Kernel Based Artificial Neural Network Technique to Enhance the Performance and Accuracy of On-Line Signature Recognition

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Abstract

Signature recognition is a standout amongst the most essential biometrics verification strategies, is an indispensable piece of current business exercises, and is considered a noninvasive and non-undermining process. For online signature recognition, many techniques had been presented before. Nevertheless, accuracy of the recognition system is further to be improved and also equal error rate is further to be reduced. To solve these problems, a novel classification technique has to be proposed. In this paper, Kernel Based Artificial Neural Network (KANN) is presented for online signature recognition. For experimental analysis, two datasets are utilized that are ICDAR Deutsche and ACT college dataset. The proposed K-ANN classification method gives lower performance in terms of accuracy value with 66% TPR, 73% FPR in ACT and 50% TPR, 56% FPR in ICDAR datasets respectively.

Keywords: Online signature recognition, Kernel Based Artificial Neural Network (KANN), Accuracy, Equal error rate

1 Introduction

Individuals acknowledgment by methods for biometrics [1-4] can be part into two fundamental classes that are Physiological biometrics and Behavioral biometrics. Physiological biometrics acknowledgment depends on direct estimations of a piece of the human body. For example, the speech signal relies upon conduct attributes, for example, semantics, word usage, elocution, quirk, and so forth (identified with financial status, training, place of birth, and so on.) [5-6]. In any case, it likewise relies upon the speaker's physiology, for example, the state of the vocal tract.

Signature recognition has a place with this last class, and as indicated by piece of the pie reports [8] it is the second most critical inside this gathering, simply behind discourse acknowledgment and over keystroke, walk, signal, and so forth. Signature acknowledgment can be part into two categories that are static and dynamic. In static mode, clients compose their mark on paper, digitize it through an optical scanner or a camera, and the biometric framework perceives the mark breaking down its shape. This gathering is otherwise called "off-line" [9]. In dynamic mode, clients compose their mark in a digitizing tablet, for example, the gadgets like CADIX, PDAs procures the mark continuously. Dynamic acknowledgment is otherwise called "on-line" [10]. Dynamic highlights [11] are elements of time and static highlights are time autonomous. For online signature recognition, many techniques such as ANN and SVM had been presented before. Those techniques seemed to improve the performance of recognition. Nevertheless, accuracy of the recognition is further to be improved. The basic idea is to investigate a signature verification technique which is not costly to develop, is reliable even if the individual is under different emotions, user friendly in terms of configuration, and robust against imposters. In signature verification application, the signatures are processed to extract features that are used for verification. Contribution of this proposed approach is described as follows.

- For online signature recognition, Kernel Based Artificial Neural Network (KANN) Technique is presented in this paper.
- Experimental analysis of this proposed approach is done with the ACT College and ICDAR datasets.
- The performance of this proposed recognition method is evaluated in terms of ROC accuracy and equal error rate.

Rest of this paper is organized as follows. Section 2 surveys some previous literatures which focused on the research of online signature recognition. Section 3 summarizes the background of this research work. Section 4 presents the proposed online signature recognition based on Kernel-Artificial Neural discussed in section 5. Finally, this paper is concluded with section 6.

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2 Problem Formulation

In this section, online signature recognition based literatures are analyzed with different techniques. Sharma and Sundaram [13] had proposed an online signature verification system based on improved Dynamic Time Warping which abbreviated as DTW, using this algorithm, distance score between genuine enrolled signatures and test signature. The authors had aimed to discriminate the genuine and forgery signatures of a user, especially, when their values are very close by presenting a novel scheme of scoring/voting the aligned pairs in the warping path by a set of code-vectors constructed from a VQ step. Also they had reduced the equal error rate of the verification system by presenting the incorporation of contextual information in the formulation.

Razzak and Alhaqbani [14] had proposed a multi-segment vector quantization based online signature recognition system. The authors had aimed to improve the accuracy of the recognition system with multi section codebooks by splitting the signature into several sections with every section having its own codebook. By presenting this proposed recognition system, the authors had improved the accuracy with least equal error rate.

Ghosh et al. [15] had proposed an innovative biometric approach for online handwritten signature recognition and verification system. The authors had aimed to improve recognition system reliability by presenting a Dempster–Shafer theory based classifier combination of different information sources. For classification, the authors combined two different classifiers such as Support Vector Machine and Hidden Markov Model. The authors had improved the accuracy and reliability of the system by presenting this proposed approach.

