG signals are nonlinear and are affected by noise, which makes decision making based on it cumbersome. The data accumulated by continuous monitoring devices need to be analysed by experts to make an informed decision. However, rather than relying on overworked caregivers to inspect and make decisions manually, a more workable solution is to employ computer-aided deep learning techniques [4]. Adopting computer-aided decision support systems helps in reducing inter-observer and intra-observer variability [5]. Many techniques have been proposed in various literature that involves preprocessing of signals, which adds to the main classification step [6]. As a result, a deep learning model with minimal preprocessing is proposed, which will assist the caregiver in making an informed decision. Furthermore, a wireless system is used to transmit ECG signals captured by continuous monitoring devices to a remote server, eliminating the need for periodic hospital visits.

Ullah et al. proposed a two-dimensional (2D) convolutional model that uses short-time Fourier transforms to convert one-dimensional (1D) signals to 2D spectrograms before classification [7]. The model divides signals into eight categories and employs data augmentation. Another deep CNN model, "DeepArrNet," is based on depth-wise temporal convolution on wavelet-denoised and augmented ECG data [8]. Kaya et al. investigated a combination of feature selection algorithms and three classifiers to detect bundle branch block (BBB) beats using statistical and temporal features [9]. A method of detecting arrhythmias using wave and Gabor features and a Bat-Rider Optimization algorithm-based Deep Convolutional Neural Networks (BaROA-based DCNN) is proposed by Atal et al. [10]. All these works make use of various pre-processing and data augmenting methods, as well as optimization algorithms. So the main aim is to create a simple and accurate ECG monitoring system with reduced complexity that produces comparable results.

In this article, ECG beats are classified into four classes using an automated deep CNN. The main goal is to create a decision support system with a low complexity level. This is accomplished by eliminating preprocessing steps and reducing the convolutional layer count in the proposed model. The main contributions of this work are as follows:

- A less complex, real-time, automated deep CNN model for arrhythmia classification based on 1D CNN is proposed.
- Preprocessing steps adding to the computational complexity is avoided.
- Due to its low complexity, it is easily deployable on both hardware and non-GPU devices.
- With the help of an Internet of Things (IoT)-enabled continuous ECG monitoring device, an automated remote monitoring system for ECG signals is proposed.
- The proposed model has higher accuracy, precision, recall, and $F1$ score when compared to models that have additional preprocessing and optimization steps.

This article is organized as follows. Section 2 discusses the literature review; Section 3 discusses the database, remote monitoring system, data extraction, and the model architecture. The final section discusses the evaluation metrics, followed by the conclusion and references.

2 Related work

The earlier methods for arrhythmia classification consisted of preprocessing, beat segmentation, feature extraction, and classification steps [6]. The main *preprocessing* steps adopted are denoising and removal of baseline wander. For noise removal, a variety of filters and wavelet transform methods are employed [11–14]. R-peak or QRS complex detection is used in the *beat segmentation* steps [15,16]. One of the most widely used methods for detecting QRS is the Pan–Tompkins method [17]. The *feature extraction* entails extracting parts of the ECG segment that contain features useful for classification. For this purpose, both RR interval [18] and T wave [19] segments are utilized. Principal component analysis [20], independent component analysis [21,22], and other techniques to reduce the dimension of the extracted feature vector are also investigated. Wavelet transforms are preferred for feature extraction because they extract information in both time and frequency domains [23,24]. The most commonly used *classification* algorithms are support vector machine (SVM) [25,26], artificial neural network [27], linear discriminant [28], and reservoir computing with logistic regression [29]. Mustaqeem et al. studied the multi-class classification of cardiac arrhythmias using enhanced feature selection and SVM [30]. Their findings show that the one-against-one method of SVM outperforms all the other classifiers by achieving an accuracy rate of 81.11% when used with 80/20 data split and 92.07% using the 90/10 data split option.

