

Kernel Based K-Nearest Neighbor Method to Enhance the Performance and Accuracy of Online Signature Recognition

R. Ravi Chakravarthi, E. Chandra

Abstract: Signature recognition is a significant among the most fundamental biometrics recognition techniques, is a key bit of current business works out, and is considered a noninvasive and non-undermining process. For online signature recognition, numerous methods had been displayed previously. In any case, accuracy of the recognition framework is further to be enhanced and furthermore equal error rate is further to be decreased. To take care of these issues, a novel order method must be proposed. In this paper, Kernel Based k-Nearest Neighbor (K-kNN) is presented for online signature recognition. For experimental analysis, two datasets are utilized that are ICDAR Deutsche and ACT college dataset. Simulation results show that, the performance of the proposed recognition technique than that of the existing techniques in terms of accuracy and equal error rate.

Keywords: Online signature recognition, Kernel Based k-Nearest Neighbor (K-kNN), accuracy, equal error rate.

I. INTRODUCTION

Biometric recognition is considered as generally dependable verification method utilized for security purposes. Biometric recognizable proof can be subdivided in to natural attributes e.g., unique mark acknowledgment, iris checking, and conduct attributes for example, manually written mark check, voice acknowledgment and so forth [1-3]. Signature recognition is one of the most established and most usually utilized strategies for an individual's identification. A recharged intrigue is taken by the exploration with the multiplication of cell phones which use marks or examples for opening the cell phones [4] [5]. Signature recognition can be delegated two classes that are disconnected and online signature recognition. The previous worries with confirmation of the signatures accessible on a paper and the later spotlights on the marks got through particular advanced equipment, for example, realistic tablet [6] [7]. Signature recognition is a two class design acknowledgment issue [8] [9] and like some other example acknowledgment issue, it depends on capacity or some likeness thereof of highlights removed from given examples. The extricated highlights from format tests/marks are later put away in a database for recognition purposes. 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. Contribution of this proposed approach is described as follows.

Revised Manuscript Received on August 05, 2019

R. Ravi Chakravarthi, Masters of Philosophy degree in Computer Science from Manonmaniam Sundaranar University (MSU), Tirunelveli, Tamilnadu, India

E. Chandra, Professor and Head, Department of Computer Science, Bharathiar University, Coimbatore, India.

- For online signature recognition, Kernel Based k-Nearest Neighbor(K-kNN) 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.

II. RELATED WORKS

In this section, online signature recognition based literatures are survived. Abhishek Sharma and Suresh Sundaram [10] had proposed an online signature recognition framework dependent on enhanced Dynamic Time Warping which contracted as DTW. Utilizing this calculation, separate score between the authentic selected signatures and test signature was determined. The ideal warping path was developed by putting limitations between the sets of the example purposes of the signatures. The creators had intended to segregate the certified and phony signatures of a client, particularly, when their qualities are close. To accomplish their objective, they had introduced a novel plan of scoring/casting a ballot the adjusted combines in the warping path by a lot of code-vectors built from a VQ step. Muhammad Imran Razzak and Bandar Alhaqbani [11] had proposed a multi-segment vector quantization based online signature recognition framework. The creators had planned to enhance the precision of the recognition framework. To accomplish their point, they had used multi-segment codebooks by part the mark into a few areas with each segment having its own codebook. By exhibiting this proposed recognition framework, the creators had enhanced the accuracy with least equal error rate. RajibGhoshPradeep Kumar and ParthaPratim Roy [12] had proposed an innovative biometric approach for online manually written signature recognition and confirmation framework. The creators had meant to enhance recognition framework unwavering quality. Mehr Yahya Durrani, Salabat Khan1 and Shehzad Khalid [13] had proposed a innovative technique for online signature recognition that was known as VerSig. The creators had meant to enhance the general exactness of forecast. They had accomplished their point by introducing this new signature recognition strategy which depended on making of a mark envelope by utilizing dynamic time traveling technique.

