A Robust Offline Handwritten Signature Verification System Using Writer Independent Approach

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***Abstract*— In this work, a writer independent offline handwritten signature verification model, also known as global model, for signature verification is proposed. Three classifiers, two back propagation Artificial Neural Networks and a Support Vector Machine with polynomial kernel are probed to develop the global model. Two databases of signatures from different writers are used to evaluate the performance of these classifiers in terms of false acceptance rate and false rejection rate. To develop the system geometric features and local binary pattern features are investigated. It is found in the study that Support Vector Machine outperforms the Artificial Neural Networks in developing handwritten signature verification system using geometric features and local binary pattern features.**

Keywords*— *Offline Handwritten Signature Verification System, Writer Dependent Approach, Writer Independent Approach, Geometric Features, Local Binary Patterns, Artificial Neural Network, Support Vector Machine

I. INTRODUCTION

The signature of a person is an accepted biometric characteristic. Individual's signature is used for the authenticity of official documents as well as personal verification. The handwritten signature verification (HSV) system is used to verify the signature of individual as genuine or forge. In previous few decades, numerous signature verification systems have been investigated, which can be majorly divided into offline and online systems [1]. In online approach, the optical pen is used by the signer for writing and the sensors are used to pick the handwriting's physical characteristics such as speed of writing, pressure at various positions of the signature, order of strokes etc. On the other hand, in offline system individual's signature is collected on paper and scanned by the optical scanner. Due to unavailability of dynamic information, offline systems are hard to design. Further, the performance achieved by online approach is found to be better than offline approach because of availability of dynamic features [2].

For developing signature verification system the forgeries set is divided into random, simple, and skilled forgeries subsets. Usually, the random forgery signature sample is a genuine signature sample of a different writer. In simple (occasionally known as unskilled) forgery the forger knows only the genuine writer's name whereas in case of skilled forgery (also known as simulated forgery) the forger knows very well the genuine signature sample and has practiced it many times [3]. The random, simple and skilled forgeries of genuine signature sample of an individual are shown in Figure 1.

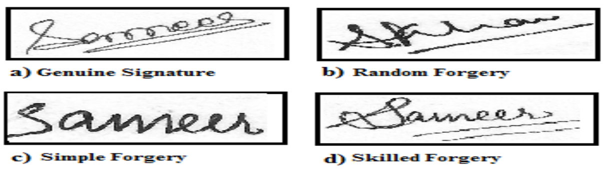

Figure 1: Genuine and Forgery Signature

The performance of handwritten signature verification system is measured in terms of False Rejection Rate (FRR) and False Acceptance Rate (FAR). The FRR, also known as type I error, is the percentage of genuine signatures rejected as false whereas the FAR, also known as type II error, is the percentage of forgery signatures accepted as genuine. Several researchers have considered Average Error Rate (AER) which is the average of FFR and FAR.

Writer dependent (WD) and writer independent (WI) are two approaches of offline signature verification systems investigated by the researchers [2]. In writer dependent approach, a personal model is built for each writer. The development of this model is a two class problem as it is based on two dissimilar pattern classes Class1 and Class2. Genuine signature samples of a specific writer constitute Class1 whereas Class2 consists of forgery signature samples. The writer independent approach models the likelihood distribution in between class and within class similarities [2]. The writer dependent approach suffers two major drawbacks, first, it requires to include vast number of genuine signature samples and second, its incapability to absorb a new individual without generating a new personal model for the

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individual. On the other hand, writer independent approach, also called global model, requires only one model to deal with all individuals and is capable to absorb unknown individual without altering the model. This approach also reduces the signature verification problem to a two class problem, where one class (C1) contains genuine samples of all individuals and other class (C2) contains forgeries (Figure 2). The main advantage of this approach is that one can build a reliable model even when few number of genuine signature samples are available.

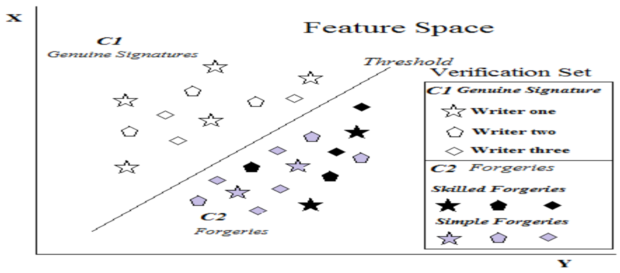

Figure 2: Global Model Signatures Area for Different Writers

The writer independent approach is proposed by Cesar Santos et al [4] to classify the signature sample as forge or genuine in the process of developing handwritten signature verification (HSV) system. The problem of writer independent HSV is also addressed by researchers using several other techniques such as Hidden Markov Models (HMM) [5] [6], machine learning models like Artificial Neural Networks (ANN) [7], Distance Classifier [8] [9] and Support Vector Machines (SVM) [10].

