Signature verification and Forgery Detection

[1)] *Diana Abd ElNasser Mostafa Salama - diana1408151@miuegypt.edu.eg*
[2)] *Hatem Herzawy - hatem1402295@miuegypt.edu.eg*
[3)] *Sylvia Hani El Maraghy - sylvia1340647@miuegypt.edu.eg*
[4)] *Caroline Kamal Kamel Kerlos - caroline1403705@miuegypt.edu.eg*

(Dated: 24 June 2018)

I. ABSTRACT

Signature verification and forgery detection is the process used to recognize an individual s handwritten signature and secure this artifact of assurance from the misuse and forgery. Security is one of the most critical issues when it comes to signature recognition, especially if used in banks. One fraud signature, can mess up transactions, causes the bank and customers financial losses, and affect the security reputation of the bank, which is a damage that cannot be easily fixed. In this paper we attempt to detect forgery in signature creating an off-line system for detecting forgery based on three main areas. First is the pre-processing stage which includes size normalization, edge detection. Second stage is the features extraction, which are run length distributions, slant distribution, entropy, Haar-like features, Histogram Of Gradients features(HoG) and Geometric features. Third stage is based on the Machine Learning techniques which are Bagging tree, Random forest, Haar-Cascade and Support Vector Machine classifiers. Then, we test the system with signature by passing its features to the built models with the SVM classifier and so the signature is verified and detected whether it is a genuine or forged one. Our purpose is to get a satisfying accuracy to detect forgery and to provide the user a trustworthy system to depend on it, to accomplish deals and business securely.

II. INTRODUCTION

The measurements of human behaviors and the ability to use them as individual recognition is associated to the bio-metrics. The biometry recognition can be useful for personal authenticity or security identification, there are systems that provide verification or identification (testing or training). **Signatures** are the keys to these systems to provide authenticity to the users by learning their identity, the signatures are the artifact that assure a person testament to his acceptance, to accomplish a deal, either being contract, sale, agreement, authorization or any desired deal. Nowadays, the fraudulently or the illegal usage of signatures is very powerful in many forms which occurs very harmful consequences on a people properties.Our procedure take place in offline verification systems for signatures which takes 2-D images of signatures, targeting detection forgeries with high accuracy that takes large number of samples of 3105 genuine and 5175 forged signatures in 2D images format which are provided by the Persian Offline Signature Data-set (UTSig)[27].

These three points are our main stages of our work:

- **Pre-processing:** Perform some enhancements to images before extracting their features (size normalization - edge detection).
- **Feature extraction:** Extracting signature's characteristics by different features(Slant Distribution, Run lengths, Entropy, Histogram of oriented gradients (HOG), Geometric features) in form of extracted vector for each image from the original image.
- **Classification:** The comparison between the similarity of the features extracted from the test signature and the the trained genuine signatures is distance-based classifiers (Support Vector Machine - Haar-Cascades - Bagging Decision Tree - Random Forest).

Handwritten Signature identification is simple, inexpensive, non-intrusive and acceptable from society.In order to measure quality performance of designed System, FAR (False Acceptance Rate), FRR (False Rejection Rate), EER (Equal Error Rate) values related to verification have been computed. FAR is the rate of accepting forgery signature as genuine signature wrongly. FRR is the rate of rejecting genuine signature as forgery one wrongly. FAR and FRR are related to each other inversely. By setting and changing a threshold, when FAR is increasing, FRR is decreasing and vice versa. At specific threshold, FRR is equal to FAR. In this case this rate is named EER. Identification rate has also been computed.[56]

III. RELATED WORKS

A. Support Vector Machine Classifier (SVM)

The handwritten recognition systems has often applied SVM classifiers as they provide very satisfying results by performing their machine learning algorithms. They separate between classes of given data to predict the identity of unseen data by applying a **Hyperplane** which is a high dimensional feature space separator. First, the process begins with extracting features from a signature. Second, the SVM classifier is trained by these features and to be classified to predict the identity of the signature. Usually SVM needs time and space to perform enough experiments. In this experiment the SVM takes 320 signatures for training,and for testing takes 8 genuine signatures with 8 forgeries and results with False Rejection Rate(FRR) 2% and False Acceptance Rate(FAR) 11%.[?, ?]