Li Yang et al [14] had proposed an element weighting calculation help based Online transcribed signature recognition. This proposed methodology expected to build the dependability of the dynamic attributes In the testing step, grouping was finished utilizing the K-nearest neighbor. By showing these proposed methodologies, the creators had decreased the false acceptance rate as well as false recognition rate. Sudhir Rohilla1 and Anuj Sharma [15] had exhibited an innovative calculation for online signature recognition. The creators had planned to diminish the false acceptance rate and false recognition rate for the proposed acknowledgment framework. To accomplish their point, they had exhibited two class strong vector machine which is abridged as SVM for signature verification. By introducing this proposed methodology, the creators had diminished the normal false acceptance rate and false recognition rate to least dimension.

III. BACKGROUND OF THE RESEARCH

3.1. Basic Concepts of K-NN

a) Principle

Once the gathering is done it recalculates the new centroid of each bunch and in light of that centroid, another Euclidean separation is computed between each inside and every datum point and doles out the focuses in the bunch which have least Euclidean separation. Each group in the segment is characterized by its part protests and by its centroid in K-kNN. The centroid for each group is the point to which the whole of separations from every one of the items in that bunch is limited. So K-implies is an iterative calculation in which it limits the aggregate of separations from each protest its bunch centroid, over all groups. In spite of the fact that k-implies has the colossal preferred standpoint of being anything but difficult to execute, it has a few downsides. The nature of the last grouping outcomes is relying upon the subjective choice of beginning centroid for KNN. So if the underlying centroid is haphazardly picked, it will get distinctive outcome for various introductory focuses. So, the underlying focus will be deliberately picked with the goal that it gets longing division. And furthermore computational many-sided quality is another term which we have to consider while outlining the K-implies grouping. It depends on the quantity of information components, number of groups and number of emphasis using KNN. Be that as it may, in our framework, we thought about examples' neighborhood data to alter the heaviness of each query item to impartially relegate KNN higher weight to the example which is more comparable with the subject, and in the meantime maintained a strategic distance from the wonder that the comparable examples with bring down positions are seriously rebuffed due to the area. This system is more sensible for class basic leadership, and it is worth further exploring for patent arrangement.

In k-Nearest Neighbor order, the training dataset is utilized to characterize each individual from an "objective" dataset. The structure of the information is that there's a characterization (all out) factor of intrigue ("purchaser," or "non-purchaser," for instance), and assortment of additional indicator factors (age, salary, location...). Generally, the formula is as per the following:

1. For each column (case) inside the objective dataset (the set to be arranged), discover the k nearest individuals (the k nearest neighbors) of the training dataset. A geometric Distance live is utilized to ascertain anyway closed every member of the training set is to the objective line that is being analyzed.
2. Look at the k closest neighbors - that grouping (class) do the majority of them have a place with? Appoint this class to the column being inspected.
3. Rehash this technique for the rest of the columns (cases) inside the objective set.
4. The client gives a chance to pick a most worth fork, fabricates models parallelly on all worth of k up to the most extreme, for example, esteem and evaluating is finished on the best of those models. Of course the computing time goes up as k goes up, however the advantage is that higher values of k give smoothing that reduces vulnerability to noise within the coaching information. In sensible applications, typically, k is in units or tens instead of in a whole lot or thousand select Classification -> k-Nearest Neighbors. Within the window that seems, enter the information to be processed, the input variables and therefore the output variable.

b) Variables

This container records every one of the factors blessing inside the dataset. In the event that the "Primary column contains headers" box is checked, the header push higher than the data is utilized to spot variable names. Variables in input information: pick one or extra factors as independent factors from the Variables box by tapping on the relating decision catch. These factors speak to the indicator factors. Yield Variable: pick one variable on the grounds that the variable from the Variables box by tapping on the relating decision catch. This is frequently the variable being characterized.

c) Normalizing the Data

Normalizing the data is vital to guarantee that the opening live accords earn back the original investment with weight to each factor - while not regulation, the variable with the most basic scale can overpower the live. Indicating the amount of Nearest Neighbours (k): there's no simple manage for picking k. On the off chance that k is simply excessively small, the characterization of a case (push) may well be frightfully delicate - snared in to the arrangement of the one case to that it's highest. a greater k decreases this changeability, anyway making k vast brings predisposition into the arrangement choices. Envision wherever k = check of the entire dataset. Amid this situation, all cases are classified, based on the grounds that the absolute most occupied class. It's occasionally a legitimate arrangement to explore different avenues regarding very surprising estimations of k, watch the misclassification rate in approval data, at that point pick a proper k.

