Sr. no.	Paper Titile	Author	Year	Journal
1	Biometric Handwritten Signature Recognition	Syed Faraz Ali Zaid, Shahzaan Mohammed	2007	
2	Towards human-assisted signature recognition: improving biometric systems through attribute-based recognition	Derlin Morocho Aythami, Morales, Julian Fierrez, Ruben Vera-Rodriguez	2016	IEEE International Conference on Identity, Security and Behavior Analysis
3	Offline Signature Recognition System Using Radon Transform	S. A. Angadi, Smita Gour, Gayatri Bajantri	2014	Fifth International Conference on Signal and Image Processing

4	On-line signature verification based on altitude and direction of pen movement	Seiichiro Hangai, Shinji Yamanaka, Takayuki Hamamoto	2000	5th International Conference on Pattern Recognition. ICPR
5	Handwritten signature recognition method based on fuzzy logic	Igor V. Anikin, Ellina S. Anisimova	2016	Dynamics of Systems, Mechanisms and Machines (Dynamics)
6	Off-line Signature Verification and Recognition by Support Vector Machine	Emre Özgündüz, Tülin Şentürk M. Elif Karslıgil	2005	European Signal Processing Conference

7	Euclidean Distance Based Offline Signature Recognition System Using Global and Local Wavelet Features	S. A. Angadi Smita Gour	2014	Fifth International Conference on Signal and Image Processing
8	Offline Handwritten Signature Recognition Using Adaptive Variance Reduction	Ruangroj Sa-Ardship, Woraratpanya, Kuntpong	2015	7th International Conference on Information Technology and Electrical Engineering (ICITEE), Chiang Mai, Thailand
9	Offline Signature Identification using the Histogram of Symbolic Representation	Abdilbaree Talib Nasser, Nuran Dogru	2017	5th International Conference on Electrical Engineering - Boumerdes (ICEE-B)
10	Offline Handwritten Signature Recognition Based on Upper and Lower Envelope Using Eigen Values	Amruta B. Jagtap, Ravindra S. Hegadi	2017	2nd World Congress on Computing and Communication Technologies, WCCCT 2017

11	Identification of authors of documents based on offline signature recognition	Tonćo Marušić*, Željko Marušić, Željko Šeremet	2015	MIPRO
12	Signature Recognition on Bank cheques using ANN	Shubhangi L. Karanjkar, P. N. Vasambekar	2016	IEEE International WIE Conference on Electrical and Computer Engineering (WIECON-ECE)
13	Computer Vision & Fuzzy Logic based Offline Signature Verification and Forgery Detection	Gautam. S. Prakash, Shanu Sharma	2014	IEEE International Conference on Computational Intelligence and Computing Research

14	Document Image Retrieval using Signature as Query	M. S. Shirdhonkar, Manesh B. Kokare	2011	2nd International Conference on Computer and Communication Technology, ICCCT
15	Offline Handwritten Signature Recognition Using Polar-Scale Normalization	Ruangroj Sa-Ardship, Kunpong Woraratpanya	2016	8th International Conference on Information Technology and Electrical Engineering (ICITEE)
16	Off-line signature verification using DTW	A. Piyush Shanker, A.N. Rajagopalan	2007	Pattern Recognition Letters
17	Signature Processing in Handwritten Bank Cheque Images	Nancy, Prof. Gulshan Goyal	2014	International Journal on Recent and Innovation Trends in Computing and Communication
18	Signature recognition by using SIFT and SURF with SVM basic on RBF for voting online	Abdilbaree Talib Nasser, Nuran Dogru	2017	Proceedings of 2017 International Conference on Engineering and Technology, ICET

