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ECG Arrhythmia Classification Using 1D CNN Leveraging the Resampling Technique and Gaussian Mixture Model

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***Abstract*—The electrocardiogram (ECG) is one of the simplest and oldest tools to assess the heart condition of cardiac patients. Heart diseases have emerged as one of the leading causes of death all over the world. According to the world health organization (WHO), millions of people are dying every year from heart-related diseases. A classification model that can early detect arrhythmia will be able to reduce this number by manyfold. Many researchers are working in this area and proposed many deep learning and machine Learning based models for arrhythmia classification. These models have high accuracy but require a machine with high computational power. Hence, these models are not sustainable options for the practical field. In this paper, we have proposed a 1D Convolutional Neural Network (CNN) model with high accuracy and low computational complexity. Our proposed methodology is appraised on the MIT-BIH arrhythmia dataset. We achieved overall 98.25% accuracy into five classes with an f1 score of 98.24%, precision 97.58%, and recall 96.79% which is better than previous results classifying arrhythmia. We can claim that our proposed method is better than most other existing models because of the higher accuracy with a simple architecture that can be run on an edge device with relatively low hardware configuration.**

Contributions: This is an original paper successfully establishing an effective method to recognize ECG arrhythmia using CNN.

***Index Terms*—ECG signal; classification; arrhythmia; 1D CNN; deep learning**

I. Introduction

The Electrocardiogram (ECG) is a graphical representation of the electrical activity of the heart rhythm. A tiny electrical impulse is produced by the heart with each beat which helps to regulate the different chambers of the heart and pump the blood out to the whole body. This electrical impulse is recorded by the ECG and displays as a trace on paper.

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ECG helps to detect abnormalities in heart or heart rhythm. An ECG is suggested as a screening test when a person feels symptoms like chest pain, dizziness, lightheadedness, shortness of breath, rapid pulse, weakness, heart palpitations, or if a person has a family history of heart disease even if they have no symptoms.

Heart disease has emerged as one of the leading causes of death all over the world. Millions of people are dying every year from heart-related diseases due to the failure of early detection. Hence, A classification model that can early detect arrhythmia can be a savior. In our paper, we have proposed a 1D Convolutional Neural Network (CNN) model to classify arrhythmia. The model has high accuracy but low computational complexity. We have used the MIT-BIH dataset for our model and achieved overall 98.25% accuracy with a precision of 97.58%, f1 score 98.24% and recall 96.79% which is better than disclosed results classifying arrhythmia.

The main contributions of our proposed system are:

- A combination of resampling and the gaussian method is used. Accordingly, it contains the simple method of an algorithmic model for preprocessing.
- We achieved state-of-the-art performance in the arrhythmia classification of ECG by using a computationally light 1D convolution neural network.

The other parts of the paper are organized as follows: Background in Section II, Related research works in section III, Methodology in section IV, Introduction to our dataset in the experiments section V, Classification results in section VI. Comparison with existing algorithms in Table IV. The conclusion in section VII and the rest of the part are references.

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II. Background

A. ECG wave

The ECG signal has three main components; P wave, QRS complex, and T wave. The P wave is the first electrical signal on a normal ECG that originates due to the depolarization of the atria. The largest part of the ECG signal is the QRS complex that resulted from the depolarization of the ventricles. QRS consists of 3 closely related waves; Q, R, and S. T wave is a positive wave after the QRS complex and can have variable amplitude and duration. T wave results from ventricular repolarization.

The length and intervals between components provide useful information about heart conditions. Each of these components has its normal range which may vary a little between males and females. The PR interval has its normal range in between 120–200 ms. The normal range of QRS duration is up to 120 ms. The QT interval has a normal range of up to 440 ms which can be slightly longer in females.

B. Arrhythmia

Arrhythmia is an abnormal rhythm or irregularity of the heartbeat; the heart beats too quickly, too slowly, or with an irregular pattern. It is a disorder of the heart. Arrhythmia beats are uncomfortable and can be life-threatening. Arrhythmia can be of 2 types; tachycardia (heart beats too quickly) and bradycardia (heart beats too slowly).

