Offline Author Identification using Non-Congruent Handwriting Data Based on Deep Convolutional Neural Network

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Abstract—**This investigation presents a novel technique for offline author identification using handwriting samples across diverse experimental conditions, addressing the intricacies of various writing styles and the imperative for organizations to authenticate authorship. Notably, the study leverages inconsistent data and develops a method independent of language constraints. Utilizing a comprehensive dataset adhering to American Society for Testing and Materials (ASTM) standards, a deep convolutional neural network (DCNN) model, enhanced with pre-trained networks, extracts features hierarchically from raw manuscript data. The inclusion of heterogeneous data underscores a significant advantage of this study, while the applicability of the proposed DCNN model to multiple languages further highlights its versatility. Experimental results demonstrate the efficacy of the proposed method in author identification. Specifically, the proposed model outperforms conventional approaches across four comprehensive datasets, exhibiting superior accuracy. Comparative analysis with engineering features and traditional methods such as Support Vector Machine (SVM) and Backpropagation Neural Network (BPNN) underscores the superiority of the proposed technique, yielding approximately a 13% increase in identification accuracy while reducing reliance on expert knowledge. The validation results, showcase the diminishing network error and increasing accuracy, with the proposed model achieving 99% accuracy after 200 iterations, surpassing the performance of the LeNet model. These findings underscore the robustness and utility of the proposed technique in diverse applications, positioning it as a valuable asset for handwriting recognition experts.**

Keywords—Handwriting recognition; offline author identification; deep convolutional neural network; image processing; language versatility; feature extraction; hierarchical model

I. INTRODUCTION

In the field of machine vision and pattern processing, manuscript recognition is one of the most active investigation areas [1-3]. The characteristics of handwriting depend on the writing styles of the language. It is considered to be one of the most important signs in the analysis of handwritten documents. There have been numerous proposals for classification methods to address the issue of author identification [4-6]. There are two categories of manuscript identification: online and offline. While, in offline methods, only the image of the manuscript is available, online methods receive the time order of the coordinates, which expresses the movements of the pen tip of the person [7].

Awaida et al. [8] offered a method for identifying authors based on statistical and structural characteristics of Arabic texts. In this method, Euclidean distance criteria were used in conjunction with the nearest neighbor algorithm. In addition, data reduction algorithms were used to reduce the dimensions of the data. Using a multi-channel Gradient-based approach, Alavi et al. [9] offered a method for offline recognition of handwritten Persian documents. A limited set of data could be extracted and classified using Euclidean distance criteria using this method. Using the described method, good performance was achieved on Persian handwritten documents. A new method for identifying Persian manuscripts online has been presented by Valikhani et al. [10]. An offline author identification algorithm based on Moore's algorithm was proposed by Keykhosravi et al. [11]. Using this method, four comprehensive data sets were analyzed, and significant accuracy was achieved in identifying handwritten documents. An offline text recognition method based on distance-based classification has been proposed by Kumar et al. [12]. Six different data sets were used in this study to extract structural features using an isotropic filter. Mamoun et al. [13] investigated an offline method for handwriting recognition. This study examined the efficacy of the described method using a neural network and a support vector machine.

Using deep learning, Ansari et al. [14] presented a system for recognizing handwritten characters. The system was trained to identify similarities as well as differences between different samples of handwriting. An image of a handwritten text was converted into a digital text using this system. Results indicated that this system is most accurate when dealing with texts that contain less noise. Additionally, the accuracy of the stated system is completely dependent on the data set, and if the data set increases, more accuracy can be achieved. Using offline Bengali manuscripts, Adak et al. [15] examined author verification and identification methods. A DCNN model was used to extract automatic features from these manuscripts. A recurrent neural network (RNN) has been proposed by Zhang et al. [16] to recognize online authors. An online handwriting recognition structure based on deep neural networks has been presented by Carbune et al. [17]. According to Chahi et al. [18], multi-path deep learning can be used to identify the author (independent of the text) of a given piece of writing. This study uses a version of ResNet that combines deep residual networks with a traditional handwriting descriptor to analyze handwriting. As a primary and necessary feature of handwriting, the descriptor analyzes the thickness of the

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handwriting. An author identification method based on this method can provide a text-independent author identity that does not require the same handwritten content to learn its model. Using feature combinations, Xu et al. [19] offered a deep learning technique for author recognition based on the Chinese language. To obtain handwriting features from handwritten images, deep features, and manual features were combined. According to the outcomes of the investigation, it was found that this method performs better than other comparative methods when it comes to identifying Chinese characters. An automatic author identification method based on deep learning was presented by Malik et al. [20]. As the proposed model, a combination of U-net and Resnet networks was considered. Using the ICDAR17 dataset, they evaluated their proposed method and found that it provided better results than the comparative models.

