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A Comparative Evaluation of Atrial Fibrillation Detection Methods in Koreans Based on Optical Recordings Using a Smartphone

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ABSTRACT This paper evaluated three methods of atrial fibrillation (AF) detection in Korean patients using 149 records of photoplethysmography signals from 148 participants: the k-nearest neighbor (kNN), neural network (NN), and support vector machine (SVM) methods. The 149 records are preprocessed to calculate the root-mean square of the successive differences in the R-R intervals and Shannon entropy which are validated from x-means and Massachusetts Institute of Technology and Beth Israel Hospital database for the features for AF detection. A smartphone camera was used to obtain photoplethysmography signals. Clinicians labeled 29 records by referring to the electrocardiogram signals. These labeled records were used as a ground truth set to evaluate the accuracy of each method. In the experiments, the kNN, NN, and SVM methods achieved 98.65%, 99.32%, and 97.98% accuracies, respectively.

INDEX TERMS Arrhythmia, atrial fibrillation, machine learning, photoplethysmography, smartphone.

I. INTRODUCTION

Atrial fibrillation (AF) is one of the most prevalent chronic rhythm disorders of the heart. AF causes various symptoms, such as palpitations, chest pain, fatigue, and breathlessness. Severe AF increases the incidence of stroke and heart failure [1], [2]. The detection of AF during the early stage helps to prevent patient deterioration [3]. The rate of diagnosis of AF is proportional to age [4]; thus, AF detection is becoming more important as the rate of AF increases with an aging society.

Electrocardiography (ECG) is used to detect AF. ECG accurately shows the heart rhythm and other information. ECG shows the P, QRS, and T waves. The P wave represents atrial depolarization, the QRS complex ventricular depolarization, and the T wave ventricular repolarization. However, ECG requires the attachment of sensors to the patient. Consequently, it is difficult to use ECG for self-monitoring in daily life. As episodes of AF are paroxysmal, a readily available, cost-effective monitoring method that can be operated by the patient on a daily basis is required. Photoplethysmography (PPG) is an alternate option to ECG. PPG uses a light-emitting diode and a photodetector to sense changes in light absorption in a patient's blood vessels. A smartphone is equipped with both a camera and a flash and can be used to obtain images of blood vessels for PPG. Therefore, PPG-based AF detection using a smartphone is a good solution for AF self-screening in daily life [5].

In Korea's aging society, 0.7% of those older than 40 years and 2.1% of those older than 65 years have AF [6]. An auto-detection system for AF that is easy to use and affordable is needed in Korea. For detecting AF, root-mean square of the successive differences (RMSSD) in the R-R intervals, mean of the standard deviation for all normal-to-normal R-R intervals (SDNN), standard deviation of all R-R intervals in successive 5-minute epochs (SDANN), and Shannon entropy (ShE) are used. RMSSD, SDNN, and SDANN are methods used to analyze heart rate variability. ShE shows the complexity representing the heartbeat. In this paper, three AF detection methods using a smartphone: the k-nearest neighbors (kNN), neural network (NN), and support vector machine (SVM) methods are evaluated using RMSSD and ShE. The dataset used for training and testing consisted of 149 records collected from 148 Koreans. Each record comprised PPG signals obtained using a smartphone. Most people have smartphones equipped with various sensors, which can be used to measure vital signs such as heart rate or respiratory rate. In addition, a smartphone is convenient in terms of daily usage and is cost efficient relative to using additional devices.

The remainder of this paper comprises four sections. Related work is described in Section II. The proposed method is presented in Section III and the experimental results in Section IV. Finally, a discussion and the conclusions are given in Section V.

II. RELATED WORK

Applications for observing the heartbeat using a smartphone can be downloaded from Google Play and the App Store. More than 120 applications are ready for download to smartphones, including Instant Heart Rate (Azumio) [7], Runtastic Heart Rate PRO (Runtastic) [8], and Heart Beat Rate Pro (Bio2Imaging) [9]. In smartphones, these applications can be used to obtain a PPG signal using the built-in camera and flash. Even though, these downloadable applications can estimate the heart rhythm using a smartphone's flash and camera, medical diagnosis such as AF detection is not provided. In some country especially in Korea, to make an autonomous medical diagnosis is against medical law. Therefore, not a medical diagnosis but a medical advice is the limitation of applications which are downloadable from Internet.