19	A Robust Offline Handwritten Signature Verification System Using Writer Independent Approach	Ashok Kumar, Karamjit Bhatia	2017	3rd International Conference on Advances in Computing,Communication & Automation (ICACCA)
20	Enhanced Signature Verification and Recognition using MATLAB	Harpreet Anand, Prof. D.L Bhombe	2014	International Journal of Innovative Research in Advanced Engineering (IJIRAE)
21	Eigen-signature: A Robust and an Efficient Offline	B H Shekar, R.K.Bharathi	2011	International Conference on Recent Trends in Information Technology, ICRTIT
22	Global Features Selection for Dynamic Signature Verification	Ano Rangga Rahardika, Aris Tjahyanto	2018	International Conference on Information and Communications Technology (ICOIACT) Global
23	Hand Signature and Handwriting Recognition as Identification of the Writer using Gray Level Co- Occurrence Matrix and Bootstrap	Teny Handhayani, Alfa Ryano Yohannis, Lely Hiryanto	2017	Intelligent Systems Conference
24	Handwritten Signature Attributes for its Verification	Anastasia Beresneva, Anna Epishkina, Darina Shingalova	2018	IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus)

25	Offline Signature Recognition System using Histogram of Oriented Gradients	Ms. Pallavi Patil, Mr. Bryan Almeida, Ms. Niketa Chettiar, Mr. Joyal Babu	2017	International Conference on Advances in Computing, Communication and Control (ICAC3)
26	Offline signature verification using the trace transform	M. Manoj Kumar, N. B. Puhan	2014	IEEE International Advance Computing Conference (IACC)
27	On-Line Signature Verification by Dynamic Time Warping and Gaussian Mixture Models	Oscar Miguel-Hurtado, Luis Mengibar-Pozo, Michael G. Lorenz, Judith Liu-Jimenez	2007	41st Annual IEEE International Carnahan Conference on Security Technology
28	Robustness of Offline Signature Verification Based on Gray Level Features	Miguel A. Ferrer, J. Francisco Vargas, Aythami Morales, and Aarón Ordóñez	2012	IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY

29	Conic section function neural network circuitry for offline signature recognition	Burcu Erkmen, Nihan Kahraman, Revna Acar Vural, and Tulay Yildirim	2010	IEEE Transactions on Neural Networks
30	Off-line Signature Verification using Local Patterns	Miguel A. Ferrer, Aythami Morales, J.F. Vargas	2011	2nd National Conference on Telecommunications (CONATEL)
31	Online Signature Verification using Hybrid Transform Features	Andile Mlaba, Mandlenkosi Gwetu, Serestina Viriri	2018	Conference on Information Communications Technology and Society (ICTAS) Online
32	Euler number based feature extraction technique for Gender Discrimination from offline Hindi signature using SVM & BPNN classifier	Moumita pal,Swapan Bhattacharyya, Tresata Sarkar	2018	Emerging Trends in Electronic Devices and Computational Techniques (EDCT)
33	A Method of Off-line Signature Verification for Digital Forensics	Weiwei Pan, Guolong Chen	2016	12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD)

34	Offline geometric parameters for automatic signature verification using fixed-point arithmetic	Miguel A. Ferrer, Jesu´ s B. Alonso, and Carlos M. Travieso Abstract—This	2005	IEEE Transactions on Pattern Analysis and Machine Intelligence
35	An HMM for Online Signature Verification Based on Velocity and Hand Movement Directions	Saeede Anbaee Farimani, Majid Vafaei Jahan	2018	6th Iranian Joint Congress on Fuzzy and Intelligent Systems (CFIS)
36	Verification of Static Signatures by Optical Flow Analysis	G. Pirlo and D. Impedovo	2013	IEEE TRANSACTIONS ON HUMAN-MACHINE SYSTEMS
37	An Efficient Signature Verification Method based on an Interval Symbolic Representation and a Fuzzy Similarity Measure	Alireza Alaei, Srikanta Pal, Umapada Pal	2017	IEEE Transactions on Information Forensics and Security
38	Online Signature Verification and Recognition: An Approach based on Symbolic Representation.	D.S. Guru and H.N. Prakash	2009	IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE

