Hybridized Convolution Neural Network and Multiclass-SVM Model for Writer Identification

Yomna M. Elbarawy and Wafaa A. Ghonaim

Abstract—**Writer identification is a quite interesting research problem in the field of writing recognition due to an ambiguous written styles of different writers. This paper proposes a model that hybridises Convolutional Neural Network (CNN) and Multiclass-Support Vector Machine (MSVM) for getting a better accuracy in writer identification using English/Arabic handwriting samples. Deep identifying writer takes local handwritten image as input and CNN used for feature extraction then classified using MSVM classifier based on the extracted features from the CNN layers. The used CNN architecture was applied with multiple kernel sizes and each time the corresponding processing time and the identification accuracy was measured. The proposed system was applied over two publicly databases Khatt as an Arabic database and IAM as an English database and able to achieve an accuracy of around 99.8% for a set of 206 writers. The performance of the proposed system was compared with other existing writer identification systems.**

Index Terms—**Deep learning, Convolutional Neural Network, Multiclass-SVM, Writer Identification, Handwriting.**

I. Introduction

WRITER Identification (WI) is a significant problem which aims to recognize the writer based on an image of his handwriting text, it belongs to the handwritten biometrics group and encountered as one of the greatest challenging problems in the pattern recognition [1], [2]. Handwriting is considered as a behavioral characteristic for some of the following reasons, no two people can create precisely the same hand script, any human cannot precisely replicate his own handwriting, and also humans cannot replicate the others writing precisely. Deep learning models are commonly used in image processing and pattern recognition. Convolutional Neural Networks (CNNs) are feed-forward artificial neural networks that are mostly used for subject detection and identification. Artificial Neural Networks (ANNs) are computational processing systems that operate as the human brain in which are heavily inspired from the biological nervous systems. CNNs are similar to traditional ANNs that they are consist of neurons that self-optimise through learning. Each neuron accept an input and performs an operation [3]. CNNs has shown a great performance in many machine learning problems and computer vision [4]. It is obvious that when the network becomes deeper the receptive field size is increased, especially when a pooling layer is added to the deep net. Unlike long-established features extraction and image processing techniques that rely on a little accepted domain, CNN computes its characteristics utilizing a bigger open domains. The bigger accepted domain distinctive the CNN which accomplished higher accuracy than traditional techniques in image recognition field [5].

The objective of this paper is to present a new model for writer identification using two different (English/Arabic) handwriting images databases. The results of this research were conducted by applying three different models. The first one applies a CNN architecture for feature extraction and the softmax as a classifier. The second model applies the same CNN architecture for the feature extraction and the MSVM for classification. The third model applies directly over the selected datasets. The remainder of the paper is structured as follows: In Section II many different WI approaches are introduced. A brief introduction about the MSVM is presented in Section III. A brief introduction about the CNN is introduced in Section IV. In Section V a detailed description of the proposed model and explanation of the used two datasets. The experimental results and analysis are stated in Section VI. Section VII demonstrated a comparison between the highest accuracy based proposed system and the highest accuracy based other existing WI systems. Finally, the conclusion is introduced in Section $VIII$.

II. Related Work

In the past twenty years the WI has ended up a really imperative in document analysis and identification, so many different approaches have been proposed. In [6] a new algorithm for WI based on non-uniformly handwriting images. Most existing techniques assume implicit assumption that the written text is fixed. The algorithm removes such an assumption and allows the use of any text based on the Weighted Euclidean Distance (WED) and the K-Nearest Neighbour classifier (KNN) as classifiers. It concluded that both classifiers have good performance, but the KNN classifier's performance is relatively poor compared to the WED classifier. In [7] WI algorithm is introduced based on Support Vector Machine (SVM) using Steered Hermite features and IAM database. It was found that the algorithm achieve an accuracy of around 90% using a set of 20 authors based on SVM for training and testing process. In [8] a new WI method is introduced based on Farsi/Arabic handwriting by assuming that the handwriting as texture image. It concluded that the method is very promising and can achieve better performance on Farsi handwritten documents. In [9] a novel hierarchical technique for offline handwritten Gurmukhi character recognition have presented based on SVMs classifier. In it four different kernels are considered linear kernel, polynomial kernel, RBF kernel and sigmoid kernel. 3,500 samples are used for classification

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training and testing, the characters written by one hundred different writers. It concluded that the maximum accuracy of recognition is equal to 91.80% and achieved with a linear kernel classifier. In [10] an automated process for distinguishing the author from manually written samples is introduced using ending codebook approach. This process extracts the code from the form location of associated components with the interest of utilizing the more than once showing up shapes which could be parts of distinctive characters. Four databases, namely, GRDS, IAM, KURD, and ICFHR were used for testing the method. The best result achieved using the ICFHR dataset having 97.12% identification rate. In [11] SVM was used as classifier and achieved 94% accuracy based on 100 writers' database and using the efficient descriptor called Block Wise Local Binary Count (BW-LBC) operator.

III. Multiclass-Support Vector Machine

SVM is considered as a supervised learning technique used for regression and classification [12]. It has been used already in wide variety of classification problems [13] since its introduction in 1990s and the optimal design for Multiclass-SVM (MSVM) classifiers requires further research [14]. MSVM is a SVM dealing with all the categories simultaneously, MSVM is an open source software package which proposed in [15]. It used in many fields for example security domain by applying it as a classifier in intrusion detection. In [16] the obtained results based on MSVM are compared by another classifiers and concluded that MSVM based results are the best. The MSVM problem can be solved, let consider that for given labelled training patterns $\{(x_i, y_i) : i \in I\}$, where a pattern x_i is from an n-dimensional space X and its label attains a value from a set K. The $I = 1, ..., l$ denotes a set of indices. The linear classification rules $f_m(x) = \langle W_m, x_i\rangle + b_m, m \in K$ (the dot product is denoted by $\langle ., ..\rangle$ can be found directly by solving the MSVM problem in [15]. There are two approaches for MSVM, the fist is combining and building numerous parallel classifiers while the second approach handles all input in one optimization figuration. It is computationally more expensive for a multiclass problem solving than a binary problem with the same number of data [17]. The CNN classifier is a deeper classifier which needs large amount of computational power and more memory to perform training and testing processes. Thus this paper aims to present a model that used the MSVM as classifier based on the extracted features from the CNN layers.

