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Automatic Identification of Arrhythmia from ECG Using AlexNet Convolutional Neural Network

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***Abstract*—Atrial fibrillation (AF) is one of the most widespread cardiovascular diseases and impacts the overall general population of the world. Most of the current techniques are based on hand-crafted features for automatic AF classification. The primary task of this work is to design a deep learning-based approach that will eliminate the necessity of manual identification of features. We have used a pre-trained convolutional neural network (CNN), namely AlexNet, to train using 5,655 single-lead ECG recordings. Initially, we have extracted a spectrogram for all 30s signals and converted them to RGB images with Continuous Wavelet Transform (CWT); later fed to transferred AlexNet and trained with some changes in specifications. The findings of the study indicate that our technique attains a state-of-the-art accuracy of 97.9% and an F1 score of 98.82% while having higher overall sensitivity (98.9%) and specificity (90.7%) and outperformed all existing methods.**

Keywords— atrial fibrillation, AlexNet, convolutional neural network, electrocardiogram

I. Introduction

One of the world's leading causes of mortality is cardiovascular disease. Cardiac arrhythmia is a significant cardiovascular disease. The most familiar type of cardiac arrhythmia is AF. It impacts millions of individuals worldwide and is also linked with significant morbidity and mortality [1]. Atrial fibrillation (AF) is a type of uneven cardiac rhythms or cardiac arrhythmia. AF currently causes 1 in 5 strokes in individuals over the age of 60 and is seen among ~2% of the general population [1]. Arrithmia takes place in the upper chambers of the human heart i.e., the atria. It occurs due to the non-systemic triggering of the heart by the natural pacemaker or the sinoatrial (SA) node that results in irregular or rapid cardiac rhythms in the resting state. If treatment is not provided timely, it may take the form of critical medical conditions like heart attack, stroke, sudden cardiac arrest, etc. later on. Therefore, early detection is of key importance for the prevention of medical complications.

The electrocardiogram (ECG) offers an efficient, non-invasive technique to clinical diagnosis in patients with cardiovascular diseases. It is a common and popular diagnosis of AF as it detects the electrical activity of the heart. The asymptomatic and short episodic nature of AF ECG signal and the subjective viewpoint of the physicians during manual diagnosis have motivated researchers to develop automatic methods for detecting arrhythmia [2]. The multi-lead ECG acquisition system is quite cumbersome to properly follow the standard signal acquisition protocol as compared to the single lead system. Prevalent analysis techniques of AF are broadly categorized into two approaches, viz. analysis based on atrial activity and analysis based on ventricular activity. In the first category, the presence of f-wave and the absence of P-wave is detected [3]. The second category focuses on the detection of unevenness in the RR interval of ECG [4]. There are limitations when using either of these approaches. As such for obtaining greater accuracy, recent studies have detected AF using a combination of these two [5], [6].

Researchers have implemented many algorithms like support vector machine (SVM) which is a non-linear classifier to classify AF [7], whereas other studies use random forest [8], and decision tree ensemble [9]. This kind of algorithm needs manual feature extraction. To overcome this problem, researchers use neural networks not only to solve the medical diagnostic problem but also other areas of research. This lets the practice of the algorithms "end-to-end" to predict real information immediately and boost training method efficiency and allow an easy way of adapting to a broader spectrum when big datasets are accessible. Some studies have been done using neural networks like convolutional recurrent neural network (CRNN) [10] and deep CNN [11].

The aim of this research is to design a deep learning-based approach that will automatically identify arrithmia eliminating the necessity of manual identification of features.

The following sections are arranged accordingly- Section II gives a description of the dataset, and theoretical background behind the applied method, section III analyzes the obtained results and section IV winds up the paper by drawing reasoning to the results and the probable future works related to this study.

II. Methodology

A. Materials

We conducted this research using the 2017 PhysioNet/CinC Challenge data. This database contains a total of 8,528 single-lead ECG recordings time range 9s to 30s [6]. The signals were annotated with four classes: atrial fibrillation (AF), normal rhythm (N), other rhythms (O) and noise (~). The recordings were filtered with a bandpass filter using the Alivecor device donated by Alivecor (California, United States) with a sampling rate of 300Hz. In this research, we used MATLAB 2018b for all the computational task.

