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Some Comparative Studies for Cursive Handwritten Tifinagh Characters Recognition Systems

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Abstract

In this research, we present two comparative studies; the first one is between two methods of features extraction which are the mathematical morphology, the zoning and the hybridization of these two methods. The second comparative study is between both supervised methods used in learning-classification which are the Multi-Layer Perceptron (MLP) and the Support Vector Machines (SVM) applied to cursive handwritten Tifinagh characters recognition. The obtained experimental result demonstrates that the hybrid method is most efficient and the SVM is more performing than the MLP.

Keywords: *The cursive handwritten Tifinagh characters, the thresholding, the centering and the normalization techniques, the zoning and the mathematical morphology methods, the Multi-Layer Perceptron (MLP), The Support Vectors Machines (SVM)*

1. Introduction

Currently, handwritten character recognition is one of the most interesting fields of pattern recognition and artificial intelligence. It undoubtedly plays a very important role in the actual world and really can solve many complex problems in different fields such as bank cheques recognition, postal code recognition, *etc*. Several studies intended for handwritten character recognition in different languages have been developed using the structural methods in features extraction [19-25] and using the support vector machines [1-7, 26, 28] or the neural networks [8-18].

This paper focuses on cursive handwritten Tifinagh characters recognition systems. In fact, a succession of operations used in this recognition system which can be fragmented into three principal phases. The first one is the preprocessing which serves to clean the character image in order to enhance its quality including median filter, thresholding, normalization and centering techniques. The second phase is features extraction for avoiding data abundance, well as reducing its dimension that is to say the character image is converted to a vector, and in this context we have used the mathematical morphology, the zoning and the hybridization between them. The last phase is the learning-classification or recognition, we have opted the multi-layer perceptron and the support vector machines. In order to improve our recognition systems performances, we present two comparative studies; the first one is between two methods of features extraction which are the mathematical morphology, the zoning and the hybridization of these two methods. The second comparative study is between both supervised methods used in learning-classification which are the Multi-Layer Perceptron (MLP) and the Support Vector Machines (SVM).

This paper is organized as follows: The proposed system is given in Section 1. Pre-processing process is presented in Section 2. In Section 3 features extraction phase is

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described. Section 4 deals with the recognition phase. Experimental results are given in Section 5. Finally, this work is ended by a conclusion.

2. Recognition System

Our recognition system is presented as follow:

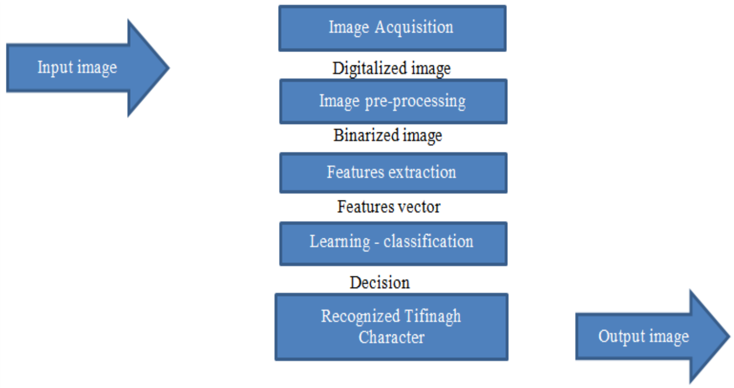

Figure 1. The Proposed Recognition System

2.1. Tifinagh Character Database

The used database contains Tifinagh cursive handwritten characters. Each character is written by many different scripters. An example of this database is presented in Figure 2.

