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Neural Network Based Intelligent Retrieval System for Verifying Dynamic Signatures

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Abstract

Mining of data is the process of discovering patterns from a large data set and uses this knowledge for matching purpose. In this paper a neural network based approach of data mining is used to verify dynamic signature patterns. In an authentication process, everyone may have a signature that is used to legally prove the document and to bind the individual with the inclination contained in the document. Signature verification is the verification process in which a given input is examined and is either rejected as forgery or accepted as genuine. The proposed algorithm is applied to a set of 500 signature samples collected from 20 individuals. Performance of the system is depicted by using three parameters that are accuracy, false acceptance rate (FAR) and false rejection rate (FRR). Experiments are performed by training the system with more and more number of samples. The results show that the system with neural network has better performance as compared to support vector machines.

Keywords: *Online signature verification, NN, MLP, FRR, FAR*

1. Introduction

Data mining is the process of discovering knowledge by extracting hidden patterns from large databases. It is applied in various machine learning applications like natural language processing, syntactic pattern recognition, fraud detection etc to predict information from past and present records. Neural networks are biological systems used to recognize patterns take decisions and learn and artificial neural networks are computer programs that implements machine learning algorithms to derive predictive models.

The requirement for a genuine means of personal identification presents a challenge to almost every modern organization. Multimedia application developers and an engine for online signature verification are provided by this system. Online verification uses shape of an individual's signature and also logs the pen timing throughout the signing process.

Characteristics of Biometric Features are:

- Features are as unique as possible *i.e.*, they don’t match with any other person.
- Occur in as many people as possible
- Appropriate and easy to measure.
- Measurable with simple technical instruments
- They don’t change with changes.

Online signatures are written with an electronic device and the dynamic information is available at high resolutions. Data such as the direction captured dynamically, stroke, pressure, and shape of an individual’s signature can enable handwriting to be a genuine indicator of one’s identity.

Advantages if dynamic signatures over static signatures:

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- The features used for online signature recognition are almost impossible to duplicate.
- Dynamic features are unique to the handwriting style of an individual.
- The changes in timing and the pressure points can be recreated by the original signer only.
- A dynamic signature does not cause any noise as static signatures due to scanning hardware.

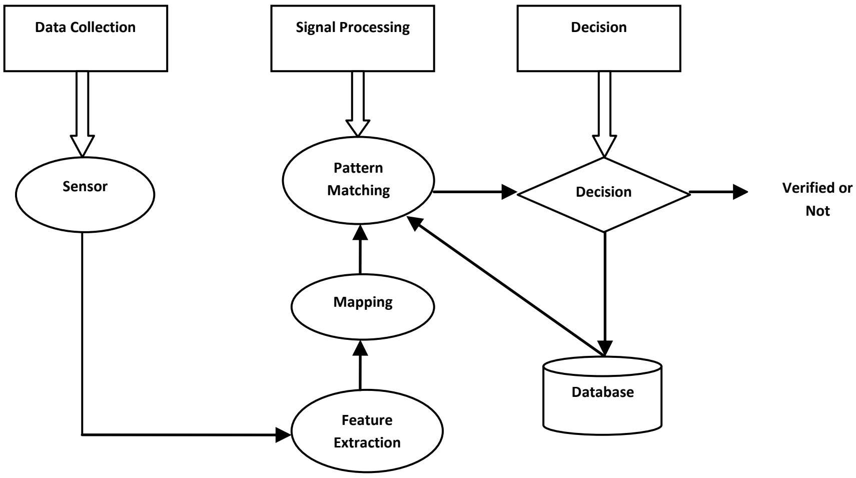

Figure 1. General Biometric System

In biometric verification systems, first, data get collected for every user with their references. Later when a user presents a signature by using an input device particular to the individual, the system compares this signature with the reference signatures stored in the database for specific individual. If the dissimilarity exceeds a certain value, the signature is rejected otherwise it is accepted as genuine.