The present work aims at developing an offline handwritten signature verification system using writer independent approach, a dissimilarity- based approach, proposed by Cesar Santos et al. In the present work, two signature databases are generated - one consisting of signature samples from 100 writers while other consisting of signature samples from 260 writers. Two feature sets, geometric features and local binary pattern features, are extracted from the signature samples for the performance evaluation of three classifiers - two back propagation Artificial Neural Networks (one with single hidden layer and the other with two hidden layers) and one Support Vector Machine with Polynomial Kernel (SVM – Poly). These classifiers aim at classifying the handwritten signature as genuine or forge.

The remaining of the paper is structured as: Section II describes the working of writer independent approach. Section III presents the details of database used in the study. Section IV describes the procedure of feature extraction from the signature image. Section V is devoted to experimental details and the concluding remarks are given in section VI.

II. Writer independent approach

Writer independent approach, also known as global approach, is used to classify offline handwritten signature samples into forge or genuine. In this approach, questioned signature sample (QS) is compared with reference signature samples RS_k (k = 1, 2,…, n) and the level of dissimilarity is computed by using the features extracted from questioned sample and reference signature samples. On the basis of the dissimilarity measurement the signature is determined (classified) as genuine of forge. The proximity, dissimilarity and similarity concepts with different perspectives are discussed in [11, 12, 13]. The concept of dissimilarity representation was introduced by E. Pekalskaet. al. [13] and the idea was that dissimilarities were supposed to be big for the objects belonging to different classes and small for objects belonging to same class. To form dissimilarity feature vector D_i, the difference between feature vector of reference sample and feature vector of questioned sample is computed and is fed to classifier to take the partial decisions. These partial decisions govern final decision through fusion strategies (Figure 3).

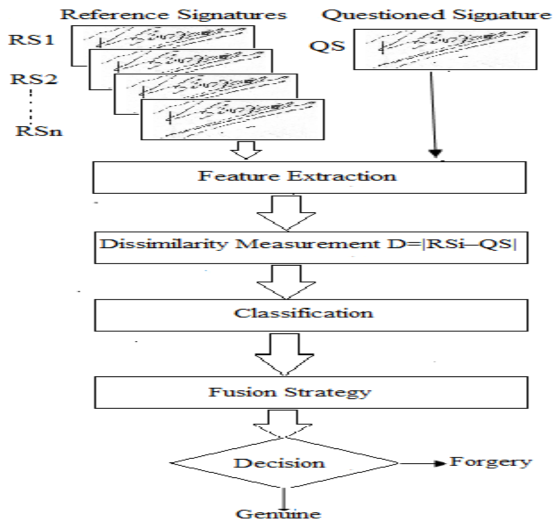

Figure 3: Writer Independent Approach for Offline Signature Verification System

III. Signature Database

Two databases DB1 and DB2 are used in present work. DB1 is composed of signature samples of 100 writers and DB2 is consisted of signature samples of 260 writers. Signature samples of 60 writers and 40 writers of DB1 are used for training and testing, respectively, whereas DB2 is divided into 160 and 100 writer's signature samples for training and testing, respectively. The signatures are collected from undergraduate and postgraduate students of an educational institute in two different sessions, once in fifteen days during one month. Paper sheet of A4 size is used to collect the signatures of writers and then scanned by scanner at 600 dpi gray level. In each session, each writer produced 20 genuine signatures. For each genuine writer, four students are selected for making forgeries and each forger signed 5 signatures for simple forgeries and 5 signatures for simulated forgeries for the assigned writer, i.e. total 20 simple forgeries and 20 simulated forgeries are collected per genuine writer. To produce simple forgeries the forger knew only the name of the writer whereas forgers practiced many times with genuine signatures of writer to produce simulated forgeries.