Fukushima and Miyake introduced Convolutional Neural Network (CNN) in 1980 as neocognitron [31]. Initially, CNN was used in image classification [32], speech processing [33], and text annotation [34]. The availability of fast memories and recent advances in machine learning have sparked renewed interest in utilizing artificial intelligence for medical diagnosis. CNN's main characteristic is its reliance on data order, and as a result, it performs well in finding patterns in 1D data vectors. According to the survey by Ebrahimi et al., CNN is the dominant choice for feature extraction among 52% of papers they surveyed [35]. Advanced research in arrhythmia classification helped researchers to eliminate the preprocessing steps like de-noising and baseline wander removal [36]. Some earlier works used CNN only for feature extraction [37], while others utilized it only for classification [38]. Some studies use separate preprocessing steps before feature extraction and classification by CNN [39].

For the 2017 PhysioNet/CinC challenges, Xiong et al. created RhythmNet, a 21-layer 1D convolutional recurrent neural network [40]. It uses single-lead ECG recordings to classify ECGs of four different rhythms, including noisy signals. The architecture has 16 convolution layers followed by 3 recurrent layers and achieved an accuracy of 82%. Another paper by Acharya et al. presented an 11-layer deep convolutional neural network model for congestive heart failure (CHF) diagnosis that requires no engineered features and minimal pre-processing of ECG signals [41]. The authors attempted to diagnose CHF from ECG signals in this study and obtained an accuracy of 98.97%. Shalin and Vahid employed the multilayer perceptron (MLP) algorithm, consisting of four hidden layers, and CNN, with four convolutional layers [42]. According to the results, the proposed algorithms can efficiently diagnose various CVD with 88.7% accuracy for MLP and 83.5% for CNN.

Kim et al. used the GoogLeNet Deep Neural Network Architecture to differentiate between five types of ECG beats. According to the authors, "The model consists of an inception module which is a method of extracting more information into a smaller layer by widening the layer of the neuron network" [43]. The inception model with a convolutional kernel size of $\{10, 50, 100\}$ achieved slightly higher accuracy ranging between 91.4 and 95.7%. Ihsanto et al. proposed a depth-wise separable Deep Convolutional Network ensemble [44]. The authors claim that the proposed method eliminates the need for preprocessing and feature extraction and achieves an overall accuracy of greater than 99% for the 16 classes they studied. The ECG signals obtained from a tertiary care hospital are investigated by Zhang et al. [45]. They claimed an overall accuracy of close to 95% and concluded that the model could detect "misdiagnosed and missed diagnosed cases" in primary care settings.

DENS-ECG, a deep learning approach that combines CNN-LSTM networks to classify P, QRS, T, and NW waveforms, is studied in ref. [46]. On the MITDB and QTDB datasets, they obtained an average $F1$-score of 99.56 and 96.78%, respectively. Zhao et al. proposed a wavelet transform method combined with 24-layer deep CNN to classify signals into four classes and obtained an accuracy of 87.1% [47]. CNN is the most computationally expensive deep learning method due to the multitude of parameters each convolution layer contributes [48]. As a result, efforts are made to reduce the complexity of the models, making them more efficient for portable device implementation [49].

3 Automated cardiac beat classifier

This article proposes an automated cardiac arrhythmia beat classification using Deep CNN trained on ECG patterns from the MIT-BIH arrhythmia database. The aim is to create a simple model in terms of architecture and which requires less preprocessing with improved performance. For the feature extraction part, the proposed model employs only two 1D convolution layers with no preprocessing. The classification part consists of the fully connected layer followed by softmax. The following sections go over the database, deep CNN, various optimization parameters, and evaluation metrics adopted.

3.1 Remote ECG processing system

It is critical for a heart patient to be monitored regularly to detect even minor variations in the heartbeat and receive proper care as needed. In this article, we propose a remote ECG processing and monitoring system that allows patients and caregivers to monitor heart conditions from the comfort of their own homes. A continuous ECG monitoring device with a wireless module is in charge of collecting data. These data are transmitted to a remote server, where they are analysed and stored for future reference. An ESP8266 Wi-Fi-enabled module along with standard ECG electrodes and instrumentation amplifier is used. The proposed arrhythmia detection model with sliding window implementation can automatically classify the beats into four classes. If an abnormality is observed the caregiver is alerted, thus ensuring continuous monitoring, increasing the patient's access to expert heart care. Figure 1 illustrates the remote ECG processing system.

