Efficient Handwritten Signatures Identification using Machine Learning

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***Abstract*—Any agreement or contract between two or more parties requires at least one party to employ a signature as evidence of the other parties' identities and as a means of establishing the parties' intent. As a result, more people are curious about Signature Recognition than other biometric methods like fingerprint scanning. Utilizing both Fourier Descriptors and histogram of oriented gradients (HOG) features, this paper presents an efficient algorithms for signature recognition. The use of Local binary patterns (LBP) features in a signature verification technique has been proposed. Using morphological techniques, the signature is encapsulated within a curve that is both symmetrical and a good match. Measured by the frequency with which incorrect patterns are confirmed by a given system, false acceptance rate (FAR) provides an indication of the effectiveness and precision of the proposed system. Using a local dataset of 60 test signature patterns, this investigation found that 10% were incorrectly accepted for FAR of 0.169. Experiments are conducted on signature photos from a local dataset. Verification of signatures has previously made use of KNN classifier. KNN classifier produced higher FARs and recognition accuracies than prior techniques.**

Keywords*—K-nearest neighbor; histogram of oriented gradients; local binary patterns; false acceptance rate; Fourier descriptors

I. Introduction

Identifying and authenticating individuals has developed into a crucial step in the provision of services in commercial and government institutions, and is also an important aspect of maintaining law and order. Biometric data from the individual being verified. The two Greek words for life and measurement provide the basis of the English word "biometrics" (to measure). Because of their uniqueness, the biometric features listed in [1] can be used to confirm or authenticate an individual's identity. Because the distinguishing trait in question is intrinsic to the individual being identified, biometric identification is more fool proof. As a result, it's extremely difficult to give away, swap, or steal from another person.

Physiological features biometrics and behavioural characteristics biometrics are the two most common types of biometrics identification. Fingerprinting, retinal scans, and handprint scans are all examples of physiological biometrics. Checking a person's signature or voice is examples of behavioural biometrics. Biometric systems are "automatic methods of identifying or validating the identity of an individual based on physiological or behavioural features" [2]. A biometric system can function in verification mode or identification mode, depending on the requirements of the application. An individual claims their identity, and the system checks to see if that assertion is true. In order for a claim to be considered "genuine," there must be a significant degree of similarity between the user's input and the template of the claimed identity. If not, the user's claim will be denied and they will be labelled a "fraud." When performing Identification, the biometric system compares the user's input to all of the stored templates and returns the identification of the individual whose template is most similar to the user's input [3]. The system will typically return a refuse decision, indicating that the user presenting the input is not one of the enrolled users, if the highest similarity between the input and all the templates is less than a defined minimum level. Accordingly, the ratio of matches in an identifying system is 1 to N.

The need for a reliable method to verify and authenticate individual signatures arises from the widespread use of signatures in financial, economic, and legal operations. Static and dynamic digital handwritten signature authentications are the two most used methods. One of the most common types of static is a visual comparison between two scanned signatures or between a scanned signature and an ink signature [4]. The signer's signature is captured in the form of coordinate values from the signing device, which is subsequently used for dynamic digital handwritten signature authentication. One part of signature recognition and verification is determining whether or not the signature is authentic, and the other part is determining who the signature belongs to. Image processing and feature extraction methods are utilised throughout the static signature verification process [5].

In order to determine if an input signature is real or forged, matching relies on authentication (false signatures of an individual). Two stages make up this section: Verifying a person's identification using the first-signature part's database and other identifying information. Identification: Basically the input signature image for each subject is compared with entire of the database i.e. with samples from all subjects in the database. Verification: Which entails the comparing of the input signature image to samples of the same subject's signature. Confirming a person's identity is the primary focus of this procedure.

Signature authentication or verification approach may be writer dependent or writer independent. Following this process allows for a writer-independent approach. Mean distances between authentic and forgery classes, as well as forgery and known classes, are used to calculate prior parameter distributions for the respective means. Posterior class probabilities for the two classes, authentic and forged signatures for a given author, are calculated. Next, the probabilities of each group are compared and select the group with the higher probability based on a signature that is under scrutiny [6].

