Pattern Analysis Towards Human Verification using Photoplethysmograph Signals

Muhammad Umar Khan
Department of Electronics Engineering, University of Engineering and Technology, Taxila
Taxila, Pakistan
sa.umarkhan@gmail.com

Sumair Aziz
Department of Electronics Engineering, University of Engineering and Technology, Taxila
Taxila, Pakistan
sumair.aziz@uettaxila.edu.pk

Syed Zohaib Hassan Naqvi
Department of Electronics Engineering, University of Engineering and Technology, Taxila
Taxila, Pakistan
zohaib.naqvi@uettaxila.edu.pk

Ahmed Zaib
Department of Electronics Engineering, University of Engineering and Technology, Taxila
Taxila, Pakistan
ahmedzaib46.az@gmail.com

Aiman Maqsood
Department of Electronics Engineering, University of Engineering and Technology, Taxila
Taxila, Pakistan
ainamaqsood770@gmail.com

***Abstract*— Photoplethysmogram (PPG) is a biomedical signal capable of detecting blood volume changes in the microvascular bed of tissues. As PPG signals are more intimate, keen, hard to replicate, and steel, they are dedicated to providing a more secure biometric approach for user recognition. This work presents a low cost, nonintellectual pattern recognition system for biometric authentication. In the proposed methodology, raw PPG signals obtained from 20 subjects are denoised using Empirical Mode Decomposition (EMD) and reconstructed using the first three IMFs. A combination of twenty time and frequency domain features is extracted from the preprocessed PPG signals. Subsequently, a range of different classifiers, including Support Vector Machines (SVM), Decision Tree (DT), and K-Nearest Neighbors (KNN), was used to classify the features extracted. When trained to quadratic SVM classifier using 10-fold cross-validation, the system achieves an accuracy of 93.10%.**

Keywords— ***Photoplethysmography, Pattern recognition system, Empirical Mode Decomposition, Support Vector Machines, Feature Extraction***

I. Introduction

In recent decades, security has become one of the challenging aspects faced by society. It is a burdensome issue for the researchers who work towards the development of smart systems. According to one research, in the US, security incidents have risen from 5,503 in 2006 to 67,168 in 2014 [1]. Hence, it is very crucial to develop such systems that can overcome the security challenge. In banking, military affairs, and traveling, these systems are broadly used [2]. The existing methods include passwords, codes, and identification cards to provide security. These techniques were not reliable because passwords, codes, and cards can be lost, forgot, or hacked by the hackers.

Biometric identification systems were introduced in 1999 [3]. 'Biometrics' is one of the emerging science which helps to demonstrate the individual's identity [4]. The existing biometric systems used different traits of humans such as speech, fingerprints, iris, gaits, sound, DNA and genes for identification. All these systems had pros and cons as fingerprints and voice can be duplicated, iris patterns can be copied by lenses [5]. ECG [6] and EEG signals were also used to identify individuals. Both these methods are impractical as many electrodes are required for acquiring these signals.

In this paper, we present another biomedical signal known as Photoplethysmogram (PPG) for biometric identification. PPG is a non-invasive electro-optical method that gives information about blood volume flowing inside the body [7]. In contrast with other biomedical signals, PPG signals have various advantages that include low development cost, easy of availability on different parts of the human body and its easy algorithms [1] [2]. PPG provides accurate physiological information about heart rate, blood flow, and blood oxygen saturation [8]. This paper describes feature extraction after pre-processing of acquired PPG signals. Performance parameters were analyzed on the basis of accuracy and reliability.