Arrhythmia may cause symptoms like chest pain, shortness of breath, palpitation, light-headedness, etc. There are several causes for arrhythmia such as heart attack that is occurring right now, scarring of heart tissue from a prior heart attack, changes the heart structure such as cardiomyopathy, blocked arteries in the heart, high blood pressure, overactive or underactive thyroid gland (hyperthyroidism), sleep apnea, infection with COVID-19, smoking, drinking too much alcohol or caffeine, drug abuse, stress or anxiety, certain medications, supplements, and genetics.

Arrhythmia can be cured by eating a healthy diet (such as eliminate salt, fiber, complex carbohydrates, garlic, onions, reduce or eliminate saturated fats, whole grains, and green leafy vegetables), staying physically active, keeping a healthy weight, avoiding smoking, caffeine, alcohol and reducing stress.

III. Related Works

The ECG signal represents the condition of the heart of humans by recording the electric variation. This EEG signal is very useful for monitoring the heart condition of a patient and provide treatment as necessary. It is also helpful to reduce death by detecting heart conditions. Detection of the clinical condition of the heart of a human is a challenging task. Condition of abnormal heartbeats may cause different kinds of cardiovascular diseases. That can bring a human towards death. Different kinds of machine learning and deep learning algorithms are used in most research fields based on the classification of various kinds of arrhythmia. There are different methods of ECG arrhythmia classification are presented based on the method like support vector machine [24], hidden Markov models [25], filter banks [27], artificial neural network [23], statistical methods [26], and also the combination of an expert method [28]. The overall accuracy of 90.6% for the arrhythmia classification into six classes [29] is achieved by an artificial neural network method. An accuracy of 98.06% for the arrhythmia classification into four classes [30] is obtained by an RNN based method. There is a wavelet-based preprocessing is used with the classification algorithm support vector machine [12] which achieved 86.40% overall accuracy for the arrhythmia classification into six classes. Some different methods of deep learning approaches are proposed for the analysis of signals which is presented in [34,35]. The overall accuracy of 92.70% is achieved by using the methods of classification probabilistic neural network [13] and 1D Convolution Neural Network [14] were used where the preprocessing method as bandpass filters and feature extraction as wavelet for the arrhythmia classification into six classes. Also, a neural network [15] classification method is achieved overall 93.00% accuracy for the classification into six classes. An arrhythmia classification accuracy of 96.72% is achieved by a 1-D convolution neural network model which is proposed in [31]. There is also an average accuracy of 97.03% [32] is achieved by another 1-D convolution neural network model. A 2-D convolution neural network [33] model is introduced which achieved an accuracy of 94.03% for the classification of arrhythmia into five classes. An accuracy of 86.40% is achieved by a support vector machine model along with the features extraction methods as wavelet and principal component analysis [12]. Also, a probabilistic neural network model is adopted and achieved an average accuracy of 92.70% where the wavelet method is used for preprocessing and feature extraction [13]. CNN-based feature extraction is used with the classification method as softmax and preprocessing method as bandpass filter which achieved average accuracy 92.70% into five classes [14]. An artificial neural network along with the preprocessing method as wavelet and feature extraction as Pan-Tompkins algorithm achieved an average accuracy of 93.00% when classifying into five classes [15]. A neural network-based algorithm [17] is achieved 96.66% overall accuracy into five classes whereas a preprocessing technique bandpass filter is used. Also, the Hermite transform is used as a feature extraction method. A support vector machine approach achieved an overall accuracy of 97.20% where the bandpass filter is used as preprocessing technique and continuous wavelet transform as feature extraction for the arrhythmia classification into five classes [18]. A one dimension convolution neural network approach is achieved an overall accuracy of 97.50%. Wavelet combination is used as preprocessing technique and one dimension convolution neural network is used as feature extraction for the arrhythmia classification into five classes [19]. Another one dimension convolution neural network approach achieved 97.60% into five classes. A DNN based method achieved an overall accuracy of 95.50% for the classification into four classes. CNN and neural networks [42-44] are very effective in signal

