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SIGNATURE RECOGNITION BASED ON SUPPORT VECTOR MACHINE AND DEEP CONVOLUTIONAL NEURAL NETWORKS FOR MULTI-REGION OF INTEREST

MAHMOUD Y. SHAMS[1*], OMAR. M. ELZEKI[2], MOHAMED E. ELARABY[3], NOHA A. HIKAL[4]

[1]Department of Machine Learning and Information Retrieval, Faculty of Artificial Intelligence, Kafrelsheikh University, Egypt.
[2]Department of Computer Science, Faculty of Computer and Information Sciences, Mansoura University, Egypt.
[3]Department of Computer Science, Faculty of Computer and Artificial Intelligence, Beni-Suef University, Egypt.
[4]Department of Information Technology, Faculty of Computer and Information Sciences, Mansoura University, Egypt.
E-mail: [1*]mahmoud.yasin@ai.kfs.edu.eg, [2]omar_m_elzeki@mans.edu.eg,
[3]mohamed.elaraby@fcis.bsu.edu.eg, [4]dr_nahikal@mans.edu.eg

ABSTRACT

Human Signatures are still used in banks, organizations, and in many other security issues. Currently, the need not to touch any physical components, minerals, or devices has become a very important necessity, especially in the spread of viruses that are transmitted and largely preserved in minerals. This paper presents a new algorithm to identify and verify humans based on the enrolled signatures. Some features may influence the shape, rotation, and structure of the digital signature. All these features should be taken into consideration as it may be varied randomly every time each person enrolled the signature to the system. In this paper, we took three important Region of Interest (RoI) named as Multi-Region of Interest (MRoI) by which most common features of the entered signatures are taken into consideration. The MRoI are equal splitted region that are convoluted to produce one template applied to support vector machine (SVM) classifier. Every RoI of the signature are then applied to local binary pattern (LBP) feature extractor, then it convoluted to one template pattern to be classified using SVM. Furthermore, Deep Convolutional Neural Networks (DCNN) is presented for both feature extraction and classification stages to boost the results obtained for MRoI using SVM. We present fully connected layer of DCNN for 128 person, Further, we implement the proposed architecture using dropout softmax based on SVM. The proposed system is designed to handle both Arabic and English handwritten signatures collected from 128 individuals and the accuracy achieved is 95%.

Keywords: *Signature Recognition, Deep Learning, Deep Convolutional Neural Network, Support Vector Machine, Region Of Interest, Dropout, Softmax.*

1. INTRODUCTION

The Signature recognition is considered as one of the dynamic behavioral characteristics of biometrics. The signature are almost dynamic and is affected by age, illness, emotions, pressure,..etc. Furthermore, signatures required more quality hardware in both on-line, and off-line signatures [1] [2].

There exist some companies and banks still used digital signatures to verify people's identity. To identify the validity of the signature of the person, this is often done by looking at the signature of the person and comparing his signature with the previously signed signatures in the customer database. Often, the client has a problem of writing an imprint in the same way as previously recorded, so we need to build a strong and reliable system to identify the person's signatures. The main hypothesis in this study includes an implementation of a system based on using Multi-Region of Interest (MRoI) for each enrolled signatures to extract more features that are required to boost the recognition process. The Multi-Region of Interest (MRoI) is convoluted to one pattern that is unique for identification and verification purposes.

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The Multi-Region of Interest (MRoI) is convoluted to one pattern that is unique for identification and verification purposes. The resulting feature vectors are then classified using Support Vector Machine (SVM). Furthermore, to test the reliability of the proposed system, we proposed a Deep Convolutional Neural Network (DCNN) to detect the signature features based on the convolutional layers. The pooling layer is well known as a down sampling layer that used to control the over-fitting problem as well as reducing the number of weights. The fully connected layer of the DCNN is applied for the classification stage. The proposed system was implemented and evaluated using a database collected from students and employees of our colleague. The collected database consists of 128 individuals. Each person signs its signatures 20 times 10 for training and 10 for testing. The main contribution of this paper is listed as follows:

1) We implement a robust algorithm to recognize the enrolled signatures using MRoI and SVM.
2) The proposed system has been tested using SVM and fully connected DCNN for the input features vectors extracted from convoluted MRoI for each signature.
3) We Integrate the extracted signature features with the MROI to enhance the signature recognition rate using DCNN and SVM.