II. Literature Review

Different authors used different techniques and biomedical signals for biometric identification. Some of them used fingerprints, iris, gaits for biometric identification while others used ECG or EEG signals for this purpose. Biometric authentication with Brain waves is done by Ramaswamy [9] using novel two stage biometric authentication system on 5 subjects that were involved in different activities. The system turns both false accept rate (FAR) and false reject rate (FER) to zero. Koksoon [10] proposes novel biometric method to identify a particular individual and to verify individual's claimed identity. 99% of accuracy was obtained from HTK toolkit and 96% of accuracy was obtained using 1000 heart sounds. Chisei Miyamoto [11] uses spectral features of EEG for biometric authentication for 23 users. The proposed method gave verification rate of 79%. EEG [12] is used by Muhammad Kamil Abdullah for biometric authentication. Features were obtained using Wavelet Decomposition from 10 male subjects which were then classified using Neural Network (NN) classifier. An accuracy of 81% was obtained. Sairul I. Safie [13] presents a novel framework method for authentication of 112 subjects using electrocardiogram signals. Pulse Active Ratio (PAR) feature extraction method give 10% better results when compared to conventional temporal and amplitude feature extraction methods.

Hand based biometry [14] is introduced by Miguel A. Ferrer in his paper that authenticates 154 individual's dataset obtained from SWIR camera in combination with optical spectrograph. Least Square Vector Machine (LSVM) classifier gives an identification rates of 96.71%. Qiong Gui

TABLE I COMPARISON OF PREVIOUS LITERATURE

Author	Data Set	Subjects	Technique	Results
Kavsaoglu [7]	PPG Signals	30	Free Ranking Algorithm, k-NN Classifier	Accuracy = 90.44%, 94.44% and 87.22%
Y. Zhang [2]	PPG Signals	17	Statistical Analysis Method, Discriminant Function	Accuracy =94%
Spachos [1]	PPG Signals	Open Signal PPG=14 Biosec Signal PPG=15	LDA tool, NN and MV classifier	FAR and FRR = 0.5% for open PPG FAR and FRR = 25% for Biosec PPG
Belgacem [24]	ECG Signals	80	DWT Features, Random Forest	100% Subject Identification.
Ramaswamy [9]	Brain Waves	5	Novel Two Stage Method	FAR=0 and FER =0
Gokhan [25]	ECG Signals	--	SODP, LGA Features, k-NN Classifier	Accuracy = 91.96%, 99.86% and 95.12%
Ateke [24]	ECG Signals	90	MP Coefficients, PNN and k-NN Classifier	Accuracy = 99.68%
Adam Page [18]	ECG Signals	310	FIR Band Pass Filter, NN Classifier	Accuracy = 99.54%
Rzecki [20]	Touch Screen Data	50	PCA and k-NN, RF, PNN, RBF, MLP, SVM Classifier	Accuracy = 96.60% to 99.29%.
Koksoon [10]	Heart Sound	128	Novel Biometric Method, Robust Feature Extraction, Gaussian Mixture Modeling	Accuracy =99%
Zhedong Zhao [21]	ECG Signals	50	Wavelet Hard Thresholding, S-Transformation, CNN Classifier	Accuracy = 99%
Vidhyapriya [23]	Finger Knuckle Images		EM and SIFT Algorithm, SVM Classifier	Accuracy = 98%
Ferrer [14]	Hands Images	154	LSVM Classifier	Accuracy= 96.71%
Abdullah [12]	EEG Signals	10	Wavelet Decomposition, NN Classifier	Accuracy =81%

in his paper [15] takes samples from 32 patients. Features of certain frequency were extracted using wavelet packet decomposition (WPD) and results were obtained using Artificial Neural Network (ANN) Classifier which gave accuracy of 90%. Semih Ergin [16] from 18 healthy individuals ECG and used Decision Tree (DT) and Bayes Network (BN) Classifier which gave better performance results. Noureddine Belgacem [17] proposed Information fusion of 120 samples of EMG and ECG. Using Spectral Coefficients, features were extracted and classified using Optimum-Path Forest (OPF) classifier which give 99.0% accuracy. Biometric Authentication using ECG [18] is also done by Adam Page who performed filtering of 310 samples using FIR Band-Pass Filter and then classified using Neural Network (NN) Classifier. When tested system gave accuracy of 99.54%. Electromyograph and Keystroke Dynamics fusion technique for Biometric Authentication is presented in [19]. Data set from 14 individuals were classified using Subspace Modeling and Bayesian Classifier which gives Genuine Accept Rate (GAR) above than 90%. Krzysztof Rzecki [20] proposed biometric authentication using touch screen gestures. The data obtained from 50 persons was preprocessed using resampling, standardization and Principal Component Analysis (PCA) and then computational intelligence methods were applied which gave an accuracy ranging between 96.60% to 99.29%.