In this research online signature verification system for verifying Punjabi signatures is proposed. Signatures are classified by using neural networks based predictive model. The system is trained with BPNN *i.e.*, back propagation neural network.

This paper is outlined as under: Section 2 describes the previous work related to the online signature verification. The implementation of all the modules is described in section 3. Section 4 describes the results obtained by using different performance metrics. The last section concludes and suggests the future scope of the system.

2. Related Work

In 1965, first signature recognition system was developed [1] and research in online signature verification was started in the 1970's [2-4].

Neural networks are used for verification process. It consists of three layers: input layer, hidden layer and output layer. Numbers of neurons present in each layer are connected to other neurons by using weights. Training is used to determine weights. In [5-7] experiments were performed on English data set using neural classifier. Bayesian regularization back propagation training function is used to train the system. Network is associated with the scaled score to which the resultant output is multiplied. The total decision is based on the sum of scaled score outputs and the accuracy of 95% is obtained [5]. Local features are classified by using back propagation neural network and global features with probabilistic model. Combination of these two classifiers was used to get the result and FRR of 3% and FAR of 5% is obtained [6]. Mel Frequency Cepstral Coefficient (MFCC) is used for feature extraction [7]. Two classifiers used were: Neural network with multi-layer perception architecture and linear classifier used in combination with PCA. Minimum error rate of 3% is achieved by the network while applying scale transform. In

[8] the experiments were performed on English and Chinese signatures and the overall handwritten recognition rate obtained using pressure pattern is between 71.2 % and 95.5 %.In [9] the software has been developed by using Pearson's correlation algorithm and fuzzy inference. FRR of 3.5% and FAR of 0% is obtained. Signature coordinate points and pen pressure of all signatures in Malaysian database were used and then, Pearson correlation coefficients were selected for feature extraction. Results are verified by using back propagation neural network and the accuracy of 82.42% is obtained. Experimental results indicate the number of false acceptance is more than false rejection [10].

An approach based on support vector machines for verifying online signatures in foreign languages is proposed [11-13]. The results showed that the combination of pen pressure and time features have better outputs as compared to the other set of features. In [14, 15] an approach for verifying online signatures of an Indian language is proposed. Punjabi signatures are verified by using support vector machines as a classifier. Experiments were performed by using radial basis function kernel. The results showed that the accuracy of the system increases as more number of samples are collected and by combining more and more features together.

Vector quantization based approach for verifying Spanish, English and Chinese signature is proposed.EER of 0.68% and 4.92% is obtained for random and skilled forgeries respectively [16].

Dynamic programming is used to match two strings based on the distance between them. In [17] 100 pattern combinations were tested to increase the reliability of the system and the accuracy of 94.57% is obtained for verifying Chinese signatures. The performance is calculated by using error rates in [18].An average FRR of 10.29%, average FAR of 9.72% and 9.96% as total error rate is obtained in signature verification method using dynamic programming. Dynamic time warping (DTW) technique is used to verify English signatures in [19, 20]. Experiments were performed on feature set of seven dynamic features. Each user is enrolled with 10 genuine signatures and distance values are generated by using six features. Skilled forgeries are rejected with an error rate of 0.5% and only 0.25% of genuine signatures are rejected [19]. In [20] two different length strings are compared by using string matching. Experiments were performed on the data set of 1232 signatures. For a common threshold 3.3% false rejects and 2.7% false accepts error rates were obtained.

Spanish signatures using DTW were verified in [21-23]. Mahalanobis distance instead of Euclidean distance is used to get correlations among various features. Feature set of x, y positions, pressure p, azimuth angle α and inclination angle β can be recorded at a specific time. Experimental results showed that the feature set of y, v_x, v_y, p has better performance with EER of 3.73% [21]. In [22] performance is measured by using FRR and FAR error rates and FRR of 1.82% and FAR of 1.74% is obtained. High dimensional feature set is formed using velocity and pressure values [23]. Signatures are separated by using Euclidean distance. EER of 0.0340 and 0.0109is achieved when the system is trained with three and five signatures respectively.

