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Electrocardiogram Signals Prediction Using Deep Convolutional Neural Networks

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Abstract: **The analysis of cardiovascular diseases which includes atrial fibrillation (AF) is a technique that frequently calls for visual inspection of Electrocardiogram (ECG) alerts through specialists.**

In this article, we classify brief segments of ECG into four classes (AF, regular, different rhythms or noise) as part of the Physionet Computing in Cardiology Challenge 2017. We evaluate ECG signals using scalogram as images characteristic primarily based classifier with convolutional neural network (CNN) techniques (GoogLeNet and AlexNet CNN deep learning). Both technique had been trained the usage of the data Challenge 2017 used is 8,528 in the public learning set and hidden data set.

Experiment on four classes ECG records classification reports 96.99% and 97.08% Accuracy scores as results of GoogLeNet and AlexNet CNN deep learning respectively.

Keywords: **Electrocardiogram (ECG), classification, Deep learning techniques.**

I. INTRODUCTION

The Electrocardiogram (ECG) sign is a "photograph document of importance of the electric activity this is generated by using the depolarization and repolarization of the atria and ventricles". So, ECG facilitates to detect coronary heart rhythm or cardiac abnormalities. The majority of the medically beneficial information in the ECG is originated from the durations and amplitudes defined via its abilities (function wave peaks and term) [1]. Each whole cardiac cycle is represented through an ECG sign that consists of P-QRS-T waves. Fig.1 shows a regular ECG sign highlighting its essential capabilities in terms of its range of waves and time period. Early and correct detection of ECG arrhythmia enables docs to diagnose distinct heart diseases. However, it is hard for medical doctors to investigate large quantities of ECG statistics in a quick period of time, because of the restrained capability of human eyes as well as the complicated variations of ECG signals themselves. Hence, automated ECG analysis and diagnoses have attracted developing interest in current years. The maximum tough hassle confronted by way of automatic ECG analysis is the big variant in the morphological of ECG waveform, not simplest of different sufferers however also a few of the identical patients.

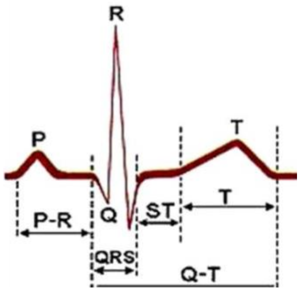

Fig.1: ECG Wave Morphology

The maximum hard problem confronted by automated ECG analysis is the massive variation within the morphological of ECG waveform, no longer most effective of different patients but also a few of the same patients [2]. The maximum critical venture concerned within the present ECG class structures is finding out the most appropriate classifier which is able to classifying arrhythmia on real time due to the fact class accuracy relies upon on many parameters which include type of arrhythmia, variety in arrhythmia, decided on arrhythmia database and selected function extraction strategies [3]. Atrial traumatic inflammation is the most commonplace sustained cardiac arrhythmia, happening in 1-2% of the general populace [4] and is related to good sized mortality and morbidity via association of danger of death, stroke, coronary heart failure and coronary artery sickness, etc. [5]. Despite the enormity of this problem, Atrial Fibrillation (AF) detection stays elaborate, because it could be episodic. AF detectors may be concept of belonging to one of two classes: atrial pastime analysis-primarily based or ventricular reaction evaluation-primarily based methods.The PhysioNet/CinC Challenge 2017 goals to categorize ECG alerts into four instructions of arrhythmias and increase an automatic algorithm to evaluate AF [6]. The aim of this research is to enhance the confidence in the results of the classifiers by conducting a comparison between two classifiers in diagnoses of four types of arrhythmia.

II. LITERATURE REVIEW

During the past few years, various techniques for ECG classification are proposed in literature Jonathan Rubin et al [7], purpose signal exquisite index on the side of dense convolutional neural networks (CNN) were used. Two fashions fundamental model that accepts 15 seconds ECG and secondary version that methods nine seconds shorter ECG) have been trained the usage of the schooling records set. If the recording is determined to be of low outstanding with the useful resource of information, it's miles right now categorized as noisy. Otherwise, its miles transformed to a time-frequency illustration and categorized with the CNN as Normal, AF, O, or noise. At the very last step, a function-primarily based post-processing set of rules classifies the rhythm as either NSR or O in case the CNN version's discrimination between the two is indeterminate. The exceptional end result carried out at the reliable phase of the PhysioNet project at the blind check set turned into 80%.

