Classification Of Arrhythmia Based On ECG Signal Using Deep Learning

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I. Abstract

A crucial step in the diagnosis of cardiovascular anarchy is the inquisition and technology of ECG signals. Ramification is the elementary reference of exploration in this discipline, and deep neural networks are increasingly countenancing it. A deep neural network was manufactured in this study to automatically to classify premier ECG signals. The study was driven using information from an MIT-BIH database. Five different neural network architectures were used: the convolutional neural network was the first, AlexNet was the second, LSTM was the third, LeNet was the fourth, and the VGG was the fifth. Training and test sets were split up into the dataset in proportions of 80% and 20%, respectively. In our investigation, CNN and VGG accomplished better, with the accuracy rates of 97.9 percent and 97.8 percent, respectively. We also oversee that why LSTM, a particular RNN variant used in deep learning algorithms to categorize cardiovascular distempers into five groups, performed infirmly.

II. Introduction

Widespread cardiovascular disease is a momentous impendence to people's health, especially in the middle-aged and elderly. The World Health Organization (WHO) reports that cardiovascular diseases (CVDs), which are the principal cause of death, claim an alloted 17.9 million existences per year. Heart attacks and strokes are included in 80% of cardiovascular cases. This research aims to properly identify prevalent heart conditions such congestive heart failure and arrhythmia (ARR) (CHF). Cardiovascular disease has grown to be a major public health concern. An examination that detects the electrical activity of the heartbeat is called an electrocardiogram (ECG). The heart sends an electrical impulse with each beat. It's a enforceable method that is widely aged to monitor cardiac health. The classification and identification of ECG signals are necessary for cardiovascular disorders. The electrical activity produced by each cardiac cycle of the heart is captured in real-time by the electrocardiogram (ECG), a visible time series. It is widely aged by cardiologists and other medical professionals to track cardiac health. The level of expertise a cardiologist or other medical professional has will significantly determine how well they can detect cardiovascular disease. Unfortunately, it takes a lot of effort and is prone to error to manually analyze a sizable number of ECG data for each individual. A new conundrum has emerged regarding how to quickly and accurately analyze particular diseases. Additionally irregular, low-recapitulation, and vulnerable ECG readings lead to uneven diagnosis outcomes. In order to increase the proficiency and accuracy of ECG recognition, intelligent automatic recognition and classification of ECG signals has become unavoidable.

In this project, we wil use deep learning models such as CNN, AlexNet, LSTM, LeNet, VGG etc. to classify heartbeats which can distinguish between five distinct arrhythmias with accuracy and show the performance of each individual in this classification based on ECG signals.

III. Related Works

The detection of ECG signal characteristics is being carried out using a variety of machine learning techniques, thanks to the advancements of Artificial Intelligence (AI) technology, to invoke problems like huge extents of ECG signal feature data and a substantial manual perception overhead. The common methods are neural networks (NN) proposed by Jiang, et al [3], path forest [2], Algorithm for Independent Component Correlation (ICA). For the classification of ECG data in terms of neural networks, Jiang, et al. [3] propose an transformative block-based neural network (BbNNs). The BbNN is a collection of two-dimensional modular networks with customizable internal syllable and synopsis. In recent years, advances in machine learning and deep learning networks have been made in a variety of sectors, including voice recognition, image processing, and many more. A approach for using ECG signals in the aided diagnosis of cardiac illness has been proposed by Zubair, et al. [1].

A. An Automated ECG Beat Classification System Using Convolutional Neural Networks

In this paper, they publicized a convolutional neural network-based ECG beat categorization method (CNNs). Their suggested obtainment combines the two key components of an ECG pattern recognition system: feature extraction and classification. From the unprocessed ECG data, their model automatically learns a compatible feature representation. In order to mete the classification performance and superior computational efficiency compared to the majority of state-of-the-art algorithms for ECG signal ramification, ECG signals from 44 recordings in the publicly available and well known MIT-BIH database are also devoted.