TABLE I: RELATED RESEARCH WORKS

Paper	Publication Year	Class	Preprocessing	Feature Extraction	Classification	Accuracy
Joshi et al. [12]	2014	N,S,V,F,Q	wavelet	wavelet+principle component analysis+independent component analysis	support vector machine	86.40%
Jose et al. [13]	2017	N,L,R,A,V	wavelet	wavelet	probabilistic neural network	92.70%
Zubiar et al. [14]	2016	N,S,V,F,Q	bandpass filter	convolution neural network	softmax	92.70%
Martis et al. [15]	2013	N,L,R,A,V	wavelet	pan-tompkins and principle component analysis	neural network+support vector machine	93.00%
Ismaiel et al. [16]	2015	N.L.R.A.V	digital filters	discrete wavelet	neural network	94.00%
Jiang et al. [17]	2007	N,S,V,F,Q	bandpass filters	hermite transform	blocked neural network	96.66%
Zadeh et al. [18]	2011	N,L,R,A,V	bandpass filter	continuous wavelet transform	support vector machine+genetic algorithm	97.20%
Dan et al. [19]	2017	N,L,R,A,V	wavelet Combination	1D CNN	softmax	97.50%

Normal beats (N), Supraventricular ectopic beats (S), Ventricular ectopic beats (V), Fusion beats (F) and Unknown beats (Q)[0]

recognition.

IV. Methodology

A. Preprocessing

In this paper, several preprocessing techniques are used for balancing the dataset and generalizing the train set with Gaussian distribution in Figure 2. ECG signals are combined with the functional channel of the node which is extended with electrical attachment. They mislead the aspect of ECG and peak critical segment that causes abnormal heartbeats. Generalization is a familiar process used to increase the aspect of ECG signal. Accordingly, the preprocessed data is used for input data in our CNN model to obtain the classification of arrhythmia. Resampling is the technique that consists of sampling repeated samples from our MIT-BIH original data samples. It defines the method of nonparametric method of statistical inference.

1) Resample: It is an efficient technique for balancing highly imbalanced datasets. It contains the set of methods where samples are repeated from a given sample or classify the precision with efficient statistics. The duplication of ECG examples from the dataset of minority classes is called oversampling. It selects the ECG examples from the minority class, then adds the examples to the training dataset by the following replacement. Also, the deletion of ECG examples from the dataset of majority classes is called undersampling. It takes the majority of examples of ECG until the balanced dataset distribution is achieved.

In this paper, we combined the two techniques, and resample technique is chosen more than the class weights with several 109446 samples which include 20,000 samples of Normal beats (N) Supraventricular ectopic beats (S), Ventricular ectopic beats(V), Fusion beats (F) and Unknown beats (Q) are shown in Figure 1.

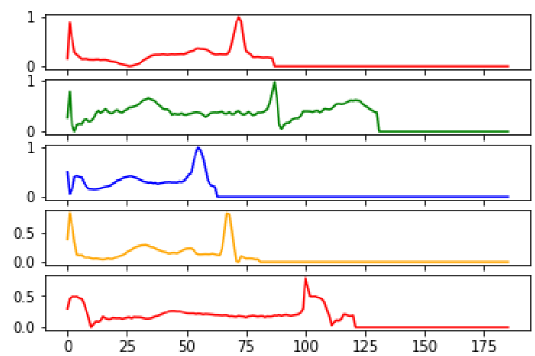

Fig. 1: Resampled Samples of Five Classes of Dataset

2) White Gaussian Noise: Gaussian noise is one kind of statistical noise that is estimated from the probability density function (PDF) which corresponds to the normal distribution. White Gaussian Noise is defined as a special case where the values of signals at any pair are uniformly distributed. We used White Gaussian Noise for getting the R wave peak of ECG where it is fallen. It is responsible for detecting the desired peak from ECG signals for arrhythmia classification which is shown in Figure 2.

