# ECG Arrhythmia Classification Using 1-D Convolution Neural Network 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 arrhythmias. 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.**

***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.

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 arrhythmias.

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 VII. The conclusion in section VII and the rest of the part are references.

## II. Background

### A. ECG wave

The ECG signal has three main components; P wave, QRS complex, and T wave. The P wave, the first electrical signal on a normal ECG, 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 repolarisation.

The length and intervals between components provide useful information about heart conditions. Each of these components has its normal range/intervals which may vary a little between males and females. The PR interval has its normal range in between 120–200 ms or (3–5 small squares). 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 a heart attack that's occurring right now, scarring of heart tissue from a prior heart attack, changes the heart's structure, such as from cardiomyopathy, blocked arteries in the heart, high blood pressure, overactive/underactive thyroid gland (hyperthyroidism/hypothyroidism), sleep apnea, infection with COVID-19, smoking, drinking too much alcohol or caffeine, drug abuse, stress or anxiety, certain medications and supplements, genetics.

Arrhythmia can be cured by eating a healthy diet ( such as eliminate salt, fiber and complex carbohydrates, garlic and onions, reduce or eliminate saturated fats, whole grains and green leafy vegetables), staying physically active, keeping a healthy weight, avoiding smoking and caffeine and alcohol, 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 arrhythmias. There are different methods of ECG arrhythmia classification are presented based on the method like support vector machine (SVM) [24], hidden Markov models [25], filter banks [27], artificial neural network (ANN) [23], statistical methods [26], 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 (SVM) which achieved 86.40% overall accuracy for the arrhythmia classification into six classes [12]. 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(PNN) [13] and 1D Convolution Neural Network [14] were used the preprocessing methods as bandpass filters and feature extraction as wavelet for the arrhythmia classification into six classes. Also, a NN ( Neural Network) classification method is achieved overall 93.00% accuracy for the classification into six classes [15]. 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 model is introduced which achieved an accuracy of 94.03% for the classification of arrhythmia into five classes [33]. An accuracy of 86.40% is achieved by a Support Vector Machine (SVM) model along with the features extraction method wavelet and principal component analysis (PCA) [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 of 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 pam 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 in five classes. As a preprocessing technique bandpass filter is used. Also, the Hermite transform is used as a feature extraction method. A support vector machine approach is achieved an overall accuracy of 97.20%. As preprocessing techniques bandpass filter and continuous wavelet transform are used for feature extraction. The arrhythmia classification is into five classes [18]. A one dimension convolution neural network approach is achieved an overall accuracy of 97.50%. As preprocessing techniques wavelet combination and one dimension convolution neural network are used for feature extraction. The arrhythmia classification is into five classes [19]. Another one dimension convolution neural network approach is achieved 97.60% into five classes. A DNN based method is achieved an overall accuracy of 95.50%. The classification result is obtained into four classes.

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 | nnws | 94.00% |
| Jiang et al. [17] | 2007 | N,S,V,F,Q | bandpass filters | hermite transform | blocked neurual 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% |

## IV. Methodology

### A. Preprocessing

In this paper, several preprocessing techniques are used for balancing the dataset and generalizing the train set with Gaussian distribution [Fig 4]. 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 the 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 [Fig 3] of Normal beats (N) Supraventricular ectopic beats (S), Ventricular ectopic beats(V), Fusion beats (F) and Unknown beats (Q).

*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.

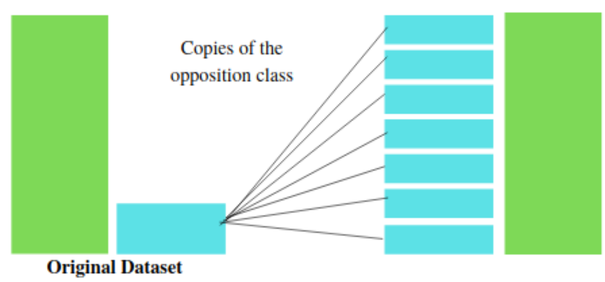


Fig. 1: Oversampling

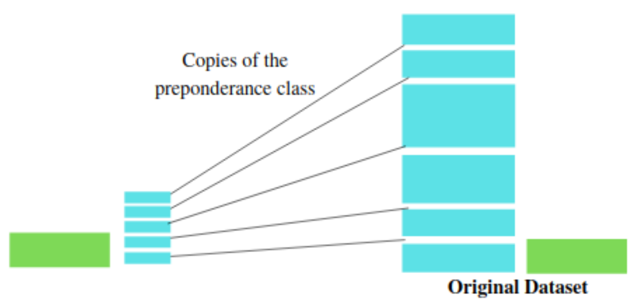


Fig. 2: Undersampling

White Gaussian Noise is defined as a special case where the values of signals at any pair are uniformly distributed.

