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Electrocardiogram Signal Classification for Diagnosis Sudden Cardiac Death Using 2D CNN and LSTM

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Abstract. Electrocardiogram (ECG) signal evaluation is routinely used in clinics as a significant diagnostic method for detecting sudden cardiac death. Using automated detection and classification methods in the clinic can assist doctors in making accurate and expeditious diagnoses of diseases. In this study, we developed a classification method for sudden cardiac death based on image 2D with the combination of a convolutional neural network and long short-term memory, which was then used to diagnose a normal sinus rhythm and sudden cardiac death. The ECG data of the experiment were derived from the MIT-BIH SCD Holter database and MIT-BIH Normal Sinus Rhythm. 2D CNN model give the best result with average accuracy 96.67%, average sensitivity 100%, average specificity 92.90%, average precision 92.90% and the average F1 score is 97.10% for 1 minutes, 2 minutes and 3 minutes before VF onset.

Keywords: *Electrocardiogram, sudden cardiac death, CNN, LSTM*

1. Introduction

Sudden Cardiac Death (SCD) is the unexpected natural death from a cardiac cause within a short time period, generally ≤1 hour from the onset of symptoms [1, 14, 15]. The World Health Organization defines sudden death as death within 24 h following onset of symptoms [16]. Although SCD can occur due to a slow heart rhythm (bradycardia) caused by a stopping or blocking of the normal sinus pacemaker, more commonly it is due to a rapid heart rhythm (tachycardia), usually originating in the ventricles – ventricular tachycardia (VT) or ventricular fibrillation (VF). One major route to SCD is secondary to a heart attack (coronary infarct) in which a coronary artery is blocked [2].

Clinical studies of risk stratification for SCD have investigated and identified many physiological and anatomical characteristics that have been associated with an elevated risk of SCD [17, 18]. There are many techniques that can be used to diagnose SCD, electrocardiography (ECG) is one of them. ECG features are widely used as the prediction input as it is non-invasive and radioactive free diagnostic tool. ECG has been recognized equally effective in predicting the SCD event as compared to the other invasive techniques [3].

Based on the abovementioned problems, a model based on the input of two-dimensional grayscale images is proposed in this paper, which combines a deep 2D CNN with long short-term memory (LSTM). In most current studies, the data used are relatively limited. Many studies need to be very careful when pre-processing the one-dimensional ECG signals because the one-dimensional ECG signals are more sensitive and have a greater impact on the final accuracy [4].

The conversion of one-dimensional ECG signals into two-dimensional ECG images can get more data and the data is effectively available. There is no need for very precise separation of individual beats when performing data conversion. Even if some adjacent signals are separated, the convolution layer of the model can ignore these small noise data [5]. Using two-dimensional ECG images does not require noise filtering and manual feature extraction because the convolution and pooling layers of the model automatically ignore the noise data when acquiring the feature map, they avoid the problems of sensitivity to noise signals and accuracy being affected.

Based on the results of previous studies, recording the ECG signal is used by doctors to determine the patient's heart condition. Early detection and prediction of ECG signals are needed to assist doctors in detecting SCD accurately and quickly. SCD diagnosis using deep learning based on ECG signals aims to provide input for doctors.

The purpose of this study is to build a better 2D-CNN and LSTM model to do SCD prediction. The rest of this paper is organized as follows: Section 2 presents the related work, Section 3 presents the preparation and methodology of results, Section 4 presents the outcome and discussion,

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and the final section holds the conclusions.

2. Related Work

Much research is going on in this field of ECG classification for detect sudden cardiac death (SCD) using deep learning.

Classification Algorithms that come under the decision model based to predict the probability of Sudden Cardiac Attack on heart disease patients. Naïve Bayes algorithm outperformed all other algorithms and get scored max 93.24% and min 65.64% [6].

Review classification method for SCD [7], some method discussed are k-Nearest Neighbor (kNN), Decision Tree (DT), Support Vector Machine (SVM), Probabilistic Neural Network (PNN), Naive Bayes, Multilayer Perceptron (MLP) Neural Network, Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN).

