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Handwritten Signature Verification Method Using Convolutional Neural Network

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Abstract

Automatic signature verification methods play a significant role in providing a secure and authenticated handwritten signature in many applications, to prevent forgery problems, specifically institutions of finance, and transections of legal papers, etc. There are two types of handwritten signature verification methods: online verification (dynamic) and offline verification (static) methods. Besides, signature verification approaches can be categorized into two styles: writer dependent (WD), and writer independent (WI) styles. Offline signature verification methods demands a high representation features for the signature image. However, lots of studies have been proposed for WI offline signature verification. Yet, there is necessity to improve the overall accuracy measurements. Therefore, a proved solution in this paper is depended on deep learning via convolutional neural network (CNN) for signature verification and optimize the overall accuracy measurements. The introduced model is trained on English signature dataset. For model evaluation, the deployed model is utilized to make predictions on new data of Arabic signature dataset to classify whether the signature is real or forged. The overall obtained accuracy is 95.36% based on validation dataset.

Keywords
Authentication , Convolutional neural network, Handwritten signature , Offline signature , Verification ,Writer independent (WI).

I. Introduction

Handwritten signature verification has gained a considerable amount of interest in the latest research, in terms of dealing with issues of authentication and fraud. Signature verification is an essential to authorize individual identity. Handwritten signature verification is a crucial task to prevent forgery problems that could lead to bad outcomes [1]. There are two types of handwritten signature verification and recognition methods: online verification (dynamic) [2] and offline verification (static) methods [3]. An online signature verification method utilizes an electronic signature based on particular devices such as pressure sensing of mobile phones, digitizers, and smart pens. Online methods use the dynamic features of a handwritten signature such as order of strikes, time, speediness, pressure [2]. On the other hand, offline signature verification and recognition methods use an ordinary procedure by signing a paper by a pen and then the image of signature is scanned and fed to a classifier to verify the signature [2–6]. Despite witnessed developments in technology lately, an offline signature verification system is still necessary in many countries that are still depends on paper works in their dealings. Offline signature verification is a difficult issue, since no dynamic features come from sensing devices are available like in online signature. Extracting sophisticated features for offline signature verification is challenging [6–9]. This paper proposes an offline signature verification method to verify whether the input signature is real or forged. Besides, signature verification approaches can be categorized into two styles: writer dependent (WD) [9, 10], and writer independent (WI) styles [9, 11]. In WD style, a classifier is trained separately on samples of signatures for each person, and when a new person's signature joins the system, the classifier is retrained. In contrast, in the WI approach the system is developed so that a new person's signature is checked without the necessity to retrain the classification model [12, 13]. This study proposes to use WI style. Signature verification is an essential part of many business processes.

