A practical system based on CNN-BLSTM network for accurate classification of ECG heartbeats of MIT-BIH imbalanced dataset

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***Abstract*— ECG beats have a key role in the reduction of fatality rate arising from cardiovascular diseases (CVDs) by using Arrhythmia diagnosis computer-aided systems and get the important information from patient cardiac conditions to the specialist. However, the accuracy and speed of arrhythmia diagnosis are challenging in ECG classification systems, and the existence of noise, instability nature, and imbalance in heartbeats challenged these systems. Accurate and on-time diagnosis of CVDs is a vital and important factor. So it has a significant effect on the treatment and recovery of patients. In this study, with the aim of accurate diagnosis of CVDs types, according to arrhythmia in ECG heartbeats, we implement an automatic ECG heartbeats classification by using discrete wavelet transformation on db2 mother wavelet and SMOTE oversampling algorithm as pre-processing level, and a classifier that consists of Convolutional neural network and BLSTM network. Then evaluate the proposed system on MIT-BIH imbalanced dataset, according to AAMI standards. The evaluations results show this approach with 50 epoch training achieved 99.78% accuracy for category F, 98.85% accuracy for category N, 99.43% accuracy for category S, 99.49% accuracy for category V, 99.87% accuracy for category Q. The source code is available at https://gitlab.com/arminshoughi/cnnlstm-ecg-classification. Our proposed classification system can be used as a tool for the automatic diagnosis of arrhythmia for CVDs specialists with the aim of primary screening of patients with heart arrhythmia.**

Keywords*— *Cardiovascular diseases, Convolutional neural network, Deep learning, Long Short Term Memory, Electrocardiogram signals, Physio Bank MIT-BIH arrhythmia database, AAMI.

I. Introduction

CVDs are the most important factor of fatality globally, which annually caused the deaths of 17.9 million people. Totally 31% of all death in the world are related to CVDs, which the age of 1/3 of patients that died because of CVDs is below 70 [1]. Arrhythmia is unusual heartbeats. Heart in time of arrhythmic cannot pump enough blood to the body. Lack of bloodstream can injure the heart, brain, and other body organs. "Arrhythmia" is said to any changes in the normal sequence of electrical impulses, which cause abnormal rhythm in the heart. Arrhythmia can be both either completely safe or periled the life of patients. Among factors that can cause arrhythmia, we can name coronary artery disease, hypertension, cardiomyopathy, and valve disorders, lack of blood electrolyte balance such as sodium and potassium, injury arising from a heart attack, recovery process after heart surgery, and other medical conditions. ECG signals record a comprehensive view of human electronic heart activities, and they are used as a source for authentic clinical diagnosis of heart arrhythmia [2]. By analyzing these signals, we can obtain morphological features and clinical information with a meaningful correlation for the automatic diagnosis of ECG patterns. On the other hand, the existence of different morphological and time feature for different patients in different body positions challenge the automatic classifying operation. According to AAMI standards, arrhythmias which patients for avoiding potential risk need treatment and taking care and are threatening the life of patients, according to TABLE I are classified into five categories: Fusion (F), Supraventricular ectopic(S), Ventricular ectopic (V), non-ectopic (N) and unknown (Q), that each of which has different symptom and needs special treatments. Thus the accurate diagnosis of arrhythmia types is significant and vital for effective treatment of patients [3]. Our purpose in this study is the presentation of an accurate classification system for classifying ECG signals into five classes identified in AAMI standards. For this purpose, we design and implement a classification system with a combination of CNN and BLSTM networks, that CNN network by extracting local feature, short term impulse pattern of ECG beats and BLSTM by extracting long term correlation in ECG beats, obtained the overall trend of changes. Thus important information of ECG signals was extracted and consequently obtained higher accuracy in classifications.

TABLE I. Categories of heartbeats existed in the MIT-BIH database based on AAMI [4].

