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Heartbeat classification based on single lead-II ECG using deep learning

Mohamed F. Issa [a,d,*], Ahmed Yousry [b], Gergely Tuboly [d], Zoltan Juhasz [d], Ahmed H. AbuEl-Atta [b], Mazen M. Selim [b,c]

[a] *Department of Scientific Computing, Faculty of Computers and Artificial Intelligence, Benha University, Benha, 13511, Egypt*
[b] *Department of Computer Science, Faculty of Computers and Artificial Intelligence, Benha University, Benha, 13511, Egypt*
[c] *Department of Mechatronics, Delta University for Science and Technology, Gamasa, 11152, Egypt*
[d] *Department of Electrical Engineering and Information Systems, University of Pannonia, 8200, Veszprém, Hungary*

A R T I C L E I N F O

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A B S T R A C T

The analysis and processing of electrocardiogram (ECG) signals is a vital step in the diagnosis of cardiovascular disease. ECG offers a non-invasive and risk-free method for monitoring the electrical activity of the heart that can assist in predicting and diagnosing heart diseases. The manual interpretation of the ECG signals, however, can be challenging and time-consuming even for experts. Machine learning techniques are increasingly being utilized to support the research and development of automatic ECG classification, which has emerged as a prominent area of study. In this paper, we propose a deep neural network model with residual blocks (DNN-RB) to classify cardiac cycles into six ECG beat classes. The MIT-BIH dataset was used to validate the model resulting in a test accuracy of 99.51%, average sensitivity of 99.7%, and average specificity of 98.2%. The DNN-RB method has achieved higher accuracy than other state-of-the-art algorithms tested on the same dataset. The proposed method is effective in the automatic classification of ECG signals and can be used for both clinical and out-of-hospital monitoring and classification combined with a single-lead mobile ECG device. The method has also been integrated into a web application designed to accept digital ECG beats as input for analyses and to display diagnostic results.

1. Introduction

Cardiovascular disease (CVD) is one of the most common worldwide diseases and a leading cause of death. In 2016 alone, more than 17.6 million people died of CVD, and the number is expected to rise to 23.6 million by 2030 [1]. CVD can lead to blood clot formation and obstruction of blood vessels, resulting in cardiac or cerebral ischemic necrosis, which eventually can cause myocardial infarction or stroke. In addition, long-term circulation problems may cause varying degrees of damage in other organs of the body [2].

Electrocardiography (ECG) is an efficient, non-invasive tool commonly used for the diagnosis of cardiac arrhythmias, electrical conduction abnormalities of the heart, and myocardial ischemia. ECG recordings are obtained by measuring the heart-related bioelectric potential changes using electrodes placed on designated positions in the human body. Conventional clinical ECG uses

* Corresponding author. Department of Scientific Computing, Faculty of Computers and Artificial Intelligence, Benha University, Benha, 13511, Egypt.

E-mail addresses: mohamed.issa@virt.uni-pannon.hu, mohamed.issa@fci.bu.edu.eg (M.F. Issa).

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12 leads [3] but mobile/wearable ECG systems with less than 12 channels are becoming increasingly popular offering the opportunity for CVD screening beyond the walls of clinics [4]. Traditionally, ECG recordings are assessed by cardiologists using a predefined set of diagnostic measures. This procedure requires time and a high level of expertise that is only available in clinical settings. Digital ECG devices provide opportunities for computer-assisted diagnosis, which can (i) reduce the workload of trained cardiologists, (ii) speed up the diagnosis process, and (iii) as a pre-screening step enable the evaluation ECG generated by wearable/mobile devices without cardiologist involvement.

Advances in ECG technology and the problem of an insufficient number of cardiologists generated interest in automated ECG signal classification. Artificial Intelligence (AI) approaches, especially Deep Neural Networks (DNNs) based methods have attracted much attention recently. Deep Learning models have demonstrated their ability to enhance the accuracy of cardiovascular disease (CVD) diagnosis based on ECG readings. This is achieved by leveraging a sequence of diverse neural network layers that successively extract higher-level features, better and better neural networks can be built.

This paper introduces a hybrid model designed to achieve accurate and automated classification of single-lead ECG beats. The aim is to facilitate its utilization in both hospital and outpatient settings. The model effectively distinguishes between normal beats, arrhythmias, and ventricular conduction abnormality patterns, aiming to improve diagnostic speed and accuracy for better patient outcomes. Our DNN method is based on a Convolutional Neural Network (CNN) model trained and evaluated on the MIT-BIH Arrhythmia dataset [5]. More than 120 layers were used to classify six beat classes, such as normal beat, premature ventricular contraction, paced beat, atrial premature beat, left and right bundle branch block beat. In this study, we focus on Lead II-type signals. Lead II ECG is a widely utilized ECG recording method that has special importance in both clinical practice and research. In the Lead II system, electrodes are placed on the right arm and left leg to capture the voltage difference, which provides valuable information about the electrical activity of the heart that can be used for the identification of cardiac abnormalities like arrhythmias, ischemia, and conduction disorders. Lead II electrode positioning facilitates clear visualization of crucial ECG components such as P waves, QRS complexes, and T waves, enabling precise interpretation. Extensive studies have been conducted to validate Lead II, establishing it as a reliable reference for comparing ECG recordings across different studies and populations. Given its accessibility, ease of use, and established significance, Lead II plays an indispensable role in cardiovascular research, enhancing the accuracy of diagnostic and monitoring procedures. During our work, we used ECG signals recorded by a modified version of lead II, which is called MLII. In this configuration, electrodes were placed on the chest instead of the limbs [6].

