Real-Time CNN Based ST Depression Episode Detection Using Single-Lead ECG

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***Abstract*—A method for real monitoring of the heart for ST-depression episodes is described here. We have developed a convolutional neural network (CNN) based machine learning algorithm for classifying ECG signals into normal or ST-depression episodes of the heart with an accuracy over 92%. Our algorithm is capable of detecting ST-depression episodes of varying duration. The algorithm is evaluated using European ST-T Database. The best results obtained here are 0.95%, 0.98%, and 0.91% respectively for accuracy, sensitivity, and specificity.**

***Index Terms*—electrocardiogram (ECG), convolutional neural network (CNN), machine learning, ST segment depression detection, real-time ST depression detection**

I. Introduction

Ischemic heart disease (IHD) is one of the leading cause of death worldwide. When sufficient amount of oxygen is not supplied to the heart, ischemia occurs. Continuous ischemia is very likely to lead to myocardial infarction, otherwise known as heart attack [1].

Electrocardiogram (ECG) is a major tool to detect cardiovascular diseases. Figure 1 shows the various ECG components with their typical duration. A depression or elevation in ST segment is an indication of IHD. ST segment is defined between the end of the QRS complex and the beginning of the T wave in an ECG. In order to detect an ST segment deviation, a reference point must be determined. The American College of Cardiology/American Heart Association recommends the PQ junction to be chosen as the reference point [10]. J point is the starting point of ST segment and is used for detecting ST segment deviations by comparing it with reference point for detection of ST segment change.

There are several studies which are focused on detection of myocardial infarction and ischemia [2], [3]. Park et al designed a convolutional neural network (CNN) based method for detection of ST elevation myocardial infarction (STEMI) using a 12 lead ECG [4]. Kayikcioglu et al proposed three different algorithms to detect ST segment changes [5]–[7]. Wang et al offered a classification method based on multiple feature extraction from ECG [8]. In another study, Kan et al revealed an automatic detection method to classify ST segment depression and other abnormalities [9].

This study proposes a CNN-based method to detect ST depression episodes of varying duration using signal from a single ECG lead. In Section 2, the proposed method

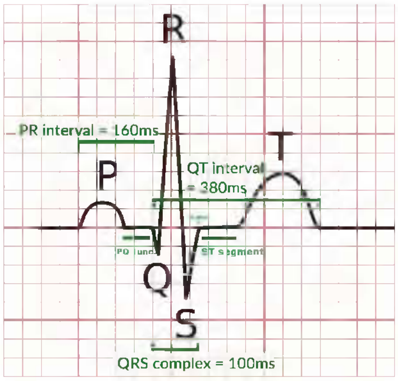

Fig. 1. An electrocardiogram with its components and time intervals of various segments

and the dataset preparation process are described. Section 3 demonstrates and analyzes the experimental results. An implementation for real time monitoring of ST Depression is described in Section 4. Finally, Section 5 provides concluding remarks to the paper.

II. Prepare Your Paper Before Styling

Convolutional neural networks (CNNs) are a form of deep neural networks which is widely used for image classification. Convolution layers are responsible for learning features. A pooling layer commonly follows each convolution layer for reduction of image size [11].

A depression in ST segment appears in three different shapes: upsloping, downsloping, and horizontal (Fig. 2). Clearly, the whole ECG beat is not necessary to detect ST depression. We used an approach of taking certain parts of an ECG: PQ junction, QRS complex, and ST segment, from each ECG beat to generate a smaller portion of the heart beat but a more meaningful dataset.

A. *Preparing Dataset*

PhysioNet European ST-T Database has 90 two-hour recording pairs of ECG (180 two-hour ECG recordings) recorded at 250 Hz sampling frequency from 79 different subjects [12]. Data collected from a variety of ECG leads are given in the database. Table I shows the number of recordings available

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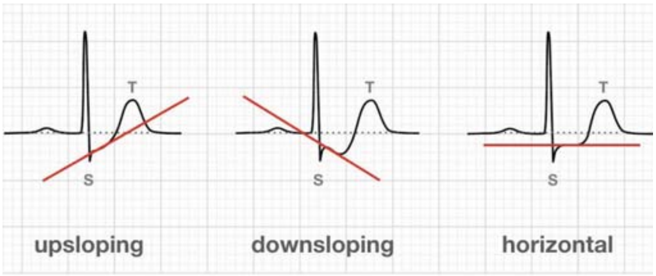

Fig. 2. Types of ST segment depressions

in the database under each of the ECG leads. While V1, V2, V3, V4, and V5 represent chest leads, MLI and MLIII represent modified ECG Lead I and Lead III respectively. ECG recordings are annotated by two different cardiologists based on ST segment and T wave abnormalities. ST segment and T wave abnormalities are annotated as episodes that are 30-second to several minutes of duration.