In our dataset, the enlarged portion of the signal includes the interval of the R wave peak. Signal-to-Noise (SNR) is a measurement that is the ratio between the flattening of the desired noise signal and the flatten of background noise. The SNR value can indicate how much noise is present in the signal. The higher the SNR value the better to detect the desired peak for classification.

$$SNR = \frac{P_{signal}}{P_{noise}} \tag{1}$$

where P is the average power function. If the signal is a constant (s) the signal-to-noise (SNR) ratio of random noise turn into:

$$SNR = \frac{S^2}{E(|N|)^2} \quad (2)$$

where E refers to the expected value In our paper, Gaussian White Noise is added for generalization of the train data which predetermined upper and lower hop of the co-ordinate axis, accomplishing each ECG beat is based in the right place as shown in Figure 2.

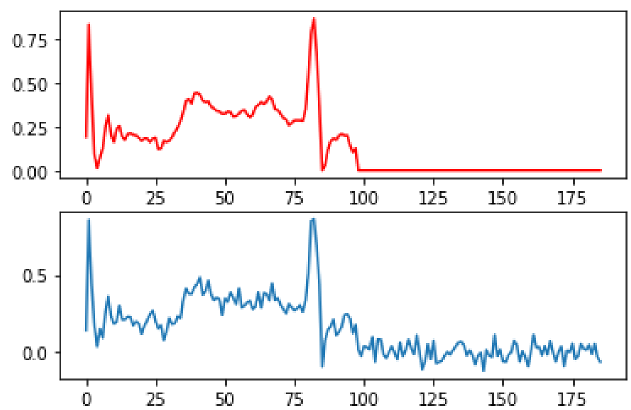

Fig. 2: Added Gaussian Noise after Resampling the Dataset

V. Experiments

A. Dataset

The MIT-BIH Arrhythmia Dataset [41] contains the collection of ECG recordings of twice channel in 48 half-hours. It is developed by the BIH Arrhythmia Laboratory. From the set of 24-hour ECG recordings, twenty-three recordings are picked continuously. From a combination of the samples of inpatients and outpatients, it is achieved. For including less common but clinically significant arrhythmias the rest of the twenty-five recordings are gathered from the same set.

In this paper, for grouping the heartbeats into five different classes the AAMI has proposed which contains 109,446 ECG samples which is shown in Table II.

TABLE II: AAMI and MIT-BIH HEARTBEATS RELATION

AAMI Classes	**MIT-BIH Heartbeats**
Normal beats (N)	left bundle branch block beats, right bundle branch block beats, nodal escape beats, atrial escape beats
Supra Ventricular ectopic beats (S)	aberrated atrial premature beats,supraventricular premature beats,atrial premature beats
Ventricular ectopic beats (V)	ventricular flutter wave, ventricular escape beats, premature ventricular contraction
Fusion beats (F)	ventricular beats, normal beats
Unknown beats (Q)	paced beats, unclassifiable beats, fusion paced beats, ectopic beats

B. 1D Convolution Neural Network

A Convolution Neural Network is widely familiar for recognizing visual patterns from the data. Numerous parts of every convolution layer can extract multiple types of deep features. The filter weights in the convolution layer work similarly to a visualization system which might not be meaningful for humans but those can be highly effective for classification. In the pooling layer, the pooling filters have decreased the adversity of training parameters and separate the data aspect which maintains the balance of training data with efficient features of parameters. This collection of parameters is used for ECG signal processing [5]. Accordingly, convolution neural networks have a convenient role in ECG signal processing [6]. Because of having 1D data, a convolution network of 1D is taken in this ECG arrhythmia classification. Convolution Neural Network (CNN) principally consisted of feature extraction and classification shown in Figure 4. The segment of feature extraction is compulsory for peaking efficient features from the raw signals. Architecture and the hyper-parameters are shown in the following Table III.

