International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 05 Issue: 04 | April-2021 ISSN: 2582-3930

ECG Data Analysis using Machine Learning

[1]Jeet Gor, [2]Yash Mehta, [3]Simran More, [4]Mrs. Shweta Sharma

[1]Jeet GorComputer Science&Atharva College of Engineering
[2]Yash MehtaComputer Science&Atharva College of Engineering
[3]Simran MoreComputer Science&Atharva College of Engineering
[4]Mrs. Shweta Sharma Asst. Professor, Computer Science & Atharva College of Engineering

---***---

Abstract -Technology is rapidly changing the lives of people around the world. Not surprisingly, it has enabled the early diagnosis of diseases in the medical sector, however, one of the most predominant medical conditions that demand early diagnosis is cardiac arrhythmia. ECG signals can be used to classify and detect the type of arrhythmia. The proposed method uses the MIT-BIH Arrhythmia Dataset and The PTB Diagnostic ECG Database. The features extracted and used for prediction are Peak to peak Interval (R-R Interval), BPM (Beats per minute), P wave to QRS peak. We propose a Deep Learning solution in which we will be using a Convolution neural network (CNN) which will be used to solve and classify electrocardiogram (ECG) beats in the diagnosis of cardiovascular disease, ECG signals are typically processed as 1D signals while CNNs are better suited to multidimensional pattern or image recognition applications. We will represent the 1D signal as a 2D graph image to pass it to CNN that includes adaptive learning rate and biased dropout methods.

***Key Words*:**Machine Learning, Artificial Intelligence, Classification,Convolution neural network (CNN), Cardiac Arrhythmia, ResNet-34, Electrocardiogram (ECG).

1.INTRODUCTION

Despite many illnesses being considered to be chronic, Cardiovascular diseases (CVDs) are considered to be the number one cause of death worldwide, wherein, in India as many as 4.77 million people have died because of it in the year 2020. As a result, it has been considered to be one of the key reasons for mortality worldwide. [2]

For the past few decades, doctors have been conscious about the fact that cardiovascular diseases are the main reason for the increased mortality rate worldwide. Myocardial infarction, a name commonly denoted as heart attack, stands for the failure of the heart to pump sufficient blood to the heart muscles resulting in damage to the heart muscles. Using appropriate treatment within an hour of the start of the heart attack will significantly improve the chances of saving an individual's life.

Normally heartbeats at 60-100 beats/minute. However, a heart rate higher than 76 beats per minute when resting may be linked to a higher risk of a heart attack.

It is very difficult for a doctor to read an ECG report with bare eyes. At times, there is a high chance to miss out on any abnormality in the ECG report as the change in the ECG wave shape is hardly noticeable.

For the past couple of decades, we have made significant advancements in the field of medical science using different approaches such as machine learning and artificial intelligence which can help us better predict diseases and provide a viable medicine for them. To emphasize, some of the methods used were based on Neural Networks, Support Vector Machines, KNN, and Markov chain. [3-6]

Due to the current popularity of deep learning algorithms such as Convolutional Neural Network, it was considered as a solution for our proposed method. To be precise, a trained CNN network on the said database was fed with the ECG signals.

In this paper, our goal is to put forward a model which will use machine learning and classification algorithm like Convolutional Neural network that can analyze the ECG data of patients for predicting the type of arrhythmia. With the help of this model, we will be able to categorize an ECG signal to one of the 5 classes of arrhythmia, in which class 1 means normal ECG signal, classes 2 to 5 are different types of arrhythmia. Machine learning will aid us in providing the highest possible accuracy, moreover, it will help us in detecting various possibilities of cardiac arrhythmia.

