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A New Design Based-SVM of the CNN Classifier Architecture with Dropout for Offline Arabic Handwritten Recognition

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Abstract
In this paper we explore a new model focused on integrating two classifiers; Convolutional Neural Network (CNN) and Support Vector Machine (SVM) for offline Arabic handwriting recognition (OAHR) on which the dropout technique was applied. The suggested system altered the trainable classifier of the CNN by the SVM classifier. A convolutional network is beneficial for extracting features information and SVM functions as a recognizer. It was found that this model both automatically extracts features from the raw images and performs classification. Additionally, we protected our model against over-fitting due to the powerful performance of dropout. In this work, the recognition on the handwritten Arabic characters was evaluated; the training and test sets were taken from the HACDB and IFN/ENIT databases. Simulation results proved that the new design based-SVM of the CNN classifier architecture with dropout performs significantly more efficiently than CNN based-SVM model without dropout and the standard CNN classifier. The performance of our model is compared with character recognition accuracies gained from state-of-the-art Arabic Optical Character Recognition, producing favorable results.

Keywords: CNN, dropout, Arabic handwritten recognition, over-fitting, based-SVM, features, HACDB

1 Introduction and Related Works

During the two last decades, on the basis of signal processing and pattern recognition, offline and online data classification, has won big concern. As a result, it has been extensively practiced to a variety of research domains like vision recognition task [1, 2], Automatic Speech Recognition (ASR) [3] and EEG signal [4] classification.

Lately, Handwriting Recognition has become a popular area of research because of the advances in technology such as the handwriting capturing devices and impressive mobile computers. Because it is a challenging topic, Arabic handwritten script recognition, in the domain of handwriting recognition

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has been deeply studied for a couple of decades by researchers who have utilized dissimilar algorithms, like Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), Hidden Model Markov (HMM), Deep Networks (DNN) , Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN), etc.,. The outcomes were various and satisfactory. These machines learning (ML) systems have demonstrated their reliability and performance in a large domain of applications as well as winning triumph in optical character recognition (OCR) in Latin and Asian languages [5, 6]. The major drawback of these architectures is the large number of parameters, so over-fitting can occur.

Considering recognition of offline Arabic handwriting, our researches have highlighted and insisted more on the recognition aspects. Because of differences in forms, concavities, curvatures, and strokes, the handwritten characters and overlapping characters are highly varying. For this reason, a special care and importance was given from our part to the recognition of intricate Arabic handwritten text. Thanks to this work [7], architecture based on CNN and SVM classifier is investigated to the handwritten Arabic domain [8]. On the other hand, in this study to prevent our architecture from over-fitting and to improve its performance, dropout is applied. This technique consists of temporarily removing a unit from the network. This removed unit is randomly selected only during the training stage [9]. This architecture mixes the advantages of the two approaches described below.

Developed by LeCun et al [10], CNN which is hierarchical neural network possesses huge representational capacity that learns the good features at every layer of the visual hierarchy. It has also been effectively applied to a lot of vision problems like visual object recognition [11] and handwriting recognition [12]. These features are automatically extracted from the input image having the benefit of being invariant to the shift and shape distortions of the input textual images.

On the other hand, Support vector machines (SVM) considered as one of the strongest and robust algorithm in machine learning (ML) created by Vapnik [13], have become a well–known approach exploited in many domains [14, 15, 16], like pattern recognition, classification, and image processing.

CNN includes a number of convolutional and sub-sampling layers which are optionally accompanied by Fully Connected Layers (FCL). The FCL are uniform to the layers in a standard Multi-Layer Perceptron. Yet, MLP offer two borders in classification tasks: To begin with, there is absence of theoretical relationship between the classification task and the MLP structure. Next, MLP drift hyper-planes separation surfaces, in feature representation space, that are not optimal in terms of margin between the examples of two different classes. To find a suitable solution to these problems, in our experiments, we modified CNN structure by replacing the output layer of the FCL with an SVM classifier. The purpose of SVM is to understate the generalization errors in the training set by using the Structural Risk Minimization (SRM) principle. Consequently, the generalization ability of SVM surpasses than that of MLP [7].

