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Detection Of Cardiac Arrhythmias Using Machine Learning

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Abstract
An irregular heartbeat caused by anomalies in the electrical conduction of the heart muscle is known as a cardiac arrhythmia. ECG devices are used to noninvasively monitor and diagnose cardiac arrhythmias in clinical settings. Visual inspection and analysis of ECG signals are difficult and time-consuming due to their dynamic nature and the abundance of complex information they convey. Therefore, an automated system that can distinguish between abnormal and normal ECG signals is required to assist doctors in quickly and reliably identifying cardiac arrhythmias. The primary objective of this work is to use transfer learning algorithms and a Morse-based time-frequency representation to improve the diagnosis of cardiac arrhythmias from ECG data. A CNN–LSTM hybrid deep learning model was shown to identify cardiac arrhythmias using CWT images of ECG data. The suggested method's accuracy for ARR, CHF, and NSR was 98.0%, 96.0%, and 98.0%, respectively.
Keywords: *CVD, Cardiac Arrhythmias, Machine Learning, information*

1. INTRODUCTION

Cardiovascular illnesses are diagnosed and evaluated by doctors using electrocardiography procedures[2]. Experts use this technique to visually evaluate the ECG signal. Because ECG signals are non-stationary, abnormalities might not always show up during recording. Therefore, it takes a lot of time to observe and analyse the recording in order to correctly diagnose a heart condition from the ECG signal [1]. However, it is exhausting and time-consuming to examine an ECG for an extended period of time since it requires a lot of data. Furthermore, there is a very significant chance of missing data because of the volume of data employed in the research[4]. Therefore, as shown, the recorded cardiac health data is represented as waves with amplitude and length known as P-QRS-T [9]. In a clinical care setting, ECG-based monitoring can be used to diagnose complex conditions like arrhythmias or to interpret the heart's basic rhythm. By examining the recorded data, cardiac arrhythmia can be identified by looking for any irregularities in the heart's rhythm or changes to the P-QRS-T wave patterns [3]. In recent years, deep learning models have been used to overcome a number of problems with traditional machine learning techniques [10]. Its primary distinction from conventional machine learning is that it automatically extracts important information from data, eliminating the need for a manually designed feature extraction and selection approach. Deep learning-based ECG signal classification has been used in a number of recent research, with encouraging results [13].

2. REVIEW OF LITERATURE

A wide range of complex algorithms were developed by numerous academics to automatically analyze ECG signals. Since ECG signals are one-dimensional (1-D) signals that reflect time series, one method for classifying them is to employ an intelligent system based on machine learning. Its main methods for classifying heartbeats are the extraction of significant traits and the choice of the best feature set [5]. The study divided heartbeats into two classes based on their morphology using a machine learning technique [6]. They used the MIT-BIH ARR and AAMI ECG datasets and a classification method known as ensemble of echo state networks [11]. For ECG signals, the study employed conventional feature extraction, feature selection, and preprocessing techniques. Thus, for ventricular ectopic beats, using lead II alone has a positive predictive value of 86.1%, whereas using lead V1 produces a positive predictive value of 75.1%. proposed a model based on the fractional Fourier transform technique for feature extraction and heartbeat classification using the MLP classifier.Four feature sets were chosen for final categorization after different features were extracted from the time series ECG. The MIT-BIH database was used to evaluate the model's performance, and the results showed an overall classification accuracy of 80% for CVD and 90.7% for the Shaoxing People's Hospital database. An additional machine learning technique for classifying ECG signals. The genetic approach is utilized for feature extraction, while the radial basis function neural network is employed for classification.The proposed RBFNN classified heartbeats into six groups with an overall accuracy of 98.5%.

3. MATERIALS AND METHODS

In addition, other people may select several attributes that aren't relevant to the problem, which would make a model more computationally complex. However, deep learning's ability to learn independently from data sets sets it apart from feature extraction-based machine learning. Therefore, feature extraction and selection are not necessary because the model handles these tasks automatically using the optimized hyperparameters. The art of deep learning is currently inspiring academics studying ECG data, and the literature has reported encouraging classification performance. Despite the fact that the literature used a deep learning model for fall detection and biometrics, the current work takes into account their positive motivational techniques [7].