2.LITERATURE SURVEY

1. *A Machine Learning Approach for the Classification of Cardiac Arrhythmia [4]*

This paper has implemented a hybrid model which is divided into three components: Principal Component Analysis, Bag of Words Approach, and various classifications techniques. In principal component analysis, they have tried to extract variables that actually affect the final decision making and provide as much information as possible. In this method, they tried to find out the best features from the dataset with a presumed criterion, without the help of any classification algorithms. In the second stage, they used the Bag of words approach on the final centroids of the newly formulated clusters that were formulated using K-means clustering. K-means clustering was used on the 150 predictors obtained from the Principal Component Analysis which in turn generated the necessary codebooks. This centroid file is stored in the codebook and used for the computation of histograms. These histograms provide the necessary information such as the features and class id which are essential for the formulation of model files. Following this, SVM, KNN, Logistic Regression, Random Forest Algorithms are used for the classification of cardiac arrhythmia using the new formulated model files and their results were compared with maximum accuracy obtained was just over 91% with Support Vector Machine Classifier.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 05 Issue: 04 | April-2021 ISSN: 2582-3930

2. *Classification of Normal and Abnormal ECG Signals Based on their PQRSTIntervals [5]*

In this paper, they have proposed a model which is able to differentiate normal and abnormal heartbeats of patients using signals from the ECG.
In this, they have used two stages in which they first looked that the normal ECG graph and tried to determine the P-QRS-T intervals, segments, and the specifications of these intervals. These readings were used further for feature extraction and classification. In the later stage, they discussed the effective features that can be extracted from the signal and used for said purpose. For example, the features used were as follows width or height of a wave or interval by using different feature extraction techniques. Heart rate (HR) is calculated with the help of the distance between two consecutive R peaks which is also known as RR interval.

They found out that the most effective features were usually found at the start, end, width, and height of the above-mentioned segments and intervals and a proper rhythmic motion of an ECG signal. For classification and comparison, they made use of the MIT-BIH database which was later filtered and carefully sorted.

Following this, they used Linear discriminant analysis for classification and comparison as it was fast and computational low in cost however the accuracy lacked at just above 80% for all the cases.

3. *Machine Learning based Cardiac Arrhythmia detection from ECG signal [7]*

This paper has implemented a model wherein the proposer has used noise filtering, feature extraction, and classification using an SVM classifier on an ECG database of different disease conditions. They have used data from the MIT-BIH database which has a collection of arrhythmia-based samples. To remove noise from the data they have used Butterworth high pass filter. Features that are required for detecting arrhythmia such as the peak-to-peak intervals (QRS-interval) was calculated using the Pan Tompkins algorithms. Since QRS peak can be recognized as T wave or P wave such chances were reduced by squaring the filtered signal to enhance the peaks. Following this SVM classifier was used for the classification of the extracted features from the dataset. The extracted features such as the heart rate, PR interval, and QRS interval were fed to the Support Vector Machine Classifier in turn SVM classifying data points into three classes as normal (NL) Tachycardia (TC), and bradycardia (BD). Results were compared achieving a prediction accuracy of 91% using the SVM classifier. Thus, to further improve this method and increase the accuracy of prediction we made use of classifier such as Convolutional Neural Network (CNN) along with Support Vector Machine (SVM) to classify the dataset, as a neural network can be used to understand the characteristics of the signal as well as assigning weights to each feature which can lead to faster optimization algorithms.

3.DATASET

ECGdata was collected from ECG Heartbeat Categorization Datasetwhich contained ECG data of two famous database: 1.MIT-BIH Arrhythmia Dataset and 2. PTB Diagnostic Database. The dataset was taken from Kaggle. The dataset contained the raw signal in .CSV files and the original annotations in .txt file. [1]

4.METHODOLOGY

CNN (Convolutional Neural Network) - In mathematics, computer science, and especially in machine learning regularization means the procedure of adding information to a model in order to reduce or prevent overfitting. CNN is considered to be a regularized model of multilayer perceptron (MLP) which is a part of Artificial Neural Network (ANN). Connection sparsity in Convolution Neural Network helps in reducing overfitting. [8] The idea for a convolutional network comes from the organization of the animal visual cortex. The visual cortex has small regions of cells that are sensitive to a specific reason of the visual field. Some of the neuronal cells respond only in presence of edges of certain orientations. For example, some respond to vertical edges while others respond to horizontal or diagonal edges.

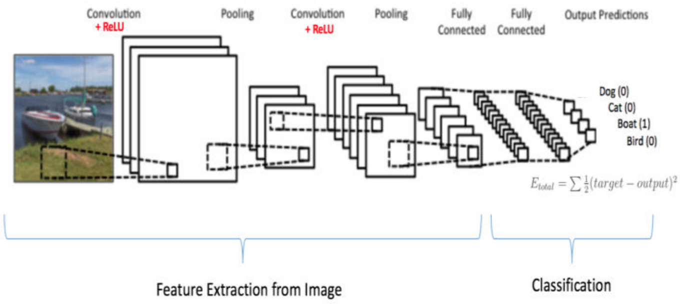

Fig-1: Typical Convolutional Neural Network.