In the another paper, a gray scale scanner scanned 336 signatures and save them as tiff file format. Each signature imitated for 4 skilled forgeries. The features that identify each signature or image uniquely, can be one of 2 kinds either global or local. Global features describe the signatures as a whole as [aspect Ratio, normalized area, horizontal and vertical profiles, vertical centroid, slant angle, edge histogram, edge direction histogram] extracted features. All the signatures that are stored in the database are prepossessed, ready for feature extraction phase. The next phase is the classification, in which the SVM classifier is fed by the dataset of features using platts sequential minimal optimization algorithm (SMO), Kernel functions, kernel perception algorithm. the kernel perception give results with FAR and FRR 4.82% and of 6.15%. the SMO algorithm gets FAR and FRR of 6.57% and 7.16%.[329]

B. Haar-Cascade Classifiers:

The Haar-cascade are from the great classifier for object detection. The Haar-cascade classifiers perform their classification by extracting Haar features and pass them to flow of weak cascaded classifiers. Haar features simply is several of adjacent light and dark rectangles, to detect objects, there are rectangular regions at particular locations in the images known as detection window that represent those adjacent rectangles of Haar features. The pixels intensities in those regions are summed and then the difference between them is calculated then the different subsections of an image are categorized if the difference exceeded a threshold Haar feature in this case found otherwise not found. Here the role of the cascade classifiers which are fed by the Haar features extracted from the images. The idea is to get a high accuracy predictor by passing the features to a combination of weak inaccurate classifiers. Each classifier is a decision stump, that give samples labels as negative and positive. If the possess result with negative, its terminates, otherwise the classifier passes to the next one. The method which is responsible for increasing the accuracy is the boosting which combine all the results of inaccurate classifiers providing satisfying results. the binary weak classifier finds as a weak hypothesis, ht : X = (-1,+1) where the training is done by taking inputs to the domain set X (-1,+1) which are positive and negative. The combined by these weak hypotheses are weighted is:

$$H(x) = \sum_{t=1}^{T} \alpha_t h_t(x)$$

This equation is the final result for an election where the majority is the factor within the winner is chosen, but each elector t may have a different weight t. Usually AdaBoost algorithm, due to the effort that has been made to explain AdaBoost as a learning algorithm,is widely used. AdaBoost classifiers comes in the first place to reduce negative regions in quite quick time. The database here composes of positive and negative images. For training 6000 positive images of landing pads withX & H features. 12000 negative images of objects, landscapes, animals and people, among others, converted to gray scale and their equalized histogram.

All the training and testing process, including preprocessing for different classifiers using Haar-like features was performed using the Open Computer Vision (OpenCV). For the experiments, a total of six classifiers were trained, one using the total set of positive samples, which includes partial or entire images of "H" and "X" landing pads, another one using only pieces of "H" and "X" samples, the last one using only entire images of "H" and "X" for training. a test database is composed by 1,218 samples, 1,100 containing pieces or entire lading pads images and 118 non-containing any. The classifiers trained with samples comprising only partial objects of interest were combined with the classifiers trained with samples containing only the entire object of interest in the same code. As a result, it was possible to compare the performances of a single classifier, trained to identify partial or complete landing pads,and a combination of each individual classifier, trained to recognize separately each of those two configurations. It is also possible to see the advantage of using the single Haar-like classifier since it seems to be more precise.The classifiers have high hit rate with good accuracy,which surpass 90%.[430]

Another research paper is providing experiment of Haar-Cascade classifier approach (HCC). By taking the steps of pre-possessing data and the HCC features extraction and classification.
Pre-processing section cleans the image using image processing techniques,includes the following steps:

1. Binarization: converting the document from a greyscale image to a binary image, Noise removal decreases small erroneous pixels from the binarized image.[12]

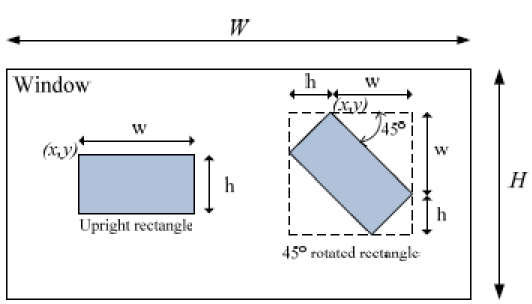
2. Thinning: removing the stroke width and leaves a skeleton stroke with a width of one pixel.[13]