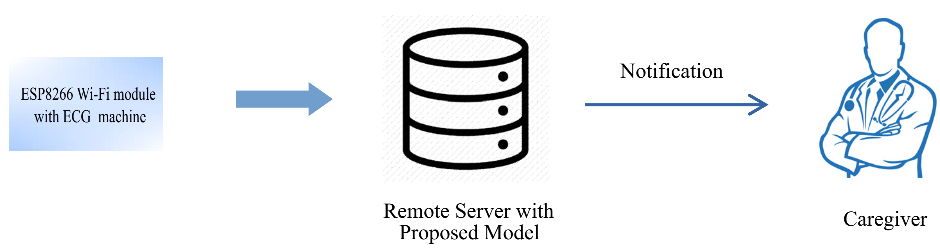

Figure 1: Remote ECG processing system.

3.2 MIT-BIH database

The MIT-BIH arrhythmia database contains 48 half-hour ECG excerpts from two-channel recordings of 47 patients collected between 1975 and 1979 by the BIH Arrhythmia Laboratory [50]. The first 23 recordings are chosen at random, and the rest are selected to include rare arrhythmia. The records are digitized with an 11-bit resolution over a 10 mV range at 360 samples per second per channel. The recordings are annotated independently by two or more cardiologists and saved as reference annotations for each beat (approximately 110,000 annotations) included with the database. Table 1 contains an index of the various beat annotations used in the MIT-BIH database [51]. Of the different beats given in Table 1, normal beat (N), left BBB beat (L), right BBB beat (R), and premature ventricular contraction (V) are chosen for classification because the number of samples for the other beat types was negligible compared to the highly sampled N beat, which would have resulted in imbalanced data issue.

To ensure that no part of the ECG is missed, the MIT-BIH data are sampled with a sliding window and an overlap size of 400 and 100, respectively. The sliding window size and overlap size are adjusted to include a complete ECG wave based on the sampling rate of the measured ECG signal. A total of 36,000 samples are obtained by taking 9,000 samples of each beat type, making it a balanced data set. The samples thus obtained are shuffled and then split into training and testing using an 80:20 ratio, as shown in Figure 2. For each beat type, 7,200 samples for training and 1,800 samples for testing are obtained. The training set is subjected to stratified tenfold cross-validation. The resulting accuracy is averaged over the ten folds. Stratified folds ensure that each test set will have the same distribution of classes or as close it can be.

Table 1: Beat annotations used in MIT-BIH database [51]

Symbol	Meaning
· or N	Normal beat
L	Left BBB beat
R	Right BBB beat
A	Atrial premature beat
a	Aberrated atrial premature beat
J	Nodal (junctional) premature beat
S	Supraventricular premature beat
V	Premature ventricular contraction
F	Fusion of ventricular and normal beat
[	Start of ventricular flutter/fibrillation
!	Ventricular flutter wave
]	End of ventricular flutter/fibrillation
e	Atrial escape beat
j	Nodal (junctional) escape beat
E	Ventricular escape beat
/	Paced beat
f	Fusion of paced and normal beat
x	Non-conducted *P*-wave (blocked APB)
Q	Unclassifiable beat
|	Isolated QRS-like artefact

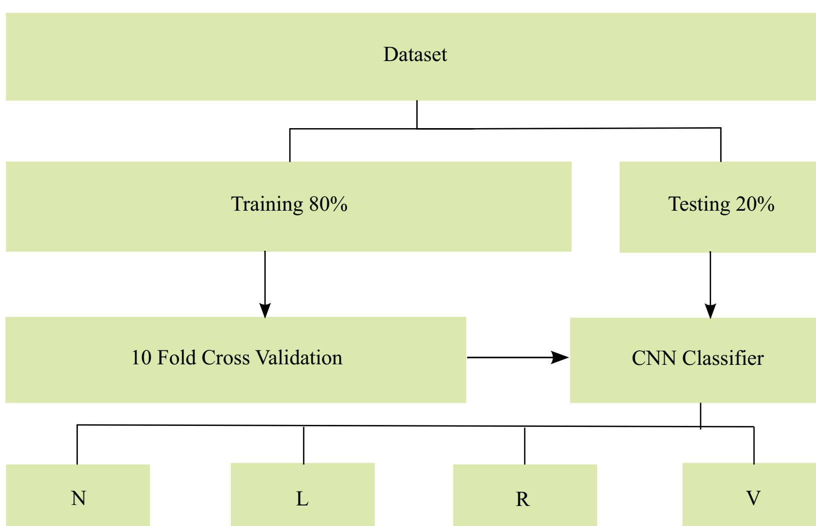

Figure 2: The train-test split and the data flow through the proposed model.

