Biometric Identification via ECG Signal using Machine Learning based approach

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July, 2019

Declaration

I certify that this research work titled "*Biometric Identification Through ECG Signal using Machine Learning based approach*" is my work. This research work has not been presented elsewhere for assessment. The material that has been used from other sources it has been properly acknowledged/referred.

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Copyright Statement

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Dedicated to my family

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Abstract

Automatic identification of individuals using biometric features is an area that has gained high importance nowadays. This study presents a novel approach for biometric identification through ECG signal using hybridization of different features and Radial Basis Function Neural Network (RBF-NN). Three different features, namely ARIMA, Wavelet Entropy, and Sample Entropy, are extracted from an ECG dataset. The features are then fed to an RBF-NN to identify different individuals. In the past, these features were used individually for person identification. This paper presents an approach for person identification by hybridization of the features mentioned above. The proposed approach shows promising results with an accuracy of 99.50% to identify 55 individuals correctly

Key Words: *Biometric identification; Electrocardiography; Sample entropy; Wavelet entropy; Radial basis function neural network.*

1. INTRODUCTION

This chapter presents an introduction to biometric person identification employing various methods. This chapter briefly describes the autoregressive moving average, research objectives of the present study, scope of subject, and motivation of present research work.

1.1. Introduction to biometric identification

The rapid evolution of modern society due to advancement in network technology, communication, transportation, and internet of things necessitates the improved and reliable identification methods. Generally, identification methods can be divided into two classes. First, elements that people remember, e.g. username and password. The second class of identification method contains physical items for identification, e.g. identification card and key (tradition, dongle). Each of class, as mentioned earlier, possesses certain advantages over the other one. However, both have limitations, and existing methods are unable to meet the requirements of the advanced security systems.

Another approach of identification is termed as biological recognition method. This method of identification utilizes certain physiological or behavioral characteristics, e.g. retina of the eye, fingerprint, voice recognition, etc. as a password to access the system. There are three most important methods of biometric identification based on retina or iris, face recognition, and fingerprints. Other methods like voice, writing, body movement and hand geometry, etc. are also valuable depending on the choice of application and purpose of using.

Among biometric identification methods, the use of fingerprints [1] as a source of identification is the oldest and most commonly used method. A dermal pattern in fingerprints are unique and cannot be changed. Various identification methods have been developed using fingerprints, e.g. feature extraction from an image of fingerprints. Generally, the pattern of finger impression is stored in a database and is used during the verification phase. Fingerprint-based biometric identification has weaknesses, e.g. fingerprint impressions might not work if an impression is damaged or eliminated in some cases. Fake fingerprint can be obtained using latex material.

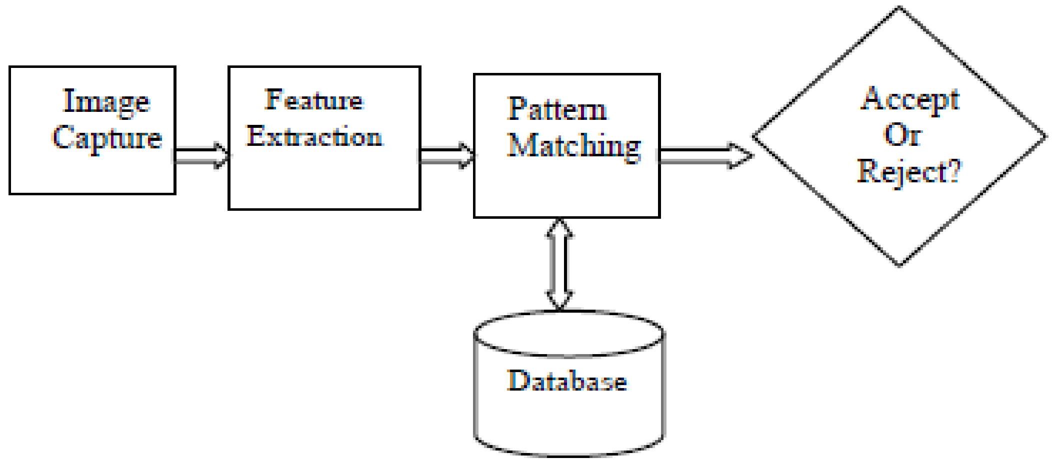

Figure 1 Fingerprint Biometric Flowchart [1]

Voice biometric [2] are often used in the manufacturing companies where voice entries are required for the data entry or giving commands. Different methods were used for voice recognition. A microphone is used for collecting the data, and analog-digital converter is employed to convert the data into digital signal. Digital Signal Processing (DSP) is used for scaling, windowing, and filtering of the voice signal. The signal is buffered for the recognition algorithm and stored for the matching. Generally, a pattern matching algorithm is employed to find the perfect match of the voice from the database. Voice biometric also have some disadvantages and have low accuracy as person voice can be recorded easily. Furthermore, illness as a cold can also change person voice, which can be difficult to recognize.

Iris recognition [3] is another biometric identification method and is gaining popularity with time due to its reliability. This method analyzes the iris pattern of a person. It should be noted that the Iris pattern is unique even in the twins. Iris recognition technique consists of three steps. Firstly, iris boundaries are extracted from the eye image in the pre-processing phase. Secondly, features are extracted from the preprocessed iris image. Lastly, features from the iris pattern are compared with those stored in the database for authentication. It is noteworthy that Iris based biometric identification also has some problems. For instance, it is quite expensive, intrusive, and requires a lot of memory for the database.

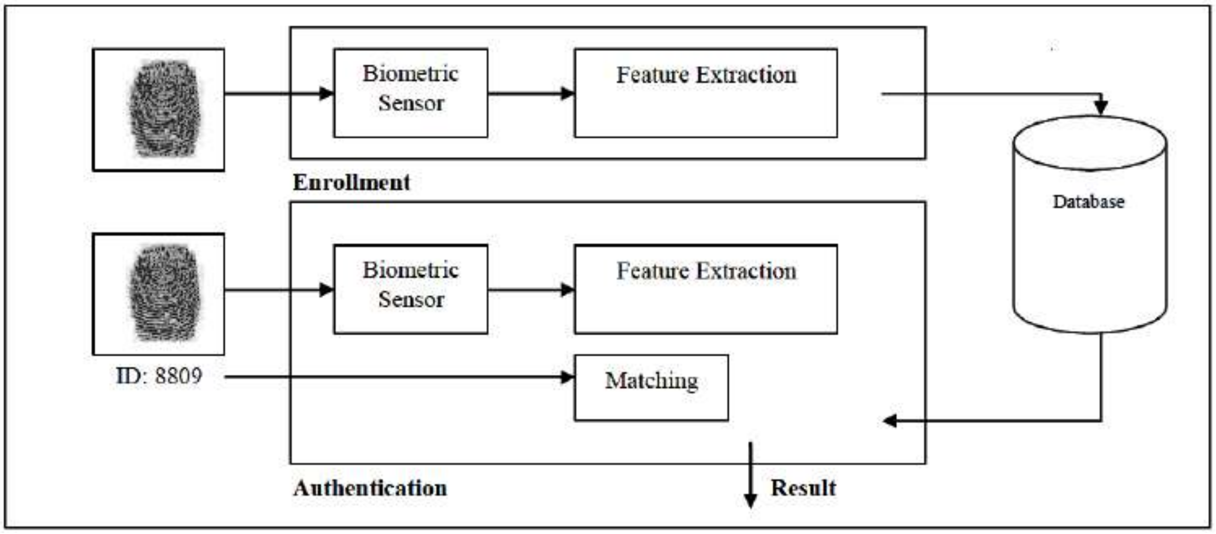

Figure 2 Flowchart of biometric System [2]

Electrocardiography (ECG) is a description of detecting the electrical signals from the cardiac beat and is generally employed for diagnosis of cardiac dysfunction if any. Data is collected/recorded using electrode placed on different locations over the body for a specific period. The movement of cardiac muscles is recorded in the form of electric signals. Recently, ECG has also been added in the group of biometric human identification methods. The electrical signals produced by the heart is employed in the identification of the person.

Biometric identification techniques built on ECG falls into two categories: fiducial and non-fiducial. Also, some techniques are a mixture of fiducial and non-fiducial methods and referred as partially fiducial methods. Fiduciary methods employed latency and amplitude characteristics extracted from cardiac signals (P-QRS-T complex). Characteristics mentioned above are extracted from ECG signals during training or registration phase and are stored in the database. The stored data is employed during the identification/authentication phase for comparison with the signals received at that instant. The comparison of data (features extracted from ECG signals) received at that instant and data stored in databases leads to a decision. The difference between fiducial and non-fiducial methods is established on the features obtained from ECG signals for decision making of the identification process. For instance, non-fiduciary methods extract characteristics in the frequency domain or use values of global patterns of heartbeat signals as characteristics.

The existing biometric identification methods based on ECG also have limitations. There is huge potential in ECG based identification methods. However, there is a dire need to stretch the boundaries of these methods to enhance its utilization and reliability. In the present study, an adaptive technique based on neural network is proposed. Firstly, The ECG signal is filtered through a band pass filter. Then, features are extracted from the filtered data, and a hybrid data set is used that contains wavelet entropy, sample entropy, and ARIMA. Lastly, the neural network is employed to classify the signal.

The document is organized in the following sections. Chapter 2 presents the previous work related to biometric person identification. The methods employed in this study has been briefly described in chapter 3. Chapter 4 contains an explanation of the experimental setup and data acquisition system. Results and discussion are presented in chapter 5. Chapter 6 offers insight into the challenges related to the implementation of the proposed technique and future work.

1.2. Summary

This study presents a new approach for the biometric identification founded on ECG signal using hybridization of different features and Radial Basis Function Neural Network (RBF-NN). Three different features, namely ARIMA, Wavelet Entropy, and Sample Entropy, are extracted from an ECG dataset. The proposed technique uses ECG signals from PTB data set, preprocess the signals using Butterworth band-pass filter. Three different types of features, namely sample entropy, wavelet entropy, and ARIMA coefficients, are extracted from de-noised and pre-processed ECG signals. The hybrid features are inputs to RBF-NN for classification and person identification. The features are then fed to an RBF-NN to identify different individuals. In the past, these features were used individually for person identification. This study presents an approach for person identification by hybridization of the above-mentioned features. The proposed approach shows promising results with an accuracy of 99.50% to identify 55 individuals correctly.

2. LITERATURE REVIEW

This chapter presents a brief discussion of various methods that have been used in biometric person identification. A comparison of techniques relevant to this study is also provided in the chapter.

Qibin and Zheng [4] presented a method for feature extraction. Preprocessing of the data, feature extraction of the data, and classification of electrocardiogram signals were three main components of the system presented in their study. Wavelet transform and autoregressive modeling were employed during the extraction phase. Classification of different ECG signals was achieved using support vector machine and Gaussian kernel. It was reported that the accuracy of their numerical simulations for the classification of singles was up to 99.68%.

Tadejko and Rakowski [5] presented a method for feature extraction using Kohonen self-organizing maps (KSOM) and Learning Vector Quantization (LVQ). ECG data was obtained from the MIT-BIH record as per the recommendations of the ANSI standard. Mathematical morphology was employed for the preprocessing of the data/signals. They compared two approaches for categorization of annotated QRS complexes. The first one employed the original ECG morphology feature whereas the second one was based on a preprocessed feature of ECG morphology. Authors reported that recognition of beats were improved with the preprocessed ECG signals.

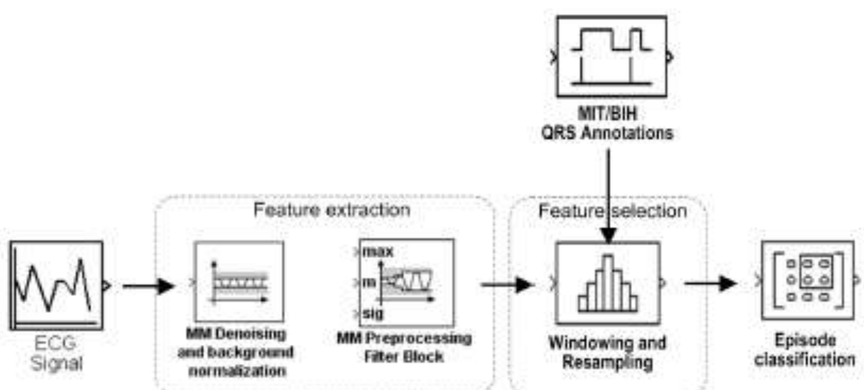

Figure 3 Flowchart of Biometric Technique [5]

Emran et al. [6] proposed a method of feature extraction employing discrete wavelet transformation (DWT), and for classification (of ECG signal) Neuro Fuzzy Model was used. For ECG data, heart sound was recorded from patients, and also the data from Physio Bank was used, simultaneously. In the preprocessing phase, notch filter, as well as band pass filter, were employed to remove the noises, including the power line noise from the ECG signals. Converter neural network was found to be less sensitive towards morphological changes in the ECG signals characteristics and noises as well.