A review of author identification studies indicates that, even though many studies have been conducted in this field, these studies have been limited in their findings. In most of these studies, the authors were identified using features extracted and selected using traditional methods. Based on a review of previous studies, it appears that there is no comprehensive database set that can be used by researchers studying right-to-left languages as a reference. The purpose of this work is to present a novel technique for identifying the author by using a right-to-left handwriting dataset. To accomplish this goal, a right-left data set containing sentences, words, and numbers has been collected. There are 86304 samples of people with differing genders, ages, occupations, and levels of education included in this data set. Based on the ASTM standard [21], different time intervals and test conditions were used to collect this data set.

Additionally, deep learning has been applied widely in the analysis of images and signals with great success. In the third objective of this study, a DCNN structure based on pre-trained networks is constructed to learn features hierarchically from the raw handwriting dataset. A significant aspect of the suggested structure is its ability to classify heterogeneous data sets. Thus, although the random samples used in the training and evaluation phases belong to a specific individual, they are not necessarily the same; they may even have nothing in common. This article focuses on using heterogeneous samples, which has been largely neglected in previous research. This innovation in the identification method is the most prominent aspect of the present study. The core contribution and novelty of our study lie in addressing the limitations identified in previous author identification studies. These studies primarily relied on traditional methods for feature extraction and selection, lacking a comprehensive database suitable for researchers studying right-to-left languages. To fill this gap, our work presents a novel technique for author identification utilizing a right-to-left handwriting dataset.

II. MATERIALS AND METHODS

The purpose of this section is to examine convolutional neural networks (CNNs) and long-short-term memory (LSTMs), which belong to recurrent neural networks.

A. Convolutional Neural Networks

The CNNs are an improved version of the neural network. Several layers in this network are trained together in a powerful manner [22-24]. The technique is very effective and is one of the most frequently used approaches in machine vision applications. There are three main layers in a convolutional network, namely the convolutional layer, the integration layer, and the fully connected (FC) layer. Random deletion and batch normalization layers are also used to prevent the process of overfitting and to improve the performance of the network [25]. Additionally, it is necessary to apply the activation function after each layer in neural networks.

By utilizing the kernel, the layer performs convolution on the input data. The convolution output is called a feature map. The convolution operator is as [25]:

$$y_k = \sum_{m=0}^{M-1} x_m R_{k-m} \tag{1}$$

In which x is the signal, R is the filter, M is the number of elements in x, and y is the output vector.

To normalize the data within a network, the batch normalization layer is employed [25]. The distribution of the data will change when different calculations are performed on the input data. As a result of this layer, the training speed of the network is increased, and the convergence rate is accelerated, which is intended to reduce the change in internal covariance. As a result of the batch normalization layer, the following transformation is achieved:

$$\mu_8 = \frac{1}{n}\sum_{i=1}^{n} y_i^{(l-1)} \quad \sigma_B^2 = \frac{1}{n}\sum_{i=1}^{n}\left(y_i^{(l-1)} - \mu_B\right)^2 \quad \hat{y}^{(l-1)} = \frac{y^{(l-1)} - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}} \quad z^{(l)} = \gamma^{(l)}\hat{y}^{(l-1)} + \beta^{(l)} \tag{2}$$

where, μ_B and σ_B^2 are the group mean and variance, respectively. l is layer number, $y^{(l-1)}$ is the input vector to the normalizer layer, $z^{(l)}$ is the normal output vector of a neuron, and $\gamma^{(l)}$ and $\beta^{(l)}$ are small constants for numerical stability. These parameters relate to changes in scale and learning rate, respectively.

An activation function is applied after each convolution layer. The activation function is an operator that maps the output to a set of inputs and is used to make the network structure nonlinear. As one of the most widely used activation functions, the Relu function has the characteristic of being nonlinear. In this manner, the network structure is resistant to minor changes in the input. An illustration of the Relu function can be found in Eq. (3) [25].

$$f(x) = \begin{cases} x & x \rangle 0 \\ 0 & x \leq 0 \end{cases} \tag{3}$$

Soft Max function: This function calculates the probability distribution of the output classes, which has the following form:

$$p_i = \frac{e^{x_j}}{\sum_1^k e^{x_k}} \qquad for = 1,...k \tag{4}$$

where, x is the input of the network and the output values of p are between zero and one, and their sum is equal to one.

