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Comparative Analysis of Machine Learning and Clustering Based Algorithm for the classification of Ear Biometric Template

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Abstract: *Ear is a standout amongst the most solid biometric feature because of its steadiness and haphazardness. In this paper, we have developed a system that can recognize human ear patterns and comparative analysis of the results is done. A novel mechanism has been used for implementation of the system. Feature training has been used to extract the most discriminating features of the ear and is done using k –means clustering scheme. And finally the biometric templates are matched using neural network and centroid method which tells us whether the two ear images are same or not and on the basis of that performance metric are evaluated like error rate and Accuracy. The whole simulation is taken place in the MATLAB environment.*

Keywords: *Biometric, Ear Recognition, Neural Network, k-mean clustering, centroid selection method, FAR, FRR, Accuracy, Error rate.*

I. INTRODUCTION

Biometrics refers to the identification or authentication of an individual based on certain unique features or characteristics. Biometric identifiers are the distinctive and measurable features that is used to label and describe individuals [1]. There are two categories of biometric identifiers namely physiological and behavioral characteristics [2]. Iris, fingerprint, DNA, etc. belong to the former kind of biometric identifiers whereas typing rhythm, gait, voice, etc. belong to the latter. A biometric system usually functions by first capturing a sample of the feature, such as capturing a digital color image of a face to be used in facial recognition or a recording a digitized sound signal to be used in voice recognition. The sample may then be refined so that the most discriminating features can be extracted and noises in the sample are reduced. The sample is then transformed into a biometric template using some sort of mathematical function [10]. The biometric template is a normalized and efficient representation of the sample which can be used for comparisons. Biometric systems usually have two modes of operations. An enrolment mode is used for adding new templates into the database and the identification mode is used for comparing a template created for an individual, who wants to be verified, with all the existing templates in the database.

A good biometrics is one which uses a feature that is highly unique. This reduces the chances of any two people having the same characteristics to the minimal. The feature should also be stable so that it does not change over the period of time.

II. EAR AS BIOMETRIC

Application of ear recognition in the field of biometrics is a new method. The structure of the ear is robust because it does not change with the facial expressions. The external ear constitutes the most unique design, characteristic features and peculiarities for the purpose of identification. As ear biometrics are suitable and also for the reason that their acquisition be likely to be perceived as less invasive. It is also very much accurate plus permits for extraordinary enrolment as well as authentication rates. This one could probably utilize with prevailing cameras in addition to picture capture gadgets will work with no problems [18].

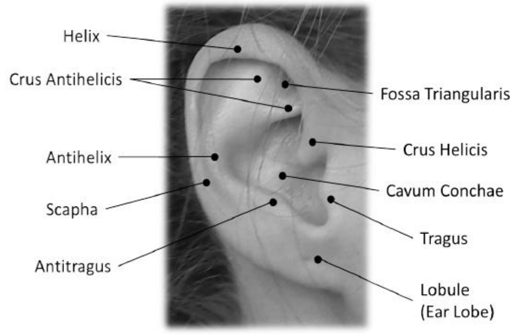

Figure 1: Ear Sample Image

Unlike iris, retina, or thumbprint capture that are touching base biometrics, whereas ear does not have need of close proximity to achieve capture [26]. Figure shows the common terminology of the external ear. Ears have a noteworthy role in forensic science. Ear detection has collect little consideration match up to other prevalent biometrics for instance face, thumbprint and gait.