The rest of the paper is structured as follows. Relevant, state-of-the-art classification methods are reviewed in Section 2. Section 3 provides the details of the proposed classification network architecture. Section 4 lists the classification results obtained with the proposed method. The results are discussed in Section 5 and conclusions are drawn in Section 6.

2. Related work

ECG analysis and classification are vital in diagnosing and managing cardiovascular disease, serving as an indispensable tool in modern healthcare. Manual interpretation of ECGs is challenging due to complexity and subjectivity, hence requires extensive training and expertise. The process is time-consuming, and can easily lead to delays or potential diagnosis errors. Inter-observer variability further complicates interpretation. Reliable automated ECG analysis methods are much needed to overcome these challenges. Advanced algorithms and models can enhance diagnosis, enable prompt identification of abnormalities, guide treatment decisions, and improve patient outcomes.

Interest in neural network-based ECG feature extraction and classification has considerably increased in recent years. The benefits of CNN for automatic feature extraction and classification in ECG arrhythmia time-series signals were demonstrated in Ref. [7]. In their research, Yang et al. introduced a hybrid model named THC-Net for automated ECG classification. This model incorporates various techniques, including a Canonical Correlation Analysis (CCA) based on Principal Component Analysis (PCA) Convolutional Network, an Independent Component Analysis (ICA)-PCA Convolutional Network, and a Dempster-Shafer (D-S) theory-based Linear Support Vector Machine (SVM) [8]. By combining these techniques, THC-Net streamlines the ECG classification process and eliminates the need for manual feature construction based on specialized knowledge. Based on leave-one-out cross-validation, an accuracy of 95.54% was demonstrated when diagnosing normal, congestive heart failure (CHF), and coronary artery disease (CAD) ECGs. The homomorphically irreducible tree (HIT) graph pattern was used by M. Baygin et al. [9] to create a feature extraction algorithm. The dataset used in this research consisted of 12-lead ECGs recordings of approximately 10,000 people. Accuracy rates of 92.95% and 97.18% were reported for two different ECG classes In Ref. [10], a DNN model was used, in which various shallow classifiers were fed feature maps derived from hierarchically organized layers in the DNN. Dimensionality was reduced using Principal Component Analysis. An accuracy of 90.30% was reached using ECG characteristics. This accuracy was enhanced to 97.26% when only deep neural network features were used. Each cardiac cycle yielded five useful features according to the researchers [11] who trained an ensemble binary classifier using the MIT-BIH Arrhythmia Dataset, achieving an F1 score of 94.35%. INCART, the St. Petersburg Institute of Cardiological Technics dataset was also used to test their system such as the MIT-BIH long-term ECG database, resulting in an F1 score of 92.06% and 91.40%, respectively.

Bidias et al. [12] provided a two-level hierarchical model for classifying ECG beats into three categories based on ordinal patterns without requiring training. Their model was validated using the MIT-BIH arrhythmia and the INCART databases, achieving a categorization rate of 93.66% and 95.43%, respectively. The permutation entropy (PE) and the conditional entropy of ordinal patterns (CEOP) were used for ECG data processing by the same authors [13]. On the MIT-BIH dataset and the European Society of Cardiology ST-T (ESC) database, a classification rate of 93.62% and 99.57%, respectively, were achieved. F. Meneguitti et al. [14], used a combination of higher-order statistics, RR intervals, and signal morphology in combination. The method was evaluated by introducing a jitter to the MIT-BIH Arrhythmia database's R-wave locations. For the normal, supraventricular premature beat, and premature ventricular contraction classes, sensitivities of 93.7%, 89.7%, and 87.9% were attained, respectively.

CNN and LSTM networks were used in Ref. [15], where they used a 12-lead ECG dataset that was generated by the Kaohsiung Medical University Hospital (KMUH) and achieved an overall accuracy of up to 94%. For an automatic classification of main ECG signals, a DNN model was employed using the Physikalisch-Technische Bundesanstalt (PTB-XL) database, while the network based on SincNet had an accuracy of 85.8%. The convolutional network with entropy as a featured network attained an accuracy of 89.82% [16]. Other researchers extracted features from ECG signals using a deep autoencoder and classified them using a system of several neural networks with an accuracy of 99.32% and 97.83%, respectively, using two separate models [17]. In contrast, the research conducted in Ref. [18] introduced an innovative approach utilizing a multi-class classification strategy for the early detection of cardiovascular autonomic neuropathy (CAN). This approach involved fusing deep learning features with selected original features to achieve multimodal feature fusion. The experimental results, obtained from extensive testing on a sizable CAN dataset, revealed that the proposed technique achieved an impressive AUC score of 0.931 when evaluated using leave-one-out cross-validation.

3. Methods

We propose a deep neural network model, specifically the DNN-RB architecture, for the classification of ECG beats. The DNN-RB model integrates numerous layers with residual connections, enabling efficient feature extraction and precise classification of the input ECG signals. By leveraging this architecture, our model can efficiently process and analyse the complex patterns present in the ECG data, leading to improved accuracy in beat classification.

