Project Title : Classification of Arrhythmia by Using Deep Learning with 2-D ECG Spectral Image Representation

Introduction:

Over 17 million people are estimated to die each year from cardiovascular diseases (CVDs), making them the largest cause of mortality in humans. Three-fourths of all CVD fatalities, according to the World Heart Federation, occur in the low- and middle-income groups of society. By offering prompt treatment, a classification model to detect CVDs in their early stages might significantly lower death rates. Cardiac arrhythmia, in which heartbeats are known to vary from their regular beating pattern, is one of the primary causes of CVDs. With age, body size, exercise, and emotions, a normal heartbeat fluctuates. Palpitations are a condition when the heartbeat seems abnormally rapid or sluggish. Although an arrhythmia may indicate that the heart is beating excessively quickly or slowly, It suggests that the heart's normal rhythm is irregular. It might indicate tachycardia (heart rate greater than 100 beats per minute (bpm)), bradycardia (heart rate less than 60 bpm), a missed pulse, or in severe circumstances, cardiac arrest. Atrial fibrillation, atrial flutter, and ventricular fibrillation are a few further typical varieties of irregular cardiac rhythms. These deviations indicate diverse heart arrhythmia types and can be divided into several subclasses. Patients with cardiac disease may benefit from a precise classification of these categories to aid in diagnosis and therapy. Arrhythmia can refer to irregular heartbeats, whether they are rapid or slow, or to patterns that cannot be explained by a regular heartbeat. In clinical practise, an automated detection of these patterns is extremely important. The recognised features of cardiac arrhythmia include, where the detection requires expert clinical knowledge

Literature Survey:

- Sannino and De Pietro (2018) proposed a novel DL approach for classifying NSR, SVEB, VEB, and fusion of Ventricular and NSR. They found the best classification performance by proposing a MLP composed of seven hidden layers with the ReLU activation function, and 5, 10, 30, 50, 30, 10 and 5 neurons in each layer, respectively. The output layer leverages *Softmax* activation function, and the cost function was the cross-entropy. Signals are located on the *P, R*, and *T* peaks and proceeded to segment the ECG signal into single heartbeats. Accuracy of the results were 100% on the training set, 99.09% on the test set and 99.68% on the Whole data.
- Li et al. (2018a) proposed a method to detect Obstructive Sleep Apnea (OSA) based on DNN and Hidden Markov model (HMM) using a single-lead ECG signal. They used the verified R-peaks position to compute the RR interval series and interpolate the *RR* interval series into 100 points. DNN extracted the features. Two types of classifiers (SVM and ANN) were used to classify the features.
- Liu, Huang, Chang, Wang, and He (2018) proposed a multiple-feature-branch Convolutional Neural Network (MFB-CNN) for automated myocardial (MI) detection and localization using

ECG. Each independent feature branch of the MFB-CNN corresponded to a particular lead. The global fully-connected Softmax layer could have exploited the integrity, summarizing all the feature branches. Based on the DL framework, no hand-designed features were used for analysis. Furthermore, the patient-specific paradigm was adopted to manage the inter-patient variability, which was a significant challenge for automated diagnosis. For class-based MI detection and localization, the average accuracies are 99.95% and 99.81%, respectively. For patient-specific experiment, the average accuracies of MI detection and localization are 98.79% and 94.82%, respectively.

- Andreotti, Carr, Pimentel, Mahdi, and De Vos (2017) classified short segments of ECG into four distinct classes as part of the PhysioNet database including NSR and AF. They compared a state-of-the-art feature-based classifier with a CNN approach. They increased the number of AF and noisy recordings by 2000 10-s ECG segments with AF from PhysioBank, Circulation 2000. Each ECG segment was preprocessed using 10th order band-pass Butterworth filters with 5Hz and 45Hz cut-off frequencies for narrow-band and 1Hz to 100Hz for wide-band filtering. They divided the preprocessed ECG signals into 10-second segments with 50% overlap. They computed the features based on each segment and then computed the summary statistics such as mean standard deviation and min/max. They used the 34 layers ResNet (see Table 2) and 16 convolutional filters per layer. The feature-based classifier obtained an F_1-score of 72.0% and 79% on the training set (5-fold cross-validation) and on the hidden test set, respectively. Similarly, CNN scored 72.1% on the augmented database and 83% on the test set. The latter method resulted in a final score of 79%.
- Another best consequence is Al Rahhal, Bazi, Al Zuair, Othman, and BenJdira (2018) proposed a CNN for VEB, and SVEB classification. They utilized a continuous wavelet transform (CWT) and an 11-layer CNN. The utilized MITDB, INCART, and SVDB databases. The maximum average accuracy on MITDB database for VEB and SVEB is 99.3% and 99.3%, respectively. Regarding the other databases, the obtained average accuracy by the method in for VEB is equal to 99.23% (INCART database), and 99.4% (SVDB database). For SVEB, the average accuracy is 99.82% for INCART database and 98.4% for SVDB database.
- Sayantan, Kien, and Kadambari (2018) proposed a feature representation using Gaussian-Bernoulli Deep Belief Network (GB-DBN), and a linear SVM classifier has been considered to train the models for the classification task. The visible layer is a Gaussian RBM since the input features are real valued and the rest of layers are Bernoulli RBMs. The method achieved an accuracy of 99.5% in for SVEB and 99.4% accuracy for VEB on MIT-BIH Arrhythmia Database. Also, it provides accuracy of 97.5% for SVEB and 98.6% for VEB on SVDB database.
- Taji, Chan, and Shirmohammadi (2018) proposed a method to reduce the false alarm rate caused by poor-quality ECG measurements during AF detection. They designed a DBN with three layers of RBMs. The first two RBMs were generative RBMs which did not need labels, and the last layer included discriminative RBM which used data with their labels and classified the input data. Results show that for ECG with low Signal-Noise-Ratio (SNR), gating which is a remember data mechanism, significantly improved the performance of AF detection. Without gating, the precision, recall, accuracy, and specificity at 20 dB were 25.5%, 29.3%, 58.7%, and 70.5%, respectively. With gating, there was a significant improvement with these metrics becoming 65%, 68.1%, 81%, and 85%.
- Wang et al. (2019) proposed a global and updatable classification scheme named Global Recurrent Neural Network (GRNN). Their has three main innovations. First, relying on the large capacity and fitting ability of GRNN. Second, the GRNN improves generalization