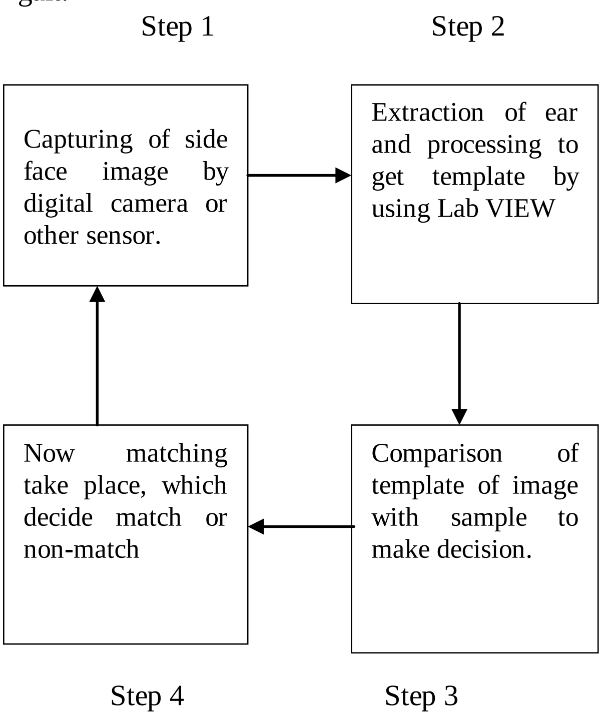

Figure 2: Steps of Ear Recognition

III. PROPOSED ALGORITHMS

3.1 K Means Clustering

K-means clustering algorithm is the basic algorithm which is based on partitioning method which is used for many clustering tasks especially with low dimension datasets. It uses k as a parameter, divide n objects into k clusters so that the objects in the same cluster are similar to each other but dissimilar to other objects in other clusters. The algorithm attempts to find the cluster centers, ($C1$ …… Ck), such that the sum of the squared distances of each data point, xi , $1 \leq i \leq n$, *to* its nearest cluster center Cj, $1 \leq j \leq k$, is minimized. First, the algorithm randomly selects the k objects, each of which initially represents a cluster mean or center. Then, each object xi in the data set is assigned to the nearest cluster center i.e. to the most similar center. The algorithm then computes the new mean for each cluster and reassigns each object to the nearest new center. This process iterates until no changes occur to the assignment of objects. The convergence results in minimizing the sum-of-squares error that is defined as the summation of the squared distances from each object to its cluster center.

The following procedure summarizes the k-means algorithms [20]:

Algorithm: k-means:- The k-means algorithm for partitioning, where each cluster's center is represented by the mean value of the objects in the cluster.
Input:
k: the number of clusters,
D: a data set containing n objects.
Output:
A set of k clusters.
Method:
(1) randomly choose k objects from D as the initial cluster centers;
(2) **repeat**
(3) (re)assign each object to the cluster to which the object is the most similar, based on the mean value of the objects in the cluster;
(4) update the cluster means, i.e., calculate the mean value of the objects for each cluster;
(5) **until** no change;

Despite being used in a wide array of applications, the k-means algorithm is not exempt of drawbacks.

- As many clustering methods, the k-means algorithm assumes that the number of clusters k in the database is known beforehand which, obviously, is not necessarily true in real-world applications.
- As an iterative technique, the k-means algorithm is especially sensitive to initial centers selection.
- The k-means algorithm may converge to local minima.

3.2 Centroid Selection Method

The centroid is defined as the centre of a cloud of points (Joining Clusters: Clustering Algorithms). Centroid linkage techniques attempt to determine the 'centre' of the cluster. One issue is that the centre will move as clusters are merged. As a result, the distance between merged clusters may actually decrease between steps, making the analysis of results problematic. This is not the issue with single and complete linkage methods. A problem with the centroid method is that some switching and reversal may take place, for example as the agglomeration proceeds some cases may need to be switched from their original clusters.

3.3 Neural Network

Neural network models seems to be a current development in today's field. Neural networks process data in a similar way as the brain of a human being works. The network is made of a huge number of highly interrelated processing components (neurones) working in corresponding to resolve a definite issue. Neural networks learns by some example. They could not be encoded to accomplish a specific job. The examples must be chosen very carefully or else valuable time is misused or even not as good as the network which might be operating inaccurately. Neural networks, with their significant ability to derive meaning from complex or indefinite information, could be utilized towards extracting patterns as well as to discover trends which are too multifaceted to be perceived by either human beings or other computer methodologies. The neural network has two modes of work operation; the training mode plus the testing mode.

Neural networks are generally systematized in layers. These specific layers are made up of a a set of interrelated 'nodes' that encompass an 'activation function'.