There are also stand-alone devices for PPG, such as PM10N (Nellcor™) [10] and ubpulse T1 (LAXTHA) [11]. These stand-alone systems acquire more reliable PPG signals comparing to a smartphone. Because a smartphone is a multi-purposed device, a camera and a flash equipped in a smartphone are not intended to acquire PPG signals. However, in the point of financial view, using a smartphone has an advantage over a stand-alone device. The cost of preparing a hardware for obtaining PPG signals is ignored if a smartphone is used for estimating a heart rhythm. And from the estimated heart rhythm, cardiac diseases such as AF are detected with ease and convenience.

Atrial fibrillation is detected from the PPG signals obtained by these applications and devices, using the following steps [12]–[18]. First, an image of the skin is captured. The reflection of blood vessels shows the oxygen saturation level. The heartbeat is deduced from the change in this level. Then, the pulse-to-pulse interval (PPI) is determined using peak detection. From the distribution of these intervals, abnormal heartbeats, which appear as an unstable PPI, are classified as AF.

Various features for analyzing the PPI and ways of using these features to detect AF will be explained in Section III.

III. METHOD

A. DATA COLLECTION

To classify AF, we collected 149 PPG signals from 148 patients at the Cardiology Center of Soonchunhyang Bucheon Hospital (SBH). This study was approved by SBH's IRB and all subjects provided informed consent prior to data recording. 120 participants are randomly selected. 28 participants who undergo medical treatment are recommended by clinicians. One patient was measured twice because he underwent cardiac surgery: one record was obtained preoperatively and the other postoperatively. Therefore, for 29 records in the dataset, clinical diagnosis is attached. These clinical diagnoses were used to evaluate the results of AF detection using each classification method. For the 120 records without clinical diagnoses, we use x-means clustering [19] to group the unlabeled records. We used x-means clustering instead of the k-means clustering, because if there are more than three clusters, the collected records are not suitable for classifying into two categories. X-means clustering produced two clusters with centroid values of (0.23, 0.77) and (0.05, 0.39) (Fig. 1). The distortion and bayesian information criterion (BIC) value, which are used to validate the generated clusters, were 22.62 and –22.97, respectively.

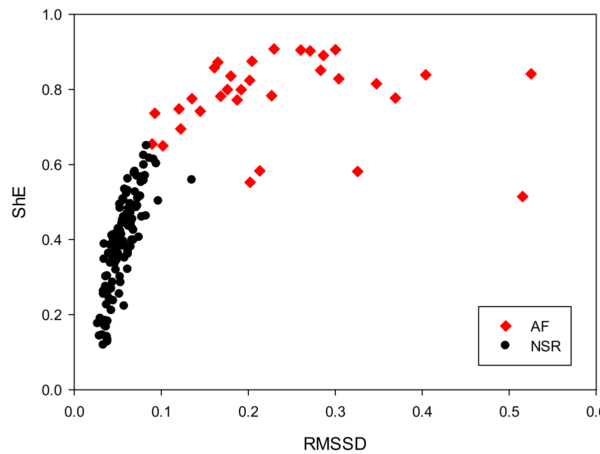
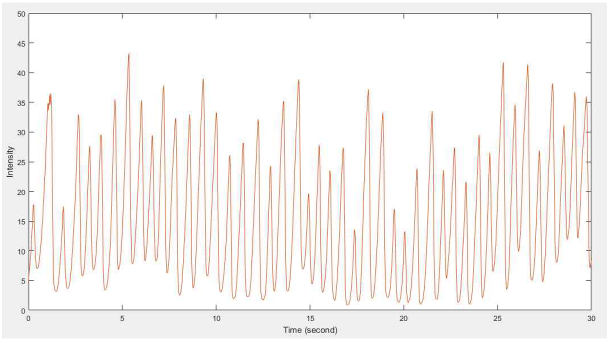
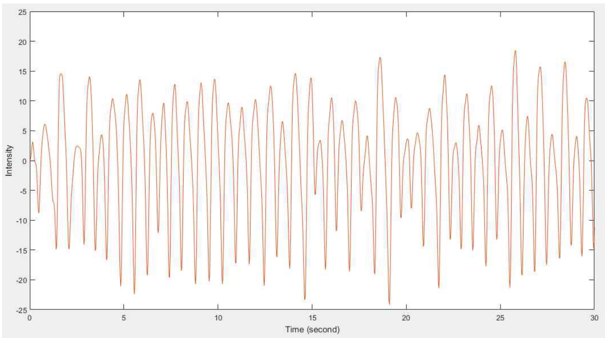


FIGURE 1. Scatterplot of the Korean PPG dataset.