3.1. Dataset description

Our proposed method in this study utilized the MIT-BIH arrhythmia database [5] for the purposes of training, testing, and validation. The MIT-BIH database contains 48 half-hour snippets of two-channel ambulatory ECG recordings from 47 patients recorded by the BIH Arrhythmia Laboratory between 1975 and 1979. The data set is freely available to the research community through the PhysioNet website (https://physionet.org/content/mitdb) for research purposes. The recordings were digitized at a 360 Hz sampling rate for each channel with 11-bit resolution and a 10 mV amplitude range. All records were carefully examined by at least two cardiologists beat to beat labeling each beat. The timestamp and label (e.g., normal, atrial premature beat) of a particular beat are referred to as beat annotation. Overall, there are around 110,000 annotations in the database.

Table 1 describes the beat annotation classes selected from the dataset: normal heartbeat (N), atrial premature beat (A), premature ventricular contraction (V), right-bundle branch block beat (R), left-bundle branch block beat (L), and paced beat (/). These classes were chosen based on their clinical significance and prevalence in ECG analysis [17,19–21]. Class N serves as a reference for comparison and provides a baseline for detecting abnormalities. Atrial premature beats (A) and premature ventricular contractions (V) are arrhythmias that require close monitoring and may indicate underlying cardiac conditions. Lastly, the/class represents paced beats, which occur in patients with implanted pacemakers.

The database records contain two leads or channels, lead 'MLII' and 'V5'. In this work, lead 'MLII' is used for the classification.

3.2. Segmentation

The initial stage of the method involves extracting the QRS complexes from the ECG signal, which is also known as signal segmentation. The QRS complexes will be used as input to the DNN-RB classifier in the training, testing, and validation steps. Fig. 1 illustrates the P-QRS-T complexes in one beat, where the R-value is the maximum value in the beat. The sample index of the R-peak is obtained from the annotation file. After locating the R-peaks, Eq. (1) and Eq. (2) are used to segment the beats from the signals. Each selected beat contains 711 ms of the ECG recordings (256 samples, fs = 360 Hz): the R peak is centered in the window, leaving 128 samples to the left and right of the R-peak.

$$P\_S = P - \text{input\_size} \ / \ 2 \tag{1}$$

$$P\_E = P + \text{input\_size} \ /2 \tag{2}$$

P_S and P_E refer to the start and the end index of the beat respectively, and P is the index of the R-peak. The input size is equal to the

Table 1
Beat annotations of the MIT-BIH Arrhythmia Database.

Class	Description
N	Normal beat
V	Premature ventricular contraction
/	Paced beat
A	Atrial premature beat
L	Left bundle branch block beat
R	Right bundle branch block beat

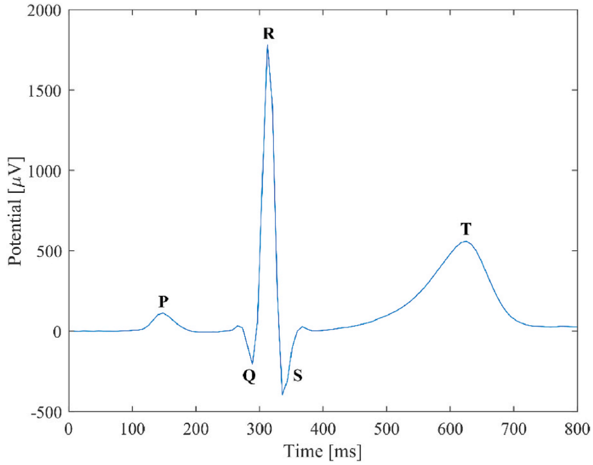

Fig. 1. PQRST beat structure.

beat length (256 samples). Fig. 2 illustrates typical beat waveforms of the six selected beat classes: 'N', 'V', '/', 'A', 'L', and 'R'.

3.3. Convolutional neural network architecture

Fig. 3 illustrates the overall architecture of the neural network proposed in this study, while for a more comprehensive understanding of the network structure, please refer to Table 2, which provides detailed information about the individual layers of the network. The network has more than 120 layers grouped into three stages. The first stage starts with the input layer which accepts the input beat of 256 samples. This is followed by a one-dimensional convolution layer of 16 kernels/filters with stride 1 and filter length 32 to create the feature maps for the third layer. The batch normalization (BN) layer is used to scale the outputs of the previous layer to overcome the problems of exploding or vanishing. The BN layer is followed by a ReLU activation function. The next block consists of a one-dimensional convolution layer with 256 * 32 nodes (kernel size = 16, filter length = 32) followed by BN, ReLU, dropout layers with a drop rate of 0.2, and finally a 1D-Conv layer. The drop rate of 0.2 in the dropout layer results in dropping 20% of nodes in the forward and backward process to overcome the problem of overfitting and underfitting.

The second stage of the network consists of 16 residual Blocks, each of which has 7 layers: BN, ReLU, 1D convolution, as well as BN, ReLU, Dropout, and 1D convolution. After constructing each residual block, the number of nodes is reduced by half from 256 to 128, …, 2, and 1 using the max-pooling procedure with a pool size of two and a stride of one.

In the concluding phase of the network, four layers are incorporated: a 1D Convolutional layer, Batch Normalization (BN), Rectified Linear Unit (ReLU), and a dense layer with a SoftMax activation function consisting of six nodes (one node for each target beat class). The model has 563366 parameters in total. The proposed CNN is made up of 36 separate 1-D CNNs. A densely connected residual block is used to extract the deep features of the signal as shown in Fig. 1. The residual block is repeated 16 times, which improves the model accuracy in terms of sensitivity and specificity. Also, these repeated blocks aid in extracting the best characteristics of the signal and outperform the use of a single block. The arrhythmia classification probability is calculated using the raw ECG data corresponding to the specified lead as input. Finally, the classification probability for various cardiac arrhythmias is calculated using two completely linked layers and the SoftMax function. In this study, ReLU is employed as the activation function, while the Adam optimizer is utilized to train the network using default settings.