B. Recurrent Neural Networks (RNN)

An RNN is a deep learning model that captures sequence dynamics through recurrent connections, which can be viewed as cycles in the network. On the surface, this may appear to be counterintuitive. The order of computation in neural networks is unambiguous due to the feedforward nature of the algorithm. It should be noted, however, that recurrent edges are defined precisely to avoid such ambiguities. In recurrent neural networks, the underlying parameters are applied at every time step (or sequence step). In contrast to standard connections, which propagate activations from one layer to the next at the same time step, recurrent connections pass information across adjacent time steps. This type of neural network can be viewed as a feedforward neural network in which the parameters of each layer (conventional and recurrent) are shared between time steps.

In sequence prediction problems, an LSTM network is a type of recurrent neural network that is capable of learning order dependence. The use of this type of behavior is necessary in several complex problem domains, consisting of speech recognition, machine translation, and others. In the field of deep learning, LSTMs are considered to be one of the most complex algorithms. The concept of LSTMs can be difficult to grasp, as can the meaning of terms such as bidirectional and sequence-to-sequence. Experts who developed LSTMs are better at explaining both their promise and how they operate than anyone else. Traditionally, RNNs have a single hidden state that is passed through time, which can impair their ability to learn long-term relationships. By introducing a memory cell, LSTMs overcome this problem by storing information for an extended period. Three gates control the memory cell: the input gate, the forget gate, and the output gate. Memory cells are controlled by these gates, which determine what information is to be added, removed, and output. A cell state and output value are transferred from the LSTM module to the next LSTM module. Fig. 1 depicts the gates and operations of an LSTM module graphically for L_p (for N the scheme would be similar), and in which it can be observed that the input for a unit is its output. LSTM modules transmit to each other their predictions, which, when combined with the current input, generate the output for the next module.
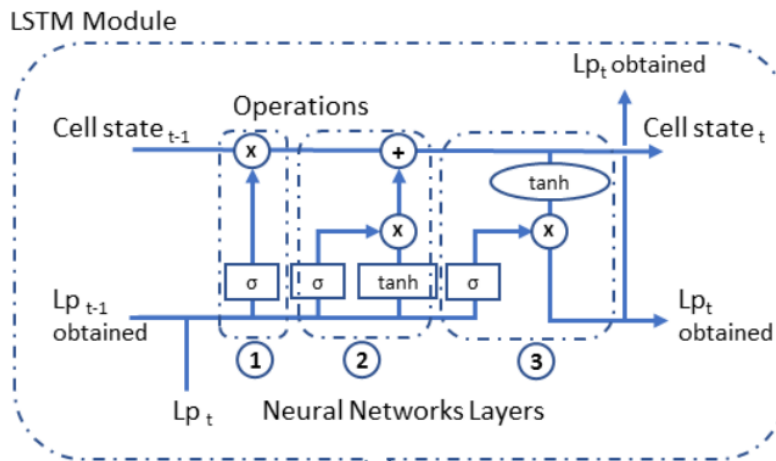

Fig. 1. An overview of an LSTM neural network for Lp [26].

III. THE PROPOSED METHOD

A. Data Collection

The evaluation of our proposed methods relies on the utilization of two publicly available datasets: CVL [27], IAM [27], IFN/ENIT [28], and KHATT [29]. These datasets contain segmented word images accompanied by labels for both word and writer. We conduct separate evaluations using these datasets due to the differences in the writers represented in each dataset. These datasets have generally been applied in recent works and are dependable and extensively used datasets in the area of author identification.