Convolutional Networks are represented in 3 dimensions: height, width, and depth. Unlike Regular Neural networks wherein a set of neurons in a layer is fully connected to every neuron in the previous layer, in CNN however, the neurons in one layer will not be fully connected to all the neurons in the next layer but only to a small portion of it. During the training phase, the weights of the filter are decided and adjusted using the backpropagation method, furthermore, improving certain characteristics of the input. CNN has two central components:

Feature extraction part/Hidden Layers: In this section, CNN uses the convolution technique on the input data along with kernels to produce a feature map. In a feature map, a unit is connected to the previous layer via the weights of the filters. It is common to use multiple filters for multiple convolutions on our input, thus resulting in multiple feature maps. These multiple feature maps will be putting together as a final output of the convolutional layer. Activation Function is used to make the output data non-linear. Herein, Rectifier linear units (ReLU) can be used as an activation function. [8-9]

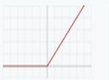	$f(x)=\begin{cases}0 & \text{for } x\le 0\\ x & \text{for } x>0\end{cases} = \max\{0,x\} = x\mathbf{1}_{x>0}$	$f'(x)=\begin{cases}0 & \text{for } x\le 0\\ 1 & \text{for } x>0\end{cases}$	$[0,\infty)$

Fig-2: ReLU activation function.

Stride is another parameter that is required to define the size of step the kernel will take each time it moves, meaning if the stride is 1 the filter moves pixel by pixel. In order to reduce the computation in the network, reduce the number of parameters, and also make the model tolerant to small distortion and variations, a pooling layer is added.

Classification Part: In the classification part, our 3D data is converted to 1D data because the fully connected layer can only work on 1D data. The last part of CNN is similar to the Regular Neural Network where the fully connected layers have access to activations in the previous layers. [8-10]

ResNets – Deep Neural networks are prone to one of the famous problems known as the vanishing gradient. During backpropagation, while using the chain rule for computing the gradients of the earlier layers in an n-layer network, repeated multiplications make the gradients so small that the weights of the initial layers don't get updated. Like in Fig.3, using activation functions such as the sigmoid function lead to vanishing gradient problems when applied on n-hidden layers. [13]

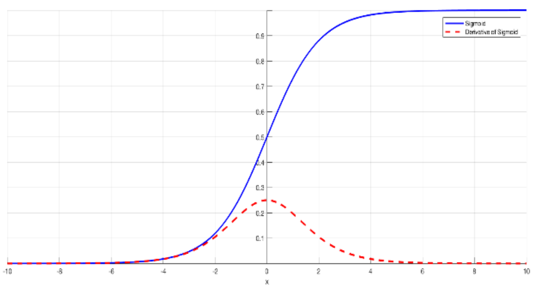

Fig-3: The sigmoid function and its derivative

As seen in Fig.4, every layer in the architecture seen is following a particular pattern. There is a 3x3 convolution with a fixed feature map dimensions like (64,128,256,512) while skipping two normal weighted layers, ReLU layers. This is somewhat reverse to the recurrent layer, while recurrent layer tends to go backward, residual moves forward. The reason to do this would be to increase the predictive power while allowing to us go much deeper into the network. This concept is explained much deeper in [11]. The dotted line in figure 3 represents the change in dimension of input due toconvolution.During the first convolution layer, max-pooling occurs while in between layers, reduction occurs due to an increasein strides.

