Offline Signature Verification Using Artificial Neural Network

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Abstract- **Signatures are widely used form of biometric that is related to human characteristics. The major applications include financial areas like banks where checks and legal documents are verified on the basis of account number and signature of the account holder. The fact that a person's signature is extensively used as a means of personal identification and verification emphasizes the need for automatic signature verification. Signatures can be either offline or online. Signature verification can be classified into online signature verification and offline signature verification. Online verification is based on dynamic capturing of signatures when they are made whereas Offline verification generally uses a scanned image of signatures. The objective of this project is to focus on the offline model of verification where several signatures are put through various processes before finally verifying it to be true or forged through Artificial Neural Networks (ANN). The proposed system compares the performances and accuracy of ANN and Decision Trees and provides promising results.**

Keywords – ANN, Decision Tree, Random Forest, HMM, SVM

I. INTRODUCTION

To link a person to his/her signature in real time is to find a biometric solution. Biometrics can be classified into physical and behavioral. Physical Biometrics include fingerprint, voice and facial recognitions whereas the latter includes Signature verification and typing rhythms. [1]
The identification of human handwriting is a key research area with respect to improvement in the interface between the computers and human beings. If computer is made smart enough to comprehend and understand human hand writing, then computers can be used for proper person authentication and attestation. This project represents an overview of offline signature verification using Artificial Neural Network. ANN is a classifier and a database in which several specimens of signatures are stored. Features of each of those signatures are extracted when a new signature is employed and thereby matched using the classifiers, and finally based on those classifiers a signature classified as genuine or forged[1].
Implementing offline signature verification is complex due to limited input feature set. It is a special form of handwriting and plays crucial role in applications like security, access control etc. The overall design of an offline signature verification system is complicated than an online signature verification system because of absence of timing and dynamic information. The challenges involved in verification process include acquiring the image to create a database and implement pre-processing techniques to reduce noise and blurring. Then features are extracted from the pre-processed image to train the classifiers to classify the signatures [2].

II. LITERATURE REVIEW

Offline Signature Verification is an important research area in the field of document processing and pattern recognition. Since it is a behavioral biometric it can be very easily imitated. The research poses to be extremely challenging trying to counter intra and inter-personal variations [1].
There are several possible implementations for recognizing and verifying handwritten offline signatures.

Hidden Markov Model (HMM) approach – Justino et al. proposed an off-line signature verification model using Discrete Cosine Transform (DCT) and Hidden Markov Model. In this proposed system, the signature is split into vertical divisions based on center of gravity by making use of space reference positions of image pixels. These divided signature parts are equated with that of the states in the Hidden Markov Model [3]. Though the experimental results are promising in Hidden Markov Model, it has limitations of having poor discriminative power that proves to be fatal which highly affects the applications it can provide [4].

Support Vector Machine (SVM) approach - Kruthi.C, Deepika.C.Shet proposed a signature verification technique using SVM where number of features are extracted after pre-processing and fed into the system. The SVM developed by using Sequential Minimal Optimization (SMO) and kernel perceptron draws a hyper plane and classifies the signature based on classifiers used into genuine and forged. About 336 signature samples were tested and reduced the classification error rate less than 7.16%. The observed FAR was 4.82% and FRR was 6.15% [10].

Statistical approach – This model follows the concept of correlation to validate a signature with the help of an average signature, which is derived from a set of, previously collected signatures to calculate to obtain the amount of variation in between them. A Bayesian model for off-line signature verification which considers a signature as a curvature representation is developed by McKeague. This model makes use of a spatial point for denoting the knots in an approximation restricted to a buffer region close to a template curvature, along with an independent time warping mechanism. Hence, shape information about the signature is converted into the analysis. The approach is implemented using Markov chain Monte Carlo (MCMC) algorithm [17].

Structural or Syntactic approach - M. Blumenstein and X. Y. Liu and B. Verma proposed a model where a neural network based technique has been used for recognizing cursive characters. It is a segmentation-based word recognition system and hence there were difficulties like ambiguity and illegibility were faced while performing segmentation. Here, patterns are represented as symbolic data structures such as strings, trees, and graphs. The Modified Direction Feature (MDF) utilizes the location of transitions from background to foreground pixels in the vertical and horizontal directions of the boundary representation of an object. The MDF extraction proved to outperform the DF extraction technique in terms of recognition accuracy [16].