By presenting a Deep CNNs trained on MNIST [17] as well as on NIST SD 19 database [18] including lower and upper case letters and digit, Ciresan et al [19] proved the robustness of their model by constructing seven CNNs. We can consider the average error rate obtained as best results. Later, a new hybrid CNN/SVM model was proposed by Niu and Suen [7] to solve the handwritten digit recognition problem exploiting MNIST digits database. It is noticeable that error classification rate gained by the hybrid model has achieved better results. Théodore et al [20] inquired into the combination of convolutional neural networks and hidden Markov models for handwritten word recognition and they achieved satisfactory results by using CNN/HMM hybrid model on IAM [21] and Rimes [22] databases.

Another classifier which is used extensively is Support Vector Machines (SVM). Survey applications of pattern recognition were presented by Byun and Lee [23]. They used SVM and they reviewed seven categories based on their aims like face detection/verification, object recognition, handwritten character/digit recognition and others while Chen et al. [24] presented a recognition system using SVM. The efficiency of Gabor features was proved over the previous used features techniques for Arabic sub-word recognition. Recently, Elleuch et al. [25] investigated the performance of Deep Network using SVM classifier (DSVM) to recognize Arabic handwritten text using HACDB Database. DSVM permits to extract high level discriminative features with support vectors maximizing the margin and it guarantees generalization performance alike. The experimental study has proved favorable results comparable to the state-of-the-art Arabic OCR.

Most of these networks and especially who have a deep architecture as CNN, Deep CNN, RNN and DNN etc., are characterized by a large number of hidden layers and too many parameters. However, over-fitting is a serious problem in such networks. Dropout is a technique for addressing this problem [9]. This technique was successfully applied with several types of neural networks and it shows a significant improvement for a recognition rate [9, 26, 27, 28].

Hinton et al. [9] introduced dropout training as a way to control over-fitting by randomly omitting subsets of features at every iteration of a training procedure. They showed that dropout improves the performance of neural networks on supervised learning tasks in vision, speech recognition, document classification and computational biology, obtaining state-of-the-art results on many benchmark data sets.

Until recently, no researchers have had applied CNN and SVM approaches yet to the handwritten Arabic field. In this study, a new design based-SVM of the CNN classifier architecture with dropout for offline Arabic handwritten text recognition has been suggested. Purposely, we study the plausible advantages of the proposed CNN and SVM classifier without and with dropout; CNN based-SVM model took the CNN as an automatic feature extractor from raw images and it let SVM do classification by analyzing the error classification rate on the Arabic handwritten character classification task. Dropout training is an effective way to control over-fitting by randomly omitting subsets of features at every iteration of a training procedure.

The organization of the rest of the paper is the following. In Section 2, we introduce the basic concepts behind Convolutional Neural Networks (CNN) and Support Vector Machine (SVM) classifiers. CNN based-SVM model designed for Arabic handwriting recognition was presented, and then dropout adapted for this model was described. Our experimental study and results are given and analyzed in Section 3. Finally, Section 4 presents some concluding remarks.

2 System Overview

In this section we briefly summarize Convolutional Neural Networks and Support Vector Machine classifier. We then describe our proposed CNN based-SVM model with dropout for offline Arabic handwriting recognition (OAHR).

2.1 CNN Classifier

Being hierarchical, multi-layer neural networks with a deep supervised learning architecture trained with the back-propagation algorithm [10], Convolutional Neural Networks are composed of an automatic feature extractor and a trainable classifier. CNN are exploited to learn complex, high-dimentional data, and differ in how convolutional and sub-sampling layers are inquired into. The difference is in their architecture. Many CNN architectures are suggested for different problems among which object recognition [29] and handwriting digit/character recognition [10, 30]. The best performance on pattern recognition task was achieved. In addition, to guarantee some degree of invariance to scale, shift and distortion, CNN mix three main hierarchical aspects such as local receptive fields, weight sharing and spatial sub-sampling [10].

