A Light weight and Hybrid Deep Learning Model based Online Signature Verification

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Abstract - ***The augmented usage of deep learning-based models for various AI related problems are as a result of modern architectures of deeper length and the availability of voluminous interpreted datasets. The models based on these architectures require huge training and storage cost, which makes them inefficient to use in real time systems like online signature verification (OSV) and to use in resource restraint devices. As a solution, in this work, our contribution is two-fold. 1) An efficient dimensionality reduction technique, to lessen the number of features to be considered and 2) a state-of-the-art model CNN-LSTM based hybrid architecture for online signature verification. Thorough experiments on the openly accessible datasets MCYT, SUSIG, SVC approves that the proposed framework attains improved precision even with as low as one training sample. The proposed framework produce state-of-the-art performance in several categories of all the three datasets.***

Keywords-OSV; hybrid features; deep learning; LSTM

I. INTRODUCTION

Online Signature Verification (OSV) is a fascinating research problem in the area of Artificial Intelligence. OSV finds numerous critical applications like e-signatures, banking transaction, online financial transactions [1,2,4,6] etc. Recent advancements in mobile networking/ devices and touchscreen technology lead to use of specialized interfaces to collect the distinctive signing features like pressure, angle of stylus pen, velocity etc., at each point of signature and analyzing these key features along with the geometric co-ordinates. This numerical information is used for online signature verification in contrast to a static image verification for offline signature system [1,4,5,7,15,16,43].

In literature[1,6-9,20], the online signature verification models are generally grouped into two types 1) Traditional feature extraction based 2) Deep learning technique based verification systems. In traditional feature extraction based OSV models, the genuineness of a test signature is classified through an appropriate similar technique based on pattern recognition methods such as Symbolic classifier [3,7,9], Dynamic Time Warping [13, 25, 31], Hidden Markov Model [4,6], Support Vector Machine [43], Neuro fuzzy [9,11,12], Random forest[2-4], Neural Networks [3,4], Viterbi path [4], etc.

The recent advancements in computing resources and increasing amount of accessibility to huge datasets leads to evolution of Machine Learning and Deep learning Techniques (MLDL). The advancements in MLDL [28,41, 42] techniques results in development of models of deeper architecture and capability to process vast amount of data. in course of conventional OSV frameworks, Zhang et al [1] put forward a novel attempt for OSV grounded on template matching procedure in which the legitimacy of a writer is decided by matching an input signature with an equivalent user reference set. Based on the similarity distance, the signature is categorised as genuine or forgery and attained an Average Error Rate (AER) of 2.2% on a convention dataset. Cpałka et al [10], proposed an OSV model by separating the signature into regions called partitions which represents the time moments. A neuro fuzzy classifier is used to categorize the signature based on partitions. The model achieved an AER of 10.70%. In their extension work, Cpałka et al [11,12] proposed novel works, in which writer specific partitions of the signatures are selected by eliminating redundant partitions and achieved an EER of 3.24%.

Limited (only two) OSV frameowrks have been put forward based on MLDL techniques. Tolosona et al [45] proposed a novel Recurrent Neural Networks (RNNs) based Siamese network to acquire a divergence metric from the sets of signatures. The divergence metric is used to categorize the signature and attained an AER of 6.22%. Lai et al [27], proposed a second framework in which RNNs learn a rotation and scale invariance feature named the 'length-normalized path signature', LNPS aids in categorizing the signature. Lai et al attained an EER of 2.37% on SVC-2004 dataset.

Despite the lower error rates, MLDL frameworks need comparatively large amount of training samples for each user to learn the inter-individual variability, intra-individual variability [1,4-6,30], to efficiently classify the genuineness of signatures [13,30,31]. Nevertheless, it is often impractical to acquire satisfactory number of signature samples from users, given the sensitivity of applications e.g., m-banking.

In this context, very few works explored the likelihood of OSV systems with few shot learning i.e. learning the user specific features with one/few signature samples. Galbally et al [16] proposed an OSV framework in which synthetic samples are generated from one signature sample by duplicating the signature using Hidden Markov Models. Another work in the same direction is by Diaz et al [24,29], in which, single samplings were duplicated grounded on the kinematic theory of rapid human movements, and its sigmalognormal factors. This model attained an Equal Error rate (EER) of 13.56% with MCYT-100 dataset, when the model is trained with single signature sample.

