

Arabic Hand Written Character Recognition Using Modified Multi-Neural Network

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ABSTRACT

Hand written recognition is an interesting area of current artificial intelligence and advanced computing's researchers. The complexity of the language controls the ability and the challenge of recognition its characters, whereas this complexity and uncertainty becomes multiplied. The use of Latin languages like English, or Spanish, limits the uncertainty because of the limited structure of the character. Arabic language characters are very complex in comparison with the most languages in the world. The character in the Arabic language is not static, it has many shapes – in almost – depends on its location in the word, in addition to the convention. More complexity of that, the Arabic characters are being written continuously connecting the character with the next or the previous – in most –. This research adopted an algorithm to recognize the single segment characters, supposing that, the connected characters are separated and already segmented. This faces all problems of the character shape, location, style, and the user's style of writing. This paper implements a neural network based system that uses cascaded networks to recognize the characters. MATLAB program is designed to test the implementation and recording the results.

Keywords: *Hand written; Arabic; character recognition; Neural Networks.*

1. INTRODUCTION

In the rise of hand written recognition researches in modern image processing and character recognition techniques, the English language becomes not the single language of researches. Current researches is being interested in complex (non-Latin based) languages, like eastern languages. The main characteristics of Latin languages is that, it can be written with non-connected characters, in addition, the character shape in almost doesn't depends on the character's location in the word. Also, the shapes of specific character in Latin based languages is very limited, for example the character "b" can be written in capital form like "B", and cannot be written in other shape.

The Arabic language has very complex writing structure, starts from the old eastern line drawing format of the character, including the dot marking of most characters, where two, three, or four characters could be discriminated by marking dots only. Also, the Arabic writing is continues / separated writing of characters, where most of characters is being connected to each other in the word, but some characters in some cases are not connectable, so, the world is consisting of continues segments where each segment is almost consist of continues characters.

Figure-1 shows the discrimination of four characters using dots. Where figure 1-a is being pronounced as "ba", figure 1-b is being pronounced as "ta", figure 1-c is being pronounced as "tha", and figure 1-d is being pronounced as "in". Figure-2 illustrates the writing the word of name "Ahmad" in Arabic language, figure 2-a shows the separated characters that consists of that word where figure 2-b shows the actual writing. Thus, it consists of two

segments; the first segment is a single character where the second is a connection of three characters together.

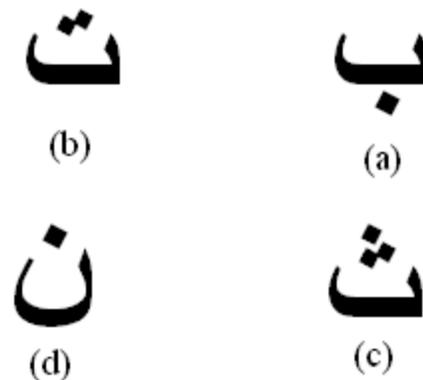


Fig 1: Discrimination of Arabic Characters Using Dot's. Three of those characters have exactly the same drawing but it discriminated from dots only, where, the fourth – lowest left – has similar drawing also.

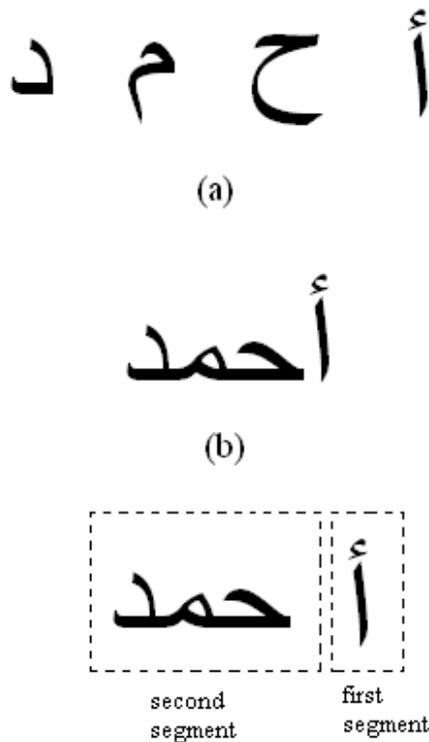


Fig 2: The Arabic writing methodology which connect the original characters in (a) to write the name “Ahmad” in (b). This word will consist of two separated segments. The first segment is drawn by a single character, where the second segment is drawn by connecting three characters.