d) Scoring decision

If we tend to pick Score on, for example, worth of k as higher than, then the yield is shown by reviewing on the required worth of k. On picking Score on best k in the vicinity of one and,

for example, worth, it assembles models parallel on all worth of k up to the most extreme, for example, esteem and evaluating is finished on the best of those models. Score instructing data: pick this component to show Associate in nursing appraisal of the execution in characterizing the training information. The report is shown in accordance with your determinations - elaborated, outline and raise outlines. Score approval data: pick this component to demonstrate Associate in nursing evaluation of the execution in arranging the approval information. The report is shown in accordance with your details - elaborated, outline and raise diagrams. Score investigate Data: the decisions amid this group enable you to apply the model for evaluating to the investigate parcel (on the off chance that one had been made before). the decision "Score investigate Data" is offered as long as the dataset contains investigate segment. Pick it to utilize the model to check data. Score new Data: the decisions amid this group enable you to apply the model for reviewing to Associate in Nursing through and through new data. Indicate wherever the new data is found. See the occurrence of Discriminate Analysis for explained headings on this. Score new data in information: See the case of Discriminate Analysis for expounded bearings on this.

Bunching is a strategy to separate an arrangement of information into a particular number of gatherings. It's one of the famous strategy is k-implies grouping. In k-implies bunching, it segments an accumulation of information into a k number gathering of data. It arranges a given arrangement of information into k number of disjoint bunch. K-implies calculation comprises of two separate stages. In the primary stage it ascertains the k centroid and in the second stage it takes each point to the bunch which has closest centroid from the individual information point. There are distinctive techniques to characterize the separation of the closestcentroid and a standout amongst the most utilized strategies is Euclidean separation.

e) Calculation of K-NN

The proposed calculation needs to scan for the k closest neighbors of the inquiry point (worldwide closest neighbors, line 5 of Algorithm 1.), same as the standard KNN calculation. Aside from finding the worldwide closest neighbors, it likewise need to figure the weighting factor for every one of the class. Following figures are engaged with the count of weighting factors: For every one of the class, discover k closest neighbors of inquiry point among that (class neighbors). We can make utilization of the way that the worldwide k closest neighbors will be among the k closest neighbors for every one of the class, to advance the pursuit. Or maybe then discovering k/m closest neighbor for each class, we initially get the k closest neighbor for each class and after that get the worldwide k closest neighbors, with some additional cost included. For instance, expecting that no file structure is introduce in the preparation information while scanning for worldwide k closest neighbors of question point a parallel store structure of size k is required. For our proposed approach, we keep up such a stack structure one for every class.

3.2) Various Techniques of K- NN

In design acknowledgment field, KNN is a standout amongst the most imperative non-parameter calculations [13] and it is a directed learning calculation. The

arrangement rules are produced by the preparation tests themselves with no extra information. The KNN arrangement calculation predicts the test's class as indicated by the K preparing tests which are the closest neighbors to the test; what's more, judge it to that classification which has the biggest class likelihood. Class based Weighting factors for the K-Nearest Neighbor calculation is proposed, with the goal that it considers the idea of the information instead of essentially overlooking it, as done in the present execution of K-Nearest Neighbor calculation. Our outlines are centered around tuning the K-Nearest Neighbor for awkwardness information, with the goal that its execution on unevenness information is upgraded.

IV. PROPOSED KERNEL BASED K-NEAREST NEIGHBOR METHOD

In our framework, parameters of KNN are prepared by the dry run informational index, which are appeared. Keeping in mind the end goal to confirm the soundness of the mutual closest neighbors calculation, we have led a multi-bunch investigates English corpus and Japanese corpus through altering the area span in K-kNN. Results are appeared, which demonstrates that the technique in view of shared closest neighbors is by and large better than the gauge KNN technique. Furthermore, when the area range is inside 100 or less, the framework's execution is about the same, which demonstrates that our framework is steady to a certain degree. In our test, the area sweep is restricted to 100.. Be that as it may, in our framework, we thought about examples' neighborhood data to alter the heaviness of each query item to impartially relegate K-kNN higher weight to the example which is more comparable with the subject, and in the meantime maintained a strategic distance from the wonder that the comparable examples with bring down positions are seriously rebuffed due to the area..