Durrani et al. [16] had proposed an innovative method for online signature recognition that was known as VerSig. The authors had aimed to improve the overall accuracy of prediction by presenting this new signature verification method which was based on creation of a signature envelope by employing dynamic time warping method. This proposed scheme utilized the general attributes such as X, Y coordinates of the signature. By presenting this proposed approach, the authors had offered important enhancement in recognition system.

Yang et al. [2, 17] had proposed a feature weighting algorithm relief based Online handwritten signature verification. This proposed approach aimed to increase the stability of the dynamic characteristics by an innovative relief-based writer-dependent online signature verification technique. This proposed scheme included two steps that are training and testing step. In training step, the authors had chosen a signature as the base signature from real signatures and more stable combined features were selected based on the Relief algorithm. In the testing step, classification was done using the K-nearest neighbor. By presenting these proposed approaches, the authors had reduced the false acceptance rate as well as false recognition rate.

Rohilla and Sharma [18] had presented an innovative algorithm for online signature recognition. The authors had aimed to reduce the false acceptance rate and false recognition rate for the proposed recognition system by presenting the two class support vector machine (SVM) for signature recognition. By presenting this proposed approach, the authors had reduced the average false acceptance rate and false recognition rate to minimum level.

Afar et al. [19], worked in such a way that first the global features are extracted from the spatial coordinates and these features are obtained during the data acquisition stage. The method used here is one dimensional wavelet transform. Then the results are obtained using K-NN classifier and proved the accuracy of the proposed technique as better in signature verification.

Next section gives the detail background of the proposed research work based on ANN.

3 Background of the Research

An ANN is framed from many single units, counterfeit neurons or preparing components (PE), associated with coefficients (weights), which constitute the neural structure and are composed in layers. The intensity of neural calculations originates from associating neurons in a system. Figure 1 shows the different layers of a neural network. Fundamentally, there are 3 distinct layers in a neural system Information Layer (All the sources of info are bolstered in the model through this layer). Shrouded Layers (There can be in excess of one concealed layers which are utilized for preparing the sources of info got from the information layers). Yield Layer (The information subsequent to handling is influenced accessible at the yield to layer).

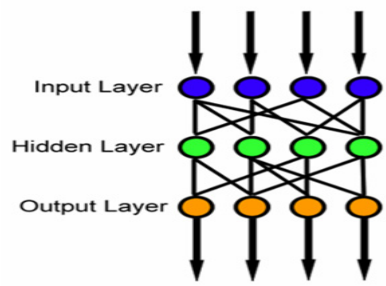

Figure 1. Different layers of a neural network

The shrouded layer is the accumulation of neurons which has enactment work connected on it and it is a moderate layer found between the information layer and the yield layer. Its activity is to process the sources of info got by its past layer. So it is the layer which is capable separating the required highlights from the information. Numerous looks into has been made in assessing the quantity of neurons in the shrouded layer yet at the same time none of them was fruitful in finding the precise outcome. The yield layer of the neural system gathers and transmits the data in like manner in way it has been intended to give. The example displayed by the yield layer can be specifically followed back to the information layer. A neural network is a sorted triple (N, V, w) A neural network is a sorted triple (N, V, w)

Where

N - Set of neurons

V - Set $\{(i, j) \mid I, j \in N\}$, denotes connections between neuron i and neuron j.

W (function) - V → R defines the weights, where w((i, j)) are the weights of the connection between neuron i and neuron j.

The weights can be implemented in a square weight matrix W. In this weight Matrix

1. Row number of the matrix indicates - beginning of connection

2. Column number of the matrix indicates - target neuron. In the matrix, if the numeric value is zero which indicates a non-existing connection.

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3.1 Propagation Function and Network Input

Let I = $\{i_1, i_2, i_3, \ldots, i_n\}$ be the set of neurons, such that $\forall z \in \{1, \ldots, n\} : \exists \omega_{iz,j}$.