There are many of introduced studies for online and offline signature verification in the literature. Ismail et al. [14] Introduced offline Arabic signature recognition and verification system of two separate phases. This technique based on a multistage classifier and a set of global and local features. The algorithms for signature verification are relies on fuzzy concepts. Iranmanesh et al. [15] was employed a systematic method for online signature verification using multilayer perceptron (MLP) on a subset of principal component analysis (PCA) features to analyze the signature time series signals. This method explain a feature selection technique utilizing information extracted from PCA on handwritten signature which can be significant by obtaining reduced error rates, this technique obtain an 93.1% accuracy on 200 users and 8,000 signatures consisting of genuine and forger signatures. In Hafemann et al. [16] the method employed the representations from signature images, using CNN to process the difficulty of obtaining good features, and improve system performance. They suggested a new formulation that includes knowledge of the professional forgeries from a subset of users in the feature learning process, which aims to capture visual sign that distinguish real signatures and forgeries regardless of the user. In Gideon et al. [17] handwritten signature forgery detection is explored on English signature dataset. The forgery signature system used the static features which involves image processing techniques to analyses the accuracy of the signatures based on a CNN. Poddar et al. [18] used a method specialize in the signature as biometric feature to discern forgery in signature. It used a Convolution Neural Network (CNN) for signature forgery detection and relies on Crest-Trough method, speeded up robust features (SURF) algorithm and Harris corner detection algorithm; this system got an accuracy of 85-89% for forgery detection and 90-94% for signature recognition. Ghanim et al. [19] introduced SVM and CNN classifiers independently for offline Arabic handwritten recognition method, by implementing multistage cascading system. This approach began with applying the Hierarchical Agglomerative Clustering (HAC) technique to divide the database into partially interrelated clusters. The inter-relations support representing the database as a big search tree model and help to reduce the recognition complexity in matching for each test image with a cluster, and higher recognition accuracy of 90%. Upadhyay et al. [20] introduced offline signature verification model based on multi-dilation convolutional neural network, the proposed model was validated using dataset of CEDAR that involves 24 images of genuine and 24 images of forgery for every 55 signer. Longjam et al. [21] proposed multi-scripted writer independent offline signature verification method by suggesting hybrid of CNN and Bi-directional Long Short Term memory (BiLstm) techniques, to recognize skilled forgery and genuine signatures. Their study used different datasets from the literature such as GPDS-300, GPDS-Bengali, GPDS-Devanagari, CEDAR, BHSig260-Bengali, BHSig260-Hindi, and Meitei Mayek signature. The system evaluated on various multi-scripted signatures based offline that belongs to multiple lingual Indian community. However, lots of studies have been proposed for WI offline signature verification. Yet, it is necessary to improve the overall accuracy measurements [7, 22–25]. Working this paper proposed a handwritten signature recognition method using CNN model architecture. The developed model is tested on Arabic handwriting signatures data to recognize whether the provided signature is real or forged. The contribution of this study is summarized as below:

1- Developing deep learning model for writer independent (WI) offline signature verification system based on convolutional neural network model architecture.
2- Developing an Arabic signature dataset that consisting of genuine signature samples and forged signature samples.
3- Evaluating and testing the deployed model to make classification and verification on the Arabic signature dataset.

The paper is organized as follows: Section II. presents the proposed method, Section III. presents the results and discussions, and Section IV. presents the conclusion.

II. Proposed Method

This paper introduced a method for offline handwritten signature recognition, by using a deep learning concept. The proposed method implemented a model architecture based on CNN [1]. Features of CNN network is proposed to extract depth and high descriptive cues from signature images, by using multiple CNN layers. Max pooling layer is proposed to interpose between CNN layers to select good and most representative features each time. The extracted features are flattened into one feature vector. Then, the fully connect layer (Dens network layer) with 128 neurons is proposed for features mapping and to make classifier learns from these features. Dropout layer of 20% is proposed here to overcome overfitting problem. At last of model architecture, Softmax classifier is proposed to recognize real signatures from forged signatures. The framework of the proposed method is depicted in Fig. 1.

A. Data Preparing

This method is utilizing two offline image datasets of handwritten signatures. The first dataset called handwritten signature, and it consisted of English signatures. This dataset was used by [26], and it was on Kaggle platform (https://www.kaggle.com/datasets/divyanshrai/handwritten-signatures).

The data consists of 360 genuine signature images and 360 forgery signature images. The total images are 720 images for both genuine and forgery. This data is prepared for model training and fitting. The second data is for Arabic signature and is prepared by this study for model testing and deployment, the number of signature images within this dataset for each category is 80 images for genuine and 80 images for forgery, where 20 different people were asked to sign 4 forged signatures and 4 real signatures.

B. Data Preprocessing

After data uploading and images are read, a pre-processing operation is performed to prepare data for features extraction and recognition process using CNN model of recognition. At a very beginning the images is resized into 64× 64 dimension, to facilitate the model process and prevent noise from getting in, then the images is converted into grayscale color in order to make the model learning easier. Normalization and Binarization process is then performed. The labels are hot-coded into binary categorical 0 for genuine class, and 1 for forgery class. Later, the data are shuffled and splits randomly into 80% train data, and 20% test data. The test data are further split into 15% validation data and 5% test data.