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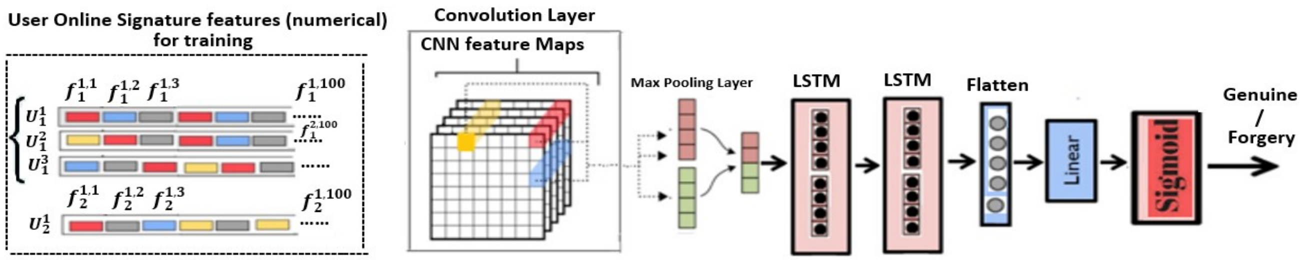

Figure 1: Proposed Deep CNN + LSTM based architecture for Online Signature Verification. In the diagram, Flatten stands for fully connected layers.

II. Our Contribution

A. The chief contributions of our work can be précised as follows:

1. In this paper, each user / writer original features from the dataset are independently clustered using traditional K-Means clustering algorithm. The clustering technique results in set of feature clusters. A cluster representative for each cluster is selected and the set of these cluster representatives forms the reduced feature subset for each user. The cluster representatives are selected through statistical dispersion measure: Mean absolute difference (MAD).

2. We put forward a mixture of two deep neural network architectures viz., a Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) in which the reduced feature set (cluster heads) are fed to the CNN layer. CNN layer generates the local deep features, which are fed into the LSTM layers. LSTM learns the long-term dependencies from input signature and use the same for classifying the signature as genuine or forgery.

3. Thorough assessment of our OSV framework by performing experimentations on three extensively used datasets for OSV i.e. MCYT-100, SUSIG and SVC.

The document is planned as follows. In Section III, we put forward varied stages of our model. In section IV, details of training and testing data, along with the experimental study are discussed. Conclusions are given in section V.

III. Proposed Model Architecture

Stimulated by the research from [39,40,41,42] in sequence modelling, sentiment analysis [39], attentiveness [44] and the fact that CNN can excerpt finest local features of input and RNN (recurrent neural network) and its variants (LSTM, RGU) can process the extracted local features and can learn the long-term dependencies, we joined both CNN and LSTM for online signature (which is a sequence of points) verification. As depicted in fig 1, the reduced feature set which are the cluster representatives forms an input to the Convolutional Neural Network layer (CNN). The CNN learns the low-level translation invariant features from the reduced feature set and feed forward to LSTMs (Long Short-Term Memory) layers in order to compose higher order features.

Our framework is a collection of the below modules: condensing the original feature set, convolutional and pooling layers, concatenation layer, LSTM layer, fully connected layer with Sigmoid output. These modules are explained below:

A. Writer Dependent Feature Clustering.

let S = $[{S_1}^j, {S_2}^j, {S_3}^j, \dots, {S_m}^j]$ be a collection of 'm' signature samples of writer 'j' i.e. U_j, j = 1, 2, 3,….M. (M signifies the number of writers). Let $F = [{F_1}^j, {F_2}^j, {F_3}^j, \dots, {F_n}^j]$ be a set of n-dimensional combined feature vectors, where ${F_i}^j = [{f_{i1}}^j, {f_{i2}}^j, {f_{i3}}^j, \dots, {f_{im}}^j]$ be the feature set describing the i[th] feature of signature samples of writer 'j' i.e. U_j. The Feature-Signature matrix (FS) of writer U_j is illustrated below:

F/S	S_1	S_2	S_3		S_m	Mean(MF_i^-)
F_1	f_{11}	f_{12}			f_{1m}	
F_2						
F_n	f_{n1}	f_{n2}			f_{nm}	

The feature vectors F_1, F_2, …, F_n forms an input to the K-Means clustering technique in which each feature is grouped under one of the 'K' clusters. For each cluster returned by the clustering technique, we will compute the cluster representative using a novel statistical dispersion metric which is described below.