Then the network input of j, called net_j, is calculated by the propagation function as follows:

$$net_j = f_{prop}(O_{i1}, O_{i2}, \ldots\ldots O_{in}, \omega_{i1,j}, \ldots\ldots \omega_{in,j}) \quad (1)$$

Here the *weighted sum* is more famous: The multiplication of the output of each neuron *i* by $\omega_{i,j}$, and summation of the results:

$$net_j = \sum_{i \in I} (O_i \cdot \omega_{i,j}) \quad (2)$$

The activation function finds the activation of a neuron dependent on network input and threshold value.At a certain time – the activation a_j of a neuron *j* depends on the previous activation state of the neuron and the external input. Dynamic variations of input can be find out by using activation function.

3.2 Activation Function

Let *j* be a neuron, then the activation function is shown as:

$$a_j(t) = f_{act}(net_j(t), a_j(t-1), \theta_j) \quad (3)$$

This converts the network input net_j, along with previous activation state $a_j(t - 1)$ into a new activation state $a_j(t)$, *with the threshold value* θ playing a vital role. Unlike the other parameters within the neural network the activation function is defined *universally* for all neurons or at least for a set of neurons and only the threshold values will be varied for every neuron. Learning procedures helps to change the threshold values. Hence the threshold values can be related to time as $\theta_j(t)$. Transfer function is another name for activation function.

4 Kernel Based Artificial Neural Network Technique for Online Signature Recognition

4.1 Proposed K-ANN

Once a system has been organized for a chosen application, setups to be prepared to start this method the underlying weights zone units are picked. At that point, the preparation, or learning, starts. There region unit 2 ways to deal with instructing - directed and unattended. administered training includes an instrument of furnishing the system with the required yield either by physically "reviewing" the system's execution or by giving the required yields the sources of information unattended training are wherever the system should be of the information sources while not outside encourage.

(i) The Iterative Learning Process is a key element of neural systems in K-ANN. It associates in nursing unvaried learning technique inside which data cases (columns) are given to the system each one in turn, and along these lines the weights identified with the info esteems are balanced unfailingly. Advantages of neural systems in K-ANN encapsulate their high resilience to clangorous data, moreover as their capacity to order designs on that they require not been prepared.

Blunders are then proliferated back through the framework, dispensing the framework to direct the weights for application to succeeding record to be handled.

This technique occurs again and again in light of the fact that the weights K-ANN much of the time changed. This may be because of the information record don't contain the specific information from that the predetermined yield springs. Systems moreover don't unite if there's insufficient data to change finish learning.

(ii) The fundamental thought is to convolute a predefined cover with the picture to allocate an incentive to a pixel as an element of the dark estimations of its neighboring pixels and to channel the character picture supplanting the convolution activity by the consistent activities. Different morphological activities have been intended to associate the broken strokes, disintegrate the associated strokes, smooth the shapes, prune wild focuses, thin the characters and concentrate the limits.

(iii) Noise can by and large be expelled by adjustment methods in K-ANN on the off chance that it would have been conceivable to display it. There exists some accessible writing on commotion demonstrating presented by optical bending, for example, spot, skew and obscure.

(b) Normalization: The standardization K-ANN strategies intend to evacuate the varieties of the composition and acquire institutionalized information. A portion of the usually utilized strategies for standardization are:

(i) Skew institutionalization and bench signature extraction: Due to botches in the checking K-ANN methodology and forming style the synthesis may be hardly tilted or twisted inside the photo. This can hurt the suitability of the counts and thusly should be perceived and amended. In addition, a couple of characters are perceived by the relative position concerning the standard, for instance, 9 and g. The methods for bench signature extraction consolidate using the projection profile of the photo, nearest neighbor bundling and Hough change.

(ii) Slant standardization: One of the quantifiable elements of various penmanship styles is the inclination point between longest stroke in a word and the vertical heading. Inclination standardization is utilized to standardize all characters to a standard frame. The inclination location is performed by isolating the picture into vertical and flat windows. A variation in K-ANN of the Hough change is utilized by examining left to ideal over the picture and ascertaining projections toward 21 unique inclinations. The main three projections for any inclination are included and the inclination with the biggest consider is taken the inclination esteem.

(iii) *Size Normalization:* It is utilized to modify the character size to a specific standard. The K-ANN techniques may apply for both flat and vertical size normalizations. The character is partitioned into number of zones and every one of these zones is independently scaled. Here the two example characters are step by step contracted to the ideal size which augments the acknowledgment rate in the preparation information in K-ANN. The word acknowledgment safeguards substantial intra class contrasts in the length of words so they may likewise aid acknowledgment.