The dataset contains 118,403 beats, which are divided into three parts. The training set comprises 70% of the data, while 15 %–15% is allocated for the validation and testing sets. Due to the limited number of records in certain beat classes, only six classes (N, V,/, A, L, and R) were included in the classifier design and training. The training set consists of 87,515 beats, while the validation and testing set each contain 15,444 beats. To address the significant imbalance in the initial dataset, a balancing technique was applied by randomly selecting a number of normal beats equal to the number of beats in other classes. This removed potential biases or skewed outcomes that could have resulted from the disproportionate distribution of beats across the various classes.

4. Results

The evaluation results of the proposed model, developed using the Keras and TensorFlow packages in Python, are presented in this section. The performance of the model was assessed based on the MIT-BIH database [5] as well as additional references [22]. The experiments were conducted on the Google Collab platform equipped with a 0.82 GHz GPU, and 12 GB RAM hardware with a performance of 4.1 TFLOPS.

Table 3 summarizes the important hyper-parameters that are employed throughout the execution of the DNN model. In training our CNN RB model, we employed the important technique of early stopping with a patience value of 10 while monitoring the validation loss. (Patience value is the number of epochs with no improvement in validation loss which is used with early stopping) By using this

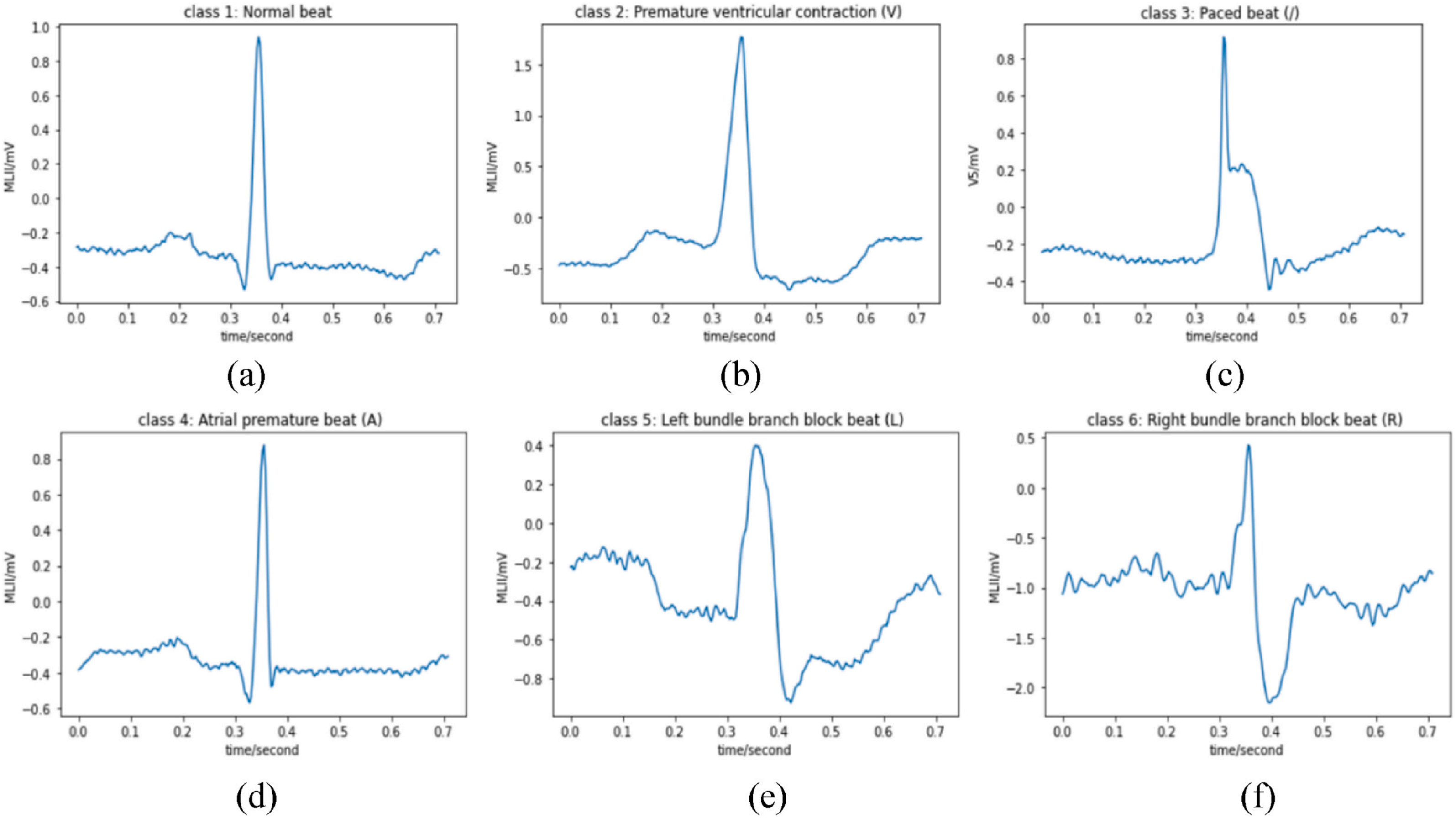

Fig. 2. Examples of ECG beat classes. (a) Shows a sample of a normal beat labeled as "A." (b) represents a sample from class V. (c) Displays a paced beat labeled with "/". (d) Shows another sample from class V. (e) Represents a sample from class L. (f) Displays a sample beat from class R.