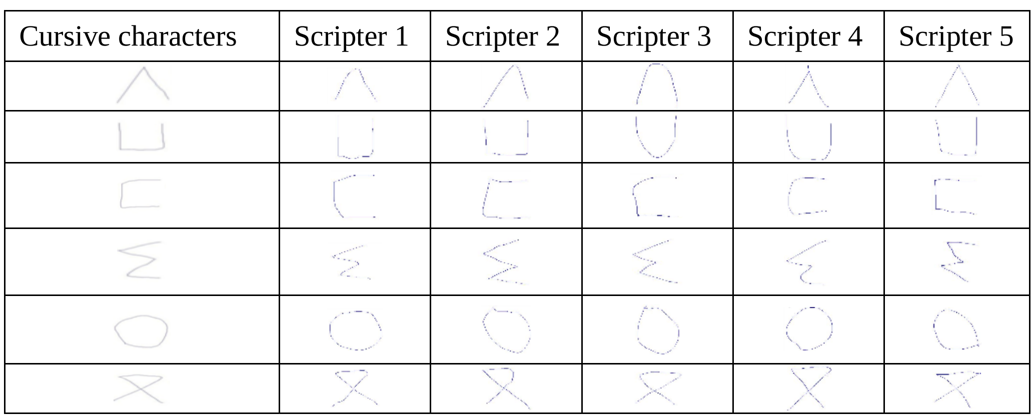

Figure 2. Example of Cursive Handwritten Tifinagh Characters

2.2. Pre-processing

The pre-processing is a very important step in pattern recognition. It's the first phase of a recognition system used to produce a cleaned up version of the original image so that it can be used efficiently in the following phase that's the feature extraction. In this paper, we have pre-processed each character image by a median filter exploited for removing each noise from image. Then the thresholding is applied to render each image containing only the black and white colors according a preset threshold and after the centering technique is employed to position the character just in the center of its image. Finally we have used the normalization technique in order to normalize all sizes of character image.

2.3. Features Extraction

This phase is exploited in order to extract from each character image its primitives which are the real values used as a components of a vector, it serves therefore to perform a vectorization of each character image which allows making easy the next phase.

In fact, several methods [19-25] can be exploited in this stage. In our recognition systems, we have used the mathematical morphology, the zoning and a hybridization method between them. Our goal is to ameliorate the performance of the proposed systems. Also we presented a comparison of theirs performances.

2.3.1. Extraction by Zoning Method: This method [21-24] can be explained as follow:
At first, given a black image containing a Tifinagh character that written in white. The zoning method consists to subdivide this image to several square or rectangular blocks or zones, then to count in each zone the number of white pixels. As consequence, the image is converted to a vector having a number of components equal to the number of zones (see Figure 3).

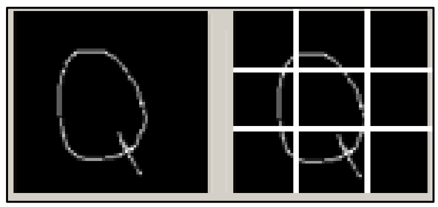

Figure 3. Features Extraction by Zoning Method from the Tifinagh Character

2.3.2. Extraction by Mathematical Morphology Method: The feature extraction is based on mathematical morphology [17-20]. The characteristic areas can be detected by the dilatation operation of the character image pre-processed in four directions. The characteristic zones can be detected by the intersections of dilations found to East, West, North and South.

Each point belongs to the characteristic area if and only if:
- This point does not belong to the limit of the object.
- From this point, moving in a straight line to the South, North, East and West we cross the object. The result of the extraction is illustrated in Figure 4.

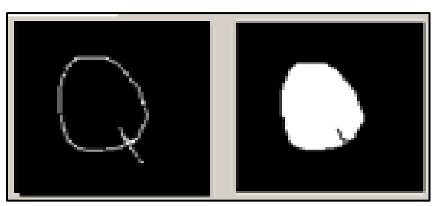

Figure 4. Features Extraction by Mathematical Morphology Method from the Tifinagh Character

2.3.3. Extraction by Hybrid Method: Mathematical Morphology + Zoning: This method consists after the features extraction by mathematical morphology to zoning it. But it is not like to that we carried previously, in fact, it comes this once around to achieve a zoning of the image by a zigzagged manner. In other words the zones in which the image is divided are a horizontal and vertical rectangles and a trapezoids which parallel to diagonal and also anti diagonal of the image. Then we will count the number of all white pixels in each of these zones in order to gather all these numbers in a vector (see Figure 5).

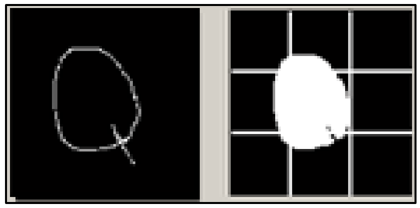

Figure 5. Features Extraction by all Method Used from Tifinagh Character

3. Learning-classification Phase

3.1. The Neural Networks (NNs)

The Neural Network [8-18] used in our work is a multi-layer perceptron (MLP) (see Figure 6).