4.1. Proposed Classification Algorithm: K-kNN

Input:

Attributeset $F = \{F_1, F_2, \dots, F_n\}$
 $K(x,y) = \langle f(x), f(y) \rangle$

Output:

Selected Attribute Feature set (without redundant features):
 F_s Redundant Attribute Feature set: F_R

Method:

1. Assign the features F F_s
2. In feature set, consider all m attributes, cluster each sample and compute cluster error \mathcal{E}_0 .
3. For $k = 1$ to m
 Do
 Apply the Kernel Function $k(x, y)$
 Eliminate F_k from F_s , i.e., $F_s = F_s - \{F_k\}$ and calculate the corresponding cluster error \mathcal{E}_k
4. Sort the \mathcal{E}_k error set values in descending Order
 $\mathcal{E}_1 > \mathcal{E}_2 > \dots > \mathcal{E}_{m-1} > \mathcal{E}_m$
5. If $\mathcal{E}_m > \mathcal{E}_0$, then
 eliminate F_m which



is related to \mathcal{E}_m in F i.e.,

$$F_s = F_s - \{F_m\}m = m - 1$$

Aggregating the entire error rate sets above (in step 3 and step 4) as one and sort the error rates in a descending order and figure out which attribute should be reduced to get the minimum error rate. Generally, the therapeutic pictures which are utilized for division have low difference. So differentiate extending is utilized to enhance the nature of the picture. In the wake of enhancing the nature of picture, subtractive bunching calculation is utilized to produce the

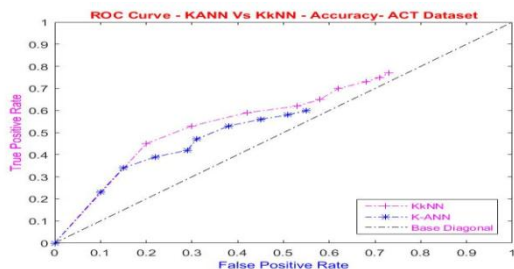
Table2:Performance of KkNN and KANN with ACT Dataset

Epochs	Training-KANN	Testing-KANN	Training-KkNN	Testing-KkNN
0	0.00	0.00	0.00	0.00
20	0.26	0.22	0.30	0.28
40	0.34	0.31	0.36	0.35
60	0.38	0.36	0.45	0.43
80	0.44	0.43	0.53	0.49
100	0.54	0.52	0.62	0.60
120	0.56	0.55	0.68	0.66
140	0.58	0.57	0.71	0.69
160	0.60	0.59	0.73	0.73
180	0.63	0.61	0.75	0.75

focuses, in view of the potential estimation of the picture. Number of fixate is created in view of number of bunch k. This inside is utilized as introductory focus in k- implies calculation. Utilizing the k-implies calculation, the picture is fragmented into k number of bunch in kNN. After the division of picture, the picture can at present contain some undesirable district or then again clamor. These commotions are evacuated by utilizing the middle channel.

V. RESULTS AND DISCUSSIONS

In this experiment, the training dataset comprises 80 writer’s samples in ACT College and ICDAR Deutsche 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:

Table 1:ROC Accuracy Comparisons forKANN andKkNN– ACTDataset

KANN~TPR	KANN~FPR	KkNN~TPR	KkNN~FPR
0.00	0.00	0.00	0.00
0.23	0.10	0.45	0.20
0.34	0.15	0.53	0.30
0.39	0.22	0.59	0.42
0.42	0.29	0.62	0.53
0.47	0.31	0.65	0.58
0.53	0.38	0.70	0.62
0.56	0.45	0.73	0.68
0.58	0.51	0.75	0.71
0.60	0.55	0.77	0.73

Figure1:ROC -Accuracy of KANN with KkNN – ACT Data

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 0.77 and False Positive Rate is 0.73 for K-kNN 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 weights value of 0.5 in the 0-60 epochs. Based on the

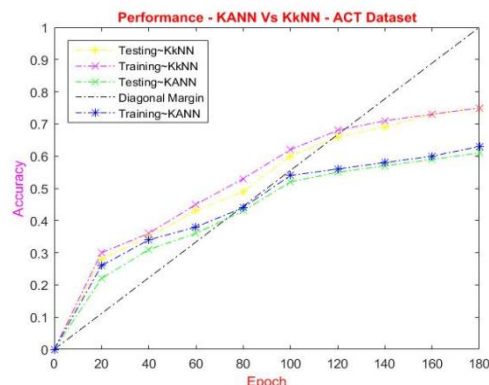


Figure2:Performance analysis for KANN with KkNN – ACT Dataset

dynamic features, the genuine signatures are recognized from 80th to 180th epochs.

