International Journal of Advance Research in Science and Engineering
Volume No.07, Special Issue No.08, March 2018
www.ijarse.com
IJARSE
ISSN: 2319-8354

Offline Signature Verification system using Geometric, DCT Feature Extractions and Neural Network

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ABSTRACT

This paper proposes the off-line signature verification system in Punjabi language. System captures the image of the handwritten signature using digital device and then crop it to get rid of white space. The cropped image is then pre-processed it into binary image for feature extraction. Self learning system uses the 2D-DCT image compression and geometric features extraction method to store sample signatures in the databases. The multilayer neural network and SOM neural network are used to determine the genuinely factor of the signature which compare the given signature with the set of stored signatures.

Keywords: Geometric features, discrete coefficient transform, Self-Organizing Map, Neural Networks, Signature Verification, Offline, Indian Languages, and Punjabi.

1.0 INTRODUCTION

Biometric tools became very popular in recent times. A person can be uniquely identified by evaluating his biometrics (biological traits) includes DNA, signature and fingerprints [38]. This paper is focused on signature verification that comes under behavioral biometrics. Signatures are usually captured online and offline. Online method captures digital signatures directly using smart touch screen devices i.e. smart phones, tablets. Biometrics can be classified in two major categories, physiological and behavioral.

Table 1: Classification of Biometric

Biometric	
Behavioral (Behavioral Biometric)	**Physiological (Physical Biometric)**

Voice	Fingerprint
	Hand
Signature	Iris
	Ear
	DNA

Offline is traditional method of capturing signature of paper at the end of the writings, forms or bank cheques.Most of the time bare eyes fail to determine the genuinity of the signatures which tend to develop a system which can does that automatically and with very high accuracy.Pre-processing, Feature extraction and Post-processing are the fundamental steps of the process.

1.1 Importance of Punjabi signature verification

According to literature survey, there are over 121 million people across the globe who can speak Punjabi and approximately 70% can write. Out of this 70% only few people can write any other language other than Punjabi. Especially in Punjab and Pakistan people use Punjabi language for their signature. On top of this, there are 35 characters in Punjabi language which are way different in shape or size compared to any other language.

2. RELATED WORK

A lot of research has been done on off-line signature verification using different techniques [13],but most of the work is done using English language. There is not much done in regional languages. Talking about Indian there are 27 official languages spoken and written, but Bangla and Hindi are only languages where signature verification research work is done [34].Adding to it, now Punjabi can be included to it.

3. SYSTEM ARCHITECTURE

System performs a sequence of steps to determine the authentication of the signature.

Fig. 1 demonstrates the steps involved in the proposed system.

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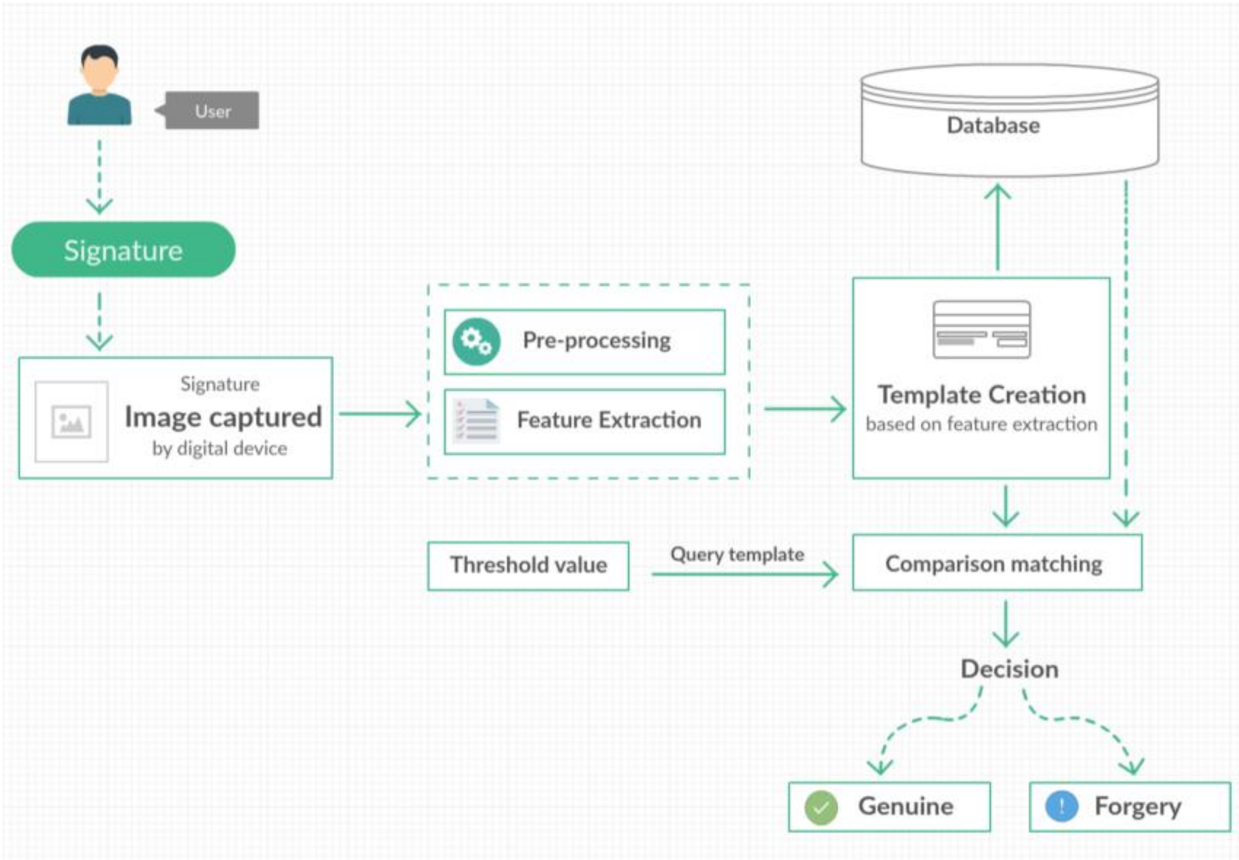