Shadi Ghiasi et al [8], uses the segments with 600 samples as the input of a 1 dimensional convolutional neural network. The output received from each technique combined using a selection desk and ultimately the recordings are labeled into three lessons. The proposed technique is evaluated the use of scoring characteristic from 2017 PhysioNet Challenge and performed score of 80% and 71% on the training and hidden dataset, respectively. Philip Warrick et al [9], advise a unique deep neural community that combines CNN and Long Short-Term Memory Networks (LSTM) to efficaciously examine collection data containing long run styles of unknown length extracted from ECG indicators. The model does not require explicit pre-processing, however can deceptively discover hidden structures of various ECG entities and automatically analyze their dependencies. The CNN is built on pinnacle of the signal vectors from a huge corpus of ECG data to research better-stage representations of PQRST areas. In our method, the venture is formulated as a temporal series predicting hassle that can be solved underneath a chain to series studying framework and performed score of 80% on the hidden data set. Fernando Andreotti et al [10], evaluate the art feature-based classifier with a convolutional neural network method. Both methods had been skilled the usage of the challenge information, supplemented with a further database derived from Physionet. The characteristic-based totally classifier obtained an F1 rating of 72% on the training set (five-fold validation), and 79% on the hidden dataset. The convolutional neural scored 72.1% and 83% on the hidden dataset.

III. MATEERIALS AND METHOD

A. Data Acquisition

In this study heartbeat electrocardiogram (ECG) information from the PhysioNet 2017 Challenge utilizing profound learning and flag handling. ECGs report the electric activity of a man's heart over some stretch of time. Doctors utilize ECGs to distinguish outwardly if a patient's pulse is typical or sporadic. Atrial fibrillation (AF) is a sort of unpredictable heartbeat that happens when the heart's upper chambers, the atria, beat out of coordination with the decrease chambers, the ventricles. The PhysioNet computing in cardiology assignment 2017 focused on differentiating AF from noise, ordinary or other rhythms using one lead (from nine to sixty one seconds) ECG recordings carried out by using patients. ECGs had been used is 8,528 in the public learning set and hidden data set.For learning, 80% of the dataset was randomly chosen and used, and for testing the remaining 20% of the data set was used. The 2017 PhysioNet Challenge aims to develop algorithms used to classify atrial fibrillation, from a single quick ECG lead recording, whether the recording shows normal sinus rhythm, AF, an opportunity rhythm, or is just too noisy to be labeled.

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B. Preprocessing using continuous wavelet transform (CWT) and convert signal to image

When a nearby height exceeds the brink, it's far stored as a QRS candidate and successive search in defined region is done for better peaks, which could replace the preceding QRS candidate. After a QRS complicated is asserted, a refractory duration of 0.2s follows, at some point of which no in addition excitation should reason heart muscle's contraction, and peaks are not registered. The average RR interval of the ultimate ten QRS complexes detected is maintained and if no peak is found within this interval, the threshold is reduced noise appeared. Thus the QRS detector adapts to the changing signal amplitude and peaks of QRS complexes.

A continuous time functions using a function, that's the main wavelet. The sign is then represented with the aid of a sequence of wavelet features which can be scaled and translated capabilities derived from the mother wavelet. CWT does provide whenever and frequency records. The widespread form of the scaling characteristic (∅) is:

$$\emptyset(x) = \sum_{k}^{N} g_k \emptyset\left(\frac{x-k}{2}\right) \quad \dots \dots . . (1)$$

Where g_k is constant.