Input layer　　Hidden layer　　Output layer

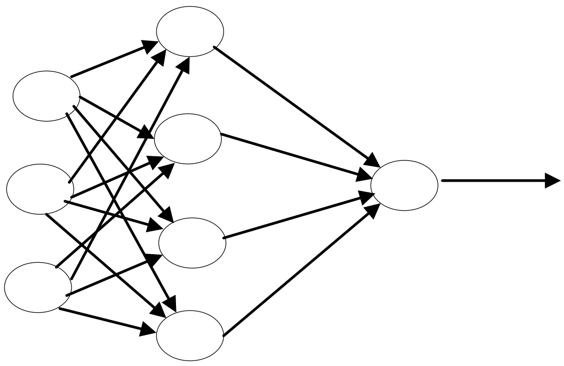

Figure 3: Neural Network

Some specific patterns are presented to the network through the 'input layer' that communicates to one or more than one 'hidden layers' where the real processing is completed by the use of a framework which have weighted 'connections'. Then the hidden layers are further connected to a specific 'output layer' where the actual solution is output as displayed in above figure.

IV.SIMULATION MODEL

Ear recognition is done In MATLAB 2010a environment using K- Means Clustering, Centroid selection and NN method. The following process will describe the ear recognition process.

4.1 Training Panel

4.1.1 Upload Image

The images from UCI Machine learning algorithms ear image database are taken. It contains 23 images of left ear. They are of 200kb .jpeg images.

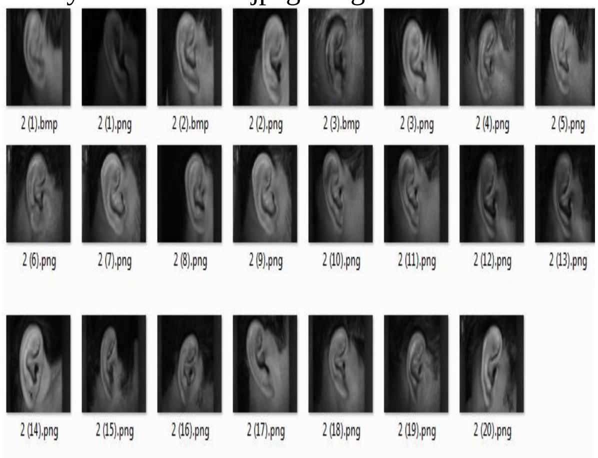

Figure Error! No text of specified style in document.**:** Ear Training Samples

4.1.2 Edge Detection

In this phase grey scale conversion has been done and edge detection. Edges characterize boundaries and are therefore a problem of fundamental importance in image processing. Edges in images are areas with strong intensity contrasts – a jump in intensity from one pixel to the next. Edge detecting an image significantly reduces the amount of data and filters out useless information, while preserving the important structural properties in an image. The Canny edge detection algorithm is known to many as the optimal edge detector.

4.1.3 K- Means clustering and feature values

Clustering is the process of grouping a non-linear set of objects. This approach assigns the database of nobjects into k-number of clusters ($k < n$). The main concept of this K-Means clustering approach is every object in the database must be located in any of the clusters or group, then every cluster must contain a minimum of one object. Then each cluster can be used to find a mean vector, according to this approach, it comes under the category of the centroid model. K-Means clustering algorithm is used to find the set key points, which are stored as the feature values in database during enrollment process. The key points taken from the feature extraction process are clustered using this algorithm.

First step of the verification phase is the same as enrollment phase to find the binary values of using K-Means clustering algorithm. The fused values of K-Means clustering algorithm is stored in the database which is compared with the query and ear centroid fused values to prove the recognition and authentication. If all the outputs of the compared values are zero, then decide whether the user is authenticated as a genuine one, or whether user is an impostor.

4.2 Neural Network for training

Back Propagation Neural Network (BPNN) is a systematic method for training multi-layer artificial neural network. The algorithm for Ear recognition using BPNN [is as follows:

- Create NN architecture having input, hidden and output layers. Predefined.
- Randomly initialize input layer.
- Train the network using ftt function.

4.3 Classification Panel

4.3.1 Upload testing image

The images from UCI Machine learning algorithms ear image database are taken for testing. It contains various images of left ear. They are of 200kb .jpeg images.

4.3.2 Matching using Neural Network

The features of the test image are compared with the features of images in the database for match or non-match using NN classifier on the basis of accuracy and error arte.

4.3.3 Matching using Centroid Method

The features of the test image are compared with the features of images in the database for match or non-match using centroid method on the basis of accuracy and error rate.

V. RESULTS AND ANALYSIS

The whole implementation has been done in MATLAB 2010a using centroid method and neural network.