In case of writer dependent technique, an individual classifier is constructed for each user using his enrolment samples. During verification, only query signature samples are analysed by the classifier [7]. The success of these systems is obviously dependent on having a large enough sample size with which to train their classifiers.

A. Objective of the Research Work

By comparing the signature to other examples, the identity of the signer is determined. Learning-based signature recognition systems necessitate a sizable training set, ideally including examples from the vast majority of the intended users. Based on the published works, it is clear that several researchers have created their own databases to test the reliability of their signature verification or identification systems. Multiple static signature databases have also been made public for study. Signatures from a variety of countries and regions, including Malaysia, Spain, China, the Netherlands, Tunisia, etc., are used to test out the methodologies suggested in the literature. However, they don't accurately reflect the diversity of Arabic signatures. Also, most Arabic signatures are written in regional scripts other than English script, hence the approaches may not produce high recognition accuracy for these signatures. That's why it was important to create a regional database of signatures for the area and develop effective algorithms for checking the offline signatures so that they can be recognised with high precision.

II. Previous Work

Using global, directional, and grid aspects of signatures, authors [8, 9] suggested a solution for an off-line signature verification and identification system. The signatures were validated and categorised using a system called a Support Vector Machine (SVM). In [10], researchers analysed two popular Tablet PCs for use in signature verification tests. Using a database of 3000 signature photos, the authors report on experimental evaluations of authentication performance. Current best practises for authenticating digital signatures are summarised in [11]. With the help of Adaptive Feature Threshold, authors [12] have presented a person-dependent off-line technique for verifying signatures (AFT). This method improves on the practise of transforming a signature's basic feature into a binary feature vector in order to increase its representational resemblance to training signatures. They employed a hybrid of spatial pyramid and equi-mass sampling grids to enhance the representation of a signature dependent on gradient direction. They employed a DWT and a graph matching technique during the classification phase. Using graph matching to compare signatures and the Euclidean distance to determine how dissimilar they are, researchers. [13] present a Cross-Validation Technique for Graph Matching based Off-Line Signature Verification (CSMOSV). In [14], authors propose using image registration to identify and authenticate off-line Persian signatures.

As for the matching, they employed Euclidean distance and DWT to extract features. The approach, however, is language specific. In [15], authors offer an offline signature verification method that uses machine learning. Directional Gradient Density characteristics have been presented for competent forgery verification. A grid-based solution employing global characteristics for offline signature verification was reported by researchers in [16].

Authors [17] describe a system that requires fewer characteristics through the use of sub-pattern analysis, which in turn results in faster responses in real-time situations. A multilayer weighted fuzzy classifier that fuses match scores via selection priority has been developed to fully leverage the potential of two sets of characteristics. Multiple features for biometric recognition systems were proposed by researchers in [18]. Signature feature extraction, which takes in data from twelve various angles, was proposed using Rotated Complex Wavelet Filters (RCWF) and Dual Tree Complex Wavelet transform (DTCWT). In [19], authors proposed the issue of handwriting biometrics and presented a method for validating handwritten signatures with an ANN. In [20], researchers offer a scale- and rotation-invariant method for signature recognition based on the extraction of invariant rotation invariant texture features (sub-uniform local binary patterns) from each of an image's 12 blocks. Verification makes use of DCT coefficients. In [21], the state-of-the-art of offline signature recognition using Computer Vision is outlined. The authors go on some of the latest developments and areas for further study, including the creation of synthetic signatures, temporal drifting, identifying forgers and impostors, and dealing with scenarios involving more than one language. The Support Local Binary Pattern (SLBP) characteristics were proposed by authors in [22] for use in offline signature verification. Several writers use LBP variants in the context of signature verification.

To quickly and accurately verify signatures with minimal effort, authors demonstrate a technique that she has developed. For feature extraction, the Discrete Wavelet Transform (DWT) with Haar wavelets is primarily studied, both for global features and grid features, in [23]. Offline verification of signatures using a small number of basic geometric features was presented by authors in [24], the features Area, Euler's Number, Eccentricity, Standard deviation, Centroid, Skewness, Kurtosis, and orientation are employed. The artificial Immune Recognition System (AIRS) and ANN employed in the verification step are supported by a novel offline signature verification technique presented by researchers in [25].