As shown in Fig. 1, the net represents a typical Convolutional Neural Network architecture for handwritten character recognition. It includes a set of several layers. Initially, the input is convoluted with a set of filters (C hidden layers) in order to obtain the values of the feature map. Next, in order to diminish the dimensionality (S hidden layers) of the spatial resolution of the feature map, each convolution layer is pursued by a sub-sampling layer. Convolutional layers alternate sub-sampling layers constitute the feature extractor to retrieves discriminating features from the raw images. Ultimately, these layers were pursued by two fully connected layers (FCL) and the output layer. The output of the previous layer is taken by each layer as the input.

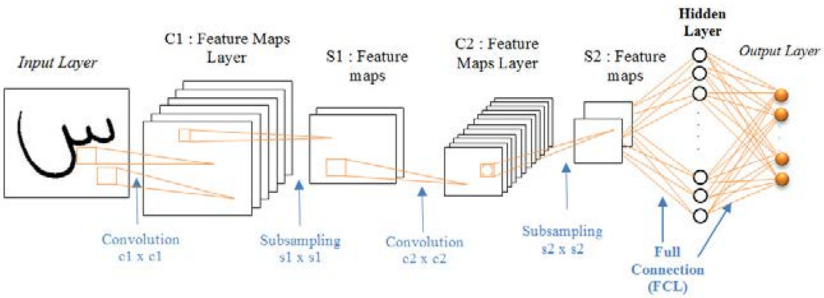

Figure 1: A typical CNN architecture composed of layers for feature maps applied for Arabic handwritten characters recognition.

2.2 SVM Classifier

Developed by Vapnik [13] and Cortes [31], Support Vector Machine is powerful discriminative classifier. It has been widely exploited with positive results for many pattern classification/recognition tasks [32]. It's regarded as the state-of-the-art tool for resolving linear and non-linear (see figure 2) classification problems [13], thanks to its parsimony, flexibility, prediction capacity and the global optimum character. The basis of their formulation is the structural risk minimization, rather than the empirical risk minimization which is traditionally used in artificial neural networks [13].

SVM is basically used to determine an optimal separating hyper-plane (equation 1) or decision surface by embracing a novel technique based on mapping the sample points into a high-dimensional feature space and it is categorized using a nonlinear transformation Φ, even when the data are linearly inseparable. The optimal hyper-plane is gained by solving a quadratic programming problem which is reliant on regularization parameters. This transformation was carried out by kernel functions like linear, radial basis function, sigmoid and polynomial kernel types;

- The linear kernel: $K(x, y) = x \times y$
- The polynomial kernel: $K(x, y) = [(x \times y) + 1]^d$
- The Sigmoid kernel: $K(x, y) = \tanh(\beta_0 \, x \, y + \beta_1)$
- RBF kernel (Radial Basis Function): $K(x, y) = \exp(- \gamma \, \|x - y\|^2)$

With d, β_0, β_1, and γ are parameters that will be determinate empirically.

$$f(x) = W^T \, \Phi(x) + b \qquad (1)$$

Where $W \in R^n$, $b \in R$ and $\Phi(x)$ is a feature map.

In this work, because the feature space is linearly inseparable, we applied a transformation by mapping the input data (x_i, y_i) into a higher dimensional feature space by using a nonlinear operator $\Phi(x)$. As a result, the optimal hyper-plane can be defined as:

$$f(x) = \mathrm{sgn}\left(\sum y_i \alpha_i K(x_i , x) + b \right) \qquad (2)$$

Where $K(x_i, x) = \exp(-\gamma\|x_i - x\|^2)$ is the kernel function founded on a radial basis function (RBF), and sgn(.) is the sign function. This classifier model called RBF kernel SVM is added to replacing the last output layers of the CNN architecture to carry out classification for Arabic Handwritten Text.

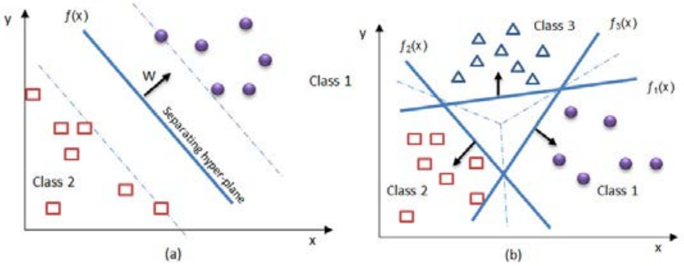

Figure 2: Principle of Support Vector Machine; (a) two-class hyper-plane example, (b) one-versus-all method

2.3 Architecture of the Proposed ML System

In this section, we present the architecture of our OAHR system based on CNN and SVM, wherein CNN is considered as a deep learning algorithm, on which the dropout technique has been applied during training. Our proposed system was tailored by altering the trainable classifier of the CNN with an SVM classifier. Our target is to mix the CNN respective capacities and the SVM to obtain a new effectual recognition system inspired by the two formalisms.