IV. Convolutional Neural Network

deep learning, specifically CNNs are becoming increasingly popular in solving many applications. The CNN implements all computation by using the convolutional operation in the hidden layer [18]. CNN distinctive from common deep learning models, directly it can process 2D images, so that it has unique advantage through image identification field [19]. CNNs mainly have three sets of layers: convolutional, sub-sampling and fully connected layers. Convolutional layers are applied with number of convolutions and kernel sizes. An additional operation after each convolutional operation is utilized called Rectified Linear Unit (ReLU) which affected every pixel by exchanging every pixel value less than 0 within the selected kernel size by zero. The sub-sampling layers minimize the selected section from the image through the convolutional layer by max-pooling which selects the most considerable pixel value and comes to a concrete degree of invariance to deformity within the feed in. At the fully connected layer, the classification is made by the softmax function [20]. The softmax treats the outputs as scores for each class. It is a form of logistic regression that normalizes an input value into a vector of values that follows a probability distribution whose total sums up to 1. The probability distribution of the different possible outcomes given in Eq. 1, where the predicted probability for the j^{th} class given a sample vector x is calculated.

$$P(y = j|x) = \frac{e^{x_j}}{\sum_{n=1}^{N} e^{x_n}} \tag{1}$$

After training, the network uses the cross entropy to calculate the distance between the output and the expected one [21]. Eq. 2 represents the cross entropy function that used for calculating the network error, where $X = \{x^{(1)}, ..., x^{(n)}\}$ are the input training images, $Y = \{y^{(1)}, ..., y^{(n)}\}$ are the corresponding labels of input images and $o(x^{(i)})$ is the output of the network given input x^i.

$$C(X,Y) = -\frac{1}{n}\sum_{i=1}^{n} y^{(i)}ln(o(x^{(i)}))+(1-y^{(i)})ln(1-o(x^{(i)})) \tag{2}$$

V. Methodology

This section introduces a system model for WI problem based on CNN and the MSVM classifier. The proposed model is illustrated in Fig. 1, where the input is a handwritten text images which belongs to the datasets that are under study. Each used dataset was manipulated to unify the size of its images. C1 and C2 are convolutional layers, S1 and S2 are sub-sampling layers and FC referred to the fully connected layer. The proposed model hybridises the CNN and the MSVM. Feature extraction is made based on CNN and the classification process is applied based on MSVM. The identification accuracy is calculated from the extracted classes. Details of each step are stated below.

A. Input Datasets

Khatt database: Contains 2000 unique paragraph images and their segmented line images handwritten in Arabic. It holds handwritten samples of 1000 different writers. These samples were scanned at different resolutions (200, 300, and 600 DPIs) and saved as tiff images. The source text subjects are varied between arts, education, health, nature and technology [22]. The system in this paper uses 300dpi binary images with unique text lines of 100 writer. 900 images for training and 500 images for testing (5 per class) were used. All images were resized to 700x50 pixels. Samples of Khatt Unique Text Lines (KhattUTL) are shown in Fig. 2.

IAM database: Holds forms of unconstrained handwritten text of 657 writers, which were scanned at a resolution of 300dpi and saved as PNG images with 256 gray levels. These forms were extracted to text lines, words and sentences and saved as PNG images [23]. This paper uses two sets of images (words and sentences). The system uses words images of 114 writers, which all were resized to 100x60 pixels. 5000 words images for training and 2850 words images for testing (25 per class). Samples of iam-word dataset are shown in Fig. 3. The sentences images were resized to 700x50 pixels and the system uses sentences images of 206 writers, 2300 sentences images for training and 1030 sentences images for testing (5 per class). Samples of iam-sentence dataset are shown in Fig. 4.

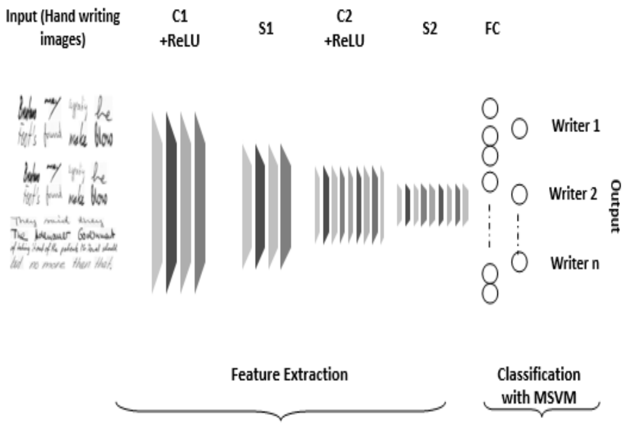


Fig. 1: System Model Design.

B. CNN architecture

CNN was solid for many identification problems with different number of layers and parameters. The basic architecture of the used CNN (Arch_Elbarawy) was proposed by Elbarawy et al. in [24]. The system applies this architecture over the three datasets with three different kernel sizes at the convolutional layers (3x3, 7x7 and 10x10). The used network consists of two convolutional layers, two sub-sampling layers and one fully connected layer. The input of the network are PNG images for IAM datasets and TIFF images for khatt dataset and outputs the credit of each writer. The detailed architecture of applying Arch_Elbarawy with kernel size 7x7 at the convolutional layers over KhattUTL dataset is illustrated in Figure 5, including images size at each layer. Figures 6 and 7 illustrate the same details related to iam-word and iam-sentence datasets. The first layer of the architecture is a convolution layer (C1), which applies a 12 convolutions with kernel of size 7x7 and stride of 1 horizontally and vertically. This layer is trailed by a sub-sampling layer (S1) that utilizes max-pooling with kernel size 2x2 at stride 2 to reduce the image to half of its size. After that a new convolution layer (C2) performs 36 convolutions with a 7x7 kernel size followed by a second sub-sampling layer (S2) having a 2x2 kernel size and stride 2. Their goal is to implement the same procedures as prior, but to handle features at a lower level and perceiving contextual elements. Finally, a fully connected layer (FC) and multiple classifiers were utilized to find the highest WI accuracy based on the extracted features.