To obtain PPG signals for each participant, the patients placed their index fingers on the built-in camera of an iPhone, with the flash on for 60 seconds. The image of a participant's index finger is recorded with a resolution of 640*480. The half of the recorded image which is near to a flash, is selected as a region of interest (ROI). From the green channel of ROI, PPG signals are extracted. Even though 30 images for a second are needed for obtaining reliable PPG signals, the computing power of iPhone is not sufficient for achieving 30 fps. Therefore, a cubic spline algorithm is used to interpolate the signal to 30 fps. To regulate the signal, bandpass filter with a range from 0.5 to 4 is applied. With the bandpass



(a) Example of obtained PPG signals



(b) Example of PPG signals after applying a bandpass filter

FIGURE 2. Example of PPG signals. (a) Example of obtained PPG signals. (b) Example of PPG signals after applying a bandpass filter.

filter eliminates noise from different Hz ranges. Fig.2 shows the example of the PPG signals obtained from a smartphone. (a) shows the signals obtained from the green channel of images. (b) shows the regulated PPG signals after the cubic spline algorithm and a bandpass filter are applied. From the PPG signals, peaks are detected. From the distance between peaks, PPIs are calculated and the heart rhythm is estimated from PPIs.

Acquiring PPG signals and estimating a heart rhythm are performed in the smartphone. For AF detection, the obtained PPG signals are analyzed using MATLAB.

B. PPG ANALYSIS AND AF DETECTION

The heartbeat interval is estimated by calculating the distance between peaks which are detected from the PPG signals. We used the RMSSD and ShE to classify the obtained PPG signals into normal sinus rhythm (NSR) and AF. ECG is required to detect conduction disorders or arrhythmias such as left or right bundle branch block, atrioventricular block, atrial and ventricular premature beats, and supraventricular tachycardia. Therefore, we could classify the cardiac disorders only as AF or non-AF. In addition, non-AF is assumed to be NSR. For correct classification, the criteria that distinguish NSR and AF need to be determined. For these criteria, the Massachusetts Institute of Technology and Beth Israel Hospital (MIT-BIH) Arrhythmia database was used [20].

From the MIT-BIH Arrhythmia database, we selected those ECGs that showed AF. Six patients (ID # 201, 202, 203, 210, 217, 219, and 221) had AF. The intervals in which AF was observed were extracted and analyzed using RMSSD and ShE. The scatterplots for each patient are shown in Fig. 3. According to the semantics of each feature, in a case of AF, RMSSD ranged from 0.0832 to 0.557 and ShE from 0.4525 to 0.9662.

Experiments to detect AF using RMSSD and ShE in 76 patients were conducted at the University of Massachusetts Medical Center (UMMC) [17]. The accuracy of AF detection was 96.76%. The recall and specificity were 96.19% and 97.52%, respectively. As those experiments enrolled Americans, we examined valid criteria for detecting AF in Koreans [21].

C. THREE METHODS OF AF DETECTION

To detect AF, kNN [22], NN [23], and SVM [24] machine-learning based methods were employed. These three methods are those most widely used for classification and require a supervised learning method. A training set composed of a set of labelled elements is needed to employ a supervised learning method. The element consists of a set of features. In this paper, we used two features, the RMSSD and ShE, to represent the heart rhythm of patients. The kNN method classifies a new element by identifying and comparing elements in the training set that are similar to the new element. The identified elements are referred to as its neighbors because of the similarity between the new and existing elements. The variable k is the number of elements identified. The new element is classified by averaging the neighbors. Although the elements near a boundary are easily confused in the kNN, this method is simple, flexible, and can handle multi-class classifications. Therefore, the kNN was selected as the first candidate for AF detection in this paper. A NN is trained using a back-propagation method. Basically, a NN has multiple layers that have multiple perceptrons. A perceptron is a simple function that mimics the process of a neuron by receiving inputs and generating outputs based on the weight of each input. Generally, a NN has three layers: one is for input, another is for output, and the third is for weight modification, which is the NN learning process. Back propagation is a method of training a NN by modifying the weights between perceptrons in different layers according to the error. This is called back propagation, because the error between the answer and the result of a NN is propagated from the output layer to the input layer. Although a NN has high computing complexity and produces results that are difficult to explain, it gives reliable results, even with insufficient input. Therefore, a NN was selected as the second candidate for AF detection. In this paper, NN is trained with one hidden layer containing five nodes. The SVM is a method of identifying a distinct path in a given feature space. The difference in the path made using the SVM is that the path is made based on the maximum margin space. Therefore, elements near the path are prevented from being misclassified. Even if the SVM is not suitable for large databases and is sensitive to noise, it works well in high-dimensional space and guarantees the global optimum. Therefore, the SVM was selected as the third candidate for AF detection.

