Fast Extreme Learning Machine for Berber Handwritten Latin Script

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Abstract—This article deals with the problem of Berber handwritten character recognition using the Extreme Learning Machine (ELM). This paradigm has gained significant attention in the pattern recognition field thanks to its efficient learning speed and its high accuracy. In this paper, we have developed a fast Extreme Learning Machine to recognize efficiently the Latin Berber characters. So, the proposed ELM has been trained over a Berber-MNIST dataset containing images of Amazigh alphabets. This algorithm learns much faster than traditional popular learning algorithms thanks to the use of the JAX library, which contains several functions to reduce the execution time of our solution. The simulation results show that the handwritten recognition system based on our developed extreme learning machine decreases computational cost and reduces the time required for the whole recognition process. Furthermore, the proposed ELM achieves high performance in terms of recognition accuracy.

Keywords—character recognition, deep learning, extreme learning machine, Amazigh Latin characters

1 Introduction

For a few decades, Handwritten Character Recognition (HCR) has been a popular research field because of its diverse application prospects. This emerging technology has achieved considerable success in several applications such as image processing [1], cognitive science, linguistics, address recognition, banking sectors, etc. Handwriting recognition is an active sub-discipline of OCR (Optical Character Recognition) which is a component of artificial intelligence [2] referring primarily to the process of converting handwritten text into a machine-editable format.

Although handwriting recognition remains a difficult and challenging task due to the wide variety of writing styles, several deep learning tools have been developed to recognize handwritten characters of different languages. For instance, a convolutional neural network has been proposed to recognize Arabic handwritten characters [3], an artificial neural network has been used in [4] for sign language recognition, a recurrent neural network has been designed for the segmentation of online handwritten English text [5], etc.

One of the most successful deep learning tools is the Extreme learning Machine. This technique is the single hidden layer neural network, largely applied in numerous applications and classification problems. Moreover, this emerging paradigm has attracted a lot of attention in the field of handwriting recognition due to its efficient learning speed and high accuracy. In this paper, we are interested in the application of this approach for the recognition of Berber Latin manuscript characters.

The Amazigh or Berber language is a part of the Afro-Asian language family, which covers North Africa extending from Morocco to Egypt, as well as from the Mediterranean Sea to the Sahara and the north and west of the Sahel, including Mali, Niger and Burkina Faso [6]. The need for HCR systems arises in the context of promoting the Berber language. In fact, this innovative technology allows the digitization of old documents, which helps in data sharing as well as in heritage preservation.

However, the development of Berber character recognition systems remains a recent and a young research field and the works on handwritten Amazigh characters are very limited, because of the existence of various writing styles and its unified writing system (Tifinagh, Latin and Arabic). In this work, we have elaborated an HCR system based on the ELM technique that includes the Latin writing system. To do so, we have used the images of the Berber Latin letters contained in the Berber-MNIST dataset (Berber-Modified National Institute of Standards and Technology dataset) [7] that we have created in previous work.

Firstly, we have reduced the execution time of the training phase compared to the work proposed by Van et al. [8], and then we performed a feature selection on the pixels of the images using variance threshold. Finally, to reduce the classification error, we have executed the training phase in that we just reduced its execution time in several iterations. Simulation results show that this work improves the accuracy of the classification and consequently the error is reduced. To the best of our knowledge, this is the first time that the recognition of the Amazigh handwritten Alphabet is dealt with an extreme learning machine.

The rest of the paper is organized as follows; Section 2 presents a brief review of related works on handwritten character recognition based on the ELM paradigm.

Section 3 discusses the enhanced ELM algorithm. Section 4 presents the new proposed architecture. Section 5 details a comprehensive evaluation of the ELM algorithm on Berber-MNIST datasets. Finally, Section 6 summarizes the conclusions and presents the future perspectives.

