Offline Arabic Handwritten Isolated Character Recognition System Using Support vector Machine and Neural Network

التَّعرف إلى الحروف العربيّة المنفصلة والمكتوبة بخط اليد باستخدام الية دعم الموجه والشبكة العصبية

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Dedication

To My

Father, Mother and my Sisters for their full support, for their great patience, endless love, attention and pray for me.

I dedicate my effort

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List of Abbreviations

ABBREVIATIONS	MEANING
AHCR	Arabic handwritten character recognition
AHOCR	Arabic handwritten optical character recognition
ANN	Artificial Neural Network
BPANN	Back Propagation Artificial Neural Network
BMP	Bitmap
DCT	District cosine transform
DPI	Dots per inches
DWT	District Wavelet Transform
EBPANN	Error Back Propagation Artificial Neural Network
ELM	Extreme Learning Machines
HMM	Hidden Markov Model
IFN/ENIT	Institut of Communications Technology/ Ecole Nationale d'Ingénieurs de Tunis
K-NN	K Nearest Neighbor
MLP	Multi-layer perceptron
MRA	Multi-Resolution Analysis
NFPD	Neighborhood Foreground Pixel Density
NN	Neural Network
OCR	Optical Character Recognition
OFHR	Off-line handwriting recognition
PCA	Principal component analysis
POW	Part of the Word
SVM	Support Vector Machine

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Abstract

Nowadays and because of the high expanses in technologies, a need to recognize a handwritten characters, words, and even sentences is being popped up. Especially for education and business institutions. Optical Character Recognition (OCR) programs eliminate human error, which can occur while the data is being input.

The Arabic Language had a little attention in this field compared with other languages due to the high cursive nature of the handwritten Arabic language, especially with their dots. The difficulty lies in the complexity of locating the wavy shape in the characters, which solved by the combination of certain features extraction methods that work in separate way. In this thesis, the proposed of Isolated Arabic off-line handwritten recognition system based on two stages classifiers (Hybrid). First stage is a linear Support Vector Machine (SVM) for splitting the dataset characters into two groups - Characters with dots and Characters without dots, by giving certain extraction features to each group. This division can reduce the error rate of characters recognition which has similar looking shape. Second stage supplies the first stage result to Neural Network (NN) stage which granted one of the best correctness and accuracy by training. Finally, a fully recognized character is acquired successfully. This work is implemented using Institut of Communications Technology/ Ecole Nationale d'Ingénieurs de Tunis (IFN/ENIT) dataset, the system significantly reduce the load of NN process by SVM classifier, which can be used for real-time applications. A total accuracy of this proposed work reaches 92.2% and in future work we look forward to getting higher rank of accuracy.

Key Words: OCR (Optical Character Recognition. SVM (Support Vector Machine), Feature Extraction, NN (Neural Network).

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الملخص

في الاونة الاخيرة و نظرا للتقدم في التكنلوجيا فان التعرف الضوئي للأحرف (OCR) وتطويره اصبح ضرورة ملحة، و انتشر انتشارا واسعا وذلك لزيادة التقنيات التي تحتاج إليه وذلك في المجالات العلمية والعملية معا، حيث تساهم هذه التقنية في تقليل الأخطاء الناتجة عن إدخال المعلومات والنصوص من قبل الإنسان.

ان الاهتمام بهذه التقنية وتطبيقها على حروف اللغة العربية يعد قليلا، وذلك لصعوبة الحروف العربية من حيث الاختلافات في الأشكال حسب موقع الانحنائات، تلك المشكلة حلت من قبل طرق معينة لاستخراج الميزات.

في هذه الأطروحة، تم اقتراح نظام للتعرف على الحروف العربية المعزولة ويمر النظام بمرحلتين: المرحلة الأولى هي SVM والتي نقوم بها بتقسيم الأحرف إلى مجموعتين الحروف التي تحتوي على النقاط والحروف بدون النقاط و يتم ذلك عن طريق إعطاء بعض الميزات وتمريرها على الحروف لاستخراج كل مجموعة. هذا التصنيف من شانه ان يقلل نسبة الخطأ بين الحروف المتشابهة، المرحلة الثانية هي

توفير نتيجة المرحلة الأولى وإدخالها إلى شبكه عصبية ذات تعلم ذاتي مدربه مسبقا" للتعرف النهائي على الحرف.

تم تنفيذ هذا العمل باستخدام قاعدة البيانات IFN/ENIT ، النظام المقترح يقلل من عبء العمليات على مصنف الشبكة العصبية بواسطة مصنف دعم التتميز الالي وبدقة إجمالية تصل 92.2٪، ونتطلع مستقبلا للحصول على درجات أعلى من الدقة.

الكلمات المفتاحية : التعرف الضوئي على المحارف، دعم التمييز الالي , استخراج الميزات , الشبكة العصبية.

Chapter 1: Introduction

1.1 Introduction

In the last few years, the technology of optical recognition has been increased, which gives a lot of new operation in characters recognition for English, Arabic words or any other complex wavy language words. The Optical character recognition (OCR) benefit is to reduce the time that the user waste in inserting the handwritten words into any computer. Character recognition can be defined as a process for recognizing any character whether it was Arabic, Dutch, Russian or any other language from human world to a computer operating system environment. There are two modes of insertion characters; handwritten and typewritten. The handwritten character recognition is more difficult to recognize than the typewritten, moreover, the availability of the handwritten characters dataset is lower and harder to get than typewritten especially in the Arabic language. There are 186 dataset plans to support Arabic fully obtained from Microsoft word (Zaghloul, et.al., 2011).

Online and offline are the main two methods used in this kind of recognition. The online process involves mostly a live input insertion to the operating system (Dedgaonkar, et.al., 2012). In other words the character insertion require real time system because it is inserted directly by the human to the machine using specific tool depending on the type of machine such as a plastic pen for latest smartphones or even by thermal vital organs like fingers. So it depend on the machine and method that the writer uses to insert the character. Here the study of the offline characters recognition, is prepared for the following reasons; firstly its needless requirement from people to use, no need for insertion device and complex machine. The offline system can work with pre-inserted image whether it was scanned or captured from camera, that makes frequency of users sample much more than the online system samples, obviously because readers more than authors. Simply a seek to find out the best way to recognize an Arabic character isolated with offline system is required.

There are many methods that can be used, and a decision made is to select dual stage classifier. The first one is Support Vector Machine (SVM) & the second is Back Propagation Neural Network (BPNN). A classifier for isolated characters recognition system to find out if it is the best way to recognize an Arabic character or not? Regardless of SVM type. This research has been introduced previously in other classifiers method, using simple schedule, comparing the differences, the similarity task and accurate operations between the previous researchers. Hopefully, to find out which one is better in overall accuracy?