The CVL dataset, as referenced in [27], comprises 310 distinct writers, each of whom has contributed a minimum of five pages written in both English and German languages. The IAM dataset, as referenced in [27], encompasses 657 individual writers, each of whom has contributed at least one page written in English. Similar to the CVL dataset, the IAM dataset also includes word images along with labels for both the word and the corresponding writer. According to ASTM standards, handwriting samples were collected from 65 participants over some time and under varying environmental conditions (see Fig. 2). A total of 65 participants participated in this investigation, of which 36 were men and 29 were women, with an average age of 20 to 50 years old. Furthermore, 10 of the participants were left-handed, and 55 were right-handed. As a last step, handwriting textural and structural characteristics were determined using predefined standards. A separate sheet of paper was used to write each sentence twelve times by the ASTM standard. After writing all four sentences on one separate sheet, the next step was to write them on a separate sheet as well. It should be noted that two different kinds of standard paper were used, "PaperOne" and "Double-A," whose qualifications can be found in Table I.
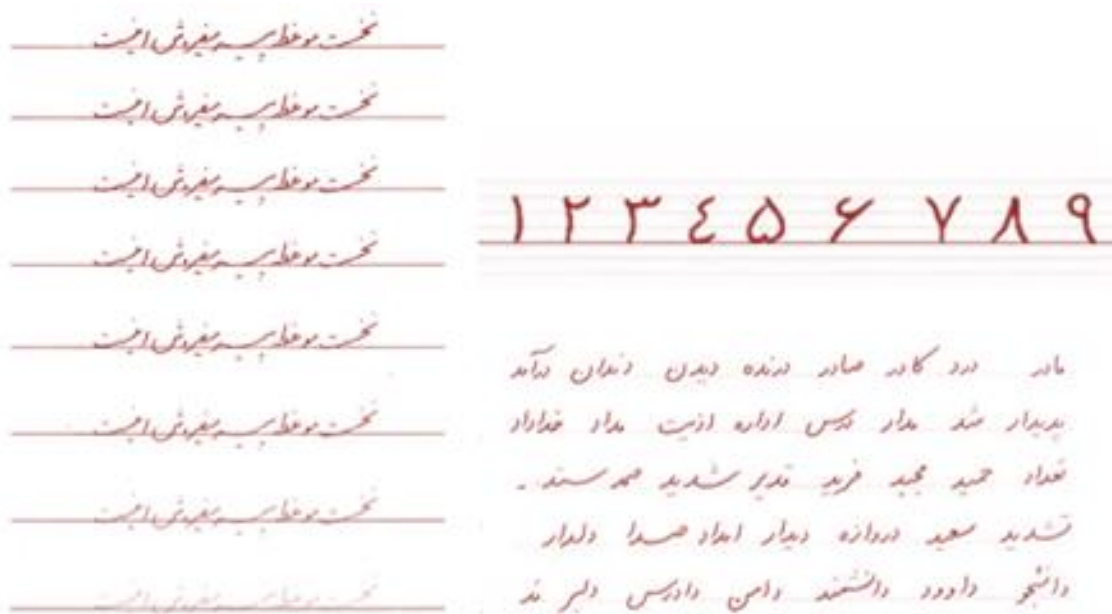
Fig. 2. Examples of handwriting collected in different situations.

TABLE I. PAPER'S SPECIFICATION DETAILS

Properties	Weight (g/m2)	Roughness (ml/s)	Thickness (μm)	Brightness (%)	Opacity (%)	CIE Whiteness
PaperOne	82±3%	145±4%	105±3%	97±2%	97±3%	159±2%
COPIMAX	81±3%	155±5%	106±2%	103±1%	-	167±2%

Two types of standard pens were used, namely "Schneider" and "Faber-Castell," which were color-coded as "blue" and "black." Each of the samples was written on a different writing pad, which is either called a "hard" pad or a "soft" pad. In the use of these two types of pads, the amount of pen pressure is intended to be shown. A RICOH Aficio MP 6001 was used to scan the collected samples at a resolution of 300 dpi in color mode. In the data set, a code book contains the order in which samples were collected and the required information and details. It is estimated that the data set collected from 65 participants contains 445 pages and 4203 sentences in total. Each sentence sample has a height of 235 pixels and a width that is variable. Page sizes for the sample pages are 1655 x 2339 pixels. Henceforth, DENE_HW will be used to identify this dataset.

B. Data Preprocessing

In this study, to reduce the execution time and volume of calculations, after separating 4203 sentences, the size of the sentences is first changed to 112 pixels and variable width. Then, using the segmentation method, 4203 sentences are divided into 86304 samples with a size of 112 x 112 pixels; after that, the samples are normalized.