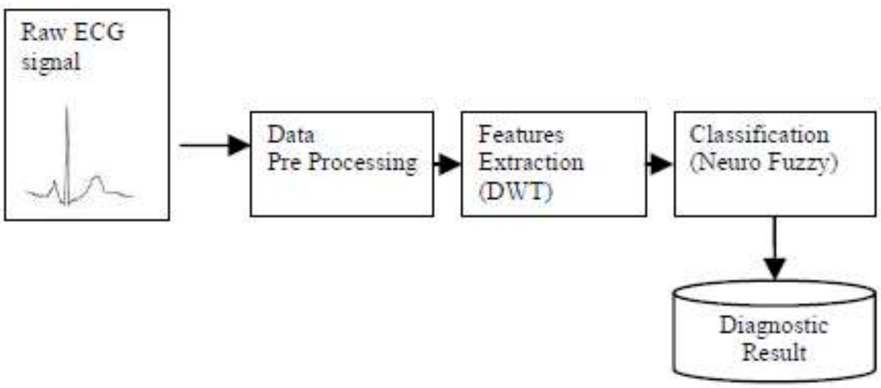

Figure 4 Block Diagram [6]

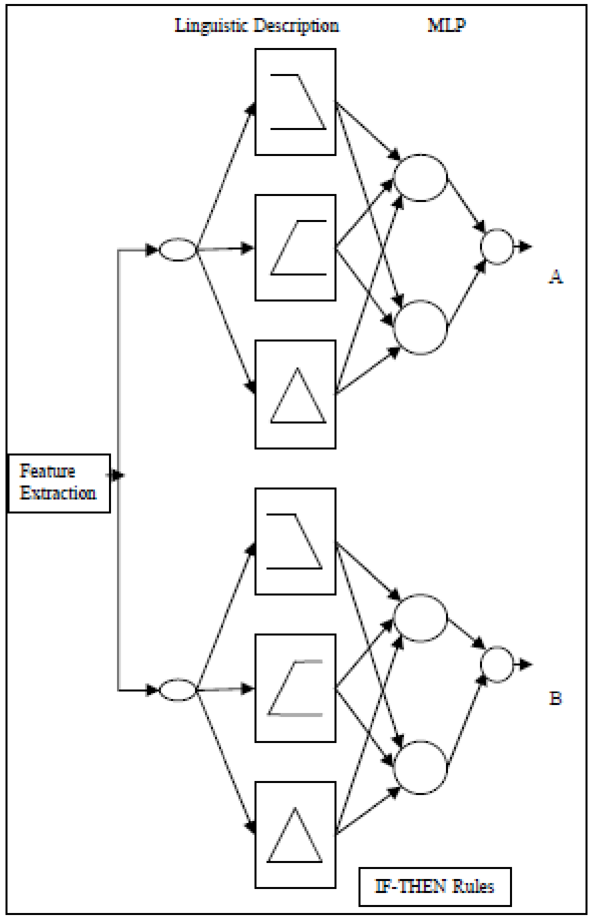

Figure 5 Neuro Fuzzy Feed Forward Structure [6]

Bassiouni et al. [7] presented a method of identification using ECG. The approach presented by the authors were comprised of four steps. The first step was data acquisition, and the rest of the three were the same as discussed already, i.e. preprocessing, feature extraction, and classification of signals. The data set was from the MIT-BIH data set of ECG. Feature extraction was made using autocorrelation and discrete cousin transformation (AC/DCT) and for classification artificial neural network (ANN) was used. It was reported that the accuracy with the use of ANN was found to be 97% in the classification of signals.

Vuksanovic and Alhamdi [8] proposed and evaluated a new method for automatic analysis of ECG signals used for biometric identification by using Autoregressive (AR) modeling. ECG data set was obtained from the standard data set of MIT-BIH. First, preprocessing was done to remove the unwanted signal components and noise. Butterworth filter was used first to down sample the raw ECG signal and passed it through the 6th order Butterworth filter. The output from filter mentioned above was sent to the power line interference filter. A 10th order Butterworth filter was also employed for the elimination of high-frequency components as well as the noise from the signal. Then, QRS detection was performed using a filter bank method. For feature extraction and classification, the AR model was employed. The analytical features were taken from the QRS detection. For model features, the AR coefficient was found to be used for the classification of the signal. K-nearest neighbor was employed for the classification phase using AR modeling features.

Carmen et al. [9] introduced an approach using the Hadamard Transformation (HT) and KNN for the feature extraction and classification. The source of dataset was the MIT-BIH. A band pass filter was employed for the removal of noise from the signals and also to get the particular signal that was required. For feature extraction, Hadamard transformation was used whereas the classification of signals was achieved using KNN. Boumbarov et al. [10] proposed a method of identification using ECGs using radial basis function neural network (RBFNN). A high pass band filter with zero phase digital filter was used for noise reduction in the signals. The hidden Markov model (HMM) was used for segmentation purposes. The aim of segmentation was that to

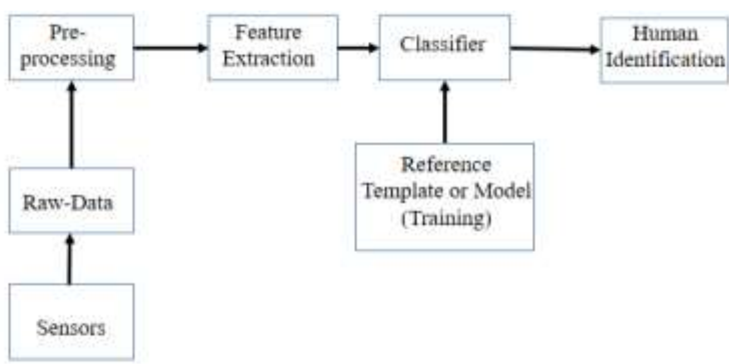

Figure 6 Flow chart of Hadamard Transformation (HT) based Biometric Verification System [9]

assign the signal sample to each class. Dimension reduction was achieved using principal component analysis (PCA) that concentrate the discriminative information in low class of coefficient. To improve and separate the selected features, LDA was applied. For the classification, RBFNN is used in this paper.

Ye et al. [11] presented a method_using wavelet transformation (WT), and for the classification, the support vector machine(SVM) was employed. The multi-lead fusion was used to compare the classification set. During preprocessing, they employed the band pass filter to remove the baseline noise and get the signal as desired. For the feature extraction, Daubechies wavelet was used to find the wavelet coefficients for carrying out the wavelet analysis. Dimension reduction was achieved using the principal component analysis (PCA). Gaussian radial basis function (RBF) kernel SVM was applied, and two classes were made. Multi-lead fusion was used to compare the classes and classify the data in this paper.

Shen et al. [12] proposed a method PLR-DTW. In their method, Piecewise Linear Representation (PLR) was employed to secure the important information from the signal. Dynamic Time Warping (DTW) was used to find the similarity measure of the two segments. Butterworth band pass filter was employed to remove noise from the signal and to obtain the desired signal. PLR was used for feature extraction. The advantage of using the PRL technique was to keep the major minima and maxima and also to discard the minor fluctuations. Moreover, it also reduces the dimension of data, if necessary. DTW was used for the classification, and to find the Euclidian distance. For testing, a threshold was set, and the results were rejected if the value appeared to be greater the threshold.

Sasikala and Banu [13] proposed a method of the classification using the template matching from correlation coefficients(CC) and mean distance measure. Fig. 2 shows the flow chart of the processes discussed in the study. The data set used was taken from the MIT-BIH. Baseline drift was removed using the median filter while for removing the noise. Discrete wavelet transformation (DCT) was used. In DCT, first, it divides the signal into different subbands. Then DCT alters each wavelet coefficient based on the threshold specified and reconstruct the signal free of noise. DCT also helps in finding the QRS detection of the wave. The selected features were found from the amplitude of the signal using the minima and maxima of the signals. Fig. 3 shows the features which were selected.

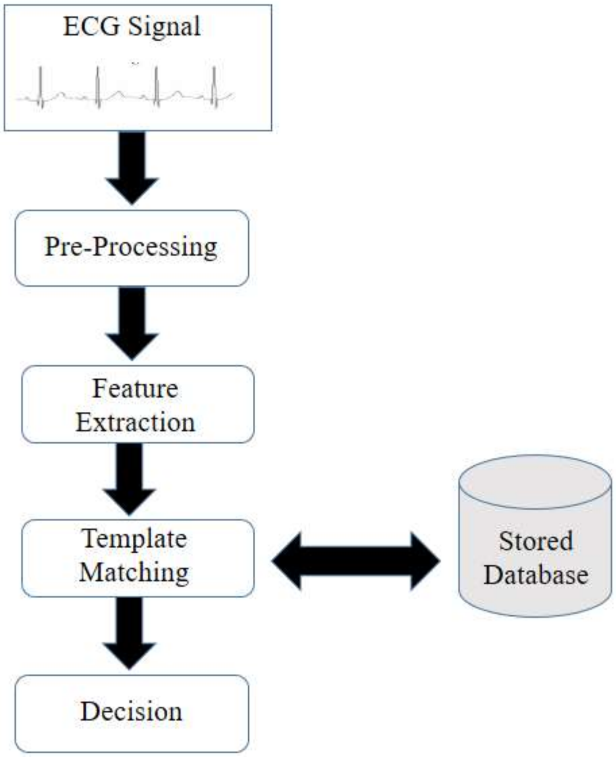

Figure 7 Flow Chart of Template Matching For Biometric Verification [13]

During the identification process, the unknown signal was compared with the data saved in the database using template matching. In CC the coefficients were found if the average of the coefficients were more than 85%, resulting a match between the template and subject. The mean distance was calculated from the amplitude features and compared with the features stored in the database.

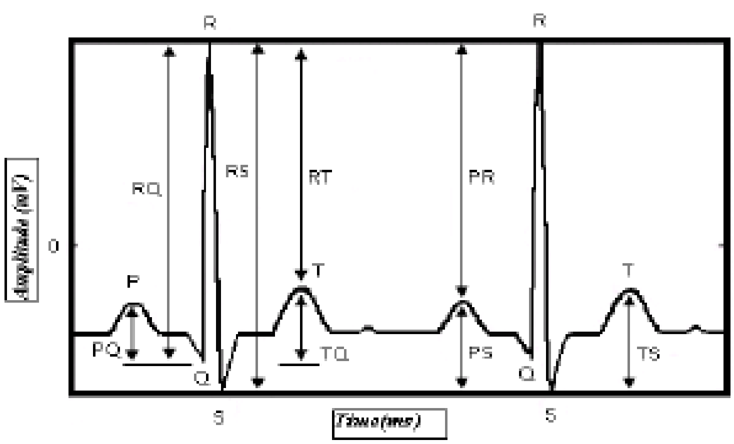

Figure 8 description of amplitudes of various sections within an ECG [14]

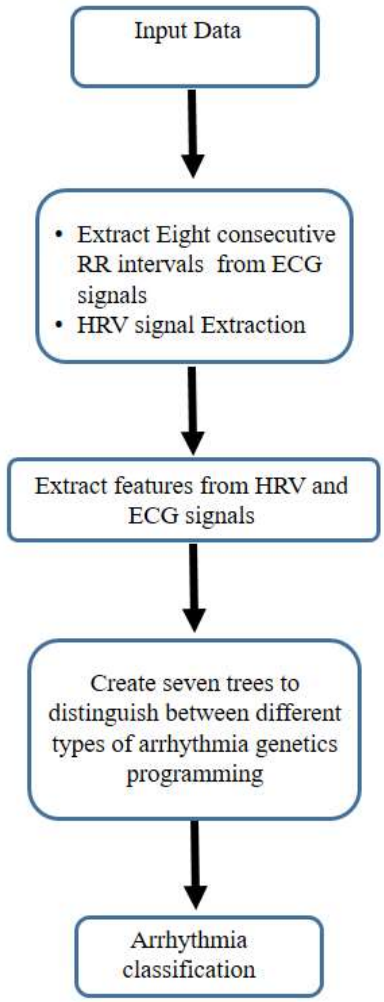

Figure 9 Flow chart of genetic programming. [14]

Masih et al. [14] presented a method of cataloging from ECG or HRV signals using genetic programming. Genetic algorithm is used to find the seven classes of arrhythmia, i.e. including normal beat, left bundle branch block beat, right bundle branch beat, premature ventricular contraction, a fusion of ventricular and normal beat, premature atrial contraction and paced beat. Flow chart of processes involved in the aforementioned study is presented as Fig. 4. The ECG data set was taken from the MIT-BIH. Eight sequential R-R intervals were taken from the ECG signal, and HRV was calculated from the time interval between two consecutive R –wave. To extract the features, first HRV features were extracted. Frequency domain, nonlinear parameters, and time domain were the features extracted from the HRV. For ECG signal fractal dimension, Lyapunov exponent and Hurst exponent were found as feature extraction. From the features, seven trees were made, and a genetic algorithm was adopted to categorize the classes.