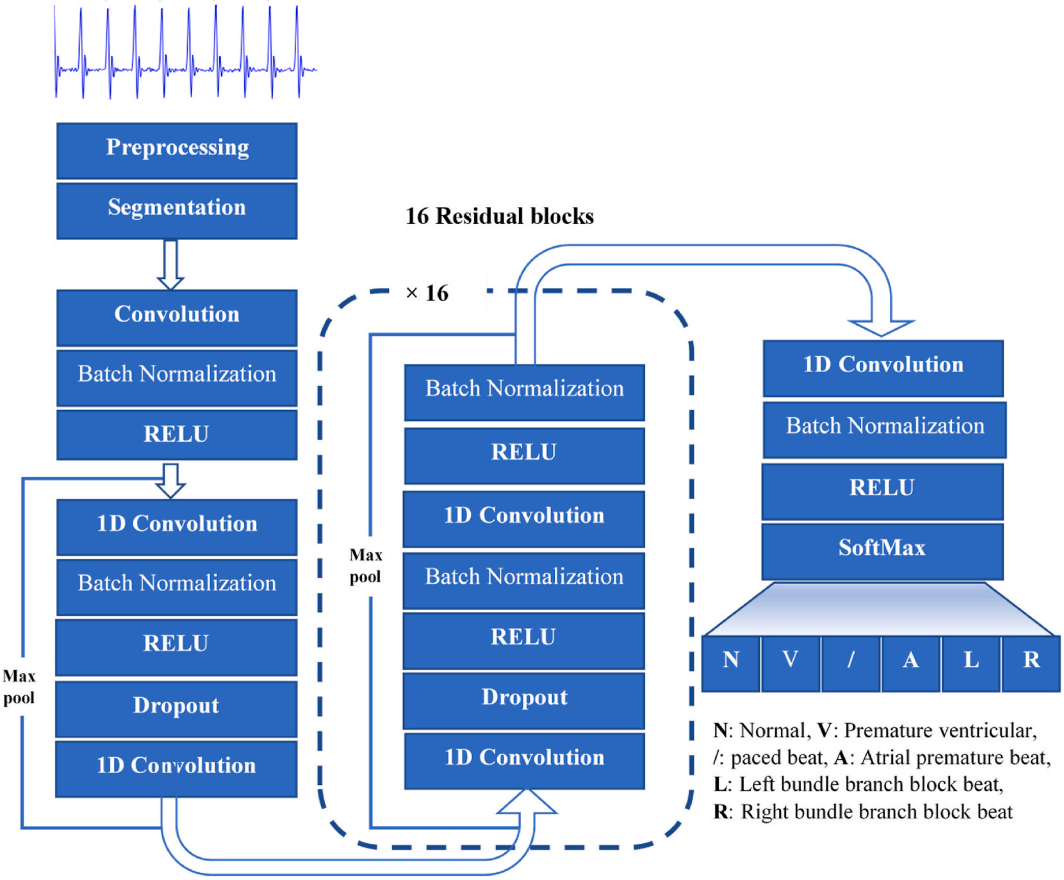

Fig. 3. Block Diagram of the proposed method.

Table 2
Detailed description of the DNN model.

No	Layer Name	Nodes	Kernel size	Associated parameters
1	Input	256*1	–	–
2	Conv-1D	256*32	16	Stride = 1,filter length = 32, padding = same
3	BN	–	–	–
4	Dense	–	–	Activation = ReLU
5	Conv-1D	256*32	16	Stride = 1,filter length = 32, padding = same
6	BN	–	–	–
7	Dense	256*32	–	Activation = ReLU
8	Dropout	–	–	Drop rate = 0.2
9	Conv-1D	256*32	16	Stride = 1,filter length = 32, padding = same
10	Residual Block	256*32	16	See Fig (1)
25	Residual Block	1*32	16	See Fig (1)
26	Conv-1D	1*32	16	Stride = 1,filter length = 32, padding = same
27	BN	–	–	–
28	Dense	1*32	–	Activation = ReLU
29	Dense	1*6	–	Activation = SoftMax

technique in the training process, the model stops training when there is no substantial reduction in loss after 10 consecutive epochs. This helps prevent overfitting, improves efficiency by terminating training when improvements are no longer significant, and ensures the model's ability to generalize well to unseen data [23]. As previously stated, the input data was split into three categories: 70% for training, 15% for validation, and 15% for assessing the model's performance.

The performance evaluation of the system utilized the following evaluation criteria: precision (Eq. (3)), recall or sensitivity (Eq. (4)), F1-Score (Eq. (5)), specificity (Eq. (6)), and accuracy (Eq. (7)). Additionally, other metrics including true positive (TP), false positive (FP), true negative (TN), and false negative (FN) were employed, as indicated by the following formulas:

Table 3
Hyper-parameters of the DNN model.

