Auto Signature Verification Using Line Projection Features Combined with Different Classifiers and Selection Methods

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***Abstract*:** Signature verification plays a role in the commercial, legal, and financial fields. The signature continues to be one of the most preferred types of authentication for many documents such as checks, credit card transaction receipts, and other legal documents. In this study, we propose a system for validating handwritten bank check signatures to determine whether the signature is original or forged. The proposed system includes several steps including improving the signature image quality, noise reduction, feature extraction, and analysis. The extracted features depend on the signature line and projection features. To verify signatures, different classification methods areused. The system is then trained with a set of signatures to demonstrate the validity of the proposed signature verification system. The experimental results show that the best accuracy of 100% was obtained by combining several classification methods.

***Keywords*:** Projection, offline signature, Principal Component Analysis, Genetic Algorithm, Support Vector Machine, K-Nearest Neighbor (KNN)

1. Introduction

Biometrics technology is used in many security demanding applications to identify a person based on physiographic or behavioural features.

The physiographic features, used to recognize and identify individuals based on biological traits, include the face, fingerprint, and iris methods, among others.Behavioural features are of special interest because they are repeated almost every time, a need arises to verify the identity of an individual; thismethod includes handwritten signature and voice [1, 23, 24].

A signature is a familiar biometric [2], commonly used to authenticate a person’s ownership of a document such as bank checks because it has a specific and distinct behavioural property [2]. Signature verification can be both offline and online, depending on the availability of data [3, 3, 5, 6].

The offline method is referred to as the static approach [34]. It utilizes signatures made by a pen, and then the signature image is extracted by a scanner from the paper source [4]. Whereas, online method is referred to as a dynamic approach when the digital signature is used and is captured in real-time [5].

Until this time, automatic signature verification is one of the most important studies of interest to researchers. Unfortunately, achieving an offline system with high accuracy is a huge challenge due to the sensitivity of handwriting signatures to forgery, so researchers try every day to find new ways to extract new features.

Various signature verification techniques can be used to verify an individual's signature. One of the most important advantages of using these technologies is

•Signatures are widely used forms of verification and identification that are acceptable to society.

•When the signature is forged by anyone, this does not mean that he has lost his identity for life.

Therefore, when adopting the signature to identify the person, we may face some of the problems, the most important of which is a forgery, Because through this forgery, theft may occur, especially in the financial transactions approved in banks, so the automatic signature verification system can solve these problems and overcome them when the accuracy rate is high.

In this paper, we use offline signature verification system. Research on offline signature verification has explored a large variety of methods, which are collected under controlled conditions. However, the signature datasets used in the process of offline verification may not completely reflect the characteristics of the signatures in practical cases. The signatures, which get extracted from real-world documents may contain different types of constrictions, such as company seals, dates, and enclosures of signatures, e.g, boxes. Moreover, such datasets may include intra-class variations, where genuine signatures would often resemble forgeries. In this paper, we address the problem of identificayion real-world offline signature verification problem, where the signature placed on a check is extracted, isolated and compared with original signature(s). Our proposed method in this study consists of 6 main phases, which start with signature acquisition, in which signature images are extracted from Kaggle free repository Next, the extracted signature images are enhanced for the purpose of reducing the noise and to recover the image quality. This way, we are able to overcome the occlusions encountered in large signature datasets such as Kaggke repository. Besides image preprocessing and cleaning, our method in this study includes features extraction, During the feature extraction phase, the system analyses a given pattern and records certain features. The output of the feature extraction phase is a structured data in the form of an observation sequence. In principle, any measurable quantity may be considered as a feature. Once the features are identified, it is necessary to classigy the features according to some crieteria, which leads to the next phase of the method used in this study, namely the classification phase. This process allows the selected a feature sets, which belong to different pattern classes to be maximally separated in the feature space [39]. The feature types considered in this study include physiographic or behavioural features [1, 23, 24]. Various features, which are commonly used by researchers include engineering features, italic distribution, entropy, and gradient features graph. Several methods have been used for feature extraction, such as signature shape [6] and wavelet transform [7]

Shape transform projects a shape contour or region into an other domain to obtain some of its intrinsic features. For shape description, there is always a trade-off between accuracy and efficiency [40].