Grid and Global based approach- Shashi Kumar D R et al. proposed a signature verification model based on Fusion of Grid and Global features in order to generate a powerful feature set and achieving classification using neural network classifiers. They were able to obtain a FAR of 4.16% and FRR of 7.51% [6].

Global Grid and Texture based approach - H. Baltzakis and N. Papamarkos used a new technique based on a two-stage neural network classifier where global, grid and texture features of signatures were implemented. For each of those features, a special two-stage Perceptron OCON (one-class-one-network) classification was achieved. This proved to be a complex design as a multi-staged neural network classifier was used and did not apply any feature reduction process. This was handled effectively by categorizing the features into sets and staging the structure and hence a complicated implementation .The first stage combines the results obtained by neural network's decisions and the Euclidean distance. This is then fed to the seconds- stage that procures final decisions using a radial based function (RBF) structure. The resultant FAR was 9.81% and FRR was 3% [7].

Angular approach - Prashanth C. R. and K. B. Raja proposed Offline Signature Verification based on Angular Features (OSVAF). They dealt with a skeletonized scanned image of signatures and extracted the actual area of it through pre-processing. They incorporated 128 angular features after dividing the signature based on center of mass. Based on the threshold value, forged ones are eliminated giving a FAR of 4.995 and FRR of 8.5 [8].

Speed Stroke based approach - L.Basavaraj and R.D Sudhaker Samuel introduced a signature verification mechanism based on four speed stroke angle. This process extracts a set of dynamic features from a static signature image. The main idea behind the implementation is that the intensity is directly proportional to the speed of the stroke used while making a signature. This method attained a FAR of 13.78% and FRR of 14.25% [9].

Neural 'Gas' Vector Quantization based approach - Zhang, Fu and Yan (1998) proposed a system where hand written signature is verified through Neural 'Gas' based Vector Quantization method. This model is trained in order to establish a set of references and then compared to test samples that possess signature inputs with that of the reference set. Though the results produced out of different feature extraction techniques were good, the scope of this paper is quite narrow and has been successful only in providing the preliminary results for signature verification [5].

Wavelet–Based approach - Deng developed a model that uses a closed curve tracing algorithm to represent the edges of each signature. The curvature data of the traced closed contours (circle) are decomposed into multi resolution signals using wavelet transforms. The zero crossings of the curvature data are extracted as features for matching. A statistical measurement is developed to find which closed contours and their associated frequency data are most stable and classifying. Based on these data, the optimal threshold value which controls the accuracy of the feature extraction process is calculated. Matching is done through dynamic time warping [14].

Smoothness Index based approach - Fang et al. proposed two methods for the detection of skilled forgeries using template matching. One method is based on the optimal matching of the one-dimensional projection profiles of the signature patterns and the other is based on the elastic matching of the strokes in the two-dimensional signature patterns. Matching is done through positional variations with the statistics of the training set and a decision based on a distance measure is made [22].

Pattern matching approach – Japanese Signature Verification performance based on pattern matching was proposed by Katsuhiko Ueda. Verification processes are generally affected by the variation of signature stroke widths in a signature. The proposed system used modified pattern matching methods that were independent of signature stroke width. Experimental results showed that the proposed methods considerably improved the verification performance [18].

Hough transform approach- Ankit Arora and Aakanksha S. Choubey proposed an alternate method for off-line signature verification using Hough transform where stroke lines are identified from signature image. The unique characteristic feature of signature is Hough space which is extracted from signature skeleton by Hough transform. The matrices point of this transform has been used as an input parameter for the neural network training performed using back propagation algorithm. This model showed recognition rate of 95% with 150 test signatures from different persons [24].

III. METHODOLOGY

Decision Tree

Decision trees are a non-parametric supervised learning method used for classification and regression. The main aim of decision tree is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data [20].