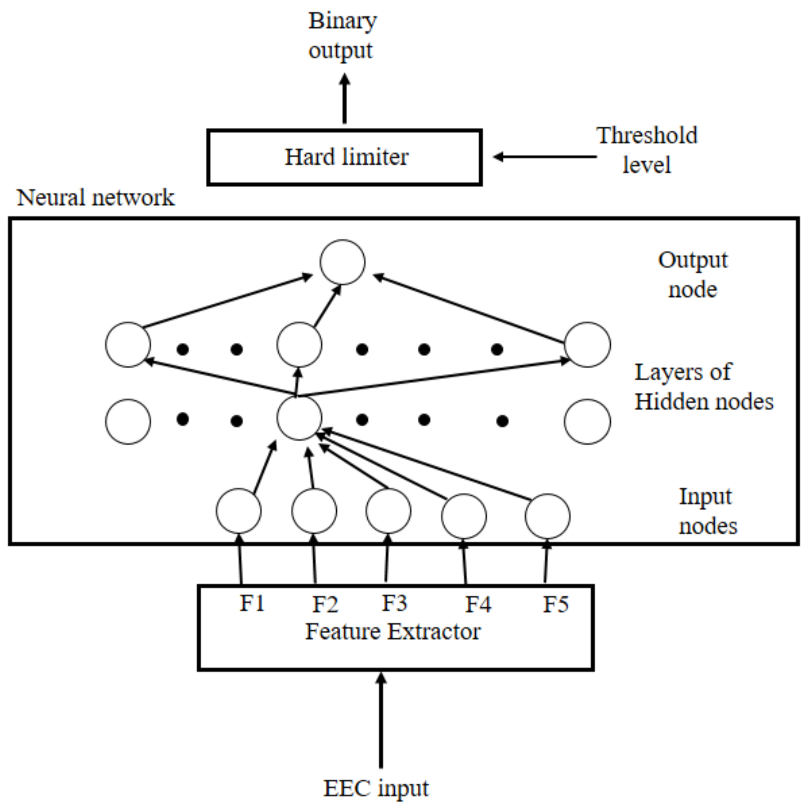

Figure 10 Structure of Back Propagation Neural Network [15]

Yeap and Johnson [15] proposed a method of classification using the back propagation neural network. American Heart Association's (AHA) data set was used. From the QRS detection, five features of the signals were extracted. A neural network was applied for the classification. The architecture of the NN is presented in Fig. 5. The five features were used as input of the NN. For the training purposes, the inputs moved to the hidden layer with the weights applied to them and later moved to the single output. Moreover, a threshold was established to classify the ECG signal.

Anderson et al. [16] presented a method based on the discriminating mental tasks using EEG from single and multi-channel AR model. EEG signals were generated from the brain, and their mental tasks were performed. The data was collected using Electro-Cap elastic electrodes. The four subjects were analyzed and two tasks were assigned to subjects. First was a baseline task, and second, was a math task. In the baseline task, subjects relaxed and did not perform any mental task. While in a math task subject had to do menial tasks like calculation ***with*** any physical movement. For the six order Scaler AR coefficients, the Burg method was used to extract. For multivariate AR coefficients, the Levinson algorithm was used. For the classification error, the back-propagation neural network was used with a single hidden layer.

Ouelli et al. [17] proposed a method of feature extraction using the Autoregressive (AR) model, and classification was made using Quadratic Discriminant Function (QDF). In their study, six elements: normal sinus rhythm, premature atrial contraction, premature ventricular contraction, ventricular tachycardia, ventricular fibrillation, and supra-ventricular tachycardia was analyzed of each ECG signal pattern. MIT-BIH data set was used. First, for noise reduction, the least square filter was employed. AR coefficients were found for the feature extraction. Burg's algorithm was employed to extract AR coefficients for all six elements produced by each data pattern. For the classification QDF was applied to classify the six elements.

Biel et al. [18] studied a SIMCA model for the classification of the signal. The data was collected using the SIEMEN model. To reduce the data, Principal component analysis(PCA) was used. Later, SMCA was applied to discover the similarities among the test object and classify the object.

Safie et al. [19] introduced a method of the classification using the Pulse Active Width (PAW). The data set recorded from the PTB database. Fig. 6 presents the block diagram regarding working of PAW process.

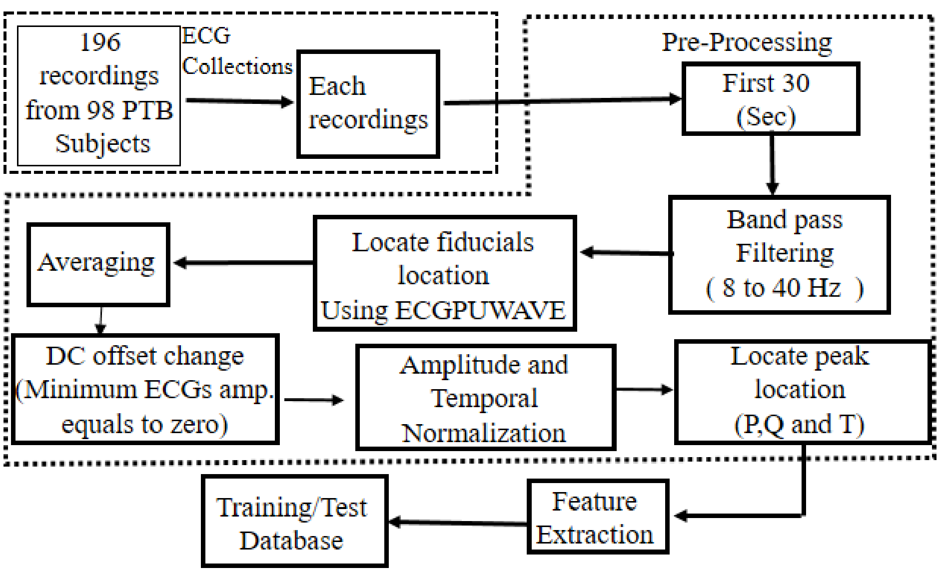

Figure 11 Working of PAW Process. [19]

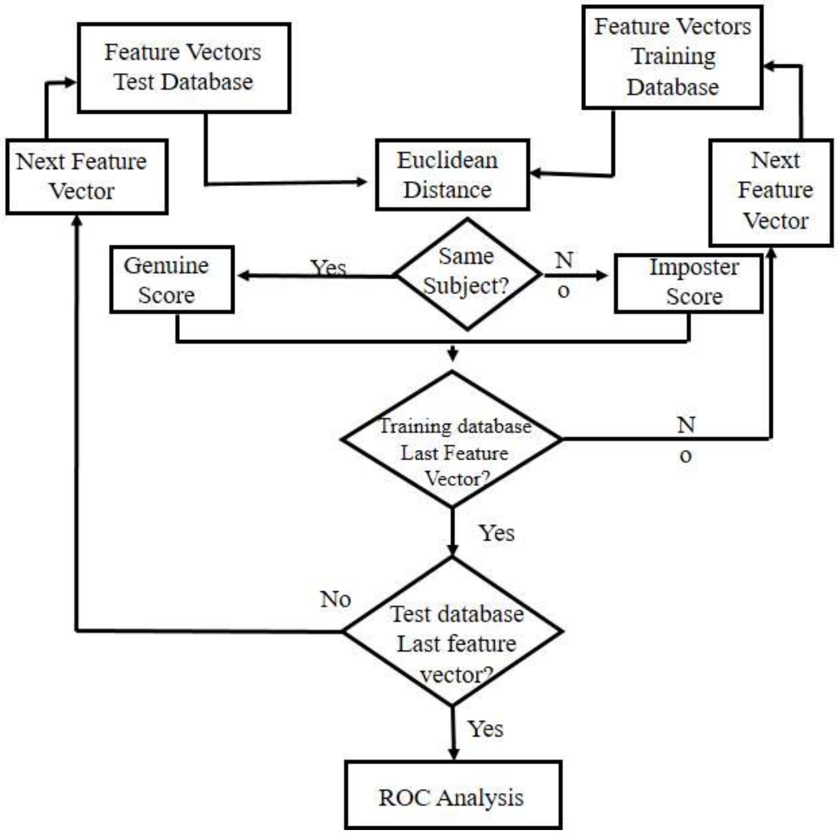

Figure 12 Flow chart of classification [19]

After preprocessing, the bandpass filter was employed to remove the noise and get the desired signal. To approximate the offset and onset P, QRS and T waves ECGPUWAVE was used. Fiducials points were used for the averaging process and amplitude and temporal duration for the averaging the ECG signals. For the local maxima, a peak detection algorithm was used. Afterward, the signals were used for feature extraction. Fig. 7 presents the block diagram of the classification process. First, the Euclidean distance (ED) of the feature vectors and then the feature vectors were subjected to a comparison with the ones from database. If the score is positive, then it was labeled as genuine otherwise imposter. Later, the receiver operating characteristics (ROC) curve was generated that showed the performance.

Jen and Hwang [20] proposed a method of feature extraction using cepstrum coefficients. ANN was used for the classification. ECG signal data was the one from the MIT-BIH database. R-peak was found by the threshold value and moving window. Three methods were employed for feature extraction. The first one was signal segmentation using a Hamming window. The second was linear predict coding (LPC) and was used to find the cepstrum coefficients. Then cepstrum

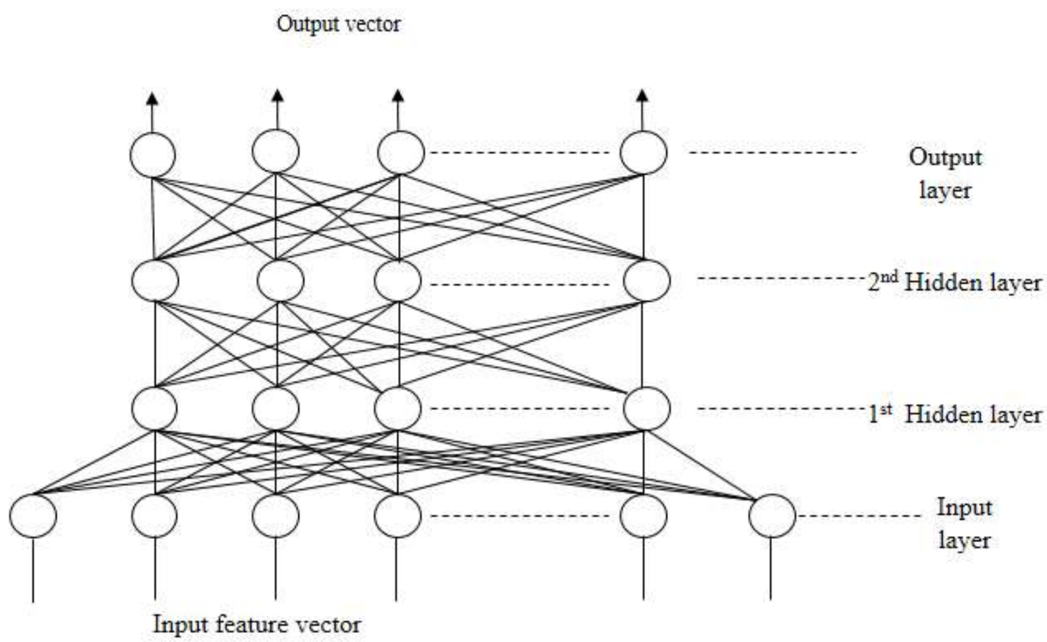

Figure 13 Neural structure of back propagation neural network. [20]

coefficients was extracted. To classify, back propagation neural-network was used. Where the weights were assigned randomly and updated with the error of the backpropagation.

Wang et al. [21] presented an analysis of biometric identification based on ECG. They were first to introduce a feature extraction technique based on analytics, and their technique combined both amplitude and temporal feature. Local information was used for the classification thus, accurate detection of fiducial was important. They claimed that their method performed better than the existing techniques in the literature.

In another study [22], ECG based identification system was proposed using a discrete wavelet for feature extraction. The proposed technique employed biorthogonal wavelet for extraction and decomposition of R-R intervals. Biorthogonal wavelet was used in the wavelet-coefficient strictures. Reduction of these structures was achieved by exclusion of non-informative coefficients. Later, these structures were employed by radial basis function for classification. Their method was found superior in performance over the auto-correlation/discrete cosine transform method.

