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Handwritten signature identification based on MobileNets model and support vector machine classifier

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ABSTRACT

Biometrics is a field that uses behavioral and biological traits to identify/verify a person. Characteristics include handwrittien signature, iris, gait, and fingerprint. Signature-based biometric systems are common due to their simple collection and non-intrusive. Identify the humans using their handwritten signatures has received an important attention in several modern crucial applications such as in automatic bank check, law-enforcements, and historical documents processing. Therefore, in this paper an accurate handwritten signatures system is proposed. The system uses a proposed preprocessing stage for the input handwritten signatures images. Besides, a new deep learning model called MobileNets, which used for classification process. Support vector machine (SVM) used as a classifier with the MobileNets inorder to get a better identifaction results. Experimental results conducted on standard CEDAR, ICDER, sigcomp handwritten signature datasets report 99.8%, 98.2%, 99.5%, identification accuracy, respectively.

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1. INTRODUCTION

A biometrics uses a person's behavioral and biological characteristics to identify and verify them. Fingerprint, iris, gait, and signature are a few examples of these characteristics. Signature-based biometric systems are widely used since they are non-intrusive and easy to acquire [1]. Using the automatic identification and verification of people is known as biometric recognition. As a result, several biometric modalities that are based on physiological and behavioral traits have been investigated in recent years. Anatomical characteristics such as a person's face, fingerprint, iris, and hand geometry are related to physiological characteristics. In contrast, behavioral traits like a persons voice, handwriting, signature, and movement demonstrate competent action [2]. A handwritten signature is still regarded as one of the most exclusive forms of interpersonal communication. Despite the widespread use of computers, many individuals still use handwritten signatures every day because they are more convenient for confirming the authenticity of different extensively used documents, especially in banking and forensic systems [3].

Signature is human identifier biometrics that is well known and recognized as a tool for identifying a person. A signature is a handwriting or hand stroke with a unique writing style, such as a line of strokes that resembles the name of the signature owner or a symbol used as proof of an individual's identity. The signature was recognized as a biometric feature after United Nations commission on international trade law (UNCITRAL) established the first digital signature law in the early 90 s. Signature recognition can be classified into two main groups, which consist of online signatures and offline signatures [4]. Online and offline systems are the two categories into which these systems fall. The first compiles time-ordered dynamic signature characteristics, while the second utilizes the image. Although storing more information about a signature online is useful, the life basic objective of offline signature verification systems is to distinguish real signatures from forgeries, which might be performed skillfully or randomly by a forger. Due to the intra-class diversity of real signatures, competent forgeries are sometimes difficult to detect from random and simple forgeries. To achieve high verification results, a thorough analysis of both local and global characteristics of genuine signatures is necessary. The verification method is further complicated by a lack of authentic samples and insufficient prior knowledge about forgeries during training. Both document work and security services require the actual practical duty of signature detection and recognition. Handwritten signatures are thought to be the most traditional and extensively used biometric method for identifying and verifying individuals. A database search for the writer's identity among the group of writers is the goal of signature identification. The signature under scrutiny is in this instance compared to every writer model in the database. The goal of the signature verification system, in contrast, is to determine whether or not a signature under scrutiny genuinely belongs to a person [5].

As a result, the state-of-the-art demonstrates significant attempts to propose numerous algorithms to achieve effective signature verification. However, despite its importance in real-world application areas, signature identification has received less attention in the most recent researches. For instance, businesses verify each person's identity before allowing them access to particular facilities that require high levels of security [6]. Another interesting use of signature identification, for instance, businesses verify each person's identity. A few intriguing uses of signature identification include the examination of some historical documents, automatic bank check processing, and law-enforcement applications where the identification of culprits is a crucial component of the solution [7]. The identification of signatures using a variety of techniques has been proposed in several papers. Gumusbas and Yildirim [8] first present capsule network for signature identification based on three different handwritten signature datasets. Their proposed method achieves 89%–97% accuracy using CEDAR, GPDS-100, and MCYT datasets and capsule network for various lower resolutions. In another hand, the paper present the verification task using capsule network. The obtained results of the verification task was 86%-91%, accuracy using capsule network and CEDAR, GPDS-100 and MCYT datasets for 64×64 resolutions.