Hidden Markov model is another technique for verifying signatures for which partial state of markov chain is observed. The system for verifying Chinese data set is proposed [24]. In this research three schemes of HMM were used. In HMM3, transition matrix can be computed directly by using the duration of pen-up state and pen-down state. In HMM2 one pen-up state and in HMM1 no pen-up state is used. It has been observed that the discriminative ability of HMM2 is highest. This technique is also used for verifying signatures of Spanish data set. Matching score is calculated by using Viterbi algorithm of HMM. The function set consists of horizontal and vertical trajectories and pressure signal. EER of 4.54% is produced when pressure signal, horizontal trajectories and vertical trajectories are used collectively. Value of EER varies for different features [25].

Spectrum analysis is another technique for verifying signatures. In this technique the division of the signature takes place by dividing the signature into number of frames using time sequences. Signature spectrum is extracted by using Fast Fourier transformation (FFT). In [26] experiments were performed to verify signatures using spectrum analysis and equal error rate of 0.07 is obtained. EER of 0.0116% is achieved for verification of English signatures based on discrimination points [27]. Signature verification based on time sequence matching is proposed for verifying English signatures and FRR of 2% is achieved [28].

In last decade, number of techniques for on-line signature verification of various languages has been observed and it has been found that very little amount of work has been done in online signature verification for Indian languages and i.e. only for Punjabi language using support vector machines as a classifier [14, 15]. The great amount of work has been performed with foreign languages like Chinese, Spanish, and English *etc.*, using several classification methods.

3. System Methodology

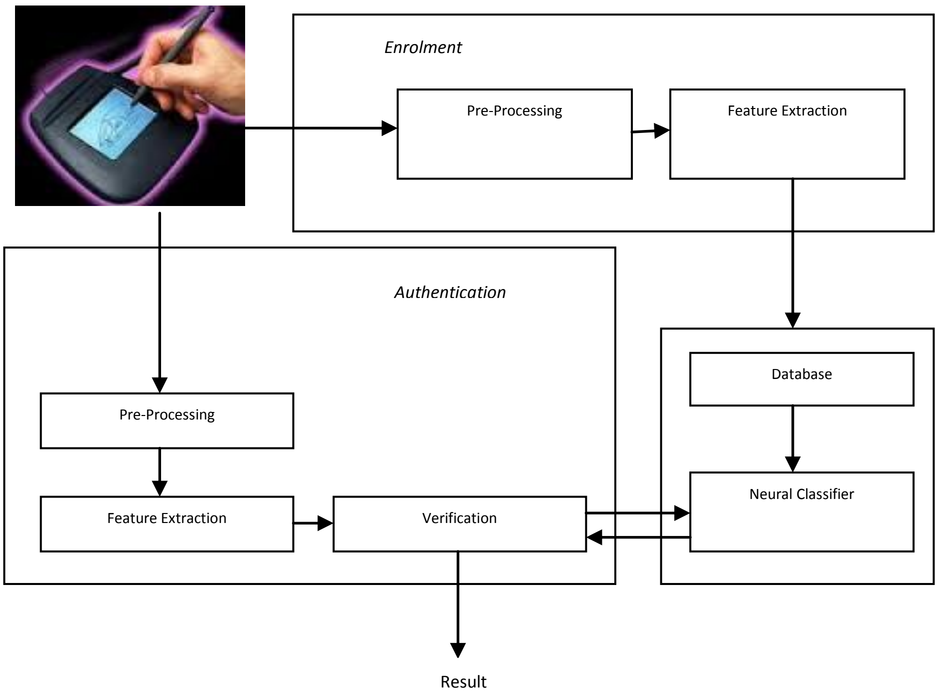

Figure 2. System Architecture

The presented system for signature verification has several significant advantages:

- Forgery is detected even when the forger has managed to get a copy of the authentic signature.
- Fast and simple training.
- One can use any kind of information as his signature: name, second name, or even curves.
- The system represents a natural way to prove authenticity.