The wavelet coefficients (WT) can be received by using the use of this formula:

$$WT_{\varphi}(f)(a,b) = \int f(t)\varphi_{a,b}(t)dt \quad \dots \dots . . (2)$$

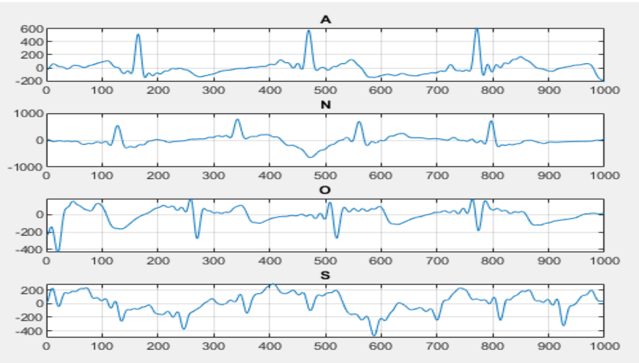
Where

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{a}}\varphi(at-b) \quad \dots \dots . . (3)$$

Where (a) is scale and (b) is shift. These representations are called scalograms.

Computing the CWT filter bank is the preferred method when obtaining the CWT of many signals using the same parameters. RGB pictures of the scalograms are created. The pictures are utilized to calibrate both profound CNN show that in Fig.2.

a)



b)

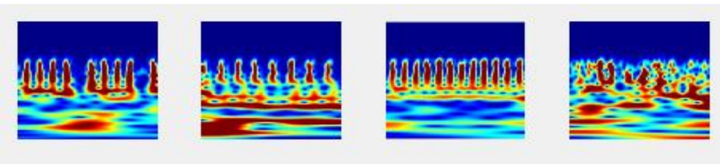


Fig.2 :a) ECG signals (four classes) are utilized to make scalograms.b) RGB pictures of the scalograms are created.

Fig.2 show the ECG signals in time domain in section(a),and in section (b) show ECG scalogram after convert signal to frequency domaim using CWT.

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A. Deep Convolutional Neural Networks

Deep learning is a type of machine learning in which a type learns used to classifications techniques. Deep learning knowledge usually applied using the neural network shape. The term "deep" refers to the sort of layers within the network the extra layers, the deeper network.

Traditional neural networks encompass handiest two or three layers, even as deep networks may have hundreds. A deep neural network combines a couple of nonlinear processing layers used in simple factors running in parallel and inspired via the use of organic involved structures. It consists of an enter layer, several hidden layers, and an output layer.

The layers are interconnected via nodes, or neurons, with every hidden layer using the output of the preceding layer because it's enter show that during Fig.3.

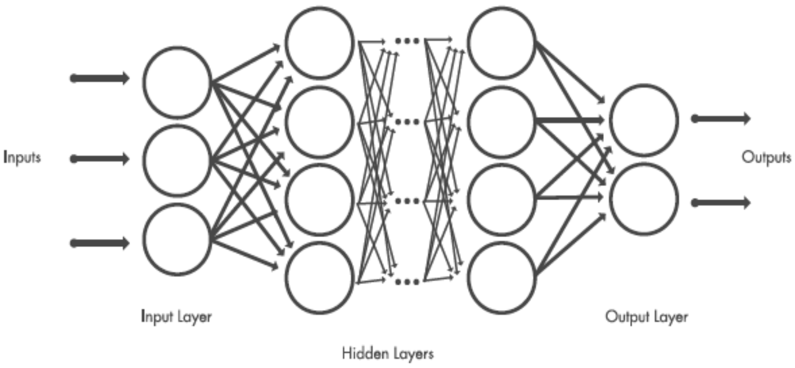

Fig.3: Inside a Deep Neural Network Architecture.

A convolutional neural network is one of the maximum famous algorithms for deep analyzing with image and video. Like different neural networks, a CNN consists of an enter layer, an output layer, and large number of layers as hidden layers in between. These layers perform one of three forms of operations at the records: convolution, pooling, or rectified linear unit (ReLU).

Convolution puts the input photos in set of convolutional filters to create activates certain features from the photos.

Pooling simplifies the output via performing nonlinear down sampling, reducing the amount of parameters that the network desires to look at.

Rectified linear unit (ReLU) permits for faster and extra effective training by way of mapping poor values to zero and maintaining excessive values to one.

These three operations are repeated over tens or hundreds of layers, with every layer learning to detect more features. Show that in Fig.4.