The segment of feature extraction contains the convolution layer and also the down-sampling layer. The convolution layer (Conv-layer) is observed because of enlarging the parameters of raw signals and separating the noise is shown in Figure 3. Convolution action is held for feature vectors of the bottom layer and kernel of the common layer. Accordingly, the result of convolution calculations is given by the activation function. Because of the non-linear feature mapping, the activation function is needed before the output of the convolution layer. In our paper, a ten-layer 1D CNN model is shown according to the study of train pre-processed data and getting the classification output. A CNN can extract effective features at the time of the training process. The proposed 1D CNN is constructed using three convolution layers, three pooling, one flattened, two dense, and a fully connected layer is shown in Figure 3. For the original ECG signal, the input size of the first convolution layer consists of filter size 64 with kernel size 6. The rectifier linear unit (ReLU) function is needed for the activation function. A pooling layer of size 3 with the size of stride of 2 is added after the previous layer. The second convolution layer consists of filters with a size of 64 and a kernel size of 3. Also, the third convolution layer is set at the same. Therefore, the second and third pooling layers have a pool of size 2 with stride size 2 are shown in Figure 3. The dropout layer indicates dropping out units in the neural network randomly. For preventing the overfitting problem dropout rate of 0.2 is selected. Decisively, the output of classification is obtained with the convolution and pooling layers which are appointed to the fully connected layer. Batch normalization is used in the CNN network. Batch normalization is an optimization method developed by Google [9] for data standardization and normalization where a group of data is referred to as batch. Therefore, The input and output data of the medium network layer which is composed of the inner neurons, and the difference may be obtained by applying

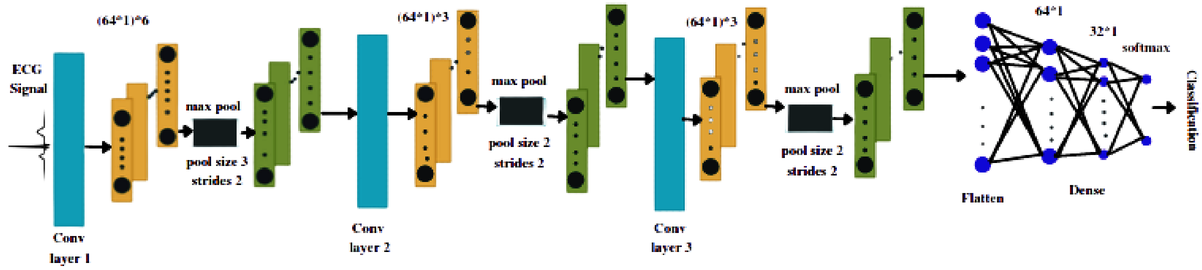

Fig. 3: Proposed Model with 1D Convolution Neural Network

TABLE III: PROPOSED 1D CNN MODEL ARCHITECTURE LAYERS

Layers	**Type**	**Filter Size**	**Strides**	**Kernel**	**Output Shape**	**Parameters**
Layer1	conv1d	6*6	-	64	(None,181,64)	448
Layer2	pooling	3*3	2*2	-	(None,91,64)	0
Layer3	conv1d	3*3	-	64	(None,89,64)	12352
Layer4	pooling	2*2	2*2	-	(None,45,64)	0
Layer5	conv1d	3*3	-	64	(None,43,64)	12352
Layer6	pooling	2*2	2*2	-	(None,22,64)	0
Layer7	pooling	2*2	2*2	-	(None,1408)	0
Layer8	dense	-	-	64	(None,64)	90176
Layer9	dense	-	-	32	(None,32)	2080
Layer10	output	-	-	5	(None,5)	165

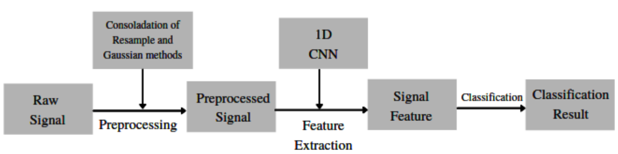

Fig. 4: Proposed Model Building Flow Chart

batch normalization [10]. In this paper, the number of total parameters is 118,341 and the total trainable parameter is 117,957 is shown in Table III.

