Automatic Classification of Cardiac Arrhythmias based on ECG Signals Using Transferred Deep Learning Convolution Neural Network

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Abstract. In the current article, an automatic classification of cardiac arrhythmias is presented using a transfer deep learning approach with the help of electrocardiography (ECG) signal analysis. Now a days, an ECG waveform serves as a powerful tool used for the analysis of cardiac arrhythmias (irregularities). The goal of the present work is to implement an algorithm based on deep learning for classification of different cardiac arrhythmias. Initially, the one dimensional (1-D) ECG signals are transformed to two dimensional (2-D) scalogram images with the help of Continuous Wavelet(CWT) . Four different categories of ECG waveform were selected from four PhysioNet MIT-BIH databases, namely arrhythmia database, Normal Sinus Rhythm database, Malignant Ventricular Ectopy database and BIDMC Congestive heart failure database to examine the proposed technique. The major interest of the present study is to develop a transferred deep learning algorithm for automatic categorization of the mentioned four different heart diseases. Final results proved that the 2-D scalogram images trained with a deep convolutional neural network CNN with transfer learning technique (AlexNet) pepped up with a prominent accuracy of 95.67%. Hence, it is worthwhile to say the above stated algorithm demonstrates as an effective automated heart disease detection tool

Index Terms—ECG classification, transfer learning, AlexNet, deep learning algorithms

1. Introduction
Cardiovascular disorders (CVDs) are the major cause of death in today’s scenario, heart diseases acts as major portion of death in humans, with over 17 million people dying each year [1], which accounts more than 30% of overall deaths, with three-fourth of the mentioned deaths occurring in undeveloped and under developing nations. A classification model that can detect CVDs early on may help to reduce mortality rates by offering timely care. The electrocardiogram (ECG) is an effective tool for assessing a patient's cardiac condition. ECG stands for electrocardiogram, which is an electrical representation of the heart's contractile movement that can be conveniently captured using electrodes placed on the patient's limbs or chest. The ECG signal is considered as prominent signal in the clinical medical field. The rate of heart beat per minute (bpm) can be found with the help of R peaks present in an ECG signal over one minute of recording (see Figure 1).
In the diagnosis of cardiac arrhythmias, ECG signal gives significant data about the functioning of heart. Arrhythmia of the heart is a common symptom of cardiovascular disease. In today's medical practice, specialist cardiologists must carefully examine the ECG signal to diagnose the heart affecting diseases. Categorization of various heart diseases automatically, on the other hand, may provide objective diagnostic results while also saving cardiologists time. These benefits have sparked a lot of interest in the pc based classification applications and provides a great deal in conclusion of ECG signals in hospitals. The analysis of ECG signal is one of the application in pattern recognition techniques. The aim behind pattern recognition is to automatically classify a structure into one of several categories.

An expert cardiologist can rapidly character numerous heart arrhythmias by essentially taking a glance at the ECG waveforms. Though in certain situations, advanced ECG analyzers can provide a greater level of precision than cardiologist, still a community of ECG signals that computers have trouble identifying.

Analysis of ECG waveforms with computer aided tools, will significantly reduce the cardiologist's workload by automatic. A few analyzers can help the cardiologist by creating a prepared to-utilize determination, while others can make their own finding dependent on the restricted scope of boundaries. Cardiac arrhythmia, in which heartbeats deviate from their normal pattern, is one of the most common causes of CVDs. The rate of a regular heartbeat varies depending on age, body size, activity, and emotions. Palpitations are a symptom that occurs when the pulse feels too quick or slow. An arrhythmia is a condition where the heart beats at sporadic stretches, doesn't imply that the heart is working excessively fast or too leisurely. It could show tachycardia (in excess of 100 beats each moment (bpm)) or bradycardia (under 60 bpm), heart failure or, in significant circumstances, overlooking anything. Arrhythmia may refer to either a slow or rapid heartbeat, as well as patterns that aren't associated with a regular heartbeat. In clinical practise, an automatic identification of such trends is critical. Certain identified symptoms of cardiac arrhythmia necessitate expert clinical expertise for diagnosis. ECG recordings are frequently used to analyze and anticipate cardiovascular arrhythmias to analyze heart sicknesses.