The normal (N) and AF ECG recordings are used for classification where the including criterion was exact 30s in length shown in Fig. 1. Each sample contains 30s × 300Hz or 9000 data points. After the screening, 5,655 valid

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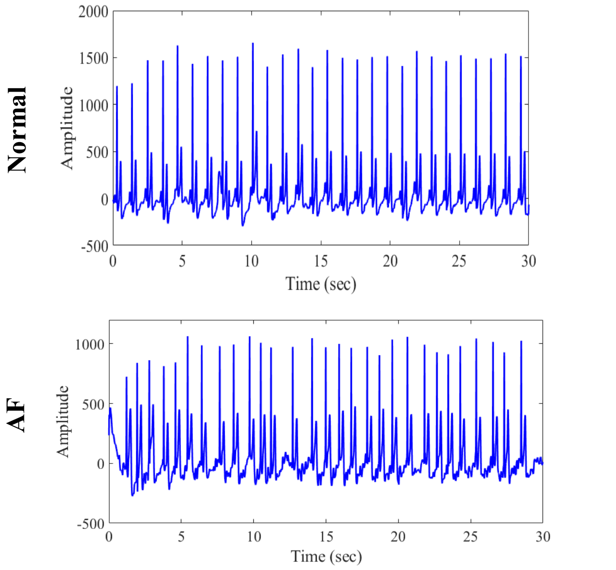

Fig. 1. Sample ECG signal of the two classes: normal and atrial fibrillation.

sample data was left for the actual study. It was split into 70% for training and rest for testing purposes. In this study, we followed a specific procedure to perform the binary classification shown in Fig. 2.

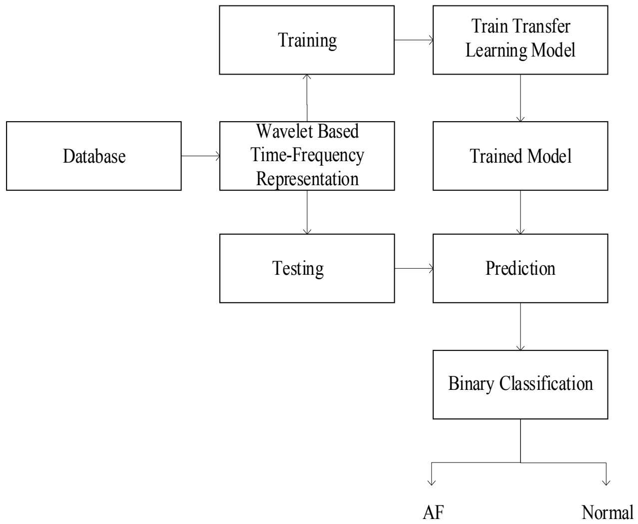

Fig. 2. The flowchart of the proposed algorithm.

B. Time-frequency Image

ECG is a non-stationary signal. Spatial or temporal representation alone does not represent data contained within ECG. Comparatively continuous wavelet transform (CWT) [12] is a good way of analyzing non-stationary signals like ECG. As CWT's window shrinks and dilates, it maps the signal differences into a time-frequency spectrogram. In this work, each 30s data is converted into a time-frequency spectrogram regarding that no data overlap with each other to avoid overfitting problems. There are some parameters within CWT including mother wavelet or sampling frequency which can influence the output of the spectrogram. Here we used Morlet (Gabor) wavelet in filterbank which is very similar to the ECG signal and produces a very sharp time-frequency image.

C. AlexNet

In 2012, Krizhevsky [13], creator of the AlexNet won the ILSVRC(2012) with a significant margin. ILSVRC is an annual competition for algorithms of large scale object detection and image classification. In contrast to other respondents using standard characteristics and classifier training techniques, Krizhevsky used neural networks, particularly convolution neural networks. The model comprises of 3 fully connected layers and 5 convolutional layers. The first layer of AlexNet is used for input of a filtered image with a dimension of $227 \times 227 \times 3$ respectively for width, height, and depth(red, green, blue). The last fully-connected layer connects 1000 connected layers and the rest of the layers work as a feature extractor. For each input image, AlexNet can produce a 4096-dimensional feature vector that includes the hidden layer activations instantly before the output layer. AlexNet itself is a huge structure containing 650,000 neurons and 60 million parameters. The model was trained on approximately 1.2 million training pictures and performed testing on 150,000 ImageNet data sets test pictures. This model is very efficient for reducing the overfitting problem with the help of maintaining dropout and data augmentation. AlexNet is selected for this study as it is the most widely researched CNN and is a proper trade-off between speed and accuracy. Fig. 3 illustrates the architecture of AlexNet.