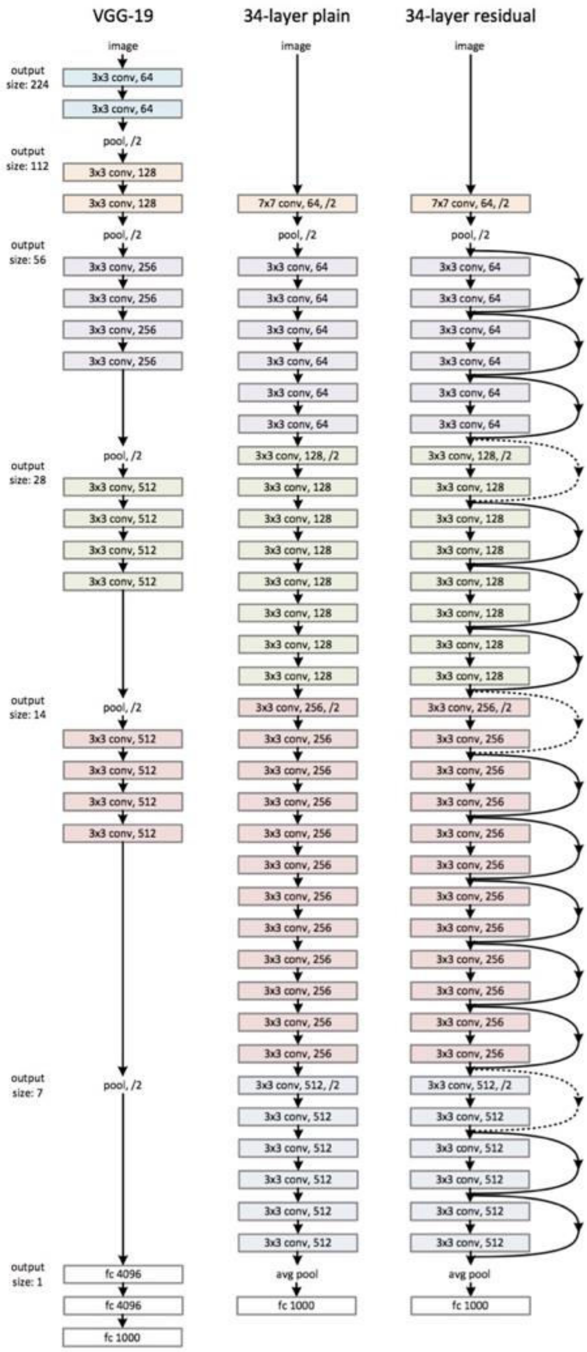

Fig-4: ResNet-34 network architecture.

As mentioned earlier, pooling operation is applied only twice, one at that start i.e., max pooling, and another one at the last layer i.e., average pooling. [12]ResNets uses batch normalization while training the data, which yields a noticeable speedup in training. Batch normalization uses the technique of normalization on mini-batches instead of one example at a time. [14] One clear advantage of normalizing on a mini-batch is that as the network gets deeper, the gradient becomes so small that using the above-said method helps in providing a higher learning rate. As stated in the paper [11] residual nets were able to achieve a 3.57% error when tested on the ImageNet test set. As it is quite evident from the previous statement as well as that for visual recognition tasks, the depth of representation plays an important role, hence, our proposed system incorporates ResNets-34 for the training dataset.

5.PROPOSED SYSTEM

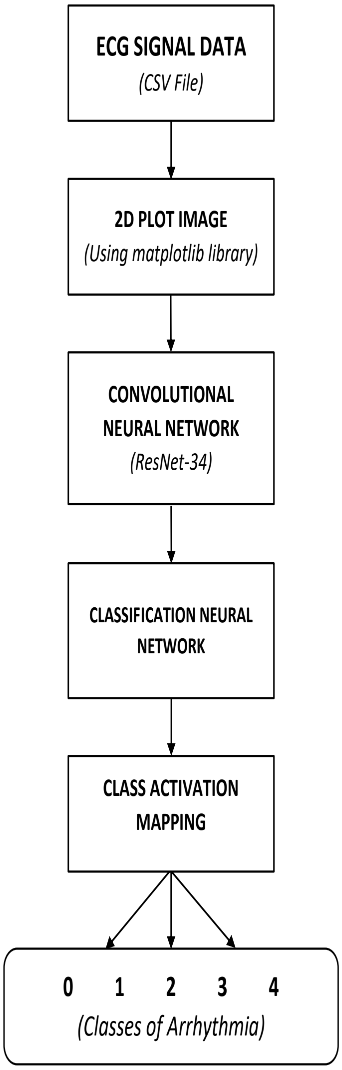

Fig-5: Proposed System.