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

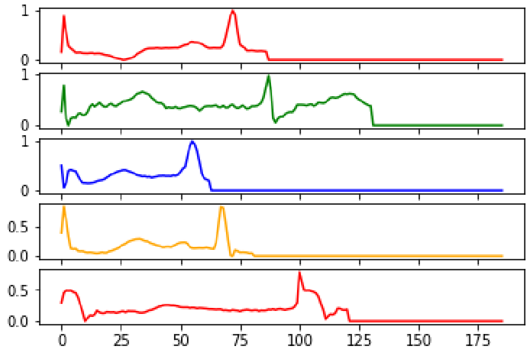

Fig. 3: Resampled samples

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:

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

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 [Fig 4].

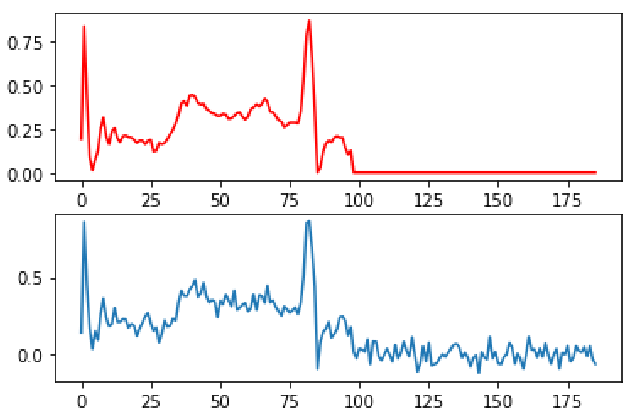

Fig. 4: Added gaussian noise

## V. Experiments

### A. Dataset

The MIT-BIH Arrhythmia Dataset 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 [TABLE II] has proposed which contains 109,446 ECG samples.

TABLE II: Relationship between AAMI and MITBIH heartbeats

| **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. The segment of feature extraction is compulsory for peaking efficient features from the raw signals. Architecture and the hyper-parameters are discussed in the following [fig 6].

The segment of feature extraction contains the convolution layer and also the down-sampling layer. The convolution layer (Conv-layer) [Fig 5] is observed because of enlarging the parameters of raw signals and separating the noise. 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 showed 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 [Fig 5]. For the original ECG signal, the input size of the first convolution layer consists of filter size 64 with kernel size 6. The rectifier

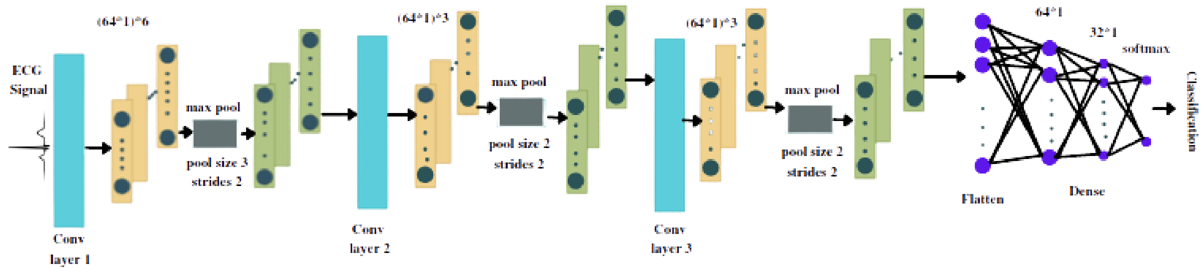


Fig. 5: Proposed model with 1D convolution neural network

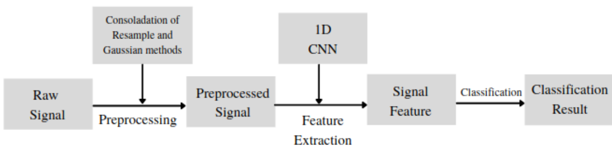


Fig. 6: Proposed model building flow chart

linear unit (ReLU) function is needed for 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 as the same. Therefore, the second and third pooling layers have a pool of size 2 with strides size 2 [Fig 5]. The dropout layer indicates dropping out units in the neural network randomly. For preventing the over-fitting 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 batch normalization [10]. In this paper, the number of total parameters is 118,341 and the total trainable parameter is 117,957 [Fig 7].

| Layers | Type | Filter Size | Strides | kernel | output shape | Parameters |
|---|---|---|---|---|---|---|
| Layer 1 | Conv1d | 6 * 6 | - | 64 | (None, 181, 64) | 448 |
| Layer 2 | Pooling | 3 * 3 | 2 * 2 | - | (None, 91, 64) | 0 |
| Layer 3 | Conv1d | 3 * 3 | - | 64 | (None, 89, 64) | 12352 |
| Layer 4 | Pooling | 2 * 2 | 2 * 2 | - | (None, 45, 64) | 0 |
| Layer 5 | Conv1d | 3 * 3 | - | 64 | (None, 43, 64) | 12352 |
| Layer 6 | Pooling | 2 * 2 | 2 * 2 | - | (None, 22, 64) | 0 |
| Layer 7 | Flatten | 2 * 2 | 2 * 2 | - | (None, 1408) | 0 |
| Layer 8 | Dense | - | - | 64 | (None, 64) | 90176 |
| Layer 9 | Dense | - | - | 32 | (None, 32) | 2080 |
| Layer 10 | Output | - | - | 5 | (None, 5) | 165 |