Wavelet transform is powerful mathematical tool for analyzing an image of several levels of resolutions. The transform of a signal is just another form of reprsenting the signal. It does not change the information contentprsent in the signal. The wavelet transform provides a time-frquency representaiton of the signal. The wavelet transofrm at high frequencies gives god time resolution and poor frequency resolution,while at low frequecies gives good frequency resoultion and poor time resolution [41].

Another method of feature extraction is based on the fusion of local and global information [8]. This nethod combines color and shape features for indexing and retrieving images. Color models are typically independent of the object geometry, object pose, and illumination. Using color models, color invariant edges are used to derive and compute shape invariant features. Computational methods are often used to combine the color and shape invariants into a unified high-dimensional invariant feature set for discriminatory object retrieval.

Different classification methods are often used and applied to the extracted features such as Support Vector Machine (SVM), and Random Forest (RF). In this study, we will use SVM, which is reported to outperform other classifiers [10]. Needless to say that feature extraction is the most critical step in the process of offline signature verification.

The main aim of this study is to improve the methods for the verification of hand signatures [23, 24, 32, 33]. We address the problem of bank check signature verification (paragraph about the impact of check signature fraud) to automate signature verification in order to reduce false positives and/or negative, and to reduce the cost and time of manual verification.This work is sought to contribute to the emerging trend of digital transformation in the financial technology sector.

2. Related Work

Following is a summary of research related to the offline signature verification system.

Ghanimet et al. [9] suggested an offline automated system for signature verification and forgery detection. Various features were extracted in the study.Extracted features include engineering features,italic distribution, entropy, and gradient features graph. Different machine learning methodswere applied to the extracted features such as, Support Vector Machine (SVM), and Random Forest (RF). The study reported that SVM outperforms other classifiers.

Kruth et al. [10] implemented the Support Vector Machine (SVM) with Minimal sequential optimization and various offline kernel functions.In a preprocessing step they applied Binarization, Canny Edge's detector, edge thinning, and filtering. Features extracted were based on aspect ratio, horizontal, and edge graph Profiles. The system was tested using 336 several types of signature and achieve error rate lower than 7.16%.

RamyaRani et al.[11] introduced offline signature verification by using SVM and features extraction based on Har waves and Gray Level Difference Matrix (GLDM),. The system achieved an error rate of 7.533%.

Soleimani et al. [12] proposed a system for offline signature verification based on Linear SVM. They used 27 real samples per writer with a data set of 115 writers. The features extracted in this study were based on the distribution of the internal stroke in polar, cartesian coordinates, signature envelope, length, and width. This system achieved a succeerate of 70.67%.

Darwish [13] introduced offline signature verification by using a tree classifier. This study was applied based on characteristic-dependent signature curves, and feature extraction basedon the occupancy rate and the total number of pixels in the signature, the dataset used consists of 100 people and each one has 5 signatures. The dataset was divided into two parts, the training dataset which, represents 60%, whilethe testing dataset represents 40%.The success rate achieved by this approach was approximately 79.8%

Calik et al.[14] proposed a system for offline signature verification based on K Nearest Neighbor (KNN) for classification, and features extraction depending on CNN and used several datasets such as GPDS-4000, MCYT and CEDAR. This system achieved an accuracy of98.30%,96.41%, and 96.91% for the CEDAR, MCYT, GPDS-4000 datasets, respectively.

Kurnaz et al.[15] proposed a system for offline signature verification based on Support vector machine (SVM) [30] with RBF kernel, and local features were extracted depending on K-means algorithm and Scale-Invariant feature transform.This system achieved an accuracy of98.86%

Jain et al and Luiz G. Hafemannet. al. [18, 25] proposed what is called a sacral convolutional neural network (SCNN) for the classifications of offline signature verification system. It is worth noting that usingthis technology, the signature features are extracted automatically. The researchers used two sets of signature datasets, namely CVBLSig-V1 andCVBLSig-V2. The authors achieved high accuracy and low error rates.

Poddar et al.[17] used several methods to recognize and verify a signature. The features were extracted using Harris' algorithms and SURF algorithm and then the signature was classified according to CNN. The conducted study achieved an accuracy in the range 85% to89%.

Hyla et al.[18] proposed BlockchainScheme and Shell model for signature verification system. Without usingtimestamps,the validity of signature verification is preserved. This system works well when using a large number of signed documents.

Ruiz et al .[19] proposed a system for verifying random forged signature as they used Siamese neural networks (SNN). The authors used DNN in the classification stage and the best results were obtained when combining synthetic and original signatures for training. They also tested their system on SigComp11, GPSSynthetic, MCYT and CEDAR datasets.