B. Computing the Cluster Representatives

In literature [2,7,14], to select a subset of 'd' writer dependent features based on their relevance from a total set of 'P' features, the widely used diffusion measures for choosing writer dependent features are: Mean absolute difference (MAD) =

$$MAD_k = \frac{1}{n} \sum_{i=1}^{n} |f_{ik} - {f_k}^-|, k = 1,2,3, \dots, P \qquad (1)$$

where ${f_k}^-$ is the mean of the k[th] feature of the user U_j and f_{ik} is the feature value of the k[th] feature for the i[th] example of the user U_j. MAD_k is calculated for each feature of the feature set i.e., $k = 1,2,3, \dots, P$.

To pick one feature amongst the features of a cluster as a cluster representative, we have computed MAD by applying the formula (2). The feature with maximum MAD value among the features of a corresponding cluster is designated as cluster representative. On computing the cluster representative for all the clusters, the set of cluster representatives are grouped to form a reduced feature subset 'FS'. The 'FS' forms an input to the Convolutional Neural Network. In case of MCYT-100 dataset, as shown in Table II, the features are reduced from 100 to 80 and 100 to 50. Each signature is a one – dimensional vector of length 50 i.e. 1* 50 in case of 50 features, 1* 80 in case of 80 features.

C. Convolution and Pooling

In receipt of the reduced feature set 1*80, the Convolutional Neural Network accomplishes a one-dimensional convolution operation (matrix-vector multiplication) between the two signals i.e. input sequence vector and the sliding kernel (weight matrix) to extract local features for respective window of the given signature. The advanced features are generated by sliding the weight matrix over the signature feature sequence and finally produces feature maps. Our framework contains 32 filters, of length 5 (one dimensional) which results in an output of a feature vector of size 80 × 36. On the output of first conv layer, batch normalization is applied to regulate the input to the activation function and for faster convergence, which results in an output of 80 × 36. Likewise, the second convolution layer uses 64 filters of size 1 ×3 and outcomes a feature vector of size 80 ×36. These feature representations form an input to the LSTM layer of 34 units.

D. Long Short Term Memory (LSTM)

LSTMs are explicitly designed with a default behavior to process sequential input and to learn the long-term dependencies and are well-suited to classify temporal data given time lags of unknown duration. The LSTMs have an exceptional property of relative insensitivity to input gap length, in which the other models like RNNs, hidden markov models and other sequence learning methods fails [39, 40, 41,42]. As online signature is a sequence of time series points, we have used LSTM layers to learn long term dependencies of signature features. LSTM layer outputs a feature vector of size 80 × 32. The deep representational features from the LSTM layers is given as an input to the fully connected layers.

E. Fully Connected Network with Sigmoid Output

The proposed framework uses a two hidden layered Multilayer Perceptron (MLP) as classifier. A deep feature vector from the LSTM layer of size 80 × 32 forms an input to the first fully connected layer of MLP. Flatten reshapes the feature vector of size 80 × 32 into a high-level feature representation of size 1×2560. The amount of neurons in the first fully connected layers are 32. The output of size 1×32 from the first fully connected layer is given as input to the second fully connected layer which contains 32 neurons. A feature vector of size 1×32 from the second fully connected layers is fed as an input to the batch normalization and dropout layers which outputs a feature of size 1×32. The final feature forms an input to final sigmoid layer for final classification into genuine or forgery. In our framework for loss function we opted 'binary_crossentropy' and for optimizer, we have chosen 'adam', with batch size of 16 and total of 800 epochs.

TABLE I. THE DATASET DETAILS USED IN THE EXPERIMENTS FOR THE PROPOSED MODEL

DataSet →	**MCYT-100**	**SVC**	**SUSIG**
# of Users	**100**	**40**	**94**
Total Number of features	**100**	**47**	**47**
Training (Genuine+Training)	3600 **(72%)**	1120 **(70%)**	1880 **(67%)**
Testing (Genuine) – FRR	700 **(14%)**	240 **(15%)**	564 **(20%)**
Testing (Forgery) - FAR	700 **(14%)**	240 **(15%)**	376 **(13%)**
Total Testing Samples %	**28%**	**30%**	**33%**
Total Number of Samples	5000	1600	2820

TABLE II. COMPARATIVE ANALYSIS OF THE PROPOSED MODEL AGAINST THE RECENT MODELS ON MCYT (DB1) DATABASE (where 'S' and 'R' represents Skilled and Random categories respectively. The number indicates the number of signature samples used for training).