The proposed system consists of four stages: pre-processing, feature selection, feature extraction, and feature classification.

As mentioned earlier, our selected dataset from Kaggle is in form of a .csv file. This data set consist of 109446 samples with sampling frequency at 125Hz and having 5 classes {'N': 0, 'S': 1, 'V': 2, 'F': 3, 'Q': 4}. The signals correspond to electrocardiogram (ECG) shapes ofheartbeats for the normal case and the cases affected by different arrhythmiasand myocardial infarction. These signals are preprocessed and segmented, witheach segment corresponding to a heartbeat. [1]

CSV files in the dataset are containing values that are basically in form of a 1D array. These values are plotted in form of a 2D graph image with the help of matplotlib library in python.

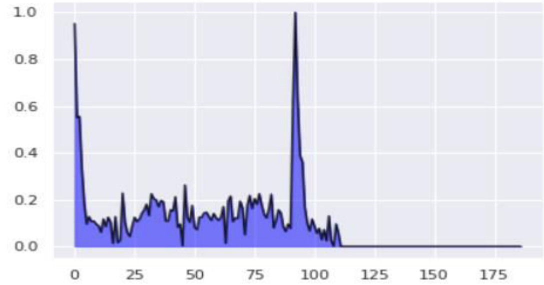

Fig-6: 2D graph image from 1D csv file of ECG signal.

Since our CNN model (ResNet-34)is trained to predict on images, it becomes mandatory to convert the 1D array into a 2D graph image. Furthermore, having converted into a graph image helps in increasing the accuracy of the model as well as the prediction. ResNet-34 is trained on these model files created from the dataset. Algorithms such as batch normalization and Adam optimizer were used in conjunction with ResNet-34 to improve the efficiency of model training.

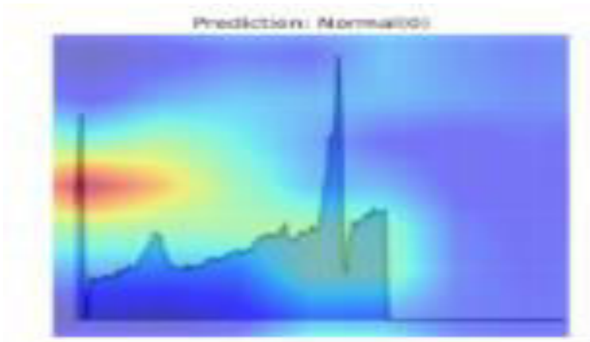

Fig-7:CAM (Class Activation Map) applied on during the final classification step.

During classification, we are using CAM (Class Activation Map) as shown in Fig.7, which creates a heatmap of attention around the region from where our Neural Network is predicting the type of arrhythmia a person is suffering from. Using such method will help novice doctors getting as accurate result as possible while, knowing how the Neural Network predicted the following arrhythmia. [15-16]

6.RESULTS

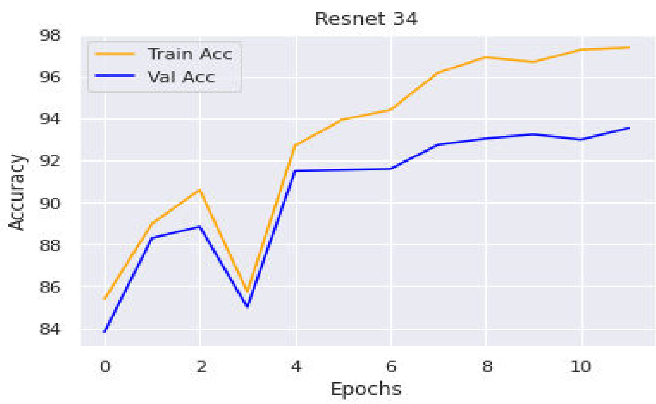

Fig-8: Training Accuracy

Dataset was trained using Convolutional Neural Network, precisely, ResNet-34 was used as a training model. The batch size was set at 16, while, epochs were set at 12 for training. As seen in Fig.8, we were able to achieve 97.38% of training accuracy while keeping the training loss as low as possible as shown from Fig.9.