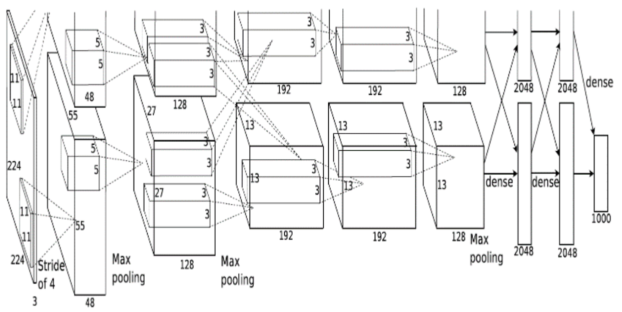

Fig. 3. The architecture of AlexNet [13]

D. Transfer Learning

AlexNet showed its excellent efficiency to classify, but it took time to train. Fig. 4 illustrates the basic diagram of a transfer learning for AlexNet.

Without creating a CNN model from scratch, transfer learning is the process of passing the learned understanding to a new deep learning model. In this work, we replaced the 23rd and the 25th layers of AlexNet: fully connected layer (for binary classification) and classification output. Hence, the rest of the layers are kept exactly the same as initialization. The structure was subsequently split into two components: the pre-trained network and the transferred network. The parameters in the pre-trained network have already been trained on ImageNet with millions of images and the extracted characteristics have been successfully classified. These parameters can only require a marginal adaptation according to the new input images. These parameters make a very tiny effect on the whole of CNN training and very suitable for training a whole new class of dataset. In transferred AlexNet we used stochastic gradient descent with momentum (SGDM) for the training options. The mini-batch size is 64 and the max epoch is 90 with the learning rate being 1e-4.

Fig. 4. The transfer learning process of AlexNet.

E. Evaluation Metrics

We have used accuracy, sensitivity, specificity and F1 score as the standard metrics to evaluate the result of transferred AlexNet. We have also used the confusion and loss matrix for demonstrating the strong outcome of our suggested architecture. Accuracy is a statistical measurement that is defined as the ratio of correctly classified data samples to all data samples. Similarly, sensitivity and specificity are statistical measurements that correctly predict the portion of all positive data samples and the portion of all negative data samples respectively.

$$F1\ score = 2 \times \frac{Precision \times Sensitivity}{Precision + Sensitivity}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$Precision = \frac{TP}{TP + FP}$$

$\mathrm{TP} = \mathrm{True\ Positive}, \mathrm{TN} = \mathrm{True\ Negative}$

$\mathrm{FP} = \mathrm{False\ Positive}, \mathrm{FN} = \mathrm{False\ Negative}$

III. Result and Discussion

Fig. 5 demonstrates the continuous wavelet transform (CWT) scalogram output for the sample in Fig. 1. Scalogram works as a function of time and frequency using the absolute value of CWT. The cone of influence shows where border impacts are important. Gray areas outside the dotted white line distinguish regions with important edge effects. In CWT, the Morlet wavelet is used as a mother wavelet. We used filterbank to make this process easier to create thousands of signals and convert them into CWT scalograms. Then, we depicted the scalograms such that the time is along the x-axis and the frequency (between 0-100 Hz) in a logarithmic scale along the y-axis.

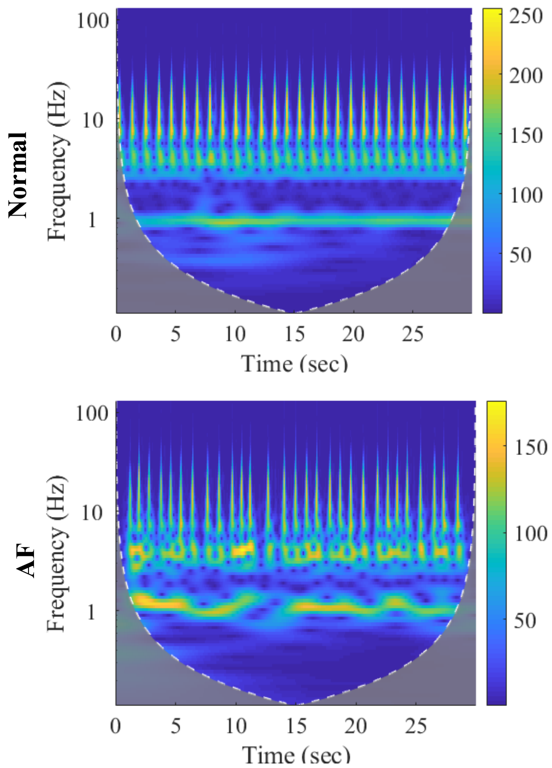

Fig. 5. CWT scalogram of normal and AF rhythm.