Narwade et al .[20] Proposed a system for offline signature verification using shape correspondence methods and support vectormachine. For correspondence pixels, they use a combination of the shape context distance and the Euclidean distance. This system with an SVM classifier and signature from the GPDS dataset achieved approximately 89.58% accuracy.

Tahir et al .[21] Proposed an offline signature verification system using a simple-shaped geometric feature.It includes the Aspect Ratio, Baseline Slant Angle, Center of Gravity and Normalized Area.They achieved an accuracy score of approximately 82.5%.

Daqrouqet et al.[22] proposed a system for offline signature verification based on probabilistic neural network, and features extracted using Discrete Wavelet Transform.The dataset used in this study contains signatures for 20 people, This system achieved an accuracy of 92.87%.

Franco et al.[36] proposed a method for offline signature verification by using ANN and feature extraction through backpropagation learning algorithm with two approaches 500 approach and 901 approach, where the second is presented as a evolution . It was found that the average error rate is 20% in the first and 5.83% in the second.

Adama et al.[37] proposed a system for offline signature verification for managing lecture attendance based on Hierarchical Clustering ,and features extraction depending on distribution of black pixels along each column ,This system achieved 96% as a mean square error .

Saxena et al.[38] proposed a system for offline signature verification based on hash functions by decrypting the hash value and checks feature vector with stored feature vector.

They also suggest several ways to secure data integrity against different types of attacks.

3. Methodology and Materials

We implemented the model inthis study usingMatlab R2020a 32 bit/64 bit on a computer with Intel Core i5-2410M CPU at 2.30 GHz , 8 GB DDR3 RAM. We used the dataset from Kaggle free online repository [16].The methodology of this study consists of 6 main phases, which start with signature acquisition, in which signature images are extracted fromKaggle free repository Next, the extracted signature images areenhanced for the purpose of reducing the noise and to recover the image quality.Then, a set of features are extracted from the signatures, which are then submitted to feature selection based on genetic algorithm methods andprincipal component analysis (PCA). To validate thefeature selection, different classification methods are used. Finally, we build a confusion matrix tocompare the expected classes with the actual classes. The details of the method steps are explained in detail in the next seubsections (see Figure 1).

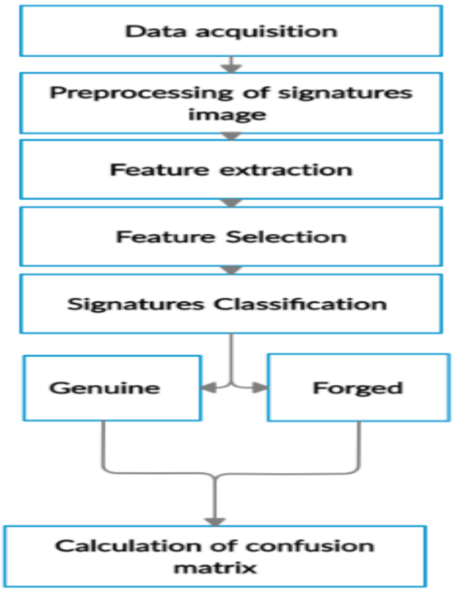

Figure 1. Flowchart for Proposed Methodology

3.1 Data acquisition

The signature images are obtained from Kaggle free repository. The dataset contains original and forged signature images for many users. Each user has a set of original signatures and a set of forged signatures [16].The set contains2149 images, with 1137 original and 1012 forged signatures for a total of69
users.

This research experiment mainly consists of 2 data analysis phases: a training phase and a testing phase. For this purpose, the used data set was partitioned into 2 parts; the first part contains 76.7% of the data, which are used for the training phase, and the second part contains the remaining 23.3% of data

Figure 2 shows a sample of the dataset for user #49 with 12genuine and 12 forged signatures.

3.2 Preprocessing of signatures

The images collected from the dataset are not perfectly suitedfor processing because of the noise that may exist in these images. Therefore, we preprocess the images to restorethe image quality, by applying contrast manipulation, noise reduction, background removal, edge crisping, image resizing, and filtering. Consequently, the signature images become more suitable for feature extraction. Figure 3 shows images after going through enhancement process.