Fig. 2: Unique text lines samples from khatt database.

VI. Experimental Results

This experiment applied over a 64 bit operating system using Matlab version R2018a. The used machine has a 4GB RAMs and processor speed 2.20GHz. All training operations were executed at constant number of training epoches equal 20. The paper applies three models, the first one uses Arch_Elbarawy for feature extraction and the softmax function for classification. The second uses the same earlier architecture with the MSVM and the third model applies the MSVM directly over the selected datasets. The details of each model results are stated below.

Fig. 3: Sample of words images from IAM database

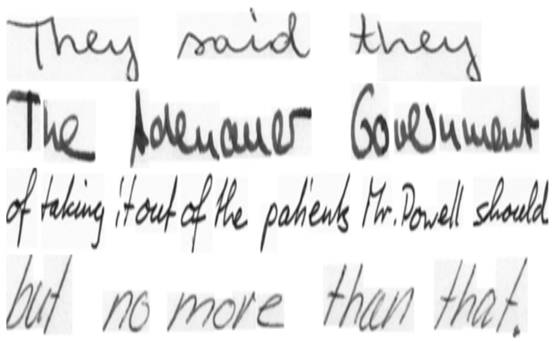


Fig. 4: Sample of sentences images from IAM database.

A. CNN+Softmax based model

The model is applying Arch_Elbarawy for feature extraction and softmax for classification with different kernel sizes to differentiate between them. Table I holds the results of applying the model over khattUTL dataset with the three different kernel sizes 3x3, 7x7 and 10x10. The table clarifies the average processing time and accuracy for each network structure. The highest accuracy 84.6% takes place at kernel size 7x7 with average processing time 37.5 minutes. The lowest accuracy 67.3% takes place at kernel size 3x3 with average processing time 21.4 minutes. Fig. 10a shows the confusion matrix of the highest accuracy 84.6% at kernel size 7x7. The confusion matrix was showed as a bitmap image holds the matrix values because of the bigness of the number of existing classes (100). Fig. 10b is a zoomed in section of the image, holds the matrix values at each cell with a maximum value 5 (number of test images per class).

Table II shows the results of applying the model over iam-sentence dataset with the three different kernel sizes 3x3, 7x7 and 10x10. The network achieves the highest identification accuracy 95.9% at kernel size 7x7 with average processing time 104.3 minutes. The lowest accuracy 74.4% takes place at kernel size 3x3 with average processing time 66.2 minutes. Fig. 11a holds the confusion matrix of the highest accuracy 95.9% at kernel size 7x7. The zoomed in section is shown in Fig. 11b, holds the matrix values at each cell with a maximum value 5 (number of test images per class).

The results of applying CNN+Softmax based model over iam-word dataset are illustrated in table III with the highest identification accuracy 98.32% at 7x7 kernel size and average time 110.3 minutes. The lowest identification accuracy 31.67% takes place with average time 94 minutes at 10x10 kernel size. Fig. 12a holds the confusion matrix of the highest accuracy 98.32% at kernel size 7x7. The zoomed in section is shown in Fig. 12b, holds the matrix values at each cell with a maximum value 25 (number of test images per class). The overall identification accuracies of all three datasets are shown in Fig. 8. The conducted results are that the highest accuracies takes place at the kernel size 7x7 and unlike other lines datasets (khattUTL and iam-sentence), iam-word dataset gives its lowest identification accuracy at the kernel size 10x10, where as khattUTL and iam-sentence gives their

TABLE I: Average identification accuracy and time using CNN+Softmax based model with different kernel sizes over khattUTL dataset.

		Accuracy(%)	Time in Minutes
Kernel Size	3x3	67.3	21.4
	7x7	84.6	37.5
	10x10	84.5	47.4

TABLE II: Average identification accuracy and time using CNN+Sostmax based model with different kernel sizes over iam-sentence dataset.

		Accuracy(%)	Time in Minutes
Kernel Size	3x3	74.4	66.2
	7x7	95.9	104.3
	10x10	95.8	161.1

lowest identification accuracy at kernel size 3x3. Fig. 9 shows different execution time values of applying Arch_Elbarawy over the three datasets with different kernel sizes.

B. CNN+MSVM based model

In CNN+MSVM model, the CNN architecture with the highest accuracy from the earlier model was selected to be used. The detailed results are shown ahead. The CNN architecture at the kernel size 7x7 is used, the extracted features from it used as input to the MSVM classifier. Table IV shows the average identification accuracy of applying the MSVM based on the extracted features from C1, C2 and FC. The table indicates that the highest accuracies 99.8% and 95.1% takes place when the input is given from the FC layer features. Table V presented the corresponding processing time (in minutes) of the given accuracies in table IV which also indicate that the minimum average time takes place when the FC layer features were used.

C. MSVM based model

This model applies the MSVM directly over the three datasets and the average accuracies and corresponding time (in minutes) are illustrated in table VI where KhattUTL dataset gives the best results of accuracy and time 99.8%, 1.6 minute respectively.

VII. Comparative analysis

The overall accuracies for the three used models: CNN+softmax, CNN+MSVM, and MSVM are represented

TABLE III: Average identification accuracy and time using CNN+Softmax based model with different kernel sizes over iam-word dataset.