In this work, the dissimilarity-based approach is adopted so the classifiers are trained with positive (genuine) and negative (forgery) samples. Positive samples are generated by computing the dissimilarity vectors among 6 genuine samples per writer, thus 15 distinct combinations are obtained. In this way, total 900 positive samples are generated from 60 writers for DB1. Likewise, 2400 positive samples from 160 writers are obtained for DB2. In this work, only random forgery samples are used to form negative sample set. To generate the negative samples for DB1, dissimilarity vectors are computed from first four genuine samples of the first five writers and first four genuine samples of randomly selected 50 writers from remaining training set. This resulted into 1000 negative samples. Further, to generate the negative samples for DB2, dissimilarity vectors are computed from first four genuine samples of the first five writers and first four genuine samples of randomly selected 140 writers from remaining training set. This produced 2800 negative samples. Thus, total 1900 (900 positive samples plus 1000 negative samples) dissimilarity vectors for DB1 and 5200 (2400 positive samples plus 2800 negative samples) dissimilarity vectors for DB2 are used to train two models of ANN and one model of SVM. The number of required genuine and forgery samples of signature is dependent on the number of references are used for questioned signature in the testing process. In present approach, forgery and genuine signature samples of those writers are used for testing which are not considered for the training process.

IV. Feature Extraction

Geometric and local binary pattern feature vectors are used in the present work for developing HSV system. Preprocessed image is used to extract the features. In preprocessing phase, median filter is used to remove the noise from signature image. After this, gray level signature image is transformed into binary image by calculating threshold value using Otsu's method [15]. The signature image is then cropped and resized to the image size 256 x 512.

a. Geometric Feature Vector

In the present study, ten features namely- signature area, mean, standard deviation, number of connected components, perimeter of signature image, number of horizontal edges, number of vertical edges, number of edge points, number of lines (horizontal and vertical), and number of branch points are adopted to constitute geometric feature vector. To extract the geometric feature vector from preprocessed signature image of size 256 x 512, following steps are performed:

1. Extract ten features from whole signature image as global features.
2. Divide the signature image into four equal parts and extract again same ten features from each part of the signature image to get local features.

Thus, in all 10 global and 40 local features are extracted from signature image to form geometric feature vector of length 50.

b. Local Binary Pattern Feature Vector

To extract the local binary pattern feature vector from preprocessed signature image of size 256 x 512, following steps are performed:

1. Divide the signature image into mutually exclusive blocks.
2. For each block do step 3 to 5.
3. Compare the central pixel value with pixels in 3 x 3 neighborhoods (8 neighbors) in anticlockwise or clockwise circular path and do the same for every pixel in the block.
4. Obtain a binary number of 8 bits by recording 1 if the value of central pixel is greater than the value of neighbor's pixel else 0.
5. Compute the histogram, over the block, of the occurrence of each number.
6. Combine the histograms of all blocks to get the local binary pattern feature vector for the image.

Above steps give LBP feature vector of length 256.

V. Experimental Details

In this work, simple and simulated forgery signature samples are not included in the training of classifiers that means classifiers are trained using only genuine and random forgery signature samples. Reason to do so is that simple and skilled forgery samples may not be available at the development of the system for most of the applications. Two scenarios (Scenario I for DB1 and Scenario II for DB2) are used in present work to evaluate the performance of three classifiers under probe. To evaluate the performance of classifiers, geometric and local binary pattern feature vectors are used for scenario I as well as for scenario II. The length of geometric feature vector is 50 and there are two output classes (genuine and forge) so 50 neurons at input layer and 1 neuron at output layer is used by each back- propagation neural network model for geometric feature set. The length of LBP feature vector is 256 and there are two output classes (genuine and forge) so 256 neurons at input layer and 1 neuron at output layer is used by each back- propagation neural network model for LBP feature set. The performance of two back-propagation neural networks, one with single hidden layer of 30 neurons (NN (50 – 30 – 1) for geometric and NN (256 – 30 – 1) for LBP), other with two hidden layers-first hidden layer of 30 neurons and second hidden layer of 10 neurons (NN(50 – 30 – 10 – 1) for geometric and NN (256 – 30 – 10 – 1) for LBP) and one SVM - Poly (support vector machine with polynomial kernel) models are evaluated using geometric and LBP features. Table 1 and Table 2 presents the time required (in seconds) in the training of both neural networks as well as SVM classifiers for geometric and LBP features, respectively.

