Classification Of Arrhythmia Based On ECG Signal Using Deep Learning

I. Abstract

A crucial step in the diagnosis of cardiovascular anarchy is the inquisition and technology of ECG signals. The 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 accuracy rates of 97.8 percent and 97.6 percent, respectively. We also oversee 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 motive of demise, claim an allotted 17.9 million existences per year [1]. Heart attacks and strokes are included in 80% of cardiovascular cases. This research aims to properly identify prevalent heart conditions such as congestive heart failure and arrhythmia (ARR) (CHF). Cardiovascular disease has grown to be a major public health concern. An examination that detects the electrical mobility of the heartbeat is called an electrocardiogram (ECG). The heart sends an electrical impulse with each beat. It's an enforceable method that is widely aged to monitor cardiac health. The classification and identification of ECG signals are necessary for cardiovascular disorders. The electrical mobility produced by each cardiac hoop of the heart is captured in actual period 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 swiftly and validly scrutinize particular diseases. Additionally irregular, low-recapitulation and vulnerable ECG readings lead to uneven diagnosis outcomes. To increase the proficiency and accuracy of ECG recognition, intelligent instinctive acceptance and stratification of ECG signals have embellish unavoidable. In this project, we will 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.

So the restatement of the main points is to use the MIT-BIH Arrhythmia dataset to precondition the data and ECG signal for our study. The dataset is divided into five groups, each with its category. To discover which deep neural network architectures perform best, we tested five distinct ones. To clarify whether or not we achieved superior outcomes, we have compared the findings of our study with those of the following articles that served as our sources of inspiration.

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 prominence data and a substantial hand-operated perception overhead. An approach for using ECG signals in the aided diagnosis of cardiac illness has been proposed by Zubair, et al. [2]. 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 characteristic representation. To meet the classification performance and superior computational competency 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. For the first time, the common methods are neural networks path forest Algorithm was used by Luz, Eduardo Jose da S. et al. [3], for Independent Component Correlation (ICA).In this article, they used features collected from six primary methodologies mentioned in the literature for ECG arrhythmia analysis to apply and examine a sturdy superintend graph-based swatch determination algorithm, the optimum-path forest (OPF) classifier combining support vector machine (SVM), Bayesian, and multilayer artificial neural network (MLP). They also used the identical Database in their investigations. And the well-known architecture (NN) method raised by Jiang, et al [4], For the ramification of ECG data in the context of neural networks, Jiang, et al. also propose a transformative block-based neural network (BbNNs). The BbNN is a collection of two-dimensional interchangeable networks with customizable internal syllables and synopsis. Latterly, advances in machine learning and deep learning neural networks have been made in a variety of sectors, including voice recognition, image processing, and many more. Pandey, S.K., Janghel, R.R., Vani, V. [6] used LSTM deep neural model on the same database and compare it with another model such as SVM, KNN, and ensembled SVM. They got almost 92.16% accuracy by using LSTM. Singh, S., Pandey, S.K., Pawar, U., Janghel, R.R. [8] used RNN with LSTM for allocating the normal and paranormal beats in an ECG signal to detect Arrhythmia and got nearly 88.1% accuracy. Isin, A., Ozdalili, S [10], used three inconsistent ECG waveforms from the MIT-BIH dataset to accomplish the final arrhythmia classification. They did this by using a reassigned deep convolutional neural network (AlexNet) as a characteristic extractor and importing the extracted characteristics up a simple back propagation neural network. Using this neural network, they achieved a testing accuracy of 92 percent overall. J. Gao, H. Zhang, P. Lu, and Z. Wang [11] proposed a version of the LSTM deep neural model with focal loss (FL) on this corresponding database to reduce the mortality of cardiovascular diseases based on ECG signals. They got almost 99.26% accuracy.

A. Several papers or Others' Writings

U. R. Acharya, [12] proposed an architecture of CNN version which requires minimum pre-processing of ECG signals for Congestive heart failure (CHF) diagnosis. They used four different types of data and got the highest accuracy approximately 98.97% from the second one. T. Santhanam E. P. Ephzibah [14], focused on culling the momentous characteristics in the data exerting Principal Component Analysis (PCA) and regression technique to classify heart diseases using the dataset of Arrhythmia which is available on UCI machine learning repository. The anticipated accuracy was 95.2 percent applying a feed-forward neural network classifier, which is much higher than the greatest predicted accuracy of 92% they obtained using regression. E. Izci, M. A. Ozdemir, R. Sadighzadeh, and A. Akan primarily evaporated on indicative arrhythmia detection method based on Empirical Mode Decomposition in their article [15] (EMD). A linear discriminant analysis (LDA) classifier was used to recognize both normal and arrhythmic signals with 87% accuracy utilizing four procedures to divide arrhythmia into six types.