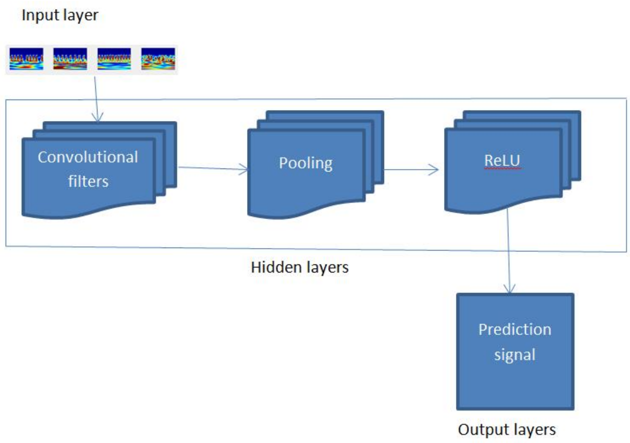

Fig.4: ECG signals predicted using deep convolutional Neural Networks to enhance the classification.

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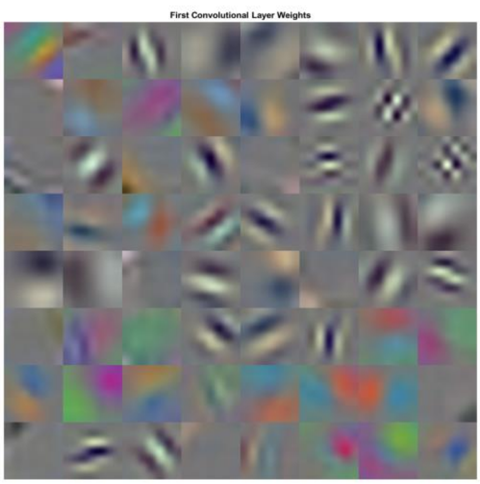
In this study, we are utilizing existing neural network that have been trained on large data sets. CNN initially intended to characterize ECG signals dependent on pictures from the CWT. Each layer in the system engineering can be viewed as a channel. The prior layers recognize more typical highlights of pictures, for example, peaks, edges, and colors. The output layers center on more explicit features in request to separate classifications. To training GoogLeNet to our ECG scalograms (RGB image size is 224-by-224-by-3) used four layers of the neural network. Used 80% of the images for training randomly chosen and for testing the remaining 20% of the images was used. The first of the four layers is a dropout layer ('pool5-drop 7x7 s1'). A dropout layer sets input components to zero with a given probability value. The dropout layer is used to help avoid over fitting. The default probability is 0.5. The three remaining layers, 'loss3-classifier', 'prob', and 'output', contain data on the most proficient method to combine the features that the system separates into class probabilities and labels. Labels are categories of classes for final result for classifications. By default, the last three layers are arranged for 1000 classes. The softmax layer and a grouping output layer set the last completely associated layer to have the same size from the number of classes. To learn quicker in the new layers than in the exchanged layers, increment the learning rate elements of the completely associated layer. The RGB pictures have measurements proper for the GoogLeNet design. Utilize those measurements to make the expanded RGB pictures for the AlexNet architecture (227-by-227-by-3). Even although the photograph dimensions are same for GoogLeNet, you do now not to have generated new RGB pictures at the AlexNet dimensions. You can use the original RGB photos. At that point train AlexNet. The preparation procedure generally takes 1-5 minutes on a work area CPU. This model demonstrates to utilize deep learning and continuous wavelet transform to characterize four classes of ECG motions by utilizing the learning CNN GoogLeNet and AlexNet. Wavelet based time-frequency coefficients of ECG signals are utilized to make scalograms. RGB pictures of the scalograms are created. The pictures are utilized to calibrate both deep CNN. Enactments of various neural network layers were additionally investigated.