Keeping in that, the shape of any character in Arabic language is complex and differs according to the location of the character in the word; also, the same location of character can has different shapes in different words. Figure-3 shows a sample character of different shapes depending on its location on the world; start of the word, middle, and end of the word, where the last one is separated and not connected to any other character.

Moreover, in Arabic writing complex style, the writing language has many different styles, each style can roughly differs from specific other one, of can have big difference. Figure 4 shows the same character “Printed” in 3 different styles, the first is “Kofi” font style, the second is “Nasikh” font style, and the last is “Roq’a” font style.

Here, the fact that will be face, the Arabic normal writers doesn’t underlay to one writing style type during writing the same documents. They always, use different styles not in the same document only, but may be in the same paragraph.

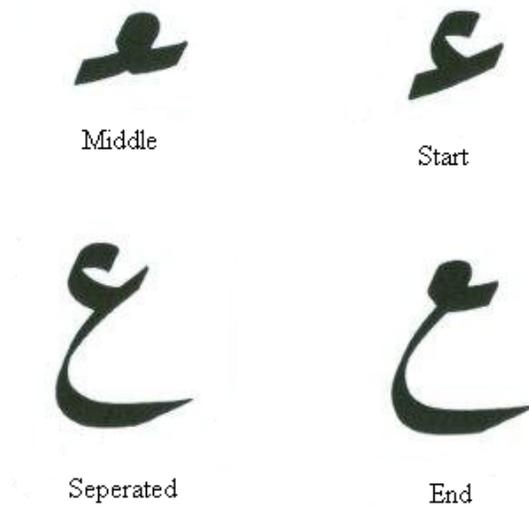


Fig 3: Different Drawing of Sample Arabic Character, Depending on Its Location on the Word.

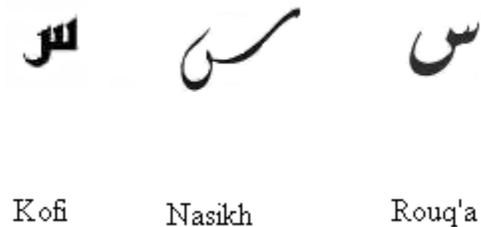


Fig 4: Arabic Character Named “Seen” And Pronounced as “Sss” Hand Written In Three Different Styles.

From figure 4 its clear that, the font style of Arabic writing difference is definitely un-negligible and should have a main place in the current researches.

The first logical think of that, is designing a separate algorithm for each writing style type, thus, this will be easier than building a single algorithm to deal with all that complexity. But actually, this still has uncertainties in hand written, because, of that, many people’s don’t write Arabic in specified uniform style format, but neither, they may write a word, where the characters of that word are occupied in two different styles. This making the thinking of recognition bulk hand written paragraph of different peoples more and more challenge in fact.

This paper concentrates on recognition of separated single characters those extracted from a paragraph. Thus, this algorithm considers the different / undetermined font style as the study style, whereas, the writer can write as he can, and designs a first step system of recognition. The

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proposed algorithm is initial design and structure for Arabic hand written separated characters recognition, where the current assumption is that the character is single and already separated, where the future main assumption is that, any character with different Font style should be recognized.

2. ARABIC CHARACTER AND FEATURE EXTRACTION

The segmented characters images can be enhanced and analyzed to get thousands of features from each. The key point of that is to extracting the minimum appropriate and meaning full features, where those are required to distinguish each character from the other in faster time and most efficiency.

In most systems design, feature extraction is a key process and controls the most proposed models. This paper considers the recognizer(s) to be artificial neural networks. Thus, the features should be suitable not to human recognition of numbers and curves, but, for artificially intelligent recognition system.

The adaptation of neural networks makes the system easier to build and more reliable, but it needs an accurate selection of features those should be extracted in order to be passed to the neural network input. The image of the character cannot be passed completely as input of neural network because its large size in addition to that there is no clear feature in the image data. Extracting features will determine the effected and recognizable data in the image in clear expression. For the size, the image segment size is 48x32, so that, its size in gray will be 1536 input. This large number of inputs requires large structure of the neural networks in implies high computational power, thus, long execution time in both, running and training.

This paper uses spatial operation of images to extract specific features, some of them may considered as not unique features, but, it represents a key features to recognize each character from the other.

The first step of feature extraction is to divide the character image into 6 by 4 spatial segments. Hence, the character image size is 48x32, so, the spatial segment size is 8x8 pixels. Figure 5 shows this spatial cutting of the image.