Zhidong Zhao [21] proposed biometric authentication using Convolution Neural Network and S- Transformation of ECG signals obtained from 50 persons obtaining accuracy of 99%. ECG Biometrics is used by Ateke Goshvarpour [22] who collected 90 ECG samples and then decomposed them using matching pursuit (MP) and several statistical and nonlinear measures. The results were determined using Probabilistic Neural Network (PNN) and k-Nearest Neighbor (K-NN) classifier which gave accuracy of 99.68%. The paper written by Vidhyapriya R [23] proposes finger knuckle point method for biometric authentication of individuals. Texture features were classified using (SVM) classifier which gives 98% accuracy.

Table I shows the previous work cited for biometric authentication. It can be seen that ECG and EEG signals were used in previous literature cited but both of them addresses many issues i.e. variability and heritability of both signals and lack of standardization of ECG and EEG features. The organization of paper is as follows. Section II describes the previous work cited. Adopted methodology is discussed in Section III. Results are presented in Section IV followed by conclusion in Section V.

III. METHODS AND MATERIALS

Fig. 1 shows the methodology used for biometric authentication using PPG signals. PPG signals were acquired from 20 healthy subjects using Photoplethysmography (PPG) sensor. The obtained signals were preprocessed using Empirical Mode Decomposition (EMD) technique. EMD decomposes the raw signals to its constituent IMF's. As, higher IMF's contain low frequency artifacts hence, original signal was reconstructed using lower IMF's to avoid these artifacts. After preprocessing, discriminative features were extracted from the signals using time domain and frequency domain features. In the end, the features of all subjects were trained to SVM classifier which gives accuracy of experiments.

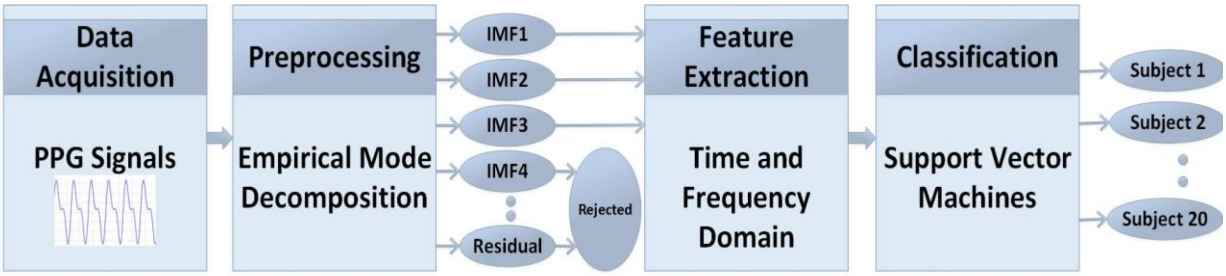

Fig. 1. Frame work of proposed methodology

TABLE II SUMMARY OF DATA ACQUISITION

Subjects	No. of Samples
Male Subjects	11
Female Subjects	9
Total	20

Fig. 2. Data Acquisition of PPG Signal from BIOPAC MP36 System

A. *Data Acquisition*

In this experiment, Photoplethysmography (PPG) signals were acquired using SS4L Photoplethysmography sensor along with MP36 BIOPAC system.

PPG is an optical measurement method used for observing blood volume changes in the microvascular bed of tissues [24]. It uses photodetector at the surface of skin to measure changes in light absorption. Pressure pulse due to change in volume is detected by illuminating the skin through light emitting diode (LED) and then light reflected is measured using a photodiode.