		Accuracy(%)	Time in Minutes
Kernel Size	3x3	98.29	59.6
	7x7	98.32	110.3
	10x10	31.67	94.0

TABLE IV: Identification average accuracy (%) of applying CNN+MSVM based model with different layers features

		Dataset		
		KhattUTL	**iam-sentence**	**iam-word**
CNN Layer	**C1**	77	35.4	71.9
	C2	93	96.4	89.1
	FC	99.8	99.8	95.1

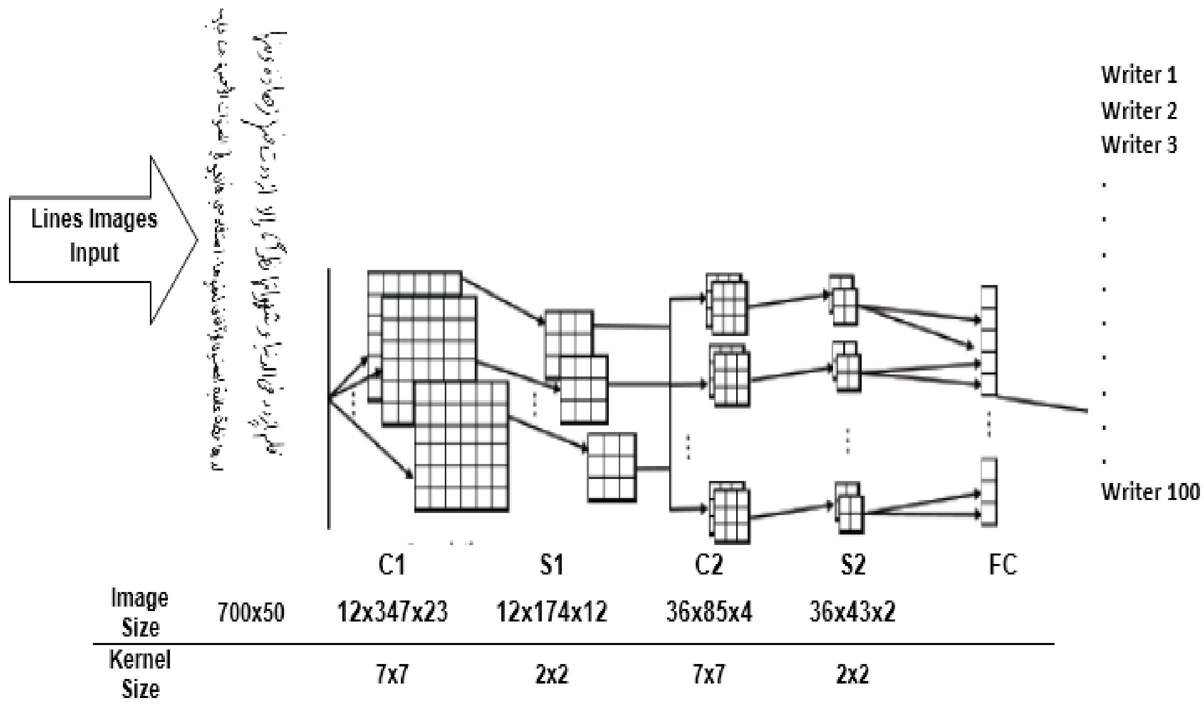


Fig. 5: CNN architecture applied over khattUTL.

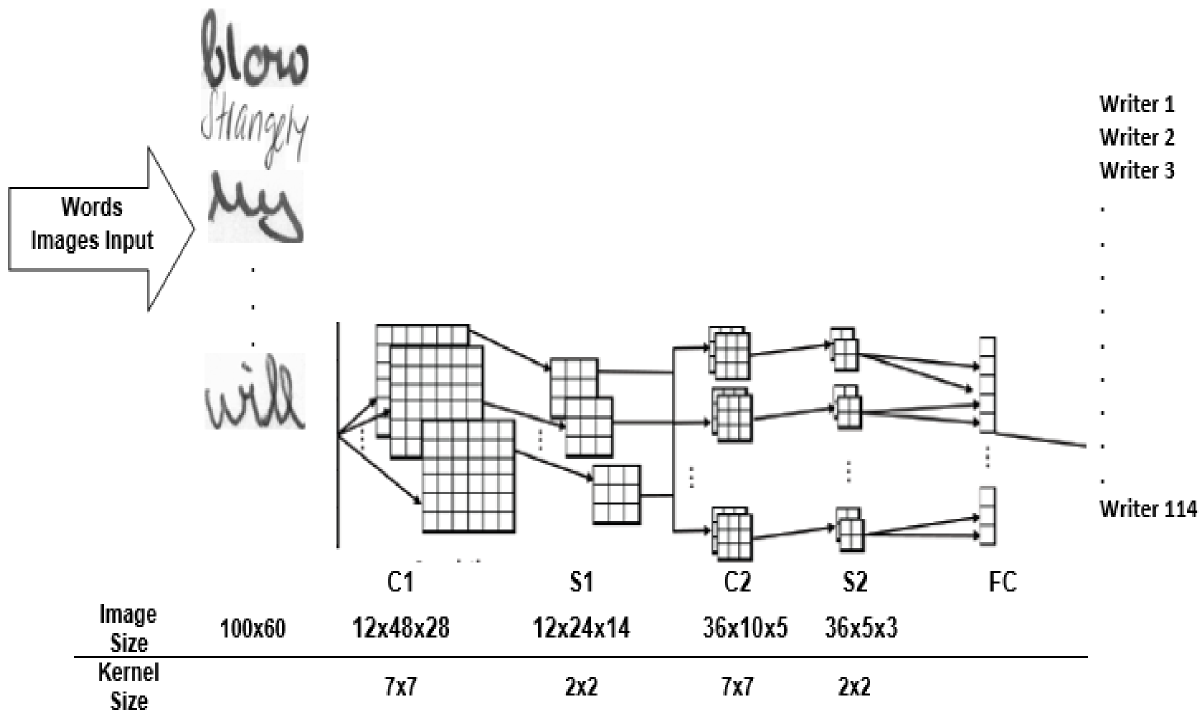


Fig. 6: CNN architecture applied over iam-word.