Gumusbas and Yildirim [9] compare the capabilities of the convolutional neural network (CNN)-based equivalent model with the capsule network to identify signatures. To determine whether texture patterns for both methods continue to be as informative as they often are, this test is conducted at two lower resolutions than is typical. CNN achieves 55.4% and 54.7% accuracy compared to capsule networks 98.8% and 98.6% accuracy for 64×64 and 32×32 input resolutions, respectively. The paper's second goal is to more broadly use capsule network's capabilities for the verification task through this assessment, the capacity of the capsule network to produce superior feature extraction and classification outcomes for the verification task as compared to the CNN-based similar model is demonstrated using two datasets (CEDER and ICDAR).

According to Djoudjai *et al.* [10] an offline method of identifying handwritten signatures using the histogram of symbolic representation (HSR) is proposed. The HSR is a one-class classifier that can create models for each writer based solely on their unique reference signatures. By taking into consideration the variation in signatures, this method also enables the modeling of each writer's writing style. Two well-known standard offline handwritten signature datasets (CEDAR-55 and GPDS-300) are utilized to assess the robustness of the proposed identification system. The experimental results have a respective accuracy of 98.63% and 97.84% for th both used datasets. When only 5 reference signatures are used, the results are still much superior to the state-of-the-art.

According to Nugraha *et al.* [11] a combination of deep learning and euclidean distance is used in this work to identify the handwrittien signatures. The private dataset, SigComp2009, and SigComp2011 are the three separate signature datasets used for evaluating the proposed work. Images are first preprocessed using binary image conversion, region of interest, and thinning, signature. Following feature extraction with DenseNet201 and additional identification with euclidean distance, applied on the preprocessed image. The robustness of the suggested method is further evaluated by utilizing a variety of testing situations, including dataset augmentation, dataset split ratio modifiers, and pretrained deep learning. The highest precision rate and best accuracy were 99.44% for the both used datasets.

Afanasyeva and Afanasyev [12] describe a straightforward signature detection approach and its subsequent signature recognition based on a convolution neural network using a deep learning model for image processing. A binary classification has been carried out to predict text or signature and signature classifications utilizing solutions to the picture recognition problem and to transfer the signature-containing region to the trained model after being extracted. The studies can be recommended to students in the study of neural networks to understand the basics of deep learning and apply a ready-made model as a template for solving practical problems in the field of computer vision. Utilizing the numpy arrays' tensor-slicing operations to choose dataset CEDAR and OpenCV tools are used to extract areas with text and signatures. Recognition of the signatures of renowned authors has yielded positive results (94%).

Culqui *et al.* [13] a model based on CNN is proposed to quickly and efficiently classify and identify a persons signature. For this purpose, two signature datasets were utilized as objectives. The first, known as CEDAR, is accessible to everyone. The researchers used uncontrolled conditions to acquire the second set, referred to as GC-DB (different signing positions). The Republic of Ecuador is represented by 121 local signatories who each provided 45 copies of their signatures for this collection. Noise removal in this set of signatures was made more difficult by implicit noise created by the capture device and the various paper thicknesses utilized in the collection. Two more algorithms that were constructed and verified using the two data sets were compared to the effectiveness of the proposed approach. The results demonstrate that using the devised technique, it is possible to efficiently classify handwritten signatures. The created algorithm is also portable and simple to use; it can be downloaded and installed on phones or tablets. Additionally, the datasets (CNN-GC accuracy 99%, DB-GC accuracy 93%, and CNN-SCN accuracy 98%) were used.

Hadjadji *et al.* [14] use both the curvelet transform (CT) and the one-class classifier based on principal component analysis (OC-PCA), for open handwritten signature identification system (OHSIS). Due to its effective characterization of curves present in the local orientations inside the signature image, CT is investigated for feature generation. While OC-PCA is employed because of its efficiency in absorbing the large feature size produced by the CT and its ability to simultaneously achieve an open system. Then, a novel combination strategy based on Choquet fuzzy integral is proposed to combine many distinct OHSISs to increase the robustness of the OHSIS when few reference signatures are available. The proposed OHSIS is effective since it can easily outperform the state-of-the-art when employing a few reference signatures. Experimental findings on the common CEDAR and GPDS handwritten signature datasets report 97.99% and 94.96% correct recognition rates, respectively.