39	On the Exploration of Information from the DTW Cost Matrix for Online Signature Verification	Abhishek Sharma and Suresh Sundaram Abstract—This	2018	IEEE TRANSACTIONS ON CYBERNETICS
40	Multidomain Verification of Dynamic Signatures Using Local Stability Analysis	G. Pirlo, V. Cuccovillo, M. Diaz-Cabrera, D. Impedovo, and P. Mignone	2015	IEEE TRANSACTIONS ON HUMAN-MACHINE SYSTEMS

Paper details	Preprocessing
Uses some simple parameters, Discuss how these parameters can be used in the lab environment to improve the performance of biometric handwritten signature, Two types of systems – online and offline, Handwritten signatures are very much dependant on the user's psychology and has great difference in different surroundings and time	Deletion of virtual pen-up strokes
Crowdsourcing experiment to establish the human baseline performance for signature recognition tasks and a novel attribute-based semi-automatic signature verification system inspired in FDE analysis Combines the DTW algorithm with Attribute based algorithm to obtain better accuracy and increase the recognition rate.	Binary image of the signature
The proposed system functions in three stages. Pre-processing stage; Feature extraction stage. Finally in Neural Network stage the trained Neural Network is further used for signature recognition after the process of feature extraction.	Gray-Scale Conversion Binarization Fitting boundary box Thinning Resizing

On-line writer authentication system using the dynamic features in real time. It is well expected that altitude and the azimuth of gripped pen under signing depends on the shape of writer's hand and the habit of writing.	
On-line writer authentication system that uses the pen altitude, pen azimuth, shape of signature, and writing pressure in real time for creating 7 fuzzy characteristics.	
Off-line signature verification and recognition system using the global, directional and grid fea- tures of signatures. Support Vector Machine (SVM) was used to verify and classify the signatures	Background Elimination, Noise Reduction, Width Normalization Thinning

A novel approach for offline signature recognition system is presented in this paper, which is based on powerful global and local wavelet features (Energy features). The	Gray scale conversion, Binarization, Thinning and Fitting boundary box
Alternative way to increase the recognition rate by analyzing an important characteristic of input information, namely variability of signatures. The variance reduction technique is applied to normalize offline handwritten signatures by means of an adaptive dilation operator.	Binarization, Cropping and Resizing, Noise Reduction
This work proposes an off-line handwritten signature identification system using the Histogram of Symbolic Representation (HSR). The HSR is considered as one-class classifier which has the ability to generate a model for each writer using only its own reference signatures	Local Iterative Method (LIM) Binarization Fitting boundary box
Proposed and implemented an innovative approach based on upper and lower envelope and Eigen values techniques. Envelope represents the shape of the signature. The	Gray scale Binary by using Otsu's method Resized Thinning Bounding box

In this paper researchers, use this daily based biometric characteristic for identification and classification of students' papers and various exam documents used at University of Mostar.	Cropping, Binarization, Noise removal, Morphological Operations, Image normalization, Skeletonization
A signature is collected from the bank cheque by cropping the area of interest. Further it is trained and stored into the trained database. Then signatures to be tested are compared with the signatures that are stored into the test database.	Otsu’s binarization algorithm Gaussian low pass filter
Fuzzy Logic and Artificial Neural Network Based Off-line Signature Verification and Forgery Detection System is presented. As there are unique and important variations in the feature elements of each signature, so in order to match a particular signature with the database, the structural parameters of the signatures along with the local variations in the signature characteristics are used.	Image Resizing Binarization Thinning Rotation Cropping of the image