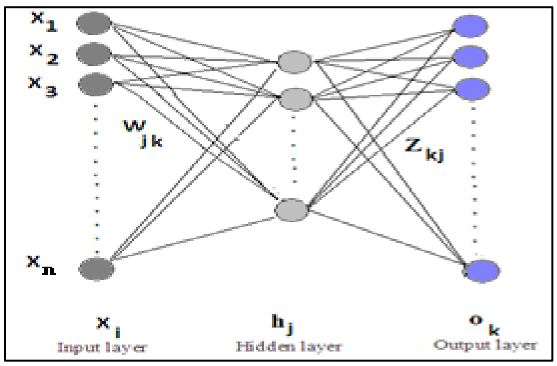

Figure 6. The Multi-layer Perceptron

The MLP is composed from the following elements:
- An input layer of N vectors, each vector has M components (features vector: X_i).
- A hidden layer of P activations neural h_j.
- An output layer of N activations neural o_k
- N×P connections between input layer and hidden layer, each weighted by W_{jk}.
- P×N connections between hidden layer and output layers, each weighted by Z_{kj}

Moreover, the operation of perceptron multi-layer learning is realized in five steps of back propagation algorithm:
- Step 1: (random Initialization of connexion weights W and Z).
- Step 2: (propagation of input vectors of MLP):

Presentation of the inputs X_i to input layer then propagation of these ones to hidden layer:

$$h_j = f(\sum_{i=1}^{n} x_i w_{ij}) \tag{1}$$

After from hidden layer to output layer

$$Z_k = f(\sum_{j=1}^{n} h_j z_{kj}) \tag{2}$$

With n: the number of hidden layer neurons.

Where f is called the activation function which is the sigmoid or logistic function:

$$f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

- **Step 3**: (calculation of error back propagation)

$$E_k = O_k(1 - O_k)(S_k - O_k) \tag{4}$$

Where S_k is the desired output (identity matrix) and O_K is the real output (supervised learning).

Next, propagation of this error on the hidden layer; the error of each neuron of the hidden layer is:

$$F_j = O_k(1 - O_k)\sum_{k=1}^{n} Z_{kj}E_k \tag{5}$$

- **Step 4**: (Correction of connections weights):

Afterward, change of the connection weights:

- Between input layer and hidden layer:

$$\Delta W_{ji} = \alpha X_i F_j \tag{6}$$

- Then between hidden layer and output layer:

$$\Delta Z_{kj} = \alpha Y_j E_k \tag{7}$$

Where α is the learning rate which is selected between 0 and 1.

- **Step 5**:

After the learning of MLP. Using the Euclidean distance for classifying the test character.

$$d(S_{kj}, O_{kj}) = \left(\sum_{i=1}^{n}(S_{kj} - O_{kj})^2\right)^{1/2} \tag{8}$$

The recognition will be attributed to the character that is very nearest to test character.

3.2. The Supports Vectors Machines

Support Vector Machines (SVM) are modern learning machines introduced by Vapnik [1], the principle of its functioning can be explained as follow:

For a two-class classification problem into space $\mathbb{R}^p$, the first one contains a set of input vectors $x_1, x_2, \ldots, x_k$ with corresponding label $y_1 = 1$, and the second class includes the vectors $x_{k+1}, x_{k+2}, \ldots, x_n$ and labeled by $y_2 = -1$.

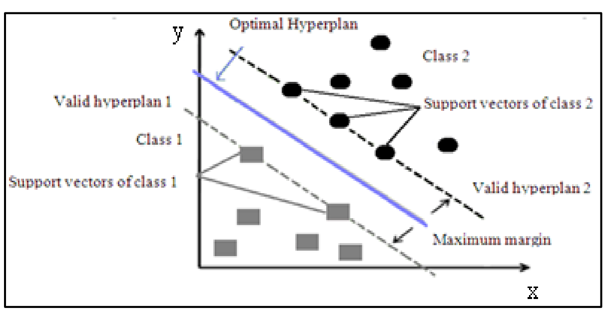

Figure 7. The Support Vectors Machines Illustration

The SVM consists to separate in an optimal manner between these both classes by mapping these vectors into a high dimensional feature space $\varphi(x_i) \in H$ (i=1, 2…..n). This separation is carried by a construction of an optimal hyper plane which maximizes as much the distance between the hyper plane and the nearest vectors of each class in the space H.

The mapping φ (.) is realized by a special type of functions called the kernel functions K (x_i, x_j) which defines an inner product in the space H. Finally the decision function implemented by SVM can be written as:

$$f(x) = sign(\sum_{i=1}^{n} \alpha_i^* y_i K(x, x_i) + b) \quad (9)$$

Where b is the offset of the optimal hyper plane from the origin, and the coefficients α_i are obtained by solving the convex quadratic programming problem.
Some example of the kernel functions:

Kernel linear	xy
Kernel polynomial of degree n	$(axy + b)^n$
Gaussian radial basis function (GRBF) of a standard deviation σ :	$e^{-\frac{\lVert x-y \rVert^2}{2\sigma^2}}$

The method described above is designed for a problem of two classes only, many studies treat a generalization of the SVM to N classes [5, 27]. Among these studies, we have used in this work the strategy of one against all that is based to use N decision functions allowing to make a discrimination of a class bearing a label equal to 1 and containing a one vector against all other vectors included in a other class opposite that is labelled by the value -1.

