Handwritten Recognition: A survey

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***Abstract*— Handwritten recognition has received considerable attention in the domain of pattern recognition, image processing, over the last few decades. As a consequence of this research effort, several algorithms were developed using different techniques. Particularly, Deep Learning has shown a remarkable capability to handle handwritten recognition in very recent years. The well-known Deep learning techniques are the Convolutional Neuronal Networks (CNNs) and Recurrent Neuronal Networks (RNNs). This paper provides a survey of the most recent handwritten recognition systems. Thus, we present the most significant algorithms for handwritten character/word/text recognition by explaining the different approaches used in the recognition process and we compare them in terms of accuracy.**

Keywords—Deep learning, Handwritten recognition, convolutional neural networks, preprocessing.

I. Introduction

Automatic handwriting recognition can be defined as the system's ability to identify handwritten input from humans. Handwriting can be from a variety of sources, such as paper documents, images, touch-screens, etc. [1]. There are two main methods of handwriting letter/digit/word recognition: offline and online. Data is captured in online systems, by sensors during the writing process, this making information dynamically available according to boundaries. While in the offline handwriting recognition system, the handwriting of the user is available as an image obtained from a scanner or a digital camera after completing the writing process. Automatic letter/word recognition with both methods represents a challenging task especially in recognizing letters outside of the line. In fact, it requires more efforts due to many reasons. The first one is related to the difference in the shape of the letters due to pen ink, type, and width. The second reason is that every person has his style of writing (shape, size…) that distinguishes him from others, for example, although identical twins are very similar their writing style is not the same. Even more, the writing style of the same person differs from time to time and it can be also influenced by physical and mental condition. All these reasons can result in the deterioration of recognition accuracy [2]. Handwritten recognition research using Deep Learning (DL) has received much attention and has shown to be relevant in recent years as it has significantly improved the recognition capability. In fact, Deep learning has accumulated tremendous success in a variety of application domains in recent years. This new field of machine learning has been rapidly increased and affected different domains [3]. Consequently, the research community has given considerable interest in deep learning-based approaches to solving a range of supervised, unsupervised, and reinforced learning problems [4]. Different techniques based on many learning categories have been proposed. Experimental results in many state-of-the-art papers have shown better performances using deep learning techniques compared to traditional machine learning approaches. This is achieved in different fields such as image processing, speech recognition, computer vision, robotics and control, machine translation, medical imaging, medical information processing, art, bioinformatics, natural language processing [3]. One of the most well-known and commonly used techniques in DL is the convolutional neural networks (CNNs). The CNNs represent a kind of neural network that is capable of extracting pertinent features of the multidimensional inputs data automatically and turn them into a very interesting alternative for solving problems within the field of computer vision [4]. They work with image classification, image recognition, image captioning, etc. These techniques are among the most widely used handwriting character recognition methodologies [5-6]. They were proved to be very effective in perceiving the structure of handwritten characters/words and thus the most suitable approach for solving handwriting recognition problems. Another type of DNNs that is also vastly used in handwriting recognition is Recurrent Neuronal Networks (RNNs), including Long Short Term Memory (LSTM), restricted Boltzmann machines (RBM), Deep Belief Networks (DBN), and others [7-8-9-10-11].

Some surveys were proposed in the literature. But, to the best of our knowledge, no survey has presented yet the most recent works (especially the works developed in 2020). Therefore, we present, in this article, the well-known and the most recent handwriting recognition works, explain the techniques used in the different methods, and compare between them in terms of accuracy.

This article is structured as follows. In Section II, we explain the main steps of offline handwritten recognition. In Section III, we present the well-known and the most recent existing methods for handwritten recognition. These methods used various techniques of NN and DL with different network architectures and for different languages. We also conduct a comparison between them. Finally, some concluding remarks will be drawn out in Section IV.

II. Steps Used in Off Line handwritten Recognition System

Performing handwritten recognition in a captured image is related to several factors including the capturing method, the clarity of the image, the segmentation method of word images into their component character images, and the recognition algorithms. A block diagram that illustrates the main steps for the mechanism for handwritten recognition is shown in Fig. 1. In the following, we will explain the role of each step.