A new approach to document image retrieval based on signature. The database contains document images with English text combined with headlines, ruling lines, logo, trade mark and signature. In searching a repository of business documents, task of interest is that of using a query signature image to retrieve from a database.	gray scale, elimination of noisy areas and smoothing of background areas, median filter
This paper focuses on the pre-processing phase, which is an alternative way to improve the accuracy and to make such factors stable. This study is based on the hypothesis; a table signature size is able to boost up the recognition rate.	Binarization, Complementation Cropping Resizing
A signature verification system based on Dynamic Time Warping (DTW). The method works by extracting the vertical projection feature from signature images and by comparing reference and probe feature templates using elastic matching.	Maximum Length Vertical Projection (MLVP) method, Minimum Length Horizontal Projection (MLHP) method
Present paper focuses on different steps including browsing a bank cheque, pre-processing, feature extraction, recognition.	Area analysis, Cropping, Binarization, noise elimination, image resizing, thinning
SIFT and a SURF algorithm which is used for enhanced offline signature recognition. This process, Bag-of-word features, was operated by making vector quantization technique, which outlined the key points for each training image inside a unified dimensional histogram	image to gray scale

A writer independent offline handwritten signature verification model, also known as global model, for signature verification is proposed.	gray level signature, median filter, Otsu's threshold cropped resized
offline signature verification using neural network is projected, where the signature is written on a paper are obtained using a scanner or a camera captured and presented in an image format.	color to grayscale, and finally to black and white, Resizing the image, Thinning
System converts a scanned signature to a shape form and eigen-signature construction is proposed for extracting the feature vector from a shape formed signature.	Binarizing, noise is eliminated using a simple morphological filter, thinned
The purpose is to select relevant features from those features set. For doing that, we compute the importance score of each features using two methods: Information Gain Ratio and Correlation.	Translation and size normalization
Signature and handwriting recognition on a mobile device using the Gray Level Co- occurrence Matrix (GLCM) for texture-based feature extraction and the bootstrap for performing single classifier model	Region of Interest (ROI)
The paper examines authentication systems based on handwritten signature and the main informative parameters of signature such as size, shape, velocity, pressure, etc.	

an offline signature recognition system which uses histogram of oriented gradients is presented. Feedforward backpropagation neural network is used for classification. The	color normalization, median filtering, angle normalization and exact bounding box, resized into 256×512 pixels
In this paper, the trace transform based affine invariant features are applied for signature verification. The trace and diametric functional are suitably chosen to derive a set of circus functions from each signature image.	
This paper deals with the analysis of discriminative powers of the features that can be extracted from an on-line signature, how it's possible to increase those discriminative powers by Dynamic Time Warping as a step in the preprocessing of the signal coming from the tablet.	Filtering , Equispacing by Linear Interpolation, Normalization, DTWAlignment, Derived Signals: Speed and Acceleration
Measure gray level features robustness when it is distorted by a complex background and also to propose more stable feature	Thresholding, Signature Segmentation Using

Conic section function neural network (CSFNN) circuitry was designed for offline signature recognition. CSFNN is a unified framework for multilayer perceptron (MLP) and radial basis function (RBF) networks to make simultaneous use of advantages of both	noise reduction algorithm, skeletonization
This paper explores the usefulness of local binary pattern (LBP) and local directional pattern (LDP) texture measures to discriminate off-line signatures. A comparison between several texture normalizations is made so as to look for reducing pen dependence.	binarized, cropped, or-exclushive operation, Texture histogram normalization
The goal of this study is to investigate the effect of combining transform features to authenticate signatures. Due to genuine human error and lack of consistency, comparing signatures requires preprocessing to assist with standardization. The	resampling and signature orientation
In this paper, gender discrimination has been proposed by feature extraction method . The proposed framework considers handwritten hindi signature of each individuals as an input for gender detection .	inverted, noise removal and smoothening is achieved using an n*n averaging filter, converted into binary image by threshold decomposition,
In order to solve the shortcomings of manual identification in technical accuracy and subjectivity, this paper proposed an off-line signature identification method based on Support Vector Machine (SVM).	Dataset are stained by useless border, Image binarization, Denoising, Removing blank margins.