(iv) *Contour smoothing:* It takes out the blunders because of the flighty K-ANN for hand movement amid the composition. It by and large diminishes the quantity of test guides required toward speak to the content and subsequently enhances effectiveness in outstanding pre-preparing steps.

(c) Compression: It is extraordinary that customary picture weight frameworks change the photo from the space territory to regions which are not suitable for affirmation. The weight for OCR requires space territory strategies for shielding the shape information. The two pervasive weight methodologies used are: (i) Thresholding and (ii) Thinning.

(i) *Thresholding:* so as to diminish capacity necessities and to build preparing speed usually alluring to speak to dim scale or shading pictures as twofold pictures by picking a limit esteem. The two imperative classifications of thresholding are via worldwide and neighborhood [7]. The worldwide thresholding picks one limit an incentive for the whole character picture which is regularly in light of an estimation of the foundation level from the force histogram of the picture. A Niblack's nearby or versatile coherent technique is produced by investigating the bunching and association attributes of the characters in debased pictures that proves to be the best in outcome.

(ii) *Thinning:* While it gives an enormous decrease in information measure, diminishing concentrates the shape data of the characters. Diminishing can be considered as transformation of disconnected penmanship to relatively online like information with deceptive branches. The two fundamental K-ANN methodologies for diminishing depend on pixel savvy and non-pixel insightful diminishing. The pixel insightful diminishing techniques locally and iteratively process the picture until one pixel wide skeleton remains. In spite of the fact that few amazing strategies have created before and an assortment of systems in K-ANN has risen, the division of cursive characters is an unsolved issue. The character division methodologies are partitioned into three classifications: (a) express division (b) understood division and (c) blended procedures.

(a) In unequivocal division the sections are recognized in light of character like properties. The way toward cutting up the character picture into important parts is accomplished through dismemberment. The accessible-ANN techniques in light of the dismemberment of the character picture utilize blank area and pitch, vertical projection examination, associated segment investigation and points of interest. The unequivocal division can be subjected to assessment utilizing the phonetic setting.

(b) The verifiable division technique depends on acknowledgment. It looks the picture for segments that matches the predefined classes. The division is performed by utilizing the acknowledgment certainty including syntactic or semantic accuracy of the general outcome. In this approach two classes of techniques are utilized viz (i) strategies that make some inquiry procedure and (ii) techniques that section an element portrayal of the picture. This should be possible either through shrouded signature of chains or non-signature based K-ANN methodologies. The non-signature approach originates from the ideas utilized as a part of machine vision for acknowledgment of blocked question.

(c) The blended K-ANN techniques consolidate unequivocal and verifiable division in a hybrid way.

An analyzation calculation is connected to the character picture; however, the purpose is to over section i.e. to cut the picture in adequately numerous spots with the end goal that the right division limits are incorporated among the cuts made. When this is guaranteed, the ideal division is looked for by assessment of subsets of the cuts made.

4.2 Proposed Classification Algorithm: K-ANN

The proposed classification algorithm K-ANN can be explaind by the following step by step details to understand the algorithm in depth

Step 1: Initialize the below parameters for simplicity, before starting the training:

- Weights (w) = 0
- Bias = 0
- Learning rate $\propto = 1$
- K (x, y) = <f(x), f(y)>

Step 2: Continue steps 3 to 8 until the stopping condition is False.

Step 3: Continue steps 4 to 6 for every training vector x.

Step 4: Activate each input as follows:

$$x_i = s_i \, (i = 1 \; ton) \tag{4}$$

Step 5: Get the net input using the following equation:

$$y_{\text{in}} = b + \sum_{i}^{n} x_i \omega_{ij} + k(x, y) \tag{5}$$

Here **'n'** is the total number of input neurons and **'b'** is bias.