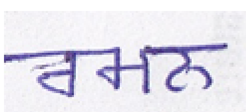
Fig 1 System architecture of offline signature verification systems

3.1 Image Acquisition and pre-processing

This system accepts the hand written signature image which is captured using any digital device. Typical step required scanner or digital camera which will scan soft copy of the signature from paper. Captured is then cropped and converted to grayscale.

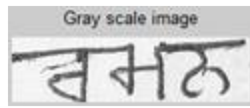
Captured is then cropped and converted to grayscale.

1. Image captured using digital device.



2. Cropped Image.

3. Imaged converted to Gray Scale.



4. Nearest-neighbor interpolation is donating resize Signature images into block size of 8X8 pixels and then convert the Image into Binary image.

Fig 2 Steps involved in preprocessing phase

Preprocessing of acquired signature is requiredto improve the quality of signature image and to verify the signature correctly. [22]

3.2 Feature Extraction

Feature extraction is the considered as most challenging step in offline signature verification system as it tends to find unique features of the signature.The biggest challenge how is to distinguish forged and genuine signatures.[5]Active trend relies on the way individual give shape to letters and scatter it. It is also heavily dependent on the thickness and the space used to write letters. The goal of the feature extraction is provide the discrete properties of the signature so that it can be distinguished from the fake signature. It works in two primary steps: feature extraction and feature matching.[34] This system use the SOM (Self Organizing map) which is type of artificial neural network that produce discretized representation of the input space of the training samples. This research work deals with two type of feature extraction method.

3.2.1 2-D Signature Image DCT Compression:

Using SOM proposed system is determining the 2D-DCT (Discrete coefficient transform) of the signature image with a blocks of size 8 × 8 pixels by means of ‘8’ out of the 64 DCT coefficients for masking. The remaining 56 leftover coefficients are discarded (set to zero). By computing the 2D-IDCT of each block using the DCT transform matrix computation method the signature image is then reconstructed. At last the output is obtained in the form of a set of arrays. The every output array is of size 8 × 8 pixels which represents a particular signature image. After implementation of DCT image compression the signature image is reshaped into 64x1 and store in database using

MATLAB. After that these features are given as input to SOM neural network for signature recognition. It is as shown in fig

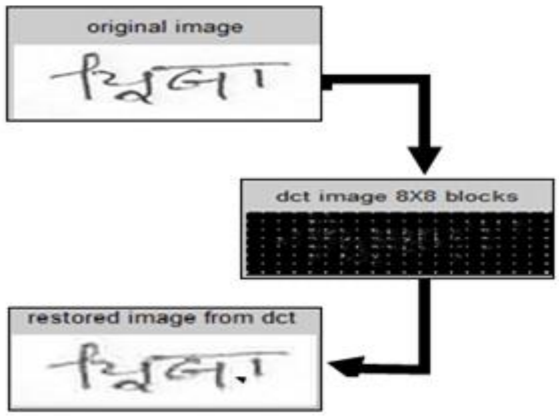


Fig 3: DCT Image Compression

3.2.2 Geometric features

Proposed system extracted 8 geometric features listed in the table below. These features are extracted in MATLAB and given as input to multilayer neural network for signature recognition as discuss in post processing. The various features that are come under category of geometric features are defined in my previous paper as given below in table 4:

Table 1.Extracted Features from a sample image

Values	**Extracted Geometric Features**
78.5 ,30.5	Centroids Coordinates
11.2799	Kurtosis
9360	Area
0	Orientation
1	Euler Number
-3.02009	Skewness