IV. RESULTS AND DISCUSSION

The scalograms have dimensions appropriate for the GoogLeNet architecture. Use those dimensions to create RGB image datastores that will automatically resize the existing RGB images for the GoogLeNetand the AlexNet architecture also. Each layer of a CNN produces an activation to input pictures. Notwithstanding, there are just only of layers inside a CNN that are suitable for picture features extraction. The layers toward the start of arrange to catch essential picture features, for example, edges and blobs. To see this, visualize the system channel weights from the first convolutional layer. There are 64 individual arrangements of weights in the main layer .Analyze which zones in the convolutional layers enact on a picture from the —N— class show first convolutional layer weights ('conv1-7x7 s1') in Fig.5 section (a).Contrast and the relating zones in the one picture. Each layer of a convolutional neural network comprises of more than one 2-D arrays called channels. Pass the picture through the CNN and analyze the output activations from the first convolutional layer to the second convolutional layer ('conv1-7x7 s2') show that in Fig.5 section (b). To examine the strongest channel for this picture (Normal class) compare the strongest channel with the original RGB image show that in Fig.5 section (c).

a)



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b)

c)

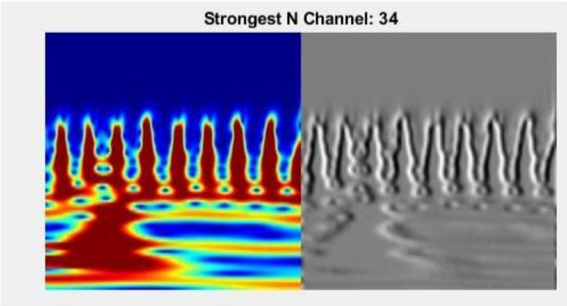

Fig.5: ECG wave features extraction using CNN deep learning.

Results comprised of iteration per epoch number, maximum iterations number, time elapsed, and validation accuracy and number of epochs. Show results in details in Table.1.

Table1: Results of GoogLeNet and AlexNet CNN deep learning.

CNN Techniques	GoogleNet	AlexNet
Validation Accuracy	96.99%	97.08%
Elapsed Time	1993 min & 53 sec	65 min & 28 sec
Maximum Iterations	6020	4520
Iteration per epoch	301	452
No. of epochs	20	10
No. of Iteration for validation frequency	10	50

The accuracy is equal to the validation accuracy suggested at the training visualization figure shows Fig.6 and Fig.7 for training and validation progress in iterations and relationship between the validation accuracy and the loss characteristic. The scalograms have been divided into training and validation data. Both collections of data have been used to teach GoogLeNet and AlexNet. The best way to assess the end result of the training is to have the network classify records it has not seen. Since there is an insufficient dataset to divide into training, validation, and testing, we treat the computed validation accuracy as the network accuracy.

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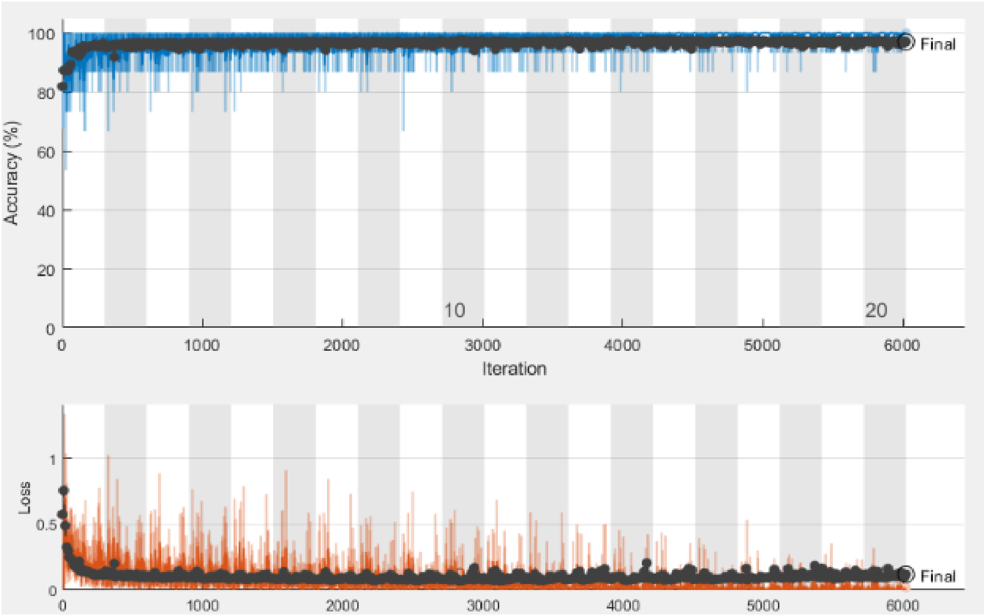

Fig.6: GoogLeNet CNN deep learning.