In a recent study [23], the application of ECG based identification has been increased to gendder recongnition as well. The algorithem was designed so that the very feature used for person authntication was also used for gender recongnition. The classification accuracy was evaluated using various algorithems based on machine learning. It was reported that the ECG based gender recognition accuracy was upto 95.1% using CYBHi database.

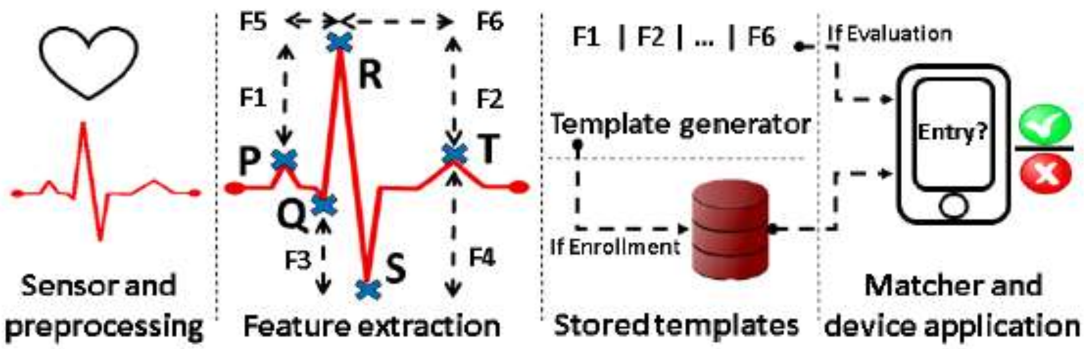

Figure 14 Flowchart of the Biometric System [23]

Hejazi et al. [24] investigated the the effect of various parameters on accuracy of ECG based authentication using Gaussian one-class as well as binary-SVM classifier. They studied seven different scenarios with different data set, feature extractors, hold out, and data labeling. The systematic investigations demonstrated that the feature extractor based on Gaussian KPCA showed highest impact on identification for both classifiers. They reported that one-class classification performed better for verification problem if the number of availbe feature vectors were sufficient enough.

Wu¨bbeler et al[25] proposed a technique using heart vector and simple distance measure for the verification and identification of person using ECG signal. PTB data set was used. Low-pass filter was for the pre-processing. Subjects were divided between sub sets , distance where measured between the sets using the two dimensional heart vector using QRS wave. A threshold was set for the verification between the sets and similarities between the heart wave could not be detect. 98.1% accuracy was achieved.

Venkatesh et al [26]proposed a method using Dynamic Time Warping (DTW) and Fisher's Linear Discriminant Analysis (FLDA) for person verification using ECG signal. MIT-BIH data was used. Two methods were used back to back for the verification. FLDA was used with K-Nearest neighbor for the classification. For more accurate results DTW was applied. The achieved accuracy was 96%.

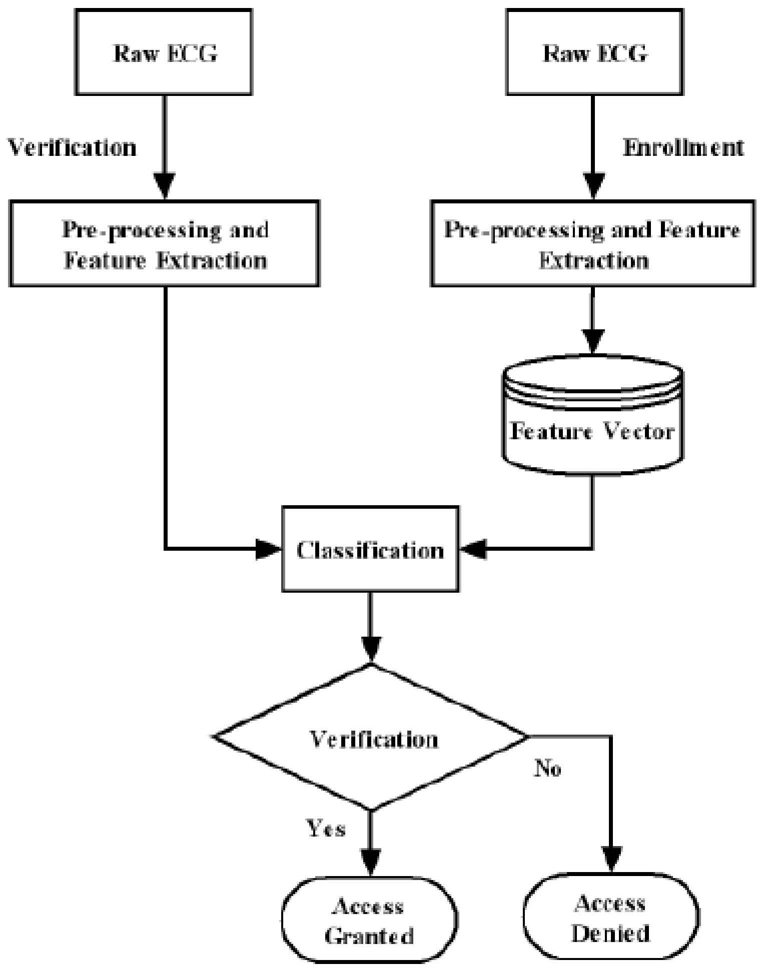

Figure 15 Architecture of the Method [26]

Irvine et al[27] proposed the techniques for the verification of the person heart using signal processing of the ECG wave. 29 subjects were used containing man and female age ranging from 18-45. Data set was filter using the band pass filter. Fiducial points of the ECG wave were extracted. These points were sampled and save in the storage point. Threshold was set and given data was compared with the stored data.

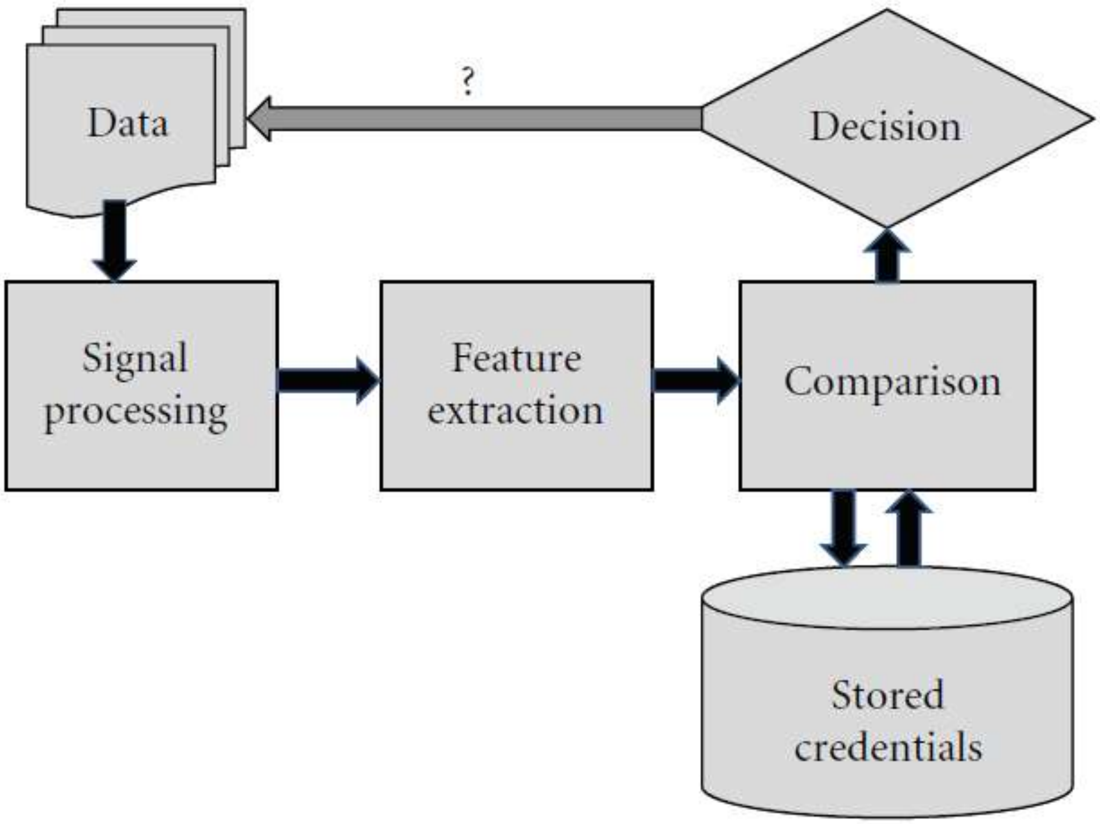

Figure 16 Block Diagram [27]

Chiu et al's[28] proposed method deals with the development of a real-time system for a person's identification using their electrocardiogram(ECG) as it is unique for every individual. It works by extracting signal features by using the wavelet coefficients of one lead ECG signal via discrete wavelet transform. His approach yields 100% verification results for normal subjects and 81% for arrhythmia ones. The false acceptance rate (FAR) and false rejection rate (FRR) were used as a criteria by Chie et al . For normal subjects, the proposed method gave excellent results.

3. METHODOLOGY

This chapter briefly presents the techniques used to fulfill the scopes of the thesis as well as the background theory related to them.

3.1. Electrocardiography

Electrocardiogram [29] presents the graphical record of heartbeat in the time and voltage graph. It should be noted that electrocardiogram is not a direct measurement of cellular domination and prejudice with heart, but its overall membrane in its relative population is likely to make possible changes in their membrane in potential changes. This shows the electrical differences in the heart when dominated by the dehydration and adrenaline cells in the etched and ventricular cells. You can imagine that the heart is suspended within the process. During cardiac cycles, in response to heart-agreements and the ability to take action. It is commonly used to detect cardio diseases like a disorder of the heart. The heartbeat of every person varies with different circumstances like age factor, exercise, with different diseases.

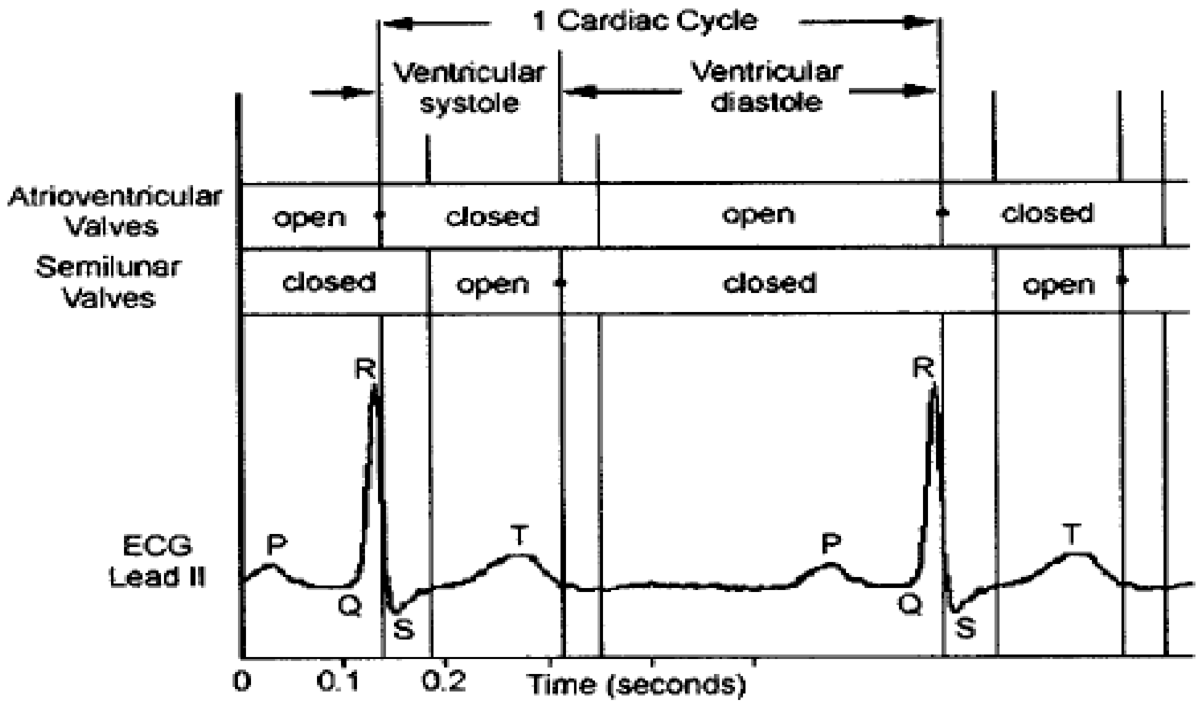

Figure 17 Description of one cardiac cycle [25]

An ECG represents the variation of voltage with time and units of voltages and time are taken as millivolts (mV) and seconds, respectively. Leads are connected to the body to record the CEG. An ECG portrays a combination of waves and peaks, and each segment of the graph represents a certain event within the cardiac cycle. Electrical depolarization makes the cardiac to contract just like other muscles of the body. At the beginning of the cardiac cycles, spontaneous depolarization of the sinoatrial node occurs. The wave of depolarization from the sinoatrial node spreads through the right atrium to left atrium across the inter-atrial septum. However, this wave is not sensed by the surface ECG. The reason for surface ECG unable to detect the wave from the sinoatrial node is an inadequate number of cell in the sinoatrial node. Theoretically, a larger number of cells in the sinoatrial node can generate an electrical potential having an adequate amplitude that can be detected by the electrodes. In the practical situation, the signal generated by the sinoatrial node is dissipated within the conductive medium.