Hardware used in any Optical character Recognition (OCR) system shows a notable improvement in the speed of insertion, fast retrieval and reduce the possibility of human error. Figure 1 shows the logical component of offline OCR system, camera and Scanner with OCR software and an output interface between the user and the machine language. The final character is even shown in a soft or hard copy nature.

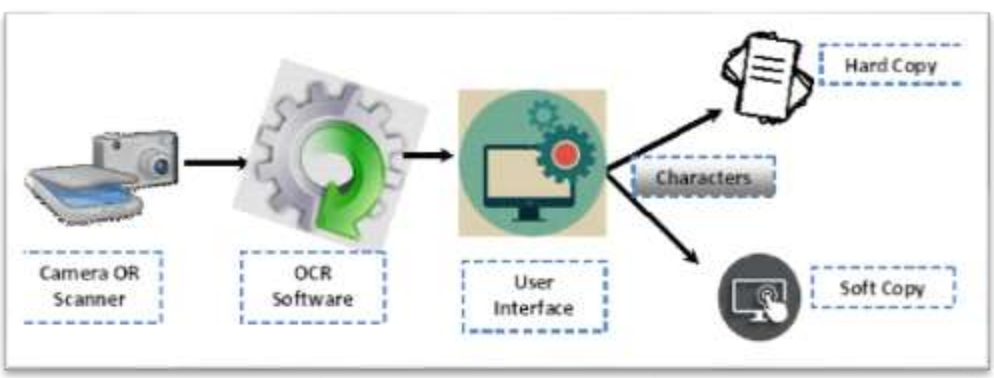


Figure 1 Logical Component of OCR System

Arabic Handwritten Character Recognition (AHCR) consists of dual stages for classifier, the first stage is linear SVM for splitting the dataset characters the one which have dots from the one which does not, By giving certain features to each group to be extracted later on. The Second stage is fed up the result of the first stage to Neural Network (NN) stage which granted one of the best accuracy by training and avoiding mistake, however NN have a vanishing gradient problem. This problem is directly proportional to the increase in the number of instances (large database), that is why the spilt of the used dataset is accomplished, which represents each member of data unit. Then the used system here "Dual Stage System" classifies each member of the data unit will achieve a highest accuracy according to their features extraction (Deka, et.al., 2012).

Artificial Neural Network (ANN) in character recognition is a subject that has been considered important because of the capability of training and reducing the gap between accuracy measurement, in the recognition of isolated letters such as Chinese and isolated English, relatively few studies are specialized of cursive letters recognition, For example cursive Farsi and cursive Arabic texts. One of the reasons of the lack of cursive letters recognition is that cursive texts characteristics are different and more complex than other types of texts (Abuhaiba, et.al., 1994). Arabic text written from right to left, each letter has two to four different forms according to its position in the word and most letters are joint with entire parts below, above, or inside the letter (Fadel, et.al., 2016).

example :(دينار) when one of these five letters is present in a word, the word is divided into sub-words, often called parts of Arabic words (POWs), (دينار) has three POWs the first one is Daal (د)is initial right-disconnected, the second part is (ينا) the Yaa (ي) in initial-form, Noon (ن)s in the middle form ,and Alif (ا) is final character of second POW, The last POW is left-disconnected Raa(ر),(Abandah, et.al., 2014). Besides those techniques still depend on character isolation , those differences indicate that cursive character recognition is not a direct implementation of the recognition techniques used for stroke , like characters ,the processing of shape information setup a major component in a recognition system , especially in character recognition the main shape is saved in its skeleton, many algorithms have been proposed to extract skeletons, current skeletonization algorithms attempt to obtain an accurate skeleton representation for further learning optimization (Abuhaiba ,et.al., 1994).

The insertion of the text into computer has other form, by typing but that will take a lot of time which the user don't have in a real-time environment (Dash, et.al., 2013). Plus the dataset of the typewritten Arabic letters is much more accurate, the formulation of that dataset is nearly perfect because basically it painted with high accuracy and posted by computers. Unicode is a standard that was created by the Unicode Consortium; an organization that develops a single letter set for all languages. Implementation of characters recognition is presented as a faster method that can insert the characters into computers without any exhausting work.

A scanned document that has text or numbers written on it, a human’s brain can read and understand what is written in it. However, to a computer, this scanned image file is just a set of pixels that is similar (in terms of storage and meaning) to a landscape photo. In order to transform this information into an editable format that you can search through, copy, and modify without retyping it manually, you will need Optical Character Recognition (hereafter OCR) software. (Lemley, 2005)

OCR systems are considered helpful with handwritten forms (governmental forms for example) or historical documents with handwriting on them. Such systems also provide users with the ability to check for typo or grammatical mistakes and rectify them.

In order to build an efficient OCR system for the Arabic handwritten letters, a Support Vector Machine (hereafter SVM) is used in this research as an initial classification tool. The classification of data (in this case images of Isolated handwritten letters) is done over two main phases: feature extraction which measures the learning set of data and the classification phase in which features that allow distinguishing different classes of test data are recognized. Several different features have to be used for classification, the set of features that are used make up a feature vector. (Abandah, et.al., 2011).

The proposed OCR system uses the IFN/ENIT dataset for training the system, and a same dataset to test the accuracy. A sequence of operations will be performed in order to measure the accuracy of the recognition system. Preparing the data includes transforming the scanned images from the training dataset into black and white, filtering, and then centralization and skew-correction. Then these pre-processed datasets are divided into two main groups by SVM: letters with dots, and letters without dots. These are then used to extract the main features to be used in classification with a curvelet/wavelet feature extraction algorithm to later fed into the BPNN to measure the accuracy of the classification process, the output of the AHCR system is a real-valued number that expresses the measurement of accuracy, a general Structure of AHCR system is given in figure 2.