From the reviewed literature, it is clear that many different approaches have been proposed for signature verification, and that experiments on both local datasets and standard datasets, such as MCYT have been used to provide verification results. It is important to note that many of the techniques described are language dependent, meaning that their effectiveness is limited to signatures written in those languages. Recognizing that offline signature verification is a challenging problem with room for further investigation, we have proposed the development of efficient verification systems that improve performance for signatures written in both local languages and other languages defined in a standard database of signature images [26].

It is well-documented that various feature extraction strategies have been developed for author-independent signature verification. Using a combination of multiple feature extraction, dichotomy transformation, and boosting feature selection, authors [27] present a writer-independent method. They used feature extraction methods that worked at various scales before applying the Dichotomy Transformation, which turned the problem into a two-class one. Finally, boosted feature selection is used to narrow down the training set to the most important features.

A writer-independent method for authenticating handwritten signatures was proposed by researchers in [28]. The primary segments' curvature was used to generate graphometric feature sets, and this was done virtually using Bezier curves. The robustness against forgeries was bolstered by employing an ensemble of classifiers.

Using the dichotomy transformation and an SVM writer-independent classifier, authors in [29] explored the usage of these deep convolution neural network (CNN) features for writer-independent offline signature verification. Experimental results on the Brazilian and GPDS datasets demonstrated that the proposed strategy outperformed its competitors [30-31].

III. The Proposed Work

If a separate model is trained for each user, the system is more robust in signature verification. Author-specific signature validations are more precise. During the training phase, authentic signatures from a given topic are considered positive examples, whereas signatures from other users are considered negative examples. Each user has their own binary classifier that they've been training. As the number of participants in the study grows, the complexity and cost of maintaining the system rises in tandem. Writer-independent signature verification techniques, on the other hand, can be used to categorise the signatures of any user in the dataset. When training a model in this setting, it is done so with all of the subjects combined into a single one. Offline and online automatic signature verification systems are available, depending on the preference of the author. Both cases involve training a classifier, in this case a supervised classifier, to verify signatures using a small subset of data drawn from a more complicated distribution than the whole. The classifier is taught using a dataset of authentic signatures that is large enough to be representative of all of the valid users that have registered for the verification service.

This paper proposes a method that allows writers to be creative while remaining untethered to any one particular platform. Extracting features involves estimating a continuous curve that best matches the signature based on Identification utilising Fourier Descriptors (FD). A closed boundary is drawn around the entire signature image, and then FDs are calculated as features of the boundary. KNN classifiers take these features as input and use them to determine whether or not a signature belongs to a certain person based on similarities between the input features and the features already stored in the database. Fig. 1 shows a general block diagram of the proposed method. The details of the method will be shown in the next subsections.