3. Slant and pre-processing: finding the slant in the document image and correct them.

Haar-features section, the Haar-Cascade Classifier in this paper is used to Arabic character recognition. The Optical Character Recognition (OCR) technology is very powerful in data entry. The problems that OCR faces in Arabic language are intensive because the script cursive is heavily connected. Haar-Cascade classifier (HCC) approach is a machine learning, that was introduced by Viola and Jones [14], to reaches the goal of object detection rapidly based on a boosted cascade of simple Haar-like features and based on the Open Computer Vision library implementation. HCC approach eliminates problems in pre-possessing and recognition steps and the most important step is character segmentation. This machine learning approach successfully combines three basic ideas[18]:
The first, is a representation for the image that manage quick computing of the features(integral image). Integral images were at first used in feature extraction but the (Lienhart and Maydt,2002) developed an algorithm that add a rotated integral image (Summed Area Table - SAT)[16]. This algorithm is calculating a single table in which pixel intensity is replaced by a value representing the sum of the intensities of all pixels contained in the rectangle.
Second, A set of features that can be computed which are Haar-Features which are captured basic visual features of objects. The feature extraction here uses greyscale differences between rectangles in order to extract object features[14]. Features are calculated by subtracting the sum of a sub-window of the feature from the sum of the remaining window of the feature[15]. The Haar-like features for an object lie within a window of W x H of pixels, which is showed in this equation:

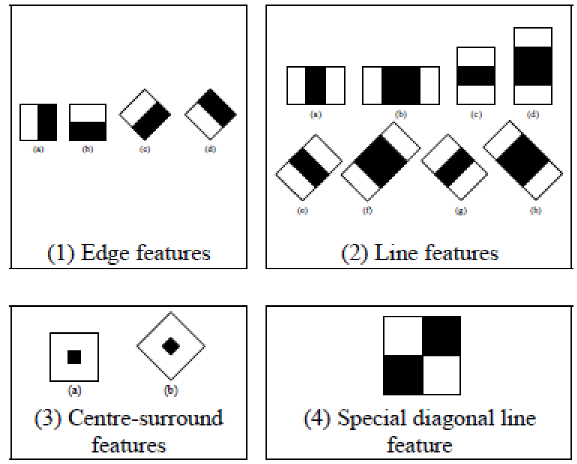
$$\text{features} = \sum_{i \in I}^{N} \omega_i \cdot \text{RecSum}(r_i)$$

where i is a weighting factor which has a default value of 0.995 "Lienhart and Kuranov et al."[17]. A rectangle is specified by five parameters r = (x,y,w,h,) and its pixel sum is denoted by RecSum(ri), 2 examples of these rectangles are given in the following figure:



Upright and 45° detection windows.

This equation generates an infinite feature set which must be eliminated in any practical application. The 15 feature prototypes are shown in the following figure:



HAAR-LIKE FEATURE PROTOTYPES

- Four edge features.
- Eight line features.
- Two centre-surround features.
- Special diagonal line feature.

Taking the value of a two-rectangle feature (edge features) the difference between the sum of the pixels in the two regions. A three-rectangle feature (line features) subtracts the sum of the two outside rectangles from the sum of the middle rectangle. A four-rectangle feature (special diagonal line feature) subtracts the sum of the two diagonal pairs of rectangles as in the previous figure. The number of features differs among prototypes. E.g., a 24 X 24 window gives 117,941 features as in "Lienhart and Kuranov et al."[17].

Third ,a cascade of more complex classifiers results in fast and efficient detection[14][18][19]. A classifier cascade is a decision tree that depends on the rejection of non-object regions which are negatives regions.Boosting algorithms use a large set of weak classifiers to get a powerful classifier. Weak classifiers distinguish objects from non-objects. Only one weak classifier is used at each stage and each depends on a binary threshold decision or small classification and regression tree (CART) for up to four features "Schapire"[20].

Applying the HCC approach by the different Arabic glyph represent different objects. Each glyph is an object, giving each glyph a distinct classifier. So it becomes a glyph recognizer. The training images are composed of 2 sets. A positive set containing images which include at least one target object and a negative set containing images which do not include any target objects. The HCC approach generates training and testing datasets for each glyph.A total of 100 datasets and classifiers are used.