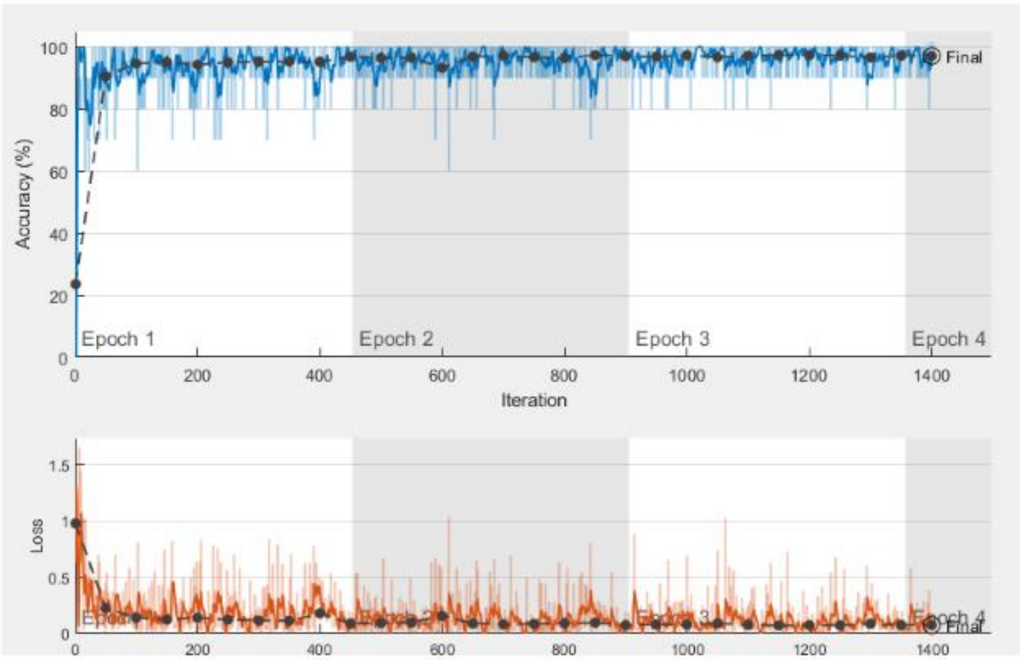

Fig.7: AlexNet CNN deep learning.

Training a neural network is an iterative manner that includes minimizing a loss characteristic. To limit the loss characteristic, a gradient descent set of rules is used. In each generation, the gradient of the loss function is evaluated and the descent algorithm weights are updated.

In training stage must be setting initial learn rate to initial step size in the direction of the negative gradient of the loss function. Number of iteration for validation frequency used to specify how large of a subset of the training set to apply in each iteration. The epoch means full pass of the entire training set for the training algorithm. Maximum iterations specify the maximum number of epochs to apply for training. Decreasing the wide variety of epochs has the impact of under fitting the model, and increasing the range of epoch consequences in over fitting. The preparation procedure generally takes from one to five minutes on iteration.

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V. CONCLUSION

This research objective to differentiate exceptional forms of arrhythmias shape normal and noisy alerts. In our study used continuous wavelet analysis to classify four classes of ECG signals by training CNNs GoogLeNet and AlexNet. Wavelet-based time-frequency of ECG signals is used to generate scalograms. RGB images of the scalograms are created. The images are used to training and validation both deep CNNs. Activations of different network layers were also created. Each the characteristic primarily based technique and deep learning technique to recognize each class. We used a CNN primarily based solution to the 2017 PhysioNet Challenge data set. We optimized weights of the convolutional layer to extract the features to maximize the classifier overall performance. The validation accuracy is 96.99% and 97.08% as results of GoogLeNet and AlexNet CNN deep learning respectively.

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