The rest of the paper is organized as follows; the related work investigates the recent signature work in section 2, the proposed system in section 3, the evaluation results in section 4, and finally the conclusion and future work in section 5.

2. RELATED WORK

Biometric recognition is very common in identifying and verifying the individuals that claim to be in the system. Perhaps, there is a great effort from the interested in security fields to improve the recognition rate of biometrics. Signatures are behavior dynamic biometrics used in many modern organizations to identify individuals.

Ahmed et al [3] introduce an online signature based on Principal Component Analysis (PCA) for dimensionality reduction and they used Multi-Layer Perceptron (MLP) for classification and matching. Their algorithm produces satisfying results with 2% False Acceptance Rate (FAR) and the produced False Rejection Rate reaches 5%. Abikoye et al [4] present an offline verification system based on classical neural networks with an FRR reaches to 10% and the average recognition rate 85%. An Efficient Fuzzy Kohonen Clustering Network (EFKCN) Algorithm is presented by Suryani et al [5] with improved results reaches 70 % accuracy and Equal Error Rate ERR 8%.

Shukla and Vikrant Bhateja [6] presented a study of determining signature accuracy using both classical neural networks and Convolutional Neural networks (CNN). They achieved 89% accuracy using CNN compared with 77 % accuracy achieved when using classical neural networks. A Dempster–Shafer theory is an efficient technique used to combine the enrolled signatures from different sources as presented in [7].

An offline signature verification system based on feature recognition of a hand-written signature image is presented in [8]. They took the intersection of the concentric circle with the signature image and enhanced results are achieved. Kamal and George [9] proposed an algorithm to measure the centroids of local binary vectors results from off-line signature and they achieved 94% accuracy with minimum elapsed time. Karouni et al [10] proposed an algorithm for offline identification of the enrolled signatures using a set of simple shape-based geometric features and Artificial Neural Networks (ANN). Calik et al [11] present an algorithm using CNN based LS2Net network and class center-based classifier for creating the boundaries decision as opposed to hyperplanes created by CNN. Shariatmadari [12] et al presents nonlinear tools for signature recognition based on the decision over acceptance or rejection of the tested signatures that relies on the Gaussian classifier of the independent parameters trained on genuine signatures.

In this paper, we attempt to handle some important issues that are faced by scientists in the signature recognition field. One of these limitations is the FRR that is slightly increased due to the speed, pressure of the signature.

3. PROPOSED ALGORITHMS

This paper presents two algorithms that investigate the major purpose of this work. The first proposed algorithm is the use of a support vector machine (SVM) that classifies the extracted features results from MRoI. The second is the use of DCNN that is used to boost the robustness of the

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proposed algorithm by handling the extracted features using convolution, max pooling, and fully connected layers of the DCNN.

3.1 Support Vector Machine

Support vectors are a learning algorithm directed under machine learning and are used for both classification and regression functions [13]. But mostly a vector is used for classification, so this will be what we focus on in this paper. The vector machine is based on the idea of finding a hyper-plane that divides the data set into two classes in the best way, as shown in Figure 1 [14].

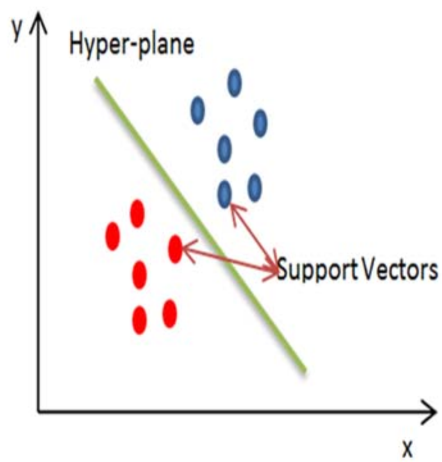

Figure 1: Support Vector Machine.