Method	S_01	S_05	S_10	S_15	S_20	R_01	R_05	R_10	R_15	R_20
Proposed Model – (Hybrid Deep Learning Model + few shot learning)	**15.57**	1.88	**0.67***	**0.73***	**0.00***	16.70	0.16	**0.04***	**0.06***	**0.00***
GMM+DTW with Fusion [16]	-	3.05	-	-	-	-	-	-	-	-
Cancelable templates - HMM Protected [17]	-	10.29	-	-	-	-	-	-	-	-
Cancelable templates - HMM[17]	-	13.30	-	-	-	-	-	-	-	-
Histogram + Manhattan [20]	-	4.02	-	-	-	-	1.15	-	-	-
discriminative feature vector + several histograms [20]	-	4.02	-	-	2.72	-	1.15	-	-	0.35
Writer dependent parameters (Symbolic) [21]	-	2.2	-	-	0.6	-	1.0	-	-	**0.1****
VQ+DTW[25]	-	**1.55***	-	-	-	-	-	-	-	-
writer dependent features and classifiers[26]	-	19.4	-	-	1.1	-	7.8	-	-	0 .8
Stroke-Wise [29]	**13.72****	-	-	-	-	**5.04***	-	-	-	-
Target-Wise [29]	**13.56***	-	-	-	-	**4.04****	-	-	-	-
Information Divergence-Based Matching [30]	-	3.16	-	-	-	-	-	-	-	-
WP+BL DTW[31]	-	2.76	-	-	-	-	-	-	-	-
Representation learning + DTW (Skilled forgery) [34]		**1.62 ****					0.23			
Representation learning + DTW (Random forgery) [34]		1.81					0.24			
Combinational Features and Secure KNN-Global features [35]	-	5.15	-	-	-	-	1.70	-	-	-

Combinational Features and Secure KNN-Regional features [35]	-	4.65	-	-	-	-	1.33	-	-	-
Stability Modulated Dynamic Time Warping (F13) [35]	-	13.56	-	-	-	-	4.31	-	-	-
Dynamic Time Warping-Normalization(F13) [35]	-	8.36	-	-	-	-	6.25	-	-	-
Writer dependent parameters (IntervalValued representation) [36]	-	2.51	-	-	**0.03****	-	0.70	-	-	**0.00***
Common feature dimension and threshold (IntervalValued representation) [36]	-	10.36	-	-	5.82	-	10.32	-	-	0.74
Writer dependent parameters (conventional) [36]	-	6.79	-	-	**0.00***	-	1.73	-	-	**0.00***
Common feature dimension and threshold (conventional) [36]	-	13.12	-	-	11.23	-	5.61	-	-	1.66
Probabilistic-DTW(case 1) [37]	-	-	-	-		-	**0.0118***	-	-	-
Probabilistic-DTW(case 2) [37]	-	-	-	-	-	-	**0.0187****	-	-	-
Curvature feature [38]	-	10.22	8.25	6.38	-	-	4.12	3.33	2.58	-
Torsion Feature [38]	-	9.22	7.04	5.12	-	-	3.42	2.25	1.90	-
Curvature feature +Torsion Feature[38]	-	6.05	**4.23****	**3.10****	-	-	2.95	**1.81****	**1.20****	-