Training and testing section The datasets used are scanned datasets of negative and positive images. the training parameters used were the width, height, number of splits, minimum hit rate and boosting type. Testing the classifiers uses Open-CV. the experiment checks the influence of the testing parameters over the classifier detection accuracy. The accuracy of the HCC approach was calculated for detection of the glyph using the 61 generated classifiers. Results showed that the HCC approach is very successful in recognizing Arabic glyph, the OpenCV testing performance utility showed high accuracy with comparison with the Arabic OCR applications. This accuracy accomplished by the HCC approach is 87%.[21][22]

C. Bagging Trees Classification:

This paper propose an offline digital signature verification technique, that depends on features that are extracted from the signatures. Some of signatures are to be used for training and others for testing only. Method such as classification using bagging trees is used in this paper to obtain results.

The features are to be extracted to signature identification are[?] :

- The curve of the signatures after the rotation of the original one around the X and Y coordinates in the center. This rotation is made to get a new curve to be used in pattern recognition.
- The total number of pixels in the signature.
- Occupancy ratio equals total number of pixels of the signature divided by total number of pixels of the signature image multiplied by 100.
- The minimum Eigen value of the signature curve that the eigen values of a matrix A are calculated by this equation:

  $$\det(A - \lambda I) = 0$$

  det is the determinant of the matrix (A - I) and I is the nn identity matrix, is the eigen value.
- Max height of the signature equals maximum x coordinate of signature minus minimum x coordinate of signature.
- Max width of the signature equals maximum y coordinate of signature minus minimum y coordinate of the signature.
- Euclidean distance and the angle that are between every two consecutive points in the signature curve.
- The ratio of height to width of the signature.

The classification technique used to recognize signatures is Tree Classification using bagged trees. The Bootstrap aggregating or bagging, trains using a randomly drawn subset of the training set. Like the random forest algorithm for example, which combines random decision trees with bagging to get highest accuracy.
Signatures that were used consist of 500 signatures for 100 persons,each person having 5 signatures, represented in 500 patterns. 60% of those patterns are for training and the rest 40% are for testing. Testing also used all the 500 patterns,which are all vectors of the same size.Each vector representing a signature. The results showed percentage of correctly classified signature,with signature recognition ratio of 79.8%.[7][31]

D. Artificial Neural Network

The Neural Networks in general known as one of the most accurate or efficient techniques for pattern recognition. The application of neural networks based on artificial intelligence which makes a computer application think like a human by data training[23]. Artificial Neural Network (ANN) uses a four-step process: separating background from signature, normalization and signature digitization, applying moment invariant vectors and then signature recognition and verification implementation. The experiment in this paper which uses 180 for training and 360 for testing. The accuracy of this experiment comes out with 89.24%.[25]

E. Random Forest

In this paper the verification of handwritten signatures is performed by the Random Forest classifier in the offline signatures verification system. The data-set used in this system is ICDAR 2009 and 800 genuine signatures are selected for training and 200 genuine signature for testing then perform pre-processing and features extraction to the images by binarlization and then breaking down into pixels where the colour of the pixels was taken into a two dimensional binary array. The next step is to pass extracted data to the Random forest classifier resulting 67% accuracy.[24]

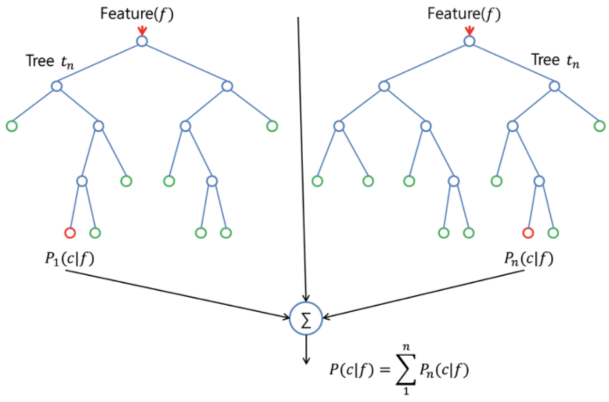


FIG. 1. Random forest classifier tree .