Step 6: Use the following activation function to get the final result for every output unit j = 1 to m-

$$f(yin) = \begin{Bmatrix} 1 & \text{if } y_{inj} > \theta \\ 0 & \text{if } -\theta \le y_{inj} \le \theta \\ -1 & \text{if } y_{inj} < -\theta \end{Bmatrix} \tag{6}$$

Step 7: Modify the weight and bias for x = 1 to n and j = 1 to m as given below

Case 1: - if $y_j \neq t_j$ then, **(7)**

$$w_{ij}(\text{new}) = w_{ij}(\text{old}) + \alpha t_j x_i \; b(\text{new}) = b(\text{old}) + \alpha t \tag{8}$$

Case 2: - if $y_j = t_j$ then,

$$wij(new) = w_{ij}(old) \tag{9}$$

$$b(new) = b(old) \tag{10}$$

here 'y' is the actual output and 't' is the target output

Step 8: Test for the halting condition that will occur when the weight w remains fixed.

5 Results and Discussions

In this experiment, the training dataset comprises 80 writer's samples in ICDAR Deutsche and ACT college dataset from a total of 40 dissimilar writer's Signatures. The test set contains 160 online digital signatures, 80 in English. The training and test data are used as a function of the tasks and evaluate the system.

5.1 Experimental Analysis with ACT College Dataset

The ROC curve is created for checking whether the classifier is good or bad and plotting the TPR against the FPR at different threshold values. The input signatures are given to the system and it recognizes a genuine signature and result obtained as positive then it's called True Positive.

If the input is recognized as a forgery signature and result obtained as negative, then it's called False Positive. In this experimental analysis, True Positive Rate is 0.66 and False Positive Rate is 0.73 for K-ANN classifier and TPR, FPR is 0.6, 0.55 respectively for OCR method.

The genuine, skilled, unskilled and random forgery signatures are used for training and testing. In this experiment, the skilled, unskilled and random forgery signatures are identified based on the dynamic features using a threshold value of 0.5 in the 0-60 epochs. Based on the dynamic features, the genuine signatures are recognized from 80th to 180th epochs.

The input layer accepts all the signatures with its features and converts it into the triplet matrix, which propagates the values to the input layer to hidden layer and hidden layer to output layer. The target values compared with actual values gathered from this process i.e., input signatures were compared with genuine signatures, if the equal error rate is high, adjust the weights from the output layer to hidden layer and hidden layer to input layer. Based on the weight adjustment and a threshold value > 0.5, the genuine signatures, Random forged, Skilled Forged and Unskilled Forged are recognized by the system.

5.2 Experimental Analysis with ICDAR Dataset

Figure 2 & Figure 5 show the ROC curve acquired at various threshold values for both ACT and ICDAR dataset. To evaluate the classifier model for better accuracy, ROC curve must have the maximum value nearer to 1. The signatures are recognized based on the existing features during the time of signing by applying back propagation technique. The weights are adjusted based on the errors at the time of propagation.

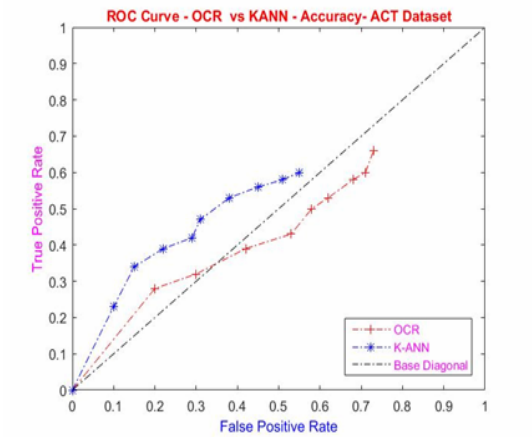


Figure 2. ROC - Accuracy of OCR with KANN – ACT Dataset

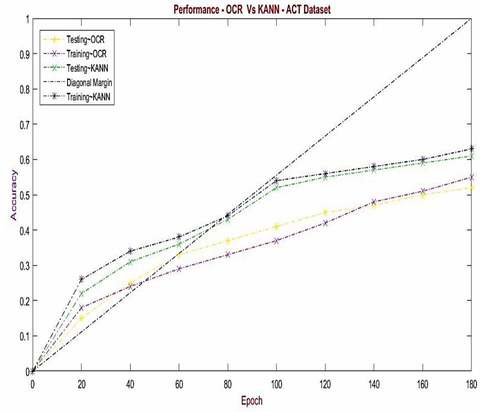
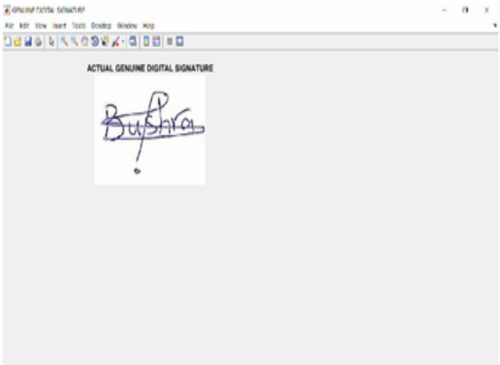