C. Model Construction

This study constructs a model for offline handwritten signature recognition utilizing a deep learning concept. The model consists of features extraction procedure and a classification or signature verification procedure. The feature's capturing procedure is done using the convolutional neural network [14], since CNN features can extract the deep cues in the image reaching into an object of interest [27]. This work proposed building three convolution layers for features extraction including three max pooling layers for features selection. The recognition and signature verification procedure is performed by proposing two fully connected layers of a deep neural network; the proposed model architecture is shown in Fig. 2. More details regarding the architecture of the proposed model can be reached in Table I.

D. Features Extraction

Three conventional layers are proposed for deep features extraction from images of signature. CNN has proved its ability to capture high hire sophisticated appearance features within the images. Convolution process is performed with filter size

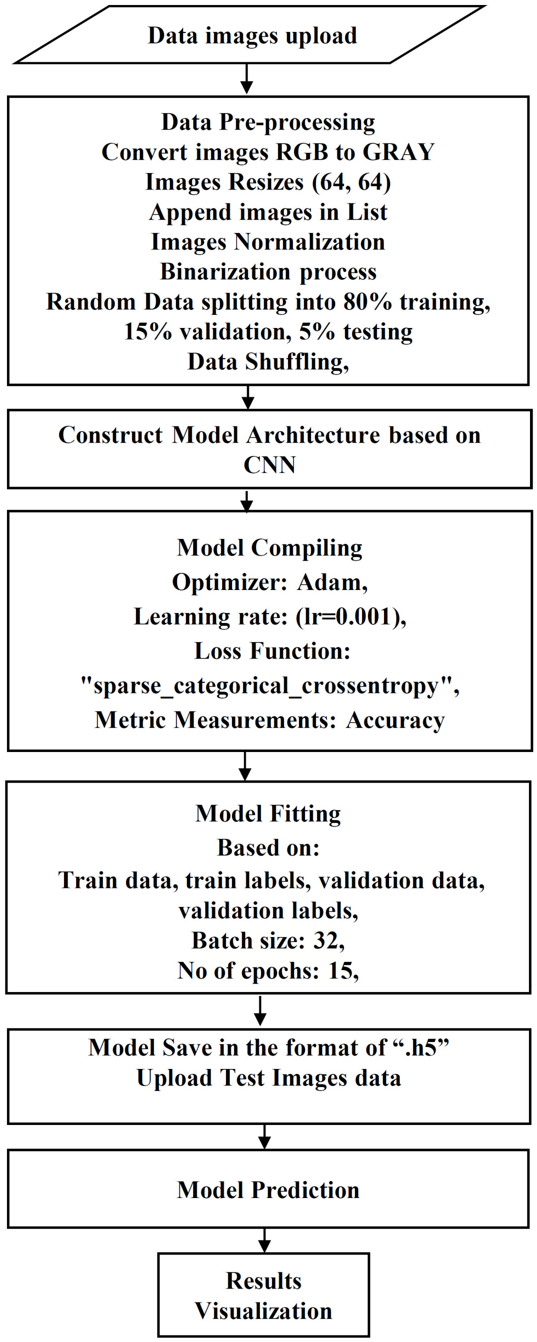

Fig. 1. The framework of the proposed method.