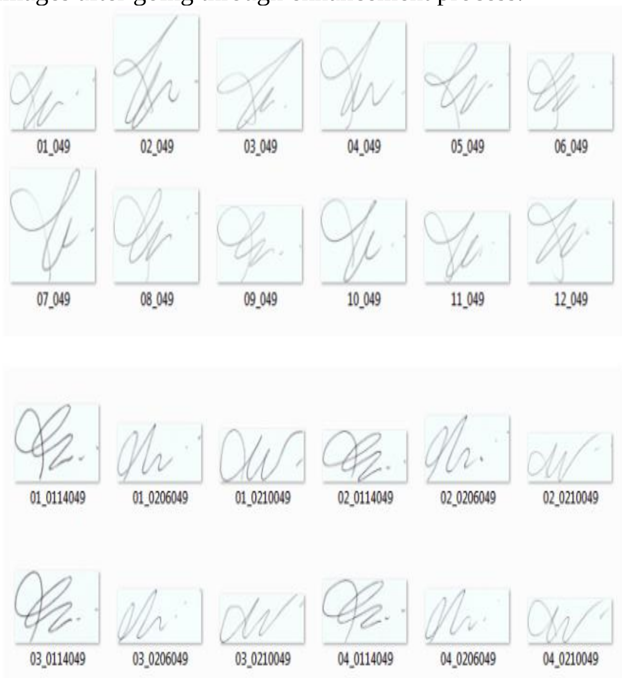

Figure 2. Forged and genuine signatures for user 49

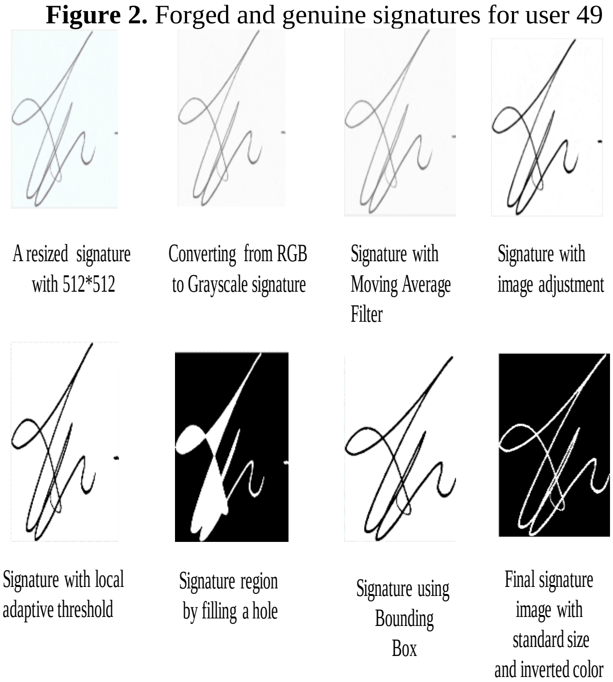

Figure 3. Example of enhancement using a different Preprocessing step

3.3 Feature extraction

Feature extraction, by and large,the most important step in every verification system.It is used to completely extract the morphological and analytical features from the selected signatures.The signatures features are classified into two main categories [17] [18] [19]: global andlocal.

- Global features extraction focuses on the image as a whole, such as height, width, and the edge of the signature, However, these features are less sensitive to noise, so they are only used for forged random signatures.
- Local features extraction focuses on the signature area specifically and extracts information in detail; it is more accurate than global features and isused in highly skilled forged signatures.

In this study, we focus on projection features for the signature line.

***Projection*: **is divided into two main parts at the level of row and is called horizontal projection or at the level of the column and called vertical projection. Horizontal projection represents the total number of non-black-pixels in the current row, and the vertical projectionrepresents the total number of non-black-pixels in the current column.

In this study we extracted 14 features based on the horizontal and vertical projection.Following is a brief description of each of the features.

***3.3.1 Mean of the horizontal and Vertical Projection*:** It represents the average of the non-black pixel for each row or column.These two features indicate the degree of signature intensity on both column and row levels. This means that there is a direct relationship between the mean for the sum of the non-black pixels and the density, which in turns indicates that the higher the mean, the greater the signature density. The mean is defined as:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} Ai \qquad (1)$$

3.3.2 The standard deviation of the horizontal and Vertical Projection: It indicates how the non-black pixels are distributed, i.e.,how the density changes during the movement of the pen when signing at the level of Row and column.