Random Forest

Random forest is a concept of collective learning technique for classification and regression that work by building a huge number of decision trees during training time and yielding the class that is a kind of grouping or mean expectation of the individual trees [21].

Artificial Neural Network

The main reason for widespread usage of neural networks (NNs) in pattern recognition is that it requires a user to gather only highly representative data set and then invoke training algorithms to learn the underlying structure of the data. The signature verification process parallels this learning mechanism. The simple approach is to primarily extract a feature set representing the signature (details like length, height, area etc.), with several samples from different persons. The second step is for the NN to learn the relationship between a signature and its classification. After the relationship is studied, the network is given with a set of test signatures that are classified as belonging to a particular person [19]. Therefore NNs are well suited for modeling handwritten signatures. The proposed system has been tested with 200 signatures from different persons from dataset revealing the recognition rate of 90.5% [23].

Fig. 1 shows the methodology of neural network.

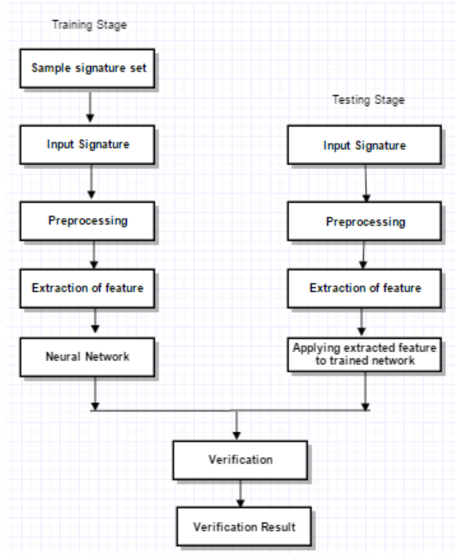

Fig. 1 Neural Network Methodology

IV. IMPLEMENTATION

1. **Image Acquisition:** Image Acquisition is a process which involves collection of signature samples. 20 signature samples are collected from 10 persons.

2. **Pre-Processing:** The acquired images are processed in order to adhere to a standard format and it makes images suitable for feature extraction. Various pre-processing techniques implemented are as follows

2.1 Image resizing: An input image is resized to standard size, 256X256. Fig 2 shows the original image and Fig 3 shows the resized image.

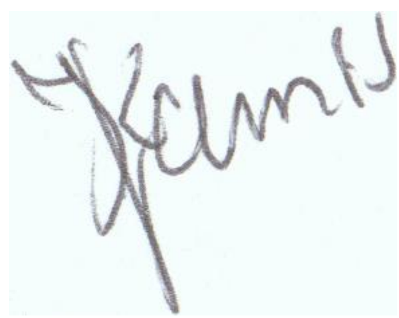

Fig 2 Original Image

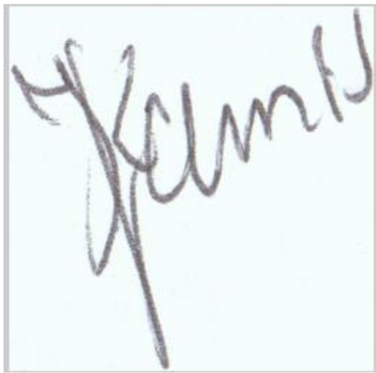

Fig. 3 Resized image

2.2 Grayscale conversion: Resized image is converted into grayscale format. Fig 4 shows the gray scale conversion of resized image.

Fig. 4 Grayscale image

2.3 Converting image to binary: The grayscale image is converted into binary image. Binary image consists of zeros and ones. Black pixels are represented as zero and white pixels as ones.

2.4 Thinning: Thinning reduces binary objects to strokes which are wide equal to single pixel.

2.5 Auto-Cropping: The image is auto cropped to eliminate the excess area of the signature. This is accomplished by finding the exact boundary of the signature. Fig 5 shows the cropped image.