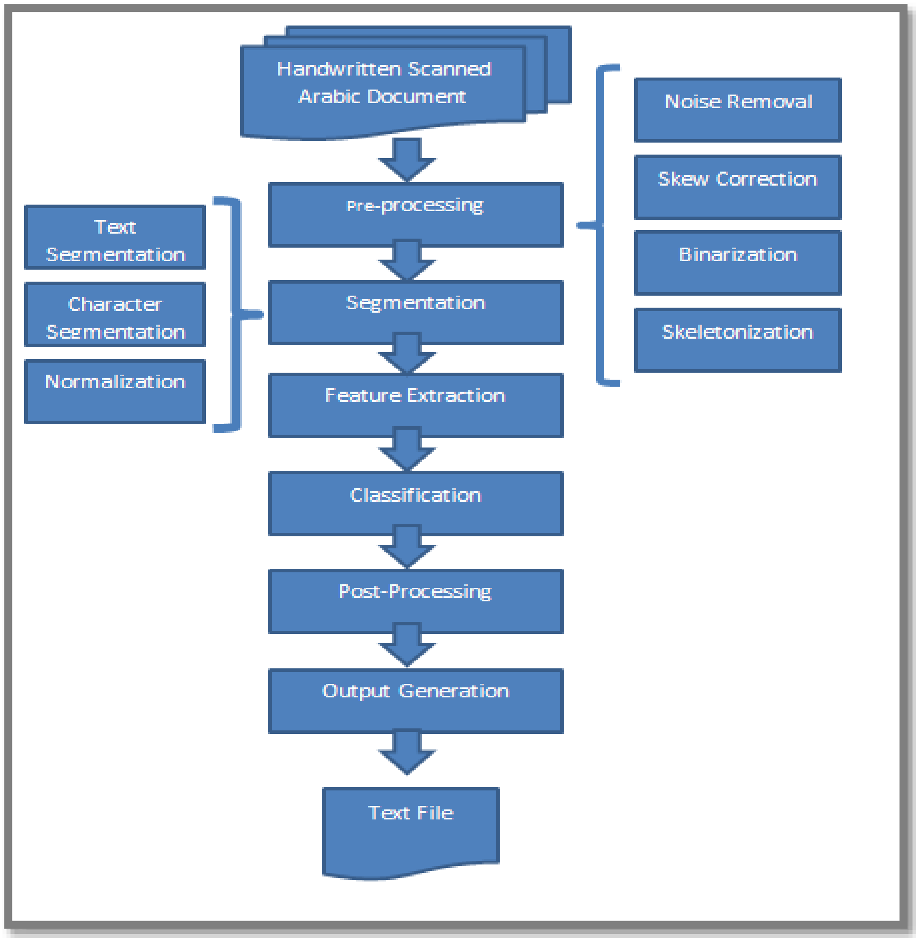


Figure 2 AHCR System's General Structure

The selection of the most suitable Feature Extraction method is very important, since it is the base of the recognition process in the system that will be used for the classification. The choice of feature extraction method limits the nature and output of the preprocessing step in developing an OCR system.

Artificial Neural Networks (ANN) has been the subject of considerable research systems that are used to recognize and classify isolated characters in different languages such as Chinese and English. Yet Arabic language have linked characters, this means that the character might have several forms (some characters have up to four different forms (Fadel, et.al., 2016). The processing of shape information constitutes a major component in a recognition system, in character recognition, the essential information about a shape is stored in its skeleton.

1.2 Optical Character Recognition (OCR) for Arabic Characters

Instead of storing images that contains text as “just images”, an OCR system makes “understanding” what’s in those images possible, by integrating the techniques and algorithms of three of the most hot areas of research in computer science: machine learning, pattern recognition, and the new “computer vision” area. Simply, an OCR system takes a scanned image that contains text, identifies the text in it and produces another electronic form of the file that is searchable and editable by a text editor. Arabic characters are considered highly cursive, which makes the recognition of Arabic characters an open and active research problem (Naz, et.al., 2016).

The first work on Arabic character recognition was published in 1975 as a thesis for the master’s degree by Nazif (Sahloul, et.al., 2014). While an efficient OCR system that recognizes Arabic characters was developed in the 1990’s the utilization of Latin languages, such as English language restricts the suspicion due to its restricted character structure. Conversely, the Arabic characters are very complicated since they are not static and have several shapes based on the location on the word, beside in some cases there are very similar characters structure like س (seen) and ش (sheen).

The available handwritten Arabic character recognition systems do not offer high levels of character recognition accuracy; thus, more researches and investigations in this field are still needed. This research aims at developing a technique that has high accuracy results.

1.3 Support Vector Machine (SVM)

In machine learning and pattern recognition systems, SVM's are typically used in the classification stage for feature extraction. Feature extraction is the measurement of a population of entities that will be classified; this assists the classification stage by looking for features that allows a system to distinguish between the different classes of the training dataset. Support Vector Machines (SVMs) classifier were introduced in 1995 by researcher called Vapnik, Within the past years the classifiers gained great attention in the research community for their good ability of classification in many machine learning applications such as handwriting recognition, face features recognition and novelty detection among others (Cristianini, et.al., 2000).

1.4 Neural Networks

Researchers developed Artificial Neural Networks (ANNs) to simulate the work of the human brain for processing information. A basic ANN is structured as a set of connected neurons (nodes). These connections have weights to signify the "strength of this connection. In a supervised learning system, weights are calculated and assigned to the connections to represent how well the system recognizes a feature (Baha'addin, 2013).

In an OCR system, after getting a set of classified instances of a dataset (images of handwritten Arabic character). A Back Propagation Artificial Neural Network (BPANN) learns to recognize new instances of such dataset, and predicts the correct class for new, un-learnt instance by measuring the weights of connected nodes in the network. Character recognition using ANN employs feed-forward back-propagation network (Al-Boeridi, et.al., 2015). This type of ANN has only three layers: an input layer, a hidden layer, and an output layer. The research focuses on studying and implementing an offline Arabic handwritten isolated character which is inserted by optical devices into computers, the dataset will be used as a data parameter that contains several isolated Arabic handwritten characters as images. In this algorithm, a predefined error-function is used to compute the error term for the output units from output layer, repeat propagating the error term backwards to the previous layer for a sufficiently large number of training cycles, and updating the weights between the two layers until the network converge to some state where the error of the calculations is small, then one can say that the system has “learnt” from the training set.

1.5 Problem Statement

There are many applications that have handwritten documents, which need to be digitized in order to facilitate archiving and searching method, In addition to some historical documents that date back to pre-computer times that should also be saved electronically for easier access (Brook, et.al., 2008). So a need For Arabic Handwritten Optical Character Recognition (AHOCR) system is being popular but with some obstacles listed as following:

- Arabic characters Nature: Arabic characters are difficult to recognize because they include straight lines, curved lines and dots on letters. This led to a very complex operation for recognizing the Arabic character (Lawgali, et.al., 2011)

- The shape of the letter varies depending on its location in the word, so a system with relatively high accuracy is needed to solve the differences between characters shape (Sahloul, et.al., 2014).
- AHOCR researches has many doubtful, low overall accuracy result (Batawi, et.al., 2012).
- The similarity of characters according to their main body (main shape), curves location and dots location (if available) like (ح), (ج) and (خ).