C. Proposed Deep Network

A description of the proposed technique of the article is provided in this section. An illustration of the proposed algorithm can be seen in Fig. 3. The proposed deep network in this study is created by combining a pre-trained convolutional network, LeNet [30], with an LSTM network. By combining the LeNet network with the LSTM network, the advantages of both networks can be used simultaneously. In many studies, the combination of LSTM networks with deep convolutional networks has been utilized to lessen feature dimensions, increase stability, reduce fluctuations, improve the training process, and increase recognition accuracy. The proposed network is based on It is assumed that it consists of two layers of LSTM, three layers of batch normalization (BN), three layers of random elimination, and two layers of FC (see Fig. 3). Pre-trained systems are composed of several layers; each layer learns certain features. There are two layers of learning: the initial layer learns basic as well as low-level features, and the next layer learns complex and high-level features. This process involves the formation and adjustment of the weight matrix based on the learning process. The architecture of the suggested block is chosen as follows: (1) an FC layer with a linear function along with a batch normalization layer with a Relu function, after which a random removal layer is placed. (2) An LSTM layer with the Relu function, after which the batch normalization and random removal layers are placed. (3) The architecture of the prior stage is repeated once more. (4) An FC layer with a non-linear softmax function is used to access the output layer. In the suggested network, the output of the pre-trained network is a feature vector with a size of 512 x 256. A linear function is applied to the learnable weights of the obtained features (w) in the first layer of the suggested block, namely FC. As a result of the predicted bias values, the dimension of the feature vector is changed from 256 x 1 to 256 x 2. A non-linear softmax function was used to transform the selected feature vector into an FC layer using a non-linear softmax function in the hidden layers (see Fig. 3).
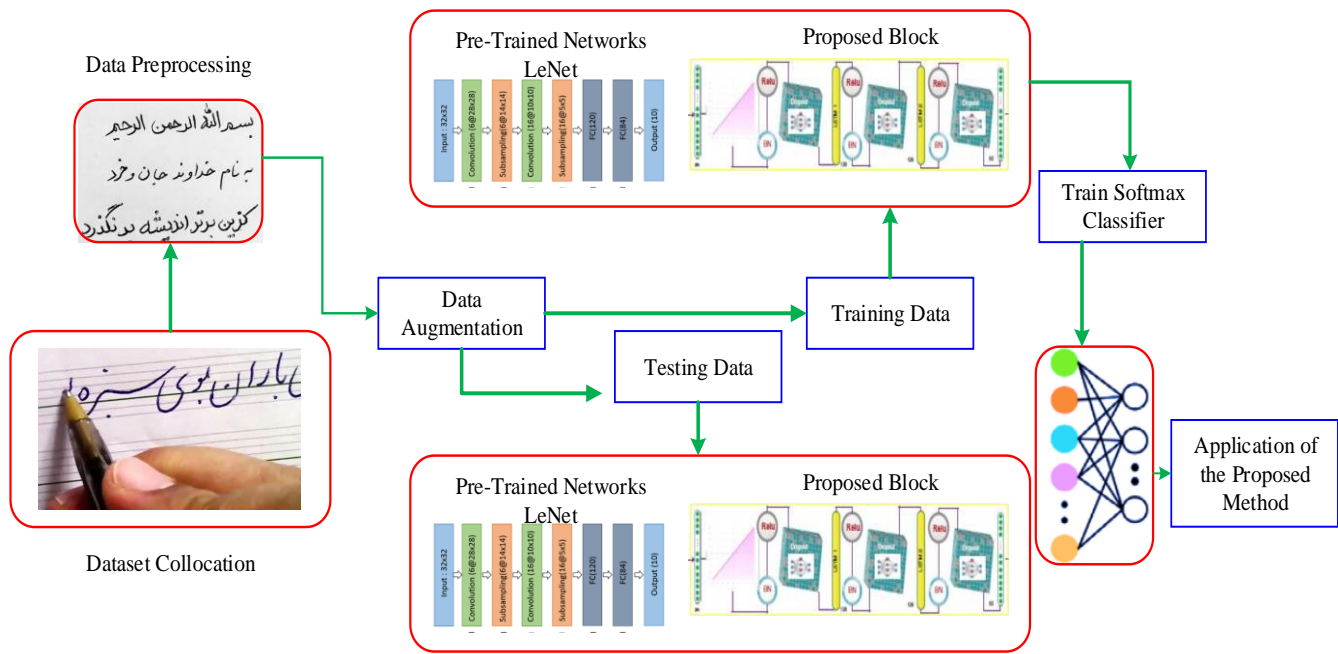
Fig. 3. The block diagram of the CNN-LSTM for automatic detection of the writer.

In this study, all the super-parameters of the proposed network have been carefully adjusted to get the best convergence rate, and finally, the cross-entropy error function and the stochastic Mini-Batch optimizer with a learning rate of 0.05 have been selected. The conventional method of error backpropagation with a batch size of 100 has been used for network training. The optimal parameters selected for the suggested method are shown in Table II. This table provides a clear overview of the parameters considered in our study, their respective search spaces, and the values deemed most suitable based on experimentation and optimization.

As it was said in this work, the training and evaluation of the suggested model are done using non-continuous data. Fig. 4 shows examples of inconsistent handwriting for the training and evaluation process. Due to the detail that all pictures 1-24 go to one person, pictures 1-15 belong to the training data set, and pictures 16-24 belong to the validation and evaluation data set. For example, pictures 1 and 3 are most similar to picture 18 (a). Also, images 6 and 16 are the same (b).

On the other hand, images 19 and 22 have no counterparts in the training data set (c). 60% of the collected samples are used for training data, 30% for validation data, and 10% for test data. A random selection of samples is also conducted for the training and evaluation sets.