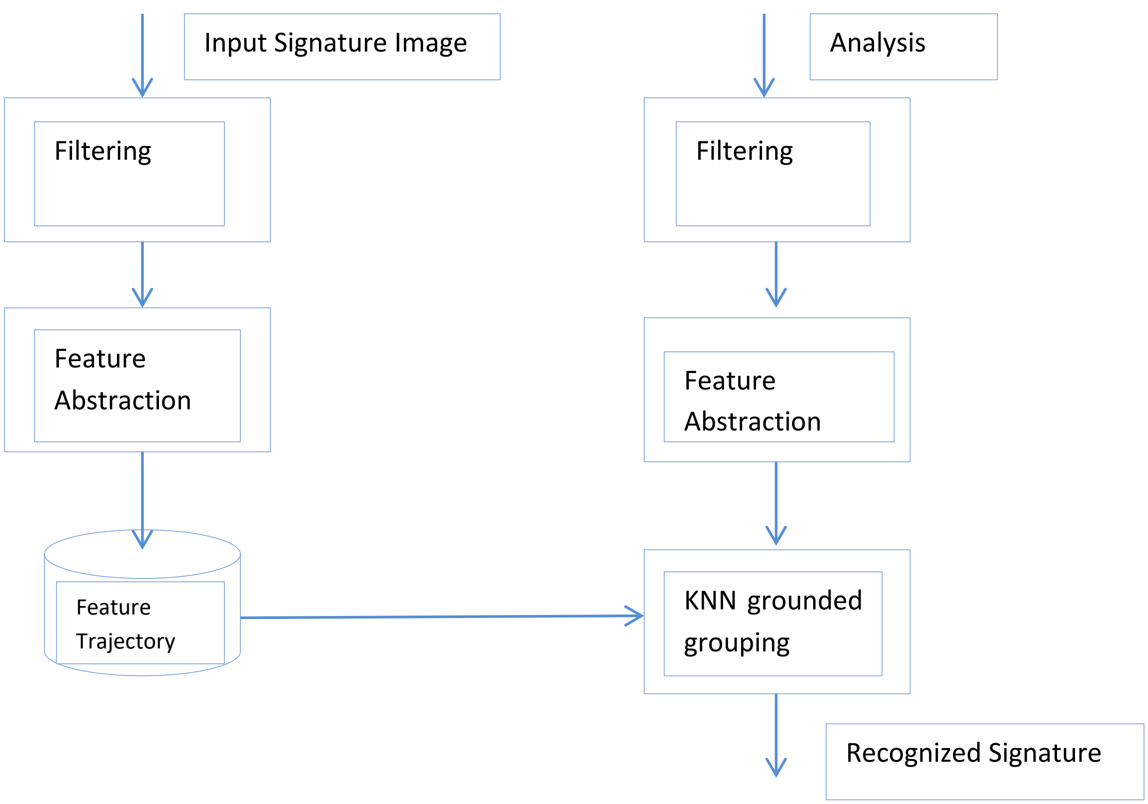

Fig. 1. The proposed block diagram.

A. Filtering

Some examples of pre-processing operations include noise reduction, binarization, rotation normalisation, resizing, and thinning. Scanning can create grey-scale signatures, although these may have unwanted extra dots. In order to get rid of the extraneous dots, median filters are applied to the gathered signature image (salt and pepper noise). Processing a grey-scale or colour image is more time-consuming than a binary one. The image is typically depicted in monochrome.

Pixels minimization is based on thresholding. Otsu's binarization strategy is suggested for use [31]. A signature's angular shifts over time are mitigated by rotation. The axes of inertia of all signatures are arranged horizontally. One approach to alignment involves finding the border of the signature with an edge detector, then thinning (or skeletonizing) it, applying the Radon transform, and determining the counter clockwise rotation angle. The signature's crookedness can be fixed by turning it around in a clockwise direction.

Signatures with a similar form but vastly different sizes have a low similarity score. This is because of the normalisation effect, which nullifies this. All normalised signatures provide comparison between reference (first-phase generated) and test samples (input signature picture classified as authentic or counterfeit). A bounding box is applied to the signature in order to normalise its proportions by erasing the surrounding space [32], [33].

The size of normalised images varies widely. Resolutions ranging from 40x40 to 200x300 were selected at random by the researchers. The width-to-height ratio (aspect ratio) is taken into account throughout the resizing process. The trademark image is reduced down to a single pixel in thickness. The operation remembers nothing beyond the bare minimum of the signature, even though this is by no means optional. It lessens the signature image should first have any unnecessary pixels removed before feature extraction can begin. The preliminary analysis is depicted in Fig. 2.