The convenient OCR system needs appeared, to enhance the low level of accuracy of single classifier or hybrid classifiers. The accuracy of Arabic recognition is optimized via splitting the dataset into subsets by SVM classifier to increasing the categorization of characters, so that the NN can recognize the characters easily and with superior speed compared with other researches, in order to apply it into a real-time system.

1.6 Research Objectives and motivation

This research aims to improve the isolated handwritten Arabic characters recognition approach that is based on using an NN and SVM in a hybrid integrated system. This approach enhanced the accuracy of recognizing handwritten-Arabic characters. Few types of research have been conducted on building an OCR system for Arabic letters that achieved good accuracy. So this research aims at expanding the research knowledge of such systems. The use of SVM combined with ANN in an OCR system is considered a good step in building a good OCR system for Arabic texts. These two techniques together were proven to be the best for pattern recognition systems like face recognition and characters recognition. In other words, this study will use the adaptive machine learning in order to increase recognition rate of each character and increase total main accuracy using BPNN and SVM classifier (Arora, et.al., 2010).

1.7 Contribution and Significance of the Research

- Building AHOCR system with single NN classifier.
- Building AHOCR system with hybrid approach SVM with NN classifier.
- This will help in improving classification of data items (instances) by the NN classifier (Kang, et.al., 2014).The system employs these two techniques in recognizing offline handwritten Arabic characters, by applying a feature extraction using curvelett and wavelet, in addition, it makes smoothing and filtering as a preprocessing stages.
- The unique segmentation technique used by this research will provide better character segmentation of graphs that are extracted from words and sub-words found in the open dataset for Arabic characters; Institute of Communications Technology (IFN) and Ecole National d'Ingénieurs de Tunis (ENIT) dataset.

1.8 Scope of the study

This study discuss the classification technique of offline Handwritten Arabic Isolated Characters based on the following dataset that develop by (IFN, Germany) and (ENIT), (IFN-ENIT), the Support Vector Machine as a light classifier tool that reduce the load for the next classifier, the neural network is heavier from process perspective, none the less it gain a high recognition accuracy result.

1.9 Thesis Outline

This research is organized as follows Chapter One: Presents an overview of the research work in general and the organization of this master scholarship of sciences work documentation.

Chapter Two: carries a literature review about the topics discussed in this chapter mainly Handwriting Character Recognition (AHCR) system.

Chapter Three: Presents the Study methodology used in developing the system, and the techniques used in details.

Chapter Four: Illustrates the implemented system, the evolution measurements that have been used to test and evaluate the technique. The chapter also includes research discussion, and results.

Chapter Five provides a conclusion of this master scholarship of Sciences work followed by suggestions and motivations for future work in the field of OCR for curvy characters.

Chapter Two: Literature Review

2.1 Handwritten Arabic Optical Character Recognition (HAOCR)

The Arabic script is written from right to left and it is composed of 28 characters with no capital or lower cases. Each character has two to four shapes where the shape of each character depends on its position in the word. The dots play a significant role in Arabic characters, in addition, some characters have similar shapes but differ in the position and number of dots (for example the letters: ج، ح، خ). Many image processing techniques along with machine learning tools were applied by researchers interested in developing an OCR system that scores high precision recognition of handwritten characters.

2.2 Related Work

Merging two of the major techniques over two stages used in the classification phase for recognizing handwritten Arabic characters was adopted by (Ali, et.al., 2015). A public classifier was applied to groups of characters with overlapped feature (like the letters ت، ث), and a private one to deal with characters within each of the groups. This system scored a recognition rate of 71.73% for the testing dataset.

The first stage accepts the features of the letters that are needed to recognize and classify to the correct group. The second stage works as sub-classifiers that are built from multiple back-propagation neural networks (BPNN) that are used to recognize only one group characters as shown in the architecture of this system in Figure 3.

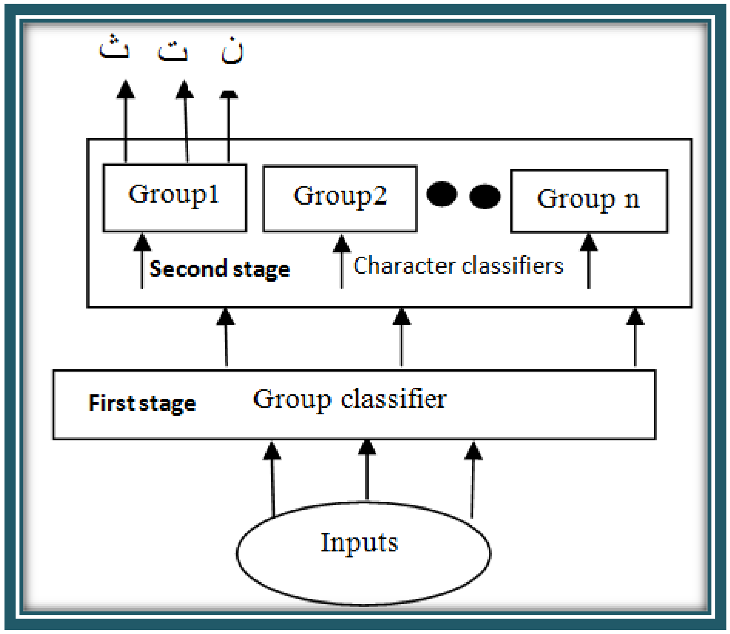


Figure 3 Two stages classifier of AHOC (Ali, et.al., 2015)

Classifying characters from offline documents as the main source of data is a hot research topic. Considering the limited number of the dataset used in the learning and then the classification processes in any OCR system. Abed, et.al., (2015) experimented on the use of both the back propagation neural network and the k nearest neighbor (K-NN) classifiers. This NN was optimized and tested on only 12 offline isolated Arabic handwritten characters (ج، ذ، ت، ش، ط، غ، ف، ك، م، و،يا) and achieved the accuracy of 93.61% using common model in ANN called Error Back-Propagation Artificial Neural Network (EBPANN). These characters were chosen because they do not have very similar features.

Kaur, et.al., (2014) see that using Support vector machine and neural network together as classifiers are slightly better with offline signature. The matching accuracy outcome between input data and target data is significantly high compared to using only NN or single stage classifier, this result is obtained by combining the linear with the nonlinear classifier.

Hassen, et.al., (2013) proposed a hybrid system that includes two classifiers to recognize Arabic Islamic Manuscripts, the first classifier is K-NN and the second is SVM classifier. They conclude that the K-NN is good, so they used SVM as a decision classifier to override the limitation of K-NN, with help of cloud computing resource they manage to reduce the overall timing process of recognition.