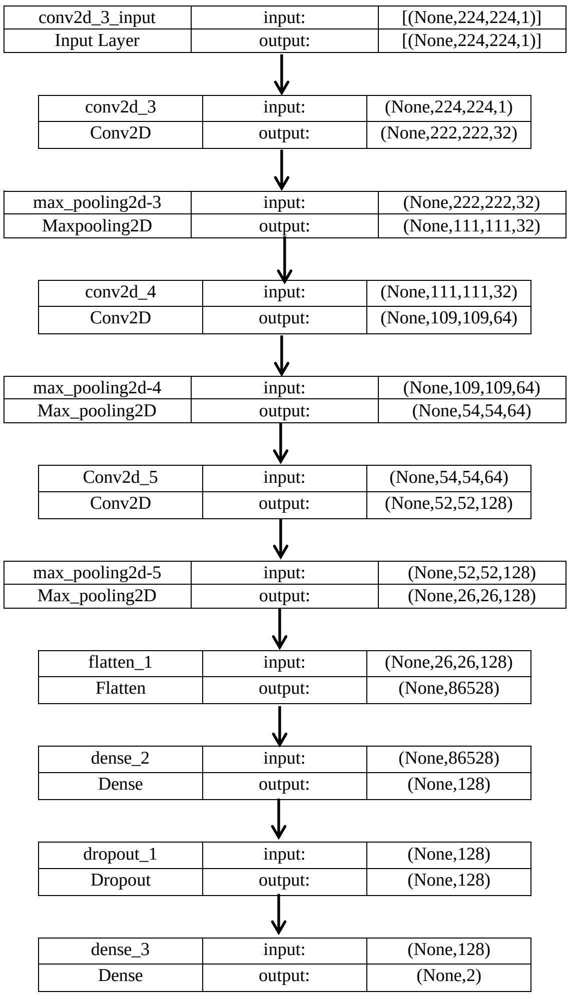

Fig. 2. Plot of the proposed model architecture.

3×3; while the number of filters for three layers is 32, 64, and 128 respectively. Max pooling layer is proposed after each convolution layer to keep good features as depicted in model architecture Table I.

E. Model Training and Fitting

For model training, the features are first flattened into features vector, and then fully connected layer (Dense network) is proposed for features processing and recognition, which assigned 128 neurons, by using activation function Relu. Dropout layer is suggested with rate 0.2 to avoid overfitting, due to dropout can skip some neurons every time to avoid too much training and by that overfitting problem could be overcome. Then dense layer with Softmax activation function is proposed to classify the features into two classes. The optimization function that has been proposed for model training is "Adam" with learning rate 0.001. This work employed

TABLE I.
THE PROPOSED MODEL ARCHITECTURE

Layer Input	Setting
Input layer	64×64×1
Convolution	32×3× 3
Max pooling	2 × 2
Convolution	64 ×3 × 3
Max pooling	2 × 2
Convolution	128 ×3 × 3
Max pooling	2 × 2
Flatten layer	
Fully connected layer	128 neurons, activation function : Relu
Dropout	0.2
Fully connected layer	2 classes , activation function : Softmax classifier

"sparse_categorical_crossentropy" as loos function to compute the error between given results and predicated results during training. Model fitting is performed based on the specified data of training and validation utilizing batch size of 32, and the no of epoch is 15.

III. RESULTS AND DISCUSSION

This paper is implemented a deep learning method for offline handwritten signature recognition via introducing a deep architecture model based on CNN network. The method implemented using programming language instructions of Keras Tensorflow library of Python. GPU of Google Colab platform is utilized to run the code on HP laptop with Intel core i7, and Nvidia Getforce GPU. This study executed a method to recognize genuine signature from forgery signature utilizing collected dataset of scanned images of handwritten signature taken from many individuals. The collected dataset consists of 720 images, 360 images for genuine signature, and 360 images for forgery signatures, to be used for training and validating the proposed model. The model is implemented after randomly splitting the data into train, validate, and test images. This work implemented a method based on CNN network for features extraction procedure while dense network or deep neural network is proposed for features classification process as illustrated in section II. This study conducted a quantitative measurement based on accuracy metric to evaluate the performance of this method. The proposed model based on CNN network utilized training accuracy, training loss error, validation accuracy, and validation loos error to evaluate the functionality of the model during fitting process. The batch size is 32 and epoch no is 15. The acquired accuracy for validation dataset is 0.9536 %. The outcomes of model train-