In this case, PPG signals were recorded in a sitting position at a resting state. Each signal was 30 minutes long, digitized at the sampling frequency of 200Hz. A total of 20 subjects (11 males and 9 female) participated in our experiments. We acquired the PPG signals from subject's index finger of right hand. Table II shows the detail of acquired dataset. Fig. 2 shows the data acquisition from BIOPAC System using PPG Sensor. Fig. 3 and 4 shows the PPG signal of subject I and II in time domain and frequency domain.

B. *Preprocessing*

Acquired PPG signals needs to be preprocessed because they contain both environmental noise and motion artifacts.

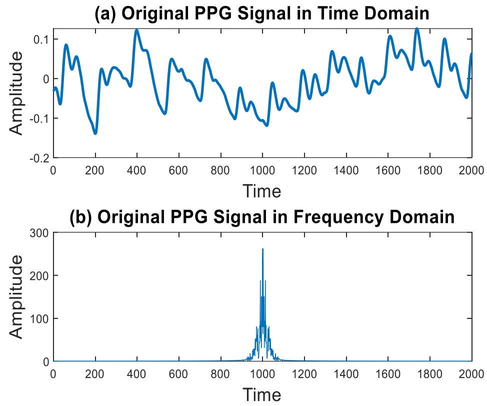

Fig. 3. (a) Subject I Waveform Without Pre-Processing in time domain (b) Subject I Waveform Without Pre-Processing in frequency domain

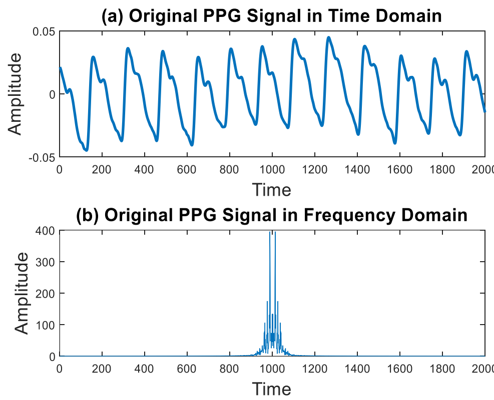

Fig. 4. (a) Subject II Waveform Without Pre-Processing in time domain (b) Subject II Waveform Without Pre-Processing in frequency domain

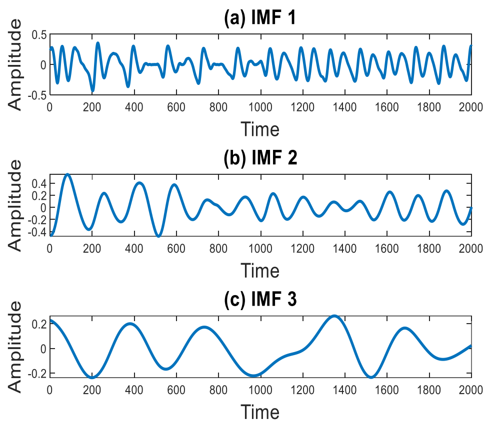

Fig. 5. Empirical Mode Decomposition of Subject I (a) IMF -1 Waveform(b) IMF-2 Waveform (c) IMF-3

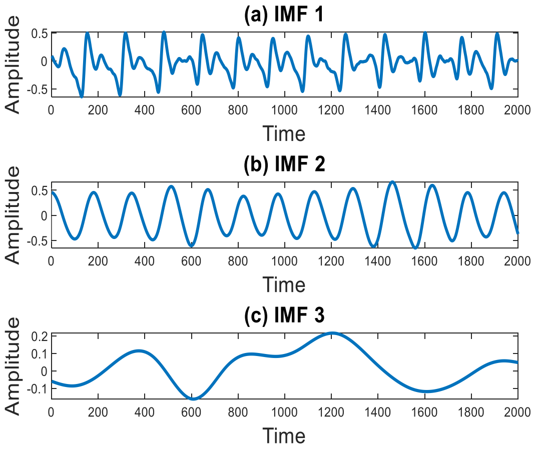

Fig. 6. Empirical Mode Decomposition of Subject II (a) IMF - 1 Waveform(b) IMF-2 Waveform (c) IMF-3 Waveform