In [8] using new method LSTM RNN architecture to segment ECG intervals. This deep learning methods outperform a traditional Markov Model and T-Wave segmentation of this experiment can achieve an accuracy of 90%, compared to that of 74.2% using Makov Models.

In [9] used classifier of DT, kNN, Naive Bayes, and SVM with 10-fold cross validation method for evaluate the classifiers performance and the authors achieved SCD detection six minutes before its onset with accuracy, specificity, and sensitivity of 95%.

In [10] use three different classifiers kNN, DT and SVM, with proposed automated SCD onset prediction method for four minutes earlier show accuracy of 94%, sensitivity 95%, and specificity of 94,4%.

They [11] can predict the SCD four minutes before its onset with an average accuracy of 86.8%, sensitivity of 80%, and specificity of 94.4% using k-NN classifier and average accuracy of 86.8%, sensitivity of 85%, specificity of 88.8% using PNN classifier.

A new methodology [12] is presented for predicting the SCD based on ECG signals employing the wavelet packet transform (WPT), homogeneity index (HI), and the Enhanced Probabilistic Neural Network classification algorithm got high accuracy of 95.8% with 12 minutes to the onset prediction.

3. Methodology

3.1. **Dataset.** The data collection method used to analyze ECG signals is the MIT-BIH SCD Holter database (SDDB) and MIT-BIH Normal Sinus Rhythm Database (NSRDB) database obtained from Physionet [10]. The total ECG signal from dataset is 41 data consisting of 23 data from SDDB and 18 data from NSRDB which will be used as a comparison of normal data. We exclude 3 data from SDDB because the data has no information when the VF onset happen.

3.2. **Purposed Solution.** In this study, the method developed is to classify ECG signals automatically to diagnose sudden cardiac death. The method to be implemented is a combination of CNN and LSTM. CNN is suitable for processing spatial or locally related data, while LSTM is suitable for capturing data characteristics related to time series. We have 4 model we tried (as seen on FIGURE 1) i.e., 1st model is combination of 2D CNN and LSTM using timeseries data produces total params of 154,252,130. 2nd and 3rd model is combination of 2D CNN and LSTM without timeseries data produces total params of 57,254,466 in the first architecture and 53,332,098 total params in the second architecture. Last model is 2D-CNN using non-timeseries data has 40,989,026 total params.

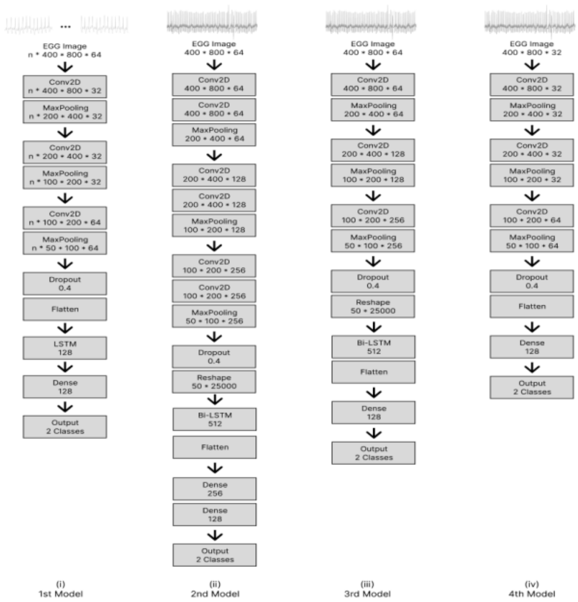

Fig. 1. One of Model Purposed 2D-CNN LSTM

3.3. **Experiment Design.** First, we got ECG signal from the dataset used from MIT-BIH SCD Holter Database for SCD data and MIT-BIH Normal Sinus Rhythm Database for normal data. The experimental method mainly consisted of two parts. The input data of the model were two-dimensional grayscale images converted from one-dimensional signals, and detection and classification of the input data was carried out using the combined model. The advantage of this method is that it does not require performing feature extraction or noise filtering on the ECG signal. The ECG signal data taken is before VF-Onset on SCD data and for normal data just get it random with same period (30 sec, 1 min, 2 min, 3 min, 4 min, 5 min and 10 min), then it is cut into one ECG image. After getting the results of the analysis using the proposed model, it is hoped that it can be classified into 2 options, namely SCD and normal.