TABLE I
NUMBER OF ECG RECORDINGS FOR EACH LEAD TYPE

V1	V2	V3	V4	V5	MLI	MLIII
11	10	7	34	51	19	47

This study proposes extracting multiple consecutive ECG pieces for each record and forming a two-dimensional matrix by combining multiple consecutive ECG beats. This matrix, acting as a gray scale image, is used in the CNN as input. Fig. 3 shows the image form of an input.

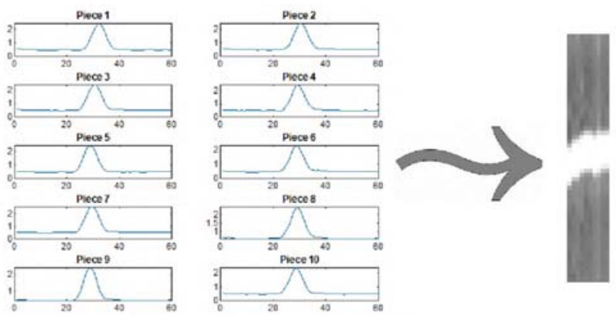

Fig. 3. Conversion of consecutive ECG beat pieces to an image

One of the challenges in ECG preprocessing is to detect QRS complexes. There are several algorithms used for QRS detection such as Pan-Tompkins algorithm, RS slope algorithm, sixth power algorithm, etc., [13]. Since PhysioNet European ST-T Database provides the R peak intervals, none of the QRS detection algorithm is performed in the preprocessing step.

Series of ECG beat pieces, each consisting of a 236 ms portion of a beat, that is made up of 60 time samples are constructed. Each piece contains PQ junction, QRS complex, and ST segment. Datasets are constructed using 10, 20, 30, and 40 consecutive ECG beats. Since the amount of data is limited, datasets are augmented using a sliding overlapping window of 10 beats. While the dataset with 10 consecutive beats has no overlapping, the datasets with 20, 30, and 40 beats have 10, 20, and 30 overlapped beats respectively. The numbers of ECG beat pieces in the overlapped datasets are slightly lesser than the ECG beat pieces in the non-overlapped datasets. The purpose of using different datasets made up of different number of ECG beats is to detect ST depression episodes of different durations by classifying the same number of normal consecutive beats.

Using 34 ECG V4 records, 12 different datasets are created. Four of them are used in subject independent analysis and 8 of them from 2 different subjects are used in subject dependent analysis.

B. *Designing CNN*

The proposed CNN structure is shown in Fig. 4. Each convolution layer is followed by a rectified linear unit (ReLU) layer, a batch normalization layer, and a Max Pooling Layer. After 3 blocks of Convolution Layer and its follow up layers, the CNN structure continues with a Fully Connected Layer, a Softmax Layer, and a Classification Layer.

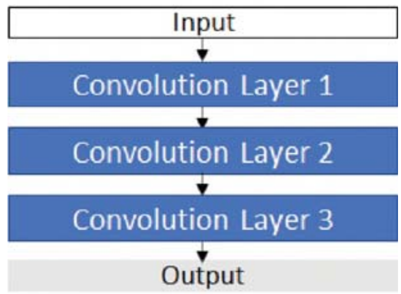

Fig. 4. Structure of the CNN model used

Deep Learning Toolbox in MATLAB is used for the model building and experimentation [14]. Experiments are performed for different number of filters in each convolution layer. Table II shows the chosen parameters for model training, convolution layer, and max pooling layer. The rest of the parameters chosen are default values that are defined in the Deep Learning Toolbox in MATLAB.

TABLE II
CNN PARAMETERS

Training Options			
k-fold	learning rate	min. batch size	max. epoch
5	0.01	100	20
Convolution Layer(each)			
num. of filters	filter size	padding mode	padding size
N_i	[3,3]	manual	[1,1,1,1]
Max Pooling Layer(each)			
pool size		stride	
[2,2]		[2,2]	

C. Subject Independent Results

Table III shows accuracy values for 4 different datasets. Datasets are generated for the cases of 10, 20, 30, and 40 consecutive ECG beats with 10472, 10346, 10228, and 10116 examples respectively.

TABLE III
ACCURACY OF CLASSIFICATION IN PERCENTAGE FOR SUBJECT INDEPENDENT CASE

$N_1xN_2xN_3$	Number of ECG beats			
	10	20	30	40
8x8x8	92.217	93.0697	93.3809	95.1363
8x16x32	93.9744	93.7559	94.2216	95.512
16x16x16	93.1818	93.8334	94.3294	95.2945
16x32x64	93.7641	94.4422	95.3851	95.3539

The results above show that the accuracy values improve when the number of consecutive beats in an example increase. The best result is over 95 percent when number of filters are 16 for all convolution layers and the training examples are made up of 40 consecutive beats. Table IV shows the confusion matrix and the detailed results .