The depolarization of atria generates P waves on ECG. The duration of P-wave is generally around 80-100 ms. P waves represent not only the depolarization of the right and left atria but also the initiation of atrial contraction. Depolarization of atria and P wave, both ends simultaneously. Afterward, the signal on ECG returns to baseline. Approximately, 160 ms after the initiation of the P wave, the QRS complex on ECG appears. The QRS complex represents the start of ventricular contraction that lasts around 60 – 100 ms. First negative deflection after the p wave is regarded as Q-wave, whereas, the positive deflection of larger magnitude right after the Q-wave is referred as R- wave. If a negative deflection appears on ECG, right after the positive peak of R-wave, it is termed as S-wave.

Atrial contraction ends with the QRS complex, and the atria begin to repolarize. Again, the repolarization of atria is masked by the tissues and is not detected and displayed in the ECG. ECG signal appears to return to baseline. After the contraction, the ventricles repolarize and results in the generation of T wave on ECG. Normally, the T-wave is considered as the last electric potential signal during a cardiac cycle, and it is followed by the next cardiac cycle starting with P-wave.

There are several important regions, or we can set parameters from an ECG. The prominent ones include P-R interval, S-T segment, and Q-T interval. Each signal has a unique beginning and ending. For instance, the P-R interval comprises of time from the initiation of P-wave to the start of QRS complex. Normally, the time of P-R interval lies in the range of 120-200 ms. In terms of physical phenomenon, the P-R interval reveals the amount of time taken by the impulse during its travel from atrial excitation, atria, nodes, and the remaining conduction system. The second parameter, i.e. S-T segment, describes the amount of time in which ventricles stay completely depolarized and also contracts. S-T wave duration consists of time from the end of the S wave to the beginning of T-wave. Another important parameter from ECG is Q-T interval taken from the start of QRS complex to the completion of T-wave and normally last approximately 400 ms. In the ECG, the most observable peak is of QRS complex and a major reason for its easy to observe is the higher peak and shorter duration than rest of waves. The higher peak and shorter duration of the QRS complex are because ventricular depolarization materializes over a large number of cardiac cells/tissues. Moreover, the process of ventricular depolarization appears to be more synchronized than that of atrial depolarization/ventricular repolarization. It should be noted that ECG does represent the variations in cardiac electrical activity over time. However, it does not implies general cardiac contractions/relaxations as contraction/relaxation time scales are slightly longer. Fig. 3 describes the relations of ECG waves with other events during a cardiac cycle.

3.2. Butterworth Band Pass Filter

The band pass filter[30] is generally employed to get rid of noise and unwanted signals from a given signal. A band pass filter is installed in the system to achieve a flat frequency response in the passband. Butterworth band pass filter. According to Butterworth, an ideal filter should be the one that can filter all the unwanted noises from a given signal. Butterworth filter can be regarded as a close approximation to an ideal filter given the right values and increased number of filter elements. Noise is removed using a combination of high and low pass filter. By adjusting these high and low values of filters, desired values can be obtained.

One of the characteristics of the Butterworth filter is its response in the passband and stopband. Generally, the normalized frequency response of all the first-order lower pass filter is the same. A first-order filter provides a response at -6 dB per octave and doubling (tripling) the order of filter results in doubling (tripling) the response. Butterworth filter distinguishes itself due to monotonic change in magnitude function with ω. The magnitude function in Butterworth filter decreases monotonically with ω. Moreover, the presentence of this shape for higher orders is the uniqueness of the Butterworth filter.

3.3. Wavelet entropy

The method of wavelet analysis[31] depends on the introduction of a suitable basis and classification of the signal by distributing the amplitude in the basis. In forming a proper orthogonal basis of wavelet, wavelet has an advantage that any arbitrary function be decamped uniquely. Moreover, the decomposition of so-called arbitrary function can be inverted. It should be noted that the wavelet is an oscillating function that is not only smooth but also vanishes quickly, and possesses the property of good spatial and temporal localization. A wavelet family $\gamma_{a,b}$ comprises of elementary functions created using dilation and translation of a parent wavelet.

γ (t):

$$\gamma_{a,b}(t) = |a|^{-\frac{1}{2}}\gamma(\frac{t-b}{a}) \tag{1}$$

Where $a, b \in \Re$, $a \neq 0$ and a represents scale, b represents the translation parameters, and t represents the time. An increase in “a” results in narrowing the wavelet further. Therefore, one can get a unique analytical pattern. Moreover, the replication of pattern at different scales with variable temporal localization. Wavelet Entropy (WE) provides a criterion to analyze and compare probability distribution. We define the total WE as

$$S_{WT} = S_{WT}(p) = -\sum_{j<0} p_j . \ln[p_j] \tag{2}$$

The wavelet entropy describes the degree of order/disorder of a given signal and enables us to get valuable information regarding the dynamical process that associates with the signal provided. For instance, a well-ordered process can be considered as a periodic signal with mono-frequency. Such a signal shows a narrow band spectrum. Such a signal will greatly be resolved using a single wavelet resolution level. In other words, all the relative wavelet energy of wavelet resolution level representing the signal frequency would be almost one while for other the resolution levels it would be close to zero. Let’s consider another process that is totally random and can also be represented by a disordered signal. Most likely, such a signal will contain a contribution from various frequency bands. Also, it is likely to happen that the contributions from various frequency bands may be of the same order. As a result, the wavelet entropy will take their maximum values due to the equal contribution of relative wavelet energy from different resolution levels.

3.4. Sample Entropy

Entropy is described as a loss of information time series or signal. Entropy is used postural control physics change activities as well as other movement measures works. Pincus introduced a method to measure orderliness related to Kolmogorov entropy. The method could be used for the analysis of clinical data that is usually noisy and typically short. The method was named as approximate entropy (ApEn). However, the ApEn results were found inconsistent (Joshua). Later, Richman and Moorman [32] proposed and implemented a new method named SamEn representing the word sample entropy. Authors claimed that the proposed method provides more consistent and improved results than that from ApEn when applied to clinical data.

SampEn can be briefly described as the method based on majorly three parameters N, m, and r and these parameters should be kept constant for one set of calculations. Where “N” represents the length of time series, “m” represents the length of sequences that are subjected to comparison, and “r” represents the tolerance, i.e. an allowable difference in the sequences to be matched. Usually, tolerance is set as r x SD. SD represents the standard deviation of the data set. The advantage of using r x SD tolerance is that it allows the comparison of data sets with different amplitudes. Authors of SampEn employed the value of SD = 1 for their calculations. SampEn can be described mathematically as the negative natural logarithm of the conditional probability such that the two given sequences that are similar for m (length of data set) points also remain similar at the next point. It should be noted that the calculation of probability does not include self-matches.

The similarity of time series can be estimated from the value of SampEn. For instance, a lower value of SampEn is an indication of self-similarity in the data sets. It is worth mentioning that SampEn is a simpler and faster method than ApEn. Roughly, SampEn is two times faster than ApEn and also capable of eliminating self-matches. Furthermore, SampEn does not heavily depend on the length of the record and also shows relatively better consistency.

3.5. Autoregressive Integrated Moving Average (ARIMA)

ARIMA is regarded as generalization of autoregressive moving average and are employed to better under the given data or to forecast the points in the series. A standard notation of present model is ARIMA (p,d,q). Here, “p”,”d”, and “q” are the parameters of the model and are specified using integers to indicate the kind of ARIMA is being used. In the present work, we divided ARIMA into tree steps: identify, estimate and forecast. Each of aforementioned steps is explained briefly

1. Identification step contains the “IDENTIFY” statement. This statement specifies the response series and points out the suitable ARIMA model to be employed. The statement of IDENTIFY takes input of time series that are also going to be employed in the later statements, differencing them. Then, computations of auto-correlations is performed and partial, inverse, and cross correlations are included in the computations. The analysis of output from IDENTIFY statement points out multiple suitable ARIMA model.

2. The second stage of diagnostic includes the ESTIMATE statement to describe the ARIMA model and also to estimate the parameters of the model. This statement also generates diagnostic statistics that helps in judgment of adequacy of model. Problems indicated by the diagnostic tests suggests the use of other possible ARIMA models and repeat the estimation and diagnostic steps. Moreover, test for white noise residual are carried out to check the possibility if residual series contains additional useful information that can be utilized by even a more complex model.

3. In the last step, we employed the FORECAST statement to predict the values of the time series. Also, it generates confidence intervals for the forecasts from the ARIMA model produced by the preceding ESTIMATE statement.

ARIMA consist of three features Auto regressive (AR), Moving Average (MA) and integrated (I) part. AR model gives variables that changes with the regresses depends on the values, lagged or prior. MA indicates regression error in the linear combination that shows that error terms occur contemporaneously and occur in past various time. The ‘I’ part show difference of the values and previous values that are replaced. These features are utilized to model fit the data. The mathematical representations given as following:

$$\varphi(L)(1-L)^{d}y_{t}=\theta(L)\varepsilon_{t} \tag{3}$$

$$\left[1-\sum_{i=1}^{p}\varphi_{i}L^{i}\right](1-L)^{d}y_{t}=\left[1+\sum_{j=1}^{q}\theta_{j}L^{j}\ ]\varepsilon_{t}\right] \tag{4}$$

Whereas p, d and q shows the integer values of the AR, MA and I, and d indicates the level of difference.

3.6 Radial Basis Function Neural Network (RBF-NN)

Radial functions[33] are referred to a particular class of function that possess the unique feature of monotonic increase/decrease in the response time with change in distance from a central point. The parameters of model includes the central distance, scale, and shape of radial functions. In case of linear function, all the parameters of model are kept fixed. Typically, a radial function of Gaussian nature is employed with scalar inputs:

$$h(x)=\exp\left(-\frac{(x-c)^{2}}{r^{2}}\right) \tag{5}$$

Radial function are the function from a class of function that works well with both linear and non-linear models as well as network of single layer or multilayer. The traditional radial basis function networks associated with single layer network is described schematically in Fig. 10

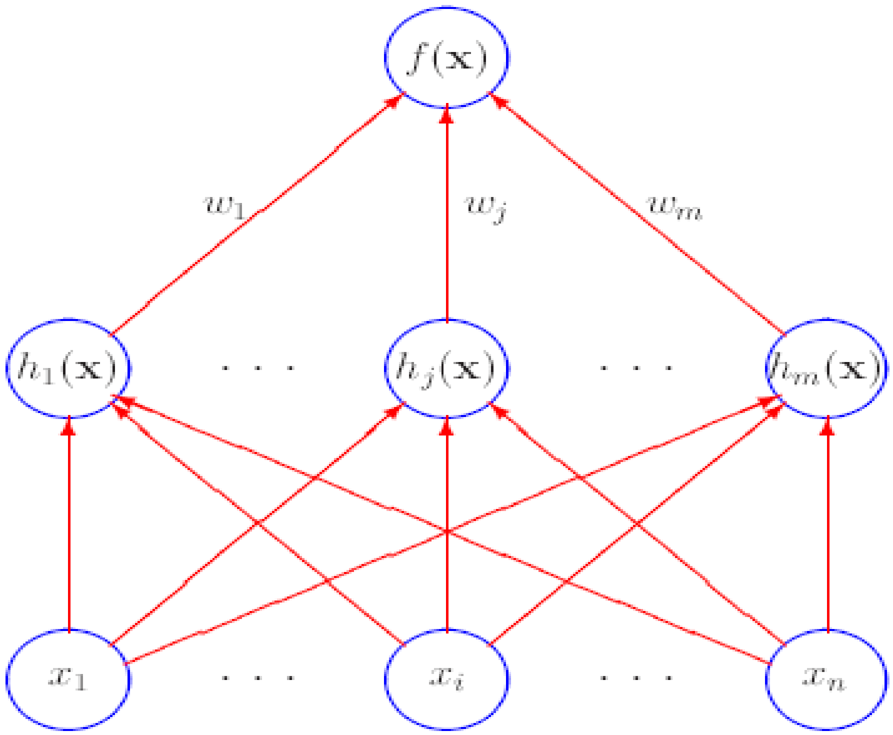

Figure 18 Neural structure of Radial basis neural network [28]

RBF-NN structure comprises of three-layer network in which the input layer gets the input variables and does not carry out any assignment. Hidden layer converts input space to higher dimension through charting to separate linearly all the non-linear patterns. The output layer performs operation with a linear output using a simple weighted sum technique. The traditional RBF-NN converts a vector 'x' of 'n' input by forward feeding 'm' basis function h(x) by combining linear results to weight wj (j=1,……,m) that outputs 'f(x)'.