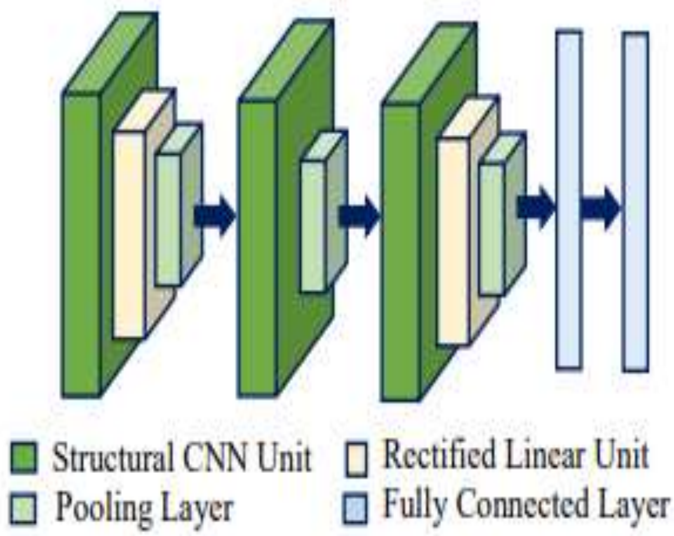


Figure 1: Layered architecture model

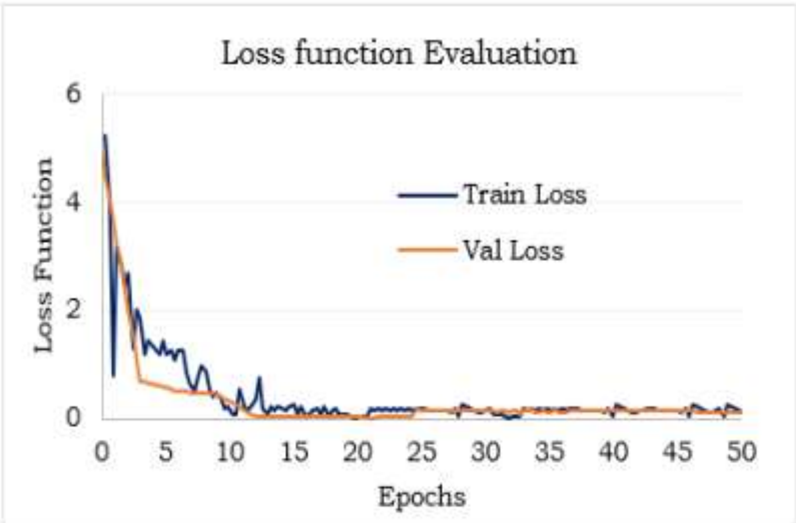
The primary contributions of the study are summarized as follows: enhancing classification performance by refining and optimizing AlexNet and ReNet 50 that have already been trained; detailing the suggested transfer learning models' design, elements, and parameters for optimization; discussing the importance of converting time series signals into two-dimensional time-frequency representation images using an analytic Morse wavelet; and providing thorough training, validation, and testing results of the suggested models, contrasting them with pertinent state-of-the-art methods.

Classifying each recording class and arranging the ECG data collected from three different sources in the PhysioNet database are the primary elements of the ECG data preparation techniques employed in this work.36 recordings for normal sinus rhythm, 30 recordings for congestive heart failure, and 96 recordings for arrhythmia were made of the 162 participants whose recordings were included in this investigation. The ECG data of each patient contained 65,536 samples. Each recording needs to be divided into an equal number of segments because delivering so much ECG signal as one data hampers the deep learning model's performance owing to deterioration.This produced 20 segments from each 65536-sample recording, each containing 500 samples.Additionally, to guarantee that the data distribution was equal for each class, only 30 patient ECG recordings were chosen per class. 1200 data points were generated for each class at this preprocessing stage. Breakdown of ECG records by recording class.

4. RESULT AND DISCUSSION

To identify atrial fibrillation from ECG measurements, a pretrained model of the EfficientNet B0 convolution neural network was suggested [8]. Since the model requires a 2D input image, they used STFT to build a 2D representation of the ECG signals [15]. Using the PhysioNet Computing in Cardiology Challenge dataset, the model demonstrated a 97.3% classification accuracy [14]. The accuracy rate of the hybrid deep learning model used to classify the PhysioNet MIT-BIH arrhythmia database was 97.15% [12]. A deep learning CNN categorized ECG signals with 91.92% accuracy using MIT-BIH arrhythmia data.

(a)



(b)

Figure 2: Training progress and loss function

A family of analytic wavelets noted for its exceptional qualities as an exactly analytic wavelet is the generalized Morse wavelet. Additionally, it does not support negative frequency.