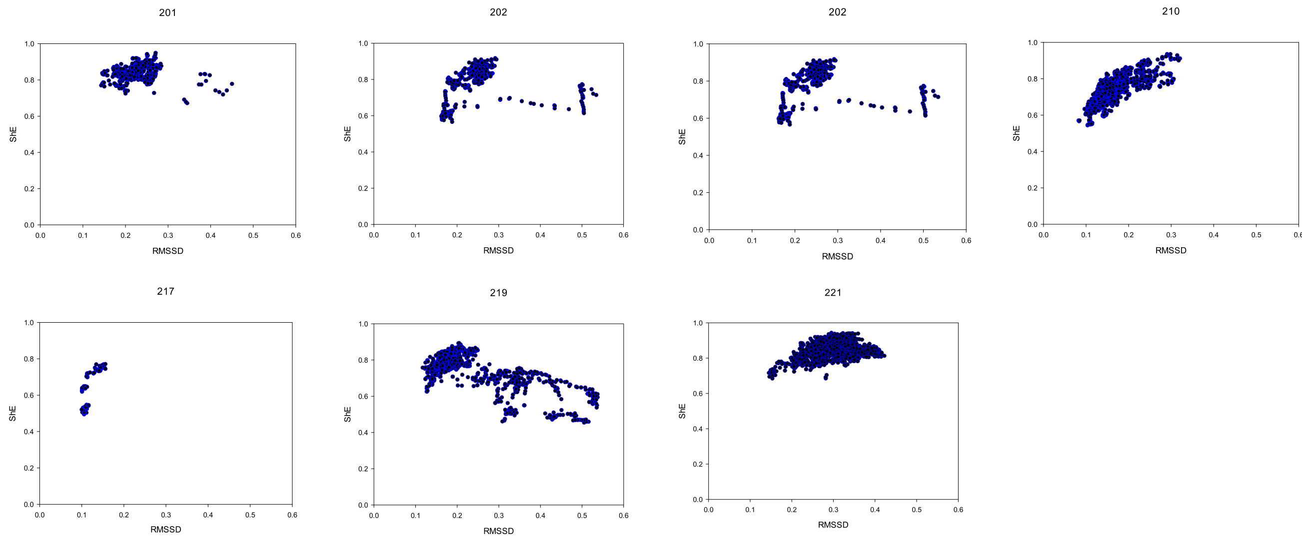


FIGURE 3. Correlations between ShE and RMSSD in the MIT-BIH database.

TABLE 1. Accuracy of AF detection using the UMMC method.

		Clinical Decision	
		AF	NSR
Automated Decision	AF	17	3
	NSR	1	8

TABLE 2. Accuracy of AF detection in Korean subjects.

		Clinical Decision	
		AF	NSR
Automated Decision	AF	18	3
	NSR	0	8

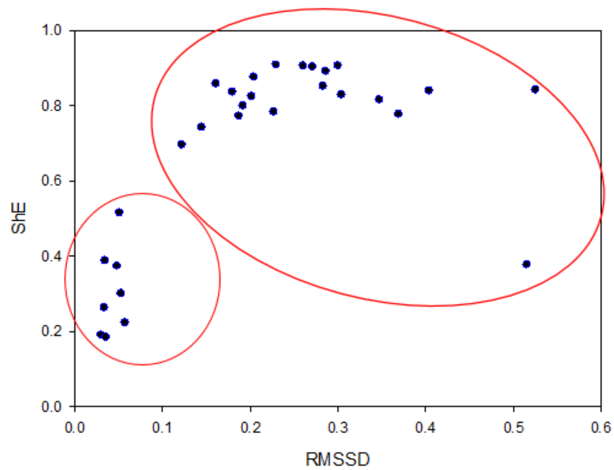


FIGURE 4. Clusters for the Korean PPG data using x-means clustering.