TABLE III. COMPARATIVE ANALYSIS OF THE PROPOSED MODEL AGAINST THE RECENT MODELS ON SVC DATASET

Method	S_01	S_05	S_10	S_15	R_01	R_05	R_10	R_15
Proposed Model – (Hybrid Deep Learning Model + few shot learning)	**6.71***	**1.05***	**0.00***	**0.10***	9.53	0.16	**0.18***	**0.16***
LCSS (User Threshold) [19]	-	-	5.33	-	-	-	-	-
RNN+LNPS[27]	-	-	-	-	-	2.37	-	-
Target-Wise [29]	18.63	-	-	-	**0.50***	-	-	-
Stroke-Wise [29]	**18.25****	-	-	-	**1.90****	-	-	-
DTW based (Common Threshold) [31]	-	-	7.80	-	-	-	-	-
Stroke Point Warping [32]	-	-	**1.00****	-		-	-	-
SPW+mRMR+SVM(10-Samples) [32]	-	-	**1.00****	-	-	-	-	-
Variance selection [33]	-	-	13.75	-	-	-	-	-
PCA [33]	-	-	7.05	-	-	-	-	-
Relief-1 (using the combined features set) [33]	-	-	8.1	-	-	-	-	-
Relief-2 [33]	-	-	5.31	-	-	-	-	-
Probabilistic-DTW(case 1) [37]	-		-	-	-	**0.0025***	-	-
Probabilistic-DTW(case 2) [37]	-	-	-	-	-	**0.0175****	-	-
Curvature feature +Torsion Feature[38]	-	**9.83****	6.61	**3.10****	-	3.54	**1.24****	**1.81****

TABLE IV. COMPARATIVE ANALYSIS OF THE PROPOSED MODEL AGAINST THE RECENT MODELS ON SUSIG DATASET

Method	S_01	S_05	S_10	R_01	R_05	R_10	Number of Samples for training
Proposed Model – (Hybrid Deep Learning Model + few shot learning)	13.09	**1.95****	**0.47***	12.40	**2.86****	**1.28***	
cosα, speed + enhanced DTW [7]	-	-	3.06	-	-	-	10
pole-zero models [22]	-	2.09	-	-	-	-	05
DCT and sparse representation [22]	-	-	0.51	-	-	-	10
with all domain [23]	-	-	3.88	-	-	-	10
with stable domain [23]	-	-	2.13	-	-	-	10
Kinematic Theory of rapid human movements[24]	7.87	-	-	3.61	-	-	01
writer dependent features and classifiers[45]	-	-	1.92	-	-	-	10
Length Normalization + Fractional Distance [45]	-	-	3.52	-	-	-	10
Target-Wise [29]	**6.67***	-	-	**1.55***	-		10
Stroke-Wise [29]	**7.74****	-	-	**2.23****	-	-	10
Information Divergence-Based Matching [30]	-	**1.6***	2.13	-	-	-	10
Association of curvature feature with Hausdorff distance [38]	-	7.05	-	-	**1.02***	-	

IV. EXPERIMENTATION AND RESULTS

Herein, we investigate on the experimental analysis, results outcome and performance evaluation with the state of the art OSV frameworks. We experimented on Ubuntu 16.04 LTS with Titan X GPU. The proposed frameworks are executed in keras using python with Tensorflow [28,41] backend. We performed experiments on three widely used datasets i.e. SVC task 2004 database, Visual Subcorpus of SUSIG and MCYT-100

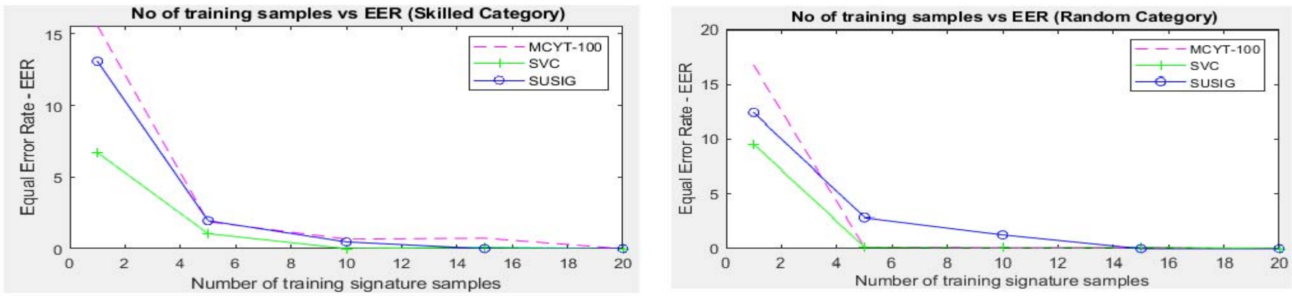

Figure. 2. The average EER with three different datasets for (a) Skilled Forgeries and (b) Random Forgeries.

online signature dataset (DB1). The full particulars of the datasets are demonstrated in Table 1.