No.	Parameter	Values
1	Optimizer	Adam, beta_1 = 0.9, beta_2 = 0.999
2	Learning Rate	0.15 to min 0.00005
3	Loss Function	Categorical cross-entropy
4	Metrics	Accuracy, loss
5	Batch Size	256
6	Epochs	25
7	patience	10
8	Decay	0.0

$$\text{Precision} : \text{PRE} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

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

$$\text{F1 score} : \text{F1} = \frac{2 \times \text{PRE} \times \text{REC}}{\text{PRE} + \text{REC}} \tag{5}$$

$$\text{Specificity} : \text{Spec} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{6}$$

$$\text{Accuracy} : \text{Acc} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \tag{7}$$

Fig. 4 shows the confusion matrix that represents the number of correct/incorrect predictions by beat classes.

A comparison between the training/validation accuracy and the training/validation loss is shown in Fig. 5 and Fig. 6, respectively. The validation accuracy begins at roughly 0.70 and gradually grows in lockstep with the training accuracy to reach 0.998 in the final epoch, depending on the proposed deep learning model. The final training accuracy is 99.81% and the validation accuracy is 99.54%. The validation loss begins at a value close to 0.90 and reduces to 0.0205, whereas the training loss ends at a 0.0058 error rate. The proposed model is neither overfitted nor underfitted, as the training and validation accuracies are quite near to each other, at 99.8% and 99.54%, respectively.

Table 4 contains the precision, and F1 scores for each class in the test dataset. Using a total number of 15,444 instances in the test set the overall average scores are precision: 98.8%, and F1 score: 98.6%. The validation accuracy result demonstrates that the proposed model can successfully classify ECG beats. Table 5 lists the obtained sensitivity and specificity scores for each class, as well as their average.

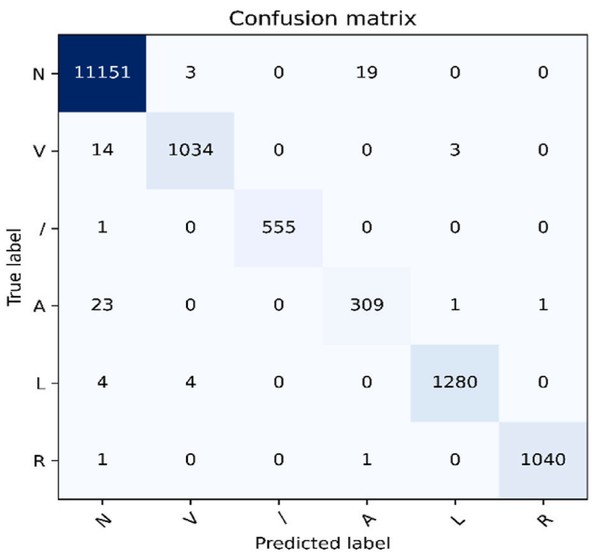

Fig. 4. Confusion matrix for the six classes. Entries represent the number of beats classified into a given beat class.

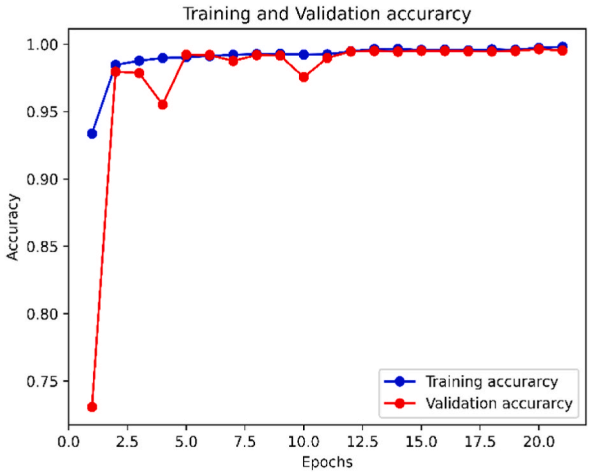

Fig. 5. Relationship between training and validation accuracy as a function of epochs.

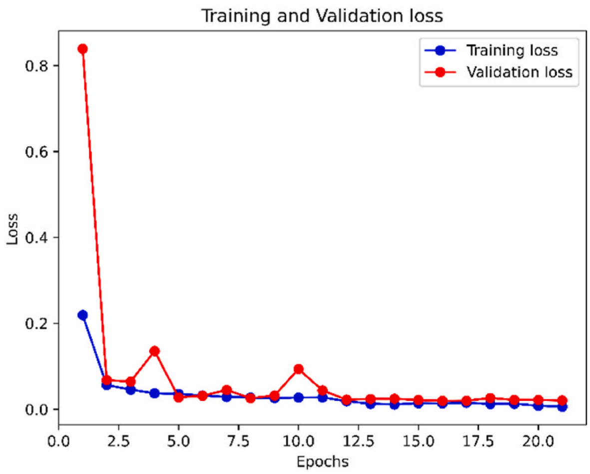

Fig. 6. Training and validation loss as a function of epochs.

Table 4
Precision, recall, and F1 scores obtained for the beat classes.

Class	Precision%	F1 Score%	instances
N	100	100	11173
V	99	99	1051
/	100	100	556
A	94	93	334
L	100	100	1288
R	100	100	1024
Average	98.8	98.6	

5. Discussion

Illustrated in Fig. 7, the collective average sensitivity and specificity reach 99.7% and 98.2%, respectively. This represents a remarkable level of precision compared to other contemporary methods, detailed below and in Table 6, using the same dataset and single lead II signals.