2. Related Work

The ECG signal which provides information about the activity of a heart in a time series representation can be analyzed with the help of machine learning techniques to detect anomalies automatically. Deep learning techniques have recently been developed, and they have shown to be effective in radiological image analysis [2]. Convolutional neural networks (CNNs) have been verified to work for multidimensional (1-D, 2-D, and sometimes, 3-D) inputs, yet they were initially intended to tackle issues with two-dimensional pictures [3]. 1-D CNNs are proposed for time series data, but they are less
flexible than 2-D CNNs. Thus, addressing time series information in a two-dimensional format could be favorable for some machine learning algorithms [4]. Accordingly, a 2-D transformation should be applied to ECG signals to make them reasonable for profound learning strategies that utilize 2-D images as input. The 2-D spectrogram coefficients matrix may be useful for extracting robust features for cardiac ECG signal representation. This representation could enable CNN architectures (planned to work on 2-D inputs) to be used in the development of CVD-related automated systems.

Recognizing the clinical issue presented by an ECG signal precisely is a troublesome errand. As a result, before prescribing a treatment, cardiologists must correctly predict and classify the type of irregular heartbeat ECG wave. This could necessitate hours of observation and analysis of ECG recordings (patients in critical care). In hybrid feature classification techniques, arrhythmia detection is done by using morphological and time-varying features. With the help of various wavelet transforms, one can determine the morphological features by varying window sizes. The time feature, R-R interval works as a time-varying (dynamic) feature in various hybrid algorithms [5].

Various techniques which utilizes the machine learning (ML) algorithms has been developed for the effective recognition and precise investigation on ECG signals [6]. Classification of ECG waveforms can also be done in different ways using Artificial Neural Networks (ANNs) and pattern recognition methods. In ANN methods, a dynamic multilayer perceptron is utilized for the enhancement of QRS peak detection. This perceptron will works as a classifier and is responsible to distinguish normal sinus ECG signal from other abnormality ECG waveforms. For improving the performance of ECG classification, a mixture of Experts (MOE) technique is developed. In this technique, initially a small classifier is developed with the help of patient’s real time data. Later this smaller classifier is tuned to work on large datasets to obtain a MOE classifier structure. For accurate classification in short time, multistage neural networks are utilized which contains multiple perceptron combined with self organizing map (SOM) achieved an accuracy of 90.6 percent for six different heart diseases. Meanwhile, a neural network with combined fuzzy C-means clustering acts as a classifier to distinguish four different forms of arrhythmias, with an accuracy of 96.95 percent.

Machine learning which is a subset of artificial intelligence utilizes in conjunction with sophisticated software to predict and diagnose various illnesses.

3. Methodology

In the present work, four major steps were used for impulsive categorization of various cardiac arrhythmias (Fig. 3) which consists of signal pre-processing, converting 1-D ECG into 2-D scalogram image using CWT, ECG classification using transferred deep convolution network (Alexnet).

![Fig 2. Block of proposed transferred deep learning CNN based model](image)

(a) ECG Data Acquisition:

For the present investigation, the required ECG data is downloaded from Arrhythmia database of physionet (MIT-BIH) for ARR signals, Normal Sinus Rhythm (NSR), Malignant Ventricular Ectopy (VF) and CHF data from BIDMC. Nearly, 30 recordings of each kind (ARR, CHF, NSR, VF) were collected to have equal distribution. Each of these records is 12 hours long having sampling frequency.
of 360Hz. These recordings are pieced into tiny segments with length of 500 samples in order to satisfy the training requirements of CNN. So each recording is broken into 10 bits of length of 500 examples. Consequently, every classification will give 300 accounts of size 500 examples and absolute will be 1200 accounts.

![Time series representation of different cardiac arrhythmia signals](image)

Fig. 3: Time series representation of different cardiac arrhythmia signals

(b) **Signal Preprocessing:**
ECG data obtained from database contains very less noise (obtained directly from a patient), still there exists some common noises such as dc noise, high and low frequency noises due to muscles contraction and respiratory movements, electrodes placement and other noises from external devices. Hence, there is a need of signal pre-processing stage to remove noise from ECG recordings. Initially, with an aim to avoid the undesirable dc noise existed in input ECG signals, subtract the mean of the 500 samples from each sample of ECG recording. This operation shifts the signal baseline amplitude to zero level. In order to reduce noise with high frequency components, a filter is selected such that it allows signals at low frequencies and attenuates high frequencies present in the noisy ECG signals. To remove noise at low frequencies, a designed high pass filter, is selected such that high frequencies are allowed and low frequencies are attenuated. To remove power line interferences, a notch filter is selected to attenuate a certain range of frequencies along with their harmonics.