Supporting vectors are the data points closest to the super plane, which are points that, if removed from the data set, will change the location of the super plane that divides the data. Therefore these points can be considered as the important elements in the dataset [15].
The distance between the super plane and the nearest point to any of the data sets is known as the margin. The goal is to choose a super level with the largest margin between it and any point in the training data set to increase the likelihood that any new data will be classified correctly [16].

A detailed step of the proposed system is shown in Figure 2. The proposed system is initialized and the signature images are enrolled sequentially, then we choose three important ROI that are automatically calculated concerning the size of the signature image [17]. The resulting MRoI is convoluted and a feature vector required for a classification process is obtained. We select one of the most reliable and robust classifiers is SVM which considered as a statistical classifier considering the noise of signature-based on median pass filter.

For each test enrolled signature x, an SVM classifier outputs a score that is determined by the distance of x to the hyperplane learned for separating accepted from rejected enrolled signatures.

The scores indicate that if the example is classified as positive or negative, The magnitude of the score can be taken as a measure of confidence in the prediction. The produces scores are mapped and rescaled to the [0,1] interval. Therefore for f(x) is the original score, and [a, –a] is the SVM scores intervals such that $s(x) = (f(x) + a)/2a$ is a re-scaled score between 0 and 1, such that if $f(x) > 0$ then $s(x) > 0.5$ and if $f(x) < 0$ then $s(x) < 0.5$. However, these scores tend to not be well-calibrated since the distance from the separating hyperplane is not exactly proportional to the chances of membership in the class [18].

The probability of different enrolled patterns is calculated to determine the threshold value. The results above the threshold value are accepted, whether the results below are rejected. We used a trial and error approach to determine the threshold value. The ROI can be defined as the most important region that contains the most significant information for the pattern. Like in fingerprint the ROI is the core of the fingerprint by which the sensor needs this part to identify the fingerprint of the person.

Signature is different because it depends on the behavioral characteristics of each person. Therefore, the need of MRoI ensures high accuracy for signature recognition. The MRoI images are convoluted to one pattern as a feature vector required for classification using SVM.

The question is why are we used only three ROI and how the probability of each convoluted image are calculated. To answer this question, assume that the image has a fixed size (180×90) then we divide all images into three equal sizes (60×90) that have the most significant information of the signature image as shown in Figure 3.

The probability calculation can be determined as in the following example with mathematical equation (1), (2), and (3) [19]. For classified features from

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MRoI the proposed SVM model response is given by:

$$Y = T\,(X) \quad (1)$$

Such that $X \in \mathbb{R}^d$ is a vector representing input parameters of d dimension, therefore the probability density function (PDF) is given by:

$$P_F = \iint I[G(x)]\, f\,(x)dx \quad (2)$$

The induction function I[G(x)] for x is the realization of a d-dimensional random vector of X sampled from joint PDF is given by:

$$I[G(x)] = \begin{cases} 1, & G(x) \le 0 \\ 0, & otherwise \end{cases} \quad (3)$$

For n subjects the probability of the enrolled signatures and the coefficient of variation is determined as in equation (4) and (5) as follows:-

$$P_N = \sum_{i=1}^{n} I[G(x)] \quad (4)$$

$$cov(P_N) = \sqrt{\frac{1-P_N}{nP_N}} \quad (5)$$

For the training process the maximum distance D(x) from the nearest existing samples of a point x to the nearest existing training sample is calculated by equation (6) and (7) as follows:

$$D(x) = \|x - x_{nearst}\| \quad (6)$$

$$L(x) = min_x \frac{S(x)}{D(x)} \quad (7)$$

where s(x) and d(x) are maximum values of the normalized s(x) and d(x) respectively.

Local binary pattern is promising feature extractor tool used in pattern recognition application [20] [21]. In this paper, LBP is introduced in order to extract the signature features from each MRoI. The output of LBP is the feature vectors with n-dimension used as an input to SVM classifier. Figure 4 illustrates an example of the input sub-image with size 3×3, the center is threshold value such that, If the gray level of the neighboring pixel is higher or equal, the value is set to one, otherwise the value is set to zero. If the gray level of the neighboring pixel is higher or equal, the value is set to one, otherwise to zero.