The Feature extraction process could be the most challenging stage in an OCR system (Trier, et.al., 1996). Many researchers performed comparison studies to determine what feature extraction method could help in achieving high recognition ratios. Lawgali, et.al., (2011) compared the use of Discrete Cosine Transform (DCT) with Discrete Wavelet transform (DWT) to capture the features that are used to discriminate Arabic handwritten characters.

The coefficients used in both techniques that have been used for classification were obtained from the implementation of an Artificial Neural Network. Analyzing the results of their experiments demonstrated that a DCT based feature extraction provides better recognition results than DWT. Figure 4 shows the results obtained from their experiment, applied to a sample of size 1600 shapes, the recognition accuracy reached the lowest pixel which is the better case (64x64) pixels for DCT 79.87% and DWT 40.71%.

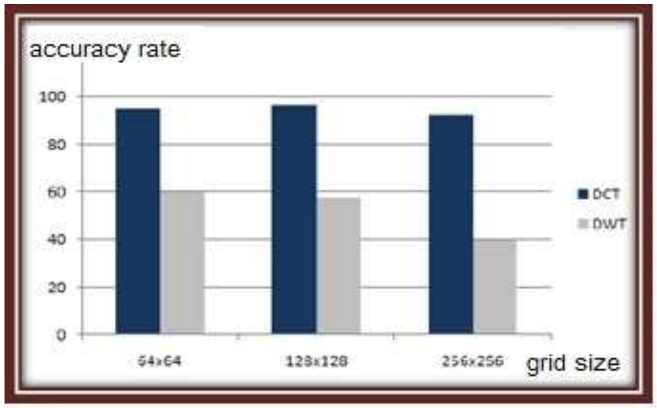


Figure 4 comparison between using DCT and DWT in an AHOCR (Lawgali, et.al., 2011)

This system worked over defined and discrete steps: first the Character gained by using a scanner or camera and translated into Bitmap (BMP) type file. Then the pre-processing step; where the scanned image was unified in size to 30x30 pixels to be used by the EPBANN. The next step was Feature Extraction which is the base for classification and image recognition, they used the zoning technique, where binary image are stored in a matrix of size 18x18 grid to hold each of the 12 Arabic characters under study. The last step included Classification of the values of the resulting features with Error Back Propagation Artificial Neural Network (EBPANN), from which they could determine the percentage of success. The tests in the neural network consist image processing phase, feature vector extraction phase, and three network phases that are Neural network structure phase, Error Back Propagation algorithm phase, Running neural network structure. Fedorovici, et.al., (2011) two recognition modules were proposed, the first one is established on a five layer neural network, the other established on an SVM classifier founded on Zernike moments features which used as basis functions of image moments. Both recognition systems were trained and tested with the same sets of dataset, the outcome of the neural network based recognition module is better than the one founded on Zernike moments, beside that the neural network have the ability of inclusion the dataset but took a lot of time to make the results satisfying (training and testing), while the SVM is much easier to train and did not take that much time.

Gazzah, et.al., (2008) used the classifiers on parallel system that in other words on separated ways to identify the writers in the same dataset, in order to identify the writers they perform characters recognition and matching, the first classifier was Multilayer perceptions and the other classifier was linear SVM. They concluded that each specific writers have different handwritten proprieties, which mean each classifier perform a medium quality recognition, for some writers the SVM was better in recognizing their handwrite words and for other writers the Multi-layer perceptron (MLP) was not good for them, MLP reach accuracy average rate of 94.7 % but with higher feature extraction that the number of neurons in the input layer is equal to the length of features, the SVM achieved the 93.76 % accuracy rate. El-Sherif, et.al., (2007) proposed a two-stage classifier for a large set of Arabic digits, the first stage is ANN. The outcome of the first stage process can't pass, only if the final maximum output obtained a doubtless low score and the first maximum output reaches the desire level of accuracy, the second stage is multi-SVM class that deals with the features extractions. This system achieved a 99.15% accuracy with balanced time spending, the ANN in this case is light process however the SVM is much complex but retrieve powerful and high result.

2.2.1 Segmentation

In order to prepare the data to be fed into a feature extraction engine the data need to be prepared or pre-processed. The most critical step in pre-processing is the segmentation of scanned text input.

Segmentation of a whole document begins with segmenting lines, then words, and finally letters. In the case of Arabic text, letters have two to four shapes depending on the position of the character in the word.

Al-Ani, et.al., (2014), developed a segmentation algorithm, it was based on the database that grouped letters according to the position of the letter (beginning, middle, end, and isolated characters). The algorithm worked over multiple segmentation levels: line segmentation, dots extraction, estimation baseline, thinning foreground pixels and character segmentation.

The results were very promising and a highly accurate recognition rate of 90.8% has been resulted when tested on a local database of 100 words from 3 different writers. Table 1 shows the different shapes of Arabic letter according to the position in the word.

Table 1 Arabic letters shapes according to position

THE ARABIC ALPHABET

Name	Isolated	Initial	Medial	Final
Alif	ا			ـا
Baa	ب	بـ	ـبـ	ـب
Taa	ت	تـ	ـتـ	ـت
Thaa	ث	ثـ	ـثـ	ـث
Jiim	ج	جـ	ـجـ	ـج
Haa	ح	حـ	ـحـ	ـح
Khaa	خ	خـ	ـخـ	ـخ
Daal	د			ـد
Dhall	ذ			ـذ
Raa	ر			ـر
Zaay	ز			ـز
Siin	س	سـ	ـسـ	ـس
Shiin	ش	شـ	ـشـ	ـش
Saad	ص	صـ	ـصـ	ـص
Daad	ض	ضـ	ـضـ	ـض
Taa	ط	طـ	ـطـ	ـط
Dhaa	ظ	ظـ	ـظـ	ـظ
Ayn	ع	عـ	ـعـ	ـع
Ghayn	غ	غـ	ـغـ	ـغ
Faa	ف	فـ	ـفـ	ـف
Qaaf	ق	قـ	ـقـ	ـق
Kaaf	ك	كـ	ـكـ	ـك
Laam	ل	لـ	ـلـ	ـل
Miim	م	مـ	ـمـ	ـم
Nuun	ن	نـ	ـنـ	ـن
Haa	ه	هـ	ـهـ	ـه
Waaw	و			ـو
Yaa	ي	يـ	ـيـ	ـي

Other researchers Abandah, et.al., (2014) used the same dataset for segmentation but with a robust rule-based segmentation algorithm that segments the cursive words into graphemes. This algorithm defines special feature point in a letter's skeleton structure.