C. Experimental setup

The proposed ECG arrhythmia classification using 1D convolution neural network is implemented with python. Also the open-source library TensorFlow and neural network library Keras is used which is introduced by Google for deep learning [11]. Keras is the high-level API that is built on the top of TensorFlow. The experiment setup consists of a second-generation HP Compaq notebook server with 4GB internal RAM, 320 GB internal hard drive, and no external hard drive included. The processor consisted of Intel(R) Celeron(R) CPU B815@1.6. The 1D ECG signal is divided into 80% data for training and 20% of data for testing. This low configuration device is used to demonstrate that this model is very lightweight and can be effectively implemented in an edge device at the user end. One of our objectives is to make the model as light as possible while maintaining the highest possible accuracy.

VI. Classification Results and Discussion

A. Results

The proposed model is trained using a set of hyper-parameters which is selected empirically. The first and second convolution layer is set as kernel size 64. The sampling of three pooling layers is set as stride size 3,2,2 which is maximizing the operation with the number of iterations 150 times. Adam optimizer is used to accelerate the gradient descent process. A softmax function is used in the final layer. As a loss function categorical-cross-entropy is used. Finally, the test result achieves an accuracy of 98.25%.

A number of CNN model is trained. Among them 4th model has achieved the higher accuracy from the previous existing works models. Therefore, we proposed 4th model as final model which achieved higher accuracy than others. The classification results of these models are demonstrated with confusion matrix which are shown in the following Figure [5-8].

The first model achieves an overall accuracy is 97.64% on the test set shown in Figure 5. In this model, the dropout rate is set to 0.2 and 0.3 for the first three Conv layers and first dense layer respectively. The convolution layers kernel and the filter size are mentioned in the Figure 3. Also, the pooling and strides size is set as Figure 3. The accuracy of all the classes is as follows. Normal beats (98.00%, Supraventricular ectopic beats(S) 85.00%, Ventricular ectopic beats(V) 96.00%, Fusion beats(F) 80.00% and Unknown beats(Q) 99.00% with 200 iterations.

In the second model, the test result achieves the overall accuracy of 98.00% where the dropout is 0.2 is kept in three pooling layers and also in the two dense layers shown in Figure 6. The kernel and filter size is kept the same as

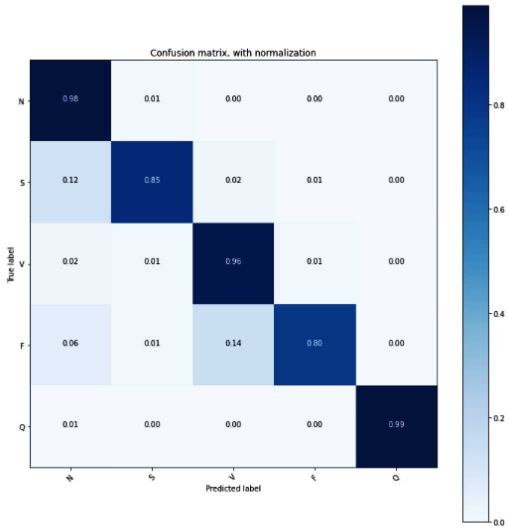

Fig. 5: Confusion Matrix of Model 1 with accuracy 97.64%

before. The accuracy of each classes are Normal beats (N) 99.00%, Supraventricular ectopic beats(S) 84.00%, Ventricular ectopic beats(V) 94.00%, Fusion beats(F) 81.00% and Unknown beats(Q) 99.00% with the number of 150 iterations. In the third model, the test result have achieved an overall