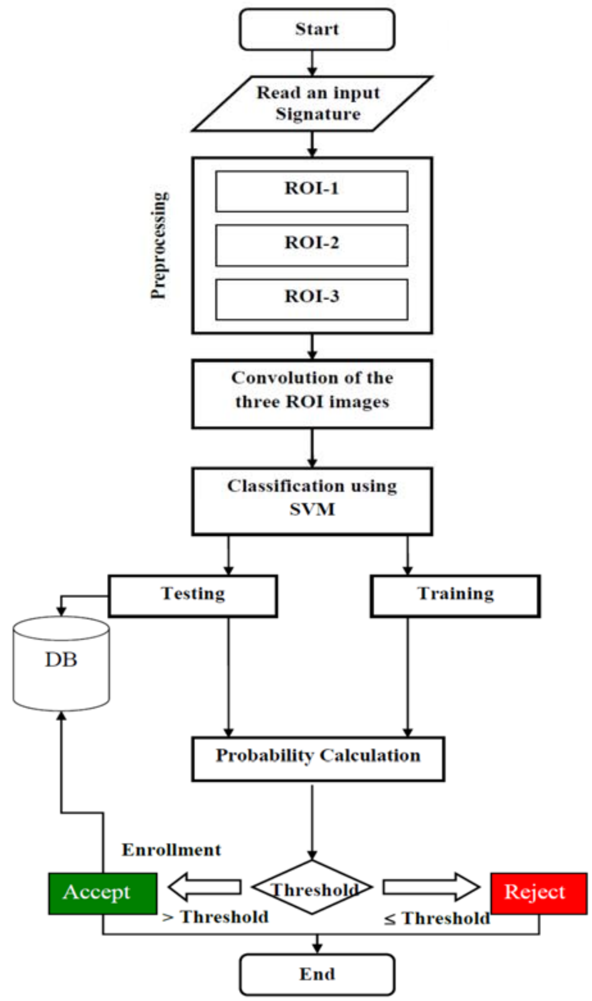

Figure 2: Flow chart of the proposed system based on a convoluted MRoI

Although using three MRoI of the signature image significantly improves the recognition accuracies as more image details will be clarified. The need of using convolutional neural networks (CNN) is mandatory to extract more features and to obtain more details and increase the signature recognition process based on different MRoIs.

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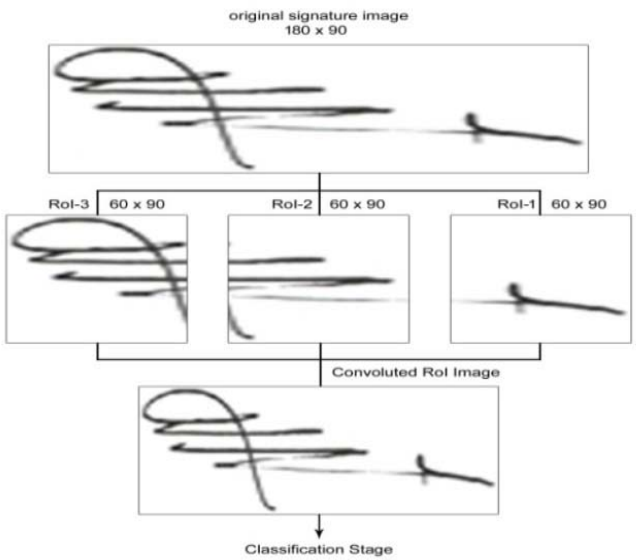

Figure 3: The steps of obtaining the three MRoI for the input signature image with a fixed 180 × 90 size.