We showed the network architecture of the CNN based-SVM model in Fig. 3. It was noted that it appears like as follow. Firstly, the first layer welcomes raw image pixels as input. Secondly, the second and fourth layer of the network is convolution layers alternator with sub-sampling layers, which take the pooled maps as input. Consequently, they are able to extract features that are more and more invariant to local transformations of the input image. FCL is the sixth layer which consists of N neurons. The final layer was substituted by SVM with an RBF kernel for classification. Because of using a huge number of data and parameters, over-fitting can occur. So to prevent our network from this problem and to improve it, dropout is applied. This technique consists of temporarily removing a unit from the network. This removed unit is randomly selected only during the training. Dropout is applied only at FCL layer and for more precisely, it is applied to feed-forward connections (perceptron). This choice is based on the fact that since the convolutional layers don't have a lot of parameters, over-fitting is not a problem and therefore dropout would not have much effect [26].

The outputs from the hidden units are taken by the SVM as a feature vector for the training process. After that, the training stage continues till realizing good trained. Finally, classification on the test set was performed by the SVM classifier with such automatically extracted features.

The structure of the CNN based-SVM model with dropout adopted in our experiments is presented in Section 3, paragraph 3.3.

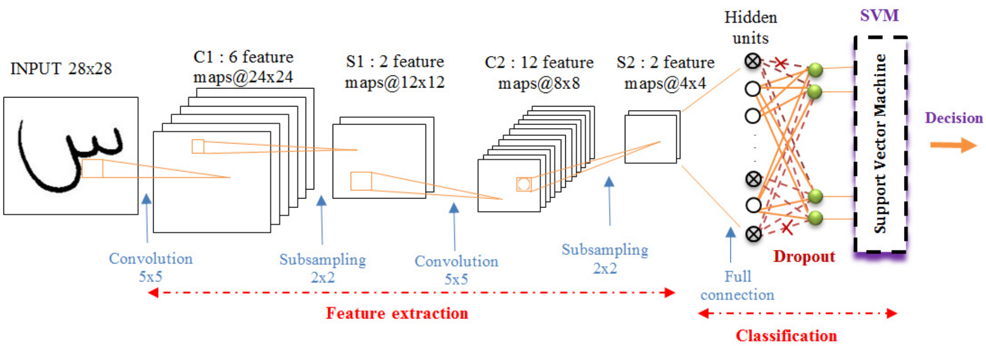

Figure 3: Architecture of the CNN based-SVM model with dropout.

3 Experiments, Results and Discussion

We carried our experimental studies so that we could explore the efficiency of dropout technique by using CNN based-SVM model in order to recognize offline Arabic character. We tested this new architecture of CNN on HACDB database [33] and IFN/ENIT database [34]. Outcomes are itemized and discussed in the following subsections.

3.1 HACDB and IFN/ENIT Databases

The HACDB database [33] contains 6.600 shapes of handwritten characters written by 50 persons (Figure 4-b). Each writer has generated two forms for 66 shapes: 58 shapes of characters and 8 shapes of overlapping characters (representing 24 basic characters/overlapping characters without dots). The dataset is divided into a training set of 5.280 images and a test set of 1.320 images [33]. The IFN/ENIT database [34] consists of 26.459 Arabic words handwritten by more than 411 different writers. The handwritten words represent 937 Tunisian town/village names. The images are partitioned into four sets (a-d). It is one of the most widely used databases. In this study words are segmented into letters from set (a) and (b). We have kept 1.120 images as test data. These images include 56 shapes of characters (Figure 4-a). The both databases consist of gray scale images normalized 28 by 28 pixels. Details of the class for each shape are presented in Table 1.