Many related papers worked on the same dataset but classify more than 5 classes or took other approaches to get better accuracy. Arrhythmia can be classified by the MIT-BIH data set, WESAD data set, and any others. We have also explored some review papers which are also referenced in our reference section.

IV. Data Descriptions

The MIT-BIH Arrhythmia Database, which demonstrates a distinctive abbreviation, was aged. For our interpretation, the BIH Arrhythmia Laboratory accumulated 48 nearly a quarter quotations of two-channel itinerant ECG documentations from 47 folks between 1975 and 1979. With an 11-bit authorization and a 10 mV range, the reportings were revolutionized to a rate of 360 samples per second per channel for the digital data. The database of mixed in- and out-patients at Boston's Beth Israel Infirmary (about 60% and 40%, respectively) was used as a contrast, and each record was independently elucidated by two or more cardiovascular specialists. Discrepancies were decisive to produce a backward-compatible allusion gloss for each beat (a total of about 110,000 elucidations). Each pulse is recorded by at least two cardiologists. This dataset has 87554 rows and 186 columns. The ANSI/AAMI (Association for the Advancement of Medical Instrumentation) confers categorizing those heartbeats into a variety of categories centered on a certain set of values ['N': 0, 'S': 1, 'V': 2, 'F': 3, 'Q': 4]. Only a few categories should be perceptible by tools or procedures, according to AAMI. 15 various forms of arrhythmia are urged to be watched closely by cardiac beat monitoring, including normal beats (N), supraventricular ectopic beats (S), ventricular ectopic beats (V), fusion beats (F), and unknown beats (U) (Q). Additional information on these various categories is included in Table 1 & Table 2, along with some raw research data. The following is an overview of our dataset:

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: Representation of different classes

N	S	V	F	Q
0.977941	0.926470	0.681373	0.245098	0.154412
0.960114	0.863248	0.461538	0.196581	0.094017
1.000000	0.659459	0.186486	0.070270	0.070270
0.9254143	0.665745	0.541436	0.276243	0.196132
0.967136	1.000000	0.830986	0.586854	0.356808
0.927461	1.000000	0.626943	0.193437	0.094991
0.423611	0.791667	1.000000	0.256944	0.000000

Table 2: Sample data of Dataset

We got this data from Kaggle and here it is-Dataset[1]

V. Background Study

A. Convolutional Neural Network

A kind of neural networks known as CNNs or ConvNets, are focused on processing data with features including local capacious fields and weight apportionment. To more successfully mine data features, CNNs can decrease the number of connections and deepen the network structure sharing. The layers are designed such that they first identify lines, curves, and other basic patterns, then go on to more complex patterns. A CNN predominantly 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. [3] Compared to tanh and sigmoid, it performed better during training and thanks to the non-saturating ReLU activation function.

C. Long Short-Term Memory Networks

In the context of deep learning, LSTM refers for long short-term memory networks. There are several types of recurrent neural networks (RNNs), among of them 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 LSTM network is integrated to update and reservoir authentic 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 Accuracy and Precision are:

$$Accuracy = (TP/TP + TN) * 100 \tag{1}$$

$$Precision = (TP/TP + FP) \tag{2}$$

[1] www.kaggle.com/datasets/taejoongyoon/mitbih-arrhythmia-database

VI. Methodology

Our main approach to classify arrhythmia 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:

A. Data Pre-processing :

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

Fig. 1. Here is the frequency of each labeled class. We can see class 1 has maximum number of data which influenced the other classes data

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. Here class 'N' have 83% data of training dataset and after downsampling it's data rate is 20%.
- 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 upsampling the data for class 'Q','V','S','F' will be- 20% where before upsampling the data was 7.2%, 6.6%, 2.5%, 0.7% respectively.