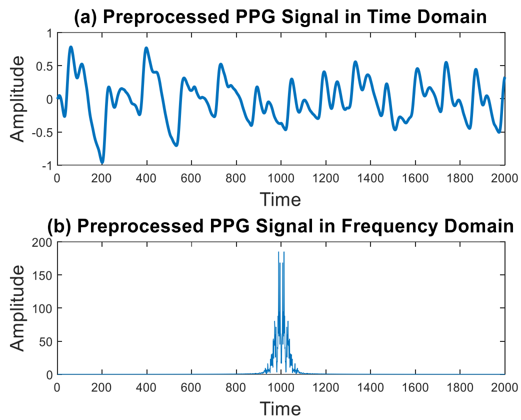

Fig. 7. (a) Subject I Waveform with Pre-Processing in Time domain (b) Subject I Waveform with Pre-Processing in Frequency domain

Preprocessing of acquired PPG signals involves two operations, de-noising of raw signals and region of interest (ROI) extraction. In our experiment, we used Empirical Mode Decomposition (EMD) technique to achieve both these objectives [25, 26].

EMD also known as Huang Transform decomposes the signals into intrinsic and simple oscillations known as Intrinsic Mode Functions (IMF's) [27, 28]. In our study, IMF-4 is rejected to avoid low frequency artifacts. whereas 1st three IMF's are selected. Fig. 5 and 6 shows the IMF's of subject I and subject II. Fig.7 and 8 shows the PPG signal of subject I and II after preprocessing.

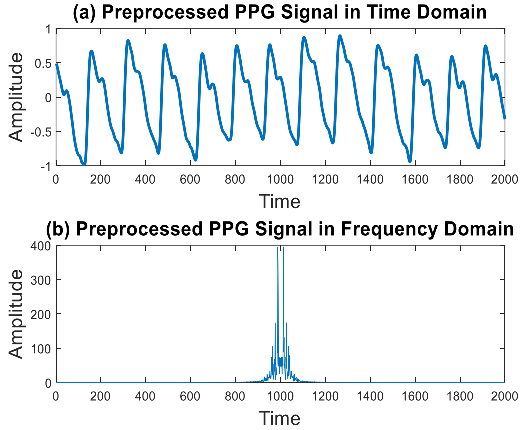

Fig. 8. (a) Subject II Waveform with Pre-Processing in Time domain (b) Subject II Waveform with Pre-Processing in Frequency domain

C. Feature Extraction

After preprocessing, discriminant features were extracted from the signals to present minimum parameters of subjects with high discriminative properties. In our experiment, we extracted 20 different time domain and frequency domain features including Mean, Kurtosis (Kur), Spectral Mean (SMean), Spectral Standard Deviation (SStd), Spectral Skewness (SSk), Spectral Kurtosis (SKr), Log Energy (LE_E), Total Harmonic Distortion (THD), Mean Absolute Deviation (MeanAD), Spectral Centroid (SCen), Zero Crossing Rate (ZCR), Higuchi Fractal Dimensions (HFD), Waveform Length Ratio (WLR), Sparseness, Irregularity, Difference Absolute Standard Deviation Value (DASDV), Root Sum of Squares (RSSQ), Inter-Quartile Range (IQR), Mean Frequency, Willison Amplitude (WA). Combination of all these features help to extract discriminant features of signals and to improve our classification accuracy. Table III shows the features we selected for achieving highest accuracy with less computational time.

D. Classification

Support Vector Machine (SVM) classifier is a binary classifier that separates data points of two classes in feature hyperspace by creating a linear decision boundary or a hyperplane. In this way, several hyperplanes are created that can classify the data. A Kernel Function K maps the input space to feature space and hence optimal boundary finds linear decision rule in Q feature space [29-31]. For reducing space and time complexity problems, SVM classifiers are widely used.