0.923077	Eccentricity
428	Perimeter

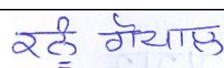
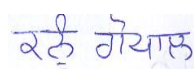
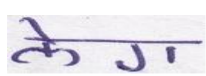
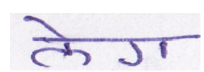
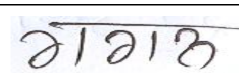
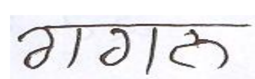
3.3 System databases

The proposed system is supported with a self created database. It consists of the tables which accept the 10 variable for the individual's record with 5 fake and 5 genuine signatures. Each variable can accept max of 50 characters. In this MS-access is used as database. The table named user information is created in database which has the following attributes:

- id as primary key
- username

The proposed system is tested with sample of 50 individuals of different age group range from 18 years to 50 years.Existing database consist of 250 records with same number of fake and genuine signatures.

Table 2. Genuine and forged Punjabi signatures

Punjabi Signature	
Genuine Signatures	**Fake Signatures**
	
	
	
	

3.4 Post processing:

Proposed system required the training of the SOM neural network. Training means unsupervised learning done by system itself without any external help to produce it own classification of features which will later used to determine the genuine factor of the signature.

In this process the extracted features which are stored in database are given as input to Self Organization Map and multilayer feed forward neural networks for training. The trained system is thentested with existingsample to check the performance and accuracy.

3.5.1 Training of ANN

It is a process in which network is trained or learned through examples. The extracted DCT features from 500 signature images (i.e. in 10 different style signature of 50 different people) that are computed during feature extraction phase of signature recognition are stored in MATLAB as set of DCT features(F) i.e. F={ F_1,F_2,F_3,….F F_{500} } as shown below in fig 4. These extracted features from signatures are given to SOM neural network as input after creation of SOM neural network by command new SOM. The parameters for the SOM network were selected to be a minimum and maximum point for each row on vector P; training database.

There were 64 minimum and 64 maximum points selected altogether. The network is trained in the form of five genuine signature and five forged signatures. In training of SOM neural network there is no need to make target while it is must in multilayer neural network. This network belongs to the grouping of competitive learning network environment. It is as shown in fig 4.

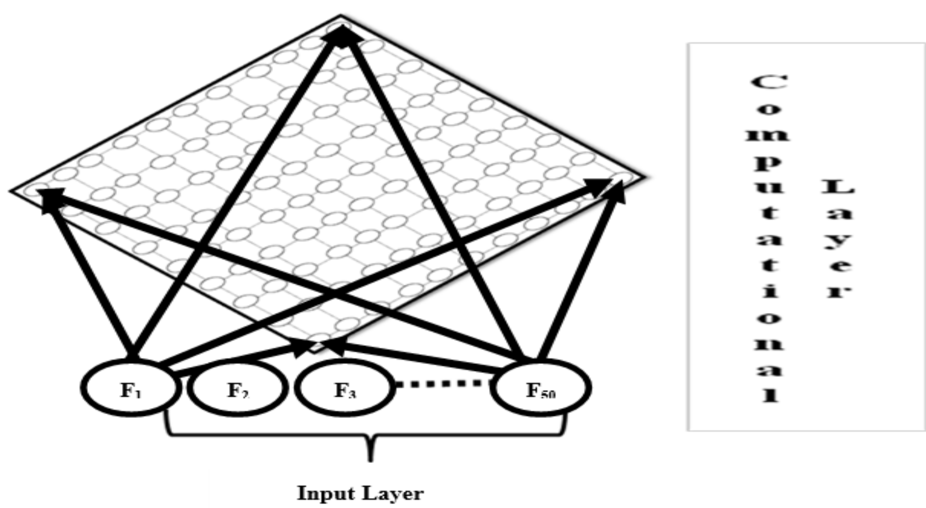


Fig 4 Architecture of SOM neural Network

The simple data interpretation and easily understandability is major advantage of SOM Neural Network. By reducing dimensions and grid clustering, this makes it simple and easy to examine similarities in the data. SOMs can handle several problems and providing interactive, precious and intelligible summary of the data. It requires sufficient data to develop a meaningful cluster which is a major drawback of SOM. The data that can successfully grouped and distinguish inputs on which weight vectors are based. The problem of SOMs is difficult to obtain a perfect mapping where groupings are unique within the map. The supervised training algorithm are trained according to set of pairs (X, T) that indicate input and equivalent target. As discussed above the extracted geometric feature from 500 signature images (i.e. in 10 different style signature of 50 different people) are stored in MATLAB as set of X={x_1, x_2,…., x_{500}}. Where X1 indicates the geometric feature of signature image1, X_2 indicates the geometric features of signature image2 and x_{500} so on up to 500 signature images and their desired targets as T={t_1, t_2 , t_3 , ….t_{500}} are input given to multilayer feed forward Neural network and also make the target corresponding to input to train network. After that train the network according to input and desired targets. The Supervised training process use set of training data like — a set of pairs (X, T) of inputs with their equivalent desired outputs. Multilayer neural network is as shown in figure 5. According to results of this research work the multilayer neural network produce better results. The target nodes (t_1. . . t_{500}) are connected with the output variables to identify signature either genuine or forgery. The hidden nodes are that nodes which are not directly connected to network while they are inside network but not visible to outer environment.