IV. Dataset

For our project, we used ECG Heartbeat classifying Dataset(MIT-BIH dataset) from Kaggle. The MIT-BIH dataset consists of ECG recordings from 47 individual participants obtained at a 360Hz sample rate from a demography of mixed in-patients and out-patients at Boston's Beth Israel Hospital (approximately 60% and 40%, respectively). At least two cardiologists annotate each beat. The dataset contains 186 columns and 87554 rows in total. We categories the dataset into five different classes ['N': 0, 'S': 1, 'V': 2, 'F': 3, 'Q': 4] depending on unique set of values. Although various types of cardiac arrhythmias exist, AAMI (Association for the Advancement of Medical Instrumentation) recommends that only a select few types be detected by tools or techniques. For cardiac beat monitoring, there are 15 arrhythmia classes that are advised, which are divided into 5 super classes: Normal beats (N), Supraventricular ectopic beat (S), Ventricular ectopic beat (V), Fusion beat (F), and Unknown beat (Q). From table.1 we can know more details of these different classes. Some sample raw data of our work is shown in Table.2 and The overview of our dataset is given below:

	Train Data	Test Data
Percentage	80%	20%
Row	87554	21892
Column	186	186

Grouped class	Symbol	Mean
N	L R e j	Left bundle branch block beat Right bundle branch block beat Atrial escape beat Nodal (junctional) escape beat
S	A a s J	Atrial premature beat Aberrated atrial premature beat Supraventricular premature beat Nodal (junctional) premature beat
V	V E	Premature ventricular contraction Ventricular escape beat
F	F	Fusion of ventricular and Normal beat
Q	P ou/ f U	paced beat Fusion of suffice and normal beat Unclassifiable beat

Table.1. Description of different classes

We collect this database from kaggle and here is the url: https://www.kaggle.com/datasets/taejoongyoon/mitbit-arrhythmia-database

0	1	2	3	4
9.78E-01	9.26E-01	6.81E-01	2.45E-01	1.54E-01
9.60E-01	8.63E-01	4.62E-01	1.97E-01	9.40E-02
1.00E+00	6.59E-01	1.86E-01	7.03E-02	7.03E-02
9.25E-01	6.66E-01	5.41E-01	2.76E-01	1.96E-01
9.67E-01	1.00E+00	8.31E-01	5.87E-01	3.57E-01
9.27E-01	1.00E+00	6.27E-01	1.93E-01	9.50E-02
4.24E-01	7.92E-01	1.00E+00	2.57E-01	0.00E+00

Table.2. Sample data of Dataset

V. Background Study

A. Convolutional Neural Network

A kind of neural networks known as convolutional neural networks, or CNNs or ConvNets, are focused on processing data with features including local capacious fields and weight apportionment. To more successfully mine data features, convolutional neural networks can decrease the number of connections and deepen the network structure sharing. To more effectively mine data features, convolutional neural networks can diminution the number of connections and condense the network structure. The layers are designed such that they first identify lines, curves, and other basic patterns, then go on to more complex patterns. One can enable sight to computers by utilizing a CNN. A CNN typically includes three layers: a convolutional layer, a pooling layer, and a fully connected layer.

B. AlexNet

Developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, AlexNet is the name of a convolutional neural network (CNN) architecture. The eight layers of AlexNet were partitioned into the following groups: the first five were convolutional layers, some of them were pursued by max-pooling layers, and the final three were fully linked layers. [2] Compared to tanh and sigmoid, it performed better during training thanks to the non-saturating ReLU activation function. AlexNet favours multi-GPU formulation by partitioning the model's neurons between two GPUs, with half of the neurons being settled on one GPU. This not only approves for the formulation of a larger model but also diminishes the formulation period.

C. Long Short-Term Memory Networks

In the context of deep learning, LSTM stands for long short-term memory networks. There are several types of recurrent neural networks (RNNs) that are operative of learning long-term servitudes, particularly in issues containing sequence prediction. The front-to-back dependence of ECG signals may be effectively captured by LSTM, which also offers significant benefits when processing ECG data as a time series. The neural network is susceptible of learning textual long-term dependent information and effectively retaining historical knowledge. The input gate, forget gate, output gate, and cell unit of the LSTM network are used to update and reservoir historical data.