ACT college Dataset – Sample: KkNN



Figure 3.A: Genuine Signature

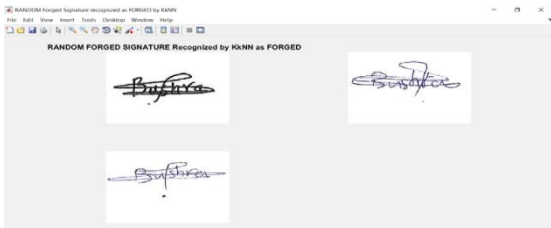


Figure 3.B: Random Forged Signature recognized as FORGED by KkNN



Figure 3.C: Random Forged Signature recognized as GENUINE by KkNN

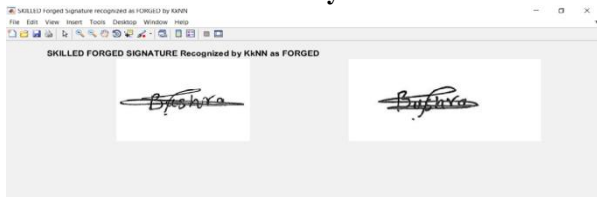


Figure 3.D: Skilled Forged Signature recognized as FORGED by KkNN



Figure 3.E: Skilled Forged Signature recognized as GENUINE by KkNN



Figure 3.F: Unskilled Forged Signature recognized as GENUINE by KkNN

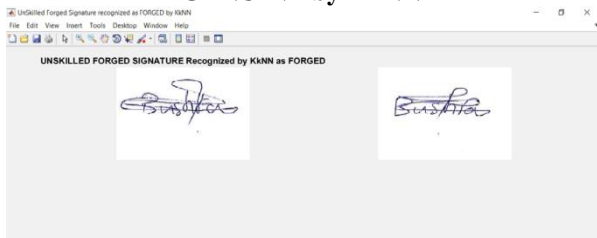


Figure 3.G: Unskilled Forged Signature recognized as FORGED by KkNN

The inputs signatures are accepted with its features and are converted into the feature set. Based on the dynamic features, the signatures are clustered using the Euclidean distance. The signatures are clustered using the similarity between them using the concept of intracluster

similarity. In this process, the new centroid values are calculated and the signatures are clustered based on the distance between points. The weighing mechanism was used to weigh the input values using the weights. The genuine signatures are identified by using similarity measure and they are clustered as one cluster. If the weight > 0.5 , then the signatures are identified as the genuine, Random forged, Skilled Forged and Unskilled Forged signatures are recognized by the system. In this experimental analysis with ACT college dataset, Figure shown in 3.A was recognized as genuine signatures. The system recognized the Randomly Forged Signatures [RF] as forged signatures based on the scoring criterion values, which is shown in Figure 3. B and some signatures were recognized as genuine signatures, which are shown in Figures 3.C. Few Skilled Forged [SF] signatures were recognized by the system as forged signatures which are shown in Figures 3.D and Some SF signatures were recognized as genuine signatures which are shown in Figures 3.E. Some Unskilled Forged Signatures [USF] were recognized as genuine signatures, which is shown in Figure 3.F. and few USF were recognized as forged signatures which is shown in Figure 3.G.