Fig. 7: Proposed 1D CNN model architecture layers

### 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%.

The first model achieves an overall accuracy is 97.64% on the test set [TABLE III]. 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 the fig. 5. Also, the pool and strides size is set as [Fig 5]. 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 finds that the overall accuracy is 98.00% [TABLE IV] where the dropout is 0.2 is kept in three pooling layers and also in the two dense layers. The kernel and filter size is kept the same as before.

TABLE II: Confusion Matrix:Accuracy 97.64%

| **Class** | **N** | **S** | **V** | **F** | **Q** |
|---|---|---|---|---|---|
| N | 0.98 | 0.01 | 0.00 | 0.00 | 0.00 |
| S | 0.12 | 0.85 | 0.02 | 0.01 | 0.00 |
| V | 0.02 | 0.01 | 0.96 | 0.01 | 0.00 |
| F | 0.06 | 0.01 | 0.14 | 0.80 | 0.00 |
| Q | 0.01 | 0.00 | 0.00 | 0.00 | 0.99 |

The accuracy of each class is found as 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.

TABLE III: Confusion Matrix:Accuracy 98.00%

| **Class** | **N** | **S** | **V** | **F** | **Q** |
|---|---|---|---|---|---|
| N | 0.99 | 0.01 | 0.00 | 0.00 | 0.00 |
| S | 0.14 | 0.84 | 0.01 | 0.00 | 0.01 |
| V | 0.03 | 0.00 | 0.94 | 0.02 | 0.00 |
| F | 0.07 | 0.01 | 0.10 | 0.81 | 0.00 |
| Q | 0.01 | 0.00 | 0.00 | 0.00 | 0.99 |

In the third model, the test result is achieved as overall accuracy is 98.02%[TABLE V] 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 model, the test result is achieved as overall accuracy is 98.25%[TABLE VI] according to the [Fig 5] proposed architecture where the dropout 0.2 is used in three pooling 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) 82.00%, Ventricular ectopic beats(V) 94.00%, Fusion beats(F) 85.00% and Unknown beats(Q) 99.00% with the number of 150 iterations.

TABLE IV: Confusion Matrix:Accuracy 98.02%

| **Class** | **N** | **S** | **V** | **F** | **Q** |
|---|---|---|---|---|---|
| N | 0.99 | 0.01 | 0.00 | 0.00 | 0.00 |
| S | 0.12 | 0.85 | 0.02 | 0.01 | 0.00 |
| V | 0.02 | 0.00 | 0.96 | 0.02 | 0.00 |
| F | 0.06 | 0.01 | 0.09 | 0.84 | 0.00 |
| Q | 0.00 | 0.00 | 0.00 | 0.00 | 0.99 |

TABLE V: Confusion Matrix:Accuracy 98.25%

| **Class** | **N** | **S** | **V** | **F** | **Q** |
|---|---|---|---|---|---|
| N | 0.99 | 0.00 | 0.00 | 0.00 | 0.00 |
| S | 0.15 | 0.82 | 0.01 | 0.01 | 0.00 |
| V | 0.03 | 0.00 | 0.94 | 0.02 | 0.00 |
| F | 0.07 | 0.01 | 0.06 | 0.85 | 0.00 |
| Q | 0.01 | 0.00 | 0.00 | 0.00 | 0.99 |

### *B. Discussion*

The comparison between our model with other past existing models is given [Table VII]. 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 high classification accuracy comparing the previous model [Fig 9]. The confusion matrix is represented in the results section in detail.

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 [TABLE III, IV, V, VI] and finally, our model which is given in this work is better and efficient than all of the previous algorithms that are proposed 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 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.

TABLE VI: Comparison with Existing Algorithms

| Paper | Class | Preprocessing | Feature Extraction | Classification | Accuracy |
|---|---|---|---|---|---|
| Dan et al. [19] | N,L,R,A,V | wavelet Combination | 1D-cnn | softmax | 97.50% |
| Model 01 | N,S,V,F,Q | Resample+Gaussian Combination | 1D-CNN | Softmax | 97.64% |
| Model 02 | N,S,V,F,Q | Resample+Gaussian Combination | 1D-CNN | Softmax | 98.00% |
| Model 03 | N,S,V,F,Q | Resample+Gaussian Combination | 1D-CNN | Softmax | 98.02% |
| **Proposed** | **N,S,V,F,Q** | **Resample+Gaussian Combination** | **1D-CNN** | **Softmax** | **98.25%** |

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