D. LeNet

LeNet was generally used by banks to recognize handwritten supervisions using the MNIST dataset. But it can produce better result, using pre-trained models are great. Two sets of convolutional and pooling layers, two fully connected layers, and an output layer with an RBD classifier make up the LeNet. The network is known as Lenet-5 since it contains five layers with learnable parameters.

E. Visual Geometry Group

A hereditary convolutional neural network architecture is the VGG. It was based on a perusal of how to make these networks deeper. The network is distinguished by its simplicity; the only superfluous elements are a fully linked layer and a pooling layer.

F. Performance Matrices

In our work, we calculate precision, Recall, F1-score, Accuracy to evaluate which model performs better among them. The equation of Acuracy and Precision are:

$$Accuracy = (TP/TP + TN) * 100 \quad (1)$$

$$Precision = (TP/TP + FP) \quad (2)$$

VI. Methodology

Our main approach to classify arrythmia based on the ECG signals using CNN with the heart beat types of the MIT-BIH dataset. It is used to build a convolutional neural network. We used the resampled data as inputs and driven a convolution layer pursued by a batch normalization layer and a max pooling layer and repeating this combination three times. Then after flattening and feeding the output data to three dense layers with two ReLU and a softmax activation function respectively, to predict output class probabilities.Every layer of convolution applies 1-D convolution over time. The final network is a deep network with 13 weighted layers in total. Data were collected at random and divided into five groups. And these are:

Class 1	Class 2	Class 3	Class 4	Class 5
72471	6431	5788	2223	641

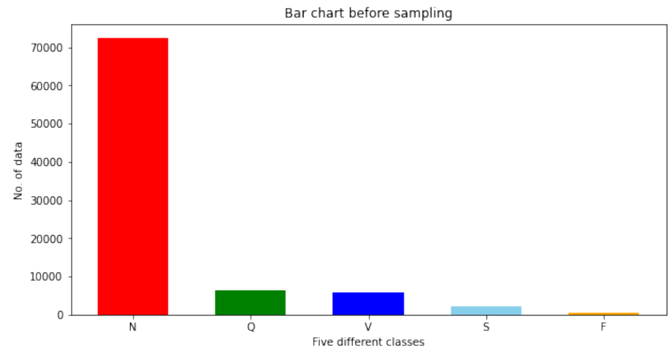

Fig. 1. Before Sampling

A. Data Pre-processing :

From the training dataset, we can see that one class has maximum number of data, which might result the model from willing towards the majority class (Fig.1). In this case, we have to do:

- Downsampling the class having maximum number of data, which minimizes the sampling rate of the inputs by an complement factor by picking up one out of N samples.
- Ignore those parameters which are simply missing (i.e., are zero) or sharing same non-zero parameter.
- Upsampled the class 2-5 to increase the sampling rate.

After this process, the counts of both labels are almost the same. This equalization procedure stops the model's willingness to favor the dominant class which we don't want. After resapmling all the classes each contained 20% of the whole training dataset.

B. flowchart

We are going to show the over all system of our work with a very simple way in fig.2.

C. Model Performances

In our work, we used CNN, AlexNet, LSTM, LeNet, VGG deep learning models for evaluation. We took values for each models after 50 epochs with batch size 32. The performance of all models in a specific way are quite good on this MIT-BIH database. In our work, CNN model approaces 98.1%, AlexNet approaches 96.8%, LSTM approaches 90.3%, LeNet approaches 97.1% and VGG approaches 98.2% accuracy.