Fig. 5 Auto cropped image

3 Feature extraction: Offline feature extraction is a challenging task since handwritten signatures vary and lack dynamic information about the signing process. An ideal feature extraction technique is to extract the minimal feature set that maximizes the relational distance between signatures of different persons. Thus it minimizes the intra-personal distance for those belonging to the same person. Feature extraction is an essential step in signature verification system. The features that are extracted in this phase are used to create a feature vector. 27 features are extracted from each image in this system. Various features extracted are as follows

3.1 Maximum black pixels: The image is scanned horizontally and vertically and the row and column with maximum black pixel is recorded. This contributes to two final features to feature vector.

3.2 Center of mass: Processed image is divided into two equal parts and center of mass for individual part is calculated. This contributes four features to feature vector.

3.3 Normalized area: It is the ratio of the area of signature image to the area of auto-cropped image. This gives one feature.

$$Normalized\ Area = \frac{Area\ of\ Singature}{Area\ of\ cropped\ image}$$

3.4 Aspect Ratio: This is defined as ratio of width of the signature to the height of the signature. This contributes one feature to feature vector.

$$Aspect\ Ratio = \frac{Width\ of\ Signature\ in\ cropped\ image}{Hegiht\ of\ Signature\ in\ cropped\ image}$$

3.5 Tri-Surface: There is a possibility where one or more images can have similar area. In such a case, the accuracy has to be increased in order to hold the genuineness of the signature. To perform this, we implement Tri-Surface feature where an image is split into three equal parts and normalized are of those parts are validated. This contributes three features to final feature vector. Fig 6 shows the image being split into three vertical equal parts.

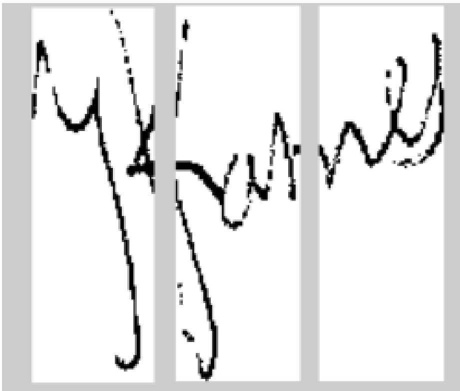

Fig 6. Tri surface

3.6 Six-Fold: The divided signature image using Tri-Surface feature is cropped to eliminate whitespace in each part. Center of mass of each part is then calculated and split according to the center into two and then area of each of them is calculated and hence providing six features. This feature gives six features to final feature vector. Fig 7 shows the image being divided vertically into three equal parts and further divide into two equal parts each based on center of mass.

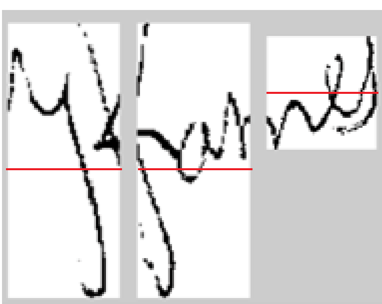

Fig 7 Six fold surface

3.7 Transition Feature: Image is traversed in all directions and each time a transition from 1 to 0 or 0 to 1 is encountered a ratio is calculated between the position of transition and width of the image traversed and is recorded as feature. The total number of 0 to 1 and 1 to 0 transition is also calculated. Transition feature contributes ten features to feature vector.

4 Creation of Feature Vector: All the features mentioned above are combined to form a feature vector of size 27.

5 Training Neural Network: Feature vector with 27 features are normalized in such a way that its value is between zero and one. This normalized feature vector is fed as an input to neural network. The network is trained with both genuine and forged signatures.

V. RESULTS AND DISCUSSION

Neural Network: 200 signatures from 10 different persons were used in this project. 80% of images are used for training the network and remaining 20% are used for testing. The input to neural network will be set of feature vectors of dimension 27 X 200 where 27 rows represents the number of features and 200 columns represents number of images. Target to neural network is specified manually in a excel sheet which is of dimension 10 X 200 where 10 is number of classes and 200 is number of images.
The confusion matrix plotted for 200 images from 10 different persons are as follows. Fig. 8 shows the 2 layer neural network with 10 classifications. Fig. 9 shows the confusion matrix plot in neural network; Fig. 10 shows the performance plot in neural network; Fig. 11 shows the ROC