In the classification phase, we calculate the value image of an unknown vector X (test character) by all N decision functions that are obtained in the learning phase. The recognition will be attributed to the character that the decision function separates its class to another class containing the rest of characters which gives the biggest value.

$$\text{Classe}(X) = \arg\max_{i=1,2,\ldots,N}(f_i(X)) \quad (10)$$

4. Experiments and Results

In this work we want to compare between the performances of different extraction methods that are:

- Zoning.
- Mathematical morphology.
- Mathematical morphology + zoning.

When using the MLP then the SVM, that is to say to realize a second comparison between the performances of these methods of learning-classification.

In this research, each Tifinagh character is converted to some vector having:

- 9 components after using the mathematical morphology method.
- 9 components after using the zoning method.

4.1. Recognition using MLP

In order to implement this recognition system, we have opted the following data:

- A learning rate equal to 0.95.
- A variable number of hidden layer neurons into {8, 9, 10, 11, 12} just for knowing the effect of this variation on the performances of MLP.

The obtained results of the recognition rates of each character τ_c and the global rate τ_g are grouped in the following table:

Table 1. The Recognition Rates τ_c and τ_g in Function of the Number of Hidden Layer Neurons by Using the Mathematical Morphology Method and the Mathematical Morphology + the Zoning Methods

Tifinagh Characters		MLP									
		τ_c obtained by the mathematical morphology					τ_c obtained by the mathematical morphology + the zoning				
		Number of hidden layer neurons					Number of hidden layer neurons				
		8	9	10	11	12	8	9	10	11	12
1		90.00	85.00	80.00	85.00	65.00	90.00	90.00	90.00	100.00	100.0
2		80.00	70.00	100.00	95.00	100.0	95.00	100.0	95.00	100.00	100.0
3		80.00	65.00	80.00	65.00	65.00	60.00	60.00	80.00	60.00	60.00
4		70.00	40.00	15.00	60.00	25.00	10.00	10.00	20.00	25.00	15.00
5		70.00	80.00	80.00	75.00	50.00	100.0	100.0	100.0	90.00	100.0
6		85.00	85.00	85.00	85.00	85.00	70.00	85.00	85.00	75.00	70.00
7		95.00	95.00	95.00	80.00	90.00	50.00	75.00	90.00	90.00	90.00
8		95.00	95.00	85.00	95.00	95.00	95.00	95.00	95.00	95.00	95.00
9		80.00	45.00	40.00	25.00	60.00	10.00	90.00	50.00	45.00	25.00
10		35.00	35.00	35.00	40.00	35.00	40.00	40.00	40.00	50.00	45.00
11		45.00	50.00	35.00	45.00	45.00	45.00	40.00	35.00	45.00	70.00
12		100.00	100.00	100.00	100.00	100.0	100.0	100.0	100.0	100.00	100.0
13		95.00	90.00	95.00	95.00	90.00	65.00	95.00	95.00	95.00	95.00
14		60.00	60.00	55.00	60.00	55.00	70.00	60.00	65.00	60.00	60.00
15		95.00	95.00	95.00	95.00	95.00	95.00	95.00	95.00	95.00	95.00
τ_g		73.44	62.75	67.20	68.75	65.94	62.20	70.94	65.56	70.32	75.63

The associated graphs to the above table are:

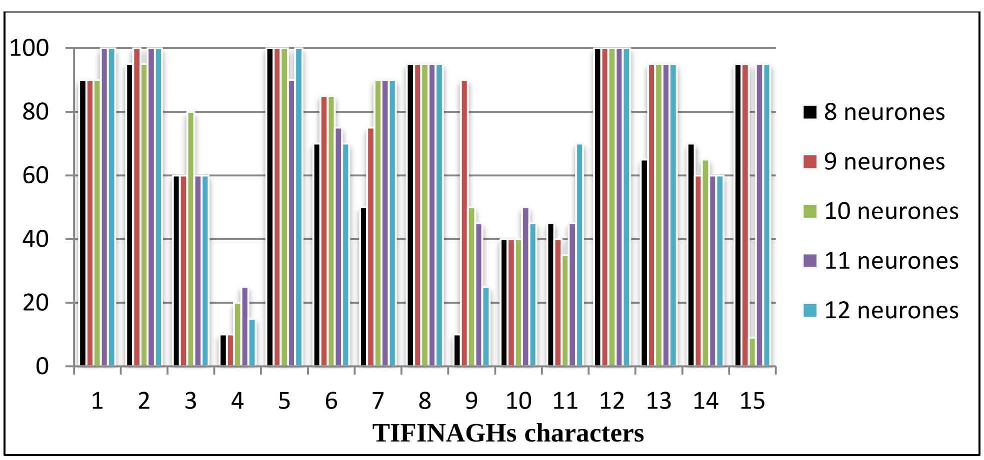

Figure 8. The Recognition Rate τ_c of each Tifinagh Character in Function of Hidden Layer Neurons by Using the Mathematical Morphology Method

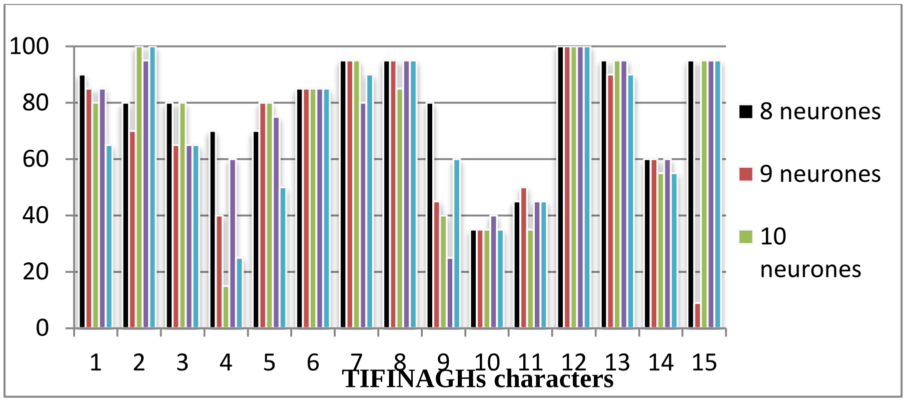

Figure 9. The Recognition Rate τ_c of each Tifinagh Character in Function of Number of Hidden Layer Neurons by Using the Mathematical Morphology and the Zoning Methods

- **Analysis and comments:**

After analysing the obtained recognition rates, we deduce that the hybrid method of mathematical morphology + zoning is more performing than that based only on mathematical morphology. Moreover, increasing the number of neurons in the hidden layer does not necessarily mean an increasing in rates.

4.2. Recognition Using the SVM

To realize a recognition system using the SVM, we have used the GBRF as a kernel function with a standard deviation σ=0,9.

Table 2. The Recognition Rates τ_c and τ_g which are Given in % by Using the Zoning, the Mathematical Morphology and the Mathematical Morphology + the Zoning and the SVM

Tifinagh Characters	SVM		
	τ_c obtained by the zoning	τ_c obtained by the mathematical morphology	τ_c obtained by the mathematical morphology + the zoning
1	60.00	56.00	80.00
2	65.00	90.00	70.00
3	55.00	58.00	60.00
4	60.00	56.00	54.00
5	50.00	54.00	50.00
6	50.00	50.00	55.00
7	70.00	55.00	80.00
8	90.00	62.00	90.00
9	70.00	51.00	98.00
10	70.00	50.00	95.00
11	50.00	40.00	56.00
12	50.00	45.00	60.00
13	80.00	92.31	93.00
14	90.00	62.00	92.00
15	60.00	60.00	60.00
τ_g x %	63.33	58.75	72.86

The associated graphs to the above table are:

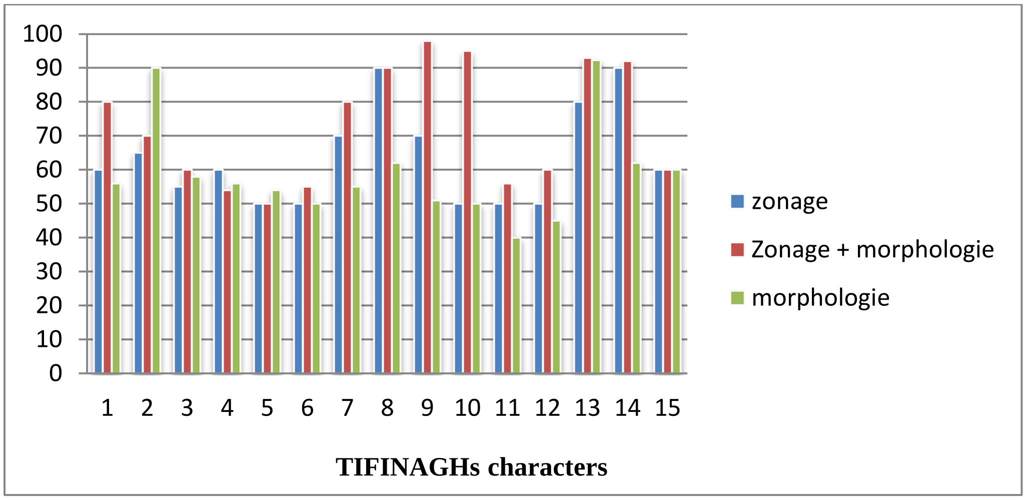

Figure 10. The Recognition Rate τ_c of each Tifinagh Character by Using the Mathematical Morphology, the Zoning Methods and the SVM

- **Analysis and Comments:**

Taking into account the results obtained after having implemented this recognition system, we can effectively conclude that the hybrid method Mathematical Morphology + Zoning is the most efficient followed by the Zoning then the Mathematical Morphology.

Finally, to schematize these two recognition systems, we present the following graphical interface that includes significantly all recognition phases.

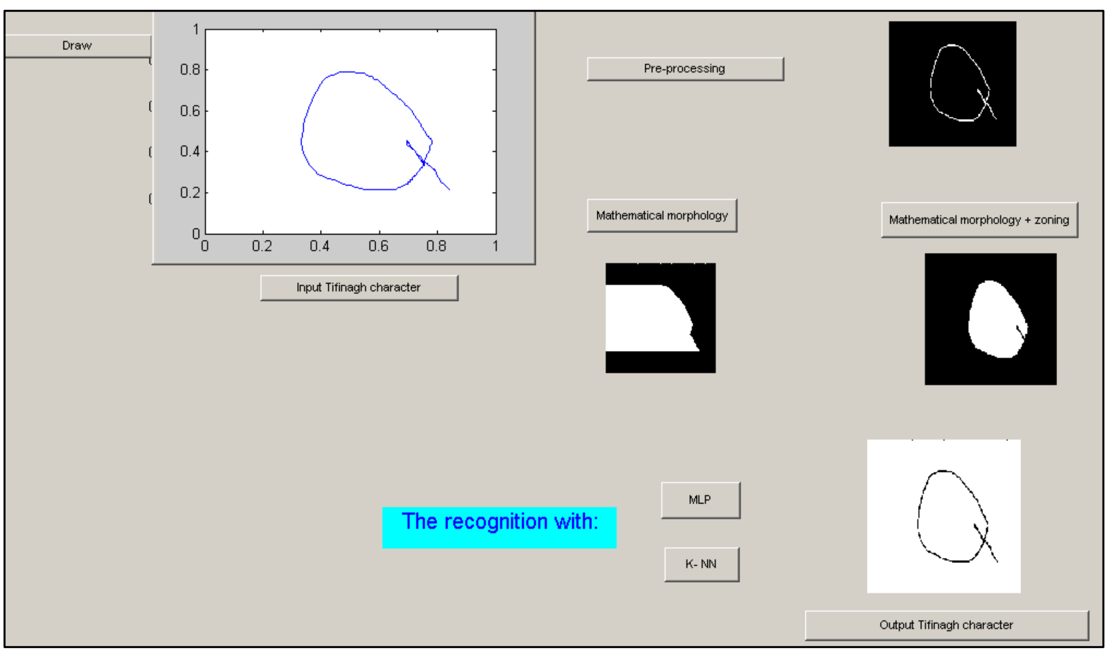

Figure 11. Implemented Graphical Interface to Recognize the Cursive Tifinagh Characters

5. Conclusion

In this paper, we have presented two comparative studies for recognition of isolated cursive handwritten Tifinagh characters, the first one is carried between some methods of features extractions that are the mathematical morphology, the zoning and the hybridization between them. While the second comparison is realized between two methods of learning-classification which are the multi-layer perceptron and the support vector machines. For both studies we have used in the pre-processing phase the median filter, the thresholding, the normalization and the cantering techniques. The simulation result demonstrates that the hybrid method morphology + zoning is that the most performing followed by the Zoning then the Morphology in the features extraction and that the SVM is more efficient than the MLP.

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