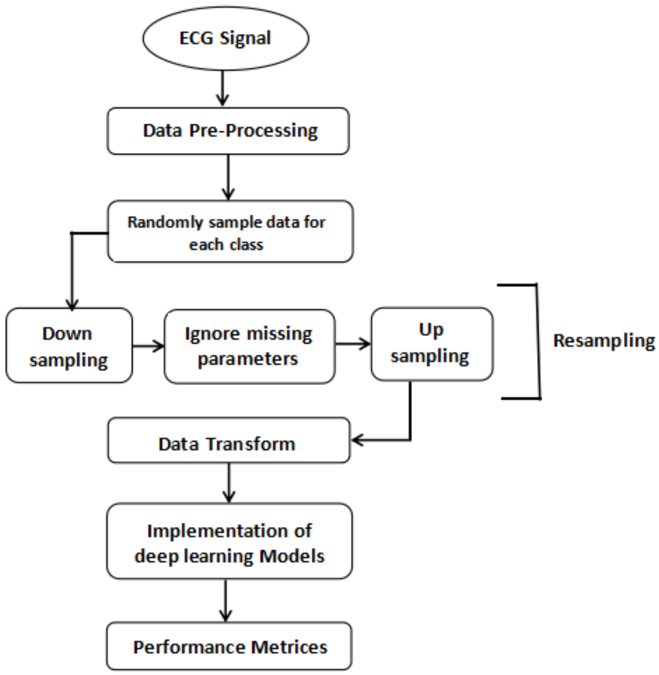

Fig. 2. Overview Of Our System

VII. Result Analysis

In this section, We give the findings and talk about the conclusion in this part. We evaluated some of the techniques' critical parameters and demonstrated how well they performed. From the accuracy and loss graph we can see that, till 30 epochs there was drastic change in both of them but after that it was almost linear. That is why we tuned the hyper parameter to 50 epochs and batch size was 32. The result we got from that was quite satisfactory. The followed paper approaches 98% accuracy using CNN whether we got 97.9% accuracy using it[3], which is almost same. Again, the paper which we followed, approaches 99.26% accuracy using LSTM whether we got 91.9% accuracy using LSTM model[6]. In this paper, they got better performance than ours as they also extract the features and took more no.of epochs with batch size but they also worked on this same MIT-BIH Arrhythmia dataset. In our work, We also used LeNet, AlexNet and VGG, Where LeNet got 97.6% accuracy ,AlexNet got 97.6% accuracy and 97.8% accuracy using VGG deep learning model. We used CNN, AlexNet, VGG, which are mainly used for image recognition or classification or detection and LSTM used for text or documentation analysis. But we used them in our work by using 1D array type data and in deep learning models, there are lots of hidden and layers. For these reason all models can be used for all type of data with some restrictions.

In our work, we almost got much satisfactory performance from all used DNN models. But among of them, we got accuracy 97.8% by using VGG (Visual Geometry Group) and 97.9% by using CNN(Convolutional Neural Network). As The highly powerful model AlexNet can achieve excellent accuracy on a very difficult and vast dataset. But CNN also give best performance on this remarkable dataset. And as we know, VGG It performs better than baselines on numerous tasks and datasets outside of ImageNet because it was designed as a deep CNN. Given that CNN has convolution layers, pooling layers, activation layers, etc., VGG performs marginally better than CNN. A particular type of convolutional network called the VGG is made for classification and location. These two model shows better performance than other DNN models, we used.

From the Table.3 , we can see that the Precision, Recall, F1 Score and Accuracy are same. When sensitivity (Recall, or TPR), specificity (selectivity, or TNR), and accuracy (TNR) are identical, then precision and recall might be the same. And when the precision and Recall have same value or equal priority of true positive and false negative value than F1 Score also be the same.

Models	Precision	Recall	F1-Score	Accuracy
CNN	0.979	0.979	0.979	0.979
AlexNet	0.976	0.976	0.976	0.976
LSTM	0.919	0.919	0.919	0.919
LeNet	0.976	0.976	0.976	0.976
VGG	0.978	0.978	0.978	0.978