AAMI Classes	**Heartbeat Types**
Normal beats (N)	Normal beats (N), Left bundle branch block (L), Right bundle branch block (R), Atrial escape beat (e), Nodal (junctional) escape beat (j)
Supraventricular ectopic Beats (S)	Atrial premature contraction (A), Aberrated atrial premature beat (a), Nodal (junctional)premature beat (J), Supraventricular premature beat (S)
Ventricular ectopic beats (V)	Ventricular premature contraction (V), Ventricular escape beat (E)
Fusion beats (F)	The fusion of ventricular and normal beat (F)
Unclassifiable beats (Q)	Paced beat (/), Fusion of paced and normal beat (f), Unclassified beat (Q)

The rest of this paper is organized as follows. Section II describes the related works. Section III introduces the database that is used for training, testing, and evaluating of the proposed method in this study. Section IV describes the proposed method. Section V presents the experimental setup and shows the achieved result by the proposed method and performance compared to the state-of-the-art approaches. Finally, we conclude the paper and discuss future work in Section VI.

II. Related Work

Due to the high rate of mortality among CVDs in the world and the high importance of diagnosis of this type of disease in the effective treatment of patients, analysis of ECG signals are be noticed by researchers with the aim of accurate diagnosis of the CVDs. In the last decades, researchers used many approaches such as neural networks [5], deep neural network [6], convolutional neural network [7], k-nearest networks [8, and 9], Random forest [9, 10], logistic regression [10], Feature selection [11, 12, 13, 14, 15, 16, 17, 18, and 19], Swarm Intelligence [20, 21, 22, 23] and ensemble learning [24] for classifying ECG heartbeats. Convolutional neural networks among the most successful deep learning and machine learning approach in a different realm such as object recognition [4], image verifications [25] and classifications [2], speech recognition [3] and so analyzing bioinformatics signals is a successful way and achieve highly accurate and speed in diagnosis. Convolutional neural networks are among end-to-end approaches that provide structure in which extraction and feature classification are blended simultaneously [27]. Zhai x et al. [25], by using 2D seven layers convolutional network, achieved an accuracy of %98.6 in classification V set and an accuracy of 97.5% in signal classification S sets. Xhang ye et al. [2] used two convolutional networks for extracting important features and then send these extracted features as an MLP network for classification ECG signals. They, by using this approach, achieved an overall accuracy of 97.8% in V and S set classification. U R Acharya et al. [28] presented nine layers of the convolutional network for automatic classifier of ECG heartbeat samples of MIT-BIH imbalanced dataset according to AAMI standards and achieved an overall accuracy of 94.3% in classification of these ECG heartbeats. S. L. Oh et al. [29], by implementing a U-net auto-encoder network, achieved an accuracy of 97.32% in ECG heartbeats classification. Zhang et al. [30], by using six layers convolutional neural network model consisting of two convolutional layers, two pooling layers, and two fully-connected layers, achieved an accuracy of 97.5% in ECG heartbeats classification according to AAMI standards. Besides CNN networks, LSTM networks are also among hopeful networks, which got good results in different views such as face recognition [31], prediction of disease [32, and 33], image classification [31], and object detection [34]. LSTM totally how a capacity of extracting long-term relative data while CNN networks can effectively extract local features of data. Thus there are a few studies that show they are using the combination of CNN and LSTM for classifying ECG signals. F zhau et al. [35], by using several independent structures of CNN and LSTM in an ensemble network, achieved an accuracy of 99.4% in diagnosis premature ventricular contraction from normal beats. They also presented a combined classification model of CNN-LSTM and achieved an accuracy of 98.3% in classifying beats into five classes. SL oh et al. [36] presented an automatic ECG heartbeats classification system by architecture consisting of sequencing six-layer convolution and pooling followed by one LSTM layer and two fully-connected layers and achieved 96.1% accuracy in ECG signals classification. G Swapna et al. [37] presented the same structure as [35] and used GRU, LSTM, RNN, CNN networks, and combined CNN-LSTM network for classifying ECG heartbeats signals and achieved an accuracy of 83.4% in classifying these heartbeats into arrhythmia and normal. Our purpose in this study is to utilization the ability of CNN networks in extracting local features and the capacity of the LSTM network in extracting long-term relative data in building a strong and compound network from these two structures for extracting useful features in diagnosis arrhythmia and accuracy classification of them.