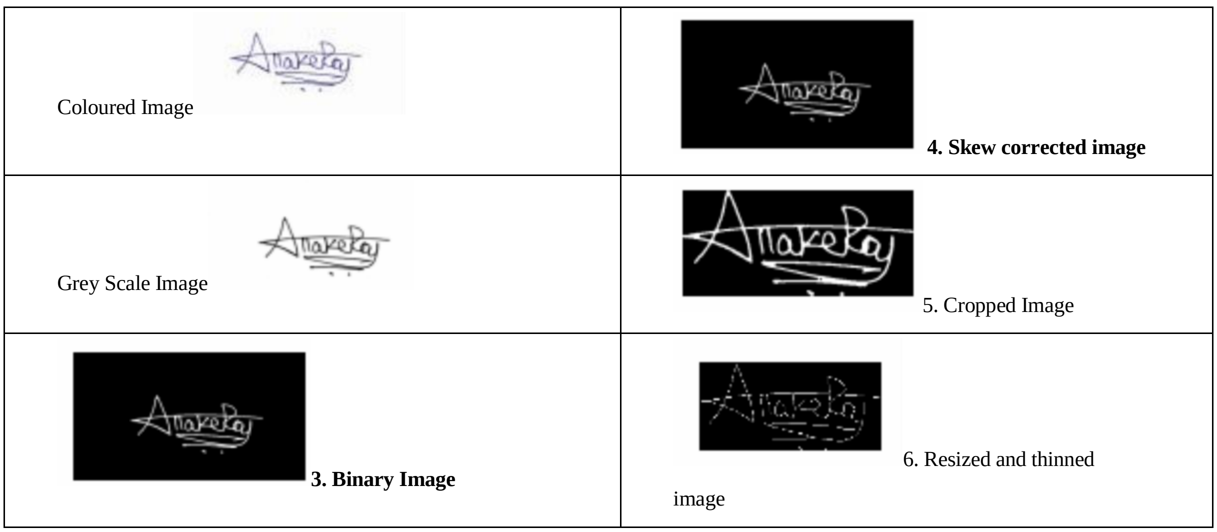

Fig. 2. Pre-processing of offline signature images.

B. Feature Abstraction

Shape analysis makes extensive use of Fourier Descriptors (FDs). Fourier descriptors of a shape are the coefficients of the Fourier transformation. The form of the object is reflected in these characterizations, which are expressed in terms of frequency. To begin, you'll need the N points that make up a region's boundary by sampling from the N pixels that make up the boundary. Just follow the perimeter around in a counter clockwise direction to get the job done. In the complex plane, the ordinate represents the imaginary axis and the abscissa represents the real axis, as seen in Fig. 3. Every point on the outline of the object has an x-coordinate pair of the form (Ak, Bk), where, $0 < k \leq$ N-1.

The boundary is completely described by a set of coordinates. Coordinate series can then be used to describe the contour.

$$P(K) = [A(k), B(k)], \text{ for k=0, 1, 2…..N-1} \quad (1)$$

Where, $P(k) = A(k) + jB(k)$

The DFT of P(K) is given as:

$$X(u) = \frac{1}{N}\sum_{k=0}^{N-1} P(k)e^{\frac{-j2\mu ku}{N}} \quad \text{for K= 0,1,2,….N-1} \quad (2)$$

The transform typically produces a large number of coefficients, but typically only a small subset of those coefficients are necessary to represent the essential properties of the shape. In this way, the FD's normalised magnitude can remove dependence on the size of the shape being examined. Information regarding the shape's finer intricacies can be found in the high frequency descriptors, while details about the shape's global or overall characteristics can be found in the low frequency descriptors. The size of the Fourier descriptors for these purposes must be increased accordingly.

Indexing forms have been drastically cut down. Since there are so many possible words, a figure out of the number of FD should be determined. Due to its position-only dependence, the DC component is useless for characterising shape and is therefore omitted. To normalise the scale, the second magnitude value is divided by each of the other descriptors' magnitude values.

In order to implement FD, the signature image will need to undergo a boundary tracing. Optimal FD for signature shape recognition are found through trial and error. Since a signature may include more than one part, we often encompass the whole thing within a closed curve that best represents it. The enclosed, closed curve is generated using morphological processes. The resulting curve is successfully computing FDs for form recognition, as they are signature-specific. Fig. 3 shows several example contour drawings.