Table 1: Elapsed Time (in seconds) for Classifiers in Training using Geometric Features

Database	Classifier Used	Elapsed Time
DB1	NN(50 – 30 – 1)	3.2120
	NN(50 – 30 – 10 – 1)	5.0455
	SVM – Poly	1.7511
DB2	NN(50 – 30 – 1)	6.9630
	NN(50 – 30 – 10 – 1)	8.4774
	SVM – Poly	4.4995

Table 2: Elapsed Time (in seconds) for Classifiers in Training using LBP Features

Database	Classifier Used	Elapsed Time
DB1	NN(256 – 30 – 1)	5.2176
	NN(256 – 30 – 10 – 1)	10.7318
	SVM – Poly	1.7907
DB2	NN(256 – 30 – 1)	9.2541
	NN(256 – 30 – 10 – 1)	15.7344
	SVM – Poly	10.8623

Table 3: Performance Evaluation of Classifiers using Geometric Features for Scenario I in Terms FRR & FAR in % and Elapsed Time (in seconds)

CF	R S	FRR* & ET**	FAR$^\#$ & ET$^{\#\#}$		
			Random	Simple	Skilled
Neural Network (50 – 30 – 1)	3	2.50*	37.50$^\#$	40.00$^\#$	30.00$^\#$
		16.61**	15.59$^{\#\#}$	15.56$^{\#\#}$	15.58$^{\#\#}$
	5	0.00	22.50	42.50	32.50
		27.63	26.82	26.88	26.79
	7	7.50	20.00	32.50	32.50
		39.36	36.18	36.20	36.19
	9	7.50	12.50	27.50	22.50
		46.51	48.03	47.70	46.51
	11	2.50	10.00	17.50	17.50
		56.81	56.75	56.78	56.88
	13	0.00	12.50	17.50	22.50
		67.06	66.79	66.92	67.14
	15	2.50	12.50	12.50	20,00
		77.40	77.23	77.93	77.40
Neural Network (50 – 30 – 10 – 1)	3	5.00	30.00	42.50	25.00
		18.72	17.68	17.66	17.76
	5	2.50	20.00	45.00	30.00
		29.41	29.47	29.51	29.57
	7	5.00	17.50	27.50	17.50
		41.21	41.32	41.49	41.24
	9	5.00	7.50	25.00	20.00
		53.33	52.92	52.94	52.93
	11	0.00	5.00	15.00	12.50
		63.76	62.84	62.87	62.99
	13	0.00	12.50	17.50	15.00
		74.29	74.67	76.54	76.64
	15	2.50	15.00	12.50	12.50
		88.47	88.37	88.63	88.39
SVM – Poly	3	0.00	10.00	12.50	15.00
		0.36	0.23	0.22	0.22
	5	0.00	5.00	10.00	22.50
		0.28	0.28	0.27	0.27
	7	0.00	5.00	10.00	22.50
		0.33	0.33	0.33	0.32
	9	0.00	0.00	7.50	30.00
		0.39	0.39	0.38	0.37
	11	0.00	0.00	15.00	27.50
		0.45	0.44	0.44	0.43
	13	0.00	0.00	17.50	30.00
		0.50	0.50	0.50	0.49
	15	0.00	5.00	15.00	30.00
		0.56	0.56	0.55	0.55

MATLAB 2013a is used to carry out the experiments in this work. The experiments are performed using 3, 5, 7, 9, 11, 13, and 15 reference signatures (RS). Reason to do so is that usually median, mean, majority voting, max and min fusion strategies are used to combine the partial decisions of classifiers and these fusion strategies perform better for odd number of partial decisions. In this work, experiments are tried out for majority voting, mean, min and max fusion strategies but mean fusion strategy produced better results. Table 3 and Table 4 present the performance of the classifiers (CF) using geometric features in terms of False Rejection Rate (FRR) and False Acceptance Rate (FAR) in % using mean fusion rule and elapsed time (ET) in seconds for scenario I and scenario II, respectively.