5.2. Experimental Analysis with ICDAR Dataset:

The figures 1 and 4, show the ROC curve acquired at various weight values for both ACT and ICDAR dataset. Also tables 1 and 3 show the ROC curve acquired at various weight 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 nearest neighboring technique. The weights are used to weigh the dynamic features for recognizing the online digital signature

Table 3: ROC Accuracy Comparisons for KANN and KkNN - ICDAR

<i>KANN</i> ~TPR	<i>KANN</i> ~FPR	<i>KkNN</i> ~TPR	<i>KkNN</i> ~FPR
0.00	0.00	0.00	0.00
0.17	0.10	0.31	0.20
0.23	0.13	0.37	0.26
0.28	0.21	0.48	0.30
0.31	0.26	0.53	0.35
0.34	0.29	0.59	0.41
0.39	0.32	0.63	0.46
0.42	0.37	0.67	0.50
0.45	0.42	0.72	0.53
0.47	0.46	0.76	0.58

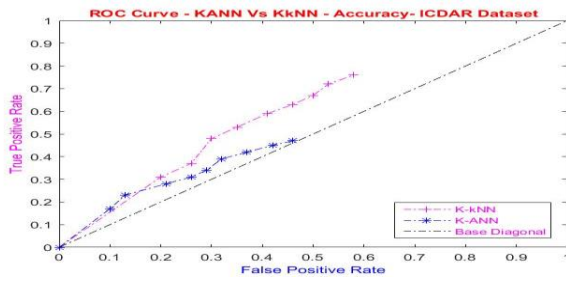


Figure 4: ROC - Accuracy of KANN with KkNN- ICDAR Dataset

Table 4: Performance of KANN and OCR with ICDAR Dataset

Epochs	Training -KANN	Testing -KANN	Training -KkNN	Testing -KkNN
0	0.00	0.00	0.00	0.00
20	0.18	0.19	0.20	0.21
40	0.21	0.22	0.30	0.29
60	0.26	0.28	0.34	0.36
80	0.31	0.32	0.45	0.42
100	0.38	0.43	0.53	0.54
120	0.42	0.51	0.60	0.59
140	0.46	0.52	0.66	0.65
160	0.53	0.56	0.71	0.70
180	0.57	0.64	0.74	0.72

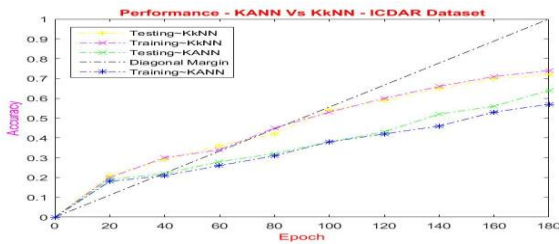


Figure 5: Performance analysis for KANN and KkNN – ICDAR Dataset

Figures 2 and 5 show the trade-off between the various epochs and the accuracy values of the KANN and K-kNN. Tables 2 and 4 show the trade-off between the various epochs and the accuracy values of the KANN and K-kNN. There is a weight value used for recognizing the signatures based on the dynamic features. The weight (w) is always denoted as a unit interval. It reveals that the nearer w is a decision criterion value (weight ($w \geq 0.5$)), which can be used for recognizing genuine, skilled, unskilled and random forgery signatures.