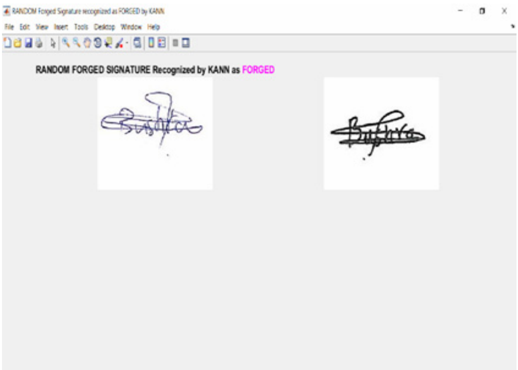
Figure 3. Performance analysis for OCR and KANN – ACT Dataset

ACT college Dataset – Sample:- KANN

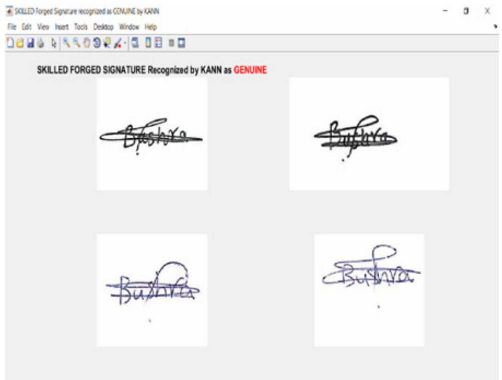


(a) Genuine Signature

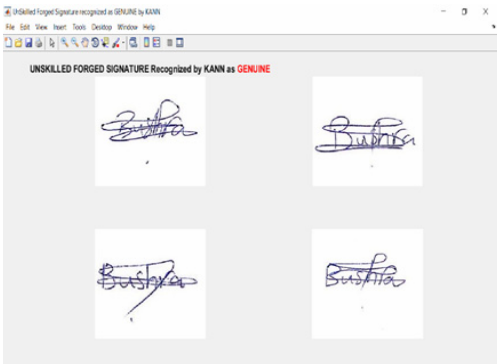
(b) Random Forged Signature recognized as GENUINE by KANN



(c) Random Forged Signature recognized as FORGED by KNN



(d) Skilled Forged Signature recognized as GENUINE by KANN



(e) Unskilled Forged Signature recognized as GENUINE by KANN

Figure 4.

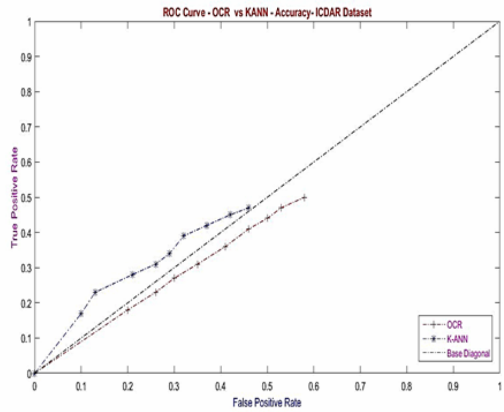


Figure 5. ROC - Accuracy of OCR with KANN-ICDAR dataset

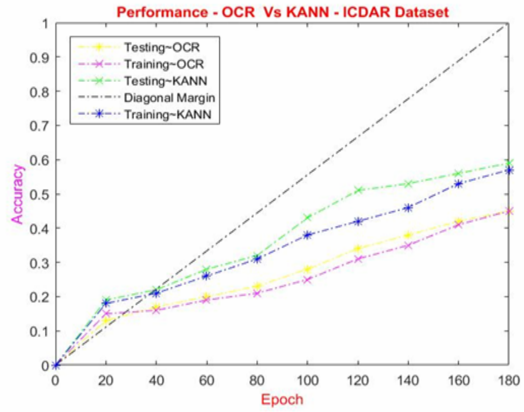


Figure 6. Performance analysis for OCR and KANN-ICDAR dataset

Figure 3 & Figure 6 show the various epochs against the accuracy values. There is a threshold value used for recognizing and classifying the genuine online signatures from other types of forged ones [12].