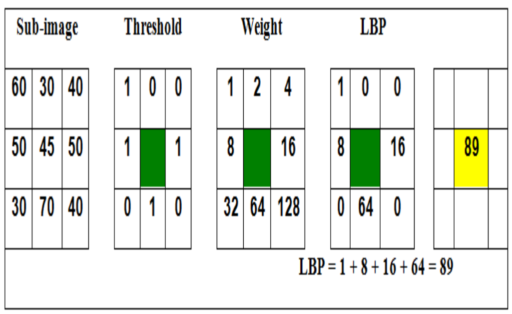

Figure 4: An Example of LBP computation

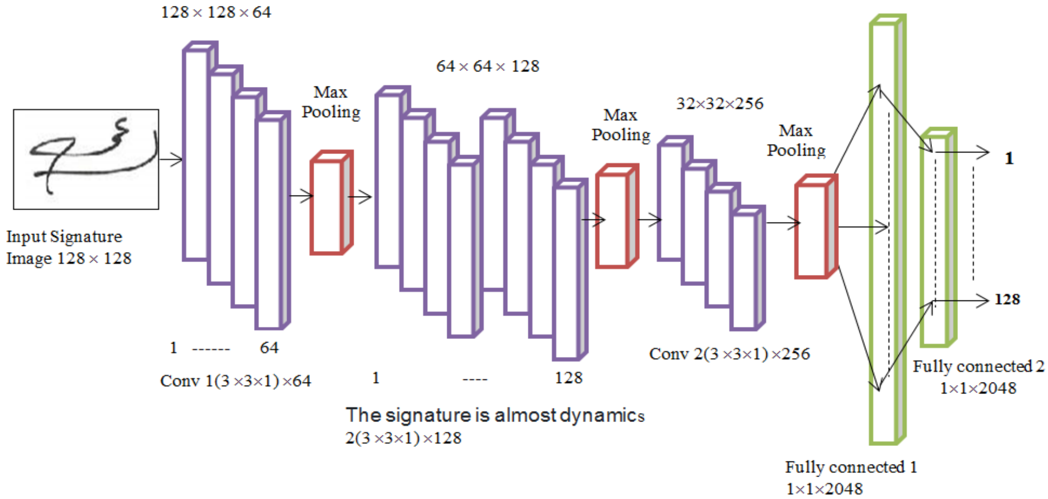

Figure 5. The proposed DCNN architecture of the input signatures. 4 convolutional layer, two fully connected layer, mini-batch gradient decent optimizer, ReLU activation function.

3.2 Deep Convolutional Neural Networks

Deep Convolutional neural networks (CNN) or abbreviated (ConvNets or CNNs) are a type of neural network that has been proven effective in multiple areas such as image discrimination and classification. The neural filtering networks have met with great success in distinguishing faces, inanimate objects, and traffic lights [22].

Consequently, anatomical neural networks are an important tool for most users of machine learning methods today, yet the understanding, learning, and use of anatomical neural networks for beginners may be impressive [23].

The primary objective of the ConvNet case is to extract the properties from the input image so that the rotation or filtering process maintains the spatial relationship between pixels in the image by learning the image properties using small squares (Kernel) on the input data. We will not explain the mathematical details behind this process, but we will explain how the images work and the recognition of enrolled signatures is realized [24].

In practice, CNN learns the values of these filters themselves during the training process (considering that we must determine in advance some parameters before the model training process such as the number of filters, the filter size, the network structure ... etc). The higher the number of filters, the greater the number of extracted properties of the input image and thus we will have a better network in defining patterns in new images that the network has never seen [25] [26]. The proposed architecture of deep convolutional neural networks (DCNN) is shown in Figure 5.

For the proposed algorithm, we used a convolutional layer for detecting the signatures features, the pooling layer that is also called the down-sampling layer to control the over-fitting and reduce the number of the weights. Finally the fully connected layer for classification.

To boost the evaluation results and to obtain enhancement accuracies, we proposed a Rectified Linear Unit (ReLU) activation function. Moreover, a mini-batch gradient decent optimizer is applied with 32 mini-batch size to enhance over-fitting problem with minimum time for local minima optimization. Furthermore, Figure 6 proposed an algorithm for signature recognition using dropout SVM as in the previous architecture except we apply a softmax layer and dropout SVM after max-pooling block.

4. EVALUATION RESULTS

In this section, the experimental results are evaluated using MATLAB 2019 a core i7 processor. The hyper-parameter values are 0.001 learning rate, 32 mini-batch size, 400 maximum number of iteration. The datasets are collected from different 128 individuals in our colleague [27]. The signatures are enrolled in the system in an off-line manner i.e. every person signs its signatures using handwritten on white paper as shown in Figure 7.