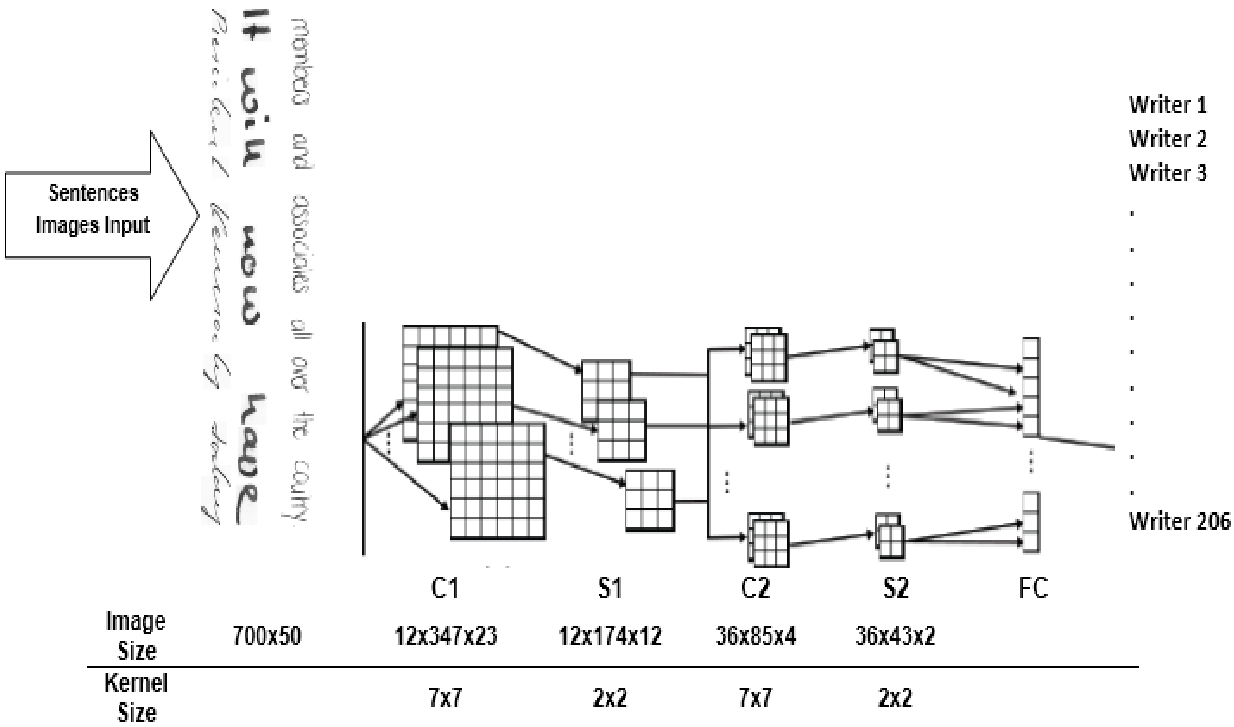


Fig. 7: CNN architecture applied over iam-sentence.

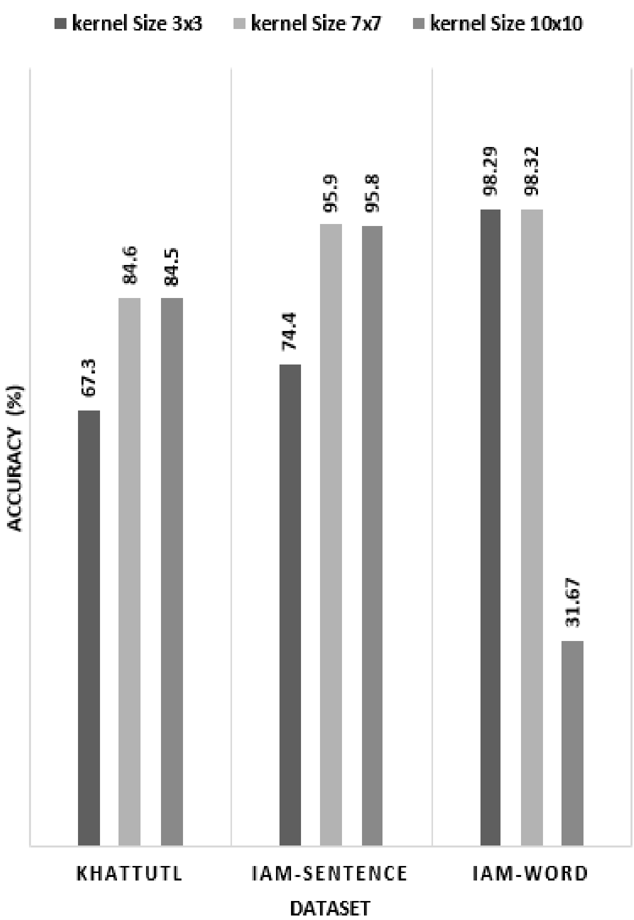


Fig. 8: Identification average accuracy of applying CNN+Softmax model over the three datasets.