Analogous to [7,9,20], the evaluation metrics used to assess the competence of the our framework are: (i) False Acceptance Rate (FAR), describes the fraction of forgery signatures that are misclassified (FAR can be calculated for skilled and random forgeries respectively), (ii) False Rejection Rate (FRR), which indicates the fraction of genuine signatures that are misclassified by the framework (iii) Average Error Rate (AER), is the average of FRR, FAR. (iv) Equal Error Rate (EER), is the point at which the FRR = FAR.

To test the proposed framework performance, we have trained the system with few shot (fewer amount of samples) i.e. 1,5 and sufficiently large quantity of genuine signatures and with equivalent forgery samples i.e. 10,15,20 for each user. Genuine signatures of other users are considered as a random forgeries for a user. In addition to that, 60% of training set is fragmented into training and validation set to fine tuning the hyper parameters (batch size, learning rate, number of CNN layers, epochs, number of filters and number of LSTM layers etc.) to achieve lesser Equal Error Rate (EER). Once the hyper parameters are fixed during validation, the same set of parameters are used in testing phase also. In our proposed framework, we have conducted experiments for twenty trials and results were recorded.

The EER outcome from the proposed model with various data sets are demonstrated in Table II, III and IV. Table II validates that in case of MCYT-100 dataset, even with the 80 features, the EER in Skilled and Random categories of 10,15,20 resulted in enhanced classification accuracy compared to state of the art models in the literature, which are experimented on examining all the 100 features. In case of SVC-2004 dataset, as illustrated in Table III, the EER outcome by considering 40 best features achieved the state-of-the art results in all Skilled categories and in case of Random 10 and 15. In case of SUSIG, as reported in Table IV, the EER outcome by taken into account 40 features surpassed the state-of-the art results in Skilled and Random categories of 05, 10. As illustrated in table II,III,IVI, even though the frameworks proposed in [32,37,38] are achieving higher EER values compared to our framework, these models have limited evaluations with only Skilled_1, and Random_1 categories, whereas our model has been thoroughly appraised with all the possible training samples (1,5,10,15,20). Hence, its real time usage and superiority is confirmed, compared to [32,37,38].

Figure 2, illustrates that our proposed model converges to zero EER as the number of training signature sample increases. In case of skilled category, SVC dataset shows faster convergence and in case of random category MCYT and SVC converges to zero EER.

V. CONCLUSION

The chief contribution of this work is to develop OSV models for resource constraint mobile devices. Based on the author's knowledge, this work delivers the first, comprehensive and effective framework on the usage of CNN and LSTM combination for OSV with reduced feature set. The foremost improvement of the proposed model is that it achieves few shot learning in which the framework learns the user specific features with one/few signature samples and realizes state of the art results in S_10,15,20,R_10,15,20 categories of MCYT, all categories of SVC datasets except R_01,R_05. S_05,10 ,R_05,10 categories of SUSIG datasets and reflects the realistic scenario.

References

[1]. K.Zhang, E.Nyssen and H.Sahli, Multi-stage Online Signature Verification System, Pattern Analysis and Applications, vol 5, pp:288-295, 2001.

[2]. L.Nanni and Lumini, A. Advanced methods for two-class problem formulation for online signature verification. Neurocomputing. Vol 69, pp: 854-857, 2006.

[3]. L. Nanni, Experimental comparison of one-class classifiers for on-line signature verification, Neurocomputing, vol 69, pp: 869-873, 2006.

[4]. B. L. Van, S. Garcia-Salicetti, and B. Dorizzi, "On using the viterbi path along with hmm likelihood information for online signature verification." IEEE Transactions on Systems, Man, Cybernetics, Part B, vol. 37, no. 5, pp. 1237–1247, 2007.

[5]. P. Porwik, R. Doroz and T. Orczyk, Signatures verification based on PNN classifier optimised by PSO algorithm, Pattern Recognit, vol 60, pp:998–1014, 2016.

[6]. J. Fierrez, J. Ortega-Garcia, D. Ramos, and J. Gonzalez-Rodriguez, "Hmm-based on-line signature verification: Feature extraction and signature modeling," Pattern Recognition Letters, vol. 28, no. 16, pp. 2325–2334, 2007.

[7]. M.I.Khalil, M.Moustafa and H.M. Abbas, Enhanced DTW based on line signature verification. In: Proceedings of the 16th IEEE InternationalConference on Image Processing (ICIP), 2009.