Table 4: Performance Evaluation of Classifiers using Geometric Features for Scenario II in Terms of FRR & FAR in % and Elapsed Time (in seconds)

CF	R S	FRR* & ET**	FAR$^\#$ & ET$^{\#\#}$		
			Random	Simple	Skilled
Neural Network (50 – 30 – 1)	3	3.00*	4.00$^\#$	6.00$^\#$	9.00$^\#$
		39.46**	38.35$^{\#\#}$	38.30$^{\#\#}$	38.55$^{\#\#}$
	5	2.00	2.00	9.00	10.00
		63.90	63.76	63.82	63.77
	7	1.00	4.00	10.00	12.00
		89.31	89.17	89.37	89.68
	9	1.00	2.00	8.00	9.00
		114.49	114.46	114.93	114.49
	11	2.00	1.00	10.00	8.00
		140.17	139.83	140.57	140.10
	13	1.00	1.00	9.00	11.00
		165.53	165.41	165.62	165.42
	15	2.00	1.00	10.00	13.00
		190.90	188.76	186.64	186.48
Neural Network (50 – 30 – 10 – 1)	3	3.00	3.00	8.00	10.00
		46.33	44.92	44.98	44.97
	5	2.00	2.00	9.00	14.00
		74.94	74.31	74.71	74.77
	7	1.00	6.00	9.00	14.00
		104.60	105.08	104.69	104.77
	9	1.00	4.00	11.00	13.00
		134.43	134.36	134.66	134.89
	11	1.00	2.00	10.00	11.00
		164.48	159.66	164.24	164.31
	13	1.00	2.00	11.00	11.00
		197.33	194.08	194.20	194.22
	15	2.00	1.00	11.00	16.00
		224.05	223.93	224.61	224.38
SVM – Poly	3	1.00	5.00	4.00	11.00
		0.62	0.61	0.61	0.60
	5	3.00	3.00	9.00	14.00
		0.92	0.91	0.91	0.91
	7	0.00	8.00	8.00	11.00
		1.23	1.22	1.21	1.20

	9	0.00	4.00	11.00	15.00
		1.53	1.52	1.53	1.51
	11	1.00	3.00	12.00	13.00
		1.84	1.83	1.83	1.83
	13	0.00	3.00	10.00	16.00
		2.15	2.16	2.15	2.14
	15	1.00	1.00	10.00	13.00
		2.46	2.45	2.45	2.46

Table 5 and Table 6 present the performance of the classifiers using local binary pattern features in terms of FRR and FAR in % using mean fusion rule and elapsed time (ET) in seconds for scenario I and scenario II, respectively. False acceptance rate is computed for random, simple and simulated forgeries of the genuine signatures. The writer's involved in training phase are not included in testing process of the system in present approach. Experiments are carried on the core 2 dual with 4 GB RAM configurations and elapsed time (in seconds) is recorded for training as well as testing of classifiers. The elapsed time is expected to vary depending upon the system configuration.

Table 5: Performance Evaluation of Classifiers using LBP Features for Scenario I in Terms of FRR & FAR in % and Elapsed Time (in seconds)

CF	**RS**	**FRR* & ET****	**FAR$^{\#}$ & ET$^{\#\#}$**		
			Random	**Simple**	**Skilled**
Neural Network (256 – 30 – 1)	3	0.00^{*}	$12.50^{\#}$	$12.50^{\#}$	$30.00^{\#}$
		85.53^{**}	$85.41^{\#\#}$	$84.52^{\#\#}$	$84.77^{\#\#}$
	5	0.00	2.50	20.00	47.50
		140.85	140.92	141.30	141.19
	7	0.00	5.00	17.50	37.50
		197.89	197.70	197.80	197.81
	9	5.00	2.50	10.00	32.50
		254.27	254.64	245.96	245.16
	11	2.50	0.00	15.00	30.00
		301.84	301.38	300.60	299.90
	13	2.50	0.00	10.00	32.50
		354.03	355.94	355.70	356.35
	15	5.00	0.00	12.50	40.00
		420.53	424.82	423.17	423.60
Neural Network (256 – 30 – 10 –1)	3	2.50	10.00	12.50	27.50
		94.14	93.21	92.68	92.65
	5	0.00	5.00	12.50	37.50
		154.57	154.95	155.59	154.61
	7	0.00	2.50	7.50	35.00
		216.65	216.84	217.16	216.93
	9	0.00	2.50	5.00	30.00
		279.16	277.89	271.50	279.03
	11	0.00	0.00	10.00	27.50
		341.71	341.29	341.65	341.00
	13	2.50	0.00	7.50	30.00
		394.22	395.26	391.01	389.69
	15	2.50	0.00	7.50	40.00
		449.10	450.81	451.64	451.20
SVM – Poly	3	0.00	5.00	22.50	17.50
		0.44	0.30	0.30	0.29
	5	0.00	7.50	20.00	27.50
		0.41	0.41	0.40	0.39
	7	5.00	5.00	15.00	20.00
		0.51	0.50	0.50	0.50