2 State-of-the-art of ELM methods in handwritten character recognition

Several ELM-based approaches have been proposed to deal with handwritten character recognition of different languages. In this section, we provide a brief overview of the related works in this research field. Chacko et al. [9] dealt with the recognition of handwritten Malayalam characters. In this work, the authors used the extraction of the division point feature and classification using an Online Sequential Extreme Learning Machine called (OS-ELM). The authors have used a feature extraction technique based on the recursive subdivision of the character image. The proposed ELM algorithm is used in hidden layer feed forward neural networks based on additive and radial functions. In the same setting, the authors address in [10] the recognition of the characters of the same language (Malayalam), but this time using two concepts, which are wavelet energy and extreme learning machine. The wavelet energy parameter is used to reduce the influence of different types of noise at different levels. The ELM algorithm is used for single hidden layer feed forward networks where the input weights are randomly chosen and the output weights are analytically determined. The study proposed by Syed et al. [11] aims to enhance the character recognition rate of Urdu-like language scripts. Thus, the authors have proposed a deep extreme learning machine-based optical character recognition. The proposed multi-hidden layers algorithm optimizes the OCR process by reducing the overhead of pre-processing, segmentation, and feature extraction layer. Das et al. [12] presented a detailed investigation of different ELM configurations by taking into account many parameters such as the hidden layer number of nodes, input weight the initialization, and the type the activation functions type. In this work, the authors have analyzed the performance of different ELM schemes, trained on four datasets of handwritten digits. This study aims to help the researcher to solve different regression and classification problems by developing ELM-based classifiers. Pang et al. [13] have combined the power of the combinational neural network and the speed learning capacity of ELM to design a deep convolutional extreme learning machine called (DC-ELM). This algorithm is mainly characterized by using multiple alternate convolution layers and pooling layers to efficiently extract the robust features from the input. Further, the ELM classifier is responsible for generalizing them at a very fast learning speed, which leads to better performances. This solution is conducted on handwritten digit recognition. Dey et al. [14] dealt with handwritten Tibetan character recognition. To do so, the authors have used a modified Histogram of Oriented Gradients (HOG) based center gravity partitioning of an image to extract features. In the second step, an ELM algorithm has been applied for the classification of the characters. Mahmoud et al. [15] have used two methods which are Support Vector (SVM) and Extreme Learning Machines (ELM) to address the automatic recognition of off-line handwritten Arabic numerals. Tal et al. [16] have used Chinese character structure features and extreme learning machine to propose a new scheme for writer recognition for Chinese handwriting. The authors have based on the trait of Chinese handwriting characters to extract special features of Chinese handwriting characters. The latter, are combined with the ELM algorithm which randomly chooses the input weights and analytically determines the output weights of a single hidden layer network. The contribution proposed by Bipu et al. [17] intends to recognize Bangla handwritten characters based on two feature extraction techniques, which are Histogram of Oriented Gradients and Gabor filter. The first method is used to encode the object information. The second one is responsible to deliver a specific and precise response to localize the target images. At the end of this process, the extracted features are introduced to the ELM classifier in order to contribute to the accuracy of a Bangla OCR system. Kumar et al. [18] dealt with the recognition of Indian Signal language to assist the communication between deaf and dumb people and normal-hearing people. For this purpose, the authors have designed an automatic computer vision using the Histogram of Oriented Gradients features technique (HOG) and extreme learning machine. The proposed system consists mainly of three steps. Thus, the authors have firstly established a new

Indian Signal alphabet. Then, a set of features are extracted using the HOG technique and finally an extreme learning machine algorithm is applied in the training and the classification phase. Another oldest language in India is addressed by Sridevi et al. [19]. In this setting, the authors have proposed an approach for the classification of handwritten ancient Tamil scripts based on extreme learning machine. The latter is trained by Zernike moments and regional features. Song et al. [20] designed a handwritten letter recognition system. The letter exploits firstly a database for handwritten letters to read and extract features of handwritten alphabet images, and then, a recognition technique based on an extreme learning machine has been applied. The contribution proposed by Jarungthai et al. [21] intends to recognize the Thai handwritten characters, Bangla numerals, and Devanagari Numerals. For this end, the authors have used the modified version of generalized radial basis function ELM. The recognition rate has been enhanced by an optimal selection of the appropriate input weighs bias. This technique was trained on all of the three datasets.

3 Recognition system design based on extreme learning machine

3.1 The extreme learning machine paradigm

ELM was first proposed for learning process in a single hidden layer neural network [22]. Then it is extended to fit a variety of architectures to address many types of applications and learning paradigms. The ELM learning process can be summarized as described in Algorithm 1.