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} |Ai - \mu|^2} \qquad (2)$$

where μ is the mean of as defined it in (1),

3.3.3 Maximum Horizontal and Vertical Projection: It represents the maximum number of the non-black pixel for each row or column. These two features indicate the part of the signature withthe highest density at the row or column level.

3.3.4 Minimum Horizontal and Vertical Projection: It represents the minimum number of the non-black pixel for each row or column.These two features define the part of the signature with the least density at the row or column level.

3.3.5 Percentile of the Horizontal and Vertical Projection: These features indicate how the density is collected after calculating the sum of the non-black pixels for the signature, and whetherthey are clustered at low values, average values, or higher values., Three percentiles are used, namely 25%, 50%, and 75%.Figures 4 and 5 demonstrate the features extracted for one signature.using line projection.

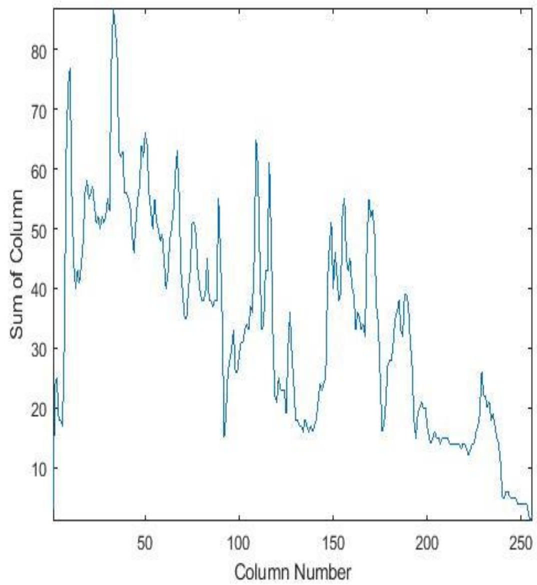

Figure 4. Example of Vertical Projection for one signature image with mean= 33.7109 ,Standard deviation=18.0599 Minimum =1 Maximum= 87 percentile 25% =18.0000 percentile 50% =33.5000 percentile 75% =48.5000

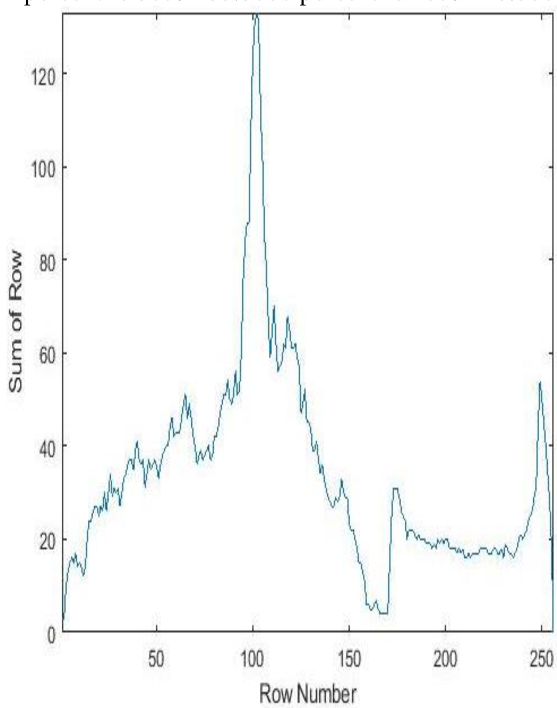

Figure 5. Example of Horizontal Projection for one signature image with mean= 33.7109,Standard deviation= 22.3365 Minimum =0 Maximum= 133.0000 percentile 25% =18.0000 percentile 50% =29.000 percentile 75% =42.5000.

3.4 Feature Selection:

Feature selection is used to reduce data and create accurate data models. Itfinds the most ideal data for the extracted features. This is useful to reduce complexity in the output and improve data models. In this study we use the Principal Component Analysis and Genetic Algorithm for feature selection.

3.4.1 Principal Component Analysis (PCA)

PCA is a statistical pattern that permits the identification of basic linear patterns in the dataset so that it can be expressed in terms of other datasets of significantly lower dimensions without losing too much information.

3.4.2 Genetic Algorithm (GA)

GA is a type of evolutionary algorithm that finds the best solution by searching in the solution area, and it is one of the most suitable algorithms to solve problems with a large number of solutions. Algorithms draw insights from evolutionary biology and genetics in that they simulate selection, crossover, and mutation processes to find optimal solutions.