5. 1 Calculate FAR (False Acceptance Rate)

FAR=

$$\mathit{Total\ Number\ of\ Illustrations} - \mathit{Number\ of\ Illustrations\ Falsely\ Rejected} / \mathit{Total\ Number\ of\ Illustrations}$$

5.2 Calculate FRR (False Rejection Rate)

FRR=

$$\mathit{Total\ Number\ of\ Illustrations} - \mathit{Number\ of\ Illustrations\ Falsely\ Rejected} / \mathit{Total\ Number\ of\ Illustrations}$$

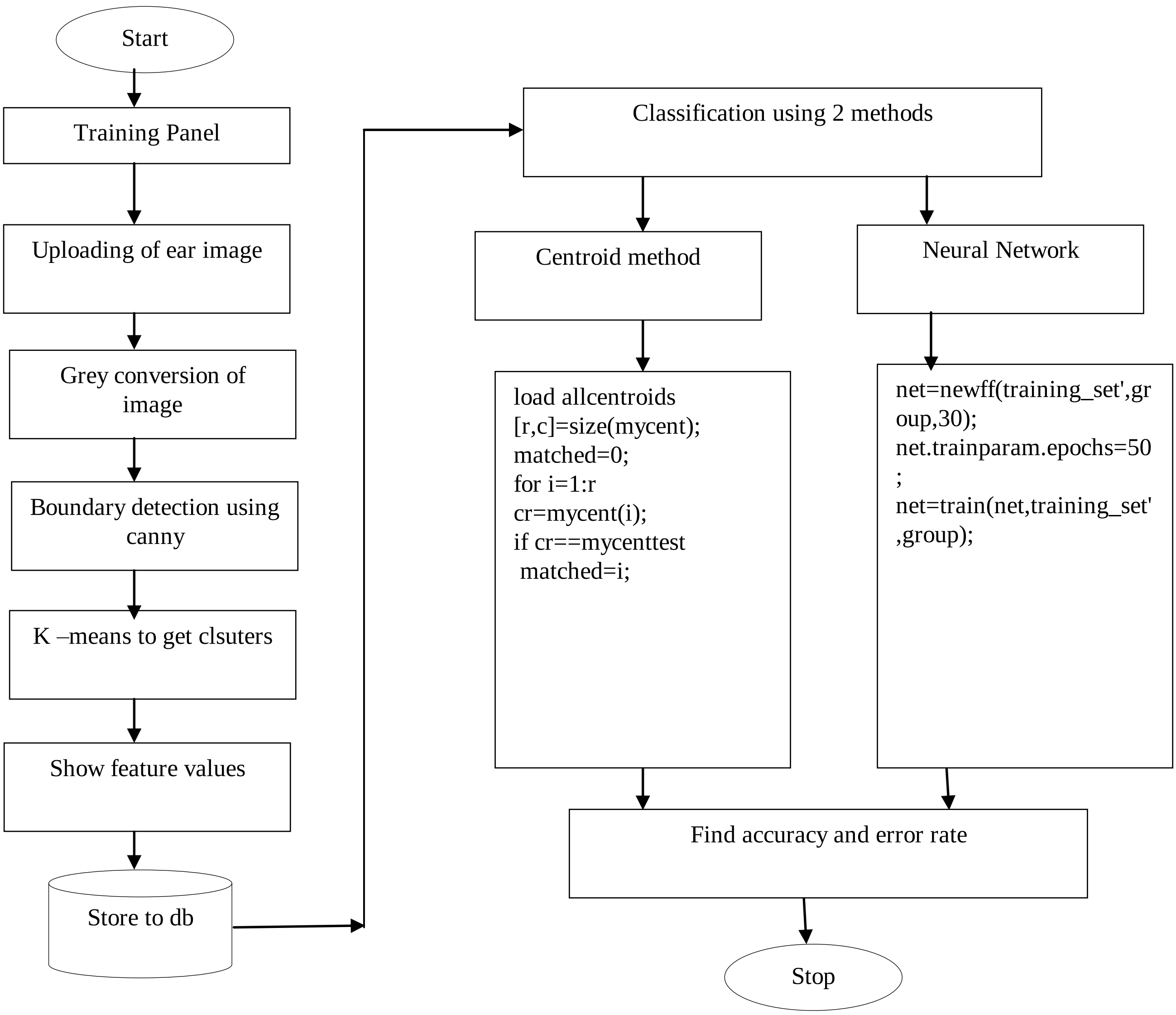

Figure 5: Methodology

5.3 Calculate Accuracy 100− (FAR+FRR) %

5.4 Error rate

$$\text{Error rate} = \frac{\text{Total no.of false accpeted samples}}{\text{Rotal no.of iamges in database}}$$