A radial basis function network would be considered as nonlinear if it can undergo a change in their size or if the number of hidden layers is more than one. In the present work, we focused on the network with single layer having functions that are fixed in both size and the position. Non-linear optimization is employed for two reasons. First, for the regularization parameter/parameters in the ridge regression. Secondly, non-linear optimization is used in forward selection of optimal subset of existing basis functions.

4. PROPOSED TECHNIQUE

4.1. Overview

The proposed technique uses ECG signals from PTB data set, preprocess the signals using Butterworth band-pass filter. Three different types of features, namely sample entropy, wavelet entropy, and ARIMA coefficients, are extracted from de-noised and pre-processed ECG signals. These hybrid features are used as inputs to RBF-NN for classification and person identification

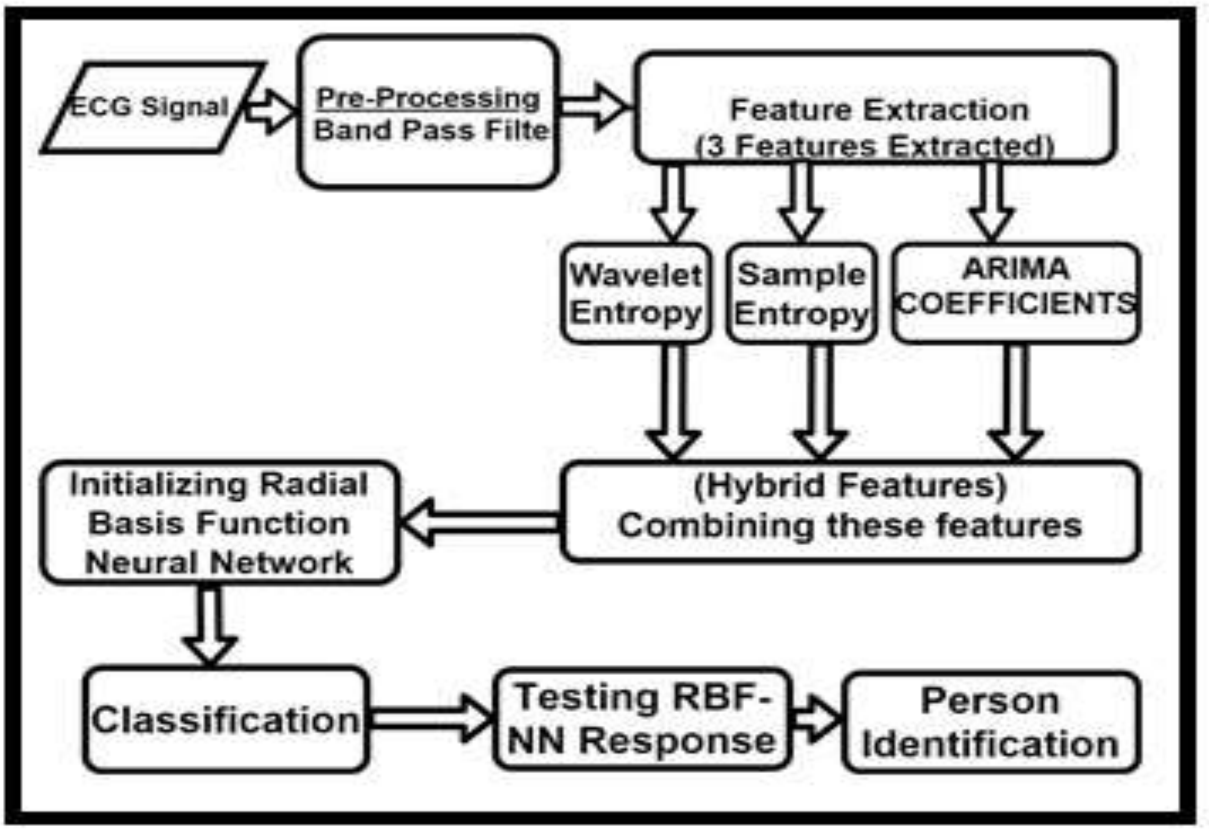

Figure 19 Flow chart of hybrid methodology.

4.2. ECG Data Set

Data set employed in the present study is Physikalisch-Technische Bundesanstalt (PTB) [34] taken from the physio bank. PTB data set has following Specification:

- Number of input channel are sixteen where fourteen channels are used for ECG, one for respiration and one for the line voltage.
- Input voltage = ±16 mV and the compensated offset voltage range up to ± 300 mV
- The input resistance of 100 Ω (DC)
- A resolution of 16 bit with 0.5 μV/LSB (2000 A/D units per mV)
- Bandwidth range is 0 - 1 kHz
- Noise voltage: max. 10 μV (pp), respectively 3 μV (RMS) with input short circuit
- Skin resistance is recorded online
- Recording the level of noise during signal/data collection.

This database consists of 549 records from a total of 290 subjects that include both men and women of different age groups. Out of 290 subjects, 209 subjects were men and the age of male subjects ranges from 17 to 87 years with a mean age of 57.2 years. On the other hand, only 81 female subjects were added into the dataset with a mean age of 61.6. For one female and fourteen male subjects, there was no record of the age. For every subject, data was recorded multiple time, i.e. 1-5. Each record in the data set contains fifteen signals that were recorded simultaneously. For precisely, twelve conventional leads and three frank lead. The digitization of each signal is achieved at a rate of one thousand samples per second with a resolution of 16 and range of ± 16.384 mV. In the present work, we employed the ECG signal of fifty-five persons for the Biometric Verification of the person.

4.3. Pre-Processing

The first process is pre-processing, removing the unwanted noise from the ECG signal. Below 0.5Hz there is the noise of lung respiration and above 45 Hz noise of muscles are recorded. Frequency of the ECG signal lies between 1Hz to 40Hz, peak values of the wave P Q R and S lies between 1 to 40Hz. For this purpose, the Butterworth band pass filter is used with the frequency of 0.5Hz to 45Hz.

4.4. Feature Extraction

Features are extracted from the filter data. 3 featured are used in this process, namely:

- ARIMA
- Wavelet Entropy
- Sample Entropy

ARIMA model is applied to extract feature. It includes 25 Autoregressive (AR) coefficient and 25 Moving Average (MA) coefficient from the ECG signal. Filtered data is divided into 50 segments to apply wavelet entropy on the ECG signal. Lastly, sample entropy is applied to the filtered ECG signal to get the last feature. All these three types of features are combined together to form the hybrid feature set

4.5 Classification

The classification has been performed through RBF-NN using hybrid features extracted from ECG signals. The input layer is fed with hybrid features, and hidden layer consists of neuron with Gaussian activation function, and the output layer consists of corresponding patterns.

Dataset consists of two parts; training data and testing data. Out of dataset, 70% is used as training data, and the trained network is tested against the remaining 30% of the testing dataset. The network is trained against the given arithmetic patterns to minimize the Mean Squared Error (MSE). RBF-NN has the capability to select the appropriate amount of hidden neurons to achieve the pre-set value of Mean Squared Error (MSE).The network is trained using 17 input and 55 output neurons. Training parameters of RBF-NN are shown in Table 1.

Table 1 Summary of training parameters for RBF-NN

Training Parameter	Value
Goal MSE	0.0001
Spread	2
Maximum Neurons	3000
DF	25

Training involves the updating of weights to minimize the MSE; once the network is trained for the set stopping criteria, updated weights are then fixed and are used to analyze and compare with testing and validation data. RBF-NN with preset values of input and output neurons selects 2784 hidden layer neurons to achieve the preset MSE of 0.0001.

5. RESULTS AND DISCUSSION

5.1. Accuracy

Accuracy depends on True positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). TP shows the actual predicted values; if the value of the actual class is positive, then the predicted value is also positive. TN is the negative predicted value, which means the actual class value is no then predicted value is also no. FP are the values when the actual class shows positive, but predicted class shows negative values. FN represents the values when the actual class is negative but predicted values are positive. Accuracy shows the performance of the classifier, which is given by the equation below.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{6}$$

RBF-NN showed a maximum of 99.50% classification accuracy with 17 input neurons, 2784 hidden layer neurons, 55 output neurons and a performance MSE of 0.00011784 for preset training MSE of 0.0001 for human biometric identification using ECG signals.

Possible reasons for the high performance of RBF-NN classifier for biometric identification using ECG signals lies in the novel hybrid feature extraction from ECG signals and the presence of Gaussian activation functions in the hidden layer of the network. Figure 12 shows the performance curve of the classifier.

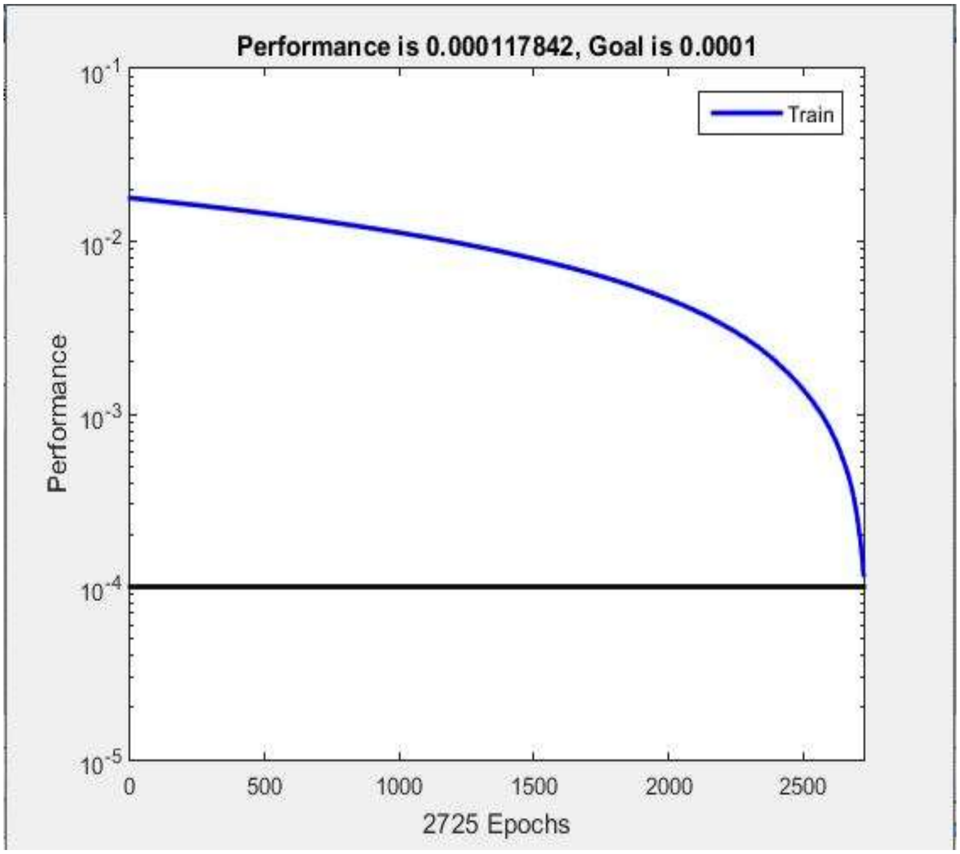

Figure 20 RBF-NN performance training curve for classification of 55 persons

Fig 20 shows the performance curve of the of Radial Basis Neural Network training of 55 persons in the present approach. Starting fig 20 clearly shows that the performance of RBF-NN increases with increase in epoch. However, the improvement/ increment in performance is not linear with respect to number of epochs. More precisely, from 0-2000 epoch the liberalization relation can be regraded as linear. However, epoch greater than 2000 sharply increases the performance. It is worth mentioning that the trend obtained by present methodology is in qualitative and quantitative agreement with the existing studies. Hence, it not only clarify performance of the present approach but also serve the purpose of validation of the current methodology. The accuracy of the 55 persons is 99.5%

