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Research Article

Design and Implementation of Deep Learning Model for Atrial Fibrillation Classification using ECG Signals

Ashok Kumar Sahoo
Department of Computer Science & Information Technology,
Graphic Era Hill University, Dehradun Uttarakhand India 248002

Abstract
Electrocardiograms (ECGs), which are an essential diagnostic tool, are required to be performed in the normal course of clinical practise in order to evaluate cardiac arrhythmias. Convolutional neural network framework is suggested for use in this method, which makes use of deep learning to carry out automatic ECG arrhythmia diagnosis by classifying patient ECGs into the proper cardiac states. The prior training for this network was done using a standard signal data set. The primary objective of this approach is to provide a basic, reliable, and easily implemented deep learning algorithm for the categorization of the two separate cardiac category scenarios that have been selected. The findings demonstrated that a conventional back propagation neural network used in cascade with transferred deep learning classification was able to accomplish exceptionally high levels of performance. The primary objective of this research is to develop an efficient classification system that can forecast the severity of a patient's sleep apnea, as well as to improve classification accuracy and reduce the number of incorrect classifications.
Keywords: Cardiac Arrhythmias, Sleep Apnea, Cardiac Conditions, Electrocardiogram (ECG), Convolution Neural Network.

1. Introduction

Systems engineering as well as applied mathematics all deal with the manipulations or analysis of analogue and digital signals that reflect time-changing or spatially variable physical values. This field is known as signal processing. Sound, electromagnetic radiation, pictures, and sensor readings for instance electrocardiograms, control system signals, telecommunication transmission signals, and many more, can all be considered signals of interest.

The following categories can be used to generally group signal processing objectives.

- Signal acquisition and reconstruction, which entails capturing and maybe subsequently reconstructing the original signal or an approximation of it. This often comprises quantization and sampling for digital systems.
- The enhancement of quality, such as echo cancellation, picture enhancement, and noise reduction.
- Signal compression (Source coding), which includes audio, picture, and video compression.
- Feature extraction, which includes speech and visual comprehension.

In older radio, telephone, radar, and television systems, analogue signal processing is used to handle signals that have not been converted to digital form. This applies to both linear and non-linear electrical circuits. Examples of the former include delay lines, integrators, additive mixers, passive and active filters, and passive filters. Compandors, multiplicators, voltage-controlled amplifiers and frequency mixers, voltage-controlled filters, and phase-locked loops are examples of non-linear circuits.

Discrete-time signal processing has been utilised for sampled signals that are exclusively described at discrete moments in time. As result, the signals are quantized in time but not in amplitude. Electronic components including sample and hold circuits, analogue time-division multiplexers, analogue delay lines, and analogue feedback shift registers are the foundation of the technology known as analogue discrete-time signal processing. The sophisticated processing of gigahertz transmissions still uses this technique, which was a forerunner to digital signal processing.

The processing of discrete-time sampled signals by digital means. General-purpose computers or digital circuits like ASICs, field-programmable gate arrays, or specialised digital signal processors are used for processing (DSP chips). Fixed-point and floating-point, real-valued and complex-valued, multiplication and addition are common mathematical operations. Circular buffers and look-up tables are two more typical hardware activities.

Audio signal processing is the deliberate alteration of acoustic perception, or sound, and it is commonly carried out using an audio effect or effects unit. Since audio signals may be electrically described in both digital and analogue ways, signal processing can be done in any of these domains. Overmodulation in audio transmission must be avoided and minimised by the audio processor. Additionally, you should rectify audio level mistakes and compensate for non-linear transmitters, which are more prevalent with medium wave and shortwave transmission. The overall loudness should be adjusted to the required level.

Electrical engineering and computer science both utilise video processing, a specific type of signal processing that frequently includes video filters but instead employs video files or video streams as both the input and output signals. Televisions, VCRs, DVD players, video codecs, video players, video scalers, as well as other gadgets all employ video processing methods. For instance, most TV sets from different manufacturers only differ in terms of visual processing and aesthetics.