Table I: Comparison Parameters for Centroid Method

Parameters	**For k = 2**	**For k = 6**	**For k = 10**	**For k = 14**
Accuracy	92.531	92.456	92.551	92.331
Error rate	7.46	7.33	7.01	7.39

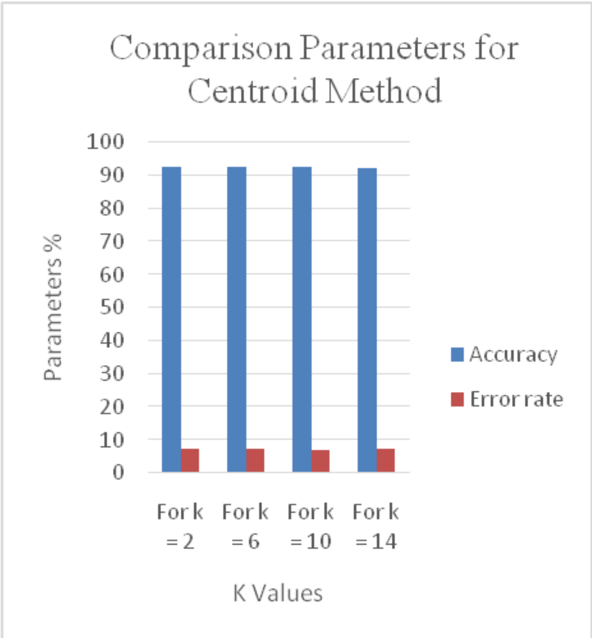

Figure 6: Comparison Parameters for Centroid Method

Table II. Comparison Parameters for Neural Network

Parameters	**For k = 2**	**For k = 6**	**For k = 10**	**For k = 14**
Accuracy	98.99	98.78	98.89	98.94
Error rate	1.0065	1.0063	1.0049	1.0087

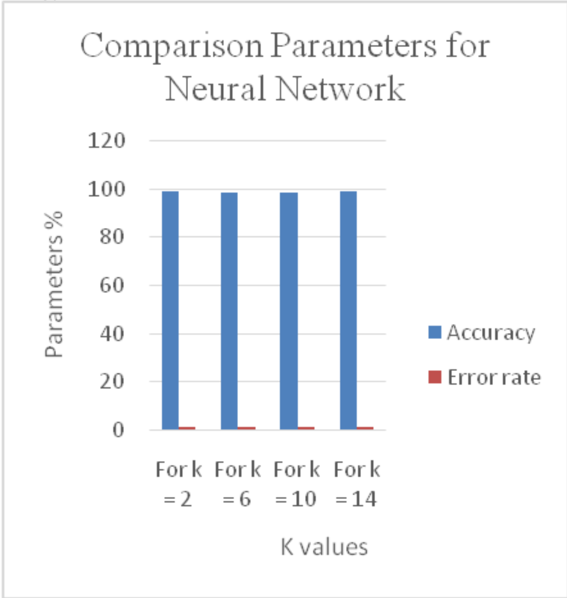

Figure 7: Comparison Parameters for Neural Network

From above graphs it has been clearly seen that neural network results are better than Centroid method in terms of accuracy and error rate because neural network has good learning rate w.r.t centroid method.

CONCLUSION

In the proposed system a comparative analysis of classification technique is done for classification to increase the accuracy of the authentication systems using centroid method and neural network. In this k-means features are extracted for ear. This proposed method decreased the error rate, & has increases the system performance on the given data set. The results showed that neural network performed well w.r.t centroid method having values accuracy is 98.99%, and Error rate is 1.0063%.
Future works could go in the direction of using more robust modeling techniques against forgeries and hybrid fusion level can be used. Multimodal modalities can be used together to make forgeries more difficult. Also, the system should be tested on a larger database to validate the robustness of the model.

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