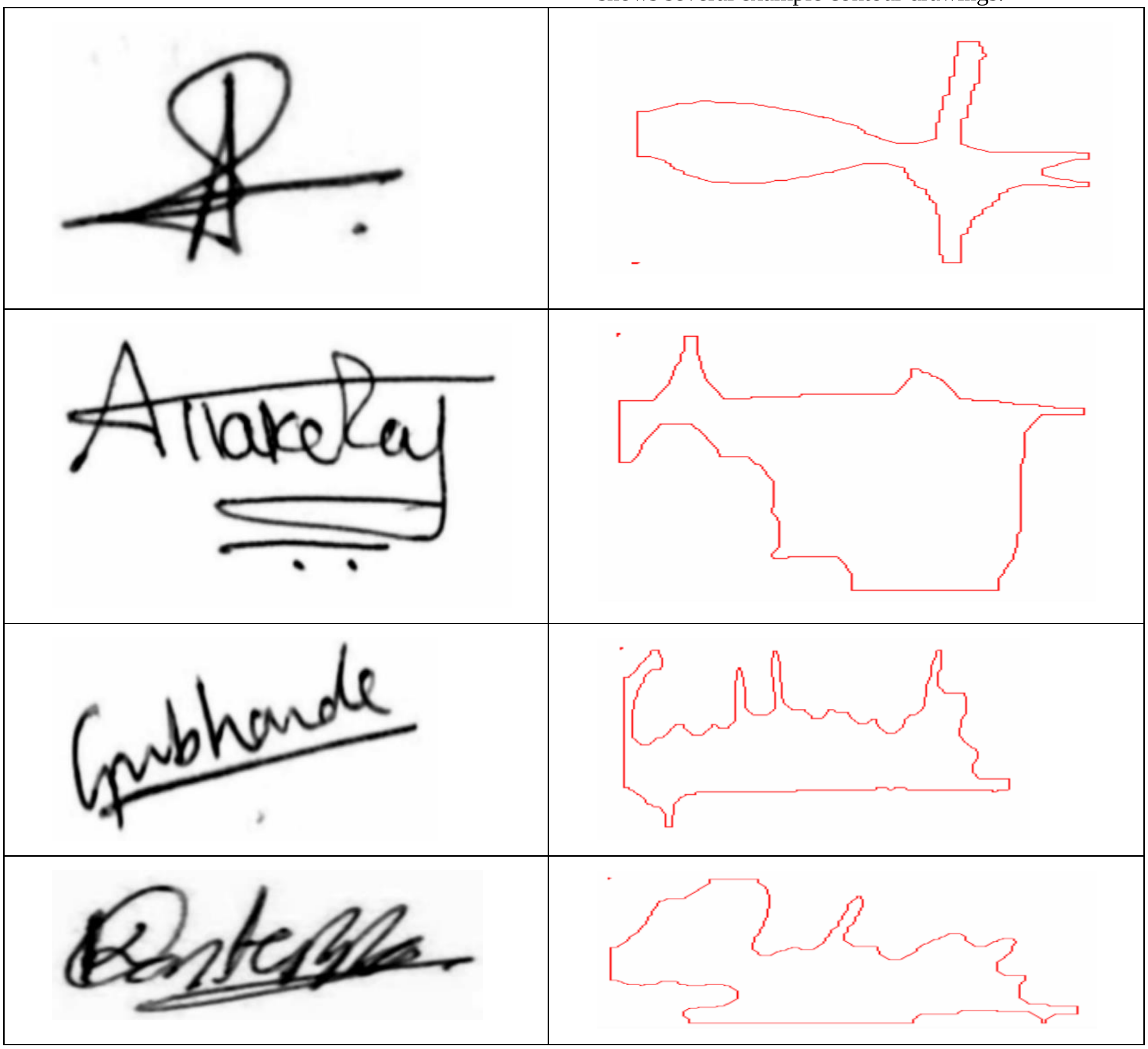

Fig. 3. Sample signature images and their enclosing curves.

C. Recognition

One common non-parametric classifier is the K-Nearest Neighbour (KNN) classifier. Classifier that uses the frequency of an unknown pattern's neighbours to estimate its posterior probability. When compared to other supervised statistical pattern recognition approaches, the KNN rule produces consistently good performance while making no a priori assumptions about the distributions from which the training examples are obtained.

To test FD's usefulness as feature vectors for signature image recognition, the KNN classifier has been selected. To do this, KNN classifier is used to compare the array of templates for the target signature to the arrays of all the other signatures in the database, with the goal of appropriately assigning the signature to a specific signature in the database based on the minimum distance attained. Specifically, the Euclidean distance is used for the calculation.

Following is a description of how to calculate the K-nearest neighbours.

Find the K value, which corresponds to the number of nearest neighbours. In most cases, an odd number (such as 1, 3, 5, etc.) is selected for K.