Segmentation works over two phases: the first phase is word segmented into sub-words, and then the sub-words are segmented into graphemes. In the first stage, a baseline is estimated using the horizontal projection histogram algorithm, then the main and secondary bodies are identified, the main bodies of the sub-words are extracted, and the secondary bodies are assigned to their respective main bodies to yield sub-words. Identifying secondary bodies is done using the contour-based connected components extraction algorithm. Figure 5 shows how the words are segmented into secondary bodies and sub-words, S_n = dots while W_n = sub-words.

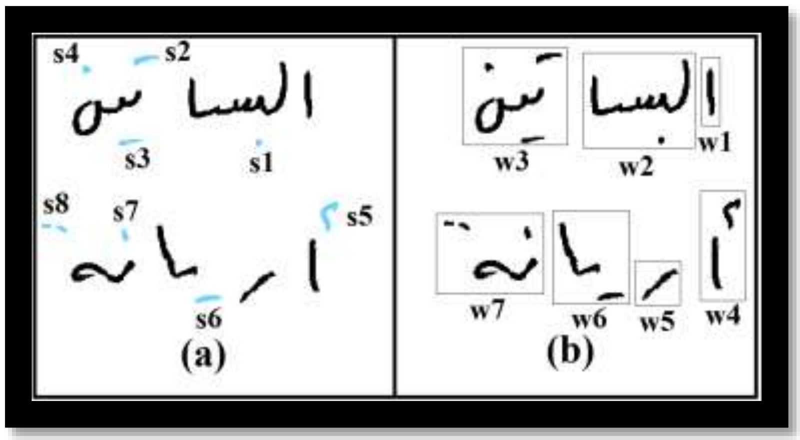


Figure 5 first stage of segmentation: a. secondary bodies' identification, and b. sub-word extraction (Abandah, et.al., 2014)

In the second phase of segmentation, graphemes are segmented from sub-words over two stages: feature points detection and grapheme separation. The feature points detected are end points, branch points, and cross points. They are detected by examining the eight neighbors of every skeleton pixel. Continuities that have some pre-defined features (like the slope's angle, the left end is an edge…) are segmented to split the sub-word into graphemes. Figure 6 is an example of how a sub-word is segmented into graphemes.

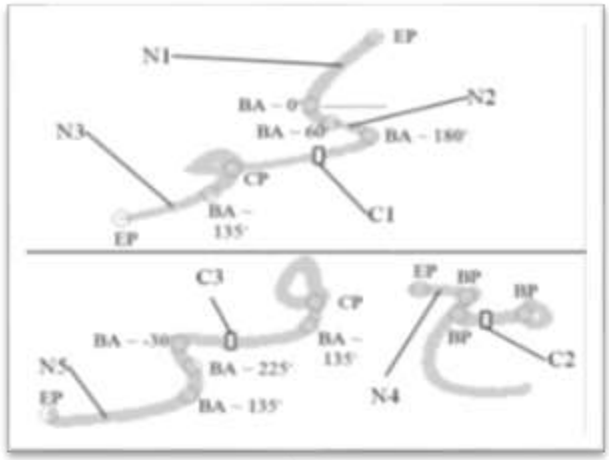


Figure 6 Grapheme segmentation examples. EP: End point, BP: Branch Point, CP: Cross point, C1, C2 and C3 are segmentation points (Abandah, et.al., 2014)

N1-N5 is non-segmented characters continuity .The research uses the same database with the similar algorithm to segment words into graphemes. Yet the features that were selected is not enough, the points (dots) that are above, below, or inside Arabic characters.

2.2.2 Feature Extraction

There weren't many studies that applied the curvelet or wavelet techniques for feature extraction of Arabic characters recognition systems, due to their complicated writing style with loops curves and dots, and the different shapes that one letter can have (Singh, et.al., 2011).. The difficulty of finding studies using this technique on the Arabic language were high, the search of alternatives of Arabic characters reach to slight Resemblance characters like bangala and Urdu (Indian) (El Moubtahij, et.al., 2014).

The use of the wavelet decomposition method proposed by Aburas, et.al., (2007) for recognizing handwritten Arabic characters represents a signal with enhanced resolution in both frequency and time based on using Haar wavelets, the wavelet transforms are divided into two types: continuous and discrete wavelet transforms, this system depends on the possession that the wavelet compressed images are considered as decomposition vectors. However, this system does not reach high accuracies for all characters, the accuracy reaches 97.9% for some letters but with an average of 80% for all Arabic graphemes. Bahashwan, et.al., (2015), combined the curvelet with the spatial domain to extract features of Arabic characters. Since curvelet domain is efficient in representing edges and curves of a character, regardless of its position, while the spatial domain preserves original aspects of the characters. The spatial domain defined the structural features from the main and secondary components of the character by counting end points, branch points, cross points, holes, connected components and secondary components in each zone as features separately (as shown in Figure 7) Curvelet domain extracted the mean, standard deviation and the number of corners in each of the parts of a character image (the image is divided into an 8×8 parts). The extracted features are then fed into a BPNN to classify the test set. The results were promising where an average success rate of 90.3% was recorded.

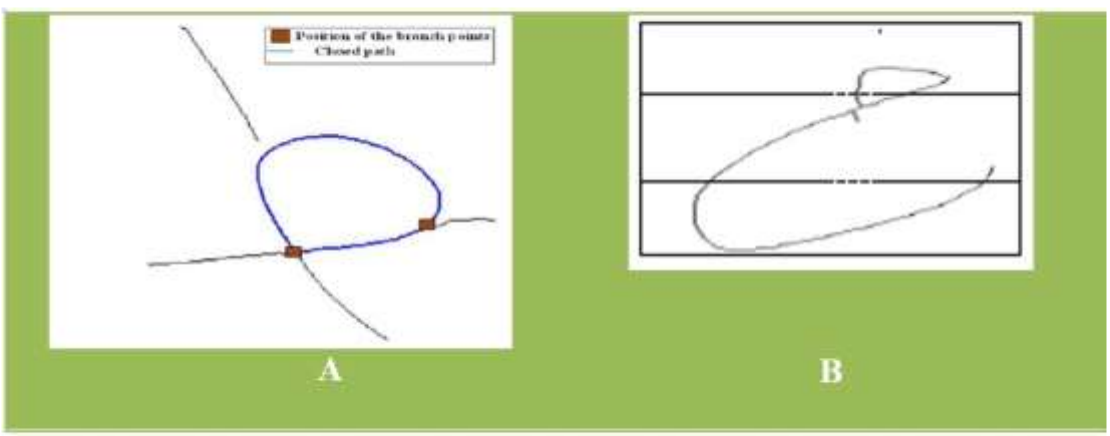


Figure 7 features extracted from spatial domain: A: branching points B: Horizontal zones (Bahashwan, et.al., 2015)

Research on a highly cursive language (bangala) was done by (Majumdar, et.al., 2007). They used a novel feature extraction scheme using curvelet transform on morphologically operated versions of the original image of characters to get 5 versions of the same character. Each was then fed into a separate SVM, and got an overall recognition accuracy of 95.5%. Figure 8 shows how this system used the curvelet transform.