IV. EXPERIMENTAL RESULTS

As shown in Fig. 1, the collected PPGs clustered into two groups. The three AF detection methods, i.e., kNN, NN, and SVM methods, were trained using this dataset. The ground truth records were used to evaluate each trained AF detection method.

To verify the ground truth records, the existing AF detection method employed at UMMC [17] was applied. Table 1 shows the results using this AF detection method. The accuracy was 86.20%, which was lower than the accuracy obtained in Americans, the subjects of the UMMC studies.

Using the x-means clustering method, two clusters with centroid values of (0.27, 0.81) and (0.04, 0.3) were observed. The distortion and BIC value, used to validate the generated clusters, were 5.35 and −21.53 respectively. Fig. 4 shows the clusters. Table 2 compares the results of these clusters with the clinical diagnoses. Although the false positives were resolved, a false negative error remained.

To resolve this type II error, the clinical diagnoses were analyzed. Fig. 5 shows the NSR elements confirmed by clinicians. There are three data points in the upper right area. Because this area belongs to the AF cluster, it is impossible to recognize these elements as NSR.

One element was measured in a patient who underwent surgery for cardioversion. He had two records in the PPG set. The preoperative record was classified as AF, and the postoperative record was deemed NSR clinically, even though it showed characteristics of AF. Accordingly, inclusion of this record may be arguable, and therefore, we excluded it from the subsequent analyses.

The two remaining misclassified elements had unusual properties, as shown in Fig. 6. Fig. 6 shows that noise in the PPG signals resulted in errors in the peak detection process. Fig. 6's (a) is an example of the obtained PPG signals without noise. Fig 6's (b) is an example of the obtained PPG signals with noise. A bandpass filter which removes the signals in

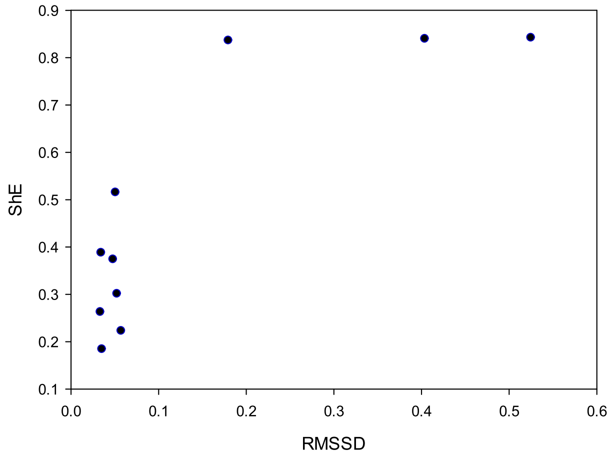
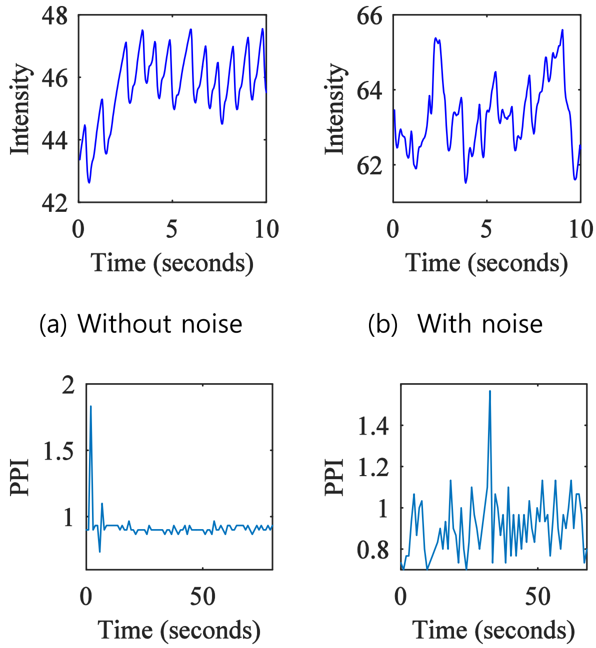


FIGURE 5. NSR elements classified by clinicians.