After that, we converted the scalograms into RGB images using Jet colormap with 128 colors depicted in Fig 6. For this particular task, we converted the index image into RGB by rescaling the output from CWT filterbank. Initially, the output was a double-precision complex-valued vector and later on was used as an absolute valued vector. In RGB, x and y axes are the same as before. The magnitude is normalized into a range 0 to 1 for using the Jet colormap.

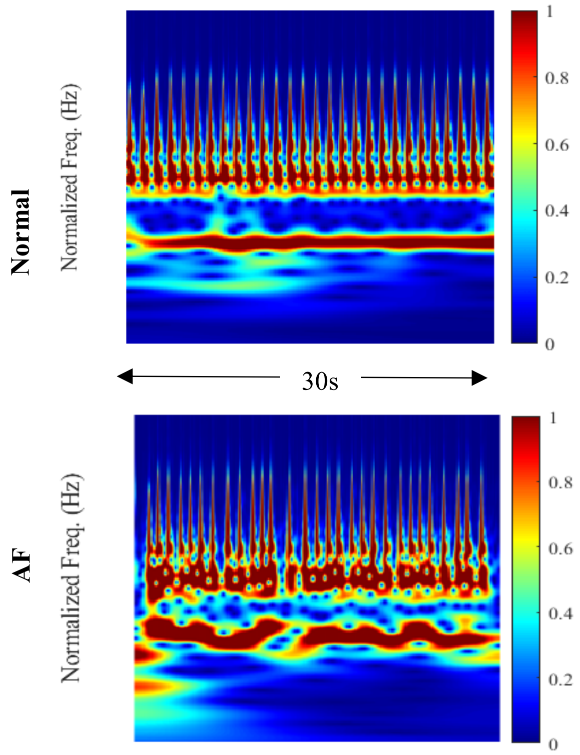

Fig. 6. Resized RGB image using the Jet colormap.