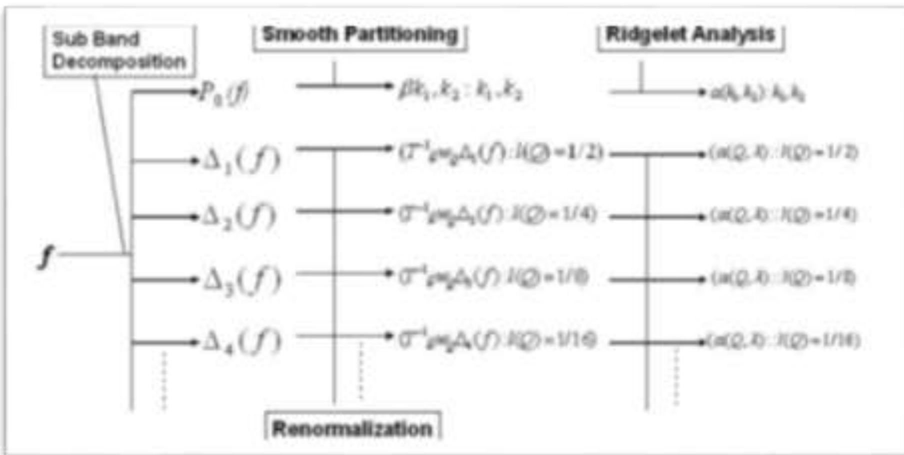


Figure 8 Overview of Curvelet Transform scheme (Majumdar, et.al., 2007)

2.2.3 Classification

The process of grouping features belongs to a certain character according to similar characteristics, in order to identify and recognize that particular character. The following classification methods will be used in this research:

2.2.3.1 Support Vector Machines

Support Vector Machines (SVMs) are modern learning systems that deliver state-of-the-art performance in real world pattern recognition, like handwriting recognition and face recognition. This sub-section presents an overview of the use of SVM's in the classification phase of Arabic handwritten characters in recent researches.

Mahmoud, et.al., (2009), combined an SVM with an Extreme Learning Machine (ELM) to classify Arabic Numerals from scanned documents. They applied an exhaustive search algorithm to estimate the suitable SVM parameters over two stages: coarse and fine search parameters. These parameters are then used in experimenting with SVM by using the extracted features. The coarse search provided classification accuracy of 87.22% (average), while the fine search that followed was 98.28% on average. Classification using the ELM technique provided comparable results, with slight superiority in favor of the SVM.

Bansal, et.al., (2014) introduced a new technique for offline handwritten Gurmukhi character recognition which depends on the feature extraction technique named as Neighborhood Foreground Pixels Density technique, this technique includes data acquisition , digitization, preprocessing , feature extraction, and classification, the classification stage uses three different classifiers SVM, MLP and Naïve Bayes, the system reached to 93.61% accuracy by SVM , with MLP it got 87.3%, finally with Naïve Bayes it got 77.7%, the SVM reach the highest result by the expansion of the block size for better extraction as tested by authors.

SVM's tradeoff parameters selection affects the end classification accuracy. This is why researchers try to find the best parameters ahead of feeding pre-processed data into the SVM. Some researchers set the value of the tradeoff parameter (C and σ) empirically, like Elleuch, et.al., (2015) by applying a grid search with the 5-fold stratified cross validation method. While Mahmoud, et.al., (2009) experimented with different values of C and σ and selected the best-performing ones by modifying the (researcher X) technique to fit their system.

2.2.3.2 Back-propagation Neural Networks

An Arabic character recognition system in the extraction of features was proposed in Sarhan, et.al., (2007), this study used two basic stage feature extraction and ANN classifier each one of the Arabic characters is symbolized by using 7 x 5 binary pixels, these binary pixels are inserted into the feature extraction system, the output is then fed to the ANN, the ANN is composed of two layers, one of them is designed to match the number of Arabic letters, this system always offers lower and higher success rates than many other ANN based handwritten Arabic characters recognition systems (irregular results), especially when the contaminating noise level is low.

Abed, et.al., (2015), proposed a review in recognizing the isolated Arabic character using error back propagation artificial neural networks, the problem is the divergences of Arabic handwriting styles, types, and the similarity in the Arabic characters, this problem was solved by a system that contains a combination of the neural network with error back propagation (EBPANN), the authors reach an accuracy of 93.61% for recognizing only 12 character (structure of the Neural Network is shown in Figure 9), they concluded that increasing the number of hidden layers will remarkably give high recognition rate and less learning time, using a good feature extraction system along with other neural network classifier performs better than a single classifier.

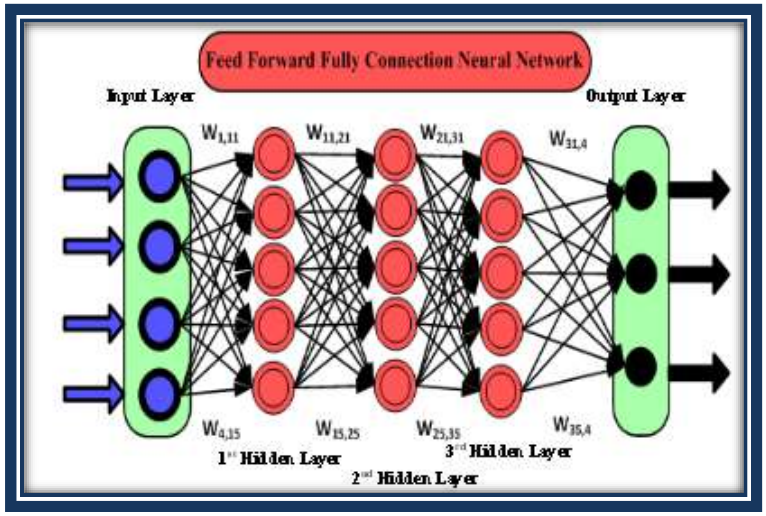


Figure 9 Neural Network Structure (Abed, et.al., 2015)

Al-Boeridi, et.al., (2015) reviewed the performance (accuracies) of a hybrid Off-line handwriting recognition (OFHR) system for Malay words written on Malaysian bank accounts to explain its details in their own language (Malay) , two classification methods have been used in this system ANN and SVM , they proposed these two classifiers as the best in the field however the hybrid method is harder to implement and takes longer time to get satisfying results, the results of the experiments show that ANN has a higher recognition rate at 99.06% and SVM at 97.15%. Figure 10 shows a flowchart of how this system works.