3.5 Signatures classification:

The classification of signature images is the most demanding process (in terms of computation power)for the auto signature verification system, and the most viable one. Classification capacity provides the answer to whether a signature image is Genuine or Forged. For classification objectives, many classifiers have been used [31].

In this study, weuse the followingclassifiers:

3.5.1 ***K -Nearest Neighbor Classifier:*** The K-Nearest Neighbor (KNN) is one of the most popular and widely used in machine learning with classification techniques. The KNN classifier is built as a dataset model to predict the value for any new example based on this model.

3.5.2 ***Support Vector Machine Classifier:*** This is one of the most important classifiers in machine learning, which is a supervised learning algorithm for analyzing classification or regression data. SVM predicts the class for each instance of test data by learning from the training data [35]. The model in this study was constructed in SVM by representing all data at a point in n-dimensional space and assigning a value to each point.

3.6 Calculation of confusion matrix:

The confusion matrixis a common machine learning matrix used to test the performance of algorithms. Itcontains information and details about the actual class and predicted class,which is predicted by the classifier.

Each column in the matrix represents the actual class, and each row represents the predicted class. Classifier performance is usually evaluated using the data in the matrix, and the size of the matrix depends on the number of classes; this will be further demonstrated in figures 8-11.

4. Results and Discussions

In the feature selection step, we use a total of 14 features shown in Table 1. Two algorithms are used for feature selection, namely genetic algorithm with 3 features and principal component analysis with all 14 features selected. Two algorithms are used in the classification step (SVM and KNN). We have applied these algorithms with all classification algorithms.

When the principal component analysis (PCA) is used, all features are returned but ranked in order of priority. However, when the genetic algorithm (GA) is used, only 3 features are returned based on fitness value. Table 2 show the ranking of these features before and after using each method.

It is worth noting that when giving the classifier the features that were selected in the feature selection step, the number of these features can be determined, as we noticed that with a specific number, we can obtain the required degree of accuracy, and thus we can reduce the computation time and space. For example when giving a KNN classifier 3 features as ordered by PCA we get same accuracy as when using all features.

Figures 6 and 7 show the degree of accuracy for SVM and KNN respectively, after the PCA feature selection step

Table 1. Original Order of the Used Features.

Original Order	**Feature Name**
1	mean of the horizontal projection
2	The standard deviation of the horizontal projection
3	Maximum horizontal projection
4	Minimum horizontal projection
5	Percentile for low values of the horizontal projection
6	Percentile for Average values of the horizontal projection
7	Percentile for higher values of the horizontal projection
8	mean of a vertical projection
9	The standard deviation of the vertical projection
10	Maximum vertical projection
11	Minimum vertical projection
12	Percentile for low values of a vertical projection
13	Percentile for Average values of the vertical projection
14	Percentile for higher values of the vertical projection

Table 2. Selected and Ordered Feature.

Method	Order Result or Selecting
GA	13,14,20
PCA	1,8,3,10, 2, 9, 7,14,12,5,13, 6

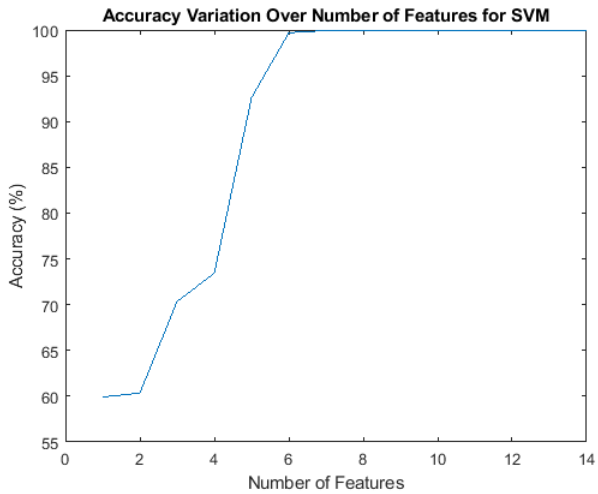

Figure 6. Accuracy Variation Over Number of features for SVM.

Note that a 60% accuracy is achieved using only one feature after PCA, while a 100% accuracy is achieved when using 7 features.