(c) **ECG signals to Image conversion using CWT:**
By using Continuous Wavelet Transform (CWT), each 1-D ecg signal is converted into images so that they can be fed as input to Alexnet for classification. For this reason, each 1D signal, CWT coefficients are orchestrated to shape a CWT Scalogram. Representation of each image is done in jet colormap which includes 128 colors. The obtained scalogram images are saved at different folders corresponding to each class. Each image is of size 227 X 227 (to be used for Alexnet) in RGB color format. After conversion we have total 900 scalogram images saved in three folders corresponding to each category ARR, CHF, NSR and SVF.

![Scalogram images of different cardiac arrhythmia signals](image)

Fig. 4: Scalogram images of different cardiac arrhythmia signals
(d) Transfer Learning via AlexNet:
For ECG signal classification, a pretrained deep CNN namely AlexNet is used. AlexNet is able to categorise 1000 objects because it is trained with some millions of images. The scheme and working of Alexnet is shown in figure 5.

Fig 5: Architecture of AlexNet

Tweaking a pretrained CNN to accomplish categorization on a set of new collected data is called “Transfer Learning”. Instead of training a neural network from scratch, in turn requires large number (millions) of images, transfer learning is quiet easy and reduces the complexity of the network.

(e) Evaluation Parameters:
To assess the exhibition of the proposed method, the following metrics were found which includes accuracy(A), precision(P), sensitivity(Sen), and specificity(Sp).

For the multi-class classification,

\[ A = \frac{1}{N} \sum_{c=1}^{N} \frac{(T_P^C + T_N^C)}{(T_P^C + T_N^C + F_P^C + F_N^C)} \]  

where \( T_P, T_N, F_P, F_N \) represents the true positives, the true negatives, false positives and the false negatives respectively, \( c \) denotes the class type, and \( N \) represents the total number of classes. For precision (P) and sensitivity (Sen) calculation,
The representation of the true negative rate, termed as specificity (Sp), was estimated using,

\[
Sp = \frac{1}{N} \sum_{C=1}^{N} \frac{T_{N}^C}{T_{N}^C + F_{P}^C}
\]

4. Results and Discussions:
ECG dataset containing 1200 signal fragments was used for performance evaluation of the transferred deep convolutional neural network (namely AlexNet) in order to classify various arrhythmias. Out of 1200 recordings, 80% of data is used for training purpose, the remaining 20% data were utilized for testing purpose.
Standard evaluation metrics namely accuracy (AC), sensitivity (SEN), specificity (SPE) and precision were evaluated to analyze the ability of the 8-layer Alexnet model.

Figure 6. Training and validation performances using proposed model with ECG datasets

Fig. 7: Confusion matrix for the proposed transferred deep learning CNN (AlexNet) based model

By using the proposed model, more number of arrhythmia classes can be classified other than the above stated CVD’s, however this work requires more time hence comparison has been made with other renowned published results which utilizes the 2-D representation of ECG data.
Table 2: Comparison of the proposed model with other ECG classification techniques.

| Model          | Classes | Accuracy % | Sensitivity % | Specificity % | Precision % |
|----------------|---------|------------|---------------|---------------|-------------|
| FFNN [6]       | 4       | 92.94      | 93.31         | 91.78         | -           |
| SVM [7]        | 6       | 91.67      | 93.83         | 90.49         | -           |
| 1-D CNN [8]    | 5       | 89.40      | 68.80         | 99.50         | 79.20       |
| Proposed (AlexNet) model | 4       | 95.31      | 94.21         | 93.26         | 93.12       |

Table 2 presents the performance evaluation of the proposed transferred deep convolutional neural network along with other classification methods. The proposed transferred Deep learning CNN technique using AlexNet attains 95.31% accuracy, 94.21% sensitivity, 93.26% specificity and 93.12% precision. From the results, it is clearly demonstrated that the proposed model has outperformed the other CNN algorithms in terms of evaluation metrics.

5. Conclusions

In the present study, transferred deep learning technique with CNN modeling was developed for automatic classification of cardiac arrhythmias with the help of ECG signals. The proposed transferred deep technique utilizing 2-D scalogram images, are able to identify four types of heart diseases, namely, ARR, CHF, NSR and SVF, with an achievement of average accuracy, precision of 93.26%, and 93.12% respectively. Also the proposed technique attains 95.31% sensitivity, 94.21% specificity. The previously mentioned results consequently demonstrates that cardiac arrhythmia classification with 2-D scalogram images with transferred deep learning technique is a usable apparatus in the finding of CVDs. Moreover, detection of arrhythmias using the proposed techniques can reduces the workload of cardiologists by using computer aided diagnosis of cardiac arrhythmias.

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