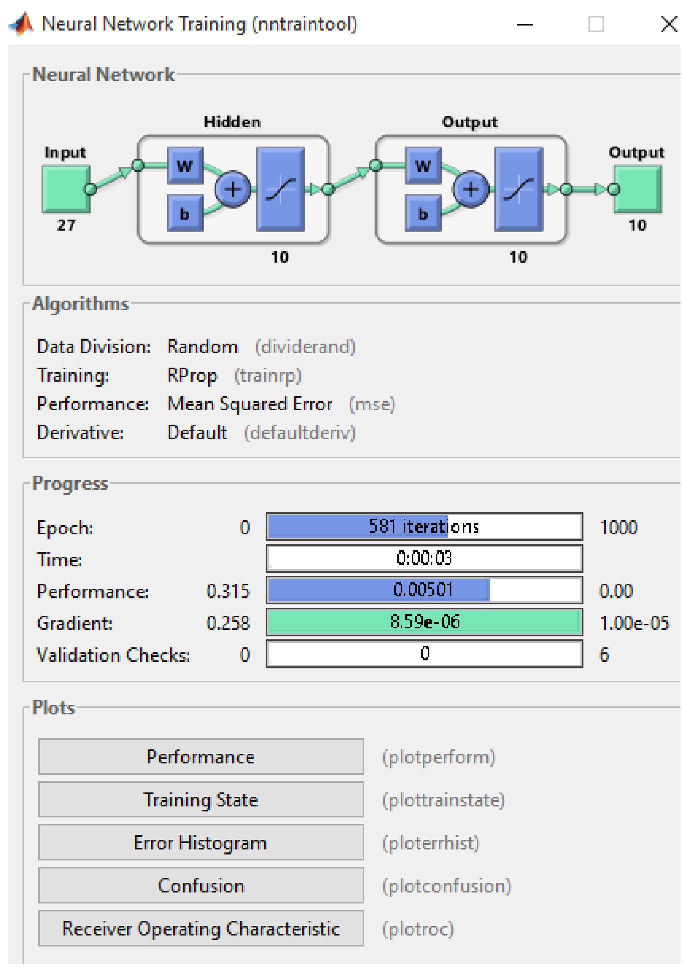

Fig 8 Neural Network

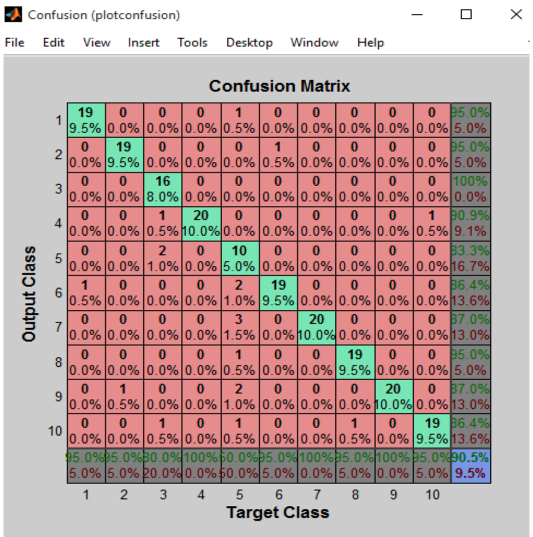

Fig 9 Confusion matrix plot in Neural Network

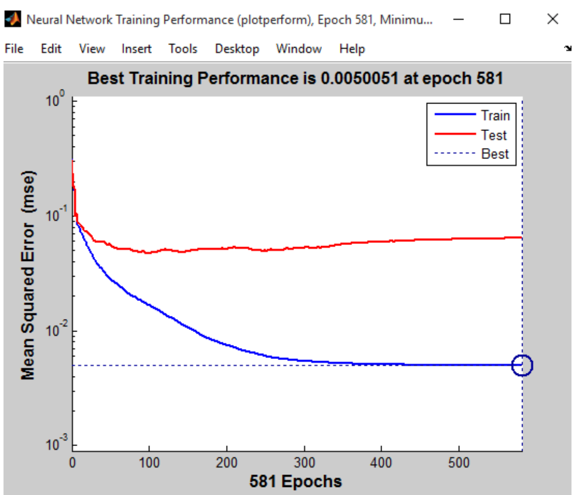

Fig 10 Performance plot in Neural Network

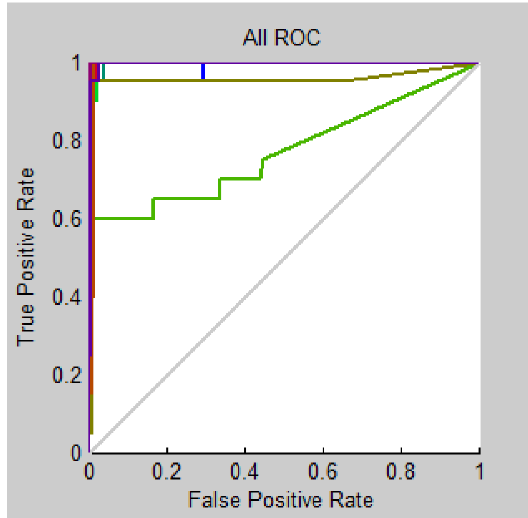

Fig 11 ROC curve plot in Neural Network

Decision Tree: 200 signatures from 10 different persons were used to classify into 10 classes. 80% of signatures were used for training and 20% for testing. The decision tree model provided an accuracy of 58.5%. Fig 12 refers confusion matrix in Decision tree.

```
> confusionMatrix(pred_dtree)
Confusion Matrix and Statistics


    1 2 3 4 5 6 7 8 9 10
 1  7 1 6 0 1 4 0 0 0  0
 2  0 6 1 0 4 1 0 0 0  0
 3  0 0 0 0 0 0 0 0 0  0
 4  0 0 0 7 0 0 0 0 0  7
 5  0 0 0 0 0 0 0 0 0  0
 6  0 0 0 0 0 0 0 0 0  0
 7  0 0 0 0 1 1 7 0 0  0
 8  0 0 0 0 0 0 0 7 0  0
 9  0 0 0 0 1 1 0 0 7  0
10  0 0 0 0 0 0 0 0 0  0

Overall Statistics

               Accuracy : 0.5857
                 95% CI : (0.4617, 0.7023)
    No Information Rate : 0.1
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.5397
 Mcnemar's Test P-Value : NA
```

Fig 12 Confusion matrix in Decision tree

Random forest: 200 signatures from 10 different persons were used to classify into 10 classes. 80% of signatures were used for training and 20% for testing. The random forest model provided an accuracy of 90%. Fig. 13 shows the confusion matrix in Random forest.