The numbers for each labels are almost equal after this procedure Fig 2. This equalization process prevents the model from favoring the dominant class, which is something we do not want. Each class included 20% of the entire training dataset just after resampling.

B. Deep learning Models

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.

C. Performance Matrices

In our work, we calculate F1 Score, Accuracy, Precision, Recall as performance matrices. CNN model approaches 97.8%, AlexNet approaches 97.5%, LSTM approaches 93.6%, LeNet approaches 97.1% and VGG approaches 97.6% accuracy.

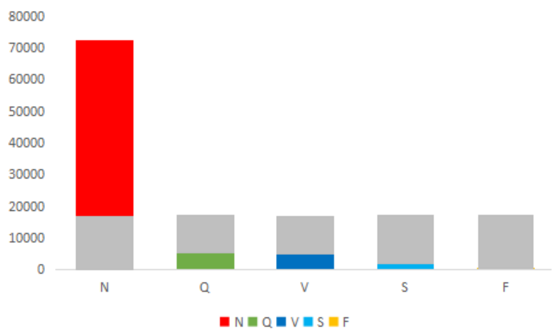

Fig. 2. After resampling, this is the overall data rate. The data rate before sampling is shown here by the colors red, green, blue, light blue, and yellow. And data rate is identical after downsampling of class 'N' and upsampling of class 'Q' 'V', 'S', and 'F'.

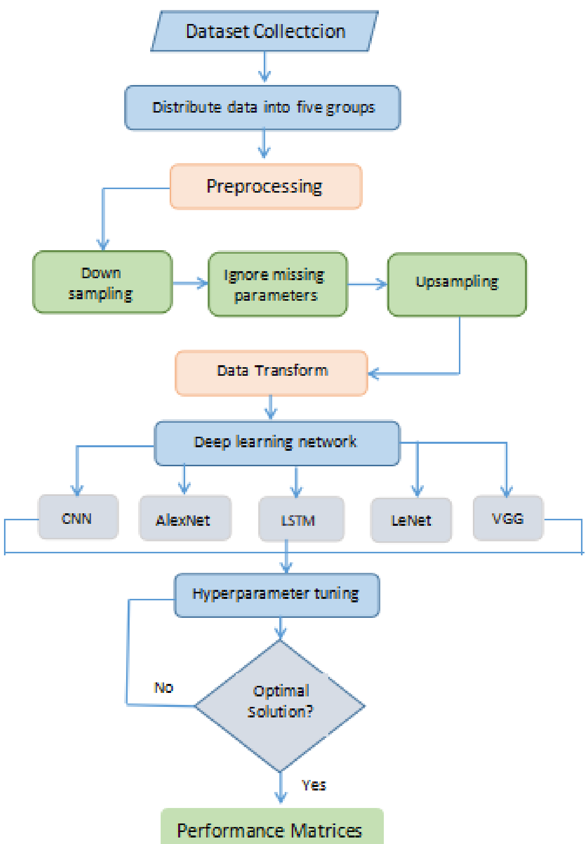

Fig. 3. Overview Of Our System

VII. Result Analysis

We present the results and discuss the conclusion in this section. We assessed some of the key aspects of the strategies and showed their effectiveness. As we can see from the accuracy and loss graph, there was a significant shift in both up to 30 epochs, but after that, it was practically linear. For this reason, the batch size was set to 32 and the hyperparameter was calibrated to 50 epochs. The outcome we received from it was pleasing. We employed LSTM, which is used for text or documentation analysis, as well as CNN, AlexNet, and VGG, which are mostly used for picture recognition, classification, or detection. But we use these models in our work by using 1D array-type data and in deep learning, there are lots of hidden layers. For these reasons, all models can be used for all types of data with some restrictions.

In our work, we almost got a satisfactory performance from all used DNN models. But among them, we got an accuracy of 97.8% by using CNN(Convolutional Neural Network) (Visual Geometry Group) and 97.6% by using VGG(Visual Geometry Group). As a highly powerful model, AlexNet can achieve excellent accuracy on a very difficult and vast dataset. But CNN also gives the best performance on this remarkable dataset. And as we know, VGG 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. An exceptional conjugation of the convolutional network called the VGG is made for classification and location. These two model shows better performance than other DNN models, we used.