3.3 Deep neural network

A set of algorithms to recognize patterns from unstructured data modelled after the human brain are called neural networks. A deep neural network is a neural network with more than two layers – higher complexity. Each layer of nodes uses the previous layer's output features and trains on it to extract additional information. The features extracted from each successive layer become more complex as the previous layer's information is aggregated and recombined. In contrast to the existing methods for beat classification, such as heartbeat segmentation and feature extraction, the proposed method does not require any preprocessing. The data are sampled and the only operation performed on it is normalization and one-hot encoding of the target data. Normalization converts data values to a standard scale, enabling the system to learn the features. One-hot encoding transforms a categorical value into a numerical value that is better suited for machine learning models. The proposed method eliminates preprocessing overhead while having lower complexity.

Deep learning is a time consuming and iterative process in which the various hyperparameters need to be tuned to better optimize the model without penalizing the cost function. Deep neural networks use optimization algorithms to optimize the cost function J, which is defined as:

$$J(W, b) = \frac{1}{m}\sum_{i=1}^{m} L(\hat{y}^{(i)}, y^{(i)}). \tag{1}$$

The value of cost function J is the mean of the loss L between the predicted value $\hat{y}$ and actual value y. W is the weight matrix, b is the bias, and m is the number of samples [52]. The main objective of this work is to adopt a computationally efficient optimization algorithm, and works well even with noisy datasets. AdaM (Adaptive Momentum) [53] is a very powerful and fast optimizer and is well suited for the adopted objectives. Another advantage of AdaM is that each network parameter has its learning rate, which gets updated as learning progresses. In addition, the cumulative history of gradients is kept, which accelerates the learning process.

The activation function is the non-linear transformation performed over the input signal. This transformed output is used as input to the next layer of neurons. Activation functions enable back-propagation because the gradients are supplied with the error to update the weights and biases. ReLU makes computation efficient, simple, and it also speeds up training. It is defined as:

$$f(x) = \max(0, x). \tag{2}$$

ReLU ensures that only a few neurons are activated at a time, resulting in a sparse network. Furthermore, ReLU is idempotent, which solves the vanishing gradient problem.

3.4 Proposed method

The model used for beat classification is of low complexity, with only two 1D convolution layers. Many existing models, such as ResNet and VGG-Net, with multiple layers, might lead to overfitting. The proposed sequential model consists of two layers of convolution, batch normalization, activation, and maxpooling. It is followed by a flatten layer and a dense layer with softmax activation. Though having more than two hidden layers is advantageous for learning complex representations in neural networks, the number of convolutions is limited to two to avoid overfitting. For real-time processing, the sliding window implementation is used. The sliding window size and overlap size can be adjusted according to the sampling rate of the measured ECG signal.

The samples extracted undergo normalization followed by shuffling. Shuffling makes sure that no bias occurs in the model. The data are split into train and test sets in an 80:20 ratio. The training set further undergoes stratified K fold cross-validation with $K = 10$. The stratified K fold ensures that all types of samples are present in each fold. Early stopping and model checkpoint callbacks are used, with cross-entropy as the loss function. The training is done for 30 epochs with validation after each epoch. The Adam optimizer is used, with a learning rate of 1×10^{-3}. Table 2 lists the various parameters chosen for different layers of the proposed model. Figure 3 depicts the model architecture and specifies the output shape of each layer.