Jean Bertin et al. [13] developed an algorithm that classifies beats into two categories: normal (N) and abnormal (A). They accomplished an accuracy rate of 93.67%, 55.75% of sensitivity, and 98.23% of specificity. Similarly, John Malik et al. [11] focused on distinguishing between ventricular ectopic beats (VEB) and non-VEB using interpretable morphological features and the Adaboost algorithm in Lead II. Their model achieved a sensitivity of 88.74% and a specificity of 99.42%. Other researchers, such as Felipe et al.

Table 5
Sensitivity and Specificity obtained results for the beat classes.

Class	Sensitivity %	Specificity %
N	98.9	99.8
V	99.9	98.3
/	100	99.8
A	99.8	92.5
L	99.9	99.3
R	99.9	99.8
Average	99.7	98.2

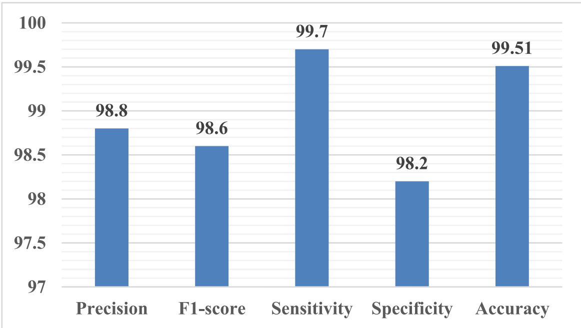

Fig. 7. Overall evaluation metric results of the DNN-RB model.

Table 6
Comparison of the proposed method with related works with the same dataset and single lead II.

Method	Classes	Algorithm	Results
Felipe et al. [14]	3 classes (N, S, V)	inter-patient paradigm	**Sensitivity** 93.7, 89.7, and 87.9, for three models
Jean Bertin et al. [13]	2 classes (N, A)	(CEOP)	**Accuracy**: 93.67% **Sensitivity**: 55.75% **Specificity**: 98.23%
Zhanhong et al. [21]	5 classes (N,S,V, F, Q)	GAN with auxiliary classifier	**Accuracy**: 99% **Sensitivity**: 87% **Specificity**:99%
Roguia Siouda et al. [17]	5 classes (N, S V, F, Q)	Single MLP, OAA-MLP system 99.32	**Accuracy**: 97.83%, 99.32%
John Malik et al. [11]	2 classes VEB (ventricular ectopic beats) and non-VEB	Interpretable morphological features with Adaboost	**Sensitivity**:88.74% **Specificity**:99.42%
Proposed Method	6 classes (N, V,/, A, L, R)	Deep Learning (CNN) With Residual Blocks (DNN-RB)	**Accuracy**: 99.51% **Sensitivity**: 99.7% **Specificity**: 98.2%

[14], categorized beats into three classes: normal (N), supraventricular (S), and ventricular (V), achieving sensitivities of 93.7%, 89.7%, and 87.9%, respectively, using an inter-patient paradigm. In contrast, Zhanhong et al. [21] utilized a GAN model for beat identification across five classes. Their approach achieved impressive results with 87% of sensitivity, 99% of specificity, and 99% accuracy. In another study, Siouda et al. [17] developed an algorithm that classified beats into five classes using a Single MLP (Multi-Layer Perceptron) and OAA-MLP system, achieving an accuracy of 97.83% and 99.32% respectively.

The methodology we proposed demonstrated very good results; 99.51% accuracy, 99.7% sensitivity and 98.2% specificity. Notably, our approach surpassed the performance of all other existing works in the field, highlighting its advantage in beat classification. We used a deep learning approach, specifically a CNN with residual Blocks (DNN-RB), to effectively classify beats into six distinct classes. Our proposed model is based on the residual block architecture proposed by Yang et al. [24], with major variations in the network design allowing the DNN-RB model to perform better in ECG classification. Rather than employing a single residual package as proposed in Ref. [24], then our model employs 16 residual packages in parallel, allowing for the retrieval and utilization of 16 distinct features, resulting in improved ECG signal classification. By incorporating information from multiple scales, the model can potentially capture fine-grained details as well as broader patterns within the ECG signals, which can aid in improving the accuracy of the classification task. To avoid overfitting and extracting meaningful features, the DNN-RB model switches between batch normalization (BN), ReLU, Dropout, and Max pooling in the residual blocks as mentioned in Fig. 3.

The findings of this study demonstrate the effectiveness of the proposed deep neural network model with residual blocks (DNN-RB) in accurately classifying cardiac cycles into six ECG beat classes. The high accuracy and performance of the DNN-RB model make it a valuable tool for the automatic classification of ECG signals. This has significant implications for clinical practice, as manual interpretation of ECG signals can be challenging and time-consuming, even for experts. The use of the DNN-RB model can greatly assist healthcare professionals in quickly and accurately diagnosing cardiovascular diseases. Furthermore, the integration of the proposed method into a web application enhances its practicality and accessibility. This application allows for the input of digital ECG beats, which can then be analyzed using the DNN-RB model. The diagnostic results are displayed, providing valuable insights to healthcare providers and aiding in the decision-making process. Moreover, the ability of the proposed method to be combined with a single-lead mobile ECG device offers promising opportunities for out-of-hospital monitoring and classification. This allows individuals to actively monitor their heart health and potentially detect abnormalities or changes in their ECG patterns. Early detection and continuous monitoring can lead to timely interventions and improved management of cardiovascular conditions.