TABLE IV
CONFUSION MATRIX FOR THE SUBJECT INDEPENDENT CASE

		Predicted Class		
		Normal	ST Depr.	
True Class	Normal	6870	184	Sensitivity 0.9879
	ST Depr.	270	2792	Specificity 0.9118
		Precision 0.9621	NPV 0.9381	Accuracy 0.9551

D. Subject Dependent Results

Subject 1 represents records e0118-e0122, and Subject 2 represents records e0123-e0126 in European ST Database. Table V shows accuracy values for Subject 1 with 4 different datasets. Again, Datasets are generated for 10, 20, 30, and 40 consecutive ECG beats with 1108, 1098, 1088, and 1078 examples respectively.

TABLE V
ACCURACY OF CLASSIFICATION IN PERCENTAGE FOR SUBJECT 1

$N_1xN_2xN_3$	Number of ECG beats			
	10	20	30	40
8x8x8	95.7572	96.8132	96.9657	97.0323
8x16x32	97.1143	97.2673	97.61	97.0271
16x16x16	95.9382	96.8128	97.4253	97.7765
16x32x64	95.5746	97.7206	96.2309	97.2158

The best result is over 97 percent when the number of filters are 16 for all convolution layers and the dataset is made up of 40 consecutive beats. Table VI show the confusion matrix and detailed results.

Table VII shows accuracy values for Subject 2 with 4 different datasets. The Datasets generated are with 10, 20, 30, and 40 consecutive ECG beats and have 1873, 1855, 1837, and 1819 examples respectively.

TABLE VI
CONFUSION MATRIX OF SUBJECT 1

		Predicted Class		
		Normal	ST Depr.	
True Class	Normal	836	9	Sensitivity 0.9893
	ST Depr.	15	218	Specificity 0.9356
		Precision 0.9823	NPV 0.9603	Accuracy 0.9777

TABLE VII
ACCURACY OF CLASSIFICATION IN PERCENTAGE FOR SUBJECT 2

$N_1xN_2xN_3$	Number of ECG beats			
	10	20	30	40
8x8x8	97.2776	98.4367	98.8568	98.8457
8x16x32	97.6512	98.5445	99.0743	98.7897
16x16x16	97.1173	98.2749	98.6933	99.1755
16x32x64	97.0632	98.0054	98.6942	99.1198

The best result here is over 99 percent when number of filters are 16 for all convolution layers and dataset is made up of 40 consecutive beats. Table VIII shows the confusion matrix and the detailed results for this case.

TABLE VIII
CONFUSION MATRIX OF SUBJECT 2

		Predicted Class		
		Normal	ST Depr.	
True Class	Normal	1443	4	Sensitivity 0.9972
	ST Depr.	11	361	Specificity 0.9704
		Precision 0.9924	NPV 0.989	Accuracy 0.9917

E. Discussion

Tables IV, VI, and VIII show the confusion matrices for the subject independent and dependent cases discussed previously. Sensitivity, specificity, precision, and NPV (negative predicted value) are determined by considering the normal class as the positive class.

In the subject independent case, the proposed method performs with more than 92 percent accuracy for all the four types of datasets. In the subject dependent cases, for the Subject 1 and the Subject 2, the proposed method performs with more than 97 and 95 percents accuracy respectively for all the four types of datasets. The accuracy improves when the training examples used are made up of 40 consecutive ECG beats. Only a slight variation in accuracy is seen with different number of filters in the convolution layers.

III. A REAL TIME APPLICATION

In the recent era, we are experiencing a trend in mobile devices. They are becoming smarter than ever because their operating systems are so capable that they can handle multiple tasks simultaneously. The high computing power and the simple user interface made them a handy device that can handle numerous applications and services without overloading the computing resources. The open-source application development functionality of these operating systems helps us to leverage the computing power to applications, popular as apps today, that can be useful for all the users. One such open-source application is TensorFlow Lite, a deep learning framework for on-device inference [16]. It is a set of tools to help developers run TensorFlow models on mobile, embedded, and IoT devices [15]. It enables on-device machine learning inference with low latency and small memory size [15].

To provide an affordable and comfortable system to detect Ischemic heart disease, we proposed an android application that detects ST depression in real-time. For this, we are using the VivaLNK Continuous ECG Recorder, which uses Bluetooth Low Energy (LE) wireless technology (IEEE 802.15.1) to transfer data between the ECG Recorder and the mobile application built over the VivaLNK SDK [17].