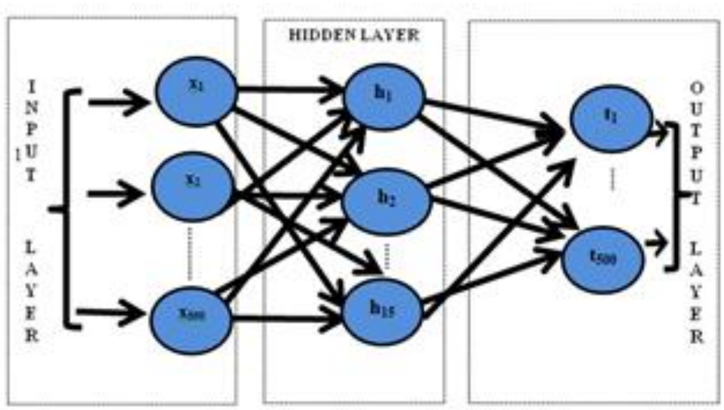


Fig: 5 Multilayer Neural network Architecture

3.5.2 ANN Testing

Finally, we reached to the step where we can compute the system's accuracy and effectiveness. Proposed system use template signature for testing which will undergo all above steps.

After preprocessing of these template signature image the 2D image DCT features for SOM and geometrical features for multilayer neural network were extracted. After feature extraction testing is performed and output is computed based on the threshold value which is taken as 90% in this research. The result and conclusion of system using both techniques are given below. Hence if the matching percentage is obtained less than 90% than signature is considered forged else if the percentage is computed as more than threshold value it will be considered as genuine signature in both of networks.

4. EXPERIMENTAL RESULTS

Experiment 1

The signature verification accuracy is tested based on the number of Epochs as shown in table 2. The accuracy is increased as the numbers of epochs are increased. The results SOM neural network is as given below in table 3 and fig 6.

Table 3: SOM neural network results based on different epochs

1000	500	400	200	100	**Number of Epochs**
0.864	0.56357	0.424	0.364	0.25399	**Training Time**
0.25	0.25	0.2	0.15	0.12	**FAR**
0.171	0.14	0.1	0.17	0.12	**FRR**
0.6	0.57	0.53	0.51	0.4	**Recognition rate (for 10 Trials)**

In testing phase, classifying the signature either genuine or forged. The accuracy of system is calculated according to values of on FAR and FRR for 10 trials of Signature verification system.

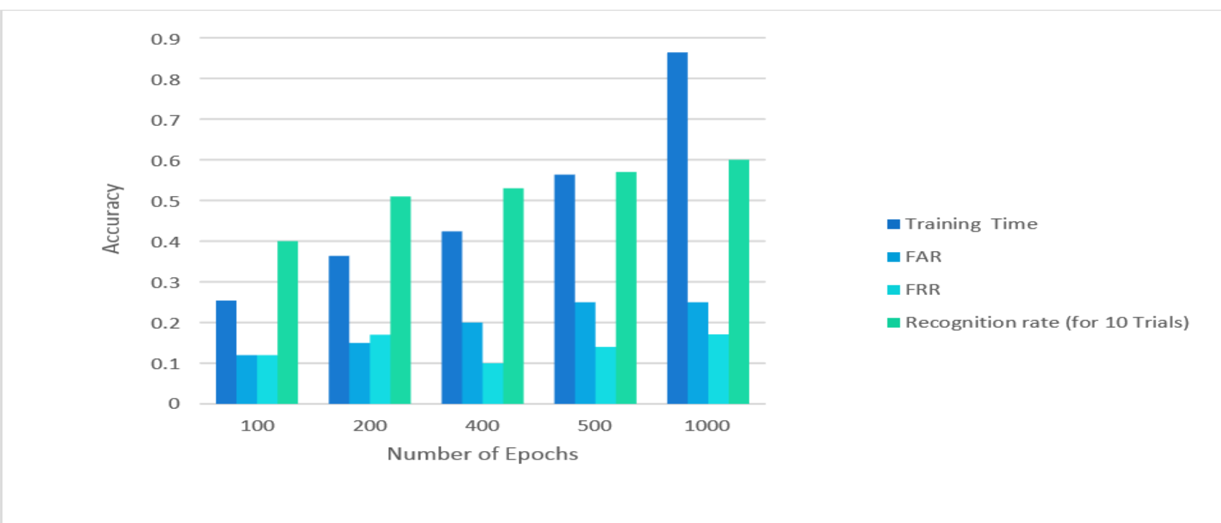


Fig 6: SOM neural network results based on different epochs

Multilayer feed forward neural network result are shown in fig 7 and table 4.