	9	0.00	2.50	7.50	22.50
		0.61	0.61	0.61	0.60
	11	0.00	0.00	7.50	22.50
		0.72	0.72	0.71	0.71
	13	2.50	2.50	5.00	17.50
		0.83	0.83	0.82	0.83
	15	0.00	0.00	5.00	20.00
		0.94	0.94	0.93	0.93

VI. Conclusion

In this work, the performance evaluation of artificial neural network(single hidden layer and two hidden layers) and SVM – Poly classifiers based on geometric and local binary pattern feature sets is carried out using two databases of handwritten signatures. The study aimed at proposing a global offline handwritten signature verification system.

Table 6: Performance Evaluation of Classifiers using LBP Features for Scenario II in Terms of FRR & FAR in % and Elapsed Time (in seconds)

CF	**RS**	**FRR* & ET****	**FAR$^{\#}$ & ET$^{\#\#}$**		
			Random	**Simple**	**Skilled**
Neural Network (256 – 30 – 1)	3	1.00^{*}	$9.00^{\#}$	$9.00^{\#}$	$19.00^{\#}$
		225.73^{**}	$224.70^{\#\#}$	$224.75^{\#\#}$	$225.04^{\#\#}$
	5	0.00	8.00	13.00	31.00
		378.19	379.99	379.66	379.25
	7	0.00	7.00	12.00	25.00
		541.26	541.25	539.88	534.94
	9	0.00	4.00	8.00	24.00
		695.37	693.42	697.14	697.44
	11	0.00	3.00	7.00	24.00
		852.34	850.33	854.55	824.83
	13	0.00	2.00	9.00	20.00
		994.22	999.00	998.46	992.68
	15	0.00	1.00	8.00	23.00
		1169.5	1168.8	1170.7	1170.0
Neural Network (256 – 30 – 10 – 1)	3	0.00	8.00	11.00	17.00
		254.86	253.43	253.45	253.74
	5	0.00	7.00	13.00	30.00
		422.86	422.68	423.71	423.67
	7	0.00	5.00	11.00	27.00
		572.68	574.39	573.41	572.34
	9	0.00	4.00	8.00	23.00
		748.05	748.77	749.72	749.33
	11	0.00	2.00	6.00	25.00
		894.72	893.22	893.79	893.05
	13	0.00	2.00	10.00	19.00
		1078.1	1078.5	1080.2	1079.3
	15	0.00	2.00	9.00	23.00
		1220.7	1219.8	1219.7	1220.6
SVM – Poly	3	2.00	6.00	4.00	9.00
		0.98	0.86	0.86	0.85
	5	0.00	3.00	5.00	22.00
		1.33	1.33	1.32	1.34
	7	0.00	5.00	4.00	18.00
		1.83	1.80	1.80	1.79
	9	**0.00**	**0.00**	**3.00**	**14.00**
		2.28	2.28	2.27	2.29
	11	0.00	0.00	2.00	17.00
		2.75	2.75	2.75	2.74

	13	0.00	0.00	5.00	15.00
		3.25	3.23	3.23	3.22
	15	0.00	0.00	5.00	17.00
		3.72	3.74	3.71	3.71

It is observed that for geometric as well as local binary pattern features the performance of SVM-Poly is better than both back-propagation artificial neural network models in terms of FRR and FAR. Further, it is also observed that

SVM- Poly took lesser time in training as well as in testing processes. Experiments also revealed that the performance of classifiers for DB2 database is better than the DB1 database for all classifiers and for both feature sets. From this it is concluded that the accuracy of the system in terms of FRR and FAR is expected to be increased by increasing the number of users in the training as well as in testing processes. It is also seen that the neural network with two hidden layers performed better than neural network with hidden layer in most of the cases for databases developed for the study but time required in training and in testing was more in the case of two hidden layers neural network. It is also concluded from the study that by increasing the number of hidden layers, the performance of neural network is expected to be better at the cost of time is required in training as well as in testing.

It is also observed from the study that , the performance of classifiers using local binary pattern features is better than geometric features. The experiment using local binary pattern feature set along with SVM – Poly classifier reported 0.00 FRR & 0.00, 3.00, and 14.00 FAR for random, simple and skilled forgeries, respectively. In nutshell it is concluded a robust and fast offline handwritten signature verification system can be developed using SVM classifier along with local binary pattern feature set.

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