Table.3. Resultant Confusion Matrices Of Each Model

From this table we can see the performance of all models are:

$$\text{CNN} \geq VGG \geq AlexNet \geq LeNet \geq LSTM.$$

The Loss and Accuracy Evolution of each model is shown in Fig.4. We got most satisfactory result from CNN and VGG deep neural network models. In this figure, blue color indicates training loss/loss, orange color indicates the test/validation loss, green color indicates training accuracy and red color indicates test/validation accuracy. Here Validation accuracy is the estimated accuracy on the data set that is used throughout the training process to validate (or "test") the generalizability of your model rather than for training. On the other hand, a deep learning model's carrying out on the validation set is form an impression of using the statistic known as validation loss. From this Fig.4, we can see that the loss and accuracy is almost flat in CNN for each epoch. The validation loss is decreasing and in accordance with some time, it's also increasing. It also shows optimum point where validation loss are almost equal at last 3 epoch, which means the model is either perfectly fit or in a local minimum. On the other hand, In VGG, distance between loss and accuracy is less than CNN.

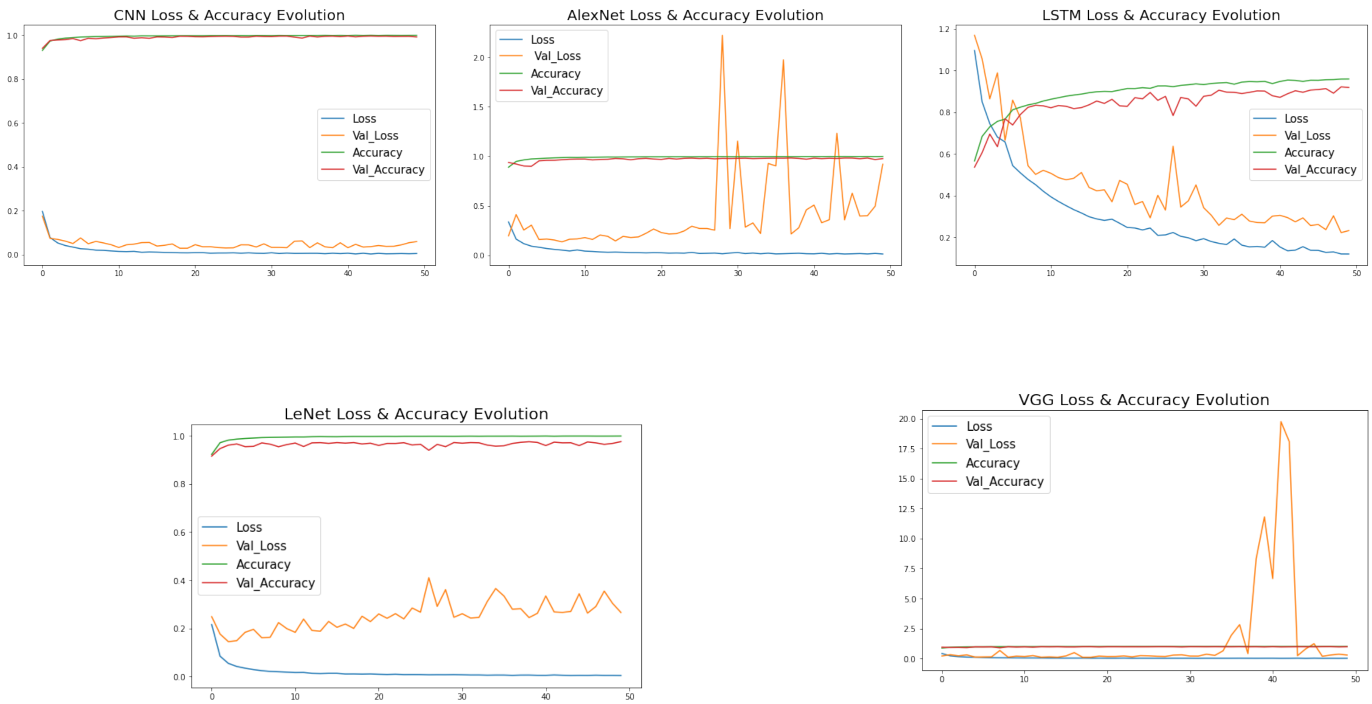

Fig. 3. Loss Accuracy Evolution Graph Of Each Model

The validation loss in decreasing and increasing heavily when training loss is decreasing. For this wild change of validation loss,the model overfits the data though it performs well on the training data. For VGG, loss and accuracy are overlapping. When the difference between the test error and training error is small, it is actually favorable. This indicates that our chosen model is not overfitting. As