Table 4: Multilayer neural network results based on different epochs

1000	500	400	200	100	**Number of Epochs**
0.4037	0.37118	0.37853	0.32291	0.31617	**Multi- Layer Training Time**
0.14	0.15	0.12	0.15	0.14	**FAR**
0.1	0.15	0.14	0.12	0.15	**FRR**
0.9	0.78	0.65	0.56	0.55	**Recognition rate (for 10 Trials)**

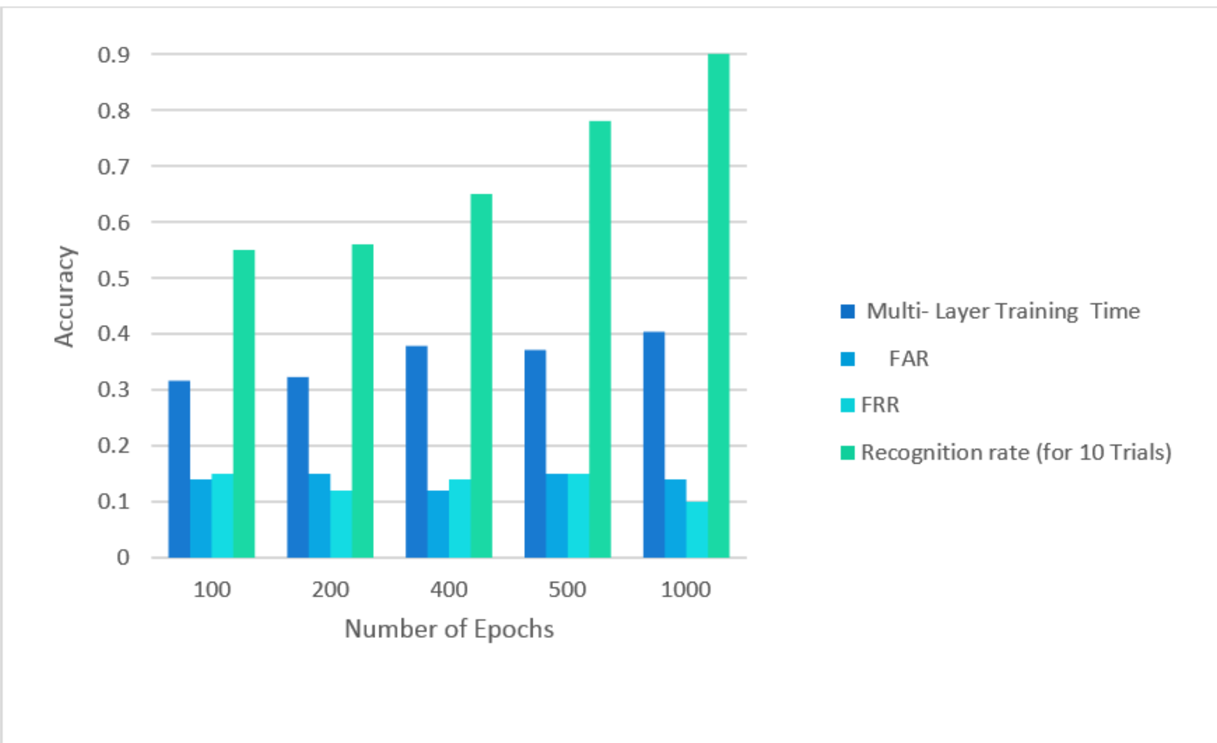


Fig 7: Multilayer neural network results based on different epochs

This system also represents the comparison of SOM and Multilayer feed forward network. The classification ratio and comparison is as shown in following table for 10 trials using different Epochs in fig 8 and table 5.

Table 5: Analysis and comparison of signature verification using SOM and Multilayer feed forward neural Network

1000	500	400	200	100	**Number of Epochs**
0.864	0.56357	0.424	0.364	0.25399	**SOM Training Time**
0.4037	0.37118	0.37853	0.32291	0.31617	**Multi- Layer Training Time**
0.25	0.25	0.20	0.15	0.12	**SOM(FAR)**
0.1710	0.14	0.10	0.17	0.12	**SOM (FRR)**
0.14	0.15	0.12	0.15	0.14	**Multi- Layer (FAR)**
0.10	0.15	0.14	0.12	0.15	**Multi- Layer (FRR)**
0.60	0.57	0.53	0.51	0.40	**Recognition rate (for 10 Trials) using SOM**
0.90	0.78	0.65	0.56	0.55	**Recognition rate (for 10 Trials) using Multi- Layer Feed Forward network**