Jampour *et al.* [15] proposed a new regularization term for CapsNet that significantly improves the generalization power of the original method from small training data while requiring much less parameters, making it suitable for large input images. An efficient DNN architecture that integrates CapsNet with ResNet to obtain the advantages of the two architectures is also proposed. This approach is general, and authors demonstrate it on the problem of signature identification from images. To show our approach superiority, authors provide several evaluations with different protocols. The proposed approache is domstrated, through extensive testing on three publicly accessible datasets—CEDAR accuracy 100%, MCYT accuracy 99.8%, and UTSig accuracy 99.3%—that our approach beats the state-of-the-art on this topic.

Research by Qiu *et al.* [16], the issue that makes it difficult to verify the validity of offline signatures is mentioned. To fully extract signatures, a segmentation model based on the notion of fuzzy sets is first built. Secondly, statistical shape model (SSM) and variance distance discretization of intraclass signatures are introduced for stability analysis and quantification. To achieve a better results of signature authentication, multilayer classifiers are built. The +e algorithm offers quick singanutrs authentication times and low false detection rates.

According to Noor *et al.* [17], the purpose of the research is to demonstrate an appropriate and reliable technology organizations may use to recognize signatures automatically. Preprocessed signature photos are used to train CNN. The code was developed using MATLAB, and results indicate our method to provide promising results and have contributed by extending the technique to be reliable. The CNN is tested with 4 different datasets with N number of individuals and M number of signatures for each individual and contains signatures that differ from each other in many aspects like the type of signature, and its readability. Authors used CNN to train and test on all the datasets to observe the performance and make interesting observations of our implementation. The network performed reasonably well on all datasets, which is presented in their results section. Therefore, in this paper, we employed MobileNets model and support vector machine (SVM) classifier for accurate offline handwritten identification results.

2. METHOD

To identify the desired handwritten signatures, several stages are involved in the proposed system. These stages are, image preprocessing, signature classification, and identification. The inputs to the system are the used handwritten signatures dataset and the outputs are the user ID which is represent the writer of the input handwrittien signature. Figure 1 illustrates the overall stages of the proposed handwritten identification system. The proposed system use a standard handwrittien signatures dataset for evaluation. The input handwrittien signature images are divided into training set within 70% of the whole images and testing set within 30% of the whole images in the used dataset. In order to obtain better results all the input handwrittien signature images are preprocessed using various method for enhancement and remove the unwanted noise and information. The most important stage of the proposed system is the classification stage. In classification, MobileNets model which is a modern and efficient deep learning model is used for extracting the required features of the input handwrittien signature images then the SVM is used for classification purpose.

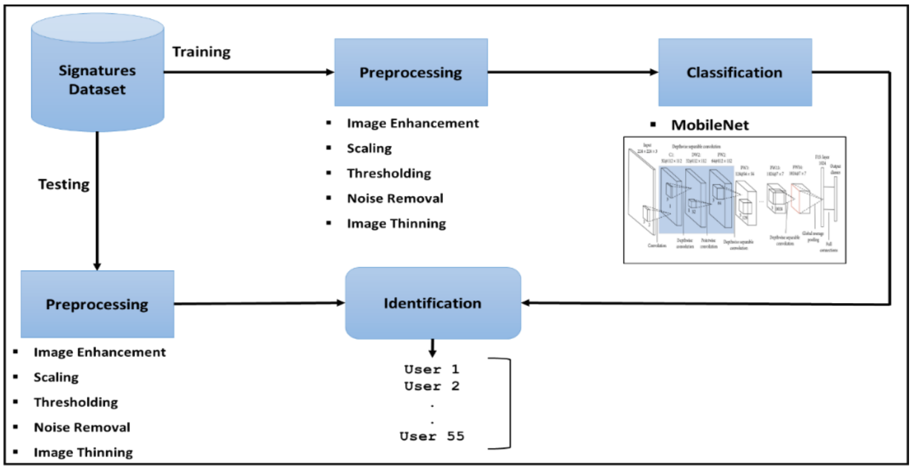

Figure 1. The proposed system

2.1. Handwritten signatures dataset

To evaluate the performance of the proposed system, a standard handwritten signatures dataset is used. There are many available datasets for handwritten signatures on the internet used by many researchers. However, the common handwritten signatures dataset used by most of the authors is CEDAR dataset [18]. Therefore, in this paper CEDAR dataset is used for evaluating the proposed system. A database of offline signatures called CEDAR Signature is used to identify and validate signatures. There were 1,320 real signatures were obtained by the contribution of 24 signatures from each of the 55 signatories. Every signature was binarized using a gray-scale histogram after being scanned in grayscale at 300 dpi. Two image preparation processes included salt pepper noise reduction and slant normalization [18]. Sample images of the handwrittien signatures images in are shown in Figure 2.