IV. METHODOLOGY

PRE-PROCESSING STAGE

- size normalization
- Using sobel filter for edge detection

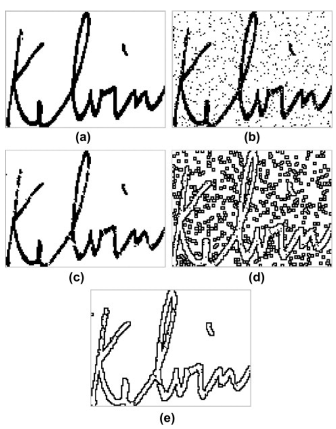


FIG. 2. Edge detection for a signature

FEATURES EXTRACTION STAGE

A. Geometric Features

Starters are the pixels that have 1 neighbour in the character skeleton. Pixels with neighbours are classified into several classes. one of this classes consists of diagonal pixels which are in a diagonal direction to the pixel, another class consists of line segments that are extracted from the image, they have to be classified into any one of the following line:

- Horizontal line.
- Vertical line.
- Right diagonal line.
- Left diagonal line.

A direction vector is extracted from each line segment that makes it simple to determine each line type, to define the position of a pixel having a neighbour with respect to the center pixel of the 3x3 matrix.

$$\left[\begin{array}{c|c|c} 4 & 5 & 6 \\ \hline 3 & C & 7 \\ \hline 2 & 1 & 8 \end{array}\right]$$

Now the following rules are defined for classifying each direction vector:

- If maximum occurring direction type is 2 or 6, so the line type is right diagonal.
- If maximum occurring direction type is 4 or 8, so the line type is left diagonal.
- If maximum occurring direction type is 1 or 5, so the line type is vertical.
- If maximum occurring direction type is 3 or 7, so the line type is horizontal.

the feature vector consists on the line type of each segment and its direction vector. Each zone has its feature vector which have the length of 8. Each zone feature vector is composed of:

1. Number of horizontal lines.
2. Number of vertical lines.
3. Number of Right diagonal lines.
4. Number of Left diagonal lines.
5. Normalized Length of all horizontal lines.
6. Normalized Length of all vertical lines.
7. Normalized Length of all right diagonal lines.
8. Normalized Length of all left diagonal lines.

Normalization of any number of particular line type uses the following method:
value = 1 - ((number of lines/10) x 2)

Normalization of length of any particular line type using the following method:
length = (Total Pixels in that line type)/ (Total zone pixels)
Those geometric features extraction resulting total vector with size 85.[8]

B. Statistical Features

This vector is combination of features which concern on size 276.

Research in writer identification has mainly focused on the statistical approach, leading to the extraction of statistical features such as run-length distributions, slant distribution, entropy, and edge-hinge distribution.[10]
Edge Hinge distribution and Slant distribution: Feature extraction starts with edge detection by using Sobel, then thresholding that generates a binary image which contains only the edge pixels[10].

Each edge pixel considered as it is in the middle of a square neighborhood, and checking in all directions from the central pixel and ending on the periphery of the neighborhood for the presence of an entire edge fragment as shown in the following figure(Fig.1):

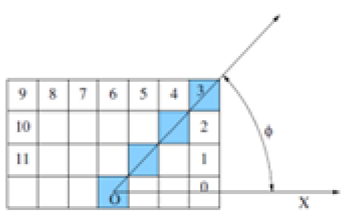


FIG 1. EXTRACTION OF EDGE DIRECTION DISTRIBUTION

A histogram that contains all the the verified instances that are counted, this histogram is normalized to a probability distribution that provides the probability of finding in the image an edge fragment oriented at the angle measured from the horizontal.*Edge-hinge distribution* is focused on the neighborhood not only one edge but on the two edges fragments from the central pixel. Then computing the joint probability distribution of the orientations of the two fragments.[9]

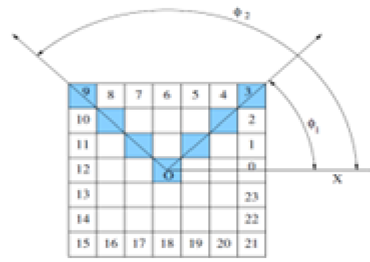


FIG 2. EXTRACTION OF EDGE-HINGE DISTRIBUTION

The feature of Edge-hinge distribution characterizes the changes in direction of a writing stroke in handwritten text. It is extracted by using a window that is slid over an edge-detected binary handwriting image When the central pixel of the window is there in its position, the two edge fragments (connected sequences of pixels) appearing from this central pixel are considered. Their directions are measured and stored as pairs. The joint probability distribution is obtained from large sample of such pairs.(p(x,y) = P(X = x and Y = y))[9].