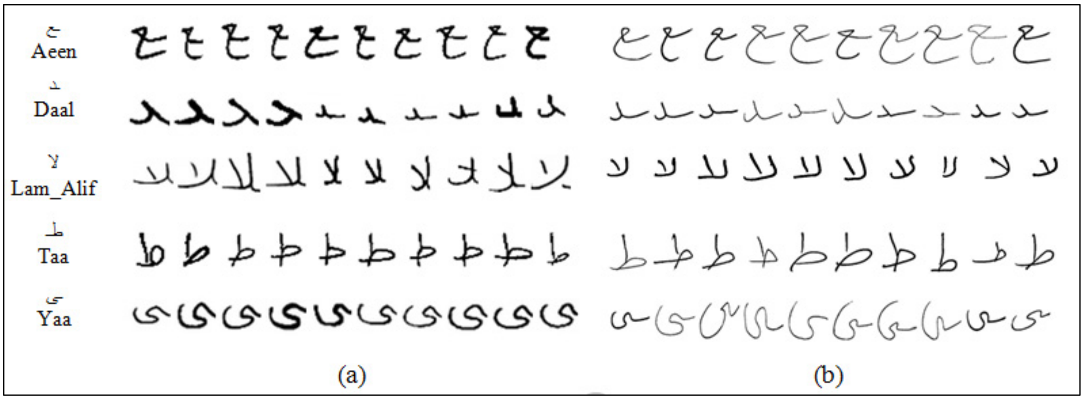

Figure 4: Samples from (a) the IFN/ENIT database and (b) the HACDB database written by 10 different writers.

Arabic Script	Shape	class	Arabic Script	Shape	class
Aeen (ع)		1			34
		2			35
		3 *	Lam_Alif (لا)		36
		4			37 *
		5 *			38
		6	Lam_Jeem (لحـ)		39 *
Alif (ا)		7	Lam_Mem (لمـ)		40 *
		8	Lam_Mem_Jeem (لمحـ)		41 *

Alif_Lam_Jeem (الحـ)		9 *	Meem (م)		42
Baa (ب)		10			43
		11			44
		12			45
		13	Mem_Jeem (ـمحـ)		46 *
Daal (د)		14	Noon (ن)		47
		15			48
Faa (ف)		16	Raa (ر)		49
		17			50
		18	Saad (ص)		51
		19			52
Haa (ه)		20			53
		21			54
		22	Seen (س)		55
		23			56 *
		24			57
Hamza (ء)		25			58 *
Jeem (ج)		26			59
		27			60
		28	Taa (ط)		61
		29			62
Kaaf (ك)		30	Waao (و)		63
		31			64
Laam (ل)		32	Yaa (ى)		65
		33			66

Table 1: Class for each shape of an Arabic script

* Classes does not exist in IFN/ENIT database

3.2 System Settings

For the purpose of evaluating the efficiency of the proposed CNN based-SVM trainable feature extractor model without and with dropout, we inquired its working performance to train and recognize characters of HACDB database. We observed that convolutional networks need a huge number of samples to learn the parameters. Hence, in order to best train the model on further data so that we can better take account the variability of handwriting, we spread out the size of the training set ten times by the technique of elastic deformation suggested by Simard et al [35]. Also, to evaluate the working of our system, the IFN/ENIT database is exploited. We give the technical implementation details of the adopted system in the following sub-section.

For the pre-processing, the HACDB Database, utilized in this experiment study, does not require to be normalized (noise reduction, segmentation). Some basic pre-processing tasks are a must in order to be performed during the database development. Yet, as for IFN/ENIT and for the sake to gain better character images after segmentation of words, pre-processing step implies binarization, noise reduction and filtrating the input text image to improve the quality of the image. As for feature extraction, CNN is utilized in this experiment as a compact end-to-end model, consequently the input to the network is the raw images. Finally, for the parameters setting: For the setting architecture, we have to define the number of convolutional layers, size of the feature maps, weights, kernel, and biais in each layer of CNN. After that, defining the optimal kernel parameter and penalty parameter of SVM.