Keras is an open-source high-level neural network library written in Python. Keras, along with TensorFlow as the backend is used in the proposed work. Nvidia GeForce GTX 1050Ti GPU with 768

Table 2: Components of the proposed deep learning model and the various parameters adopted

Layer (type)	Parameters
Input layer	Input_shape = (400,2)
Conv1D	Number of filters: 64
	Kernel size: 3
	Stride: 1
Activation	ReLu
MaxPooling1D	Pool_size: 2
	Stride: 2
	Padding: 0
FC layer	6,272 neurons
Dense layer	SoftMax
Output layer	4 classes
Weight optimization function	Adam (learning rate: 1×10^{-3})

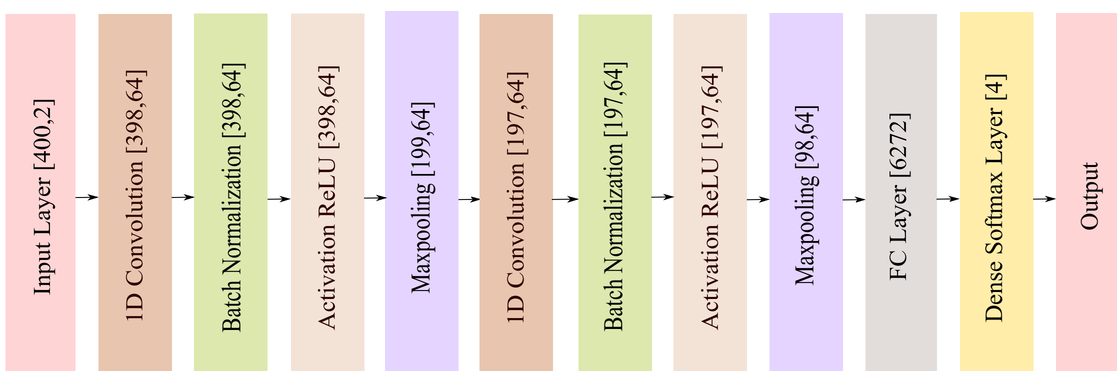

Figure 3: Proposed model architecture containing the two convolution layers followed by the fully connected layer and softmax.

CUDA cores accelerates learning in Ubuntu 16.04 platform. TensorBoard is used to track and visualize parameters such as loss and accuracy.

4 Results

4.1 Evaluation metrics

The standard metrics used are accuracy, precision, recall, and $F1$ score. Classification accuracy is defined as the percentage of correct predictions to total predictions.

$$\text{Classification accuracy} = \frac{\text{Correct predictions}}{\text{Total predictions}} \times 100\%. \tag{3}$$

When an observation is both positive and predicted to be positive, it is referred to as a true positive (TP). When an observation is positive but is predicted to be negative, this is referred to as a false negative (FN). True Negative (TN) occurs when an observation is negative and is predicted to be negative. False Positive (FP) is characterized by a negative observation but a positive prediction. The total number of correctly classified positive examples divided by the total number of positive examples is defined as recall.

$$\text{Recall (Sensitivity)} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{4}$$

Precision is calculated by dividing the total number of positively classified examples by the total number of positively predicted examples. A high precision value indicates that an example labelled as positive is, in fact, positive.

$$\text{Precision (Predictivity)} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \tag{5}$$

The F-measure is a metric that represents both precision and recall. The F-measure will always be closer to the smaller among precision and recall values.

$$F1 \text{ score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}. \tag{6}$$

4.2 Analysis

A training and testing accuracy of 99.09 and 99.03%, respectively, are achieved. The confusion matrix in Figure 4 shows that the N beat is identified with 100% accuracy while identifying L, R, and V beat with 98, 100, and 99% accuracy. Precision, recall, and $F1$ score all obtained an overall score of 0.99. Table 3 summarizes the precision, recall, and $F1$ scores. The four output classes are visualized in Figure 5 using t-distributed stochastic neighbour embedding (t-SNE). The t-SNE method is a dimensionality reduction technique for visualizing high-dimensional data in 2D and 3D maps. t-SNE employs gradient descent to transform the dataset into a low-dimensional space so that the joint probability distribution representing