In order to use the model we have developed here for real time monitoring with VivaLNK Continuous ECG Recorder, a resampling step is required in the pre-processing because the recorder's sampling frequency is 128 Hz while the training dataset's is 250 Hz. We have developed and trained the TensorFlow model for the CNN architecture discussed in the previous section. The Subject independent model is used and is tuned for the best accuracy. Then we deployed this model into our proposed mobile application by converting it into a TensorFlow Lite version. Either we can deploy the deep-learning model by an Application Programming Interface (API) or adding directly in the application as an external asset. In the API scenario, the model is available on the web or on the cloud server, and we provide an interface to our application to use it. But the disadvantages of this option are internet availability, bandwidth overloading, and network latency. Hence, to avoid these issues, we decided to go with the latter option.

Fig. 5. VivaLNK Continuous ECG Recorder

A. Implementation of the Proposed Work

First, the user will open the mobile application and provide the necessary permission of the location and Bluetooth to connect and work with the ECG Recorder, shown in Fig. 6. After the conditions get completed, the application will then search for the VivaLNK Continuous ECG Recorder and then send a request to connect via the Bluetooth channel. The Recorder then accepts the request and sends an acknowledgment to get paired with the mobile application. Once the connections is established, the user will then be redirected to the home page of our application.

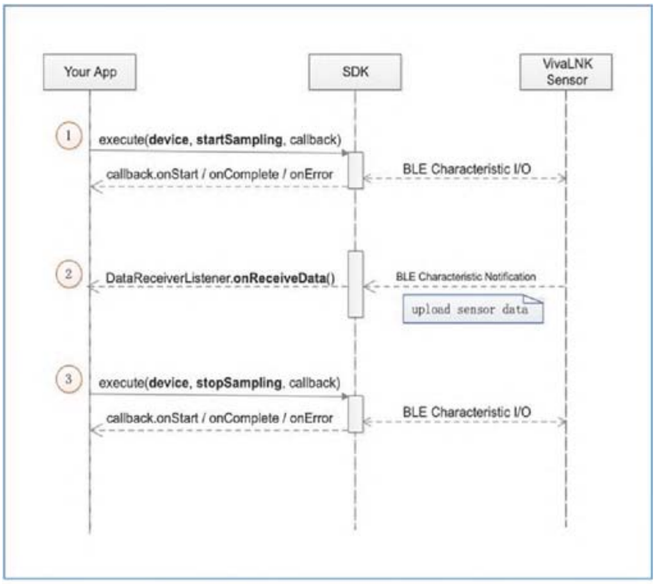

Fig. 6. Application working cycle

On the homepage, the user can invoke and execute (device, command, callback) by pressing the 'Predict' button to start sampling and classifying the ST Depression Episodes. After pressed, the execute (device, startSampling, callback) command will trigger, which requests the ECG recording of the user via the Bluetooth adapter of the patch. For this, the patch needs to be attached to the chest. The patch then starts sending a continuous recording of the ECG to the application. In-order to avoid data loss and latency, we created a buffer that stores the raw ECG data signals for 10 seconds. After 10 seconds or when the buffer is full, the application will pass the stored data for pre-processing. Since we do not have R peak information, we additionally applied Pan-Tompkins algorithm for QRS detection in the pre-processing. The raw signal is converted into the required input format of the CNN model described in an earlier section by taking 10 consecutive ECG beats. After the pre-processing, the application passes the new data to the TensorFlow Lite model.

Once the model receives the new data, it starts classifying the ST depression episodes from the 10 seconds of these data received from the buffer and displays the result. To continuously predict the ongoing data, we developed a database that stores the classification results for every 10 seconds of the data.

The results get stored till the user executes the stopSampling method or remove the patch. The application will display the ongoing as well as the hourly results from the database.

When the execute(device, stopSampling, callback) routine gets a trigger from the user, the patch receives the stop request. All the data received finally is passed to the TensorFlow Lite, and the result makes the registry on the database. The patch then stops sending the raw ECG data. And the application finally displays the report of the last inferences made by the core Lite model.

Thus, by using this android application, the user can assess Ischemic heart disease in the comfort of their home just by attaching a small single-lead ECG patch to their chest. The patch requires charging, but once charged can run for up to four hours continuously. Therefore makes it handy while sleeping at night.

IV. Conclusions

The proposed algorithm is a powerful method to detect ST depression episodes of different duration. Both sensitivity and specificity are above 91% for both subject independent and subject dependent cases. A method for continuous monitoring of the ECG for ST-depression is also described.

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