3.4. **Evaluation Metric.** After getting the classification results, the results obtained for predicting SCD will be evaluated using accuracy (AC), sensitivity (SN), specificity (SP), precision (P) and F-measure (F1).

4. Result and Discussion

In the preprocessing stage, the signal from the SDDB and NSRDB datasets goes through the same preprocessing process, the ECG signal data is converted from one-dimension to two dimensions greyscale image and as the result image is resized to 800 x 400 pixels and dpi of 400. In the SDDB dataset that uses non-timeseries data, only 1 image is taken based on the time before VF-onset according to the desired duration (as seen on FIGURE 2).

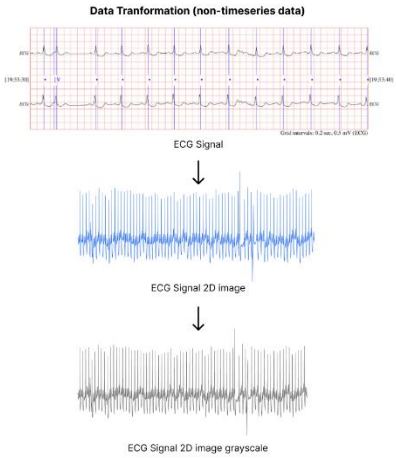

Fig. 2. Data Transformation with non-timeseries data

In the time series data, there are several pictures taken at the desired duration on the ECG signal. The SDDB dataset is taken based on the time before VF-Onset occurs, while in the NSRDB it is taken randomly along the ECG signal (as seen on FIGURE 3).

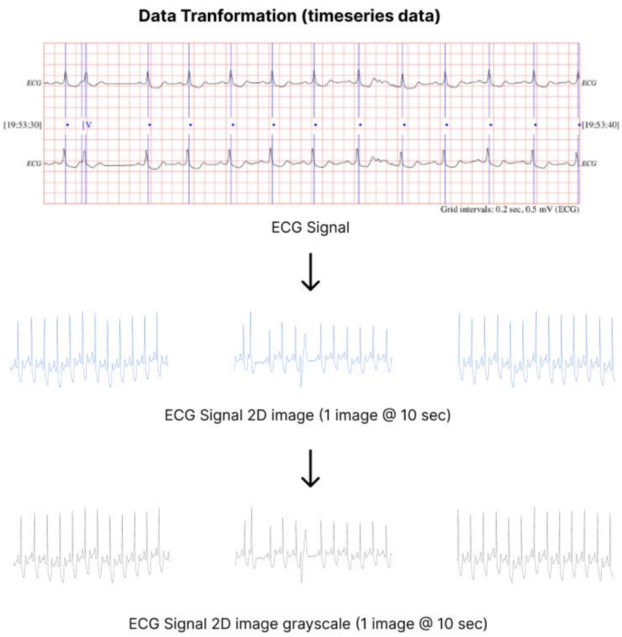

Fig. 3. Data Transformation with timeseries data

TABLE 1 shows the results to evaluate the performance of combine 2D-CNN LSTM models using 1 image with 30-second and 1 image with 60-second taken from the ECG signal. and get an average accuracy of 53.94%, an average sensitivity of 100%, the average specificity is 0%, the average precision is 53.90 and the F1 score average is 70.10%. The results obtained in the first and second models are the same value.