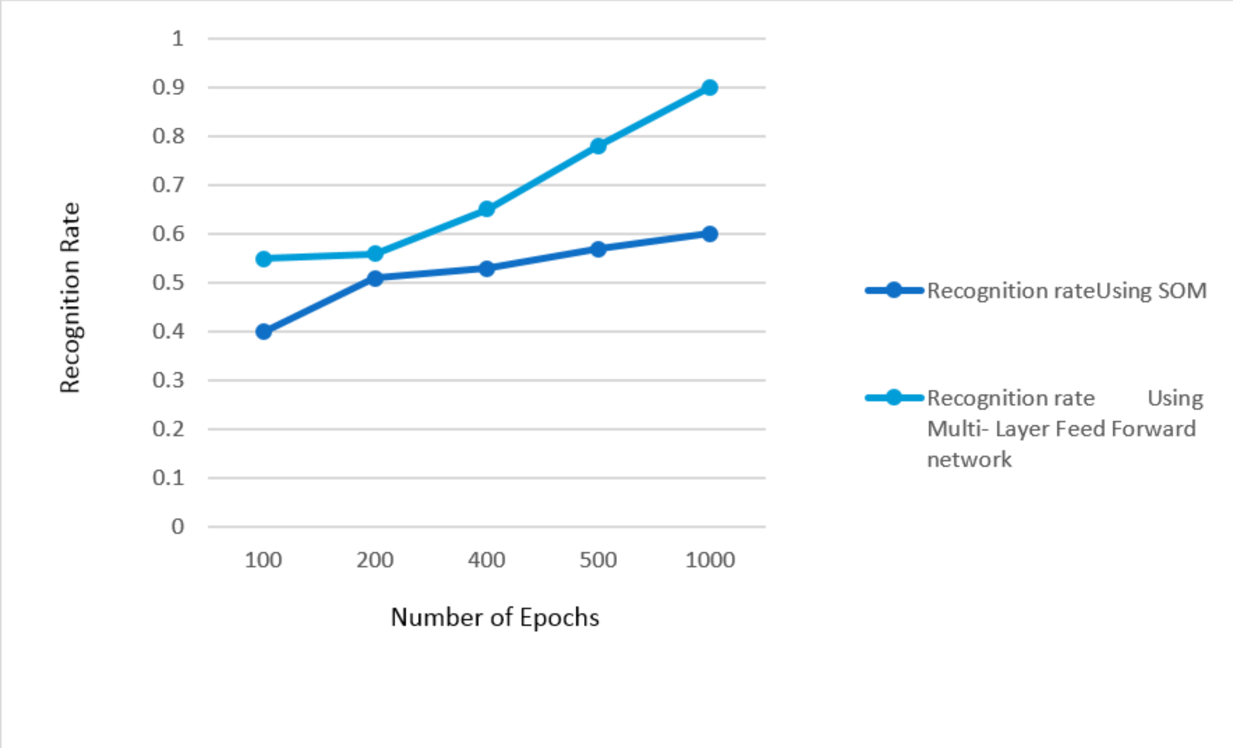


Fig:8 Comparison of Multilayer and SOM based on different Epochs

Experiment 2:

In second experiment five different datasets are collected by combining all the features together (Centroids Coordinate, Kurtosis, area, Equiv Diameter, Skewness, Euler Number, Eccentricity, and Perimeter) based on which results are obtained.

Dataset 1: In first data set 100 genuine Punjabi signature samples are collected from 20 individuals, out of which, 80% samples are used to train the system and 20% are used to test the system. The accuracy of 60% is obtained using multilayer feed forward ANN and in case of SOM it is 80%.

Dataset 2: In first data set 200 genuine Punjabi signature samples are collected from 10 individuals, out of which, 80% samples are used to train the system and 20% are used to test the system. The accuracy of 70% is obtained using multilayer feed forward ANN and in case of SOM it is 80%.

Dataset 3: In first data set 300 genuine Punjabi signature samples are collected from 10 individuals, out of which, 80% samples are used to train the system and 20% are used to test the system. The accuracy of 75.3% is obtained using multilayer feed forward ANN and using SOM it is 70%.

Dataset 4: In first data set 400 genuine Punjabi signature samples are collected from 10 individuals, out of which, 80% samples are used to train the system and 20% are used to test the system. The accuracy of 80% is obtained using multilayer feed forward ANN and using SOM it is 65%.

Dataset 5: In first data set 500 genuine Punjabi signature samples are collected from 10 individuals, out of which, 80% samples are used to train the system and 20% are used to test the system. The accuracy of 90% is obtained by using multilayer feed forward neural ANN and using SOM it is 60% as shown in fig 9.The results show that the accuracy of the system increases as the system is trained by multilayer neural network and decrease in case of SOM. The accuracy results are shown in table 6 .The graphs below represent the accuracy and comparison of both systems.