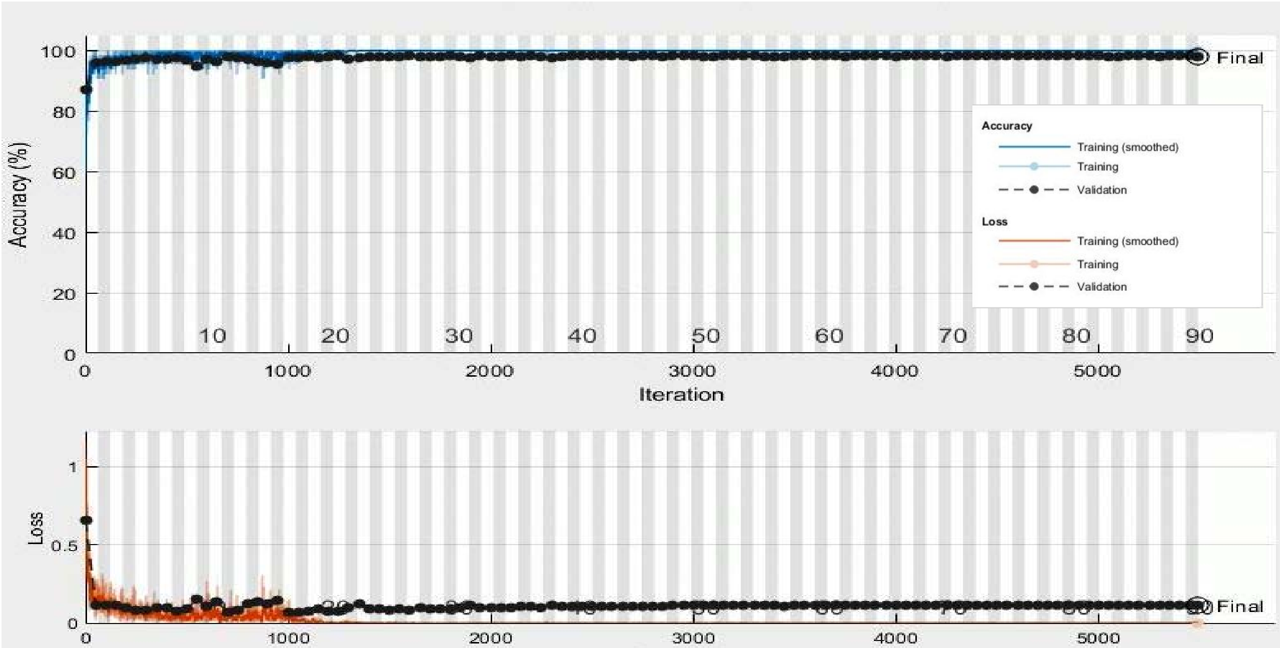

Fig. 7. Training progress with Transferred ALexNet.

From Fig. 6 one can easily interpret the time-frequency localization of normal and AF rhythmic ECG. In AF, the pulses lose the regular rhythm and there is certain distortion in high magnitude in low frequency.

The performance evaluation of this study includes accuracy, sensitivity, specificity and F1 score as the standard metrics. Overall accuracy was 97.9% where 92.9% was for AF and 98.7% for normal rhythm. The values of other metrics are 98.8%, 98.9%, 90.70% and 98.6% for F1 score, sensitivity, specificity, and precision respectively. The Two-Class Confusion Matrix corresponding to the accuracy is shown in Fig. 8.

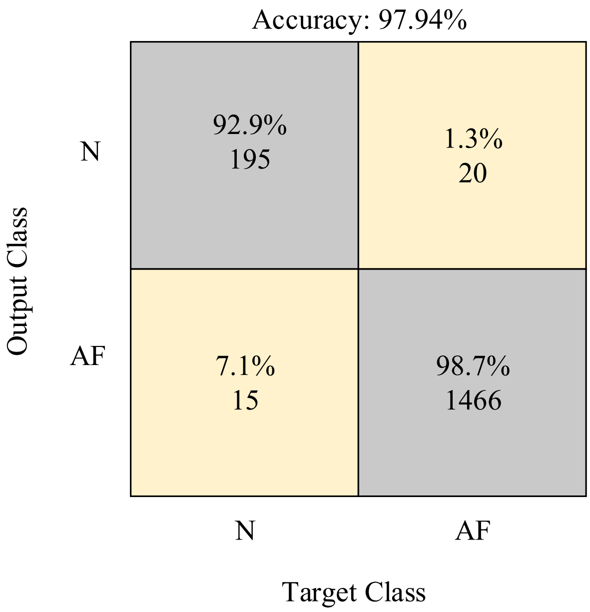

Fig. 8. The confusion matrix of the analysis.

Comparing the overall accuracy of other works with our research on AF detection, it is suitable to outline that this method outperformed all the other methods.

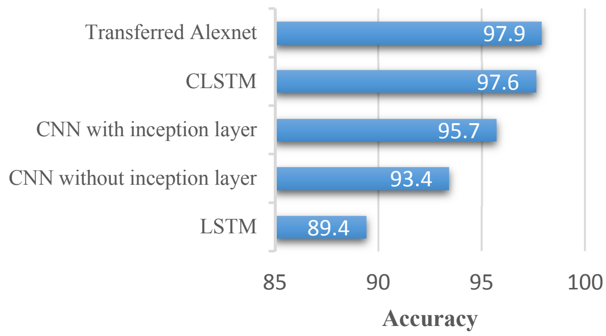

Fig. 9. Comparison with other algorithms [14].

IV. CONCLUSION

In this research, we have developed a method for automatic detection of AF. CNN provided a significant advantage in providing the concept of using 2D images and getting rid of the process of extracting features and selecting them manually. Also, the progress in the domain of deep image classification came as an added assistance. CWT is used to extract the time-frequency scalogram of each ECG recording. The scalograms are converted into RGB images with required dimensions to train the image in AlexNet. The images are very easy to interpret according to the actual reading of AF. Images are fed into CNN (transferred AlexNet) and then, trained. And after that, a CNN model is designed for our desired purpose which has given a fruitful outcome while evaluating the test dataset. Further work may comprise hyper tuning AlexNet or different pre-trained network to obtain a better result. Other datasets can also be used to test the competency of this algorithm.

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