The proposed system consists of number of phases. The complete architecture for the proposed system is shown in Figure 2. The handwritten signature is captured using digitizing tablet. The signatures will be pre-processed before they get stored in the database. The collected data will be divided into two sets, one is training set used to train the system and other is the testing set.

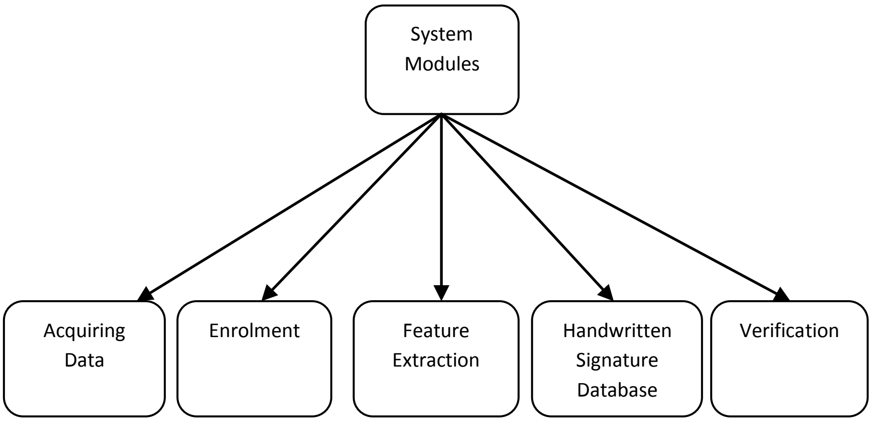

Figure 3. System Modules

3.1 Acquiring Data

Dynamic signature recognition uses multiple characteristics in the analysis of one's handwriting. These characteristics vary in use from vendor to vendor and are collected using sensitive technologies, such as digitizing tablets.

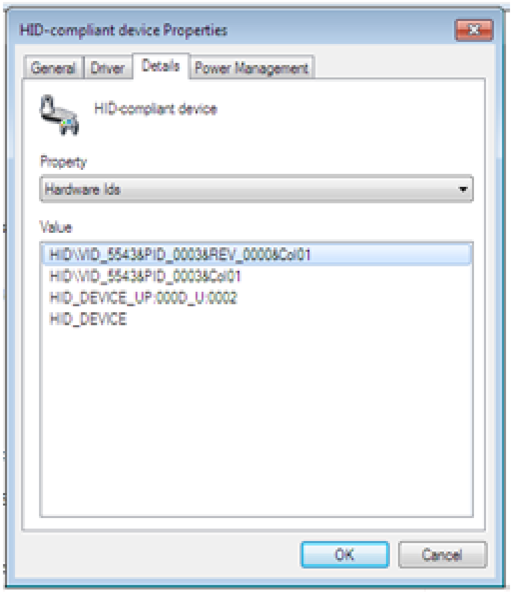

Figure 4. Vendor ID and Product ID

In this system data is acquired by using USB pen tablet and is stored in the database for further processing. USB protocols are used for configuring devices during start up of the system. The descriptors of human interface device (HID) are used for routing of data in and out of the system. Each device is associated with unique VID (vendor ID) and PID (Product ID). The device used for this system has VID: 5543 and PID: 0003 as highlighted in Figure 4.

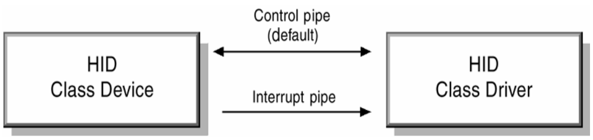

Figure 5. HID Class Device Communication

3.2 Enrolment

Enrolment, defined as an entry or a record. It is the process of registration of the user. Each user has to enlist himself into the system. In this phase signatures of each user get stored in the database and are used in future to train the system.