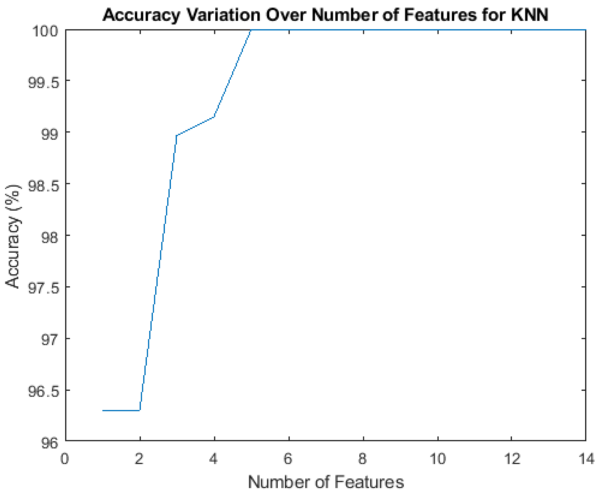

Figure 7. Accuracy Variation Over Number of features for KNN.

Note that a 96.3% accuracy is achieved using only one feature when using PCA, while a 100% accuracy is achieved when using 5 features.

Confusion Matrix Analysis.

The confusion matrix is designed to show several measurements metrics including the accuracy, sensitivity and specificity of the algorithms.

4.1 Accuracy: represents the total percentage of signatures that are correctly classified in the model. Accuracy is defined as follows:

$$\text{Accuracy} = \frac{\text{True Positive (TP)} + \text{True Negative (TN)}}{\text{True Positive(TP)} + \text{False Positive (FP)} + \text{True Negative(TN)} + \text{False Negative (FN)}} \quad (3)$$

4.2 Sensitivity: Sensitivity metric computes the ratio of a true positive instance to the total number of actual positive cases for that class. Sensitivity is defined as follows:

$$\text{Sensitivity} \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Negative (FN)}} \quad (4)$$

4.3 Specificity: This metric measures the ratio of negative patterns that were correctly classified. The Specificity is defined as follows:

$$\text{Specificity} = \frac{\text{True Negative (TN)}}{\text{True Negative (TN)} + \text{False Positive (FP)}} \quad (5)$$

Figures 8-11 show the confusion matrices for all classifiers with all selection methods used in this study. For example, figure 8 shows the confusion matrix for PCA when using the SVM classifier. As shown in the matrix, the 252 non forged signatures were identified as authentic with 100% accuracy, while the remaining 248 forged signatures were also identified as forged with 100% accuracy.

Figure 10 shows the results for GA and the SVM classifier. Non-Forged signatures were detected with 98.4% accuracy, while the forged signatures were identified with 97.6%accuracy.