III. ECG Dataset

Due to propositions of association for the advancement of medical instrumentation [38], we used from physio bank MIT-BIH arrhythmia dataset [4] for training and evaluation of the proposed classification system, to provide a possible comparison of proposed classification systems with other state-of-art approaches, because this dataset in wide range is used for validation of approaches and as a reference dataset for diagnosis and arrhythmia classification. MIT-BIH dataset consists of 48 signal sequences from 47 different subjects that the length of each of which is 30 minute part, selected from recorded 24 hours and ECG sampling with 360 HZ frequency in 2 channels of V and II. In this study, we also used lead II for extraction of ECG beats and then for their classifications. This dataset also has information like the kind of arrhythmia class and location of R-peak of each ECG heartbeat in ECG signals, which was reviewed by two or more cardiologists and confirmed by them.

IV. System Architecture

A. Preprocessing

MIT-BIH is a highly imbalanced dataset and the number of heartbeat samples in each arrhythmia class compared to the other arrhythmia classes is completely different. This imbalance in the number of samples in each class cause overfit of the classification system on the class with more samples and consequently decrease in overall accuracy. On the other hand, the existence of noise in ECG signals leading from different factors such as power cables, incidental body movements, etc., makes feature extraction and heartbeat classifications operations mistakes. Another key challenge about automatic ECG heartbeat classification is extracting ECG heartbeats from ECG signals. In this study, we implement three preprocessing levels for overcoming existing problems.

1) QRS Complex detection

At first, we were normalizing ECG signals that exist in lead II of the MIT-BIH dataset according to equation (1) between 0-1.

$$X_{\text{normalized}} = \frac{[\,X - X_{\text{minimum}}\,]}{[\,X_{\text{maximum}} - X_{\text{minimum}}\,]} \tag{1}$$

Where X is the value of each sample, $X_{minimum}$ is minimum, and $X_{maximum}$ is the maximum value of X among all samples, and $X_{normalized}$ is the normalized sample. Then we extract the T waves set related to each ECG signal according to information from R-peak in the signals annotation file, then we divided ECG signals into ECG beats according to the extracted T waves. Then the arrhythmia type of each heartbeat is assigned to that, according to its annotation file. Finally, we consider the length of each heartbeat as 280 samples.The number of ECG heartbeats extracted from the MIT-BIH dataset ECG signals by using this approach is 109338. The number of extracted samples is shown in TABLE II.

TABLE II. The number of extracted beats from MIT-BIH dataset ECG signals.

Type	N	S	V	F	Q	Total
beats	90502	2777	7226	802	8031	109338

2) *Noise Removal*

ECG signals due to the existence of different factors like power cables, incidental body movements engaged with the noise that to increase in accuracy of classification needed to be removed by using different removal approaches. In this study, to remove the noise of ECG signals, we used DWT with mother wavelet db2 due to high complexity and similarity to ECG signals that used in signal preprocessing widely. The basic merit of DWT is the size of its changeable window that is widespread in low frequency and narrow in high frequency and causing clarity of time-frequency in all frequency domains. This approach by using a generator function named mother wavelet, and by performing Translation and Dilation is implemented. The following is a summary of the discrete wavelet transformation used in this study presented. To access comprehensive information in this field, refer to Mallat studies [39]. The discrete wavelet transformation function is identified as the following:

$$\varphi_{j\,k}(t) = \frac{1}{\sqrt{|s_0^j|}}\varphi\left(\frac{t-k\tau_0 s_0^j}{s_0^j}\right) \quad (2)$$

Where $\varphi_{j\,k}$ is wavelet function for the specific amounts of k and j, t time, $s_0>1$ constant dilation step, τ_0 is time transformation constant and depends on s_0. By performing DWT, primary data becomes wavy and divided into two sections. The first section is named approximation and has a low frequency and shows the overall trend of data, which plays a key role in the calculation, and we classified ECG signals according to this set. The second section is a detailed section that has high frequency and explained limit changes in data. After performing the DWT function, the length of the ECG heartbeats decreases from 280 to 141 samples. Thus, in addition to noise removal of these beats, one level feature reduction is made. Removal beat noise from different classes along with basic heartbeats are shown in Fig 1.