The results presented in Tables 4 and 5 provide valuable insights into the performance of the proposed classification model for different beat classes in single-lead ECG analysis. Table 4 displays the precision and F1 score for each beat class. The model achieves outstanding precision and F1 score for all beat classes, indicating its ability to accurately classify ECG beats. Class N (normal heartbeat) achieves a perfect precision and F1 score of 100%, demonstrating the model's capability to precisely identify normal heart rhythms. The remaining beat classes (V,/, A, L, R) also exhibit high precision and F1 score, ranging from 94% to 100%. These results highlight the model's effectiveness in correctly classifying various beat types. Table 5 presents the sensitivity and specificity results for the beat classes, demonstrating the model's ability to detect instances of each beat class accurately. The sensitivity values for Class N (normal heartbeats) and other beat classes (V,/, A, L, R) range from 98.9% to 100%, indicating the model's effectiveness in capturing the unique characteristics of different beats. Furthermore, the model exhibits high specificity values across all beat classes (92.5%–99.8%), showcasing its capacity to correctly classify beats that do not belong to a specific class. This capability reduces false positives and enhances the overall accuracy of the classification process.

The proposed classification model demonstrates robust performance, as indicated by the average precision, F1 score, sensitivity, and specificity values of 98.8%, 98.6%, 99.7%, and 98.2% respectively. These results attest to the accuracy of the model in identifying different beat classes, such as normal heartbeats, left and right bundle branch block beats, atrial premature beats, premature ventricular contractions, and paced beats. Importantly, our findings indicate that the proposed method holds promise for detecting specific arrhythmias and ventricular conduction abnormalities. Although heart rate and rhythm information is not directly included in our DNN model, the algorithm is able to identify premature beats based on the ECG waveform. The difference between atrial and ventricular premature beat detection efficiency can be explained by the amplitude difference between the atrial and ventricular depolarization wave (i.e. P wave and QRS complex). Even though abnormalities in the small P waves typical for atrial premature beats (class A) are more difficult to detect than irregularities in the QRS complex characteristic of ventricular premature beats (or bundle branch block), compared to other methods, our model had the best results. Since our algorithm analyses single-lead ECG, it can be combined with the increasingly popular mobile ECG technology. Therefore, it can be used to screen rhythm and conduction abnormalities out of hospital, contributing to the identification of a possible underlying heart disease.

While these results demonstrate the effectiveness of the proposed model, It is worth emphasizing that the evaluation was conducted using the MIT-BIH Arrhythmia dataset. Further validation on larger and more diverse datasets would be beneficial to assess the model's generalizability and reliability in real-world scenarios. Additionally, our model only classifies six predefined arrhythmia classes, which may not cover the full range of cardiac conditions. To address this, a larger dataset with a more diverse representation will have to be used in the future. Despite these shortcomings, our research lays the foundation for future research and shows ways to enhance the accuracy of ECG classification using hybrid models.

6. Conclusions

This paper addressed the need for automated classification of single-lead ECG beats to improve the diagnosis of cardiovascular diseases. It focused on Lead II signals and proposed a hybrid model based on a Convolutional Neural Network (CNN). The performance of the model was evaluated using the MIT-BIH Arrhythmia dataset, and the paper reviewed existing classification methods in the field. The aim was to enhance diagnostic speed and accuracy in both hospital and outpatient settings, ultimately improving patient outcomes in the detection and management of cardiovascular diseases. We used a DNN model with residual blocks where 1-D CNNs are used to extract the features. The DNN-RB method was tested on the MIT-BIH database of 15444 beats for the multiple classifications process, and the number of beats used for training, validation, and testing is 118,403. The results demonstrated that the DNN-RB model achieves an accuracy of 99.51% which achieves superior performance compared to the state-of-the-art techniques that used the same dataset and the same single lead ECG signals. The proposed method allows the identification of multiple beat classes using a single lead, which can be used as a suitable supporting tool in both clinical and out-of-hospital settings for CVD diagnosis and patient monitoring.

Data availability statement

Data associated with this study has been deposited at https://physionet.org/about/database/.

Author contribution statement

Mohmed F. Issa: Ahmed Yousry: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Gergely Tuboly: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

Zoltan Juhasz: Analyzed and interpreted the data; Wrote the paper.

Ahmed H. AbuEl-Atta: Mazen M. Selim: Contributed reagents, materials, analysis tools or data.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

We have developed a web-based application that leverages the proposed model to classify ECG beats into their respective six classes, providing probabilities for each class. The application that can be accessed at the following link http://ecgclassification.pythonanywhere.com is designed to be utilized in both clinical and non-clinical settings, enabling its widespread use in the diagnosis of CVD. By integrating this classification process into the diagnostic workflow, the application can significantly enhance the accuracy and efficiency of CVD diagnosis. Healthcare professionals as well as individuals outside of medical facilities can benefit from this user-friendly tool, which facilitates the prompt and accurate identification of cardiac abnormalities. The application allows cardiac monitoring without frequent clinic visits, promoting early detection of abnormalities and leading to timely intervention. It can also be used for remote monitoring and telemedicine applications in which healthcare professionals can review records remotely. The application requires a minimum of 9000 ECG recording samples which contain about 31 beats at fs = 360 Hz sampling rate. Each beat consists of 256 samples. The system excludes the first and last beats, as well as any beats with noise. The output of the system provides the predicted count for each class, namely N, V, A,/, L, and R.

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