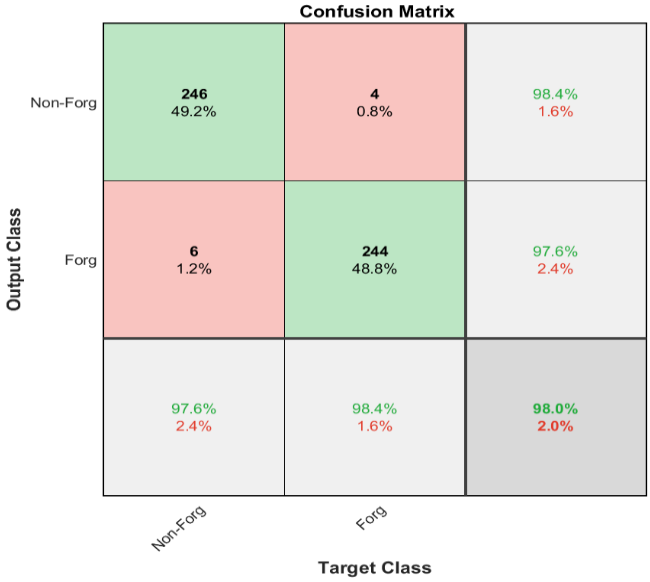

Figure 8. KNN confusion matrix after feature selection by PCA

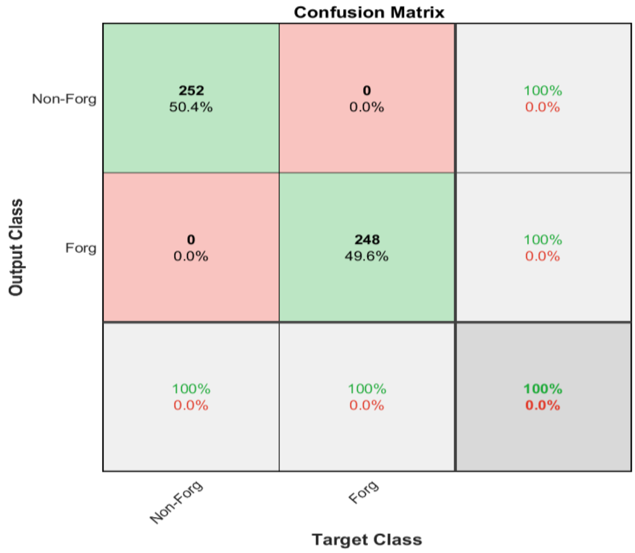

Figure 9. SVM confusion matrix after feature selection by PCA

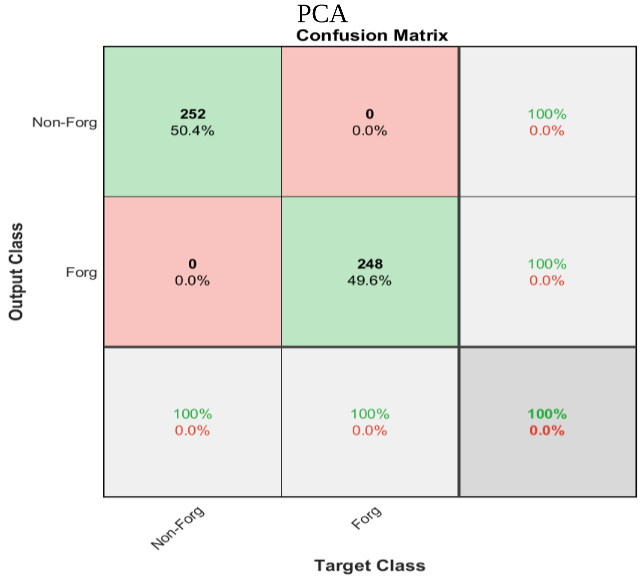

Figure 10. SVM confusion matrix after feature selection by GA

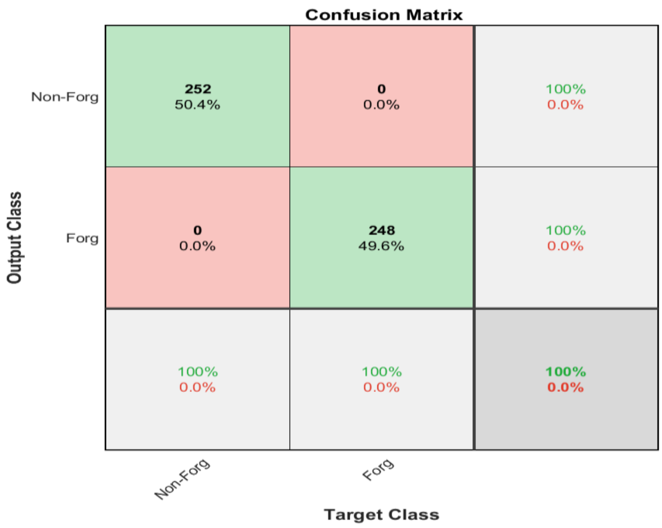

Figure 11. KNN confusion matrix after feature selection by GA

The accuracy, sensitivity, and specificity results are summarized in Table 3**.**

Table 3. Summary of Results

Classifier	**Accuracy**	**Sensitivity**	**Specificity**
SVM+PCA	100	100	100
SVM+GA	98	97.619	98.3871
KNN+PCA	100	100	100
KNN+GA	100	100	100

5. Conclusions

In this paper, handwritten signature verification is performed and tested. A comparison was made between five classifiers, KNN and RF. We relied on more than one theory to extract features such as line projection and signature line features. And we. We also compared two feature selection methods, PCA and GA. In this study, we find that image preprocessing greatly enhances the auto verification of handwritten signatures. Most effective preprocessing methods are image adjustment, local adaptive threshold, and bounding box on grayscale images. Our study was able to achieve high verification performance without draining the storage account space and computation complexity. SVM, KNN and RF is shown to achieve high accuracy. The degree of accuracy is highly enhanced when using the PCA classifier. Initial testing, which was conducted in this study shows that the use of transformation technology to extract line thickness can bed used to further enhance the accuracy of signature offline verification. This will be the subject of our next research project.

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