In order to do this, the distance between the query instance and all of the training samples is computed. A distance criterion, such as the Euclidean distance, can be used to calculate the distance between two points.

Find the closest neighbours by sorting the distances from closest to farthest.

Collect the neighbourhood's classification or tag. In most cases, labels are merely connected to the training sets.

In this method, the prediction value (label) of the query instance is determined by taking the simple majority of the category of the nearest neighbours.

IV. Result and Discussion

The goal here is to evaluate and contrast how various methods of approaching the problem fare. Method of identifying signatures is proposed. Ten participants from various occupations were selected at random. Variations, if any, in signatures were recorded by collecting them on white A4 paper at various intervals. Each participant signed 16 consent forms. A flatbed scanner is used to scan the signature pages at 300 dpi in grey-scale, and then a software is used to clip out each signer.

Profile work can be done in both the horizontal and vertical planes. From a total of 16, only 10 signatures were used for training and the remaining six were used for testing. This meant that there were 100 signatures in the training set and 60 in the test set. Training samples had 64-dimensional feature descriptors (FDs) generated for them and labelled with 10 topic labels for every 100 features.

Dimensions, each of which is a 64-dimensional vector of FDs. Label-free 64-dimensional FDs were calculated for each of the test samples. Using the generated FDs as features to describe the signature images, the training and test vectors were fed into a KNN classifier. To keep track of which feature vector xr from the signature picture corresponds to which reference signature Sr, a training phase is employed, when the system acquires its foundational knowledge. In recognition mode, the picture of the suspect signature Sq is displayed to the system, and the feature vector xq is fed into the KNN module alongside the reference set xr of signatures from users who have opted into the knowledge base.

In both cases, the outcomes are enhanced when K=1 is used. Using the MCYT database photos, the suggested technique performs better at K=1 than it does with images taken from the local dataset. The incorrect classification may be traced back to the fact that the enclosing boundary for that signature instance was different from the samples used for the rest of the image, which meant that the pre-processed image had gaps that weren't filled properly.

The classifier results are presented in Table I. The comparison of these subjects performance with different values of KNN classifier is plotted in Fig. 4.

TABLE I. Recognition Results using KNN Classifier

Subjects	**No. of assessment**	**Recognition Local Database**		**MCYT Recognition**	
		K=1	**K=3**	**K=1**	**K=3**
1	10/6	6	6	6	5
2	10/6	6	5	5	6
3	10/6	5	6	6	5
4	10/6	6	6	5	5
5	10/6	5	5	5	5
6	10/6	5	4	5	6
7	10/6	4	2	4	5
8	10/6	5	4	5	5
9	10/6	4	5	6	5
10	10/6	6	6	6	6
Recognition accuracy in %		88.35	82.35	89.61	86.62