TABLE II. THE OPTIMAL HYPERPARAMETERS FOR THE DCNN MODEL

| Parameter	Methods	Optimal value
Optimizer	Gradient Descent, Adam, Adagrad, SGD, Mini-Batch	Mini-Batch
Dropout ratio	0.0, 0.1, 0.15, 0.2, 0.25, 0.3	0.15
Batch dimension	2, 4, 6, 8, 20, 60	2
Loss function	Cross-entropy, Regression, AutoEncoder, GAN	GAN
Learning rate	0.05, 0.005, 0.0005	0.05
Activation function after BN layer	Binary Step, Tanh, ReLU, Parametric ReLU	ReLU
Momentum parameters	0.2, 0.4, 0.5, 0.6	0.4
Activation function in FC layer	Binary Step, Tanh, ReLU, Parametric ReLU	Tanh
Decay Rate of the weights	1e-3, 2e-3, 3e-3, 5e-3	2e-3
Activation function	Logistic, hyperbolic tangent, Softmax	Softmax
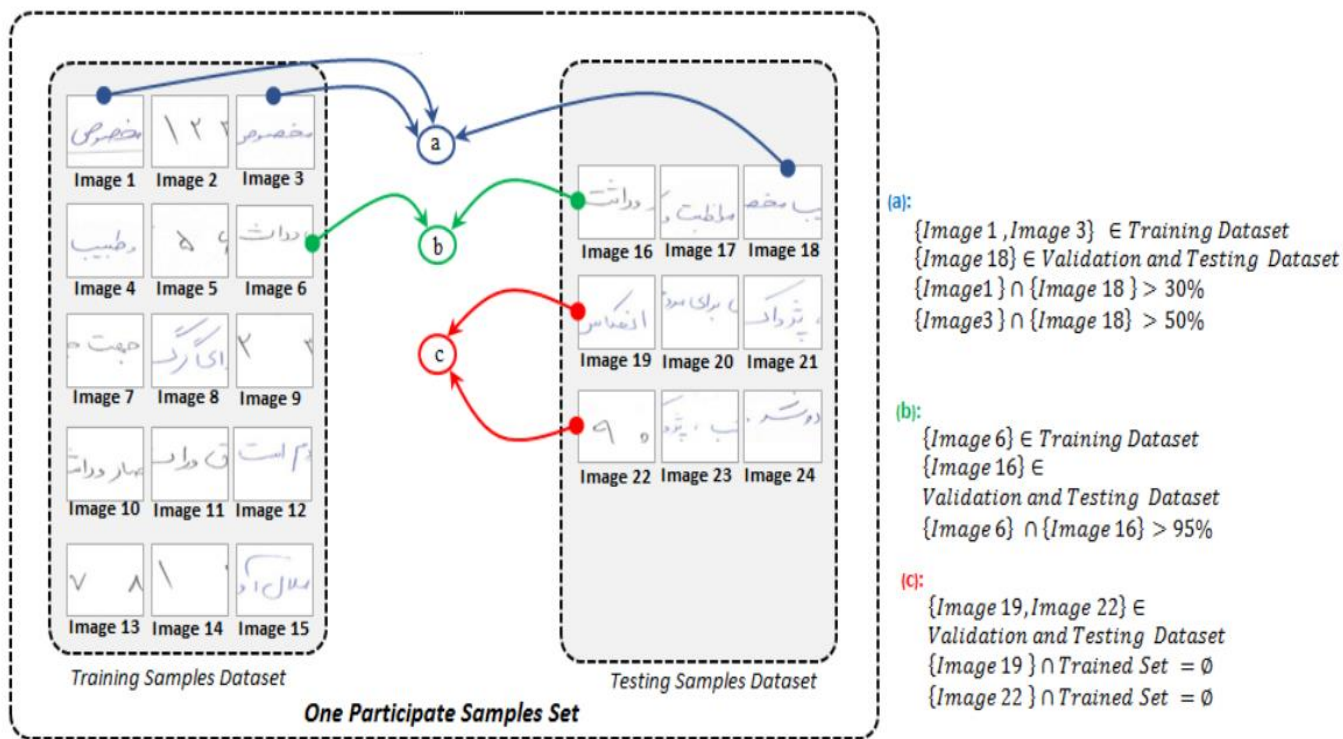
Fig. 4. Examples of inconsistent handwriting for the training and evaluation process.

IV. RESULTS AND DISCUSSION

Several libraries, including PyTorch and NumPy, were used to carry out the suggested author identification method and all results and reviews. These tests were performed on a computer with specifications of Intel Core i9-6700K CPU, GeForce GTX TIAN X 36GB graphics processor, 128GB DDR IV RAM, and 2TB SSD hard disk. To evaluate the performance of the proposed method, we have used the relationship related to accuracy, which is expressed as follows:

$$ACC = \frac{T_N + T_P}{T_P + T_N + F_P + F_N} \qquad (5)$$

In which, T_P is the positive cases that have been correctly diagnosed as positive. F_P is a negative case that is falsely diagnosed as positive. T_N is a negative case that is correctly diagnosed as negative. F_N is a positive case that was wrongly diagnosed as negative.

