PROBLEM STATEMENT:

Electrocardiography (ECG) is a method for monitoring the human heart's electrical activity. ECG signal is often used by clinical experts in the collected time arrangement for the evaluation of any rhythmic circumstances of a topic. The research was carried to make the assignment computerized by displaying the problem with encoder-decoder methods, by using misfortune appropriation to predict standard or anomalous information. The two Convolutional Neural Networks (CNNs) and the Long Short-Term Memory (LSTM) fully connected layer (FCL) have shown improved levels over deep learning networks (DLNs) across a wide range of applications such as speech recognition, prediction etc., As CNNs are suitable to reduce recurrence types, LSTMs are reasonable for temporary displays and DNNs are appropriate for preparing highlights for a more divisible area. CNN, LSTM, and DNNs are appropriate to view. The complementarity of CNNs, LSTMs, and DNNs was explored in this paper by consolidating them through a single architecture firm. Our findings show that the methodology suggested can expressively explain ECG series and of detection of anomalies through scores that beat other techniques supervised as well as unsupervised technique. The LSTM-Network and FL also showed that the imbalanced data sets of the ECG beat detection issue have been consistently solved and that they have not been prone to the accuracy of ECG-Signals. The novel approach should be used to assist cardiologists in their accurate and unbiased analysis of ECG signals in telemedicine scenarios.

An electrocardiogram (ECG) is a significant indicative device for the appraisal of cardiovascular arrhythmias in clinical daily practice. In this study, a profound learning system beforehand prepared on an overall picture informational index is moved to do programmed ECG arrhythmia diagnostics by arranging patient ECG's into comparing heart conditions. Arrhythmias are more normal in individuals who are 60 years and more established. A convolutional neural organization (in particular AlexNet) is utilized for feature extraction and the removed highlights are taken care of into a basic back spread neural organization to complete the last classification. Fundamental focal point of this investigation is to execute a basic, solid and effectively pertinent learning method for the grouping of the chosen three diverse heart conditions (heart arrhythmia, Congestive Heart Failure, Normal sinus rhythm) so that diagnosis can be done for the same. The results exhibited that the moved profound learning highlight extractor fell with a traditional back proliferation neural organization had the option to get exceptionally elite rates. A comparison study was done where validation accuracy is 100% in GoogleNet, 94% in Squeezenet while it was near 97.33% in AlexNet.

Given the influence of available laboratory equipment, we converted 1D ECG signals into 2D image signals and used spatiotemporal characteristics to perform classification experiments on eight ECG signal types in the MIT-BIH arrhythmia database, achieving relatively high accuracy of 99.54% based on the improved EfficientNet-B0 network. Most medical data sets have sample imbalance problems, which are generally mitigated by increasing a few types of samples or decreasing most types of samples. In this study, we applied the preprocessing method of 1D to 2D ECG signal conversion, which increased the amount of data, and selected the best length. Additionally, we performed data augmentation for two categories, VEB and VFW, and we added four similar groups of different-length images to this data set, which alleviated the data imbalance problem to some extent. Finally, we employed three evaluation indices, namely, sensitivity, specificity, and precision rate ground, to evaluate the model's effect, all of which were found to be high, indicating that the model has a good classification effect.

The automatic classification of electrocardiogram (ECG) signals has played an important role in cardiovascular diseases diagnosis and prediction. Deep neural networks (DNNs), particularly Convolutional Neural Networks (CNNs), have excelled in a variety of intelligent tasks including biomedical and health informatics. Most the existing approaches either partition the ECG time series into a set of segments and apply 1D-CNNs or divide the ECG signal into a set of spectrogram images and apply 2D-CNNs. These studies, however, suffer from the limitation that temporal dependencies between 1D segments or 2D spectrograms are not considered during network construction. Furthermore, meta-data including gender and age has not been well studied in these researches. To address those limitations, we propose a multi-module Recurrent Convolutional Neural Networks (RCNNs) consisting of both CNNs to learn spatial representation and Recurrent Neural Networks (RNNs) to model the temporal relationship. Our multi-module RCNNs architecture is designed as an end-to-end deep framework with four modules: (i) timeseries module by 1D RCNNs which extracts spatio-temporal information of ECG time series; (ii) spectrogram module by 2D RCNNs which learns visual-temporal representation of ECG spectrogram ; (iii) metadata module which vectorizes age and gender information; (iv) fusion module which semantically fuses the information from three above modules by a transformer encoder. Ten-fold cross validation was used to evaluate the approach on the MIT-BIH arrhythmia database (MIT-BIH) under different network configurations. The experimental results have proved that our proposed multi-module RCNNs with transformer encoder achieves the state-of-the-art with 99.14% F1 score and 98.29% accuracy

ABSTRACT:

Cardiac arrhythmia is a leading cause of cardiovascular disease, with a high fatality rate worldwide. The timely diagnosis of cardiac arrhythmias, determined by irregular and fast heart rate, may help lower the risk of strokes. Electrocardiogram signals have been widely used to identify arrhythmias due to their non-invasive approach. However, the manual process is error-prone and time-consuming. A better alternative is to utilize deep learning models for early automatic identification of cardiac arrhythmia, thereby enhancing diagnosis and treatment. In this article, a novel deep learning model, combining convolutional neural network and bi-directional long short-term memory, is proposed for arrhythmia classification. Specifically, the classification comprises five different classes: non-ectopic (N), supraventricular ectopic (S), ventricular ectopic (V), fusion (F), and unknown (Q) beats. The proposed model is trained, validated, and tested using MIT-BIH and St-Petersburg data sets separately. Also, the performance was measured in terms of precision, accuracy, recall, specificity, and f1-score. The results show that the proposed model achieves training, validation, and testing accuracies of 100%, 98%, and 98%, respectively with the MIT-BIH data set. Lower accuracies were shown for the St-Petersburg data set. The performance of the proposed model based on the MIT-BIH data set is also compared with the performance of existing models based on the MIT-BIH data set.