TABLE III NAME OF FEATURES EXTRACTED

Time Domain Features							Frequency Domain Features		
Zero Crossing Rate (ZCR)	Waveform Length Ratio (WLR)	Willison Amplitude (WA)	Higuchi Fractal Dimensions (HFD)	Difference Absolute Standard Deviation Value (DASDV)	Mean Absolute Deviation (MeanAD)	Root Sum of Squares (RSSQ)	Spectral Mean (SMean)	Spectral Standard Deviation (SStd)	Spectral Skewness (SSk)
Kurtosis (Kur)	Sparseness	Log Energy (LE_E)	Mean	Inter-Quartile Range (IQR)	Irregularity		Spectral Centroid (SCen)	Mean Frequency (MF)	Spectral Kurtosis (SKur)

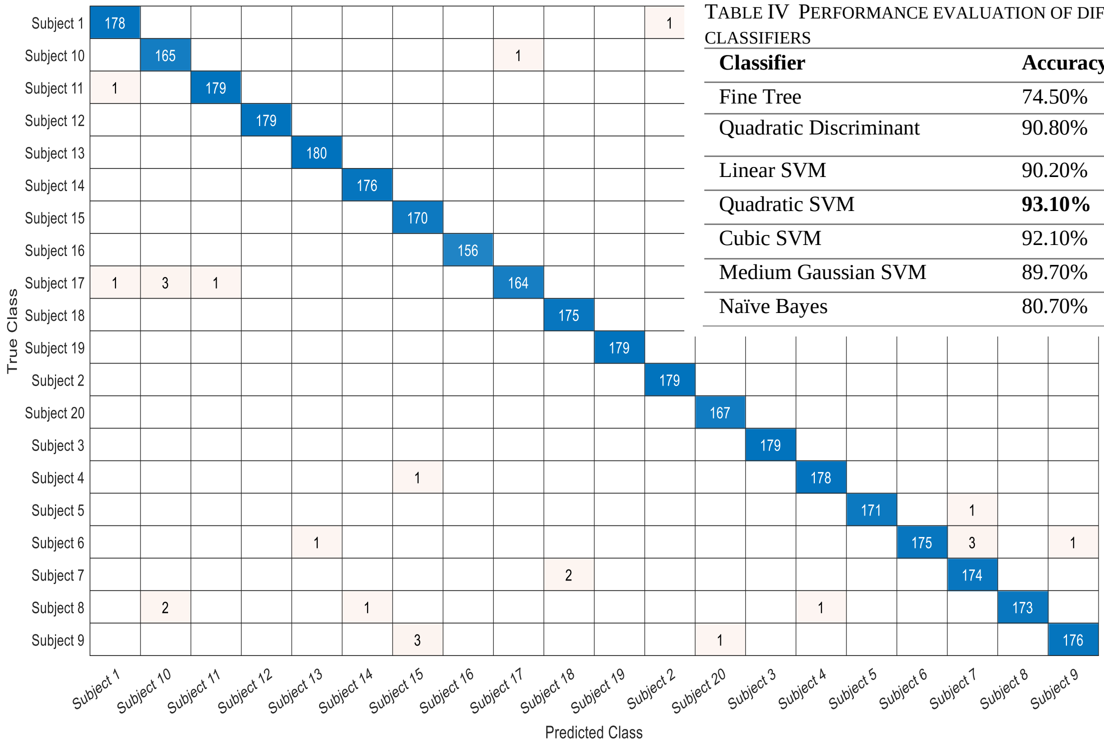

TABLE IV PERFORMANCE EVALUATION OF DIFFERENT CLASSIFIERS

Classifier	Accuracy
Fine Tree	74.50%
Quadratic Discriminant	90.80%
Linear SVM	90.20%
Quadratic SVM	**93.10%**
Cubic SVM	92.10%
Medium Gaussian SVM	89.70%
Naïve Bayes	80.70%

Fig. 9. Confusion Matrix of Quadratic SVM Classifier

In our methodology, we trained our data set to different classifiers for attaining maximum accuracy. These classifiers include Quadratic Discriminant (QD), Linear Discriminant (LD), SVM-linear (SVM-L), SVM-Quadratic (SVM-Q), SVM-Cubic (SVM-C), SVM-Medium Gaussian (SVM-MG), Fine Tree (FT) and Naïve Bayes (NV).