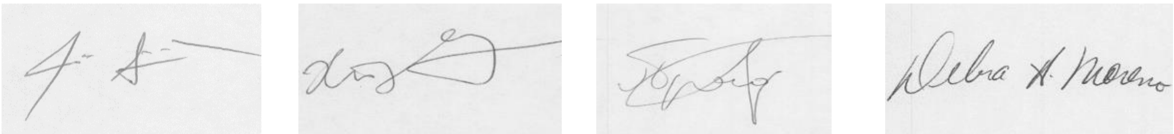

Figure 2. Samples signatures images of CEDAR dataset [18]

2.2. Preprocessing

Preprocessing is a very useful stage in any system that deals with various type of images. This stage prepares the input image for the next stages and could lead the system to better results. In the proposed system, five steps are applied to obtain the better preprocessing output. Since the input to the proposed system is a grayscale image of the handwritten signatures, the first step is enhancing the input images [19]. In this paper, two dimensions of wavelet transform (WT) are used for enhancement [20]. The result of applying the WT for the input image is shown in Figure 3. Besides, the second step of the proposed preprocessing stage is image scaling [21]. Reducing the input handwritten signature image size makes the computation timeless. In another hand, the size of the input images must be the same to build the proposed model in the next stage. Figure 4 shows the output image after applying the image-scaling step.

Thresholding is the third step of the proposed preprocessing stage in the propsed system [22]. It is the process of converting the input Grayscale image into a binary image using one of the thresholding methods. In this step, fuzzy C-mean clustering (FCM) is used to convert the image to binary [23]. Converting the image to binary is reducing the image size and the unwanted information in the background, thus increasing the computation time. In Figure 5, the output binary image after applying the thresholding step is illustrated. For further size reduction and removing the unwanted pixels in the input handwritten signatures images, noise removal and image thinning in [24] are applied. Figure 6 shows the final output handwritten signature image of the proposed preprocessing stage.

Figure 3. Image enhancement

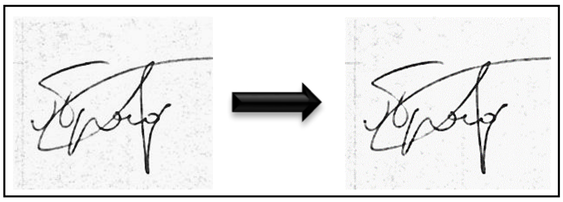

Figure 4. Image scaling

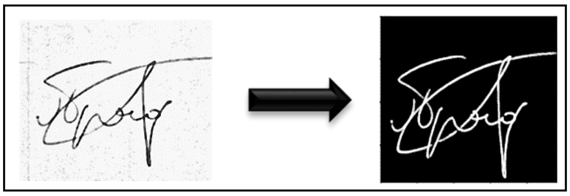

Figure 5. Image thresholding

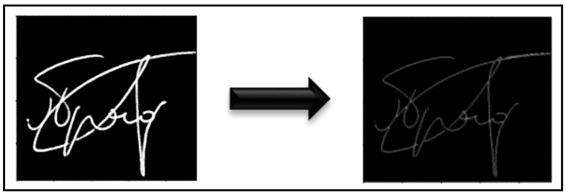

Figure 6. Image thinning and noise removal

2.3. Classification

The second stage of the proposed system is handwritten signature classification. This stage is used to classify the handwritten signatures of the signatures writers. MobileNets is used to classify the used handwritten signatures according to their desired users. MobileNets model is a deep learning model that designed to be used in mobile applications. Additionally, it is the initial mobile computer vision model for TensorFlow library. Depthwise separable convolutions are used by MobileNets for extracting the required features from the preprocessed handwrittien signature images. When compared to a network with regular convolutions of the same depth in the nets, it dramatically reduces the number is dramatically reduced. Lightweight deep neural networks are produced as a result using pointwise and the Softmax classifier. The foundation of the MobileNet model is a type of factorized convolution that factorize a standard convolution as depthwise separable convolutions, and an 11 convolution known as a pointwise convolution [25]. In this paper, a proposed MobileNets architecture is proposed for classification the input handwritten signature from the previous stage. The proposed architecture depends on using a SVM [26] instead of Sfotmax classifier in standard MobileNets for obtaining better accuracy results. The proposed MobileNets architecture of the proposed system is illustrated in Figure 7.