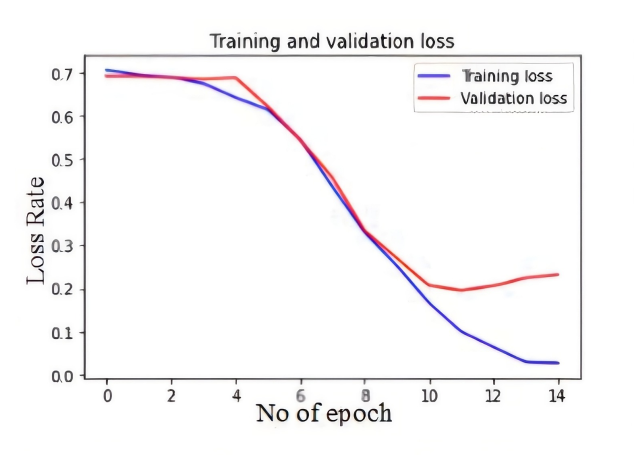

Fig. 3. Progress of model fitting using loss error metric.

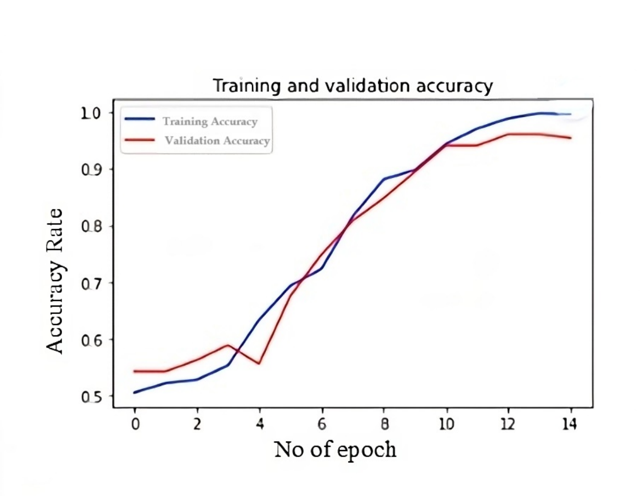

Fig. 4. Progress of model fitting based on accuracy metric.

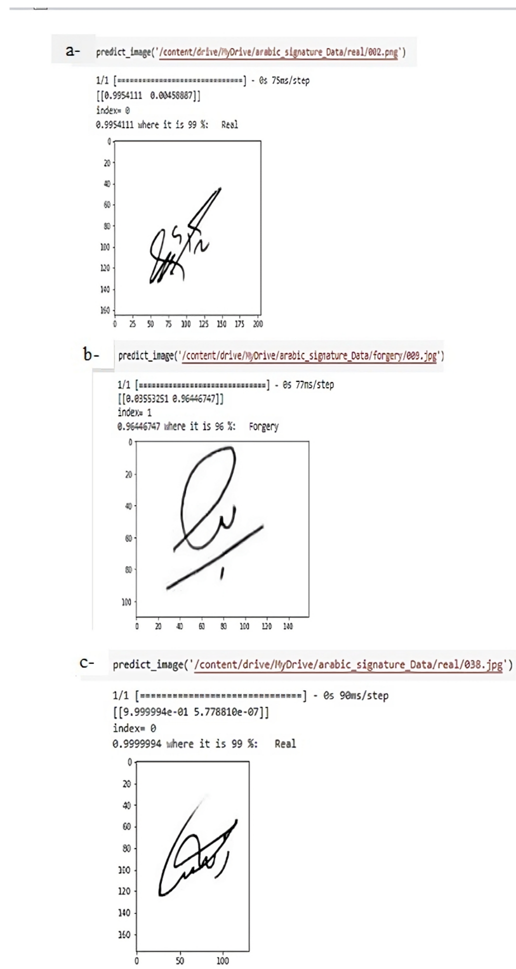

Fig. 5. The outcomes of signature recognition using images from Arabic dataset.