Run Length: Run lengths, at first by proposed Arazi[11] for writer identification. Run lengths determination are on binarized image. The black runs corresponds to the signature we intended for extraction and the properties of the white runs provide the character placement statistics indication. Two scanning methods needed horizontal along the rows of the image and vertical along the columns of the image. The similarly compared to the edge-based directional features, the histogram of run lengths is normalized and is interpreted as a probability distribution.[9][10]

Entropy: The focusing of entropy measurement used on the amount of information,normalized by the amount black pixels in the regions of interest (ROI). The size resulting file in bytes is divided by the total number of black pixels[10].

C. Gabor Wavelet Features: Features vector number 3

The Gabor transformation is very useful especially in extracting textural information from images due to its optimal localization property in the frequency and spatial domains. 2-D Gabor filter used as following:

$$g(x,y;u,v) = \frac{k^2}{\sigma^2}\exp\left(-\frac{k^2(x^2+y^2)}{2\sigma^2}\right)\cdot\left[\exp(ik\cdot(x,y)) - \exp\left(-\frac{\sigma^2}{2}\right)\right]$$

$$k = \begin{pmatrix} k_x \\ k_y \end{pmatrix} = \begin{pmatrix} k_v \cos\theta_u \\ k_v \sin\theta_u \end{pmatrix}$$

$$k_v = 2^{-\frac{v+2}{2}}\pi$$

$$\theta_u = u\frac{\pi}{M}$$

Where $i = \sqrt{-1}$ and u=0, 1…M-1.

M is the number of orientations, v is the frequency, u is the orientation, and is the space constant of the Gabor envelope.[26]

D. Histogram of Oriented Gradients (HOG)

Histogram of Oriented Gradients (HOG), HOG features used for description of the statistical information of local gradient directions. These features compute the gradient information at all pixels in a particular zone, then the histogram of gradient orientations in that zone is computed.[28]

CLASSIFICATION STAGE

1. **Support Vector Machine**

SVM classifier are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis also Can be used to build model to predict new examples and there is a two type for support vector machine.

- Linear Classifier
- Non-Linear Classifier

We used Linear classifier that gives high accuracy with the data sets we specify the linear classifier with it's Kernel function we used Linear kernel it's work good with our data set . We have tested many of Kernel function but the best was Linear Kernel Function.
Depending on the system identifying the writer signature status either it would be fraud or genuine, we get all the probabilities of threshold of accuracy of each writer of the signature images in the data set and pass this probabilities to histogram count, to threshold the probability(in figure 3) of whether the signature is fraud or genuine, that is done by fixing a resulted probability done by threshold and classifying the images based on that probability and figuring out whether the signature if forged or not if it's accuracy were to be found below the histogram probability.

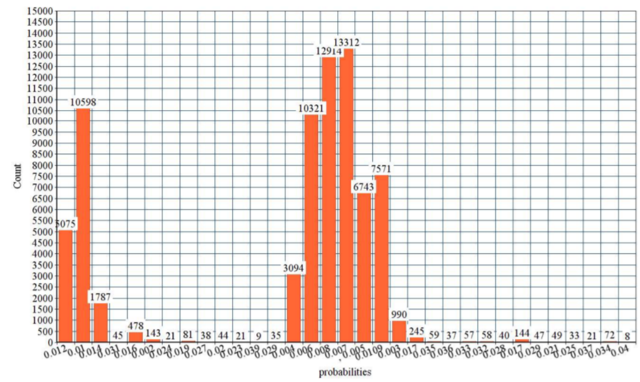


FIG. 3. Histogram of probabilities for SVM detecting forgery.

2. **Bagging Trees**

Bagging trees can be used to obtain classification trees and regression trees,in this paper classification trees were used. both are used to obtain a response, they both follow the tree of decisions starting from the root node of the tree to the leaf node that contains the response.

Classification trees predictions gives nominal responses such as 'True' or 'False' responses. Classification decision trees combine the results of many decision trees, which decrease the effects overfitting and enhances generalization. The classification tree perform the following steps to create decision trees:

- Use all input data, and examine them all for possible binary splits on every predictor found.
- Select a split with best optimization criterion.
- If the chosen split leads to a child node that found having very few observations, then select a split with the best optimization criterion subject to the minimum leaf constraint.