Every person enrolled made 20 different signatures, we used 10 signatures for training and another different 10 signatures for testing as shown in Figure (7-a, and b). For both training and testing phases, we have two images, one contains 10 signatures for training and the second contains another different 10 signatures for testing. The 10 signatures of one image are divided into 10 distinct images with a fixed size 180 × 90 jpg format. Figure 8 shows different samples of the input signatures.

The enrolled signatures are initialized by a fixed size, then the total area is divided into three equal MRoI that are automatically determined concerning image size. The convolution of the three RoIs is performed to measure the effect of the MRoI in the whole signature image. Furthermore, we determine the correlation between the MRoI of the convoluted images by calculating the coefficient variances of each 128 as shown in Figure 9.

A confusion matrix is considered as one of the most common and precise tools for evaluating the practical and benchmarks of the system. Therefore in this paper, a confusion matrix is used to evaluate the proposed system based on sensitivity, specificity, precision, accuracy, and F1 score of the input signatures as investigated in Table 1. Figure 10 summarized all results evaluation of the proposed signatures in both training and testing phases to indicate that by using fully connected DCNN a slightly improved accuracy is achieved

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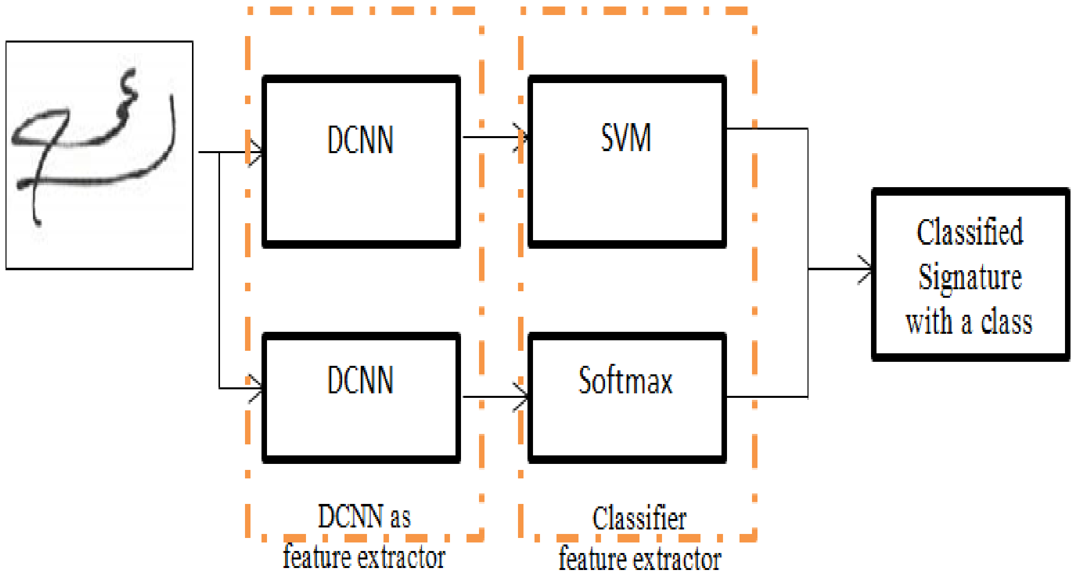

Figure 6. The proposed dropout SVM for the proposed DCNN architecture of the input signatures. The DCNN operates as feature extractor and SVM as softmax classifier to classify each signature with a class label.