1) *Oversampling*

In this study, to remove the problem of being highly imbalanced MIT-BIH and avoiding overfitting classifiers on classes with more samples, we used the SMOTE approach to produce artificial data. This approach by using the similarity among the existing samples produces artificial data points. Thus it selected the n number of neighbors sample and randomly select a sample from n neighbors as a new data sample [40]. Therefore, after performing noise removal, we divided data using 10-fold cross-validation in a ratio of 9-1 into sets for training and testing the proposed model. Then we performed the production process of artificial data by using from SMOTE approach on the training set to avoid the use of artificial samples in performing the model evaluation. For avoiding irregular incrementation of the number of samples and avoiding too much production of artificial data, we only double the number of data in classes of F and S with producing artificial data. Thus, the overall number of samples increases from 109338 to 113131. TABLE III shows the number of ECG heartbeat samples per class before and after oversampling.

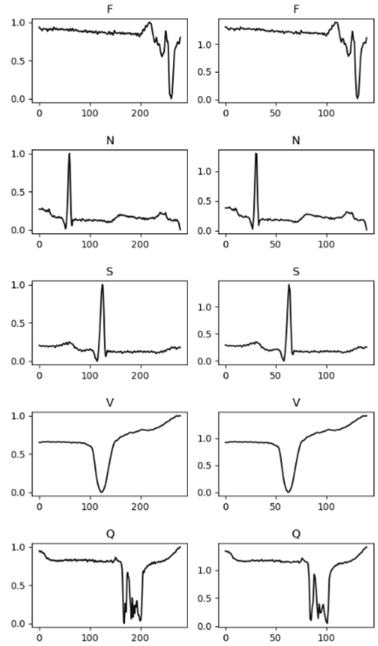

Fig 1. Five class different arrhythmia heartbeat samples, before and after performing the noise removal level.

B. *Classifier structure*

After performing the entire noise removal level for each heartbeat sample, there will be 141 features that are sent as input to the classifier. In this study, we design and implement a classification system consisting of two CNN and BLSTM networks. CNN networks are among prevalent neural networks. These networks consist of three basic layers, a convolutional layer that performs convolve kernel operation on inputs, a pooling layer that decreases input dimensions, minimize output forms and by keeping input recognized features, decrease calculations, and a fully-connected layer and these networks belong to feed-forward neural networks. RNN networks are among successful networks in the last decades that obtained good results in different fields such as NLP [41], speech recognition [42], image processing [43], and signal processing [44]. LSTM is the most useful network among other RNN networks, which build up from memory blocks, memory cells, and gate unit's ingredients of them. BLSTM is a bidirectional LSTM and proposed for removing its restriction. On the other hand, in these networks, two different LSTM are trained for the input sequence. Thus show better performance than LSTM networks. The basic structure of BLSTM networks for performing on input sequences is shown in Fig 2.

TABLE III. The number of heartbeat samples extracted from MIT-BIH dataset, before and after producing artificial data by SMOTE approach.

	Before oversampling			After oversampling		
	Train data	***Test data***	***Total***	***Train data***	***Test data***	***Total***
F	722	80	802	2000	80	2083
N	81430	9072	90502	81464	9072	90502
S	2515	262	2777	5000	262	5289
V	6526	700	7226	6478	700	7226
Q	7211	820	8031	7255	820	8031

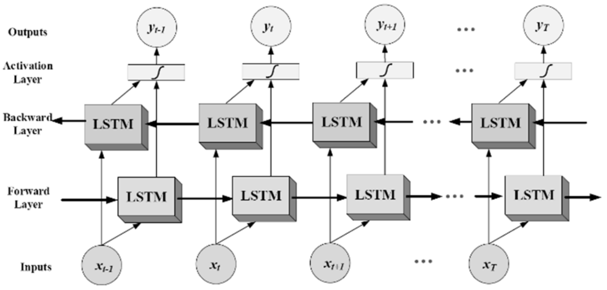

Fig 2. BLSM basic structure that lover LSTM networks use of them for moving forward and upper LSTM networks used them for moving backward. Finally, double networks are connected for the production of output to a common activation layer.