3.3 Feature Extraction

Feature extraction is the main step in pattern recognition. The main problem in data mining is to determine the most relevant features which help in building the most accurate prediction models. The functionality of this module is to transform the raw data into meaningful patterns.

The raw data of a signature consists of the following information:

- Pen-up status
- Pen-down status
- X co-ordinate
- Y co-ordinate
- Pressure of pen point
- Button status of pen

By using this raw data six features are extracted and used for verification of samples. Extracted features are: signature length, total signing time, total pen down count, minimum pressure, average pressure and maximum pressure.

3.4 Handwritten Signature Database

The database used for this study consists of 500 genuine Punjabi signatures and 100 forged signatures. The signatures in this database are represented signature length, total signing time, total pen down count, minimum pressure, average pressure and maximum pressure.

Punjabi, an Indo-Aryan language is the official language of the state of Punjab in India. It is written in 'Gurmukhi' script in eastern Punjab (India). Different dialects of Punjabi language spoken in the different sub-regions of greater Punjab are Majhi, Doabi, Malwai, Powadhi, Pothohari, and Multani.

Essential Features of the Gurmukhi Script

- No concept of upper or lower case letters.
- The Gurmukhi script is arranged in a logical fashion: first vowels, then consonants and semi-vowels.
- This is a syllabic script in which all consonants have an inherent vowel. Diacritics, which can appear before, after, above or below the consonant they belong to, are used to change the inherent vowel.
- Vowels are written as independent letters, when the Gurmukhi letters appear in the beginning of a syllable.

Figure 6. Representations of Punjabi Characters

Punjabi is a phonetic language therefore it is quite possible to learn the characters of the Gurmukhi script as well as sounds of the language at the same time.

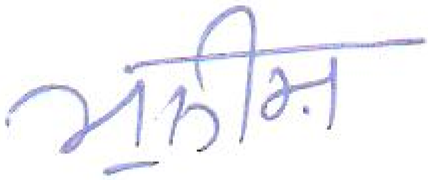

Figure 7. An English Word 'Munish' written in Punjabi

3.5 Verification

There is a challenge for proposing a system with the ability to recognize handwritten online signatures and verify its identity. For verification neural networks, a technique of data mining is used.

3.5.1 Working of the Human Brain: A neural network is a computational model which process information in a collective manner throughout a network of nodes. It is biologically inspired by the structure of the brain. The brain consists of a large number of neurons interconnected with each other. Each neuron generates an electrochemical signal and has a branching input structure called as dendrites, a cell body and a branching output structure called as axon. The axons of one cell are connected with the dendrites of another cell via synapse. This interconnection helps in the transmission of electrochemical signals along axon whenever it is fired by the neuron.

3.5.2 Artificial Neurons: Artificial neural networks are inspired by biological neural networks, used to make estimates and are capable of matching patterns. It has two modes of operation:

1) The Training Mode: this mode deals with the training of the neuron.
2) The Usage Mode: this mode makes use of the already taught pattern to check whether the input pattern belongs to it or not. Firing rule is used to determine whether to fire a neuron or not.

Firing rules in neural networks are used to determine how to identify whether a neuron should fire for a given input or not.