ICDAR-SigComp2012 Dataset – Sample: KkNN



Figure 6.A: Genuine Signature

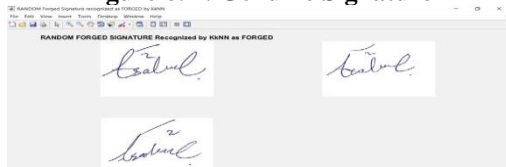


Figure 6.B: Random Forged Signature recognized as FORGED by KkNN

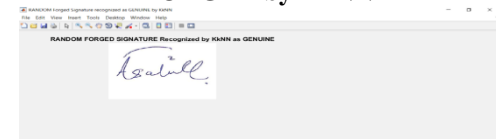


Figure 6.C: Random Forged Signature recognized as GENUINE by KkNN



Figure 6.D: Skilled Forged Signature recognized as FORGED by KkNN



Figure 6.E: Skilled Forged Signature recognized as GENUINE by KkNN



Figure 6.F: Unskilled Forged Signature recognized as GENUINE by KkNN



Figure 6.G: Unskilled Forged Signature recognized as FORGED by KkNN

In contrast to execution of our calculation and K-kNN as far as general exactness and precision to group minority class, as the estimation of k changes for both datasets. It turns out to be obvious that our calculation based classifier are more delicate to characterize minority class and are still very precise. Likewise, classifier gained from our approach are more precise for bigger estimations of k , this is clear from the way that, for high estimation of k expansive locale around the area of inquiry point is considered to decide the neighborhood class dissemination. In this experimental analysis with ICDAR dataset, Figure shown in 6.A was recognized as genuine signatures. The system recognized the Randomly Forged Signatures [RF] as forged signatures based on the scoring criterion values, which are shown in Figures 6.B and some signatures were recognized as genuine signatures, which are shown in Figure 6.C. Few Skilled Forged [SF] signatures were recognized by the system as forged signatures which are shown in Figure 6.D and Some SF signatures were recognized as genuine signatures that are given in Figure 6.E. Some Unskilled Forged Signatures [USF] were recognized as genuine signatures, which are shown in Figure 6.F. and few USF were recognized as forged signatures which are shown in Figure 6.G.

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 ICDAR datasets when different number of samples was used.

Table 5: EER in Training phase with ACT and ICDAR Datasets

Number	EER – SF	EER -USF	EER – RF
--------	----------	----------	----------

of Training samples	ACT		ICDAR		ACT		ICDAR	
	ACT	ICDAR	ACT	ICDAR	ACT	ICDAR	ACT	ICDAR
2	2.27	3.30	2.32	2.69	1.64	2.06		
5	4.11	5.16	3.29	4.08	3.27	5.89		
9	5.92	6.98	4.87	5.73	5.64	6.73		
11	7.16	8.29	6.18	7.53	6.98	7.38		
13	8.73	9.37	7.02	8.16	7.82	8.84		

Table 6: 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	2.43	3.14	2.09	2.39	1.48	2.01
6	3.26	4.89	3.13	4.27	3.96	4.92
10	5.74	6.15	6.27	6.36	5.27	5.31
12	7.83	7.64	7.05	7.10	6.32	6.96
15	8.46	8.91	8.43	8.03	7.39	8.16

The above Tables 5 & 6, 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 ICDAR datasets. It shows that Equal Error Rate (EER) value gets increased with the more number of samples that had been trained and tested.

VI. CONCLUSION

The computing world features is a heap to realize from K Nearest Neighbor technique. Their ability to find out by example makes them terribly versatile and powerful for the K-kNN method. The training and test set were prepared using one-against-all approach. The results show that K-kNN performs well than K-ANN in both verification and recognition processes. Carefully chosen discriminating features of signatures combined with the use of K-kNN made our system more powerful compared to K-ANN. The proposed K-kNN classification method when compared with KANN method, gives better performance in terms of accuracy, value with 77% TPR, 73% FPR in ACT and 76% TPR, 58% FPR in ICDAR datasets respectively.

REFERENCES

1. Y. Chen, J. Yang, C. Wang and N. Liu, "Multimodal biometrics recognition based on local fusion visual features and variational Bayesian extreme learning machine", *Expert Systems with Applications*, vol. 64, pp. 93-103, 2016. Available: 10.1016/j.eswa.2016.07.009 [Accessed 23 December 2018].
2. W. Kang, X. Chen and Q. Wu, "The biometric recognition on contactless multi-spectrum finger images", *Infrared Physics &*