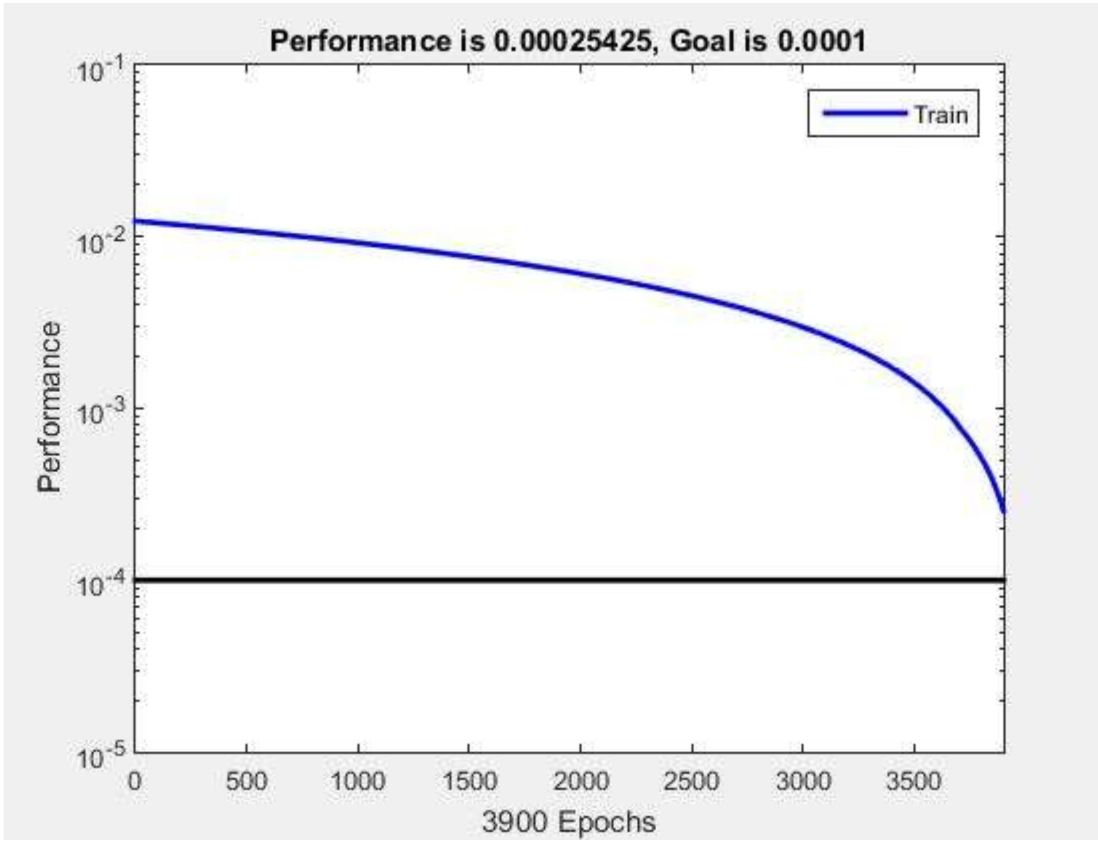

Figure 21 RBF-NN performance training curve for classification of 60 persons

Fig 21 shows the performance curve of the of Radial Basis Neural Network training of 60 persons in the present approach. Starting fig 21 clearly shows that the performance of RBF-NN increases with increase in epoch. However, the improvement/ increment in performance is not linear with respect to number of epochs. More precisely, from 0-2000 epoch the liberalization relation can be regraded as linear. However, epoch greater than 2000 sharply increases the performance. It is worth mentioning that the trend obtained by present methodology is in qualitative and quantitative agreement with the existing studies. Hence, it not only clarify performance of the present approach but also serve the purpose of validation of the current methodology. The accuracy of the 60 persons is 99.4%

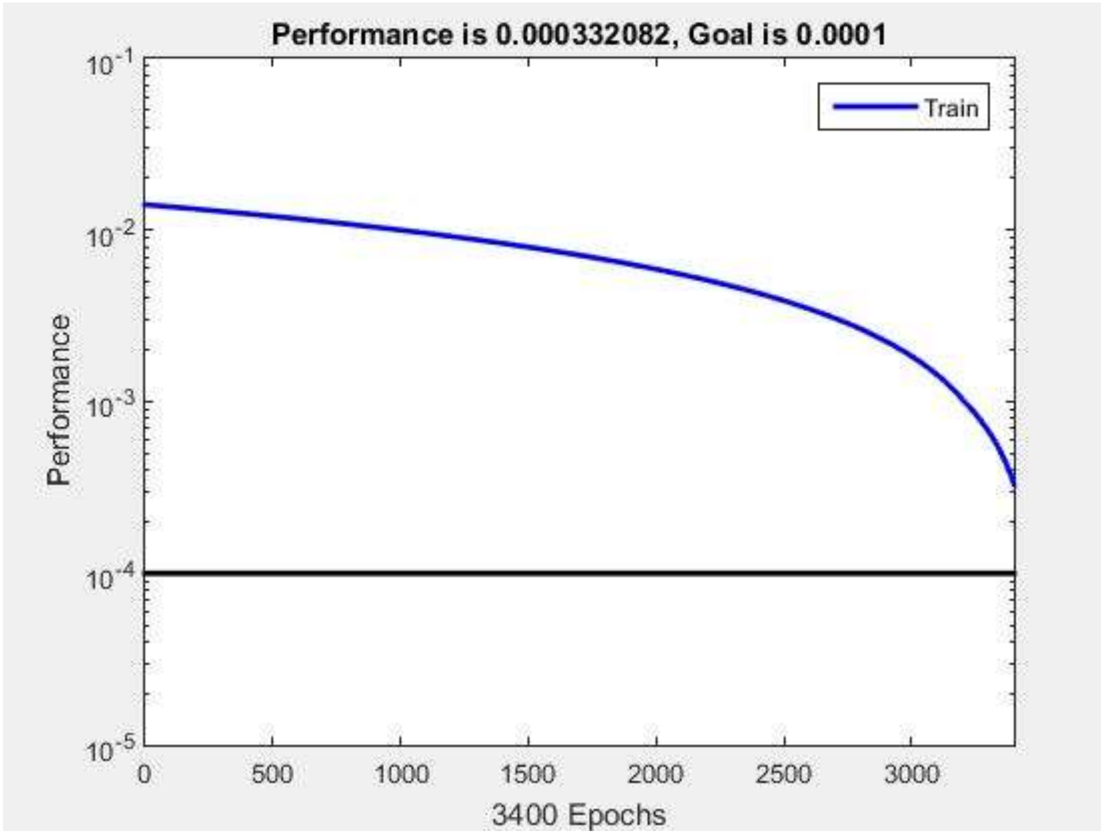

Figure 22 RBF-NN performance training curve for classification of 70 persons

Fig 22 shows the performance curve of the of Radial Basis Neural Network training of 70 persons in the present approach. Starting fig 22 clearly shows that the performance of RBF-NN increases with increase in epoch. However, the improvement/ increment in performance is not linear with respect to number of epochs. More precisely, from 0-2000 epoch the liberalization relation can be regraded as linear. However, epoch greater than 2000 sharply increases the performance. It is worth mentioning that the trend obtained by present methodology is in qualitative and quantitative agreement with the existing studies. Hence, it not only clarify performance of the present approach but also serve the purpose of validation of the current methodology. The accuracy of the 70 persons is 99.4%

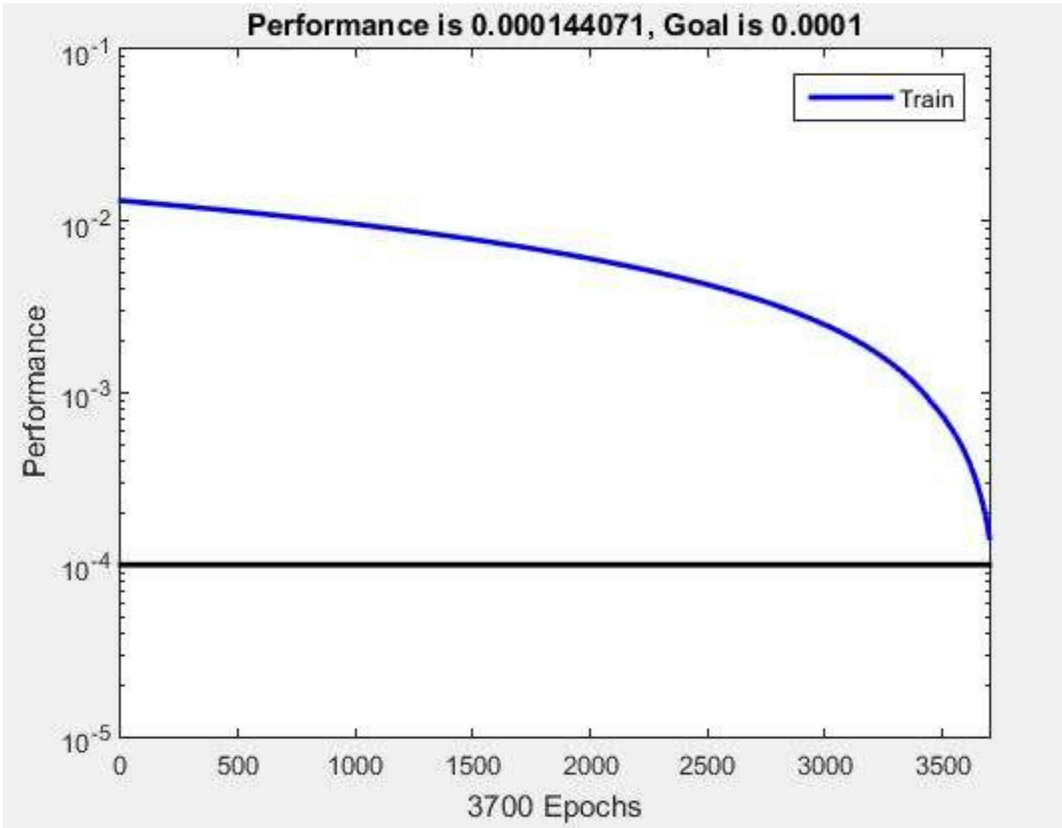

Figure 23 RBF-NN performance training curve for classification of 75 persons

Fig 23 shows the performance curve of the of Radial Basis Neural Network training of 75 persons in the present approach. Starting fig 23 clearly shows that the performance of RBF-NN increases with increase in epoch. However, the improvement/ increment in performance is not linear with respect to number of epochs. More precisely, from 0-2000 epoch the liberalization relation can be regraded as linear. However, epoch greater than 2000 sharply increases the performance. It is worth mentioning that the trend obtained by present methodology is in qualitative and quantitative agreement with the existing studies. Hence, it not only clarify performance of the present approach but also serve the purpose of validation of the current methodology. The accuracy of the 75 persons is 99.3%

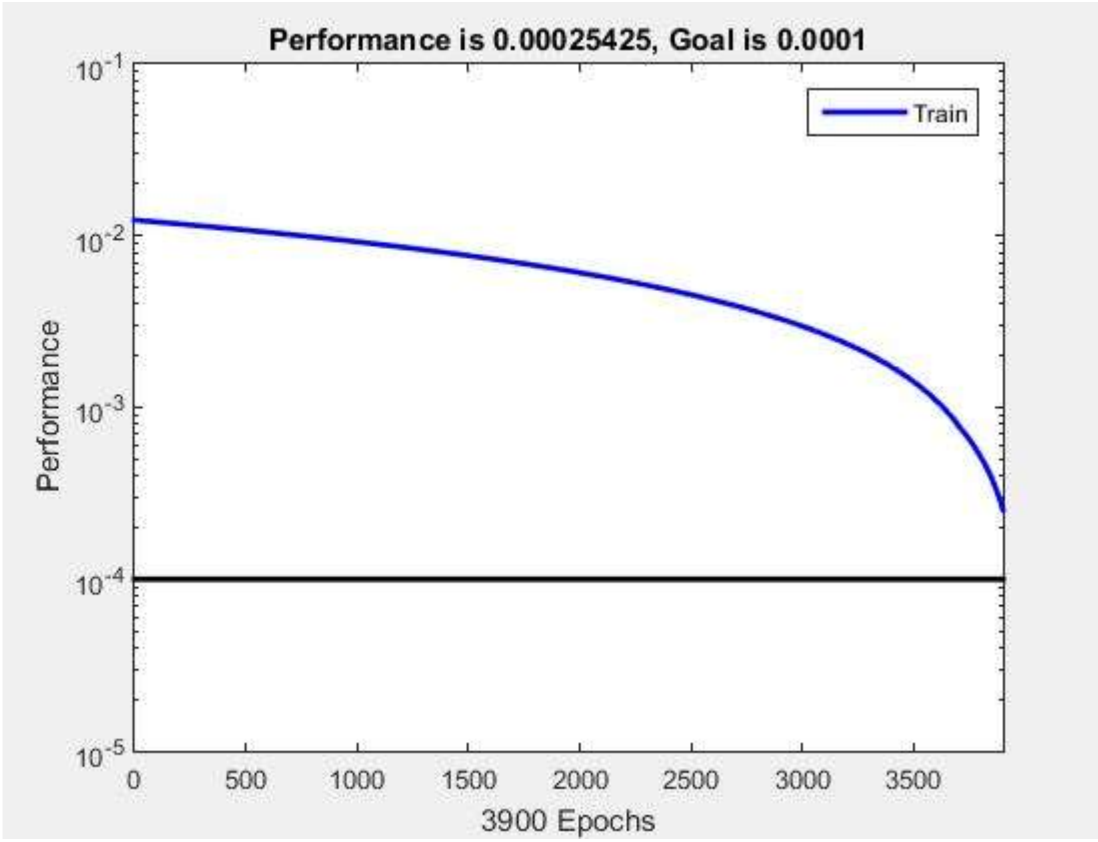

Figure 24 RBF-NN performance training curve for classification of 80 persons

Fig 24 shows the performance curve of the of Radial Basis Neural Network training of 80 persons in the present approach. Starting fig 24 clearly shows that the performance of RBF-NN increases with increase in epoch. However, the improvement/ increment in performance is not linear with respect to number of epochs. More precisely, from 0-2000 epoch the liberalization relation can be regraded as linear. However, epoch greater than 2000 sharply increases the performance. It is worth mentioning that the trend obtained by present methodology is in qualitative and quantitative agreement with the existing studies. Hence, it not only clarify performance of the present approach but also serve the purpose of validation of the current methodology. The accuracy of the 80 persons is 99.3%