Each segment is ready to extract some features from in. So, five features are being calculated from each 8x8 segment separately. Thus, 120 features will be gotten from the overall character segment. Those features represent the uniqueness of the hand written character feature set. And those are:

- The ratio of white pixels to black pixels in binary converted image of the segment. This is calculated as equation-1.

- The ratio between the two farthest pixels with respect to diagonal of the segment. This is calculated as equation-2.
- The normalized average of the spatial segment. That is calculated as equation-3.
- The variance of the farthest two vertical pixels divided into the variance of the farthest two horizontal pixels. This is calculated as equations-4 and equation-5.

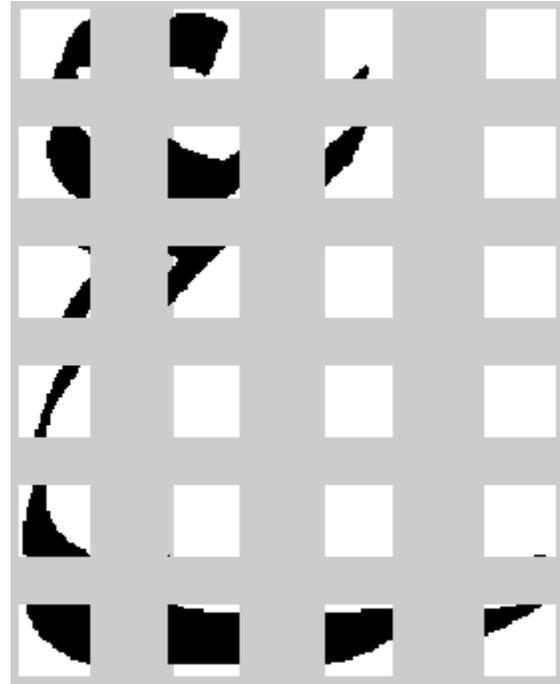


Fig 5: Spatial Segmentation of Sample Image, 6 By 4 Segments.

- The average value of the line that is orthogonal to the main diagonal of the special segment. This is calculated as equation-6
- The total variance of the segment pixels. This is calculated as equation-4 and equation-5.

Those features are being passed to the neural network input as a single column. Training of the neural network in such features will result to build a structure of the recognizer.

$$Rwb = \frac{\sum_{i=0}^7 \sum_{j=0}^7 I(i,j)}{1 - \sum_{i=0}^7 \sum_{j=0}^7 I(i,j)} \quad (1)$$

$$Rfbd = \frac{I(ior,jor) - I(jol,jol)}{\sqrt{(rs^2 - cs^2)}} \quad (2)$$

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$$Mn = \frac{\sum_{i=0}^r \sum_{j=0}^c I(i,j)}{(rs \times cs)} \tag{3}$$

$$Var(x) = \int (x - u)^2 \cdot f(x) dx \tag{4}$$

$$u = \int x f(x) dx \tag{5}$$

$$Mn = \frac{\sum_{i=0}^{rc} I(r-l, c-l)}{\sqrt{(rs^2 - cs^2)}} \tag{6}$$

Where "u" is defined in equation-5, "Rs" and "Cs" are the character's segment number of row and number of columns respectively, I (I,J) is a pixel of the image. "JOR", "JOR", "IOL, and "JOL, are the coordination's of the farthest pixels of the character object in the image.

3. PROPOSED MODEL

Figure-6 illustrates the proposed model structure, which consists of two main modules; feature extraction phase, and neural network recognition phase. Preprocessing and post-processing are complementary phases.