is well known, the model is still underfitting when the validation loss is decreasing, and it is overfitting when the validation loss is increasing. In other words, the model is well generalized, as it's flat for each epoch. In opposite way, LSTM performs worse than other models. Because LSTM is a unique variant of RNN, which exhibits great carrying out on a very wide variety of data. when this model don't get enough data like more than 1,000,000 elements, than it shows poor performance than other deep neural network models.
Here Fig.4 displays the confusion matrices of CNN and VGG for five different classes.

VIII. Conclusion And Future work

In the modern world, Cardiovascular disease is a major health problem. The ECG is crucial for making an early diagnosis of cardiac arrhythmia. Unfortunately, expert-level medical resources are hard to come by, making it difficult and time-consuming to visually detect the ECG signal. The used VGG and CNN exhibit exceptional performance with a 98 percent overall classification accuracy. In this study, we employed convolutional neural network (CNN), AlexNet, LSTM, LeNet, and VGG to accurately classify heartbeats based on ECG readings utilizing five different arrhythmias.

In terms of future study, Using rejuvenate artifices to develop a workable design and solution would be fascinating to investigate. Our study's drawback is that we haven't yet used any optimization approaches to enhance the model parameters, but we think that if we do, the performance of the suggested solution will be susceptible to advance significantly.

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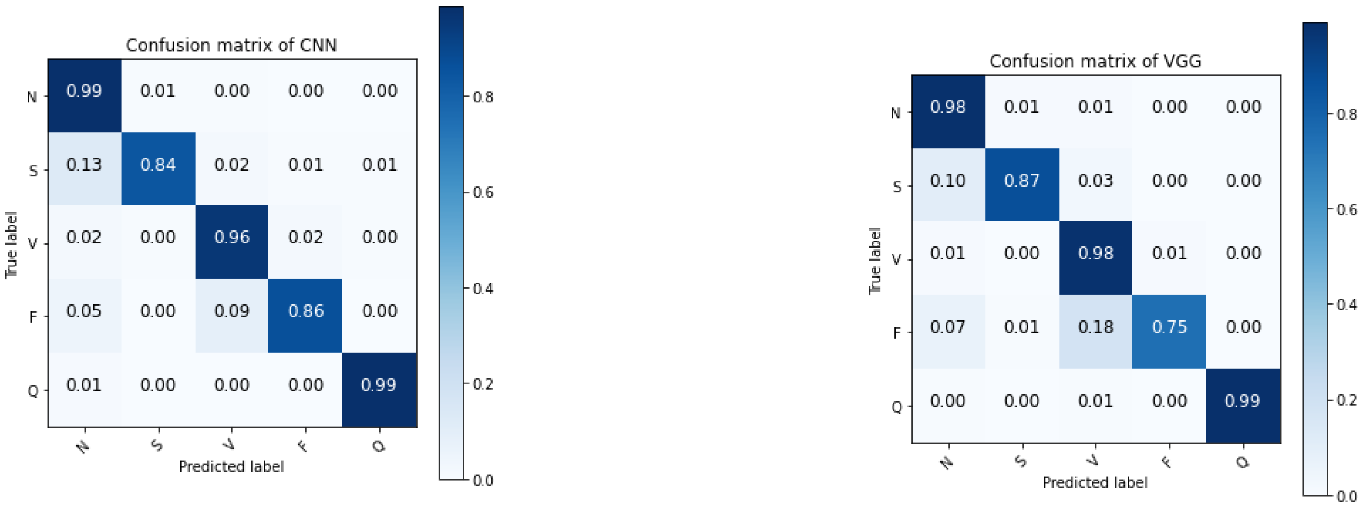

Fig. 4. Confusion matrices of CNN and VGG

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