By default, the classification bagged tree minimal leaf sizes are set to 1, number of predictors selected randomly for every decision split is made for every split occurred, and every deep tree involves other many splits. the number of trees were changed for experimentation, what could be the best number of trees to result the most rightful predictions, after few experiments were done the best number of trees were used is 80 trees iterations that resulted of 79.7% accuracy.

3. **Random Forest**

   A random forest is a classifier consisting of a collection of decision trees, where each tree is constructed by applying an random forest classifier on the training set S and an additional random vector, , where default is used, there are 3 types of method in random forest to be used (regression, classification, unsupervised) in this experiment Random forest classification was used. The prediction of the random forest is obtained by a majority vote over the predictions of the individual trees.

4. **Haar Cascade** Haar Cascade classifier mostly used as an object detection classifier, and here is the first time to be used as signature recognition and verification one. It works on different phases to build the classifier model and test it.
   Creating dataset: By applying different rotation angles which are 20, -20, 30, -30 , 15, -15 degrees, and different noises types which are Gaussian and Salt& Pepper noises , we have a suitable count of images to train the classifier.
   Creating Samples (positive and negative): using different types of negative images which are images for different objects not including signatures and images for different writers that are trained as positive images. The best accuracy is given by training other signatures for different writers as negative or background images and creating the background vector file from them. Then creating the positive file that contains the paths and bounding boxes for the positive images.
   Training the classifier: each writer signatures has his own classifier created with his unique dataset, then the created cascade XML file will be used to test his signature images.

Bagging trees			
Features	vector size	No. trees iterations	Accuracy
Slant distribution, entropy, run length	5	100	**79.7 %**
Slant distribution, entropy, run length	5	100	75.5%
Slant distribution, entropy, run length	5	200	77.7%
Slant distribution, entropy, run length	3	80	76.2%
Slant distribution, entropy, run length	3	100	73.7%
Geometric features	-	100	47.9%
Geometric features	-	80	54.8%

Random Forest			
Features	vector size	No. trees iterations	Accuracy
HOG Features	-	3000	**86%**
HOG Features	-	2000	81.8%
Slant distribution, entropy, run length	3	200	80.2%
Slant distribution, entropy, run length	3	100	76.8%
Slant distribution, entropy, run length	5	200	72.2%

Support Vector Machine	
Features	Accuracy
HOG Features	**94%**
Geometric features and Slant distribution, entropy, run length	77%
Geometric features and Slant distribution, entropy, run length	64%
Slant distribution, entropy, run length	52%

V. RESULT AND CONCLUSION

For holding the experiments for the bagging trees the classifier was used over 115 writers each writer has 20 images for training (total 3200 images for all writers) and 7 images for testing (total 805 for all writers).
Support vector machine (SVM) classifier had the best accuracy of **94%** of detecting forgery in signatures based on histogram of probabilities.

Haar Cascade		
Testing & Training Data-set	Scale Factor	Accuracy
Source Images	1.98	66%
	2.5	67.1%
	3	70.6%
	3.3	68.6%
Rotated + Noised Images only	1.98	88.9%
	2.5	88.7%
	3	92.3%
	3.1	92.3%
	3.2	**92.42%**
	3.3	91.7%
	3.4	91.93%
Source + Rotated + Noised + Average filtered images	1.98	75.7%
	2.5	77%
	3	82.13%
	3.5	83.18%
Source + Rotated + Noised images	1.98	88.4%
	2.5	89.7%
	3	91.8%
	3.2	91.57%
	3.3	91.14%
	3.4	91.06%
Same as previous one But applied on randomly chosen testing and training images	1.98	78.3%
	2.5	86.2%
	3	89%
	3.3	89.6%
	3.6	89.4%

VI. REFERENCES

[1] Ahmad Sanmorino and Setiadi Yazid,"A Survey for Handwritten Signature Verification",2012.

[2] A. Pansare, and S. Bhatia,"Handwritten Signature Verification using Neural Network.Januari,2012.

[3] Kruthi.C and Deepika.C.Shet,"Offline Signature Verification Using Support Vector Machine",2014.

[4] C.S. de Oliveira A.P. Anvary, A. Anvary, M.C. Silva Jr., A. Alves Neto, L.A. Mozelli,"COMPARISON OF CASCADE CLASSIFIERS FOR AUTOMATIC LANDING PAD DETECTION IN DIGITAL IMAGES",2015.