Algorithm 1: Typical ELM algorithm
1: For a given learning set $S = \{X, T\}$, such that X is the set of inputs and T is the set of outputs.
2: Generate randomly the input weights Matrix W and biases vector b.
3: Calculate the hidden layer output matrix, $H = G(WX + b)$
4: Determine analytically the output weights β using the pseudo-inverse of the hidden layer, $\beta = H^{-1}T$
5: Solve the minimization problem, $e = min(H\beta - T)$.

Several ELM-based approaches have been proposed based on this basic algorithm. In this paper, we have enhanced the performance of the methods proposed in [8], and we have subsequently applied it on the Berber-EMNIST database. The reference work applied two main methods which fit very well with the ELM framework.

- ***Greville's method:***
  This incremental approach concerns the use of pseudo-inverse to address linear regression problems. The main purpose of this incremental approach is to produce a weight matrix identical to the weight matrix generated by SVD (singular value decomposition).
- ***Opium method (Online Pseudo-Inverse Update Method):***
  This approach produces the exact same weights matrix as the SVD and it is a simplification of the first method, by reducing the necessary computation in the incremental process and minimizing the loss of accuracy. Two other methods have been

derived from this method, which are OPIUM light and OPIUM dynamic. OPIUM light is less precise but faster. The second derived method (OPIUM Dynamic) is more adapted to non-stationary data.

3.2 The enhanced extreme learning machine

Due to a large number of neurons in the hidden layer, a large number of parameters to be adjusted and managed, the size of the inputs and the number of classes to be predicted, the ELM network requires a lot of resources (computing power) and needs a lot of time to perform the required tasks. In this work, we have enhanced the ELM algorithm given by [8] by reducing significantly the execution time of the training phase. For that, we have adopted it for GPU machine (Graphics processing units) and used JAX library [23]. JAXnet is a deep learning library based on the JAX. The functional API of JAXnet offers the advantage of compiling the NumPy code by GPU, thus reducing its execution time considerably. The following table summarizes the strengths of our solution compared to [8].

Table 1. Comparison of the ELM CPU version versus the ELM GPU version

	Van et al. [8]	**Our solution**	**Reduction %**
Greville	/	8.5 minutes	/
Opium	20 h	**25 minutes**	**97%**
Opium light	7 minutes	**4.5 minutes**	**35%**
Opium Dynamic	/	10.5 minutes	/

Note that we have used the same EMNIST digit subset [24] and ELM parameters to perform our comparison.

Table 1 shows the results of each ELM variant used in [8] and executed on the CPU, and the obtained results of our solution performed on the virtual machine with GPU provided by Google Colab (Colaboratory) [24]. The obtained results show the significant improvement in our solution in terms of execution time, reaching a 97% reduction compared to the solution given by [8].

4 The proposed architecture

The process of our proposed model (Figure 1) is carried out mainly in two steps: feature selection and results injection.

4.1 Feature selection

This phase consists to reduce the number of pixels that constitute the image using the threshold variance. This technique calculates the variance of each pixel and eliminates the pixels whose variance is lower than a threshold that we have defined to 1. Knowing that a pixel takes a value between 0 and 255, means that pixels with a variance lower than this threshold in the whole dataset will be removed. This allows finding the most useful pixels in the images (28x28 pixels) available in the Berber-MNIST Latin version subset. This pre-processing step provides to our model a reduced number of pixels which positively affects its performance.

4.2 Results injection

This second step consists to inject the results provided by the first step, which are 580 features for each image of the dataset in the ELM network. The latter is composed of 19720 neurons in the hidden layer and 34 neurons in the output layer, which represents the number of classes to predict.