TABLE 1. Result of 2D CNN and LSTM Model with non-timeseries data

Model	Acc	SN	SP	P	F1
1st 2D CNN-LSTM (1pic=30sec)	53.94%	100%	0%	53.90%	70.10%
1st 2D CNN-LSTM (1pic=30sec)	53.94%	100%	0%	53.90%	70.10%
2nd 2D CNN-LSTM (1pic=30sec)	53.94%	100%	0%	53.90%	70.10%
2nd 2D CNN-LSTM (1pic=30sec)	53.94%	100%	0%	53.90%	70.10%

In the third we tried model of the combined 2D-CNN and LSTM using timeseries data, and the result is shown in TABLE 2 and the results that we got is average accuracy 53.94%, average sensitivity 100%, average specificity 0%, average precision 53.90% and average F1 score 70.10%. The results obtained did not get an increase from the previous model test.

TABLE 2. Result of 2D CNN and LSTM Model with timeseries data

Model	Acc	SN	SP	P	F1
2D CNN-LSTM 2 Timeseries (1pic=30sec)	53.94%	100%	0%	53.90%	70.10%
2D CNN-LSTM 3 Timeseries (1pic=30sec)	53.94%	100%	0%	53.90%	70.10%
2D CNN-LSTM 5 Timeseries (1pic=1sec)	53.94%	100%	0%	53.90%	70.10%
2D CNN-LSTM 5 Timeseries (1pic= 30sec)	46.06%	0%	100%	0%	0%
2D CNN-LSTM 10 Timeseries (1pic=1sec)	53.94%	100%	0%	53.90%	70.10%
2D CNN-LSTM 10 Timeseries (1pic=5sec)	46.06%	0%	100%	0%	0%
2D CNN-LSTM 10 Timeseries (1pic=30sec)	53.94%	100%	0%	53.90%	70.10%
2D CNN-LSTM 10 Timeseries (1pic=60sec)	53.94%	100%	0%	53.90%	70.10%

The last model, the result is shown in TABLE 3 and we are testing the ECG signal image with a duration of 30 seconds, average accuracy is 90.00%, average sensitivity is 87.50%, average specificity 92.90%, average precision is 92.90% and average F1 score 90.00%. While the ECG signal images with a duration of 4 minutes and 10 minutes also get the same results with the average accuracy value 96.67%, average sensitivity 93.80%, average specificity 100%, average precision 100% and average F1 score is 96.70%. In the 5-minute ECG signal image, the average accuracy is 93.33%, average sensitivity 87.50%, average specificity 100%, average precision 100% and average F1 score is 92.90%.

TABLE 3. Result of 2D CNN Model with non-timeseries data

Model	Acc	SN	SP	P	F1
2D CNN (1 pic = 30 sec)	90.00%	87.50%	92.90%	92.90%	90.00%
2D CNN (1 pic = 60 sec)	96.67%	100%	92.90%	94.40%	97.10%
2D CNN (1 pic = 2 min)	96.67%	100%	92.90%	94.40%	97.10%
2D CNN (1 pic = 3 min)	96.67%	100%	92.90%	94.40%	97.10%
2D CNN (1 pic = 4 min)	96.67%	93.80%	100%	100%	96.70%
2D CNN (1 pic = 5 min)	93.33%	87.50%	100%	100%	92.90%
2D CNN (1 pic = 10 min)	96.67%	93.80%	100%	100%	96.70%