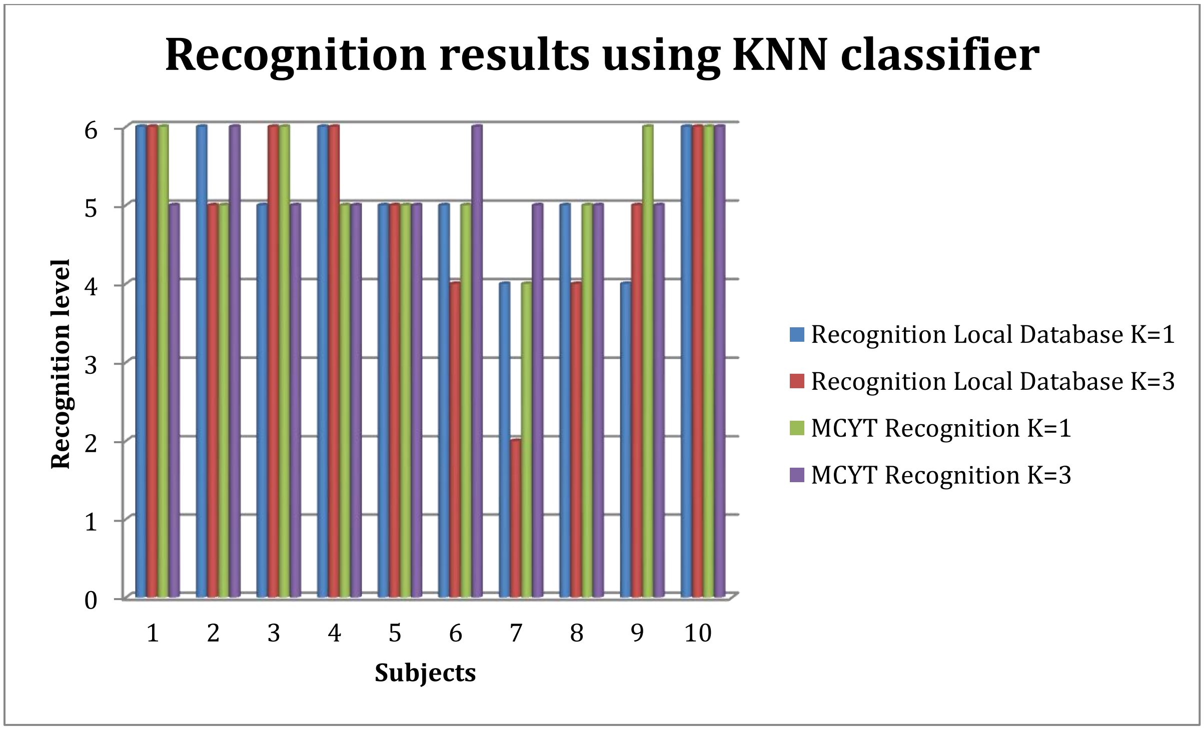

Fig. 4. Recognition results comparison using KNN classifier.

Form this comparison plot, we can conclude that KNN classifier with K=1 performs better and accuracy improved.

It is possible for a biometric security system to accept an access attempt from an unauthorised user; this possibility is quantified by the false acceptance rate (FAR). The false acceptance rate (FAR) of a system is sometimes described in terms of the fraction of identification efforts that result in a false positive.

$$false\ acceptance\ rate\ (FAR) = \frac{number\ of\ false\ acceptence}{number\ of\ identification\ attempts} \quad (3)$$

The accuracy and FAR for different data-set and for different value of K is presented and compared in Table II.

TABLE II. ACCURACY AND FAR VALUE OF CLASSIFIER

Data-set	Classifier	Accuracy	FAR
Local Data-set	KNN for K=1	88.35	0.1672
	KNN for K=3	82.35	0.2187
MCYT Data-set	KNN for K=1	89.61	0.1772
	KNN for K=3	86.62	0.2192

From this Table II, we can conclude that MCYT dataset and KNN classifier with K=1 perform best for signature identification.

V. CONCLUSION AND FUTURE SCOPE

A. Conclusion

The writer's characteristic patterns of behaviour during the signature-making process are retrieved as distinct features and then saved and compared in a Signature Recognition system. While signature verification seeks to confirm or reject a particular sample, signature recognition seeks to identify the author of that sample. Through the use of Fourier Descriptors and HOG features, we have presented efficient algorithms for signature recognition. Using LBP characteristics, a signature verification technique has been presented. An effective method for signature identification is given in this study. Features are extracted using FDs, and recognition is accomplished with KNN. The acquired findings validate the usefulness of the proposed method. In order to proceed with the recognition process, authentication must first take place. However, we found that there is a substantial class overlap in authentication when using the proposed technique, particularly between the confined boundaries of authentic signatures and forged ones are often confused. The challenge is deciding what level of confidence to assign to the recognised signature. Accuracy and false alarm rate (FAR) comparisons are shown with the experimental results. Functioning Area Ratio (FAR) is a tool for gauging and assessing the effectiveness reliability of a suggested system by counting the number of times incorrect patterns were confirmed using that system. Ten incorrectly accepted patterns out of 60 in the test signature dataset resulted in a FAR of 0.1672 and an accuracy of 88.35% for K=1.

B. Future Work

FDs and HOG characteristics, which are used in the signature identification method, broadened to include signature authentication. Signature images written in different Arabic and non-Arabic scripts can be studied using the methods provided in this experimental results have validated the effectiveness of the proposed system. While each of the proposed features may improve performance individually, they can be coupled for even greater gains. The performance can be enhanced by using an ensemble of classifiers.

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