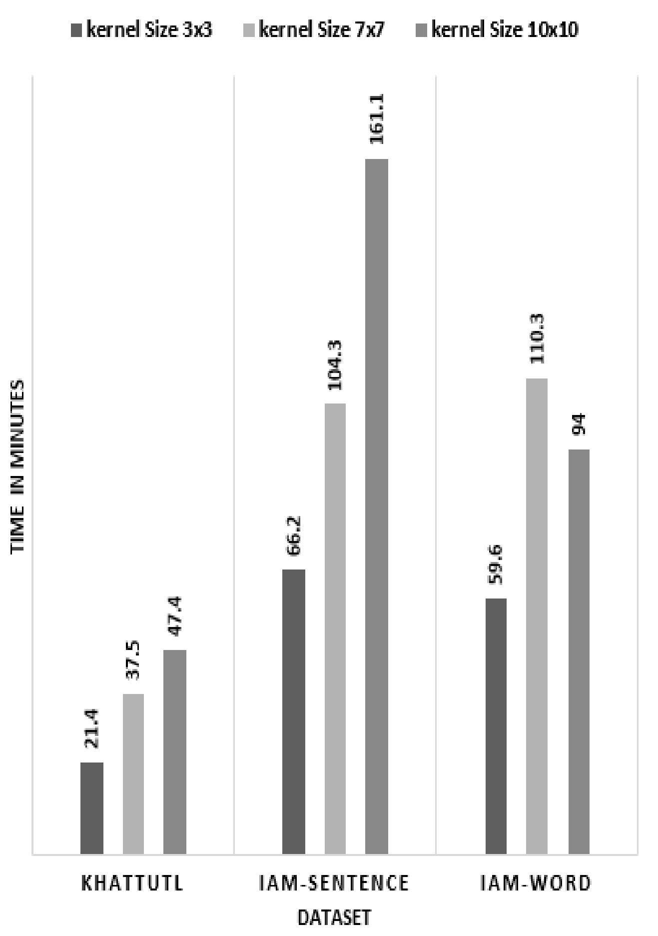
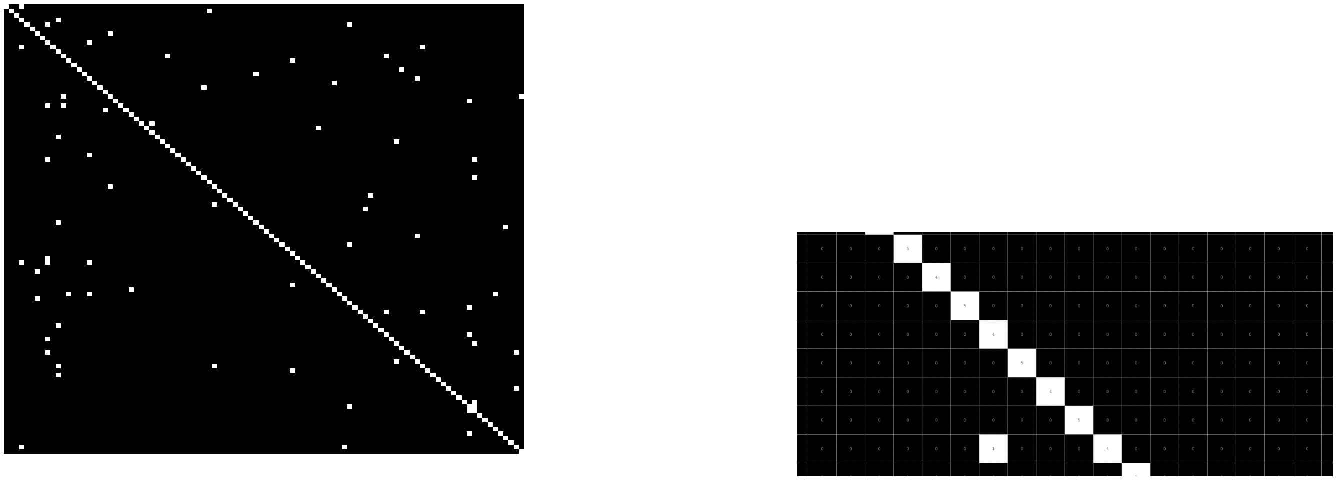
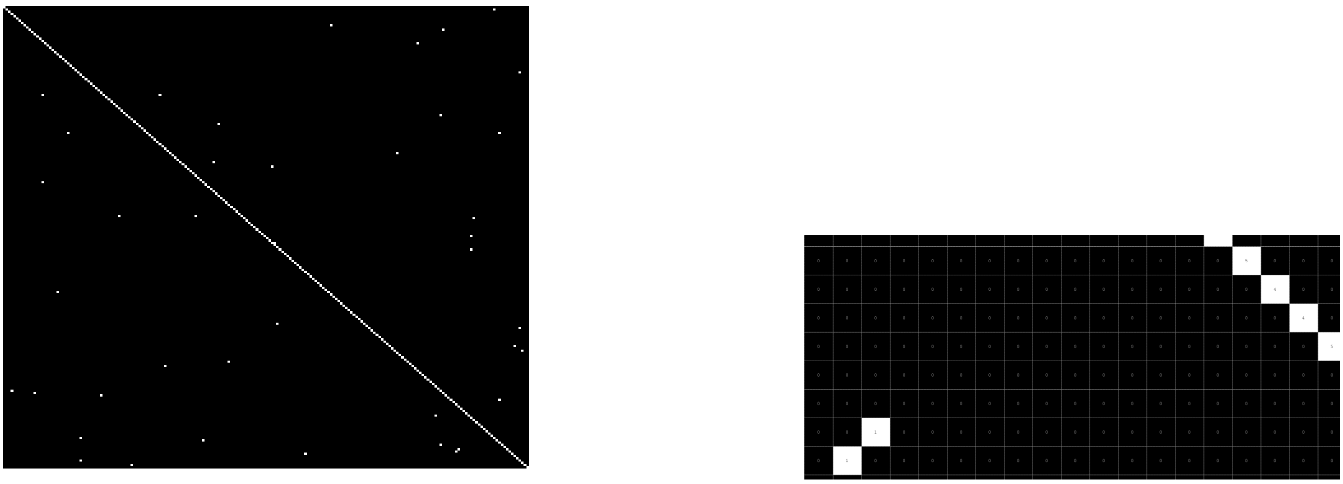


Fig. 9: Average processing time of applying CNN+Softmax model over the three datasets.



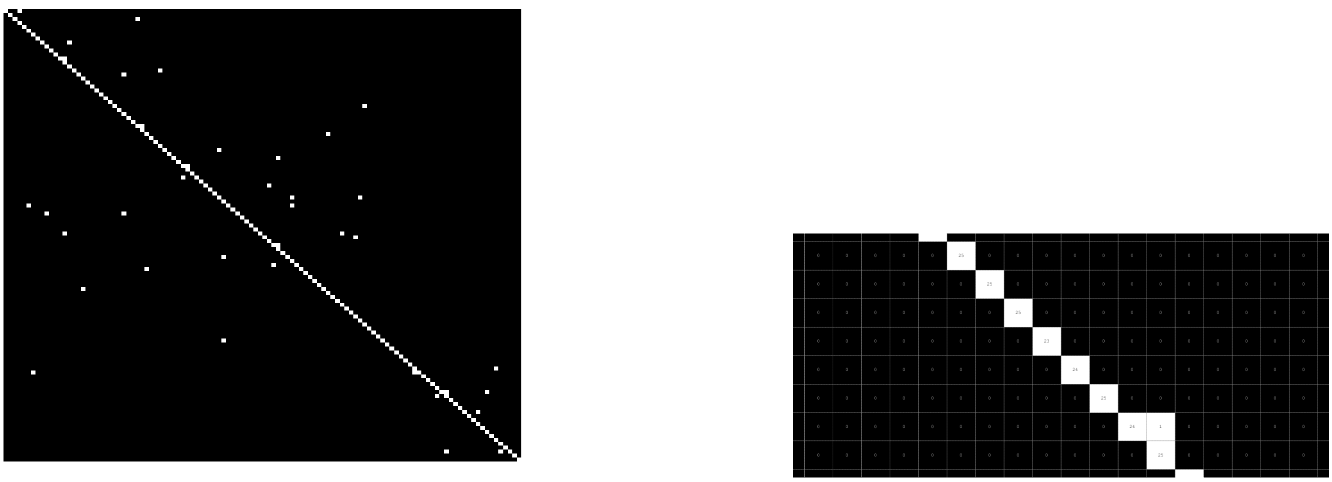
(a) (b)