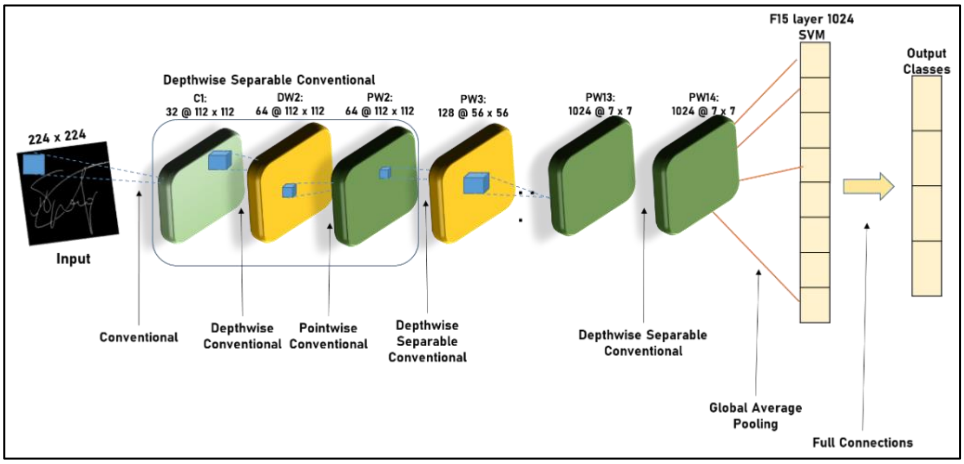

Figure 7. Proposed MobileNets architecture

2.4. Identification

The final stage of the proposed system is identify the desired writer of the classified handwritten signature. In this stage, the output classes of the previous stage are assigned to their desired users of the classified handwritten signature. Since the dataset has 55 users of the handwritten signatures, 30% of the dataset is used to evaluate the proposed work in this stage and check whether the handwritten signatures are assigned correctly to their users or not.

3. RESULTS AND DISCUSSION

The proposed work is implemented on Windows 10, 64 bits environment, and Python 3.11 on CoLab [27] is used for coding. Several experiments have been done for evaluating the system. First, the proposed work used three standard datasets CEDAR, ICDAR [28], and Sigcomp [29], to test the performance. The used dataset is divided into train and test sets when 70% of the images are used for training the proposed work and the rest of 30% is used for testing. The results of the proposed work are not affected by increasing or reducing the number of training and testing sets. Table 1 shows the identification results using the three mentioned handwritten signatures datasets.

Table 1. Identification results from applying different handwritten signatures datasets

No.	Dataset	Accuracy (%)
1	CEDAR	99.8
2	ICDER	98.2
3	Sigcomp	99.5

The proposed work achieved high identification accuracy with the used dataset. The highest obtained result was using the most common signatures handwritten dataset (CEDAR) since it has 1320 handwritten signatures images for 55 different users. Further, the proposed preprocessing stage leads to better identification results. All the used steps in preprocessing made the input handwritten signatures images clear and remove the unwanted information that may create differences between the handwritten signatures images for the same user. The obtained results of applying the proposed preprocessing stage are shown in Figure 8.