[8]. J. M. Pascual-Gaspar, V. Carde˜noso-Payo, and C. Vivaracho-Pascual, “Practical on-line signature verification,” in International Conference on Biometrics. Springer, pp. 1180–1189,2009.

[9]. M.T.Ibrahim, M. A. Khan, K.S. Alimgeer, M.K. Khan, I.A.Taj, L.Guan, Velocity and pressure-based partitions of horizontal and vertical trajectories for on-line signature verification. Pattern Recognition, vol 43,pp: 2817–2832, 2010.

[10]. M.Zalasinski and K.Cpałka, New approach for the on-line signature verification based on method of horizontal partitioning. Lecture Notes in Artificial Intelligence, 7895, 342–350., 2013.

[11]. K.Cpałka, M.Zalasiński and L.Rutkowski, 'New method for the on-line signature verification based on horizontal partitioning', Pattern Recognition, vol 47, pp:2652– 2661,2014.

[12]. K. Cpałka, M. Zalasinski and L. Rutkowski, A new algorithm for identity verification based on the analysis of a handwritten dynamic signature, Applied Soft Computing, vol 43, pp:47–56, 2016.

[13]. A. Sharma and S. Sundaram, “An enhanced contextual dtw based system for online signature verification using vector quantization,” Pattern Recognition Letters, vol. 84, pp. 22–28, 2016.

[14]. K.S. Manjunatha, S. Manjunath, D.S. Guru and M.T. Somashekara, 'Online signature verification based on writer dependent features and classifiers', Pattern Recognition Letters, vol 80, pp:129-136, 2016.

[15] M.I.Khalil, M.Moustafa and H.M. Abbas, Enhanced DTW based on-line signature verification. In: Proceedings of the 16th IEEE InternationalConference on Image Processing (ICIP), 2009.

[16] J. Galbally, J. Fiérrez, M. Diaz, and J. O.Garcia, “Improving the enrollment in dynamic signature verfication with synthetic samples,” in IntConf on DocAnal. Recognit. (ICDAR), pp. 1295–1299,Barcelona, Spain, 2009.

[17] E. Maiorana, P. Campisi, J. Fierrez, J. O.Garcia, and A. Neri, “Cancelable templates for sequence-based biometrics with application to on-line signature recognition,” IEEE Trans. Syst., Man, Cybern. A, Syst., Humans, vol. 40, no. 3, pp. 525–538, May 2010.

[18] S. Rashidi , A. Fallah , F. Towhidkhah , Authentication based on pole-zero models of signature velocity, Journal of Medical Signals Sens, vol 3, pp:195–208,2013.

[19] K. Barkoula, G. Economou and S. Fotopoulos, Online signature verification based on signatures turning angle representation using longest common subsequence matching, Int Journal of Doc Analysis and Recognition, vol 16, pp:261–272 , 2013.

[20] N. Sae-Bae and N. Memon, “Online signature verification on mobile devices,” IEEE Trans. Inf. Forensics Security, vol. 9, no. 6, pp. 933–947, Jun. 2014.

[21] A. Q. Ansari, M. Hanmandlu, J. Kour, and A. Singh, “Online signature verification using segment-level fuzzy modelling,” IET Biometrics, vol. 3, no. 3, pp. 113–127, Sep. 2014

[22] Y. Liu, Z. Yang, and L. Yang, “Online signature verification based on DCT and sparse representation,” IEEE Trans. Cybern., vol. 45, no. 11, pp. 2498–2511, Nov. 2015.

[23] G. Pirlo, V. Cuccovillo, M. Diaz-Cabrera,D. Impedovo and P. Mignone, Multidomain Verification of Dynamic Signatures Using Local Stability Analysis, IEEE Transon Human-Machine Systems, vol 45, Dec. 2015.

[24] M. Diaz, A. Fischer, R. Plamondon, and M. A. Ferrer, “Towards an automatic on-line signature verifier using only one reference per signer,” in Int. Conf. Document Anal. Recognit. (ICDAR), Tunis, Tunisia, pp. 631–635,2015.

[25] A.Sharma and S.Sundaram, An enhanced contextual dtw based system for online signature verification using vector quantization. Pattern Recognition Letters,vol 84, pp:22–28, 2016.

[26] K.S. Manjunatha, S. Manjunath,D.S. Guru and M.T. Somashekara, 'Online signature verification based on writer dependent features and classifiers', Pattern Recognition Letters vol 80, pp: 129–136, 2016.