Fig. 10: Confusion matrix visualization of applying CNN+Softmax model over khattULT dataset with kernel size 7x7



(a) (b)

Fig. 11: Confusion matrix visualization of applying CNN+Softmax model over iam-sentence dataset with kernel size 7x7



(a) (b)

Fig. 12: Confusion matrix visualization of applying CNN+Softmax model over iam-word dataset with kernel size 7x7

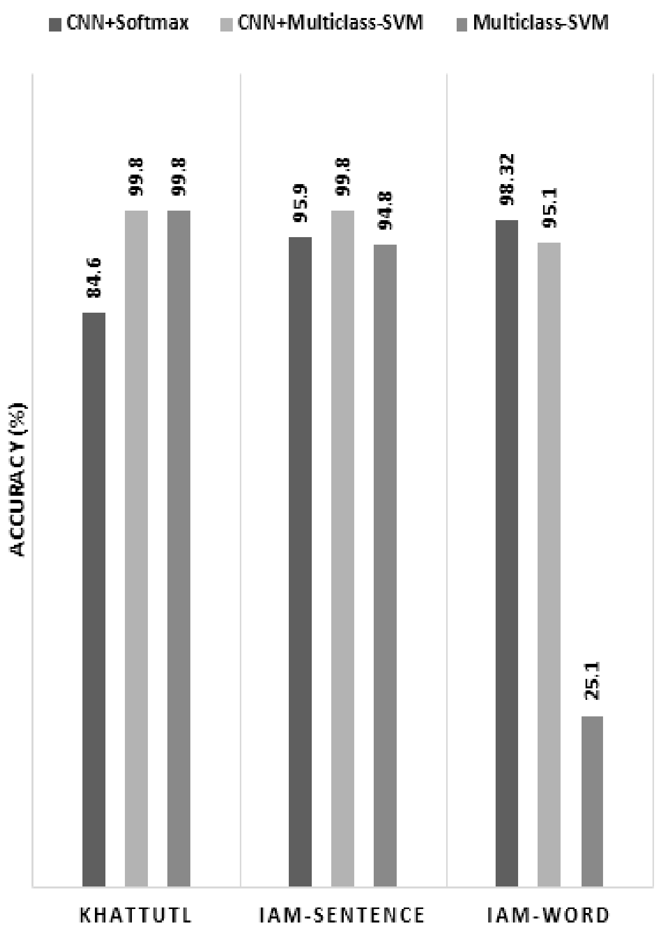


Fig. 13: Comparison of identification accuracy results of applying the three models: CNN+Softmax, CNN+MSVM, and MSVM over the three datasets

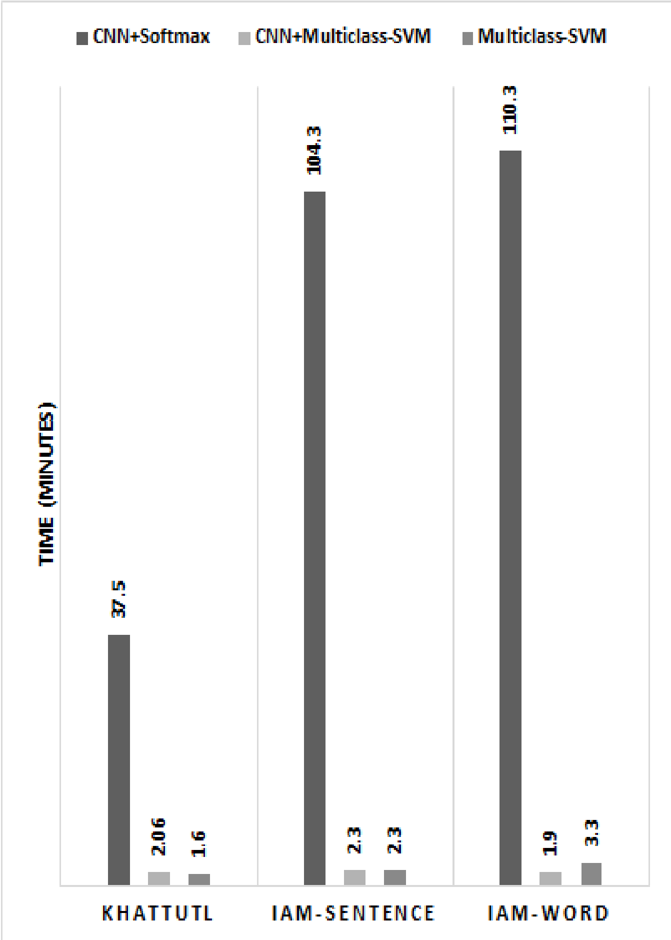


Fig. 14: Comparison of average processing time of applying the three models: CNN+Softmax, CNN+MSVM, and MSVM over the three datasets.

TABLE V: Identification average processing time (in minutes) of applying CNN+MSVM based model with different layers features.

		Dataset		
		KhattUTL	iam-sentence	iam-word
CNN Layer	C1	27.8	60.5	39.4
	C2	7.8	10.7	11.3
	FC	2.1	1.8	1.9

in Fig. 13 and their average processing time is illustrated in Fig. 14. The overall results indicate that CNN+MSVM based model gives the best identification accuracy reached to 99.8 % and by using FC features as input to MSVM gives better identification accuracy and minimum processing time.