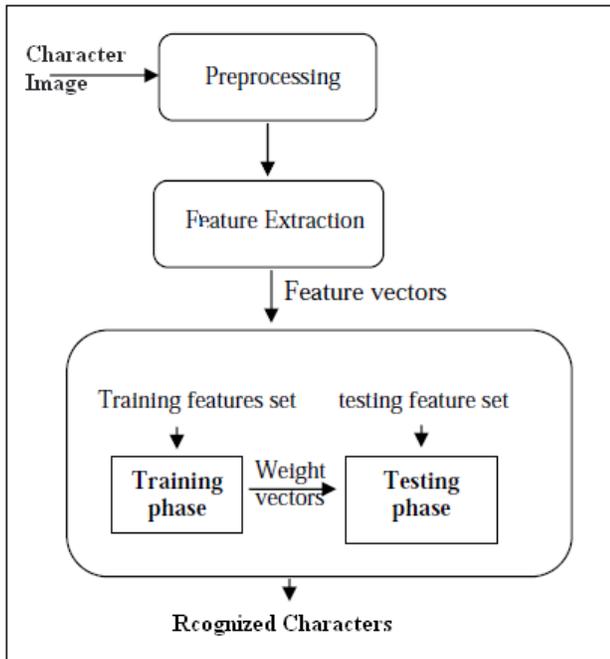


Fig 6: Diagram of the Proposed System

In general, two modes of operation is being developed; one for training where historical data of 28 separated Arabic character is being input to neural network(s) and thus, structure of the neural network(s) is being auto-built. The other modes of operation is running mode, where in such the system is ready to read an offline Arabic character and out the result of recognition of that character's image.

The feature extraction is the function of measure and save 120 feature of each character's image, where the image is being divided into 6 by 4 spatial segments with 8x8 pixels each segment's size. Each of the 24 spatial segments is being processed to calculate 5 features from each as illustrated in section 2.

Preprocessing of the input character image include resizing of that image, filtration, and converting to binary. De-blurring filter is being used to remove the noise and any blurring effects on the image.

The cascaded design of neural network ensures that, the correct character has been recognized. The similarities of Arabic characters in addition to dot marking discrimination of the characters make the recognition using single neural network near to impossible chase.

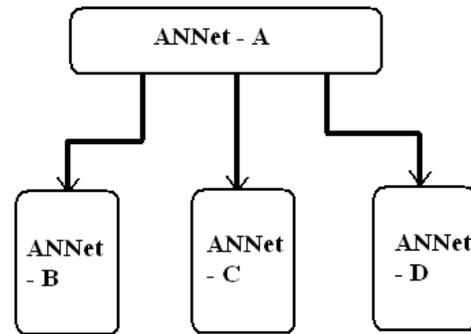


Fig 7: Cascaded Design of The Neural Networks In This Paper.

The basic structure consists of four neural networks, connected as shown in figure-7; where the features data of the image is being input to the neural network "A". The recognition result of A will be as shown in table-1. The similar characters are being recognized as the same in order to minimize the complexity of the network.

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Table 1: The Assumed Results versus Input the Accuracy of Actual Testing.

Input character	Neural Network-A assumed output	Testing Accuracy
ب, ت, ث, ن, ي, ف, ق	1	%79
د, ذ, ر, ز, ه, و, م	1	%75
س, ش, ص, ض, ط, ظ	2	%83
أ, ك, ل, ج, ح, خ, ع, غ	2	%81

Then, the output of neural net “A” is divided into three categories; each category consists of sum of characters probability where the exact character will be recognized by this network.

This adapted structure consists of four separated neural networks; where the first is Multi-Layer Perceptron (MLP) network and the other networks are Linear-Vector Quantizer (LVQ) networks

The linear vector quantizer network has the ability to recognize very close features with lower processing time. In contrast, the multi-layer perceptron neural network can recognize the unique feature from many different input scopes.

4. RESULTS

The data set that is being used in order to test and measure the proposed system performance of this paper are consists of that, 100 different separated characters. The data set were recorded by 10 different persons; all of those use the most common Arabic characters styles which is “Roq’a” style.



Fig 8: Sample characters of the data set that was being tested and the result was being taken on.

A sample character is being shown in figure-8. A program designated on MATLAB is used to implement the contributed algorithm in a program.

Table-2 shows the results of recognition for each single character. Where, table-3 shows the Mean Absolute Percentage Error (MAPE) for different trials of validation test. The first record in table-3 is measuring the MAPE of 50 characters those written by different persons. While, the next record is the same but the test data set is written by another different persons. The last record is the net using all data set.

Table 2: Recognition results for each character

Input Character of the networks B, C, and D	Testing Accuracy of the Character
أ	%77
ب	%61
ت	%63
ث	%63
ج	%75
ح	%75
خ	%75
د	%61
ذ	%58
ر	%59
ز	%55
س	%70
ش	%73
ص	%73
ض	%72
ط	%72
ظ	%70
ع	%67
غ	%68
ف	%62
ق	%61
ك	%77
ل	%76
م	%51
ن	%68
ه	%76
و	%59
ي	%71

Table 3: MAPE for different testing datasets

Trial	MAPE
Trial 1, on 5 different persons	66.76
Trial 2, on another 5 different persons	68.10%
Trial 3, on total persons	67.43%

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