Fig-9: Training Loss

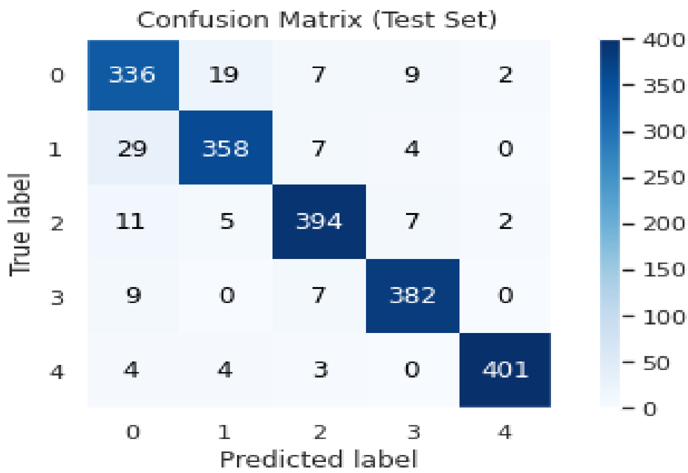

Fig-10: Confusion Matrix for the predicted and actual condition.

Figure 10 shows us the true label and the predicted label of the classified data in form of a confusion matrix. As seen from the matrix the diagonal element should be as high as possible while the neighboring element gives the number of times a particular type was incorrectly classified. For example, out of all the Brady arrhythmia passed top the model, four times it was predicted incorrectly as Normal. Similarly, for all Tachycardia Arrhythmia passed to the model, four times it was detected as Ventricular Arrhythmia.

Figure 11, 12, and 13 gives us a general idea of how the predicted result looks like as well as how by applying Class Activation Mapping (CAM) helps us produce a heatmap of attention around the region from where the Neural Network makes the said prediction. [15-16]

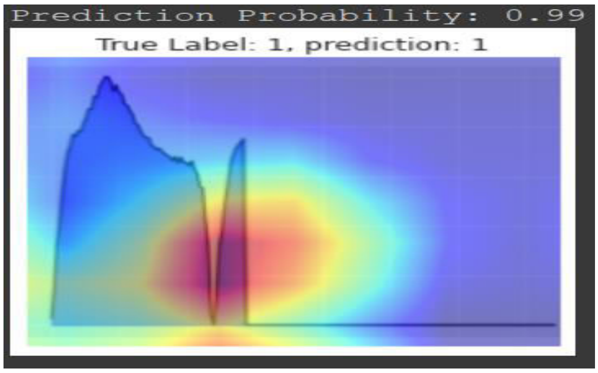

Fig-11: Predicted result for label: 1 (Tachycardia Arrhythmia).

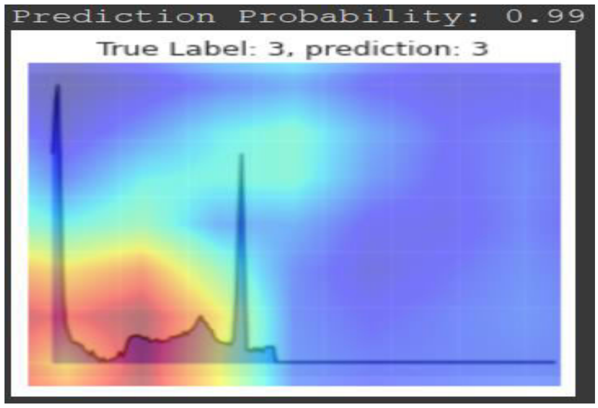

Fig-12: Predicted resultfor label: 3 (Ventricular Arrhythmia).

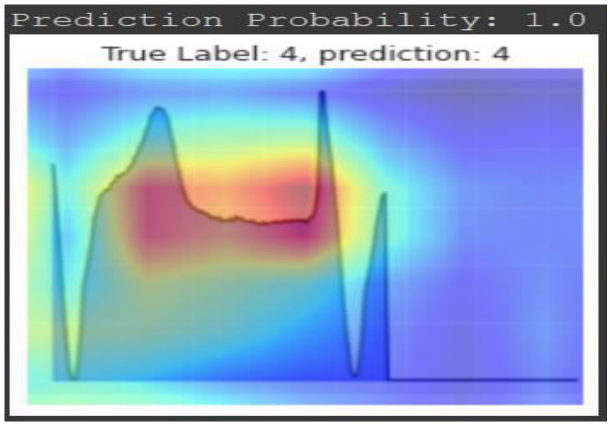

Fig-13: Predicted resultforlabel: 4 (Brady Arrhythmia).