A. Image Acquisition

The machine input is an image taken from a scanner or a digital camera or any digital input device in a specific format such as JPEG, BMP, etc. [12].

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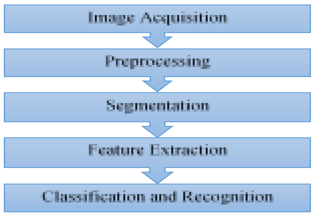

Fig. 1. Block diagram of basic mechanism in character recognition.

B. Preprocessing

Preprocessing step represents an important task in the character recognition process. It aims to enhance the readability of the text image and remove the details and features that have no discriminative power in the process of recognition [13]. In fact, this task allows the normalization of the strokes and also helps to eliminate variations able to deteriorate the performance of the handwritten recognition process. It primarily treats different distortions, such as the unequal size of text, lost points during the motion of the pen, left to right bending, jitters, and irregular spaces. The preprocessing step contains several operations applied directly to the scanned image such as binarization, size normalization, complement, morphological operation, thresholding, noise removal, baseline detection, thinning, skeletonization, cleaning techniques, filtering mechanisms, and RGB to Gray Image [14-15]. These operations simplify the processing of the input image aiming thus to increase the recognition accuracy rate of the overall system [14-15].

C. Segmentation

Segmentation consists of extracting script core symbols. It aims to segment the image into its sub-units such as lines, words, characters, or strokes so that each part of the image is readable. Therefore, there are mainly three types of segmentation: segmenting a page into lines, a line into words, and word into characters [13-14]. Segmentation is a critical stage because it influences the rate accuracy of recognition and represents the fundamental source of recognition errors so that it should be always improved [13].

D. Feature Extraction

At this stage, the most relevant patterns are extracted. These patterns will have a fundamental role in the classification process. This is an important step because it eliminates misclassification and gives high recognition accuracy. Moreover, performing this step allows saving time in training and classification step.

Features of handwritten texts can be classified into three main categories: structural features showing the geometrical and topological characteristics of the text image, statistical features analyzing the spatial distribution of pixels such as pixel densities, chain code direction, histograms, projections, moments, and zoning, crossings and distances and global transformation converting pixel representation into a more compact form. common transformation techniques used in character recognition are: series expansion such as Discrete Cosine Transform, Hough Transform, Fourier transform, wavelet, curvelet, and Gabor transform [13-15].

E. Classification and Recognition

Classification is a task that consists of identifying an object by comparing its features to one of a given set of classes. It represents the basic phase of the character recognition process and the decision-making phase depends on the accuracy of the features extracted in the previous step. There are many existing techniques for handwriting classification. The well-known are the Support Vector Machines (SVM), the Hidden Markov Model (HMM), the Artificial Neural Network (ANN), the fuzzy logic, K-Nearest Neighbor, and the Deep Neural Network (DNN) [13]. Some authors combined techniques of classification for better accuracy.

III. Literature Survey

In this section, we expose the most recent handwritten (characters/digit/words) recognition techniques for different languages. Tables 1, 2 and 3 compare the well-known approaches for character (letter/ digit and special characters) recognition while Table 4 presents the recent approaches for word/text recognition.

A. George, F. Gafoor, developed, in 2014, an efficient method for offline handwritten recognition for separate Malayalam characters. It is based on artificial neural networks using the backpropagation algorithm as a classifier. The ANNs are composed of three hidden layers using log sigmoid activation function [12]. The proposed model includes all the steps of the handwritten recognition: image acquisition, preprocessing (noise reduction, binarization, Smoothing...), segmentation (line, word, character segmentation), extraction of the features, classification, and recognition. For the features' extraction operation, the system used the contourlet transform, besides the aspect ratio and the ratios of the net values in the vertical and horizontal directions [12]. The proposed feature extraction method was proved to be efficient as it allows higher recognition accuracy and demands less time for training and classifications. The system has been trained with different size characters of different handwritings. It has been reported that the proposed system succeeds to recognize separate Malayalam characters with a high accuracy rate equal to 97.3 % [12].