Sleep apnea is the term used to describe someone who has breathing pauses or very low breathing while they are asleep. The analysis of short-duration electrocardiogram (ECG) data epochs is the main objective of an automated classification approach utilised in this operation. Sleep apnea recording datasets have been used to train and test support vector machines (SVM), which have been used to categorise apnea features. In this process, it is discussed how different sleep disorders impact the electrical activity of the human brain. Using time-frequency analysis of an electrocardiogram (ECG) signal and data on internal changes in brain state, the study aims to pinpoint distinct types of sleep disorders in humans. The method illustrates the identification of sleep issues relying on a few significant ECG signal features. Thus the major purpose of this study is to predict the severity of sleep apnea using a reliable classification system, increase classification accuracy, and decrease miss class.

An electrocardiogram, also known as an ECG, is an essential diagnostic tool that is utilised in a variety of medical settings for the routine assessment of cardiac arrhythmias. The deep learning-based method that we apply in this procedure is called a convolutional neural network framework. This framework is utilised to carry out automatic ECG arrhythmia diagnosis by classifying patient ECGs into the right cardiac states. The prior training for this network was done using a standard signal data set. The primary objective of this approach is to provide a basic, reliable, and easily implemented deep learning algorithm for the categorization of the two separate cardiac category scenarios that have been selected. The primary objective of this research is to develop a reliable classification strategy capable of accurately predicting the severity of sleep apnea, as well as to reduce the number of incorrect classifications and improve classification accuracy.

2. Literature Survey

Signals from electroencephalograms (ECGs) are frequently used to examine brain activity, such as to identify different stages of sleep. These ECG signals are by their very nature nonlinear and nonstationary. Sleep staging using linear methods and visual interpretation is challenging. Therefore, to uncover buried information in the sleep ECG signal, we employ a nonlinear method called higher order spectra (HOS). This study provided novel bi-spectrum and bi-coherence plots for distinct stages of sleep. These can be applied in a variety of diagnostic applications as visual aids. Over the course of the several phases, these plots of sleep (Wakefulness, Rapid Eye Movement, Stage 1-4 Non-REM), a number of HOS-based characteristics were retrieved. Using the ANOVA test, these features were determined to be deemed statistically significant at p-values under 0.001 [1].

Through the use of "THE SMART CAP" technology, accidents caused by intoxicated drivers are prevented. Based on the fact that an alcoholic's theta activity rises while their alpha activity declines, this theory (Different frequency bands of brain activity, including alpha and theta,). In order to collect the ECG signal, the smart hat has five implanted electrodes in the shape of a forehead band. The obtained ECG signal is preprocessed before being sent over Bluetooth to the intelligence unit, which is made up of a microprocessor. The ECG signal is split into alpha, beta, gamma, and delta waves using this processor loaded with algorithms. Alcohol use is investigated in the decomposed ECG signal. Depending on whether there are or are not ECG irregularities, the algorithm's voltage is employed to power the relay system. The relay system has taken the place of the car's keyhole. As a result, the engine won't start unless the decomposed ECG signal is completely free of anomalies [2].

Through several electrode sensors positioned on the scalp, an electroencephalogram (ECG) records electrical activity in the brain. Waves that represent the electrical signal are captured and can be categorised as normal or aberrant. Distinct forms of normal waves might signify different mental states or levels of activity. ECG signal pattern analysis can be used to identify several brain illnesses that may manifest as abnormal brain electrical.

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However, it is quite challenging to infer anything helpful from these signals in the temporal domain simply by seeing them. In essence, they are non-stationary as well as non-linear. As a result, utilising cutting-edge engineering methods, their key characteristics may be retrieved for the diagnosis of various ailments. Electroencephalogram (ECG) at rest and Evoked Potentials are two methods used to monitor brain impulses (EPs). Alcoholics and non-alcoholics have quite different brain activities. Additionally, their brains' excitement and inhibitory processes are out of balance, these differences are prevalent among alcoholics. The analysis of brain pictures and the electrophysiological mapping of the brain are two methods for revealing the activity of the alcoholics' brains. The methods that create pictures of the brain's structure include positron emission tomography and magnetic resonance imaging. The mapping of brain signals approaches that can most effectively show alcoholism's impact on a person's brain function as develops over time are summarized in this procedure [3].