The proposed classifier system is a twenty layers network that is implemented in seven different parts. Each first, second, and third part consists of four layers. The first layer in each part is a 1D convolutional layer that its aim is the extraction of local features. Later layer in this part is a batch-normalization layer, which it proposes is preventing inner variables changes with input normalization. After batch-normalization is a ReLU layer, to define the non-linear section in CNN network and training it's the non-linear and 1D max-pooling layer with the aim of decrease in the calculation and keeping the most prominent information. These four layers are located in a sequence manner. In section fourth, there is a Flatter layer for flatting the output of the last section. Section five involve four BLSTM layers that are used for extracting long term correlations. Part six consists of two fully-connected layers, and finally, part seven consists of a Softmax layer for classifying inputs into five sets. Proposed system by using Adam algorithm along with setting assumption [45], Sparse categorical cross-entropy loss function, batch size 20 and 50 epoch are trained. The architecture of the classifier and its structure are shown in Fig 3.

V. Results

We evaluate the classifier system by using after dividing data Intel(R) Core(TM) i7-4710HQ CPU @ 2.50GHz, 8 GB DDR3 RAM, NVIDIA GeForce 840M, Ubuntu 20.04 OS, python programming language, Keras platform, and GPU based Tensorflow backend. After dividing data by using 10-fold cross-validation in the rate of 9-1 into the training and testing set. Training data are also divided into training and evaluation set at the rate of 9-1. Thus in each training level, nine sets are used for training, and 1 set used for evaluating the network. Fig 4 shows how data are divided into training, testing, and evaluating sets.

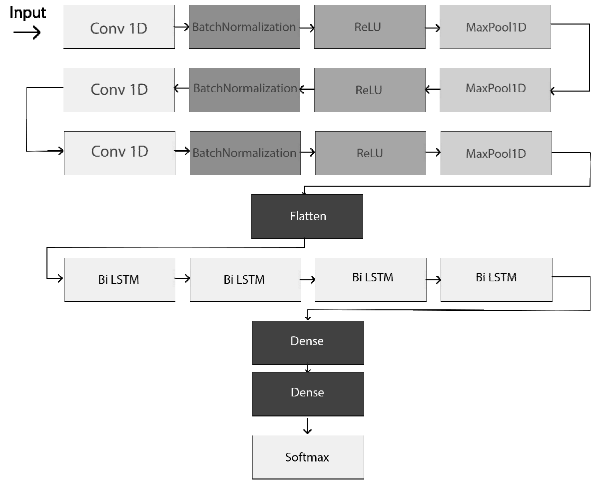

Fig 3. Proposed CNN-BLSTM network structure.

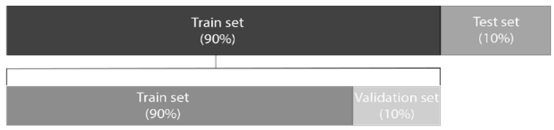

Fig 4. Dividing data into training, testing, and evaluating data sets.

At first, we extracted 109338 ECG beat samples from MIT-BIH, then by using SMOTE oversampling approach and producing artificial data, increase the number of samples to 113131. TABLE V shows the number of extracted features in this study compared with three state-of-the-art studies along with the number of features for each ECG beat sample. In general, from 113131 existence heartbeat, 102197 samples for training, 10934 samples for the testing network are used. The total number of used samples for each class in testing and training is shown in TABLE IV.

TABLE IV. The number of samples for each class to training and testing the proposed classifier system.

Class	Train data	Test data	Total
F	2000	80	2083
N	81464	9072	90502
S	5000	262	5289
V	6478	700	7226
Q	7255	820	8031
Total	102197	10934	113131

Then proposed classifier system by using loss function sparse categorical cross-entropy, Adam optimization algorithm, and 102197 ECG heartbeats in 50 epochs are trained. The training process is performed in 117 minutes. Diagram related to the accuracy of classifier in training level and evaluation is shown in Fig 5. Then proposed classifier system by using

10937 ECG heartbeats is tested and achieved an accuracy of 98.71% in classification of beats, and only 1.2% of heartbeats are classified wrongly.