IV. RESULTS AND DISCUSSION

Human Verification EMD-SVM based system using PPG signals is proposed in this paper. Presented method used Empirical Mode Decomposition technique for removing low frequency artifacts from acquired PPG signals. After this, set of 20 different time domain and frequency domain features are extracted and trained to different classifiers using 10 fold cross validation for achieving maximum accuracy. In 10 fold cross validation, entire data set is divided into 10 subsets of uniform lengths. Each subset is used as test set while 9 sets are used as a training set which after iteration of 10 times are averaged to form result. It is evident from table IV that Quadratic SVM gives maximum accuracy of 93.10%, while Linear SVM (SVM-L), Cubic SVM (SVM-C), Median Gaussian SVM (SVM-G) gives accuracies of 90.20%, 92.10% and 89.70% respectively. The dataset is also evaluated on Fine Tree (FT), Quadratic Discriminant (QD) and Naïve Bayes (NB) classifier which gives accuracy of 74.50%, 90.80% and 80.70% respectively.

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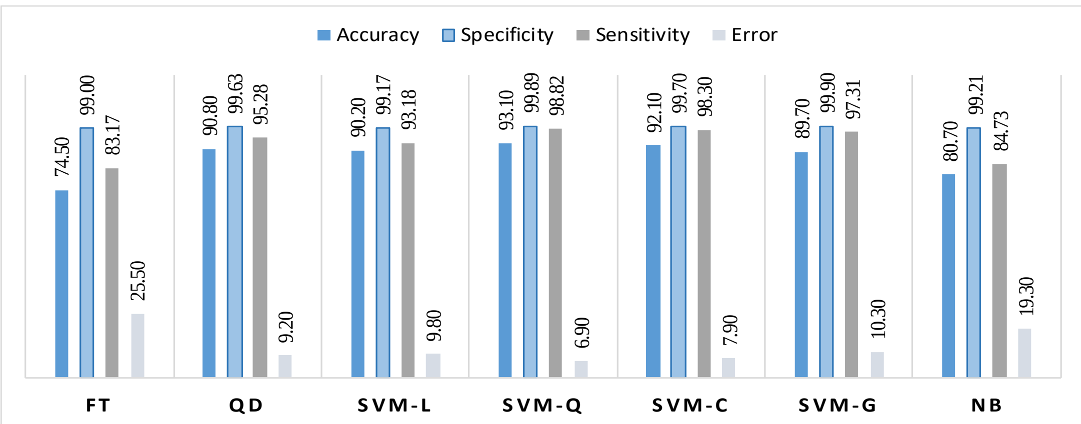

Fig. 10. Comparison Graph of Different Classifiers

confusion matrix of Quadratic SVM classifier is shown in Fig. 9. Maximum accuracy of 93.10% achieved by Quadratic SVM can be seen in Fig. 10 which shows the graph comparing accuracies of all classifiers followed with specificity, sensitivity and error rate in each case. Fine Tree achieved an accuracy of 74.50% with highest error rate of 25.50%.

V. CONCLUSION

PPG based biometric authentication system is proposed in this research. The proposed system employed EMD for signal denoising and ROI extraction. The conjunction of frequency and time-domain features were extracted for the authentication of different data classes. The range of different classifiers was used to evaluate the selected features in which Quadratic-SVM achieved the highest classification accuracy of 93.10%. PPG dataset from 20 subjects was collected for this study. An experimental study shows that the proposed method is more feasible, accurate, and takes less computational time as compared to traditional methods used. In the future, we aim to expand the dataset in order to design a highly reliable embedded system for real-time applications based on the proposed methodology.

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