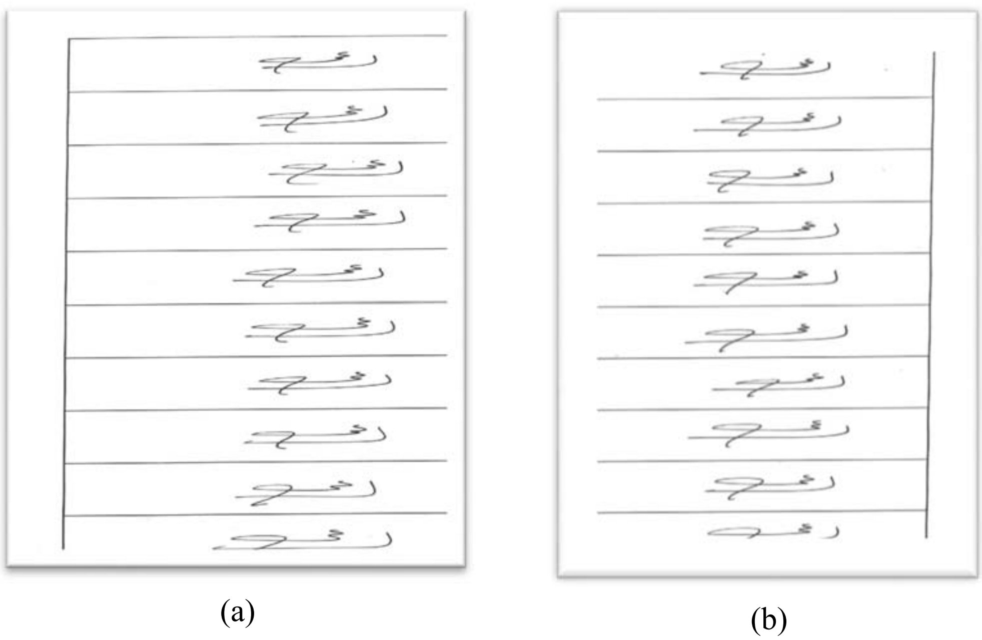

Figure 7. Collected signatures from one person. (a) 10 trained images (b) 10 tested images.

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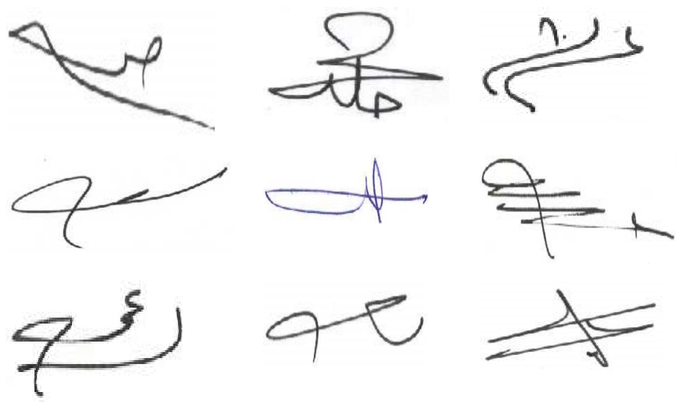

Figure 8. Samples of collected signatures.

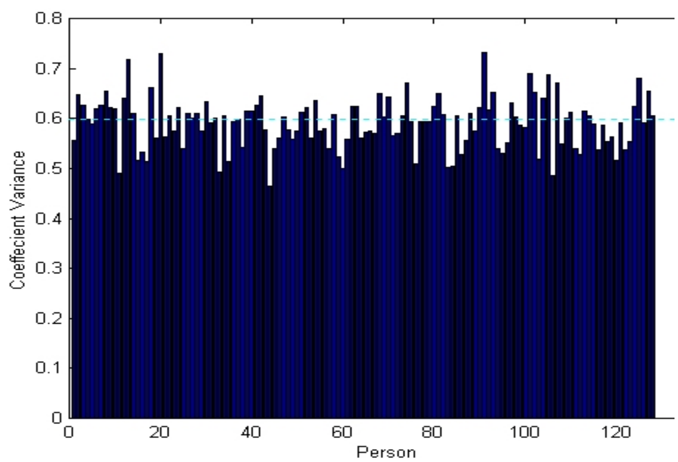

Figure 9: The coefficient variance of the 128 individuals signatures.

Table1: The confusion matrix for the proposed signature recognition algorithm.