In this experimental analysis with ICDAR dataset, Figure shown in Figure 7(a) was recognized as genuine signatures. Based on the Threshold value the system recognized the Randomly Forged Signatures [RF] as genuine signatures, which is Shown in Figure 7(b) and some signatures were recognized as Forged signatures, which are shown in Figure 7(c) Some signatures were recognized by the system as Skilled Forged signatures [SF] as genuine signatures which are shown in Figure 7(d) and some signatures were recognized Un Skilled Forged signatures [USF] as genuine signatures, which are shown in Figure 7(e).

5.3 Equal Error Rate in Training and Testing with ACT and ICDAR Dataset

Equal Error Rate (EER) of the proposed system derived from ACT College and ICDRAI datasets when different number of samples was used.

The above Table 1 & Table 2, shows the EER values, when the proposed K-ANN classifier algorithm was used in the various genuine and forged samples of digital signatures in ACT College and ICDRAI datasets. It shows that Equal Error Rate (EER) value gets increased with the greater number of samples that had been trained and tested.

6 Conclusion

The target of highlight extraction is to catch the fundamental K-ANN attributes of the images, and it's normally acknowledged this is frequently one in everything about chief intense issues of example acknowledgment. The results show that the K-ANN is better when compared to OCR. The training set was prepared using one-against-all approach. It was due to the time complexities involved in the back propagation process. The proposed KANN classification method gives lower performance in terms of accuracy value with 66% TPR, 73% FPR in ACT and 50% TPR, 56% FPR in ICDAR datasets respectively.

References

[1] Y. Chen, J. Yang, C. Wang, N. Liu, Multimodal Biometrics Recognition Based on Local Fusion Visual Features and Variation Bayesian Extreme Learning Machine, *Expert Systems with Applications*, Vol. 64, pp. 93-103, December, 2016.

[2] Y.-L. Huang, C.-H. Lin, F.-Y. Leu, A Batch Verification Scheme by Using the Matrix-Detection Algorithm, *Journal of Internet Technology*, Vol. 13, No. 4, pp. 681-690, July, 2012.

[3] W. Kang, X. Chen, Q. Wu, The Biometric Recognition on Contactless Multi-spectrum Finger Images, *Infrared Physics & Technology*, Vol. 68, pp. 19-27, January, 2015.

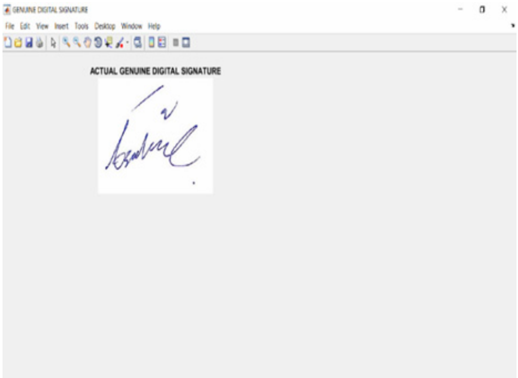
[4] K. Reshmi, P. Muhammed, V. Priya, V. Akhila, A Novel Approach to Brain Biometric User Recognition, *Procedia Technology*, Vol. 25, pp. 240-247, August, 2016, DOI: 10.1016/j.protcy.2016.08.103.

[5] C. You, B. Ma, Spectral-domain Speech Enhancement for Speech Recognition, *Speech Communication*, Vol. 94, pp. 30-41, November, 2017

[6] T. Davis, D. Grantham, R. Gifford, Effect of Motion on Speech Recognition, *Hearing Research*, Vol. 337, pp. 80-88, July, 2016.

[7] D.-R. Lin, C.-I. Wang, D. J. Guan, An Efficient Blind Verifying for Firewall Using Online/Offline Signcryption, *Journal of Internet Technology*, Vol. 13, No. 4, pp. 607-613, July, 2012.