This paper presents a set of geometric signature features for offline automatic Signature verification based on the description of the signature envelope and the interior stroke distribution in polar and Cartesian coordinates	
The proposed system segments each signature curve based on pen's velocity value. The signature curve, would be decomposed in low or high partition according to velocity's value. For each partition, hand movement direction between two consequent point Extracted.	Remove nise, translation invariance, rotation 7 scale invariance
Optical flow is used to define a stability model of the genuine signatures for each signer.	Signature image size was adjusted to a fixed area
In this paper an efficient off-line signature verification method based on an interval symbolic representation and a fuzzy similarity measure is proposed.	A histogram-based threshold technique, mean filter for noise removal, minimum bounding boxes
A new method of representing online signatures by interval-valued symbolic features. Global features of online signatures are used to form an interval-valued feature vectors. Methods for signature verification and recognition based on the symbolic representation are also proposed	

This paper explores the utility of information derived from the dynamic time warping (DTW) cost matrix for the problem of online signature verification. The prior works in literature primarily utilize only the DTW scores to authenticate a test signature.

This paper presents a new approach for online signature verification that exploits the potential of local stability information in handwritten signatures. Different from previous models, this approach classifies a signature using a multidomain strategy.

value normalization and length normalization

Feature Exctraction	Classification	Accuracy
Euclidian distance of all the points, Speed vx and vy, Acceleration Ax and Ay, Total time taken Tk , Length-to-width ratio, Amount of zero speed in direction x and y directions Nvx and Nvy , Amount of zero acceleration in direction x and y directions Nax and Nay	Compare the distance or time computed with the threshold decided	97.50%
Shape (A1) Proportionality (A2) Text-loops (A3) Order (A4) Punctuation (A5) Flourish-characteristics (A6-A8) Hesitation (A9) Alignment to the baseline (A10) Strokes-length (A12) Character spacing (A13)	Euclidean distance between the time functions (five correspondences among samples of the two sequences are allowed).	95.00%
Height of the signature Width of the signature Centroid along both X and Y axis Mean30, STD30 - Radon transform Mean60, STD60 - Radon transform Mean90, STD90 - Radon transform Mean120, STD120 - Radon transform Mean150, STD150 - Radon transform Mean180, STD180 - Radon transform	Back Propagation Neural Network	93.00%

X-coordinate: x(t) Y-coordinate: y(t) Pressure: p(t) Azimuth: q(t) Altitude: f(t)	Using a threshold value	98.20%
The trapezoid bounded area (F1) The fuzzy number (F2) of peaks The fuzzy number of increasing (F3) parts; The fuzzy number of decreasing (F4) parts; The convoluted acceleration (F5) The standard deviation (F6) of the reference curve values of the corresponding user; The total length of increasing parts (F7).	Threshold value pi of the author	99.80%
Global Features: Signature area, Signature height-to-width ratio, Maximum horizontal histogram and maximum horizontal histogram, Maximum vertical histogram and maximum vertical histogram, Horizontal and vertical centre, Local maxima numbers of the signature, the number of local maxima of the vertical and horizontal histogram, Edge point numbers Mask features: information about directions of the lines Grid features: finding densities of signature parts.	2 class SVM (Support Vector Machine)	95.00%

Global features: height, width and area are extracted DWT (Discrete Wavelet Transform) is applied on signature image and maximum vertical projection position and maximum horizontal projection position features are extracted from each of the 3 sub images. Image is divided into 16 blocks and DWT is applied to each block to get 16*3 sub-images.	Euclidean metric or Euclidean distance	95.00%
WT is the process to decompose an image into sub-bands The HOG features are constructed by concatenating all HOG coefficients.	Feed forward neural network with a log sigmoid function	94.87%
Histogram of Oriented Gradients (HOG) Interval Symbolic Writer Identifier	Similarity Measure	98.75%
Upper and Lower Envelope Large and small Eigen	Support Vector Machine.	98.50%