[27] S.Lai, L.Jin and W.Yang, Online Signature Verification Using Recurrent Neural Network and Length-Normalized Path Signature Descriptor, 14th IAPR IntConfon DocAna and Rec (ICDAR), 2017.

[28] R.Tolosana, R.V.Rodriguez, J.Fierrez and J.Ortega-Garcia, Biometric Signature Verification Using Recurrent Neural Networks, 14th International Conference on Document Analysis and Recognition (ICDAR), Nov. 2017, Kyoto, Japan

[29] M.Diaz, A.Fischer, M. A. Ferrer and R.Plamondon, Dynamic Signature Verification System Based on One Real Signature, IEEE Transactions On Cybernetics, vol 48, Jan 2018.

[30] L.Tang, W.Kang and Y.Fang, Information Divergence-Based Matching Strategy for Online Signature Verification, IEEE Transon Information Forensics and Security, vol 13, April 2018.

[31] A.Sharma and S.Sundaram, 'On the Exploration of Information From the DTW Cost Matrix for Online Signature Verification', IEEE Transactions on Cybernetics, vol 48, ffeb. 2018 .

[32] B.Kar, A.Mukherjee and P.K.Dutta, Stroke Point Warping-Based Reference Selection and Verification of Online Signature, IEEE Transactions On Instrumentation and Measurement, vol. 67, Jan 2018.

[33] L.Yang, Y.Cheng, X.Wang and Q.Liu, Online handwritten signature verification using feature weighting algorithm relief, Soft Computing, Vol 22, December 2018.

[34] S.Lai and L.Jin, Recurrent Adaptation Networks for Online Signature Verification, IEEE Trans on Information Forensics and Security, Nov 2018.

[35] R.Doroz, P.Kudlacik and P.Porwika, Online signature verification modeled by stability oriented reference signatures, vol 460–461, pp: 151-171, Sep 2018.

[36] C.S.Vorugunti, D.S.Guru and P.Viswanath, An Efficient Online Signature Verification Based on Feature Fusion and Interval Valued Representation of Writer Dependent Features, 'IEEE fifth International Conference on Identity, Security and Behavior Analysis (ISBA)', Jan 2019.

[37] R.Al-Hmouz, W.Pedrycz, K.Daqrouq, A.Morfeq and A.Al-Hmouz, Quantifying dynamic time warping distance using probabilistic model in verification of dynamic signatures, Elsevier-Soft Computing, vol 23, vol 23, pp 407–418, Jan 2019.

[38] L.He, H.Tan and Z.Huang, Online handwritten signature verification based on association of curvature and torsion feature with Hausdorff distance, springer : Multimedia Tools and Applications, Jan 2019.

[39]. S.Yuan, X.Wu and Y.Xiang, Incorporating pre-training in long short-term memory networks for tweet classification, Social Network Analysis and Mining, vol 5, Dec 2018.

[40]. Z.He, S.Gao, L.Xiao, D.Liu, H.He and D.Barber, Wider and Deeper, Cheaper and Faster: Tensorized LSTMs for Sequence Learning,Thirty-first Conference on Neural Information Processing Systems (NIPS), 2017.

[41]. W.Byeon,T.M.Breuel,F.Raue and M.Liwicki, Scene labeling with LSTM recurrent neural networks, IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Boston, USA, 2015.

[42]. Y.Luo,J.Ren, Z.Wang, W.Sun,J.Pan,J.Liu,J.Pang and L.Lin, LSTM Pose Machines,IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018

[43]. X.Xia,X.Song,F.Luan, J.Zheng, Z.Chen and X.Ma, Discriminative feature selection for on-line signature verification, Pattern Recognition, vol 74, pp:422-433, 2018.

[44] P.Zhang, J.Xue, C.Lan, W.Zeng, Z.Gao and N.Zheng, SAdding Attentiveness to the Neurons in Recurrent Neural Networks, European Conference on Computer Vision, Sep 2018, Germany.

[45]. R.Tolosana, R. Vera-Rodriguez, J.Fierrez, and J.Ortega-Garcia, Exploring Recurrent Neural Networks for On-Line Handwritten Signature Biometrics, IEEE Access, vol 6, pp:5128-5138, Jan 2018.