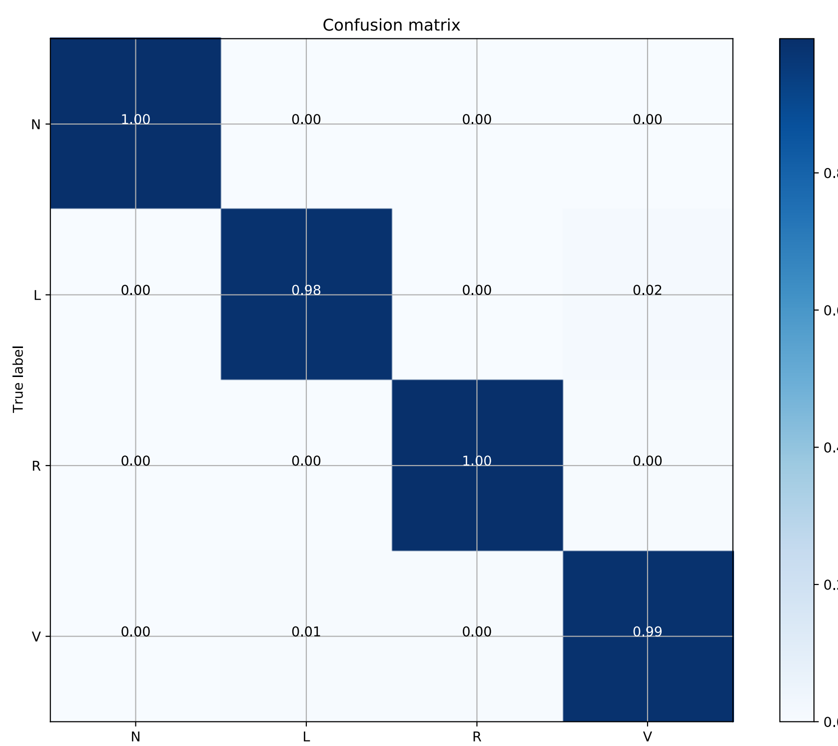

Figure 4: Confusion matrix for the testing data.

Table 3: Results obtained for the testing set

Label	Precision	Recall	*F*1 score
N	1.00	1.00	1.00
L	0.99	0.98	0.99
R	0.99	1.00	1.00
V	0.98	0.99	0.98

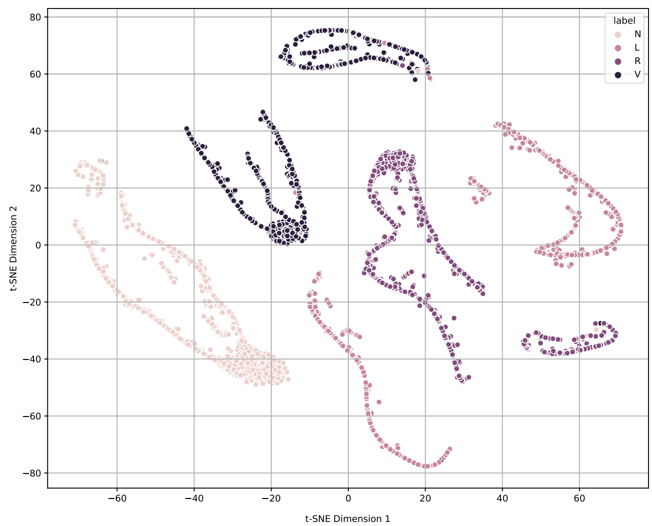

Figure 5: t-SNE visualization of the four classes N, L, R, and V.

the data points is as similar to the one in the high dimension as possible. In this case, the dense layer output is fed into t-SNE to visualize the four classes.

Table 4 shows a comparison of similar results with the proposed work using the MIT-BIH database. A 3-layer CNN-LSTM is investigated in ref. [54] to classify normal and abnormal arrhythmia with 83.4% accuracy. Brito et al. used AdaM optimizer with a 12-layer ResNet architecture to classify arrhythmias into four categories and achieve an accuracy of 83.00% [55]. A 9-layer CNN with three convolutions for classifying five different types of beats is studied in ref. [36] and obtained an accuracy of 89.07% with no data augmentations. Fujita et al. employed a similar approach in their work, with no preprocessing but requiring knowledge of feature extraction before training the model and achieving comparable results [56]. To classify ECG beats, Zhou et al. proposed a hybrid CNN - Extreme Learning Machine (ELM) method [57].