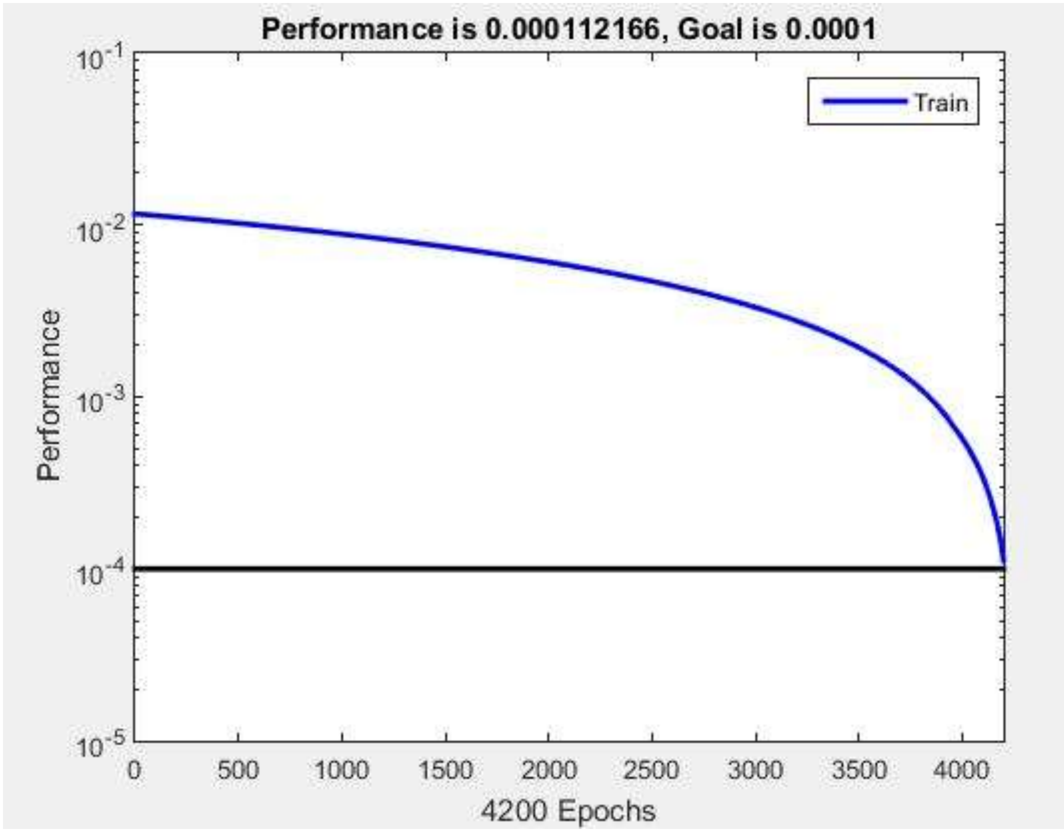

Figure 25 RBF-NN performance training curve for classification of 85 persons

Fig 25 shows the performance curve of the of Radial Basis Neural Network training of 85 persons in the present approach. Starting fig 25 clearly shows that the performance of RBF-NN increases with increase in epoch. However, the improvement/ increment in performance is not linear with respect to number of epochs. More precisely, from 0-2000 epoch the liberalization relation can be regraded as linear. However, epoch greater than 2000 sharply increases the performance. It is worth mentioning that the trend obtained by present methodology is in qualitative and quantitative agreement with the existing studies. Hence, it not only clarify performance of the present approach but also serve the purpose of validation of the current methodology. The accuracy of the 85 persons is 99.2%

Table 2 provides the details of performance of present method. For number of persons ranging in 55-85, the accuracy of proposed method stays more than 99 %. It should be noted that with increase in number of persons, number of neurons has also been increased to get the accurate results. However, number of inputs for the cases stayed fix, i.e. 17.

No. of Persons	Goal MSE	Performance MSE	No. of Inputs	No. of Outputs	No. of Neurons	Accuracy
55	0.0001	0.00017842	17	55	2725	99.5%
60	0.0001	0.00018564	17	60	2900	99.4%
70	0.0001	0.000332082	17	70	3400	99.4%
75	0.0001	0.000144071	17	75	3700	99.3%
80	0.0001	0.000125864	17	80	4100	99.3%
85	0.0001	0.000112166	17	85	4200	99.2%

Table 2. Performance of the system with different no of persons

We compared the accuracy of present hybrid approach of biometric identification with the methods already exist in literature. In this study, number of persons studies ranges from 55 to 85 with the increment of 5. For different number of persons, the accuracy of methods varies. Among the studies selected for the comparison with the present results, Tantawi et al. [22] method showed approximately same accuracy as of present approach. Moreover, the number of persons in the present test and in the one carried out by Tantawi were little different. It should be noted that our approach provide substantially accurate results that other methods/studies in Fig. 26 except Tantawi [13].

Comparing present results with the results of Jun Shen [12], based as Piecewise Linear Representation (PLR) and Dynamic Time Warping (DTW), presents approach at performance the equivalent study[12] with the increment in the number of persons.

Similar to study the Jose Shen [14], presents approach also outperform the approach introduced by Jose Shen [14]. Also, the number of persons in present techniques is higher than that of Jose Shen [14]. The accuracy of proposed technique is far more better than that of Jose Shen [14] both qualitative and quantitative.

The approach based on Support Vector Machine (SVM) [23] showed the lowest accuracy any all the existing studies mentioned in fig 26. Also it is way too low even comparison with present technique.

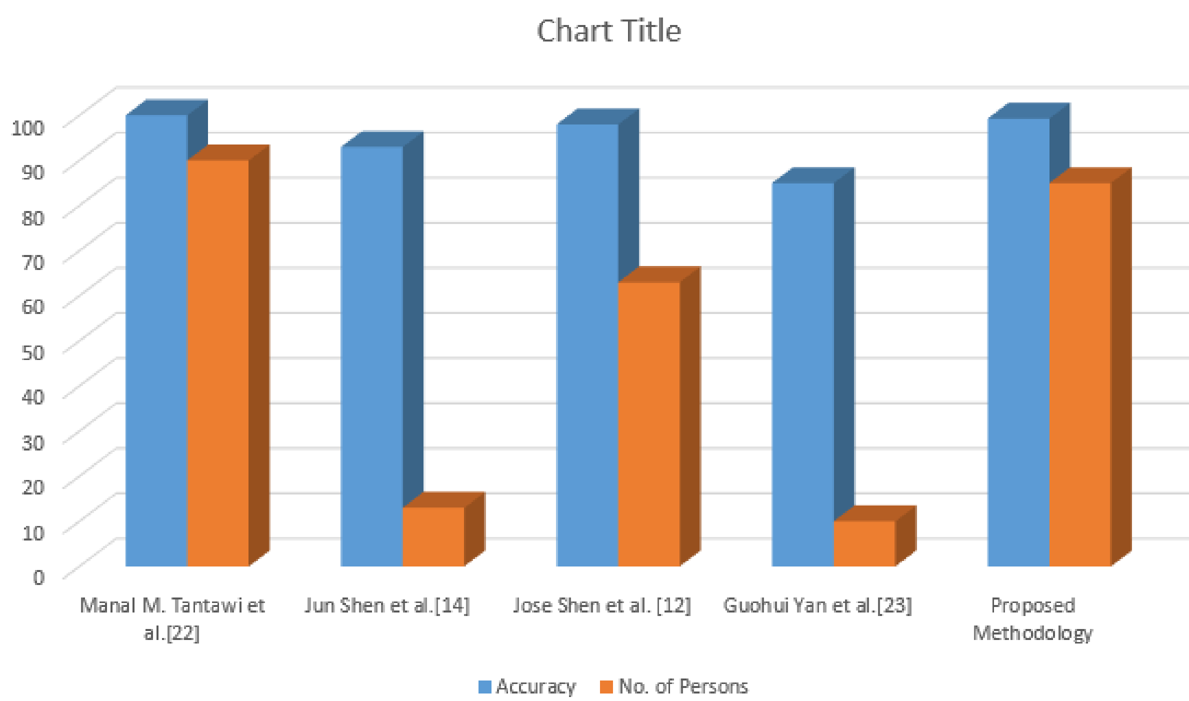

Figure 26 Comparison of accuracy between present study and the studies in the literature.

The under mentioned table 3 shows the comparison between miscellaneous MSEs of the hybridized biometric verification by using ECG signals. Specific number of 55 persons considered with the 17 input layer neurons and 55 output neuron layers. The accuracy varies with different MSEs with the same number of persons. By using this technique, the maximum and required accuracy can be obtained for MSE value of 0.0001.

Goal MSE	No. of input layer neuron	No. of hidden layer neuron	No. of output layer neuron	Performance MSE	Accuracy
0.1	17	57	55	0.178512	2%
0.01	17	1241	55	0.0100683	46.10%
0.001	17	2654	55	0.00110013	94.90%
0.0001	17	2784	55	0.00011784	99.50%

Table 3. Comparison of different MSEs

6. CONCLUSION AND FUTURE WORK

6.1. Conclusion

The proposed approach presents a novel technique for biometric identification of people using ECG signals. A hybrid approach was proposed by combining ARIMA, Wavelet Entropy and Sample Entropy were used as input features to a Radial Basis Function Neural Networks.

This study presents a new approach for the biometric identification founded on ECG signal using hybridization of different features and Radial Basis Function Neural Network (RBF-NN). Three different features, namely ARIMA, Wavelet Entropy, and Sample Entropy, are extracted from an ECG dataset. The proposed technique uses ECG signals from PTB data set, preprocess the signals using Butterworth band-pass filter. Three different types of features, namely sample entropy, wavelet entropy, and ARIMA coefficients, are extracted from de-noised and pre-processed ECG signals. The hybrid features are inputs to RBF-NN for classification and person identification. The features are then fed to an RBF-NN to identify different individuals. In the past, these features were used individually for person identification.

Possible reasons for the high performance of RBF-NN classifier for biometric identification using ECG signals lies in the novel hybrid feature extraction from ECG signals and the presence of Gaussian activation functions in the hidden layer of the network. Figure 12 shows the performance curve of the classifier.

We compared the accuracy of present hybrid approach of biometric identification with the methods already exist in literature. In this study, number of persons studies ranges from 55 to 85 with the increment of 5. For different number of persons, the accuracy of methods varies. Among the studies selected for the comparison with the present results, Tantawi et al. [22] method showed approximately same accuracy as of present approach. Moreover, the number of persons in the present test and in the one carried out by Tantawi were little different

The result shows a promising future for the proposed approach with an accuracy of 99.5% for the identification of 55 individuals. Future work involves further improvement in the proposed technique to identify an increased number of individuals with high accuracy.

6.2. Future Work

In the field of research and development, there are always room of improvement and meet the new challenges. The proposed technique is tested up to 85 persons. In future following work will be done:

- Increase number of persons.
- Application of different Artificial Intelligent algorithm and cross check its effect of accuracy.
- Study/develop the algorithm to enhance the application of the proposed technique and can be applied in different organization for the security purposes.

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