Models	Accuracy	Precision	F1-Score	Recall
CNN	**0.978**	**0.865**	**0.892**	0.924
AlexNet	0.975	0.833	0.874	0.932
LSTM	0.936	0.710	0.777	0.919
LeNet	0.971	0.848	0.871	0.899
VGG	0.976	0.858	0.891	**0.937**

Table 3: Resultant performance Matrices Of Each Model

From this Table 3 we can observe the performance of all DNN models which we have used in our work.

CNN $\geq VGG \geq AlexNet \geq LeNet \geq LSTM$.

The performance of all models according to the F1-score is shown by a bar chart in Fig 5, where the F1-score for CNN, AlexNet, LSTM, LeNet, VGG is 89.2%, 87.4%, 77.7%, 87.1%, and 89.1% respectively.

The Loss and Accuracy Evolution of each model is shown in Fig 4. We got the most satisfactory result from CNN and VGG deep neural network models. In this figure, the blue color indicates training loss, the orange color indicates the test/validation loss, the green color indicates training accuracy and the 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 carried out on the validation set is form an impression of using the statistic known as validation loss. From this figure, we can see that the loss and accuracy are 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 the optimum point where validation losses are almost equal at the last 3 epochs, which means the model is either perfectly fit or in a local minimum. On the other hand, In VGG, the distance between loss and accuracy is less than in CNN.

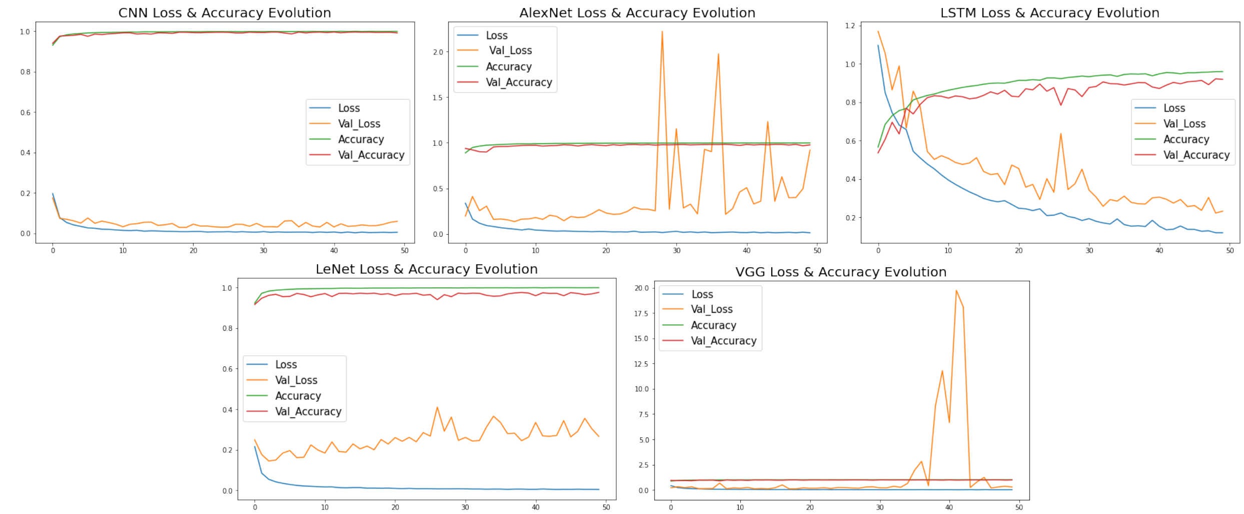

Fig. 4. Loss Accuracy Evolution Graph Of Each Model. Here top three shows the loss and evaluation graph of CNN, AlexNet, LSTM and bottom two shows the graph of LeNet and VGG.

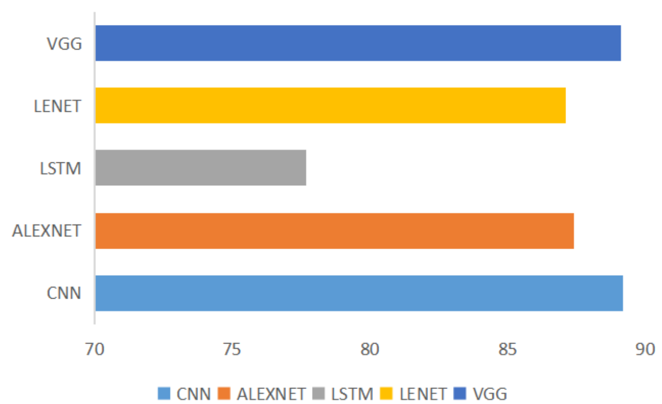

Fig. 5. Performance of different DNN models where we can see the level of F1-Score for all implemented models.