K.V. Kale, P.D. Deshmukhy, et al., in 2014, a new offline system for the recognition of handwritten characters for Devanagari-derived Basic Marathi Script. In the proposed system, the input handwritten character images were preprocessed (converted from RGB to gray, filtered, normalized, skeletonized) and then segmented into zones before the features extraction step. At this stage, the system used the Zernike moment feature descriptor to extract relevant features without redundancy. Finally, it achieved the classification step with SVM and K-NN techniques.
Because the dataset was not available, a dataset named KVKPR2013 was created from different age groups of writers. It was shown that using a Zernike moment feature for the recognition process of a Devanagari compound character gives high accuracy [2]. It was also proved that the recognition accuracy rate of the new system using SVM and K-NN classifiers is slightly better for a basic character (with 98.37% and 95.82%, respectively) than for a compound character (with 98.32% and 95.42%, respectively). Moreover, the new system is more efficient than other existing handwritten recognition systems with an improvement of 0.37% [2].

S. Afroge, B. Ahmed, et al., introduced in 2016, a new method to recognize English alphanumeric characters [16]. This method is based on ANN. The network contained one input layer, one hidden layer, and one output layer. There were two main parts of the recognition scheme for the proposed model: training and recognition. Each part contained image acquisition, pre-processing and features extraction. Moreover, the two sections involved the classifier's training and its simulation sequentially. The pre-processing step involved several operations such as conversion from RGB to gray, digitization, reduction of the noise, binarization, and line and character extraction. The extracted character matrix was then normalized into a 12x8 binary matrix and converted to a column matrix as feature vector. This columnized matrix went after to the classifier [16]. It was shown that the proposed system succeeds to recognize characters with an accuracy of 99% for only numeric (0~9), 96% for only small letters (a-z), 97% for only capital letters (A-Z), and 93% for characters in alphanumeric form by taking into consideration inter-class similarity measurement. The result of the system is very good for isolated classes [16].

L. Sadouk, T. Gadi, et al., presented in 2017, two different DL networks for Tifinagh character recognition from AMHCD database [17]. These two networks are DBNs and CNNs. The CNN is composed of seven layers with Relu activation function: four convolutional layers and three fully connected ones. Whereas the DBN is composed of three and four hidden layers by varying the number of neurons in each hidden layer from 500-500-2000-31 to 1000-1000-1000-2000-31. For the two proposed models, the training dataset was preprocessed (resized, converted to a grayscale format, binarized using the Otsu threshold method…) then increased via multiple transformations. Both approaches (CNNs and DBNs) provide an efficient feature extraction by detecting relevant all level features (low-mid-, and high-level features). For simulating the new approaches, the authors used the AMHCD database with 31 class labels of character patterns. It was proved that the system with CNNs reaches an accuracy rate of 98.25% while it achieves an accuracy rate of 95.47% with DBNs. Although DBNs are less efficient than CNNs, they have a simpler architecture and they demand less time for the recognition process [17].

M. Z. Alom, P. Sidike, et al., proposed in 2017 different DL techniques for Bangla digit recognition. These techniques are based on Deep CNN (six layers), DBN (two RBM hidden layers and soft-max layer), CNN without dropout, CNN with dropout and Gaussian filters, and CNN with dropout and Gabor filters. CMATERdb 3:1:1 is the database used to evaluate the method performance. Most of the techniques for deep learning do not require extraction of features and take raw images as inputs followed by normalization of images. As a result, it is structured as a single framework integrated with all the necessary modules within a single network [18]. It was shown that CNN with a Gaussian filter gives an accuracy rate of 97.70%, CNN with Gabor filter reaches 98.30% whereas a dropout CNN with Gabor and Gaussian filters provides accuracy rates of 98.78% and 98.64%, respectively. Moreover, the proposed system when using the technique of CNN with dropout and Gabor filter achieves more accuracy than other ML methods such as SVM and DBN that achieve accuracy rates of 95.50% and 97.20%, respectively [18].