As it goes without saying, alcohol driving is a key contributing factor in accidents. Driving while intoxicated, often known as Driving while intoxicated, sometimes known as drunk driving, drinking and driving, or impaired driving, is against the law levels that are over the legal limit. Even though drunk driving is regarded as a criminal infraction in the majority of nations, it is nevertheless a significant, inevitable problem. In order to safeguard the public from the realities of intoxicated driving among men, society now needs a very effective system that offers early prevention of DUI. In this procedure, the author aimed to provide a mechanical system that, by keeping an eye on the driver's ECG, avoids intoxicated driving and the accidents that follow. As alcohol consumption rises, the strength of the ECG signal in the frontal area (alpha waves) declines while the strength of the signal in the central, occipital region (delta, beta) rises. As a result, the author uses alpha, beta, and theta wave threshold values in this approach to distinguish between an alcoholic ECG and a non-alcoholic ECG. The suggested approach for preventing drunk driving accidents is extremely reliable since the driver is continuously monitored by an ECG. To minimise inconveniencing other drivers and to stop accidents caused by vehicle collisions, the proposed system also uses unique indications called preventative indicators [4].

Electroencephalography (ECG), which measures brain electrical activity, has been examined and diagnosed using a variety of methods. Because of the nonlinear interaction involving functional also anatomical subsystems that formed in the brain during both healthy conditions and various disorders, complexity measure, nonlinearity, disorder, and unpredictability play a crucial contribution among them. Alcohol consumption causes various social and economic problems, such as memory loss, poor decision-making, concentration problems, etc. Alcoholism damages the white and grey brain tissue in addition to the brains, since it is linked to emotional, behavioural, and cognitive deficits. Multiscale Permutation Entropy (MPE), a recently developed signal analysis technique, is suggested to quantify the complexity of long-range temporal correlation time series ECGs of Alcoholic and Control patients obtained from the University of California Machine Learning repository, and MSE comparisons are made between the outcomes. First, coarse-grained time series are created using MPE, and then the PE is calculated for each coarse-grained time series over the electrodes O1, O2, C3, C4, F2, F3, F4, F7, F8, Fp1, Fp2, P3, P4, and T7 and T8. Higher significant values are obtained from the findings computed using MPE against each electrode than using MSE or mean rank differences, respectively. Similar to how MPE delivers stronger separation against each electrode than MSE, ROC and Area under the ROC similarly do so [5].

3. Proposed System

To automate the detection of irregular heartbeats using the ECG data, we suggest a deep arrhythmia-diagnosis technique called the deep CNN-BLSTM network model. Four convolution layers, including two BLSTM layers and two fully linked layers, make up the majority of this classification model. The aforementioned model is given datasets of RR intervals (referred to as set A) and P-QRS-T waves (referred to as set B). The accuracy of our suggested technique was 99.94% in the training set and 98.63% in the validation set of set A, which is crucially relevant. We achieved accuracy, sensitivity, and specificity values of 96.59%, 99.93%, and 97.03% for the validation set (unseen data sets).

The following are some benefits of the suggested system:

- When contrasted to other classifiers, the multi SVM's key benefit is its ability to reduce the cross validation and post optimization operations.

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- SVM outperforms other classifiers in terms of classification results, primarily because it includes global optimization functions.
- SVM has demonstrated strong performance in classification.

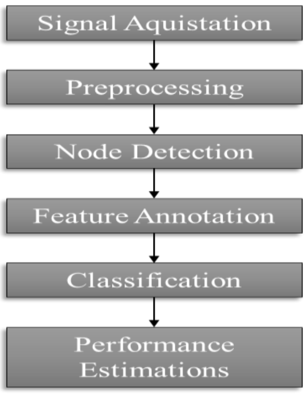

Fig 1: Block Diagram

Various steps that are involved in the implementation of suggested approach are being explained as follows:

1. **Signal Aquistation**
The electrical activity of the brain is captured using the electrophysiological monitoring method known as electroencephalography (ECG). The electrodes are normally inserted along the scalp, making it noninvasive, while invasive electrodes may occasionally be employed in certain applications. The ECG monitors voltage alterations caused by ionic current passing via brain neurons. When used in a clinical setting, the term "ECG" refers to a method of capturing the spontaneous electrical activity of the brain from many electrodes positioned on the scalp over a period of time. The majority of diagnostic applications concentrate on the spectrum content of the ECG, or the kinds of neural oscillations (often referred to as "brain waves") that may be seen in ECG data.
2. **Signal Variational Mode**
The Hilbert transform, used in both mathematics and a linear operator in signal processing accepts a function of a real variable, u(t), and generates another function of a real variable, H(u) (t).
The analytical version of a signal is derived using the Hilbert transform, which is crucial in signal processing (t). in order to fulfil the Cauchy-Riemann equations, the real signal u(t) must be expanded into the complex plane. For instance, in Fourier analysis, also known as harmonic analysis, the Hilbert transform results in the harmonic conjugate of a given function. It serves as an example of both a single integral operator and a Fourier multiplier, respectively.

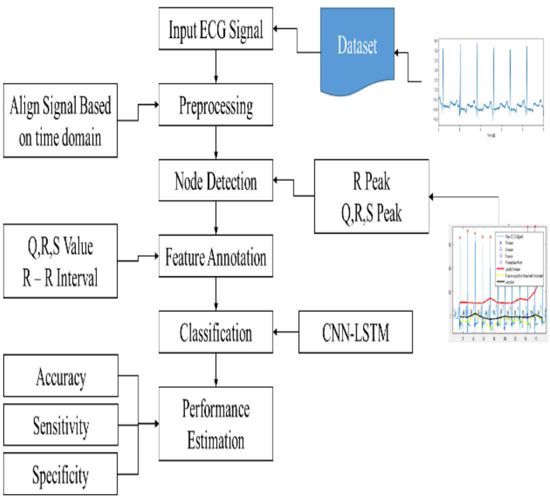

Fig 2: Flow Diagram

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3. Feature Extraction

With this approach, the major track's energy, frequency, and duration are used to determine how many features are extracted. The values for each segment are, and. The ECG signal is initially segmented; following this, a three-dimensional feature vector is constructed for each segment.

A distribution's variance and the corresponding standard deviation are indicators of how dispersed it is. They serve as indices of variability, in other words. The average squared departure of each integer from its mean is used to calculate the variance. For instance, the mean for the integers 1, 2, and 3 is 2.

4. Classification

Convolutional neural networks have the potential to learn the spatial organisation of data inputs with a high degree of success. With the IMDB review data, the word order of reviews does exhibit a one-dimensional spatial structure, and the CNN may be able to identify invariant aspects of positive and negative emotion based on this structure. Then, an LSTM layer may learn these learnt spatial properties as sequences. After the Embedding layer, we can quickly add a one-dimensional CNN and max pooling layer, which will feed the LSTM with the consolidated features. With a short filter length of 3, we can employ a relatively modest collection of 32 characteristics. The standard length of 2 can be used by the pooling layer to cut the size of the feature map in half.

5. Performance Estimations

Accuracy, Sensitivity, Specificity, and Time Consumption are some examples of performance metrics that are used to evaluate a process's effectiveness. The total number of successfully identified foreground objects is expressed as TP (true positives). The number of incorrectly categorised foreground instances is represented by the symbol TN (true negatives). The total number of false negatives (FN) is what determines how many foreground pixels were mistakenly identified as background (false negatives). FP stands for false positives, or the total number of pixels that were mistakenly categorised as foreground (false positives). Based on the measures mentioned above, performance values for each frame of the input video were determined.

4. Result

The major the development of an effective classification approach for predicting the severity of sleep apnea is the aim of this research. And to decrease miss classes and increase classification accuracy. Electrocardiograms (ECGs), which are an essential diagnostic tool, are required to be performed in the normal course of clinical practise in order to evaluate cardiac arrhythmias. Throughout this operation, a deep learning-based convolutional neural network technique has been suggested. This methodology is used to carry out automatic ECG arrhythmia diagnosis by categorising patient ECGs into the relevant cardiovascular problems. The prior training for this network was done using a standard signal data set. The primary objective of this methodology is to provide a simple, reliable, and easily implemented deep learning algorithm for the categorization of the two separate cardiac category circumstances that have been selected.