Proposed Method	MRoI-SVM (%)	DCNN-dropout-SVM (%)	Fully connected DCNN (%)
Sensitivity	92.56%	94.40%	95.24%
Specificity	94.29%	86.67%	78.95%
Precision	99.64%	99.66%	99.67%
Accuracy	92.66%	94.22%	95.00%
F1score	95.97%	96.96%	97.40%

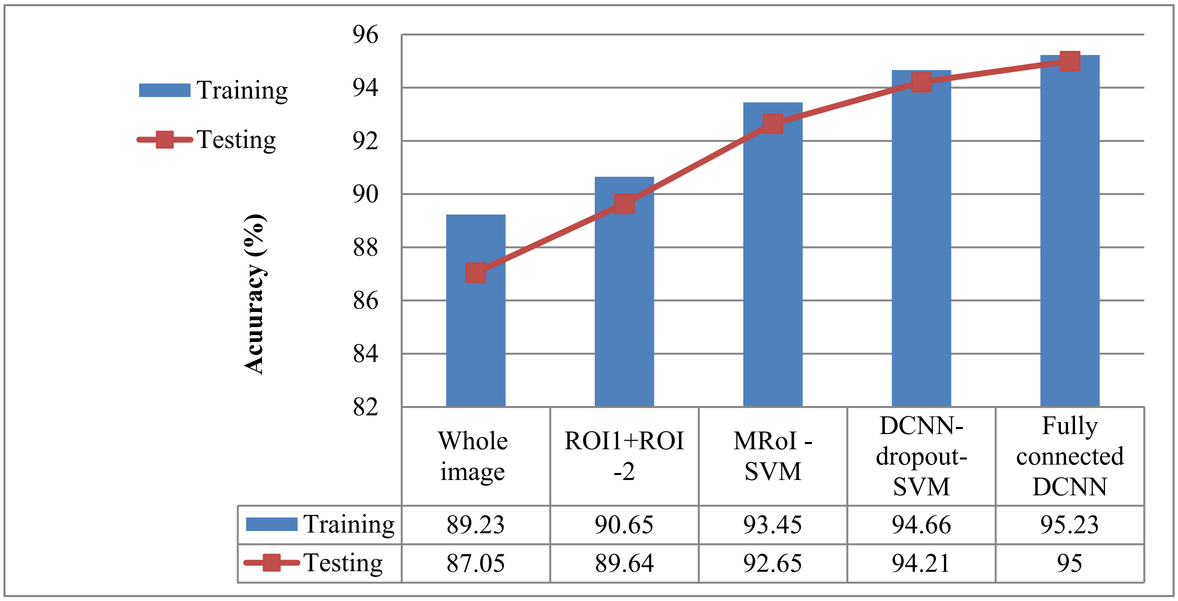

Figure 10. The Accuracy Of The Proposed Signature In Both Training And Testing Phases.

The comparison between the proposed method based on DCNN and SVM with the recent Learning Vector Quantization (LVQ), Self Organizing Map (SOM), and Radial basis function (RBF) [28] is shown in Table (2). This comparison investigated that the proposed system is able to recognize the enrolled signatures more efficiently than the classical neural network approaches using the same protocols. Moreover, we compare the proposed system for both training and testing phases. As shown in Table 2, in the testing phase the results of SOM, RBF, and LVQ are 82%, 86.24%, and 91.35% respectively. While the proposed architecture based on MROI-SVM, DCNN-SVM, and fully connected DCNN are 92.64%, 94.26%, and 95% respectively.

Table 2: The comparison of the proposed system with LVQ, SOM, and RBF.

Approach	Accuracy (%)
SOM	82.00
RBF	86.24
LVQ	91.35
Proposed System MRoI-SVM	92.64
DCNN-dropout-SVM	94.26
Fully connected DCNN	95.00

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5. CONCLUSION AND FUTURE WORK

This paper presents a new system used to recognize the off-line handwritten signatures depends on MRoI. The experimental results investigated that the use of MRoI signature images the more accuracy achieved to identify the signatures of each person. Using the convoluted signature images as well as determining the coefficient variance of the signatures are required to increase the reliability and efficiency of the proposed system. DCNN is one of the most crucial techniques used for improving the accuracy of the image processing toolbox. Therefore in this paper, we proposed an architecture based on DCNN in both fully connected layer and dropout-SVM layers to ensure the reliability and robustness of the proposed system. The comparison between the proposed system and the classical approaches SOM, RBF, and LVQ is performed to ensure the superiority of the proposed system. In the future, we plan to use an online signature based on deep neural network approaches to detect and classify imposter and genuine persons.

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