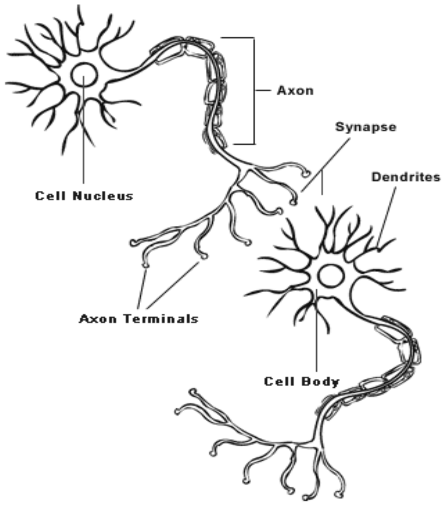

Figure 8. Neuron Structure

3.5.3 Architecture of MLP: A perceptron, invented by Frank Rosenblatt at the Cornell Aeronautical Laboratory in 1957. MLP consists of three layers:

Input Layer: this layer contains the inputs of the network. Inputs to the neurons are the features of the signature.
Hidden Layer: this layer receives the weighted inputs from the input layer and works as a transfer agent to send data from the previous layer to the next layer.
Output Layer: this layer contains the output data.

In this system a multilayer perceptron (MLP) is used which is a "feed forward model", in which inputs are forwarded to neurons, processed and results in an output. The network is shown in Figure 9.

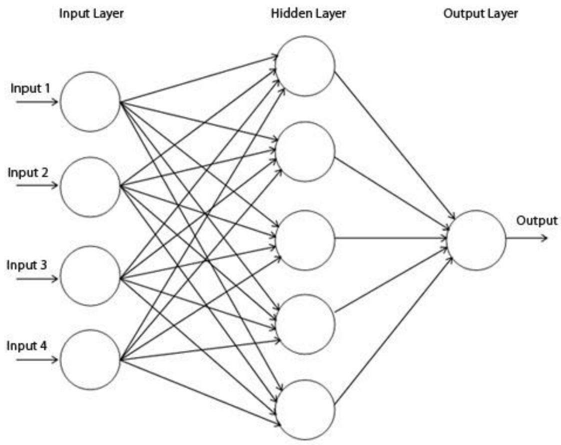

Figure 9. Neural Network Architecture

The system is trained with a common supervised learning technique called back propagation which means "propagation of errors". It consists of four stages:

- Initializing weights
- Fed Forward
- Back Propagation of errors
- Weight Updation

Algorithm used for processing inputs in a three-layer network:

1. Let's have a perceptron with two inputs
Input 0: a1= 25
Input 1: a2=2

2. Each input is then multiplied by weight whose value must be between 1 and -1.

Let Weight 0= 0.2 and
Weight 1= -1 then,

Input 0 * Weight 0 => 25 * 0.2 = 5
Input 1 * Weight 1 => 2 * -1 = - 2

3. All the inputs are then added
Sum = 5 + (-2) = 3

4. An output of the perceptron is generated based on the sum passed through an activation function. The activations are forwarded to the other neurons. If the sum passed is a positive number, the output is 1, and if it is negative, -1 output is generated.

In back propagation technique, the output error moves back to the input layer to calculate the errors. The behavior of the neural network changes slowly by changing the values of the weights. Values are optimized to calculate the loss function that maps one or more values and results in a minimum error. The error can be defined as:

ERROR = DESIRED OUTPUT - ESTIMATED OUTPUT (1)

An error is the factor used to determine how weights are adjusted. Weights are adjusted for each step and will come to an end as loss function reaches to the minimum. Training of the network is an iterative process. Weight coefficients of nodes are updated using new data from the training set during every iteration.

4. Experimental Results

In this system three parameters are used to measure the performance of the system. Following parameters are used:

- Accuracy: *i.e.*, the exactness. It is the degree to which the result of any calculation conforms to be correct.
- False rejection rate (FRR): It is defined as the number of genuine signatures rejected by the system.
- False acceptance rate (FAR): It is defined as the number forged signatures accepted by the system.

Experiments are performed by using multilayer perceptron and feature set of six features that are signature length, total signing time, total pen down count, minimum pressure, average pressure and maximum pressure. The system is trained with back propagation neural network in which errors are back propagated to adjust weights. FRR of 0.12% and FAR of 0.41% is achieved in the proposed system.