- Technology, vol. 68, pp. 19-27, 2015. Available: 10.1016/j.infrared.2014.10.007 [Accessed 23 December 2018].
3. K. Reshmi, P. Muhammed, V. Priya and V. Akhila, "A Novel Approach to Brain Biometric User Recognition", *Procedia Technology*, vol. 25, pp. 240-247, 2016. Available: 10.1016/j.protcy.2016.08.103 [Accessed 23 December 2018].
4. C. YOU and B. MA, "Spectral-domain speech enhancement for speech recognition", *Speech Communication*, vol. 94, pp. 30-41, 2017. Available: 10.1016/j.specom.2017.08.007 [Accessed 23 December 2018].
5. T. Davis, D. Grantham and R. Gifford, "Effect of motion on speech recognition", *Hearing Research*, vol. 337, pp. 80-88, 2016. Available: 10.1016/j.heares.2016.05.011 [Accessed 23 December 2018].
6. C. Vivaracho-Pascual, A. Simon-Hurtado and 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, 2017. Available: 10.1016/j.neucom.2016.11.080 [Accessed 23 December 2018].
7. A. Soleimani, B. Araabi and K. Fouladi, "Deep Multitask Metric Learning for Offline Signature Verification", *Pattern Recognition Letters*, vol. 80, pp. 84-90, 2016. Available: 10.1016/j.patrec.2016.05.023 [Accessed 23 December 2018].
8. J. Galbally, M. Diaz-Cabrera, M. Ferrer, M. Gomez-Barrero, A. Morales and 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, 2015. Available: 10.1016/j.patcog.2015.03.019 [Accessed 23 December 2018].
9. R. Doroz, P. Porwik and T. Orczyk, "Dynamic signature verification method based on association of features with similarity measures", *Neurocomputing*, vol. 171, pp. 921-931, 2016. Available: 10.1016/j.neucom.2015.07.026 [Accessed 23 December 2018].
10. A. Sharma and S. Sundaram, "An enhanced contextual DTW based system for online signature verification using Vector Quantization", 2018.
11. M. Razzak and B. Alhaqani, "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, 2014. Available: 10.1007/s00521-014-1779-6 [Accessed 23 December 2018].
12. R. Ghosh, P. Kumar and P. Roy, "A Dempster-Shafer theory based classifier combination for online Signature recognition and verification systems", *International Journal of Machine Learning and Cybernetics*, 2018. Available: 10.1007/s13042-018-0883-9 [Accessed 23 December 2018].
13. M. Durrani, S. Khan and S. Khalid, "VerSig: a new approach for online signature verification", *Cluster Computing*, 2017. Available: 10.1007/s10586-017-1129-4 [Accessed 23 December 2018].
14. L. Yang, Y. Cheng, X. Wang and Q. Liu, "Online handwritten signature verification using feature weighting algorithm relief", *Soft Computing*, vol. 22, no. 23, pp. 7811-7823, 2018. Available: 10.1007/s00500-018-3477-2 [Accessed 23 December 2018].
15. S. Rohilla and 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, 2016. Available: 10.1007/s40010-016-0293-x [Accessed 23 December 2018].



AUTHORS PROFILE

Mr R. Ravi Chakravarthi, obtained his Masters of Science degree in Applied Sciences- Computer Technology faculty from Bharathiar University, Coimbatore, Tamilnadu, India in May 1999. He had received his Masters of Philosophy degree in Computer Science from Manonmaniam Sundaranar University (MSU), Tirunelveli, Tamilnadu, India in May 2007. He is presently a Research Scholar of Ph.D., at MSU in the faculty of Computer Technology. He had published his several research papers in the area of enriching the performance and accuracy of Online Digital signature recognition using the classification techniques like Kernel based Support Vector Method, Self-Organizing Map Method, in the reputed Science Cited Index (SCI), Scopus Indexed and UGC listed journals. He has 19 years of teaching experiences in many Universities, Colleges as Lecturer / Senior Lecturer in India and Abroad. He has attended many workshops and conferences in micro-teaching, Quality Assurance for enhancing the quality of student centred teaching and learning process.



Dr E. Chandra, obtained her PhD degree in the area of Speech recognition system from Alagappa University Karaikudi in 2007. She has totally 23 years of Experience in teaching including 6 months in the industry. At present she is working as Professor and Head, Department of Computer Science, Bharathiar

University, Coimbatore. She has published more than 60 research papers in National, International reputed journals and conferences in India and abroad. She is a Reviewer of international journals. She has guided 7 PhD Scholars. At Present 4 Ph.D. Scholars and 2 M.Phil., Scholars are working under her guidance. She wrote a book on “Fractal Image Compression Techniques: Genetic Algorithm and Efficient Domain Pool Algorithm for Fractal Image Compression” and “Distributed Data Mining “. She has completed a Minor Research Project on “Diverse Sub-band Adaptive Speech Enhancement for Hearing Aids” which is sanctioned by UGC. She has received best actively participating woman in CSI (India) for Coimbatore Chapter during the year 2012 and Best Oral Presenter Award from EEET 2018. She has delivered lectures to various Colleges in Tamil Nadu & Kerala. She is a Board of studies member at various colleges. Her research interest lies in the area of Neural Networks, Speech Recognition Systems, Fuzzy Logic and Machine Learning Techniques. She is a Life member of CSI, Member - ACM, Life Member of International Association of Computer Science and Information Technology (IACSIT), Life member of Society of Statistics and Computer Applications. She has 3 Patent filed.