Table 4: Result comparison for beat classification using MIT-BIH dataset

Author	Approach	Pre-processing	Classes	Convolutions	Accuracy (%)
Acharya et al. [36]	CNN	Yes	5	3	89.07
Swapna et al. [54]	RNN/LSTM/GRU/CNN	Yes	2	3	83.40
Brito et al. [55]	CNN - ResNet	Yes	4	12	83.00
Fujita et al. [56]	CNN	No	4	2	97.78
Zhou et al. [57]	CNN - ELM	Yes	4	2	97.50
Atal et al. [10]	BaROA-DCNN	Yes	2	50/100	93.19
Shaker et al. [59]	2 stage DCNN	Yes	16	14	97.30
Harrane and Belkhiri [60]	CNN - LSTM	No	6	4	98.60
Çınar and Tuncer [58]	Hybrid Alexnet-SVM	Yes	3	5	96.77
Proposed method	1DCNN	No	4	2	99.03

They used the Pan–Tompkins algorithm to determine the R peak, followed by CNN for feature extraction and ELM for classification and achieved 98.77% accuracy in distinguishing four classes. An architecture based on hybrid Alexnet-SVM is investigated in ref. [58] for classifying three types of ECG signals with 96.77% accuracy, which is higher than the conventional methods. For arrhythmia detection, Atal et al. used an optimization enabled deep CNN and achieved an accuracy of 93.19%. They examined the model with 50 and 100 convolutional layers since accuracy is proportional to the number of convolutional layers involved [10]. A two-stage hierarchical deep CNN classification system for 16 classes is proposed in ref. [59]. The first stage categorizes the ECG into the five classes N, S, V, F, and Q, while the second stage categorizes the beats into the subclasses specified by the AAMI standards. They achieved an average accuracy of 97.30%. Harrane and Belkhiri used CNN for feature extraction and LSTM for classification across six classes, achieving 98.60% accuracy [60].

The proposed work achieved relatively significant accuracy with an excellent *F*1 score. The novelty of this work is that it trains a lower complexity CNN model with no preprocessing for use with real-time streamed data. The ECG data are sent to a remote server for analysis. As a result, the patient is no longer required to be admitted to a care facility. In addition, there is no need for P wave or QRS complex position detection, R peak determination, or noise removal to perform the classification. Though the results are specific to GPU training, the same can run with remarkable speed on non-GPU devices. The only disadvantage is that it requires a large amount of data for performing the initial training. The lower number of convolution layers used makes it suitable to deploy on hardware.

An automated ECG heartbeat classifier based on 1D CNNs is proposed in this study. The feature extraction and classification blocks are combined into a single learning body in this method. The need for feature extraction and preprocessing for real-time implementation of heart monitoring is thus eliminated. The proposed method only uses 1D convolutions reducing computational complexity and making it suitable for hardware implementation. The model achieved good classification results with minimal error. The obtained results did not show overfitting, and the test set performed well in terms of accuracy and *F*1-score. The model is able to classify all four classes remarkably well. Compared with related works in which the authors perform a beat-to-beat classification using CNN on the MIT-BIH arrhythmia database, this work outperforms other approaches in terms of accuracy using a model with lower complexity.

5 Conclusion and future works

In summary, an automated IoT-enabled arrhythmia detection system is proposed with a deep learning model to classify the heartbeat with an overall testing accuracy of 99.03%, which is higher than reported in the literature. A training accuracy of 99.09% with precision, recall, and *F*1-scores of 0.99 is achieved. An ESP8266 Wi-Fi-enabled module is used for real-time ECG signal transfer from the source to the server where the analysis is performed. Model complexity is minimized due to fewer convolution layers employed, making it suitable for hardware implementation. The heartbeats are classified into four types: N, L, R, and V. There is no preprocessing reducing the computational overhead.

In the future, the system can be fine-tuned with additional methods such as data augmentation, dropout, and learning rate optimization and expand it to classify other types of arrhythmias. The system can also be implemented in hardware, as low-cost embedded processors are now available, reducing power consumption. The current work uses the most widely used MIT-BIH data set. Another future work direction is to collect an indigenous data set and evaluate model performance on it. The classification results are promising, indicating that this path for beat classification should be investigated further and provides a foundation for future research. Hopefully, the proposed system will assist the caregiver in arrhythmia classification by acting as a decision support system.

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