In this system 500 genuine Punjabi signatures are collected from 20 individuals out of which 80% of the signatures are used for training and 20% for testing.

Table 1. Verification Accuracy

Number of Samples	Accuracy %
100	68
200	69
300	75
400	82
500	88

The graph shows that the exactness of the system increases with the increase in signature samples. The system accuracy graph is shown in Figure 10.

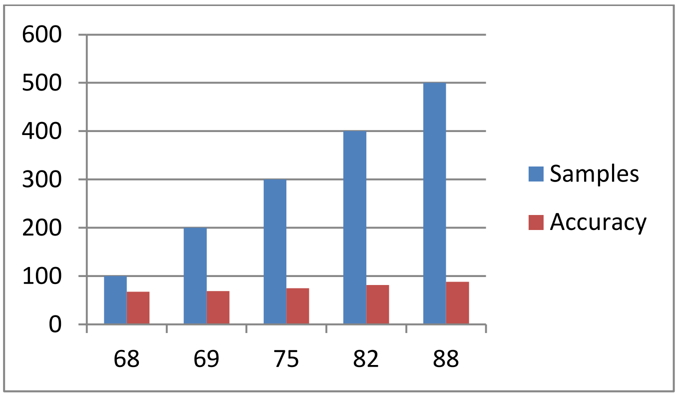

Figure 10. Accuracy Graph of System

Experiments are performed by using neural networks on the data set of Punjabi signatures and it has been found that the neural network prediction model performs better as compared to support vector machines. Comparative study is shown in Table 2. The system is trained with the same number of samples and the experiments are performed on the same database in both the studies.

Table 2. Comparative Study of SVM and NN

Technique Used	**Accuracy %**	**FRR %**	**FAR%**
SVM [15]	85	0.16	0.49
NN	88	0.12	0.41

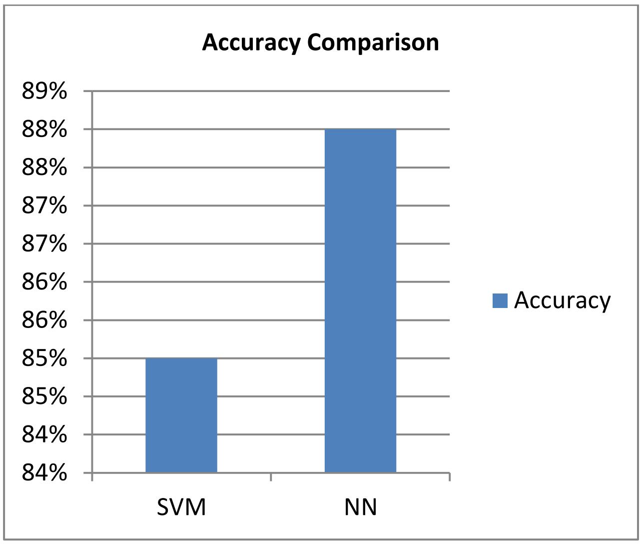

Figure 11. Accuracy Comparison Graph

5. Conclusion and Future Scope

In this paper an approach for verification of online Punjabi signatures using data mining is proposed, as very large amount of work has been done in various foreign languages and very little amount of work has been done in Indian language for online signature verification i.e. only using support vector machines as a classifier. In this research signatures are classified by using neural networks in which multilayer perceptron identify the signatures as either genuine or forged. Performance of the system is measured on the basis of accuracy, FRR and FAR.

The result shows that neural networks outperform SVMs. Neural networks are more flexible in deriving features from the data set. The problem with SVM is choosing and optimizing kernel. If over optimized, regularization parameters can lead to over-fitting. ANN are parametric models *i.e.*, their size is fixed and it contains the number of hidden layers depending upon the number of features. The advantage of MLP is that it has higher learning capability due to multiple layers present in the network.

In future this work can be extended by extracting more features and classify the signature samples written in other Indian languages. It also aims at using training algorithm for adjusting weights.

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