The experimental results for the proposed model (pre-trained network with the suggested block) and the pre-trained LeNet network without the proposed block are shown in Table III. These results indicate that both models perform better when using the TTA technique than when using the TTA technique. The accuracy of the evaluation of the suggested model using the TTA technique is 99.66%; however, the accuracy of the evaluation without using the TTA technique is 95.78%. In addition, LeNet evaluation accuracy with the TTA technique is 96.51%, while Resnet-152 evaluation accuracy without the TTA technique is 93.45%. According to Table IV, the accuracy and execution time of the suggested model are higher than those of LeNet.

The accuracy and error diagram for the validation data for the proposed model and Resnet-152 model using the TTA technique is displayed in Fig. 5. In this figure, it can be seen that the network error of the proposed model and the LeNet model decreases as the number of repetitions of the algorithm increases. As can also be seen, both the suggested model and the LeNet model reach 99% and 96% accuracy after 200 repetitions, respectively.

A total of four data sets described in Section III(A) have been used to estimate the suggested model. Table IV summarizes the recognition outcomes of the suggested model and the LeNet model with the TTA technique for identifying authors based on each of the four data sets. According to Table V, the suggested model based on the improved LeNet network performs better than the Lenet model for identifying authors using each of the four datasets.

TABLE III. EXPERIMENTAL OUTCOMES OF THE SUGGESTED MODIFIED DCNN MODEL AND LENET NETWORK

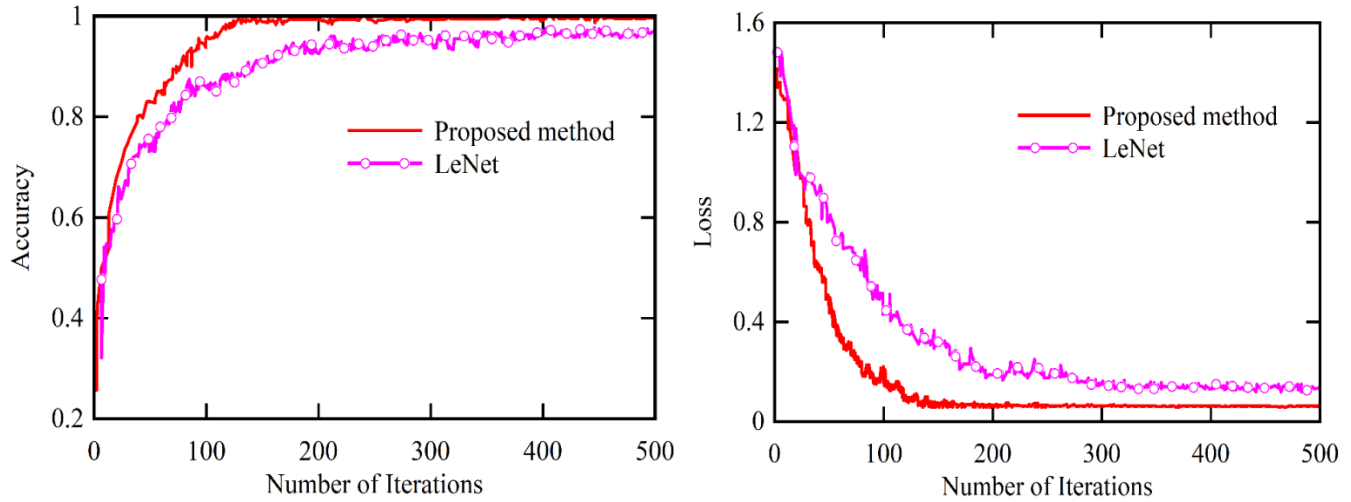| Network	without TTA	with TTA	Time with TTA (ms)	
	Acc.	*Acc.*	*Train*	*Test*
LeNet + Proposed method	94.76	99.57	16.57	1.70
LeNet	92.06	96.92	13.24	1.14

Fig. 5.   Accuracy and loss curve of the suggested model constructed on modified pre-trained networks.