```
> confusionMatrix(pred_rf)
Confusion Matrix and Statistics

    1 2 3 4 5 6 7 8 9 10
 1  5 0 0 0 1 0 0 0 0  0
 2  0 7 0 0 0 0 0 0 0  0
 3  0 0 6 0 0 1 0 0 0  0
 4  1 0 1 7 0 0 0 0 0  0
 5  1 0 0 0 4 0 0 0 0  0
 6  0 0 0 0 0 6 0 0 0  0
 7  0 0 0 0 0 0 7 0 0  0
 8  0 0 0 0 0 0 0 7 0  0
 9  0 0 0 0 1 0 0 0 7  0
 10 0 0 0 0 1 0 0 0 0  7

Overall Statistics

               Accuracy : 0.9
                 95% CI : (0.8048, 0.9588)
    No Information Rate : 0.1
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.8889
 Mcnemar's Test P-Value : NA
```

Fig 13 Confusion matrix in Random Forest

VI. CONCLUSION

Signature represents the identity of the person. Handwritten signature is the crucial aspect in the identity verification. This model presents the handwritten signature verification approach using Artificial Neural Network. The network is trained using back propagation with genuine and forged signatures. A recognition rate of 90.5% is obtained in this model. A comparison is also made with Decision tree and Random forest.

VII. FUTURE SCOPE

The future scope is to provide a more robust ANN system for signature verification and to handle the non-signature images.

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