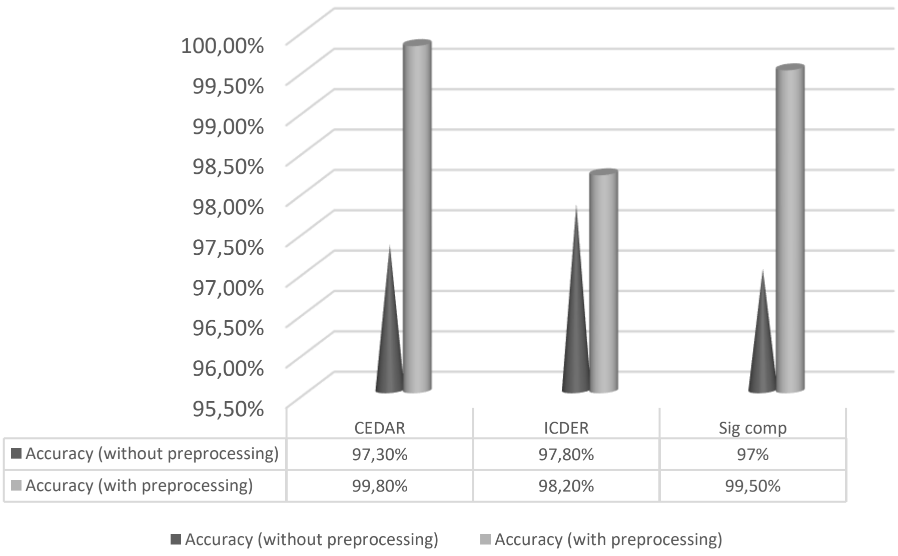

Figure 8. Identification results from applying the proposed preprocessing stage

In addition, MobileNets is a powerful deep learning network that is successfully applied for many image classification systems. Although the standard Mobilnets achieved satisfactory results, an improvement for better results could be reached. In machine learning, SVM is a powerful classifier that is used in many applications and achieved a very high accuracy rate. Using SVM as a classifier in our work increased the accuracy and reduced the classification errors. Table 2 shows the results of applying the standard MobileNets and the proposed architecture based on the SVM classifier.

Table 2. Identification results from applying the standard MobileNets and the proposed

No.	Dataset	Accuracy of MobileNets (%)	Accuracy of the proposed work (%)
1	CEDAR	99	99.8
2	ICDER	97.5	98.2
3	Sigcomp	97	99.5

Many testing processes have been performed to get better identification results. The used dataset is divided many times with various numbers of training and testing sets. Besides, a validation set is taking place in our experiment to reduce classification errors during the training phase. An example of achieved results using some experimental is illustrated in Table 3. The results in Table 3 shows the impact of changing the number of the training, testing, and validiation sets on the obtained results for the thress used datasets. Increasing or decrasing the number of each set does not have a critical eefictes on the results which means that the proposed system will accurately work with various divided sets.

Table 3. Accuracy off different divided sets of the three datasets

Dataset	Number of training set (%)	Number of testing set (%)	Number of validation set (%)	Accuracy (%)
CEDAR	70	20	10	99.8
CEDAR	60	20	20	100
CEDAR	50	30	20	100
ICDER	70	20	10	98.2
ICDER	60	20	20	98.5
ICDER	50	30	20	98.2
Sigcomp	70	20	10	99.5
Sigcomp	60	20	20	99.6
Sigcomp	50	30	20	99.5

Comparisons between the results of the proposed work with other existing works are performed. Several works in recent years have been done for signature recognition and verification. However, very few works are designed for signature identifications. In Table 4, the results of the proposed work are compared with the most recent works of handwritten signatures.

Table 4. Comparisons results from the proposed work and other works

Reference	Dataset	Method	Accuracy (%)
[8]	CEDAR/Gods/Mcyt	CNN/capsule	91-89
[9]	CEDAR/Icdar	CNN/capsule	90
[10]	Gpds/CEDAR	HSR	97-98
[11]	Sigcomp2009, Sigcomp2011, private dataset	Euclidean distance	99.4
[12]	CEDAR	CNN	94
[13]	CEDAR	CNN-GC DB-GC	99 93
[14]	CEDAR/ Gpds	CNN-SCN TC OC-PCA	98 97.9 94.9
[15]	CEDAR MCYT UTSig	CapsNet ResNet	100 99.8 99.3
[16]	CEDAR	FUZZY	FAR 6.3 FRR 4.8
[17]	Private dataset	CNN	72.7-99
Proposed	CEDAR, ICDER, Sigcomp	MobileNets	98.2-100

4. CONCLUSION

The paper proposed an accurate handwritten signature system based on MobileNets model and SVM classifier. The proposed system achieved a high identification rate of 98.2%-100% using different standard handwritten signature datasets, which are CEDAR, ICDER, and Sigcomp. The use of an efficient preprocessing stage based on enhancing the input images with a suitable thresholding method leads to better identification results. On another hand, the SVM classifier enhanced the Mobilenets model results at the classification part of the proposed architecture. In future work, the proposed architecture could be modified to work for online handwritten signatures.

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