The findings shown in the pictures below reveal that a standard back propagation neural network in combination with transferred deep learning classification was able to achieve extremely high performance rates.

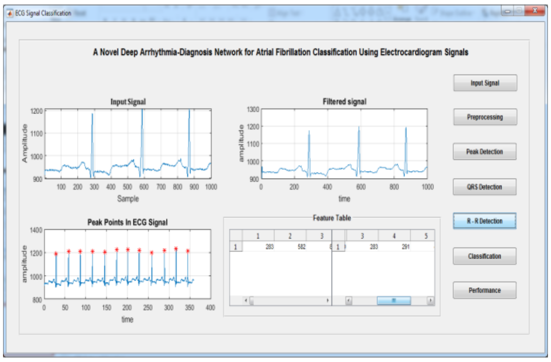

Fig 3: R-R Detection

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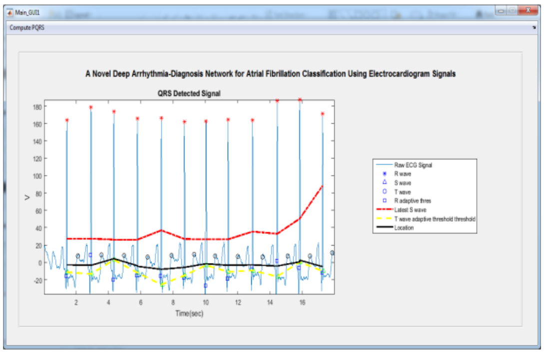

Fig 4: QRS Detected Signal

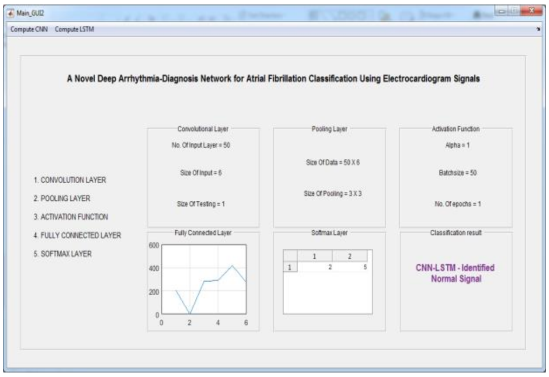

Fig 5: CNN-LSTM Identified Normal Signal

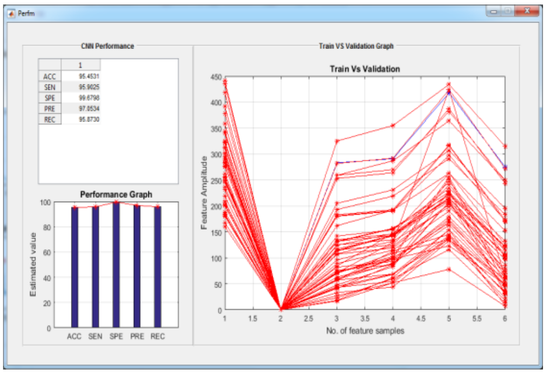

Fig 6: Performance Analysis

5. Conclusion

We have presented a one-of-a-kind deep CNN-BLSTM network as a means of determining whether or not ECG records contain an atrial fibrillation signal. The illustration, which combines the feature extraction strategies of CNN and BLSTM, is made up of four CNN layers, two BLSTM blocks, and two completely linked layers. Layers such as the CNN and BLSTM layers are utilised in the process of extracting characteristics from electrocardiogram (ECG) data. In the event that it is not available, the two databases of RR intervals, which are denoted as set A, and Heartbeat sequences, which are labelled as set B, are trained independently as described in section IV. The results of set A are noticeably more favourable than those of set B. According to the findings of the research, the fact that the AF signal and the RR interval data are closely coupled is the fundamental culprit.

6. Future Enhancement

A set of probabilistic classifiers called naive Bayes classifiers is utilised in machine learning. They are founded on the use of the Bayes theorem along with fervent (naive) independence hypotheses on the relationships between

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the attributes. For instance, a fruit may be categorised as an apple if it is red, spherical, and around 10 cm in diameter. These models go by the titles simple Bayes and independent Bayes.

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