Table 6: System Accuracy Results

ACCURACY USING MULTILAYER FEED FORWARD NETWORK	**ACCURACY USING SOM**	**Training Dataset**
70	80	100
70	80	200
75.3	70	300
80	65	400
90	60	500

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www.ijarse.com
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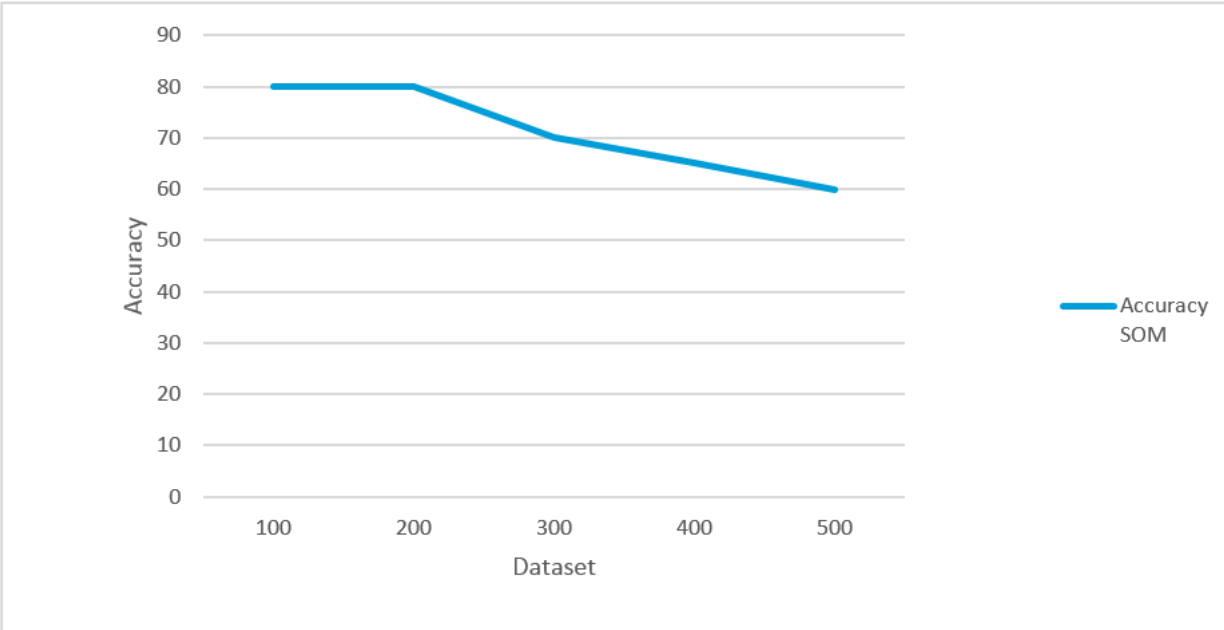