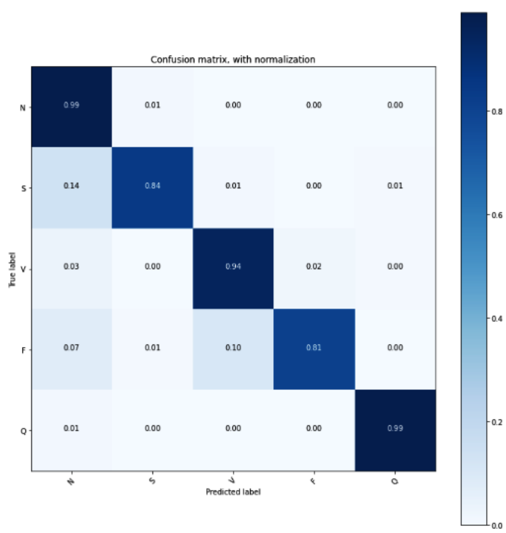

Fig. 6: Confusion Matrix of Model 2 with accuracy 98.00%

accuracy of 98.02% where the dropout of 0.2 is used in three pooling layers and the first dense layers. The kernel and filter size is set as the same. The accuracy of each class is found as Normal beats (N) 99.00%, Supraventricular ectopic beats(S) 85.00%, Ventricular ectopic beats(V) 96.00%, Fusion beats(F) 84.00% and Unknown beats(Q) 99.00% with the number of 150 iterations.

In the final proposed model, the test result have achieved as overall accuracy of 98.25% where the dropout 0.2 is used in three pooling layers shown in Figure 8. The kernel and filter size is set as the same before. The accuracy of each class is found as Normal beats (N) 98.00%, Supraventricular ectopic beats(S) 83.00%, Ventricular ectopic beats(V) 95.00%, Fusion beats(F) 86.00% and Unknown beats(Q) 99.00% with the number of 150 iterations.

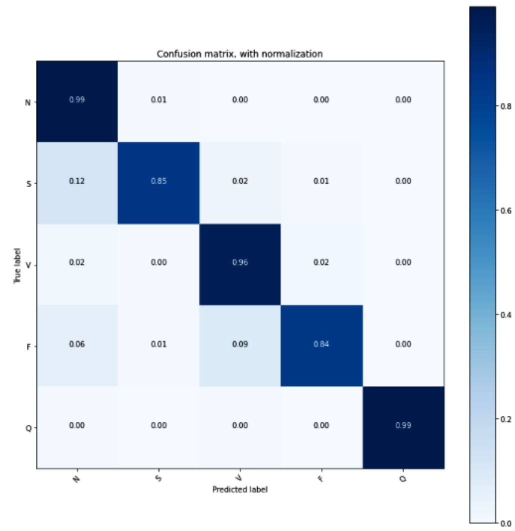

Fig. 7: Confusion Matrix of Model 3 with accuracy 98.02%

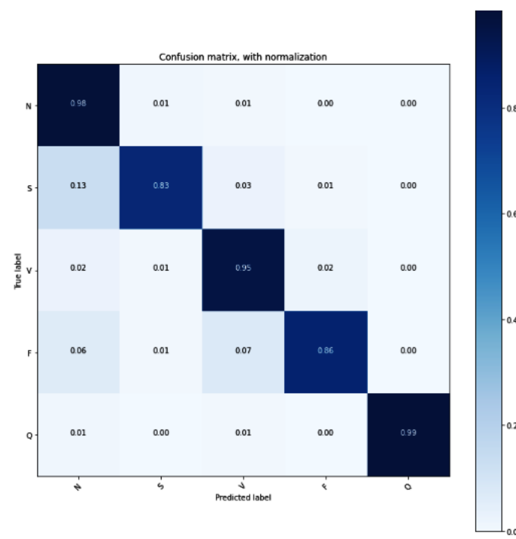

Fig. 8: Confusion Matrix of Proposed Model with accuracy 98.25%

B. Discussion

The comparison between our model with other past existing models is given in Table IV. The proposed method is obtained the highest accuracy of arrhythmia classification compared to the previously published classification results into five classes using one dimension convolution neural network. The proposed method represents a comparatively lightweight CNN model that is suitable for one-dimension ECG signals.