S. S. Kharkar, H. J. Mali, et al., proposed in 2017, an offline handwritten recognition algorithm based on NN (feed forward backpropagation algorithm) to recognize numbers (0-9), English small and capital letters (a-z, A-Z), as well special symbols (&,$,#,^,%,*) [19]. The offline recognition of the free handwritten characters was ensured by the Back-Propagation algorithm that allows to train enough the NN. In the proposed model, the preprocessing step was performed by many operations such as gray image conversion, noise removal, thresholding, binarization, segmentation, normalization of the extracted character matrix into 12x8 and then conversion of this matrix to a column one. The feature vector went after to the classifier. It was proved that the proposed method based on the NN is efficient and more reliable than other many existing methods as it gives a higher accuracy rate [19].

D. Firmani, P. Merialdo, et al., in 2017, a deep convolutional network CNN classifier to design a novel approach for optical character recognition (OCR) of Latin characters extracted from the text [20]. The first layer of the DCNN is responsible for detecting the edges, while the second layer shows more intricate geometric patterns. Finally, the third (deeper) layer detects full character strokes. The aim of the proposed system was automatically transcribing a large corpus of documents contained in the Vatican Secret Archives. For this purpose, the authors firstly implemented a custom crowdsourcing platform using high school students to manually annotate a huge of Latin characters for the dataset. Moreover, a preprocessing step was applied to all pages. It contains removing the background, splitting the text into lines, then extracting tentative character' segmentations. It was shown that the trained CNN achieves an accuracy rate of 96% over the entire dataset. This result was considered one of the highest results compared to other existing works [20].

S. Gupta, T. Bansal et al., introduced in 2018, a new method to recognize English handwritten characters. This method is based on a CNN to extract relevant features and the SVM to classify them. A pre-processing step was applied in the recognition process including cropping and resizing of the own dataset whose samples were gathered from 50-60 people. It was proved that the new proposed system achieves an accuracy rate of 93%. Therefore, it is more efficient than other previous models [21].

T. S. Gunawan, A. F. Razi, et al., proposed in 2018 a new handwritten system based on DNN as feature extraction and classifier. Two stacked auto-encoding layers and one softmax layer were used by the suggested DNN. Moreover, the datasets used in this system consisted of the common English letters and numbers MNIST and EMNIST. A preprocessing step was applied in this model and involved image threshold, slant correction. character thinning using the morphological process, in addition to image segmentation. The pixel value from image segmentation was then treated as input to the DNN [22]. It was shown that the accuracy of the English numerals and letters recognition achieved by the system is 97.7% and 88.8%, respectively. Furthermore, by comparing the new system to other neural networks, it was proven that the recognition rates for the feeding network, pattern network, as well the proposed model DNN are 68.3%, 80.3%, and 90.4%, sequentially [22].

M. Yadav, R. K. Purwar, developed in 2018, a new model that integrates wavelet coefficients with CNN for the recognition of Indian characters using an offline database containing 4428 characters collected from 108 persons. As the authors observed an increased network training time due to the presence of redundant data, they used wavelet coefficients in horizontal, vertical, and diagonal directions as input to the network. After training the coefficients on different networks, the pertinent features were extracted and then incorporated at a dense layer [23]. Therefore, CNN receives relevant information as a feature and reduces network training time compared to traditional CNN. It was proved that the proposed method achieves good performances with a recognition rate of 96.58%. [23].

A. Duc Le, H. Tuan, et al., introduced, in 2018, a new approach to recognize handwritten text in the Vietnamese language depending on an attention-based encoder decoder (AED). The new approach consists of three stages. It firstly uses CNN to extract invariant pertinent features. The extracted features pass then to a Bidirectional Long Short-Term Memory Network (BLSTM encoder) to be encoded. Finally, the output text is generated using LSTM with an incorporated attention model. To study the performances of the proposed model, the authors used the VNOnDB-Word database [24]. It was shown that the word error rate (WER) of the proposed model is 12.30%. Furthermore, the obtained results show that the system is rival with the GoogleTask1 system without any use of the language model [24].