ing progress based on loss error and accuracy are depicted in Fig. 3, and Fig. 4. The obtained results from model training and fitting are summarized in Table II. The model is saved using ".h5" file and deployed on test data (non-trained images) to make prediction, the obtained accuracy and loss error are 100%, and 0.0488 consecutively as illustrated in Table II, which demonstrate that the model has succeed in recognizing all images of test data. Furthermore, the deployed model is used to make prediction on Arabic signature data images as non-trained data. Arabic signature dataset was prepared by this study, which consists of 80 images of forgery signature and 80 images of real signatures. Consequently, the gained outcomes presented a good performance for the proposed method including the deployed model based on the proposed architecture of CNN network for both features extraction and recognition procedure. The method can perform correct predication and recognize the genuine signatures from forgery signature based on Arabic signature data as depicted in Fig. 5, and Fig. 6. The Arabic signature dataset has prepared by this work to be employed within this prediction task.

Comparison evaluation with recent studies has been made to recognize the performance of the proposed method from previous studies performance. Table III. conducts a comparison with previous methods based on accuracy metric, which reveals that the proposed method has good performance versus other stated studies in Table III.

IV. Conclusion

This paper highlighted the challenges of WI offline signature verification systems and the necessity to improve the perfor-

TABLE II.
SUMMARY OF MODEL TRAINING, FITTING, AND TESTING RESULTS.

Data	Obtained accuracy	Obtained loss Error
Training set	0.995	0.0273
Validation-set	0.9536	0.2322
Test-set	1.000	0.0488

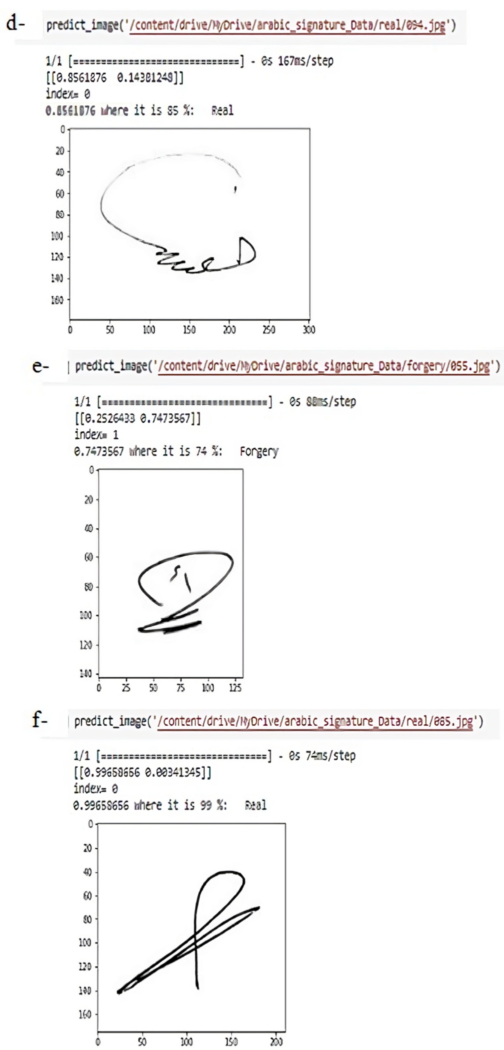

Fig. 6. The outcomes of signature recognition using images from Arabic dataset.

TABLE III.
COMPARISON EVALUATION WITH RECENT STUDIES

Study	Accuracy
Wei et al.,2019 [22]	90.17%
Xiao & Ding (2022) [23]	95.66%
Ren et al., 2022 [24]	93.25%,
Lopes et al., 2022 [25]	85.0 %
The proposed method	95.36 %

mance of existing methods. Therefore, this work proposed to develop deep learning model-based CNN to perform WI offline signature verification. The proposed model was trained, validated and tested on collected English signature dataset. The developed model is utilized to make prediction and verification on Arabic signature samples which was created for this study. The experimental outcomes have shown a good performance in term of accuracy. However, this work needs to enhance the accuracy via increasing the training dataset samples. Fore future work, to improve the accuracy, this work aims at exploring different techniques for features extraction, selection, and classification. Exploring other datasets challenges.

CONFLICT OF INTEREST

The authors have no conflict of relevant interest to this article.

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