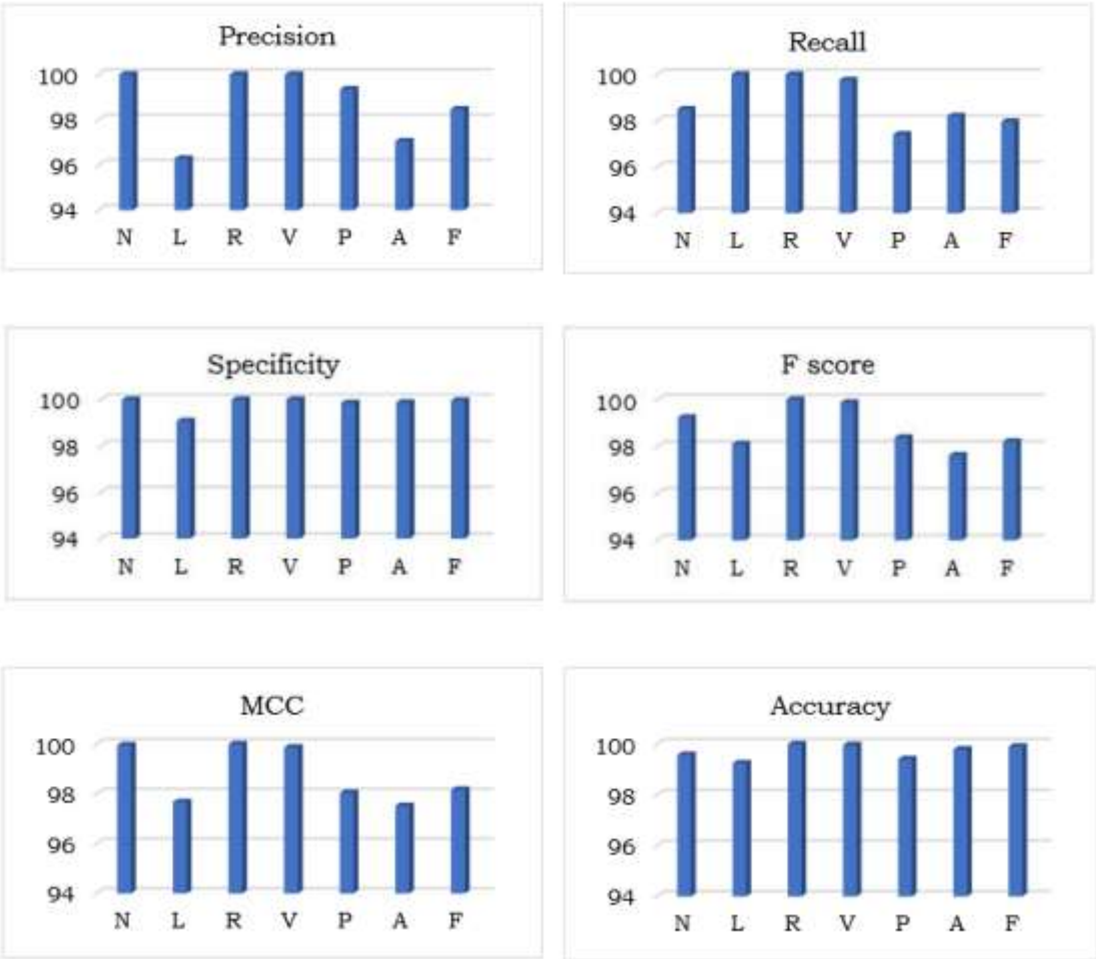


Figure 3: Comparison graphs of performance measure

The generalized Morse wavelet is the greatest option for time–frequency representation of nonstationary signals like the ECG since it can determine short duration, frequency, localize discontinuities, amplitude, transient, and integrated time–frequency representation of time-varying amplitude. Moreover, Morse parameters can be applied to any other class of analytic wavelets due to their versatility.

5. CONCLUSION

Two separate works have been completed in the current project. First, Morse wavelets are used to preprocess and convert the 1D ECG signal into 2D pictures. The hidden and visible features of nonstationary signals in the time and frequency domains are simultaneously revealed by this technique of displaying the time series signal in image form. It is the best option for turning a 1D ECG into an image because of its feature. In this study, a Morse wavelet with $\gamma = 3$, P2 = 60, sampling frequency = 128 Hz, and voice for an octave value of 12 was used to transform the 1D ECG data into a picture using MATLAB. Second, in order to classify ECG data, pretrained AlexNet and ResNet 50 were optimized using an optimizer and hyperparameter-adjusted. Consequently, ResNet50 outperformed AlexNet in both training and validation. Even though the ResNet 50 model showed remarkable training and validation performance above AlexNet mode, the network's depth meant that ResNet's calculation time during training was much longer than AlexNet's. Therefore, it is recommended to train such a deep neural network on GPUs. Furthermore, as the suggested method only focused on classifying the ECG signal into three classes, it is suggested that future study broaden the class of the ECG data by collecting additional data. The technique successfully distinguishes between arrhythmia, normal sinus rhythm, and congestive heart failure using the PhysioNet database; nevertheless, real-time data is required to evaluate its efficacy.

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