3.3 Experiments using CNN based-SVM Model

In this section, we investigated the performance of the CNN based-SVM model with dropout for training and recognizing Arabic characters. We parameterize a convolutional layer for the setting architecture, by the size and the number of the maps, kernel sizes, skipping factors, and the connection table. About SVM classifier we have to define mainly two parameters of the RBF kernel; Gamma (γ) and C. We chose the appropriate parameters for our suggested model by making empirical tests. An experimental study was created to assess the proposed model and we chose the parameters on the basis of the criterion of the error classification rate on the train set.

CNN based-SVM network architecture with dropout is shown in Fig. 3, utilized in experiments applied to HACDB database with elastic distortion and is given in the following way: 1×28×28-6C2S-12C2S represents a net with input images of size 28 × 28 pixels giving an input dimensionality of 784 with four Convolutional-Subsampling layers that is possibly to be viewed as a trainable feature extractor. The final output layer of the fully connected hidden layers of CNN was substituted by an SVM classifier to recognize the anonymous handwriting text. The one-versus-all method with 66 way is utilized for the multi-class SVM.

It is noted that first convolutional layer “C1” possesses 6 feature maps each having 25 weights, constituting a 5 × 5 trainable kernel, and a bias. The feature maps’ size is 24 × 24. This guarantees a low-level feature extraction. The second hidden layer “S1” named sub-sampling includes 2 features maps with size 12 × 12. This lowers their sensitivity to shifts, variations in scale and distortions and rotation. The third layer “C2” possesses 12 convolutional maps of size 8 × 8 and the fourth layer “S2” possesses 2 sub-sampling maps of size 4 × 4. When training this architecture, the feature maps of the 4th layer are merged into a feature vector feeds into the fully connected layers. Then, dropout was applied to convolutional neural networks only to fully connected hidden layers with the probability of retaining a hidden unit $p=0.5$. We temporarily remove 50% of nodes. Those units are randomly selected only during the training stage. Finally, the SVM takes the outputs from the hidden units as a feature vector for classification.

We noted that in our experiments LIBSVM [36] is utilized to construct multi-class SVM with RBF kernel. We successfully found that the selection of the best parameters (C, γ) to be experimentally efficient by using cross-validation method. The optimal values of main parameters got after the tests on the training Arabic handwritten text database HACDB were synthesized in table 2. After training, we test our best network with two test sets; the first contains 1.320 images of the HACDB database and the second composes of 1.120 images extracted from sets (a) and (b) of IFN/ENIT database.

CNN based-SVM Model with dropout			
Learning rate	0.8	Kernel parameter γ	2
Batch size	40	Penalty parameter C	30

Table 2: Training parameters for CNN based-SVM model

3.4 Results and Discussion

The new architecture of CNN classifier, introduced in this work, enabled to couple a CNN method with RBF kernel SVM classifier. In order to improve this architecture, we added a dropout technique. Our proposed system was compared to a number of other methods being recently proposed.

The best performing convolutional neural network achieve an error classification rate of 14.71% [37]. A novel architecture of CNN based on SVM as well further reduces the error to 6.59% [8] on the testing HACDB dataset with 66 classes. Adding dropout to the CNN based-SVM model, only to the fully connected hidden layers, reduces the error to 5.83% (see figure 5). Even more decrease in error rate was obtained by our system using dropout technique applying with IFN/ENIT database (see Table 3). Our network was trained using gradient descent for 200 epochs.

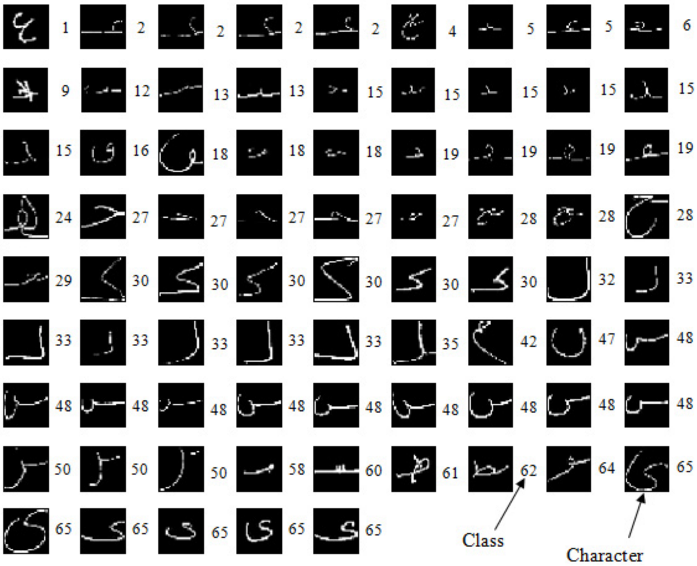

Figure 5: Samples of 77 misclassified characters using CNN based-SVM model with dropout