(a) Without noise (b) With noise

(c) Without noise (d) With noise

FIGURE 6. Noises and distortion in the PPG signal. (a) Without noise. (b) With noise. (c) Without noise. (d) With noise.

other than the heart beat range, is applied to the obtained PPG signals. Fig. 6's (c) is an example of the PPG signals after applying a filter. However, when noises are remained in the obtained PPG signals, the bandpass filter does not work as shown in Fig. 6's (d). The noise in the PPG signal likely occurred during the examination, for example, from a tremor of the finger when touching the lens of the smartphone, the vibration of the smartphone itself, or the pressure of the finger on the lens.

The three AF detection methods trained using the database in Section III.C are shown in Table 3. The training process was executed using 10-fold cross-validation.

The false detections resulting from each AF detection method were caused by the records near the boundary used

TABLE 3. Training results from the dataset using the x-means clustering method.

		X-means Clusters	
		AF	NSR
kNN	AF	31	1
	NSR	1	116
NNs	AF	32	0
	NSR	1	116
SVM	AF	29	3
	NSR	0	117

TABLE 4. Accuracy of AF detection for the ground truth dataset using all three methods.

		Clinical Decision	
		AF	NSR
kNN/NNs/SVM	AF	18	0
	NSR	0	8

to distinguish AF from NSR. Therefore, it is more important to determine why such records exist, rather than to determine the proper classification method. Although the NN gave the best result in Table 3, other classification methods may work better for different test datasets. When the boundaries of a classification are within a small crowded area, the possibility of overfitting becomes too high to avoid.

The most significant cause of a small crowded area is noise during PPG signal collection. As shown in Fig. 6, noises can confuse the signals from NSR with those from AF. Moreover, it is difficult to distinguish NSR with noise from AF. Nevertheless, the three classification methods used in the experiment attained greater than 98% accuracy using the 149 records.

Table 4 shows that the three AF detection methods achieved 100% accuracy for the ground truth dataset. Because the three records in Fig. 3 were removed from the ground truth dataset, the number of records in the ground truth dataset is 26. If we regulate the PPG signal by removing noise, the classification methods will give better results. Our future work will examine methods to avoid and eliminate noise from the PPG signal.

V. DISCUSSION AND CONCLUSION

A. DISCUSSION

As shown in the experiment, the RMSSD and ShE were able to distinguish AF from normal heartbeats. However, three different methods show similar result as shown in Table 3 and 4. Considering the difference of each method's training process, the similarity of the result seems to be caused from the small number of features. RMSSD and ShE are abstract features which are resulted by processing the raw signals. However, the abandoned signals which are not used for calculating RMSSD and ShE may have unknown semantics. For example, a cubic spline algorithm is used to make 30 fps. However, the variability of fps while obtaining PPG signals can be the evidence for removing noises. The ratio of signals in difference frequency which are removed by bandpass filter may be used as a feature for detecting cardiac disease. The features in the obtained PPG signal which are not related to the calculation of RMSSD and ShE need to be considered for training the three classifiers.

With more features, the difference of each method will be stood out. Then, instead of selecting the most reliable method, combining the whole three methods will be required. Because each method has its own advantages and disadvantages. The ensemble of three methods to maximize the advantages and minimize the disadvantages of three methods will be the key factor for increasing the accuracy of detecting various cardiac disease. As a future work, we will research on finding features in PPG signals and method of combing the various trained classifiers.

B. CONCLUSION

Detecting AF will become more important as society ages. Automatic AF detection using a smartphone camera is a convenient way of monitoring AF in everyday life. With smartphones, PPG signals are obtained from a finger placed on the camera lens. AF is detected by determining the RMSSD and ShE. The classification process involves two steps. First, cases of AF and non-AF are clustered using the x-means clustering method. Using these clusters, three classification methods based on kNN, NN, and SVM methods are trained. The, kNN-, NN-, and SVM-based methods had respective accuracies of 98.65%, 99.32%, and 97.98%. Therefore, we concluded that AF detection based on the RMSSD and ShE is applicable to Koreans. Machine-learning-based classification methods increase the accuracy of detecting AF. The NN method had the highest accuracy, because the noise in the PPG signals obstructs AF detection, and NN is more robust to noise.

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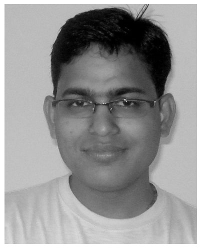

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