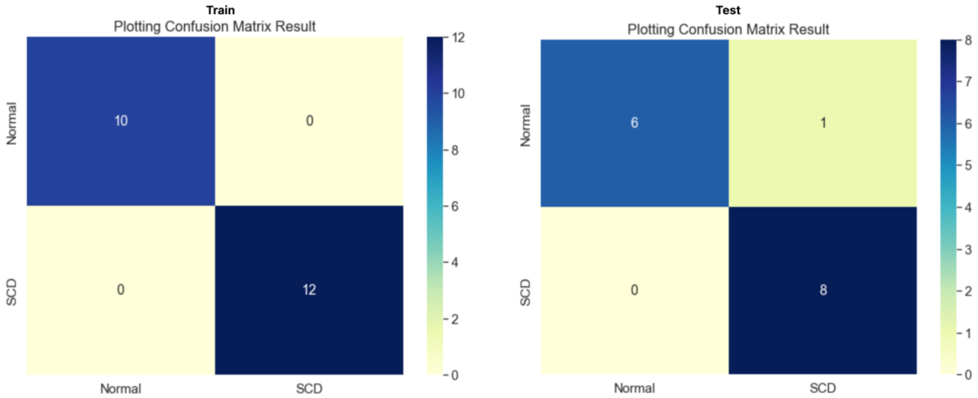

Fig. 4. Confusion matrix result for 1,2,3 minutes

The best results are obtained on ECG signal images with a duration of 1 minute, 2 minutes and 3 minutes with an average accuracy value of 96.67%, an average sensitivity of 100%, an average specificity of 92.90%, an average precision of 94, 40% and an average F1 score of 97.10%.

In FIGURE 4 the results of the confusion matrix show that there is 1 data that is predicted to be wrong from the Normal class while the SCD class can be predicted entirely by the model being tested. The main purpose of this research is to achieve good results in detecting SCD and not detecting false SCD cases.

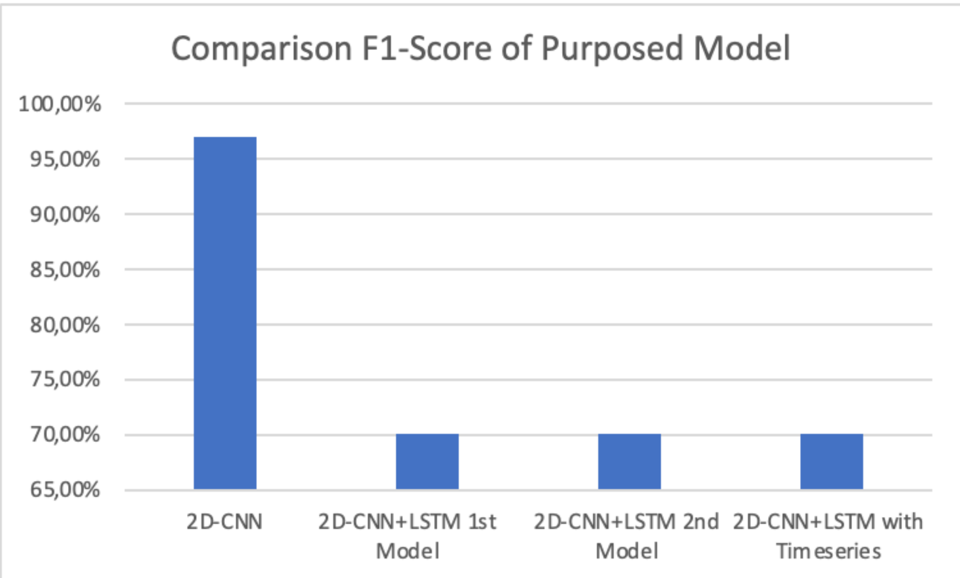

Fig. 5. Comparison F1-Score of Purpose Model

Then in the 2D-CNN model, the results obtained are superior to the combined 2D-CNN and LSTM architectural models (as seen on FIGURE 5). The best results were obtained on the ECG signal images with a duration of 1 minute, 2 minutes and 3 minutes with an average F1-score of 97.10%. For the results obtained in the ECG signal image which lasts 4 minutes and 10 minutes, it is only 0.40% different from the average F1-score value obtained, which is 96.70%. Meanwhile, when compared with the other 3 models, the results are quite far which is 27% different from the best one.

5. Conclusions

In this study, we do classification for SCD with transformed ECG signal images without feature extraction (Non-QRS Complex) and investigated the data that we make is not suitable for LSTM, so we used 2D CNN model to classify SCD few minutes before incident. With this model, the highest accuracy we got is on average 96.67% and the F1 score is on average 97.10% for 1 minutes, 2 minutes and 3 minutes before VF onset come.

For future works, we suggest making images smaller and crop the image based on QRS Complex for get more data to training and testing dataset.

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