TABLE V.Comparison of the number of each ECG beat sample and the overall number of the extracted sample from MIT-BIH in the proposed approach with other state-of-the-art approaches.

Article	Sample length	Total
S. L. Oh et al. [42]	259	16499
U. R. Acharya [28]	260	109449
F. Zhou et al. [35]	360	100410
Proposed approach	280	109338

TABLE VI indicated a confusion matrix related to results obtained from evaluating the proposed classification system by using ECG heartbeats of testing data, and TABLE VII shows the evaluation criteria of PPV, accuracy, sensitivity, and specificity, which calculated for each class. TABLE VIII indicated the comparison between accuracy accrued in the proposed classification system and three state-of-the-art studies in this field.

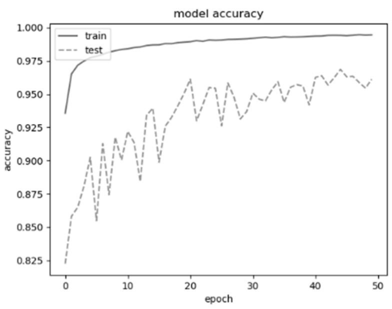

Fig 5. Diagram related to the accuracy of training and evaluation on MIT-BIH dataset according to the epoch's number.

TABLE VI. Confusion matrix of evaluating proposed classification system by using the test set.

		True Label				
	Class	***F***	***N***	***S***	***V***	***Q***
Predicted Label	***F***	70	8	0	6	0
	N	7	9036	43	29	11
	S	0	14	217	3	0
	V	3	12	2	662	1
	Q	0	2	0	0	808

TABLE VII. Calculated evaluation criteria for each class of ECG heartbeats.

Class	Acc (%)	Sen (%)	Spec (%)	PPV (%)
F	99.78	83.33	99.91	87.50
N	98.85	99.01	98.01	99.60
S	99.43	92.74	99.58	82.82
V	99.49	97.35	99.63	94.57
Q	99.87	99.75	99.88	98.54

VI. Conclusion and Feature Work

ECG signals are the most important tools for diagnosing cardiovascular arrhythmia according to the high mortality arising from CVDs. Early diagnosis and accurate arrhythmia type and accelerate in diagnosis trend and treatment of cardiovascular diseases got an important position. Our purpose in this study is to present an accurate classifier system for ECG heartbeats classification into five arrhythmia classes according to AAMI standards. In the preprocessing level of the classifier system, by using SMOTE oversampling algorithm, we produce new artificial data to overcome the imbalanced problem in the number of samples in different arrhythmia classes and to prevent overfitting of the classifier on accurate classification of classes with more numbers. According to the existence of noise that arises from different factors such as accidental body movement or the existence of power coble, we performed one level of noise removal by using DWT and db2 mother wavelet on ECG heartbeats. In the following, a classifier is designed and implemented with the combination of CNN and BLSTM. The purpose of combining these two networks is the extraction of local features and long-term correlation among data simultaneously, and by using them for increasing the accuracy of classification. The proposed classification system extracted important features automatically and performed classification according to them. After evaluating the proposed system, this system can achieve an accuracy of 98.71% in classifying ECG heartbeats into five classes that, according to TABLE VII compared with other works, it is more successful in this field. Amongst the advantages of the proposed classification system is of being fully automatic. Also, by noticing that system used 10-fold cross-validation, this system is repeatable. In future works, and finding out a strong classifier structure for heartbeats classification, we can focus on accurate and better noise removal and oversampling approaches for reduction of the efficacy of excitant noise and imbalance in the number of samples in each class, in accuracy.

TABLE VIII. The comparison of the proposed classification system with three state-of-the-art approaches.

Article	Preprocessing	Feature Extraction	Classification	accuracy
U. R. Acharya [28]	Daubechies wavelet 6 filters	-	CNN	94.3%
S. L. Oh et al. [42]	-	CNN and LSTM	Deep learning	98.10%
F. Zhou et al. [35]	-	-	CNN-LSTM	98.03
Proposed approach	SMOTE	DWT	CNN-BLSTM	98.71%

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