Global features : Aspect ratio, number of pixels that belong to the signature, Baseline shift, Global Slant Angle, Number of Edge Points, Number of Cross-Points and Spatial Symbols, Horizontal and vertical center of gravity, Length name, Length surname, Maximal horizontal and vertical histogram, the length and ratio of Adjacency Columns, Heaviness of signature, Ratio of first vertical pixel to height, Number of Closed Loops Grid Features SIFT features	Support Vector Machine.	88.97%
Area, Centroid, Mean, Eccentricity, Variance, Standard Deviation, Kurtosis, Skewness	Feed forward back propagation Neural network	85.00%
Height-Width Ratio Centroid of Signature First Derivatives Second Derivative Quadrant Areas COM Matrix Edge Point Calculation Horizontal and Vertical Histogram	Pattern Recognition ANN with back propagation algorithm	

DT-CWT and DT-RCWF Energy Ek and Standard deviation kσ of kth sub band	Canberra distance	79.32%
Polar Scale Normalization Adaptive Variance Reduction Histogram of Oriented Gradients	Neural Network	98.39%
Dynamic Time Warping (DTW) algorithm: End-point constraints, Continuity constraint, Monotonicity constraint, Global path constraint Modified DTW algorithm	Simple hard thresholding scheme for dissimilarity measures	98.00%
Contrast Homogenity Energy Entropy	template matching approach	
SURF Features SIFT Features	Support Vector Machine	98.75%

Geometric Feature Vector, Local Binary Pattern Feature Vector	SVM	95.75%
Eccentricity, Skewness, Kurtois, Orientation Entropy, Euler number, Solidity, Mean, Standard deviation	Cascaded feed-forward back-propagation networks	92.50%
Construction of eigen-signature Corresponding knowledgebase	The test feature vector is said to belong to ith class, if it posses minimum distance with ith class sample when compared to other class samples	91.40%
440 Histogram features 550 Fresh features 220 DCT features Features importance measurement : Correlation, Information Gain Ratio	SVM	95.50%
Gray Level Co-occurrence Matrix, Bootstrap	Euclidian dist similarity score (sim) between training and testing	88.46%
Discrete Fourier Transform, Discrete Wavelet transform, Signature Characteristics : speed, length of intervals and magnitude of bending on the indirect parts of the signature	KNN, Random Forest	95.00%

Histogram of Gradient Histogram: Gradient Computation, Gradient Vote, Normalization Computation	Three layer feedforward back-propagation network is	96.87%
TRACE TRANSFORM	Similarity measures thresholding	76.00%
GAUSSIANS MIXTURE MODELS Init minus min End minus min Average Root Square Average Time over 0 Crossing 0 Mean over 0 Standard deviation Number of traces, Time of signature, Writing Time of signature / Time of Signature, Height / Width, Area, Length		99.40%
Local patterns: LBP, LDP and LDerivP features. Histogram of Local Patterns The	Histogram Similarity Measures, support vector machine (SVM)	87.75%

Principle Component Analysis	Linear Scaling Values, Selecting Centers of CSFNN, Applying the Database to CSFNN	9550.00%
LBP, LDP	Least Squares Support Vector Machine (LS-SVM) to	91.92%
x coordinate, y coordinate, pen pressure, azimuth, altitude, DFT, DCT and DWT	Fast Dynamic Time Warping (FastDTW) algorithm	99.40%
The probability of occurrence, Skewness Euler number	support vector machine and hamming distance measurement	92.90%
Global Feature Extraction : height, width, area and slant angle, sum of black pixels	SVM SVMs	85.00%