Fig 9:Accuracy of SOM using different dataset

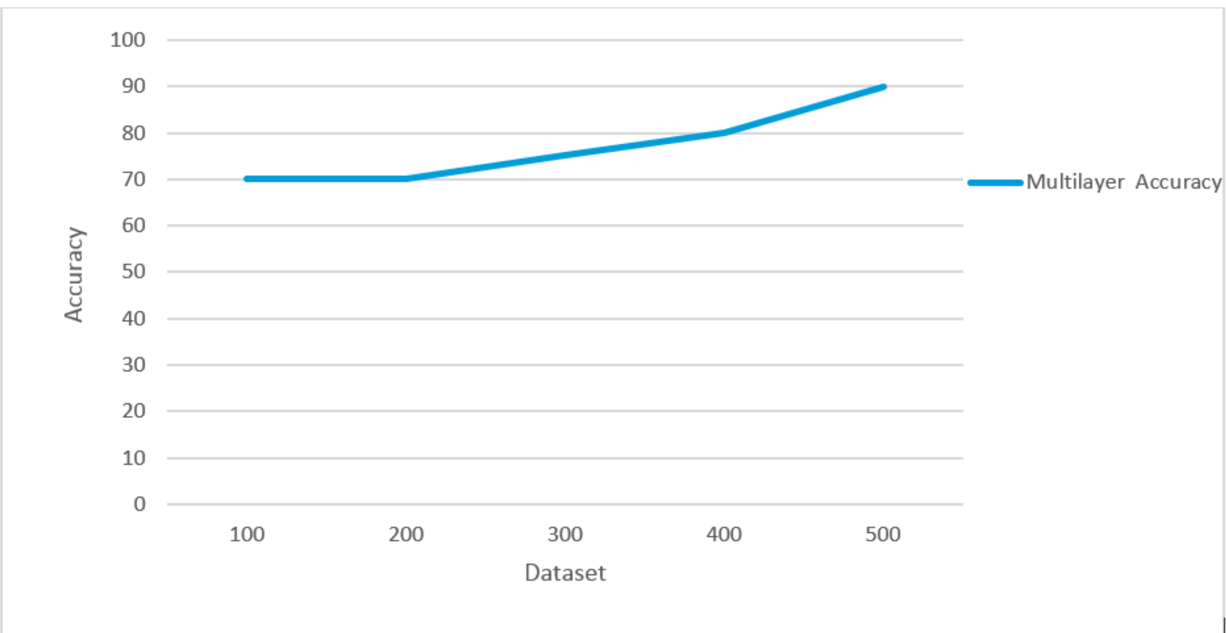

Fig 10:Accuracy of Multilayer feed forward network using different dataset

International Journal of Advance Research in Science and Engineering
Volume No.07, Special Issue No.08, March 2018
www.ijarse.com
IJARSE
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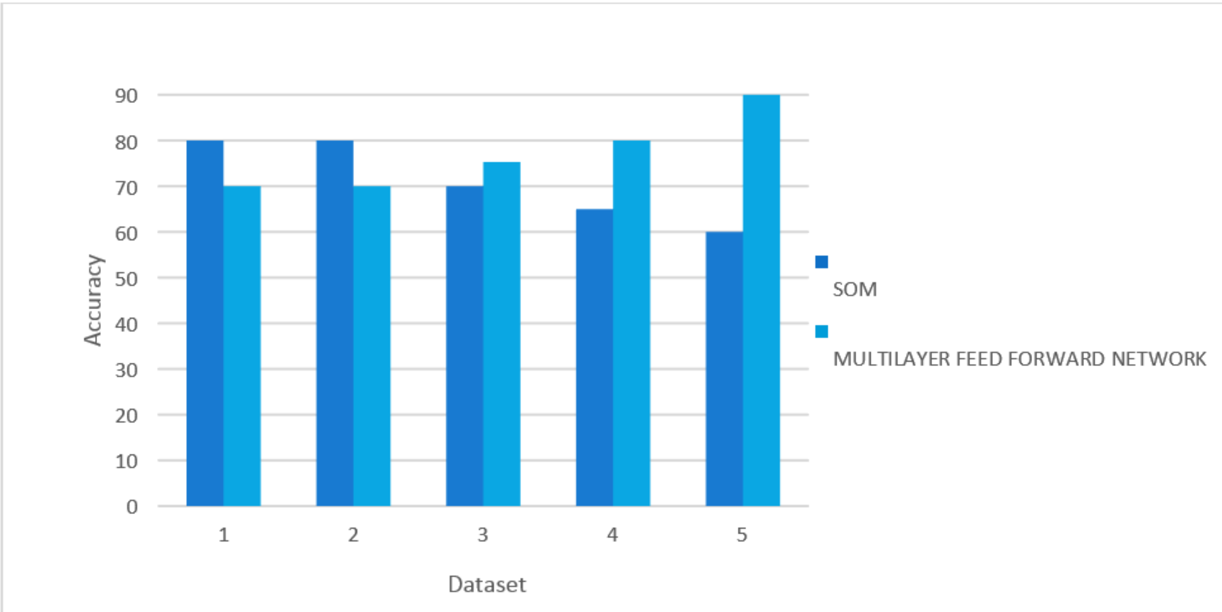

Fig 11:Comparison of Multilayer feed forward network and SOM based on different datasets

Errors:

Errors are of two types in signature verification: False Rejection and False Acceptance Also, there are two types of error rates: False Rejection Rate (FRR) and False Acceptance Rate (FAR) [6].For the evaluation purposes we have used to following measures of the signature identification system [11]:

4.1 False Acceptance Ratio (FAR):

The false acceptance ratio is defined as the number of fake signatures accepted by the system with respect to the total number of comparisons made. It is represented below:

*FAR = No of forgery signatures rejected by system / total number of forgery signatures tested * 100*

4.2 False Rejection Ratio (FRR):

The false rejection ratio is defined as the total number of genuine signatures rejected by the system with respect to the total number of comparisons made. It is as represent below:

*FRR = No of genuine signatures rejected by system / total number of genuine signatures tested * 100*

4.3 Accuracy:

Accuracy of any system is defined as the total number of signature correctly recognized by the system with respect to the total number of tested signatures. It is represented below:

*Accuracy = No of signatures correctly recognized by system / total number of tested signatures * 100*

5. CONCLUSION AND FUTURE SCOPE

This research paper based on offline Punjabi signature recognition system comparison using two different neural network techniques. In this research, for signature recognition SOM Artificial neural network technique and multilayer feed forward neural network technique are used. Offline signature identification advantages are flexibility and performance. In this paper we present a state of the art for the latest methods used in Punjabi offline signature identification system. The offline signature identification techniques and algorithm can improved by improving feature extraction and matching algorithms. Work is done only in few Indian languages so it has more research field. It was concluded that the one has to wisely choose the feature set, when performing applications like verifying signatures. Feature vector used here consisted of six features. Our method considers the overall likelihood of a whole signature instead of considering the local properties of the signature.

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