[8] C. Vivaracho-Pascual, A. Simon-Hurtado, E. Manso-Martinez, Using the Score Ratio with Distance-based Classifiers: A Theoretical and Practical Study in Biometric Signature Recognition, *Neurocomputing*, Vol. 248, pp. 57-66, July, 2017.



(a) Genuine Signature

(b) Random Forged Signature recognized as GENUINE by KANN

(c) Random Forged Signature recognized as FORGED by KANN

(d) Skilled Forged Signature recognized as GENUINE by KANN

(e) Unskilled Forged Signature recognized as GENUINE by KANN

Figure 7.

Table 1. EER in training phase with ACT and ICDAR datasets

Number of Testing samples	EER –SF		EER - USF		EER – RF	
	ACT	ICDAR	ACT	ICDAR	ACT	ICDAR
2	2.57	3.27	2.68	2.98	1.89	2.32
5	4.28	5.32	3.49	4.35	5.62	6.12
9	7.84	8.13	5.14	6.24	6.73	7.46
11	8.32	9.46	6.21	7.89	7.94	8.64
13	9.69	10.56	7.58	8.76	8.52	9.53

Table 2. EER in Testing phase with ACT and ICDAR datasets

Number of Testing samples	EER –SF		EER - USF		EER – RF	
	ACT	ICDAR	ACT	ICDAR	ACT	ICDAR
3	2.79	3.23	2.13	2.18	1.53	2.46
6	3.82	4.14	3.32	4.2	4.26	4.67
10	7.24	6.85	6.65	6.94	5.47	5.79
12	8.63	8.31	7.34	7.16	6.78	7.11
15	9.12	9.11	8.77	8.49	7.42	7.83

[9] A. Soleimani, B. Araabi, K. Fouladi, Deep Multitask Metric Learning for Offline Signature Verification, *Pattern Recognition Letters*, Vol. 80, pp. 84-90, September, 2016.

[10] J. Galbally, M. Diaz-Cabrera, M. Ferrer, M. Gomez-Barrero, A. Morales, J. Fierrez, On-line Signature Recognition through the Combination of Real Dynamic Data and Synthetically Generated Static Data, *Pattern Recognition*, Vol. 48, No. 9, pp. 2921-2934, September, 2015.

[11] R. Doroz, P. Porwik, T. Orczyk, Dynamic Signature Verification Method Based on Association of Features with Similarity Measures, *Neurocomputing*, Vol. 171, pp. 921-931, January, 2016.

[12]. F.-Y. Yang, Signature Schemes with Efficient Online Computation, *Journal of Internet Technology*, Vol. 11, No. 4, pp. 451-456, July, 2010.

[13] A. Sharma, S. Sundaram, An Enhanced Contextual DTW Based System for Online Signature Verification Using Vector Quantization, *Pattern Recognition Letters*, Vol. 84, pp. 22-28, December, 2016.

[14] M. Razzak, B. Alhaqbani, Multilevel Fusion for Fast Online Signature Recognition Using Multi-section VQ and Time Modelling, *Neural Computing and Applications*, Vol. 26, No. 5, pp. 1117-1127, July, 2015.

[15] R. Ghosh, P. Kumar, P. Roy, A Dempster-Shafer Theory Based Classifier Combination for Online Signature Recognition and Verification Systems, *International Journal of Machine Learning and Cybernetics*, pp. 1-16, November, 2018.

[16] M. Durrani, S. Khan, S. Khalid, VerSig: A New Approach for Online Signature Verification, *Cluster Computing*, pp. 1-11, August, 2017.

[17] L. Yang, Y. Cheng, X. Wang, Q. Liu, Online Handwritten Signature Verification Using Feature Weighting Algorithm Relief, *Soft Computing*, Vol. 22, No. 23, pp. 7811-7823, December, 2018.

[18] S Rohilla, A. Sharma, SVM Based Online Signature Verification Technique Using Reference Feature Vector, *Proceedings of the National Academy of Sciences*, India, Section A: Physical Sciences, Vol. 87, No. 1, pp. 125-136, March, 2017.

[19] F. A. Afsar, M. Arif, U. Farrukh, Wavelet Transform Based Global Features for Online Signature Recognition, *Proceeding of IEEE International Multi-Topic Conference INMIC*, Karachi, Pakistan, pp. 1-6, 2005.

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