F. P. Such, D. Peri, et al., proposed, in 2019, a fully CNN architecture (FCN) for recognizing offline handwritten characters. The new system consists of three phases. In the first phase, a CNN was trained to speedily predict the word label for usual words such as "her", "the", "this". In the second phase, a CNN was trained to predict the number of symbols in a word block. Finally, in the third phase, a dual stream FCN predicted a random length order of characters from a variable length word block. Contrarily to restrictive lexicon methods, this method can recognize both common words as well as unlimited fuzzy length code blocks such as surnames, telephone numbers, and acronyms and then generates a random stream of symbols. The dual-stream architecture with blank space symbol alignment eliminates the need for character alignments used in other methods, such as CTC complex methods, and the need for the preprocessing step. It is an attention-based mechanism that can target a range of handwriting, such as stroke, slant, noise, and width, automatically [25]. It was proved that the proposed model gives an accuracy of 92.4% on a subset containing 12,000 word blocks (including special characters, French, and English) and created from the NIST dataset. Moreover, it achieves a character error rate (CER) of 4.43%, a WER of 8.71% on the IAM English handwritten dataset. Furthermore, it achieves a CER of 2.22% and a WER of 5.68% in the RIMES dataset [25].

Al-M .Rasool, R.Fareed, introduced in 2019, an accurate and robust classifier based on CNN. This classifier allows an accurate recognition of numbers and letters for images (visual as well as landscape). In this new approach, due to consecutive convolutional activation (CCA), a high accuracy of recognition was achieved. Moreover, Adam optimizer was used to reduce the Learning rate. The proposed model was trained with a combination of Char74k and EMNIST datasets and random data [26]. It was shown that the presented system achieves the best accuracy in EMINST at approximately 92%. Moreover, it reaches an accuracy of 83% on an unseen dataset (ICDAR2003). These results prove that the new model is the best compared to previous research using the same data collection. They also indicate the durability and the high generality of the classifier [26].

R. Ahmad, S. Naz, et al., presented in 2020, a DL technique to recognize Handwritten Arabic Text (KFUPM) on the KHATT dataset. The new technique relies on multi dimensional Long Short Term Memory (MDLSTM) in addition to Connectionist Temporal Classification (CTC) networks. The proposed system includes three stages: data augmentation, preprocessing, and a deep learning-based approach. The preprocessing phase involves pruning white spaces, removal of extra information, skewed correction, and normalization. The benefit of MDLSTM is that Arabic text lines are scanned in both directions (vertical and horizontal) to strokes, mask dots, diacritics, and fine inflammations. A deep learning approach with the data augmentation showed better performances [27]. It was proved than the system achieves an accuracy rate of 80.02% for character recognition that represents a better result compared to 75.08% obtained in other works [27].

S. Ahlawat, A. Choudhary, et al., introduced in 2020, a new method of digit recognition. Instead of using ensemble CNN network architectures for the same dataset, this method is based on a pure CNN. This was achieved by exploring the various design options for handwritten digit recognition such as kernel size, stride size, number of layers, padding, receptive field, and dilution. In fact, despite the high accuracy of the CNN architectures of the ensemble, they show high computational cost and high testing complexity. Then, in designing a CNN, the authors presented a suitable combination of learning parameters to enable them to reach a new absolute record in classifying handwritten MNIST digits and then improve the performance of the CNN architecture [28]. It was shown that the introduced model for a pure CNN architecture with three layers and the Adam optimizer (adaptive moment) on the MNIST digits dataset succeeds the recognition process with an accuracy of 99.89% compared to many results obtained in other works [28].