Thus, the test accuracy was calculated around 93.57% or near to 94%. Thus, our suggested model was able successfully classify various ECG signals into right kind of arrhythmia with the help of CNN (ResNet-34).

7. CONCLUSIONS

In this paper,the dataset is trained and test samples are checked using CNN (ResNet-34) to predict the type ofarrhythmia the patient is having.Python was used toimplement the CNN, matplotlib to convert 1D data into 2Dgraph images and feature extraction. Thesystemimplemented of ResNet-34 along with optimization functionas Adam is able to achieve an accuracy of 93.57%with successfully classified into four types of arrhythmia i.e., Atrialpremature, Premature Ventricular Contraction, Fusion of ventricular, Fusion ofPaced and Normal.

REFERENCES

1."ECG Heartbeat Categorization Dataset," 2018. [Online].Available: https://www.kaggle.com/shayanfazeli/heartbeat.
2. "Cardiovascular diseases (CVDs)," 2017. [Online].Available:https://www.who.int/news-room/factsheets/detail/cardiovascular-diseases-(cvds)
3. W. T. Cheng and K. L. Chan, "Classification of electrocardiogram using hidden Markov models," Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. Vol.20 Biomedical Engineering Towards the Year 2000 and Beyond (Cat. No.98CH36286), Hong Kong, China, 1998, pp. 143-146 vol.1, doi: 10.1109/IEMBS.1998.745850.
4. P. Shimpi, S. Shah, M. Shroff and A. Godbole, "A machine learning approach for the classification of cardiac arrhythmia," 2017 International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2017, pp. 603-607, doi: 10.1109/ICCMC.2017.8282537.
5. K. Subramanian and N. K. Prakash, "Machine Learning based Cardiac Arrhythmia detection from ECG signal," 2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 2020, pp. 1137-1141, doi: 10.1109/ICSSIT48917.2020.9214077.
6. S. Singh, Animesh and T. Penzel, "Classification and Detection of Heart Rhythm Irregularities using Machine Learning," 2020 First International Conference on Power, Control and Computing Technologies (ICPC2T), Raipur, India, 2020, pp. 438-442, doi: 10.1109/ICPC2T48082.2020.9071495.
7. N. Naseer and H. Nazeer, "Classification of normal and abnormal ECG signals based on their PQRST intervals," 2017 International Conference on Mechanical, System and Control Engineering (ICMSC), St. Petersburg, Russia, 2017, pp. 388-391, doi: 10.1109/ICMSC.2017.7959507.
8. S. Albawi, T. A. Mohammed and S. Al-Zawi, "Understanding of a convolutional neural network," 2017 International Conference on Engineering and Technology (ICET), Antalya, Turkey, 2017, pp. 1-6, doi: 10.1109/ICEngTechnol.2017.8308186.
9. "An intuitive guide to Convolutional Neural Networks", 2018. [Online] Available: https://www.freecodecamp.org/news/an-intuitive-guide-to-convolutional-neural-networks-260c2de0a050/
10. "Visualizing the Fundamentals of Convolutional Neural Networks", 2019. [Online]. Available: https://towardsdatascience.com/visualizing-the-fundamentals-of-convolutional-neural-networks-6021e5b07f69.
11. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).
12. "Understanding and visualizing ResNets", 2018. [Online]. Available: https://towardsdatascience.com/understanding-and-visualizing-resnets-442284831be8
13. "The Vanishing Gradient Problem", 2019. [Online]. Available: https://towardsdatascience.com/the-vanishing-gradient-problem-69bf08b15484
14. Ioffe, S., &Szegedy, C. (2015, June). Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *International conference on machine learning* (pp. 448-456). PMLR.
15. Zhou, B., Khosla, A., Lapedriza, A., Oliva, A., & Torralba, A. (2016). Learning deep features for discriminative localization. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2921-2929).
16."Class activation maps: Visualizing neural network decision-making",2019. [Online]. Available:https://heartbeat.fritz.ai/class-activation-maps-visualizing-neural-network-decision-making-92efa5af9a33