Approach	HACDB database		IFN/ENIT database
	24 classes	*66 classes*	*56 classes*
CNN [37]	5 %	14.71 %	-
CNN based-SVM	2.65 %	6.59 %	7.32 %
CNN based-SVM with Dropout	2.09 %	**5.83 %**	7.05 %

Table 3: Error rate for our proposed systems applied on HACDB and IFN/ENIT Databases

It was obviously noted that our model based on dropout outperforms any other methods. In table 3, it is shown that CNN based-SVM model with dropout outperforms highly the basic CNN classifier and lightly CNN based-SVM model without dropout once tested on HACDB database (dropped by 0.76% with 66 classes and 0.56% with 24 classes) or IFN/ENIT database (dropped by 0.27%). It proved that there is quite an enormous gain in error classification rate (ECR) compared to typical CNN in which the absolute recognition rate was ameliorated by 8.88% with the suggested CNN and SVM system with dropout for the 66 class problem. We came to a result that the error rate gained with the CNN based-SVM model with dropout (with 66 classes) on the HACDB database equals to 5.83%

which means that it is statistically significantly important compared to character recognition accuracies obtained from state-of-the-art offline digit/Latin/Arabic systems (see Table 4) mainly that they were gained with raw data without any feature extraction step [19,20]. Again the same architecture is used with the 24 class problem; error rate decrease approximately two times giving 2.09% when applied dropout technique in CNN based-SVM model.

Authors	Methods	Databases (class)	ECR
Present work	CNN based-SVM with Dropout	HACDB (24) HACDB (66) IFN/ENIT (56)	2.09% 5.83% 7.05%
Lawgali et al [38]	ANN	Arabic characters (old version of HACDB)	3.44% (1600 shapes) 21.18% (5600 shapes)
Azeem and Ahmad [39]	HMM (128 Mixtures)	IFN/ENIT	7%
Ciresan et al [19]	Deep CNN	NIST [40] (62) NIST (52)	11.88% 21.41%
Théodore et al [20]	CNN/HMM	Rimes database [22] IAM database [21]	19.5% 10%
Chen et al [24]	SVM	AMA Arabic Dataset (34) [41]	17.3%

Table 4: Performance comparisons with other methods

A comparative study of the performance of our architecture was also performed with other methods utilizing handwritten Arabic database. Our CNN based-SVM model with dropout still outperforms hand-crafted features-based approach stating as example ANN, HMM and SVM methods [24, 38, 39]. In fact, CNN, with automatic feature extractor stage, deduces features that differentiate between characters, and then SVM classifier insists on predicting the correct class of character. These learned features, being more robust than computed hand-crafted features, establish an adequate representation for characters. Thanks to these experimental results which enabled us to achieve higher recognition rates, it is demonstrated that the proposed architecture of CNN based-SVM outperforms the other current methods. Furthermore, additional gain in performance was obtained by adding dropout technique in the fully connected hidden layers.

4 Conclusion and Perspectives

In this study, we have explored the applicability of dropout in our CNN based-SVM model on Arabic handwritten recognition and demonstrated the efficiency of the system for Arabic handwritten character recognition applied on HACDB and IFN/ENIT databases.

Overall, we deduce that CNN based on SVM classifier offers the state-of-the-art significant results without much emphasis on feature extraction and pre-processing stages. CNN based-SVM model is indeed a full of promise classification method in the handwriting recognition domain. Yet, it is a must, to extend our proposed architecture so that we will be able to deal with handwritten words in different languages and to enhance the recognition rate. In addition, ensembles of pre-trained and fine-tuned CNNs could be explored as well.

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