Outline Detection and Representation, Feature Vector Based on Polar Coordinates, Feature Vector Based on Cartesian Coordinates	The HMM Signature Model, Support Vector Machine Signature Mode, Euclidean Distance-Based Signature Model	
Shape of signature would be partitioned based on dynamic feature such as velocity or pressure.	Hidden Markov Model	95.10%
Optical flow vectors were used for the analysis of the local stability of a signer to detect the stable regions in the signature	Stability between the unknown signature and reference signatures is estimated and consistency with the stability model of the signer is evaluated.	96.00%
Local Binary Pattern, interval-valued symbolic model	Based on the similarity value, an adaptive writer-dependent acceptance threshold	88.26%
Total duration of signature, Number of pen ups, Sign changes of dx/dt & dy/dt, Average jerk, SD of velocity in Y direction, SD of acceleration in X direction, SD of Vy/del y, No of local maximas in x, SD of acceleration in X direction, SD of velocity in X direction	Writer-dependent threshold over similarity value between a test signature and each of the conflicting classes,	95.40%

First Order Difference Second Order Difference of Spatial Coordinates Sine and Cosine Measures Length-Based Features	DTW-BASED MATCHING & cost matrix	97.24%
Displacement, Velocity, Acceleration, Pressure	Local stability function/model	97.90%

Limitations
Improvement is possible by adding some adhoc and simple parameters Feature extraction is more complex and time consuming in local parameters.
Dynamic data is not used for annotation of attributes Performance is lower than online systems Human interventions would anyway add to the complexity and time it takes to evaluate a signature.
Neural network takes more time for processing as the number of persons in the database increase. The accuracy of recognition can also be increased by increasing number of trained images for each Person.

Complex to perform and build,
expensive, since it requires advanced acquisition devices,

Can be improved the accuracy of suggested method in future by using several classifiers.

Can be improved still with the more number of samples of each signature used.
Lack of samples needed to build a reliable signature recognition system and asses the performance.
System fails to recognize the some rotated signatures.

proposed method is robust to various languages.

Use of a limited number of reference signaturesin these systems is problematic, since the identification results fall systematically

Showed significantly lower results.
Boundary lines should not be touched while signing

20 signatures only
Database can be maintained and made dynamic by changing the parameters

The variation in personality of signatures, because of age, sickness, geographic location and emotional state of the person actuates the problem

Retrieval
rate for proposed method is satisfactory.

Image variation to specify an optimal scale for recognition system

Choice of the threshold value (''m'') is critical for the performance

SVM classification has limitations in speed and size while both phase
of try and test of the algorithm and the chosen of the kernel function parameters.

the cost of time is required in training as well as in testing.

absolute to other biometric authentication system like handwriting analysis

rotation normalization and time normalization

Can identify the users only using their own data as the single class classification. Average running time of the proposed method is much higher than that of VFI5 algorithm

With more intra- class variation and comparatively less training samples system achieves fairly good recognition rate. The system is also robust while dealing with random and simple forgeries.

Low accuracy,
more invariant functional will be designed for usefulness in signature verification.

Major problem LBP has is its sensitivity when noise is present in the signature, high dimension and high computational load.

The size of feature vectors was not suitable for designed CSFNN chip structure owing to the input limitations of the circuit.
The main draw- backs ofanalog systems include sensitivity to ambient noise and to tem- perature

Major problem of LBP is its sensitivity to the presence of noise.
histogram equalization supremacy is not clear in all the performed experiments.

different ways in which transform features can be combined and explore more databases

the results that identification rates within and between writing systems is prone to swing in some degree under different partitioning strategy.

Due to the small number of observations and velocity based decomposition techniques, this method had less complexity and had high accuracy.

More research will be necessary to verify the capability of optical flow in recognizing factors such as short-term and long-term variability or performing script-based characterization

In the case of training with very few samples, the proposed method is not as efficient as when the training is performed with 6 or more signatures.

local features & histogram representation shall be an interesting extension

Both stable and variable regions of a signature could be considered for supporting the advanced personalized approaches in signature verification, since probably, from a behavioral point of view, a variability model of a signer could also be very informative and complementary to a stability model.