The dataset is trained with a different number of epochs and values of hyper-parameters. Each model demonstrates a

TABLE IV: COMPARISON WITH EXISTING MODELS

Paper	Class	Preprocessing	Feature Extraction	Classification	Accuracy
Joshi et al. [12]	N,S,V,F,Q	wavelet	wavelet+principle component analysis+independent component analysis	support vector machine	86.40%
Jose et al. [13]	N,L,R,A,V	wavelet	wavelet	probabilistic neural network	92.70%
Zubiar et al. [14]	N,S,V,F,Q	bandpass filter	convolution neural network	softmax	92.70%
Martis et al. [15]	N,L,R,A,V	wavelet	pan-tompkins and principle component analysis	neural network+support vector machine	93.00%
Ismaiel et al. [16]	N.L.R.A.V	digital filters	discrete wavelet	neural network	94.00%
Jiang et al. [17]	N,S,V,F,Q	bandpass filters	hermite transform	blocked nerural network	96.66%
Zadeh et al. [18]	N,L,R,A,V	bandpass filter	continuous wavelet transform	support vector machine+genetic algorithm	97.20%
Dan et al. [19]	N,L,R,A,V	wavelet Combination	1D CNN	softmax	97.50%
Proposed	**N,S,V,F,Q**	**Resample+Gaussian Combination**	**1D CNN**	**Softmax**	**98.25%**

high classification accuracy comparing the previous model. The confusion matrix is represented in the results section in detail following Figure [5-8].

However, we have faced a problem while tracking the wave R peak for getting the desired SNR (signal-to-noise). Thus we have used the White Gaussian Noise as a solution. Also encountered another problem with the generalization of the dataset. This problem is solved by utilizing the resample techniques functionalities.

Constructing a lightweight method with 1D Convolution Neural Network while keeping a high accuracy is also challenging. The previous deep learning models are very complex and take a good amount of time to train and test. To make this model lightweight and effective, we created and tested more than 50 CNN models. Surprisingly, several lightweight models achieved very high accuracy and even some model beat the previous existing model accuracy.

The performances of selected models are shown in the Figure [5-8] and finally, our model which is proposed in this work is better and efficient than all of the previous algorithms with a one-dimension convolution neural network into five classes. In this paper, the deep feature extraction is performed by the one-dimensional convolution neural network and the classification is done at the output layer with a soft-max function. Our proposed model has the highest accuracy of 98.25% which is a classification result of all five classes of arrhythmia.

VII. Conclusion

CNN can be effectively used to analyze the ECG signals to determine cardiovascular diseases. It is a very active and essential research area. The convolution neural network determines adequate features and exhaustive classification of different kinds of arrhythmia. In this paper, the classification is obtained by two approaches. They are the Resampling Technique with Gaussian Mixture Model and 1D CNN. In our paper, Preprocessing technique is worked for the generalization of balance data and track the R peak with the desired SNR. By processing the several epochs the highest accuracy is achieved. A satisfactory classification overall accuracy of 98.25% is achieved with an f1 score of 98.24%, positive predictive value (precision) 97.58% and recall 96.79% by comparing with previous work. We are hopeful that the proposed model architecture will help medical experts diagnose cardiovascular diseases by giving the efficient classification of ECG signals which observes less computational power.

For future work, the two-dimension peak of a signal can be used for arrhythmia classification into more classes. Also, with the growth of mobile applications, a prenotification system can be developed to notify arrhythmias probability.

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