A. Duc Le, H. Tuan, et al., presented in 2020, a model to recognize Vietnamese handwritten text depending on an attention-based encoder decoder (AED). Instead of using three phases and testing on one dataset VNOnDB-Word as in [24], this model includes two stages. The first stage is to encode extracted features by using CNN based on DenseNet. The second stage generates the output text by using Long Short-Term Memory Network (LSTM decoder) combined with an incorporated attention model. The proposed model was tested on both VNOnDB-Line, VNOnDB-Word datasets [29]. It was proved that the proposed model achieves 10.24 % of WER and 4.10 % of CER on the VNOnDB-Word test set, and 13.33 % of WER and 4.67 % of CER on the VNOnDB-Line test set. It was also shown that the model without using any language model exceeds the GoogleTask1, IVTOVTask2, and GoogleTask2 [29].

V.Garg, provided in 2020, an effective model for recognizing handwritten text based on DNN. This method can recognize English words in the text for an IAM dataset. The proposed model consists of a CNN including five layers for extracting features from the picture in addition to a recurrent neural network (RNN) including two layers to propagate data through the image. CTC operation decodes the output matrix of the RNN to yield the final text. The preprocessing of the dataset is an important reason to optimize the input images simplifying thus the classifier problem and increasing the model accuracy. It consists of contrast normalization in addition to data augmentation to grower the size of the dataset [30].

TABLE 1: COMPARISON BETWEEN DIFFERENT CONVENTIONAL APPROACHES FOR CHARACTER (DIGIT/ LETTER/ SPECIAL CHARACTERS) RECOGNITION

Ref.	Feature extraction	Classification	Accuracy recognition	Language
[2]	Zernike moment	SVM and k-NN	recognition rate 0.37% basic character 98.37% SVM, 95.82% k-NN compound character 98.32% SVM , 95.42% k-NN	Hindi Marathi derived Devanagari Script basic &compound character KVKPR2013 dataset
[12]	Contourlet transform	Feedforward back propagation neural network	97.3%	Malayalam character
[16]	-	Feedforward back propagation neural network	digits(0~9) 99%, capital letters (A~Z) 97 %, small letters (a~z) 96% ,alphanumeric characters (0~9,A~Z,a~z) more than 93%	English characters
[19]	-	Feedforward back propagation neural network	higher accuracy rate	English , numerals (0-9) , characters (A-Z,a-z), special characters (#,$,%,^,& ,*)

TABLE 2: COMPARISON BETWEEN DIFFERENT DEEP LEARNING APPROACHES FOR CHARACTER RECOGNITION

Ref.	Feature extraction & Classification	Accuracy recognition	Language
[17]	DBN, CNN	DBN 95.47% CNN 98.25%	Tifinagh character, AMHCD dataset
[18]	CNN, DBN	SVM 95.50% DBN 97.20% CNN+ GAUSSIAN 97.70% CNN + GABOR 98.30% CNN+ GAUSSIAN + Dropout 98.64% CNN+ GABOR + Dropout 98:78%	Bangla numeral ,CMATERdb 3:1:1 database
[20]	CNN, Adam optimization	96%	Latin characters
[22]	DNN	digits 97.7% letters 88.8%	English digits and letters, MNIST and EMNISTdataset
[26]	CNN, Activations (CCA), Adam optimizer	92% EMNIST 83% ICDAR2003	English character , digit, EMNIST data set, Char74k
[28]	(CNNs) with gradient descent optimizers	99.89%	MNIST digits

TABLE 3: METHODS COMBINING CONVENTIONAL APPROACHES WITH DEEP LEARNING APPROACHES FOR CHARACTER RECOGNITION

Ref.	Feature extraction	Classification	Accuracy recognition	Language
[21]	CNN	SVM	93%	English character, Own database
[23]	Wavelet transform +CNN	Wavelet transform +CNN	96.58 %	Hindi handwritten character, Own database