[5] Elaheh Soleymanpour, Boshra Rajae, Hamid Reza Pourreza,"Offline Handwritten Signature Identification and Verification Using Contourlet Transform and Support Vector Machine",2010.

[6] M. H. Sigari, M. R. Pourshahabi, and H. R. Pourreza, "Offline Handwritten Signature Identification using Grid Gabor Features and Support Vector Machine",2008.

[7] C.Sutton,"Assessment of Offline Digital Signature Recognition Classification Techniques",2013.

[8] Dinesh Dileep,A FEATURE EXTRACTION TECHNIQUE BASED ON CHARACTER GEOMETRY FOR CHARACTER RECOGNITION,2012.

[9] M. K. Konstantakis, E. J. Yannakoudakis, A Writer Identification System of Greek Historical Documents using MATLAB,2014.

[10] *Writer identification using edge-based directional features.* Bulacu, M., Schomaker, L., Vuurpijl, L., 2003.

[11] *Handwriting identification by means of run-length measurements.* Arazi, 1977.

[12] *Automatic Filter Selection Using Image Quality Assessment.* A. Souza, M. Cheriet, S. Naoi, and C. Y. Suen, 2003.

[13] "Arabic Text Recognition",R. Harty and C. Ghaddar,2004.

[14] P. Viola and M. Jones,"Rapid Object Detection using a Boosted Cascade of Simple Features",2001.

[15] Messom, C. and A. Barczak ,"Fast and Efficient Rotated Haar-like Features using Rotated Integral Images",2006.

[16] Lienhart, R. and J. Maydt ,"An Extended Set of Haar-like Features for Rapid Object Detection",2002.

[17] Lienhart, R., A. Kuranov and V. Pisarevsky ,Empirical Analysis of Detection Cascades of Boosted Classifiers for Rapid Object Detection",2002.

[18] A. Kasinski and A. Schmidt ,"The architecture and performance of the face and eyes detection system based on the Haar cascade classifiers",2010.

[19] Wang, G.-h., J.-c. Deng and D.-b. Zhou ,Face Detection Technology Research Based on AdaBoost Algorithm and Haar Features,2013.

[20] Schapire, R. E. ,"The Boosting Approach to Machine Learning",2002.

[21] *Arabic character recognition using a Haar- Cascade Classifier approach (HCC).* Ashraf AbdelRaouf, Colin Anthony Higgins, Tony Pridmore, Mahmoud I. Khalil, 2015.

[22] Ashraf AbdelRaouf, Colin A. Higgins, Tony Pridmore and Mahmoud I. Khalil,"Fast Arabic Glyph Recognizer based on Haar Cascade Classifiers",2014.

[23] Suhail M. Odeh, Manal Khalil,"Off-line signature verification and recognition: Neural Network Approach",2011.

[24] Maduhansi Thenuwara1, Harshani R. K. Nagahamulla,"Offline Handwritten Signature Verification System Using Random Forest Classifier", In: 2017 International Conference on Advances in ICT for Emerging Regions (ICTer),2017

[25] Subhash Chandra and Sushila Maheskar,"Offline signature verification based on geometric feature extraction using artificial neural network",2016.

[26] JING WEN1, BIN FANG1,YUAN-YAN TANG,TAI-PING ZHANG,HENG-XIN CHEN,"OFFLINE SIGNATURE VERIFICATION BASED ON THE GABOR TRANSFORM",2007.

[27] Amir Soleimani, Kazim Fouladi , Babak N. Araabi,"UTSig: A Persian Offline Signature Dataset",2017.

[28] Juan Hu, Youbin Chen,"Offline Signature Verification Using Real Adaboost Classifier Combination of Pseudo-dynamic Features",2013.

[29] Edson J.R. Justino, Flavio Bortolozzi , Robert Sabourin,"A comparison of SVM and HMM classifiers in the offline signature verification",rue Notre-Dame Ouest, Montre al, Quebec, Canada H3C 1K3,18 October 2004.

[30] Yoav Freund, Robert E Schapire,"A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting",In: Journal of Computer and System Sciences - Special issue: 26th annual ACM symposium on the theory of computing,Aug. 1997.

[31] DINA DARWISH," Classification and Regression Trees, Bagging, and Boosting, Handbook of Statistics",2005.

[32] Hilton Bristow, Simon Lucey,"Why do linear SVMs trained on HOG features perform so well?",Jun 2014