The validation loss is changing 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 the 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 doesn't get enough data like more than 1,000,000 elements then it shows poor performance than other deep neural network models.

Used Model	Accuracy of followed paper	Accuracy of our work
CNN [4]	98%	97.9%
LSTM [6]	92.16%	93.6%
ALEXNET [10]	92%	97.5%

Table 4: Comparison between followed paper and our work

We can perceive from this Table 4 that the following paper approaches 98% accuracy using CNN and we got 97.8% accuracy using it [4], which is almost the same. Again, the paper which we followed, approaches 92.16% accuracy using LSTM while we got 93.6% accuracy using the LSTM model which is higher than the followed paper which is a state-of-the-art paper. In [6] this paper, they used MIT-BIH dataset and classify into four classes using LSTM which is similar to RNN architecture. On the other hand, we obtained 97.5% accuracy, which is higher than the 92% accuracy obtained by the following paper using Alexnet on the same dataset, because four major steps were used to address the concerns of ECG pattern identification and categorization, refer to this study [10]. These include signal pre-processing, QRS detection (which offers additional details about the heart rate, the speed of conduction, the health of the heart's tissues, as well as various other abnormalities), the extraction of ECG factors using transferred deep learning, and ECG signal classification. This study's main objective was to apply a straightforward, trustworthy, and simply applicable deep learning approach to the categorization of three distinct cardiac diseases using ECG waveforms attained from this database. In our work, we also employed LeNet and VGG, with LeNet achieving an accuracy of 97.1% and VGG's deep learning model pursuing a precision of 97.6%.
Here Fig 6 displays the confusion matrices of CNN, VGG and Alexnet for five different classes.

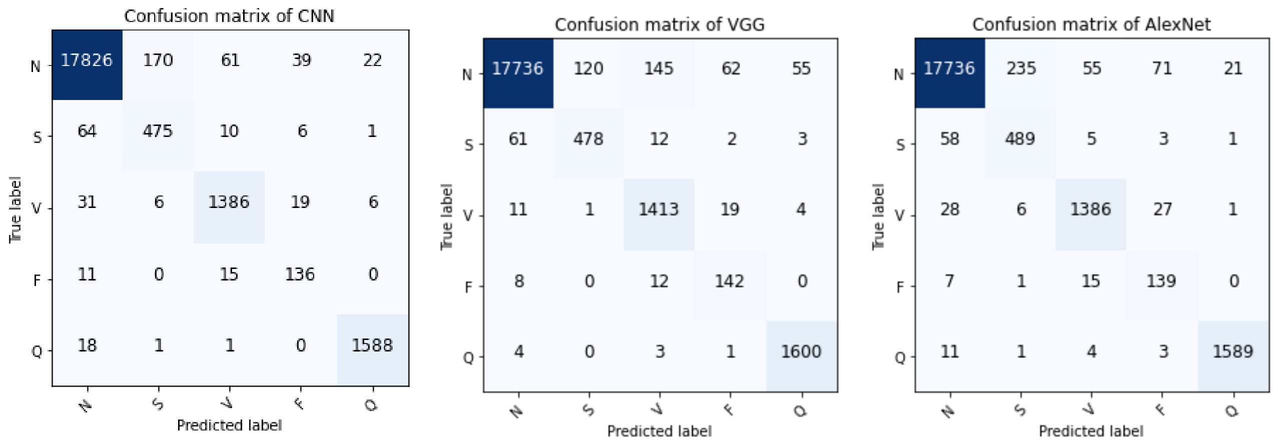

Fig. 6. Confusion matrices of CNN, VGG and AlexNet for five individual classes

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 galenical resources are hard to come by, making it difficult and time-consuming to perceptibly detect the ECG signal. The used VGG and CNN exhibit exceptional performance with a 98 percent overall classification accuracy. In this study, we accomplished convolutional neural networks (CNN), AlexNet, LSTM, LeNet, and VGG to appropriately categorize heartbeats based on ECG data using five distinct 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 escalation 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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