TABLE 4: COMPARISON BETWEEN DIFFERENT APPROACHES FOR WORD AND TEXT RECOGNITION

Ref.	Feature extraction	Classification	Accuracy recognition	Language
[24]	CNN	BLSTM encoding, LSTM with attention, LSTM decoder	12.30% of WER	Vietnamese VNOnDB-Word database
[25]	-	FCNN+ attention-based mechanism	92.4% CER 4.43%, WER8.71%, CER 2.22%, WER 5.68%	NIST arbitrary symbol (word) handwritten dataset,Lam English, RIMES, French
[27]	Raw Pixels	MDLSTM-CTC	80.02%	Arabic text-line, KHATT dataset
[29]	CNN based on DenseNet	(LSTM) with the attention mechanism	CER 4.10% WER10.24% on NOnDB-Word CER 4.67% WER13.33% on NOnDB-Line	Vietnamese VNOnDB-Word, VNOnDB-Line datasets
[30]	CNN	CRNN [CNN-RNN(LSTM) +CTC]	-	English text, IAM data set

By comparing Tables 1, 2 and 3 to Table 4, it can be clearly seen that the different proposed methods succeed in recognizing characters much better than words and texts. Therefore, more efforts should be directed to developing works that improve the word/ text recognition accuracy.

Moreover, by analyzing tables 1, 2 and 3, we can conclude that the recognition of digit characters is more accurate than the recognition of other characters (letters, special characters). Furthermore, using DL approaches in the recognition system ensures better performances compared to traditional ML approaches.

It can be also seen, by comparing the systems developed in [22, 26] to the method proposed in [21] for English character recognition, that using the SVM with the CNN can slightly improve the recognition accuracy.

To summarize, the most recent works used DL techniques especially CNNs for character recognition for different languages: English, French, Arabic, Bangla, Latin, Chinese, Devanagari from their proper datasets. It is clear that the architecture of the recognition system differs from a language to another because every language has different style directed and characters of writing. However, from all the surveyed works, we can conclude that preprocessing and data augmentation techniques can improve the performances of character recognition methods. The data augmentation techniques are most often achieved with SVMs or NNs. Moreover, using dropout SVM with the CNN for classification can increase the accuracy rate of the recognition system. In fact, it allows the classification and recognition of the missing features that are not properly classified by CNN. Furthermore, ensuring high recognition accuracy with less complexity remains a challenge that researchers are trying to achieve.

For example, in [28] a new method of digit recognition from the MNIST digits dataset was developed. This method uses a pure CNN instead of ensemble CNN network architectures by thoroughly investigating all the parameters of the CNN architecture to reduce the system's complexity. The proposed method achieves the highest accuracy rate of 99.89% compared to other existing methods [28]. A future work that extends the work in [28] to the EMNIST (the extended version of MNIST that comprises both handwritten digits and handwritten letters) [4], a more complex dataset, is then a challenging task. In addition, as future works, researchers can further test more architectures of CNN, especially hybrid CNN like CNN-RNN model and explore more evolutionary algorithms by more optimizing CNN learning parameters such as the number of layers, kernel sizes of convolutional filters, and learning rate.

Finally, we can see from all the surveyed articles that most works succeed particularly to recognize digits and letters and only some works investigated on the recognition of special symbols [19] and unlimited fuzzy length code blocks such as surnames, telephone numbers, and acronyms [25]. Therefore, future works can focus even on the recognition of special and arbitrary symbols.

IV. CONCLUSION

We presented in this paper, the new and the well-known methods for offline handwritten recognition, explained the various techniques used in these methods, and compared between them in terms of efficiency and accuracy. Furthermore, we discussed the different features extraction techniques and the various classifiers used in the recognition process. We can conclude from the results obtained from different studies that the preprocessing stage such as noise reduction, binarization, thinning, resizing, and insulation has a special role in improving the accuracy rate. Moreover, the choice of the optimal relevant feature extraction and the adequate classification algorithm is an important task to achieve a good recognition rate. The most recent works showed that DL techniques especially the CNNs are very efficient in realizing the structure of handwritten words/characters and thus the most appropriate approach for solving the problems of handwriting recognition. For the future research, we will explore new strategies that may further improve the performance for handwritten recognition. For example, we can apply additional preprocessing techniques to have more compelling and robust training. We can also test some achieved models that succeeded in some languages for other languages.

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