TABLE IV.   EVALUATION OUTCOMES OF THE PROPOSED MODEL AND LENET MODEL FOR FOUR COMPREHENSIVE DATASETS

Network	Dataset				Acc. with TTA
	Name	*Language*	*Writer*	*Sample*	
Proposed method	IAM	English	150	4035	98.65
	CVL	English	305	1726	99.31
	KHATT	Arabic	798	10342	98.97
	IFN	Arabic	433	27983	99.35
LeNet	IAM	English	140	4035	96.35
	CVL	English	305	1726	98.18
	KHATT	Arabic	798	10342	95.35
	IFN	Arabic	433	27983	97.48

A comparison of the evaluation accuracy of different approaches for identifying authors is shown in Table V. A summary of the outcomes of the suggested model is presented in Table V. The comparisons are made based on two data sets, namely IAM as well as IFN/ENIT. The quantity of authors in each review is also shown in Table V. It ought to be mentioned that the differences presented in Table V regarding the number of examined samples in the stated data set are due to their availability. As displayed in Table V, about all the evaluation datasets, the classification accuracy indicators show better performance of the suggested model compared to other approaches.

To demonstrate the performance of the deep convolutional neural network (DCNN) model with the DENE_HW data set as input, the evaluation accuracy has also been obtained using other models. Based on this, the raw data of DENE_HW and several engineering features from the DENE_HW dataset, together with the fault backpropagation network (BPNN) and the support vector machine (SVM), have been selected as comparative models. A variety of models according to feature learning from raw data and engineering features are presented in Table VI, while the results of the suggested DCNN model with raw data as input, which is the suggested method, are highlighted. In Table VI, a comparison of the performance of features and engineering features is presented. With the proposed DCNN model, it appears that feature learning is more accurate than engineering features (with an increase of about 13%). This illustrates that DCNNs cannot perform better than traditional methods in author recognition without the ability to learn features.

TABLE V.   A SUMMARY OF THE OUTCOMES OF THE SUGGESTED MODEL COMPARED WITH OTHER METHODS

dataset	Ref.	Language	Writer number	Acc. (%)
IAM	[31]	English	640	89.53
	[32]		647	97.20
	[33]		647	69.47
	Proposed method		150	98.65

TABLE VI.   ACCURACY OF THE SUGGESTED TECHNIQUE COMPARED WITH OTHER APPROACHES

Method	Feature learning from raw data	Manual features
Back Propagation Neural Network (BPNN)	88.06	85.67
Support vector machines (SVM)	85.65	83.69
Proposed method	99.57	85.16

The significance of considering additional factors influencing the accuracy of writer recognition in handwriting analysis cannot be overstated. Variables such as the type of pen, paper, environmental conditions, noise, and light intensity can exert a substantial influence on recognition accuracy. In furtherance of this research endeavor, we propose the systematic collection of a new dataset that comprehensively incorporates these parameters. Through meticulous control of these variables, we aim to evaluate their singular and collective impacts on the efficacy of author identification methodologies. This meticulously curated dataset holds promise for yielding valuable insights into the resilience and dependability of handwriting recognition systems across diverse conditions. Moreover, we advocate for the evaluation of various methodologies, encompassing both deep learning models and traditional approaches, using this novel dataset. A comparative examination will facilitate the elucidation of the strengths and weaknesses inherent in different techniques when confronted with the variability inherent in real-world handwriting samples. Such a comprehensive study holds the potential to deepen our understanding of the determinants of writer recognition accuracy and foster the evolution of more resilient and adaptable handwriting recognition systems.

V.   CONCLUSION

This investigation aims to present a new technique for offline identification of the writer using handwriting samples under different experimental conditions, taking into account the complexity of writing styles and the need for organizations to recognize the handwriting of authors. The present study has two noteworthy and important characteristics. First, inconsistent data have been used in the present study, and second, the suggested method is independent of the language in question. Based on ASTM standards, a comprehensive data set was developed for this study. We have developed a DCNN model that extracts features from raw manuscripts based on a pre-trained network.

Based on the results of the present work, it was demonstrated that the suggested method can learn features from raw handwriting data and reach acceptable accuracy for author identification. The proposed model was based on the pre-trained network along with the designed data set and four types of comprehensive data sets. The outcomes indicated that the proposed model (pre-trained network with proposed block) performed more effectively in identifying the author for each of the five data sets than the pre-trained network without the proposed block. In addition, the proposed model was compared with the accuracy of different approaches for four types of comprehensive data sets. According to the outcomes, the suggested model was found to be more accurate than other methods for all data sets compared with other methods. In addition, the designed data set was analyzed with DCNN and compared with engineering features and two intelligent approaches, SVM and BPNN. Based on the outcomes of the study, the suggested technique is capable of learning the features and providing convincing predictions. In comparison with engineering features, the suggested technique increases the accuracy of identification by approximately 13% and is less dependent on expert knowledge. The presented results indicate that the suggested technique for automatic author identification is very satisfactory and suitable for use in a variety of applications, and it could prove to be a useful tool for handwriting recognition experts when entering the field.

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