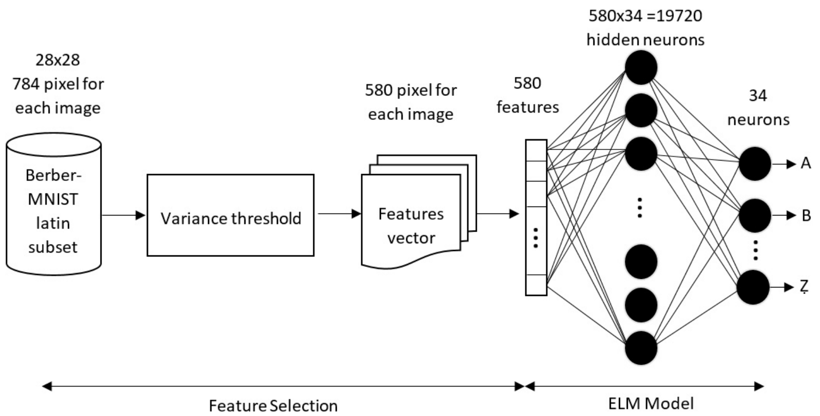

Fig. 1. The proposed system architecture

5 Test and results

5.1 Data set

To evaluate the proposed system, we have carried out a series of experiments on the images of characters contained in the Berber-MNIST database. The latter is a large dataset of Berber handwritten characters that we have already created in further work, by combining two databases: AMHCD [25] and EMNIST [26] with further modifications. To obtain the first database, we have applied a conversion algorithm that reduces the size of the original images of Tifinagh characters extracted from the AMHCD database. The second subset contains the images of Berber Latin characters. This sub-database was created by reusing the whole uppercase subcategory of the EMNIST and extending with some characters specific to the Berber language, such as Č, Ṣ, etc. In this work, we have used the second subset. Figure 2 shows a sample of dataset content.

Fig. 2. A sample of Berber-MNIST dataset content

5.2 Results and discussion

We have empirically performed a series of experiments on the Berber-MNIST Latin subset using the ELM Opium variant. Table 2 shows the obtained results. Note that due to the limit of resources that can manage the virtual session provided by google Colab [22]; we increased the number of neurons of the hidden layer until reaching the number of 19720, which represents 580x34 as in the article [8]. This indicates that the performance of each class increases if the number of hidden layer neurons increases.

Table 2. Result of Berber-MNIST on OPIUM GPU version

Number of Features	Number of Hidden Neurons	Running Time	Error
580	19720	2h25	4.48%

We noticed in Table 1, a significant reduction in the training phase time for the Greville and Opium light variants that we modified to run on the GPU. This allowed us to reduce the error rate further by running the training phase in several iterations.

Table 3. Result of Berber-MNIST on OPIUM GPU version

Opium Light				
Iteration	1	2	3	4
Error	4.51%	3.63%	3.54%	3.44%

Table 3 shows the obtained results for the Opium Light variant for one, two, three, and four iterations. The detailed results for each character of Berber-MNIST runon the OPIUM light classifier are given by the following Figure 3.

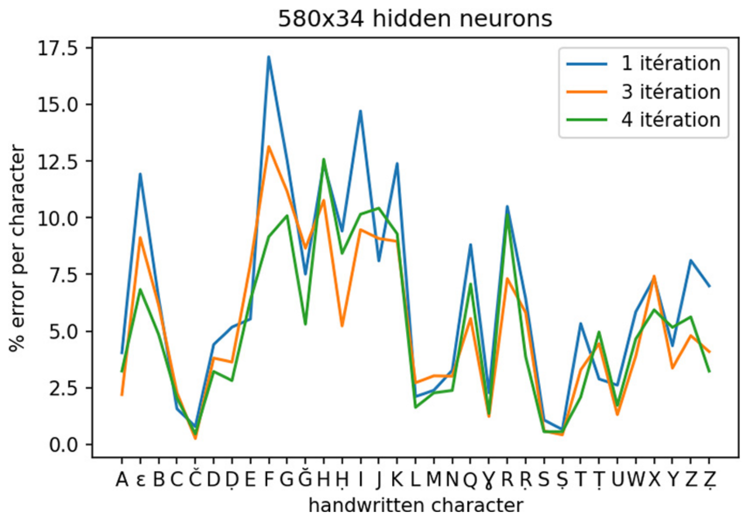

Fig. 3. The detailed results for each character

This figure depicts the error rate for each character obtained in the previous table for three and four iterations. We notice that most characters are better detected after the first iteration.

6 Conclusion

In this paper, we have presented a recognition system for Berber handwritten Latin characters based on the Extreme Learning Machine technique. This solution is characterized by a fast-training phase and a reduced input layer thanks to the threshold variance that we have used in the feature selection step. The proposed system operates with the original character images in the Latin Berber-MNIST dataset and the effectiveness of Amazigh handwritten character recognition is proved by the experiments. The work can be extended to recognize Berber words written by different scripts and future research is in the direction of improving the performance by using more complex deep learning techniques.

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