performance when training samples and test samples are from distinct databases. Finally, GRNN automatically learns the underlying differences among the samples from different classes. The GRNN has four layers in total. In the morphological part, LSTM blocks were applied instead of traditional RNN to memorize longer history. A 20-node fully-connected layer was added after the second LSTM layer. The GRNN showed great fitting ability and high performance on the training set, with a minimum accuracy of 99.8% in VEB and SVEB detection.

- Zhang et al. (2017) proposed a patient-specific ECG classification to detect NSR, VEB, and SVEB. They use RNN to learn time correlation of ECG signal points. Morphology information of the ECG signal including the*T* wave of former beat and present beat are fed into RNN to learn the deep features automatically. According to the experimental results, the classification accuracy for SVEB and VEB are 98.7% and 99.4%, respectively.
- Yildirim (2018) proposed a new model named () for classifying ECG signals. Two filter banks consisted of high-pass and low-pass filters used for reducing noises. A new wavelet-based layer is used to generate ECG signal sequences. In this layer, the ECG signals were decomposed into frequency sub-bands at different scales. These sub-bands were used as sequences for the input of LSTM networks. They used the MIT-BIH arrhythmia database for considering five different types of heartbeats. These five types were NSR, PVC, Paced Beat, RBBB, and LBBB. The results showed that the model gave a high recognition performance of 99.39%. It had been observed that the wavelet-based layer proposed in the study significantly improved the recognition performance of CNN.
- Faust et al. (2018) proposed a DL model to detect AF beats. The data was partitioned with a sliding window of 100 beats. The resulting signal blocks were directly fed into an RNN with LSTM. The system was validated and tested with data from the MIT-BIH Atrial Fibrillation Database. It achieved 98.51% accuracy with 10-fold cross-validation (20 subjects) and 99.77% with blindfold validation (3 subjects). The proposed structure of system was straight forward because there was no need for information reduction through feature extraction.
- Singh, Pandey, Pawar, and Janghel (2018) proposed GRU, RNN and LSTM models for the effective detection of arrhythmia from ECG signals that consisted of sixteen types of heartbeats divided into two groups of normal and arrhythmia heartbeats. They evaluated three different neural networks. First, three layers of RNN had been used with 128, 256 and 100 neurons in each layer, respectively, with nine iterations. Second, a GRU with two gates, a reset gate, and an update gate. In this paper, three layers of RNN-GRU (Gated Recurrent Unit) have been used with 64, 128 and 100 number of neurons in each layer, respectively (with five iterations). Third, using LSTM to model temporal sequences and the long-range dependencies. The LSTM showed accuracy of 88.1%, sensitivity of 92.4% and specificity of 83.35%. There were 64, 256 and 100 neurons per hidden layer, respectively which showed better detection of arrhythmia than RNN and GRU as the accuracy of RNN was 85.4%, sensitivity was 80.6%, specificity was 85.7%, and GRU accuracy was 82.5%, sensitivity was 78.9%, and specificity was 81.5%.
- Sujadevi, Soman, and Vinayakumar (2017) employed different DL methods such as RNN, LSTM, and GRU to detect the AF faster in the given electrocardiogram traces. Their methodology did not require any de-noising, filtering, and preprocessing methods. The networks distinguished a signal as NSR and AF. They used the publicly available MIT-BIH PhysioNet database. The experimental results demonstrate that the achieved accuracy by RNN, LSTM, and GRU is 95.0%, 100%, and 100%, respectively. Results were encouraging enough to use clinical trials for the real-time AF classification.
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