To compare the proposed CNN+MSVM based model with other existing models table VII summarize the performance evaluation for WI systems that used different techniques

TABLE VI: Identification average accuracy and time of applying MSVM directly over the datasets.

		Accuracy (%)	Time (in minutes)
Dataset	KhattUTL	99.8	1.6
	iam-sentence	94.8	2.3
	iam-word	25.2	3.3

over IAM database as KNN, NN, Naive Bayes (NB), CNN, Nearest Neighbor, Hamming Distance, and SVM. Fig. 15 illustrates the identification accuracies according to the year. The used of CNN for features extraction and MSVM for classification achieved the highest value of identification accuracy, reached to 99.8%.

VIII. Conclusion

Writer identification is considered as a difficult problem to solve due to the variations that exist in the writing, even if it is from the same writer. In this paper, three based models were implemented. CNN+Softmax, CNN+MSVM, and MSVM. For CNN+MSVM based model, the MSVM classified the local features that have been acquired from English/Arabic handwritten samples by applying the selected architecture of the convolutional neural network. From the experimental results, 99.8% identification accuracy was achieved by applying CNN+MSVM model over iam-sentence and KhattUTL datasets which is high compared with other existing writer identification systems results. By applying CNN+Softmax model, the highest values of identification accuracies 98.3% and 95.9% achieved at kernel size 7x7 over the two English datasets (iam-word and iam-sentence) respectively. The conducted results showed that the English datasets achieved a larger identification accuracy of writer than the Arabic dataset when using the softmax

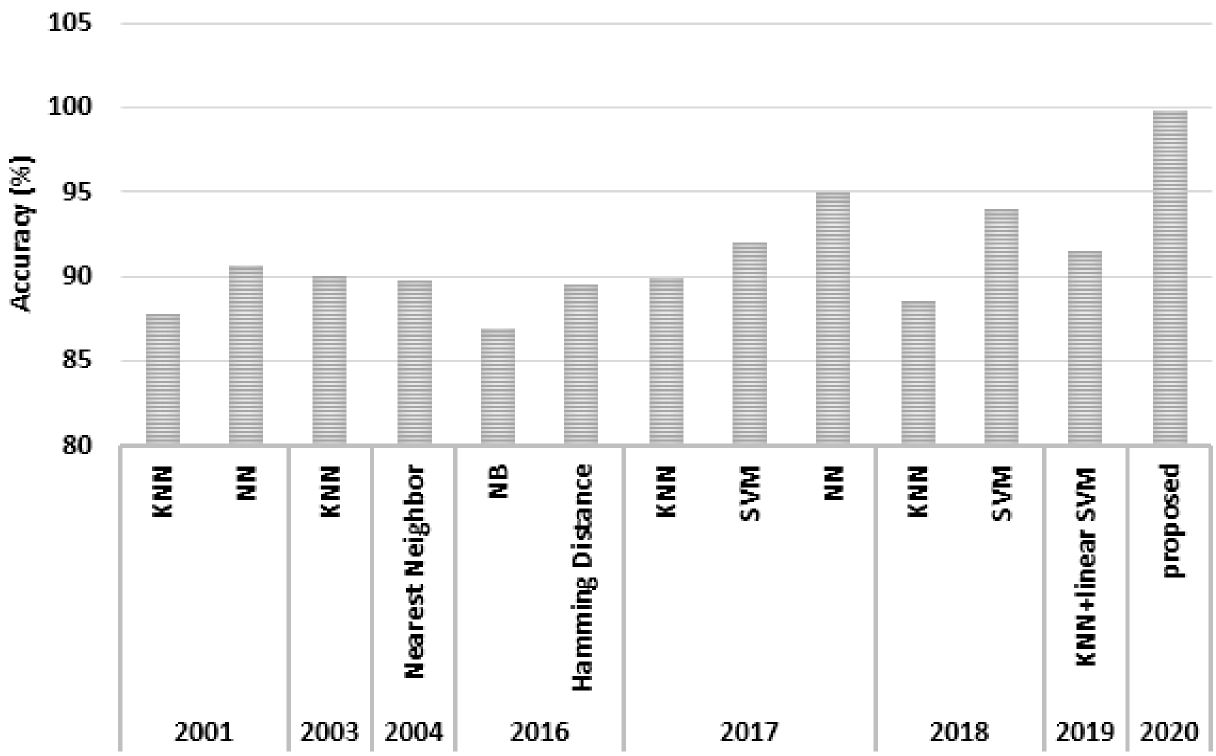


Fig. 15: Comparison between WI accuracy of the proposed model and different IAM based systems.

TABLE VII: Review over WI systems with different models using IAM database

Year	Reference	Sample Space and features	Models	Identification Accuracy (%)	Language
2001	Marti et al. [25]	100 pages of text written by 20 different writers are used. Using text line based features	KNN, NN	87.8, 90.7	English
2003	Hertel & Bunke [26]	First the page of handwritten text segments into individual lines. Pages of handwritten text produced by 50 writers.	KNN	90	English
2004	He et al. in [27]	regard the global text and single character of Chinese as textures	Nearest Neighbor	89.8	English, Chinese
2016	Garz et al. [28]	657 writers	NB	86.9	English
2016	Hannad and Siddiqi [29]	Handwritten text is divided into small fragments as a texture.	Hamming Distance	89.54	Arabic and English,
2017	He et al. [30]	curvature-free features	KNN	89.9	English, Chinese, Dutch
2017	Kumar and Kaur [31]	A Character Based Handwritten Identification	SVM and NN	92 and 95	English
2018	Pandey and Seeja [32]	650 writers, Number of clusters 240	KNN	88.57	English
2018	Chahi et al. [11]	100 writers	SVM	94	English, Arabic, German
2019	Dargan et al. [33]	corpus consisting of five copies of each character of Devanagari script written by 100 different writers	KNN and linear SVM	91.53	Devanagari

classifier over the CNN features. While applying the MSVM directly over the three datasets, the identification accuracy of the English datasets (iam-word and iam-sentence) was less than the identification accuracy of the Arabic dataset (KhattUTL).

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