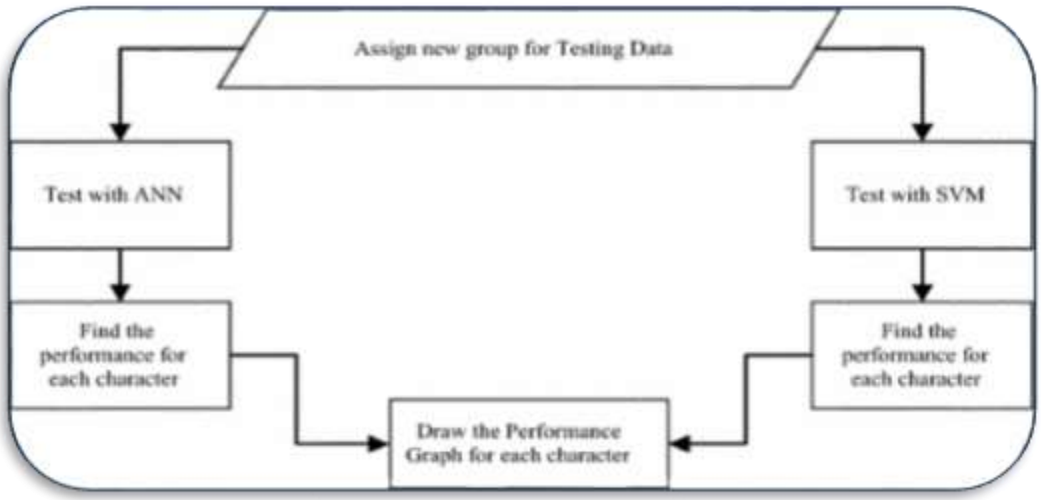


Figure 10 Hybrid System Flowchart (Al-Boeridi, et.al., 2015)

The following chapter explains in technical details how a combination for some of the aforementioned techniques that were proven by extensive testing and experiments to be effective in pattern recognition in general and OCR systems in particular. Applying these techniques and algorithms to Handwritten Arabic documents is considered important to this research work, since as the literature review showed; there is very little work on this field that applies theses effective techniques.

2.2.4 IFN-ENIT Dataset

The following related work is based on IFN-ENIT with no characters segmentation applied.

Alkhateeb, et.al., (2011) proposed a combination of classifiers, the first one is Hidden Markov Model (HMM) than re ranking to improve the accuracy, the re ranking used with topological feature extraction, the features are collected from 500 word, the accuracy reach 84.09%. The hybrid classifier approached by Bouchareb, et.al., (2008) has a satisfying result in the accuracy of recognition which reach 96% by using SVM and Principal component analysis (PCA) for 1000 isolated character principal shape (main body of the characters without dots). Shanbehzadeh, et.al., (2007) proposed a method to choose the best feature extraction among others that boosted the accuracy by algorithm, the system achieved 85.59% accuracy for 3000 Farsi characters that normalize to (50x50) grid than classified by Vector Quantization. Al-HAJJ, et.al., (2007) offline recognition of cursive Arabic handwritten words is proposed using combination of multi-stage classifier generated from fusing three HMM classifiers, the system reach 90.96% accuracy rate for 6,709 images. Dupre, (2003) proposed a system that extracted from the graphemes and a hybrid HMM/ANN is used for classification. HMM is used to represent each character- categorization, while NN make the calculations of the remaining process. This system was tested and achieved an 87.40% recognition rate. Mowlaei, et.al., (2002) proposed a very fast system for recognition of handwritten Farsi characters and numerals, Haar wavelet transform and Multi-Resolution Analysis (MRA) for feature extraction has been used. This system achieved 97.24 % for recognition the isolated handwritten postal addresses. Maddouri, et.al., (2002) present a system that take advantage from feature extraction which use combination of local and global vision modelling, the system reach an accuracy 97% for 70 word. Dehghani, et.al., (2001) proposed a system that use HMM as a single classifiers with one dimensional process based on model with 6 states and 8 mixtures for 17000 Persian characters, the system reach a recognition accuracy 65% (Lawgali, 2015).

2.3 Summary

Table 2 explain the related work based on IFN-ENIT that has no segmantion techniqe applied on the charcater inside the image.

Table 2 Related work based on IFN-ENIT

Authors	Classifier	Disadvantage	Conclusion
(Alkhateeb, et.al., 2011)	DCT/ ANN	16.45% error rate	the best results are acquired by using multiple HMMs
(Bouchareb, et.al., 2008)	PCA & SVM	Dots segmentation require	The use of categorization increases the recognition rate of characters
(Shanbehzadeh, et.al., 2007)	Vector Quantization	The features are extracted Only from 60% of samples	The characters were divided into several frames and for each frame 2 groups of features were obtained
(Al-HAJJ, et.al., 2007)	HMM/MLP	Need to classifier switcher algorithm	The higher number of classifiers the higher result of accuracy
(Dupre, 2003)	HMM /NN	designed for Latin cursive writing	HMM assign the characters to groups ,NN classify them
(Mowlaei, et.al., 2002)	Haar wavelet	Image Reduced to 64 pixels	Classification of isolated characters gained without dots
(Maddouri, et.al., 2002)	NN combining global and local vision modeling	The handwritten letter compared to printed character	combination of local and global vision modelling can increases the recognition accuracy with the proper features
(Dehghani, et.al., 2001)	Semi continuous one dimensional HMM	Dataset is modified to be compatible with the system	Certain image filtering slightly improve the accuracy of recognition.

Chapter Three: The Research Methodology

3.1 Introduction

The Artificial Neural Networks (ANN) system can be defined as a process that can adjust and learn from previous mistake, and it capable to deal with real and noisy data. The Support Vector Machines are based on the concept of decision levels. The decision level is one that separates between a set of objects having different classes. This decision is based on human intelligence, and made by the human expertise, while the ANN deals with the accumulated information and training.

The OCR strategy of AHCR include the following steps:

- Character Input: character input via scan or image based on written models (static images of the characters).
- Preprocesses the input such as thinning, Binarization, etc.
- Segmentation and normalization: The segmentation of characters are not required; because the dataset is pre-segmented as isolated characters.
- Feature extraction: a predefined Featured is extracted to ensure the best accuracy.
- Classification: The last important step, which aims to utilize the information acquired from classifier analysis to training the computer in order to accomplish the character retrieval for next classification process. Figure 11 illustrated the main differences between training and testing phases in this system, as block diagram.

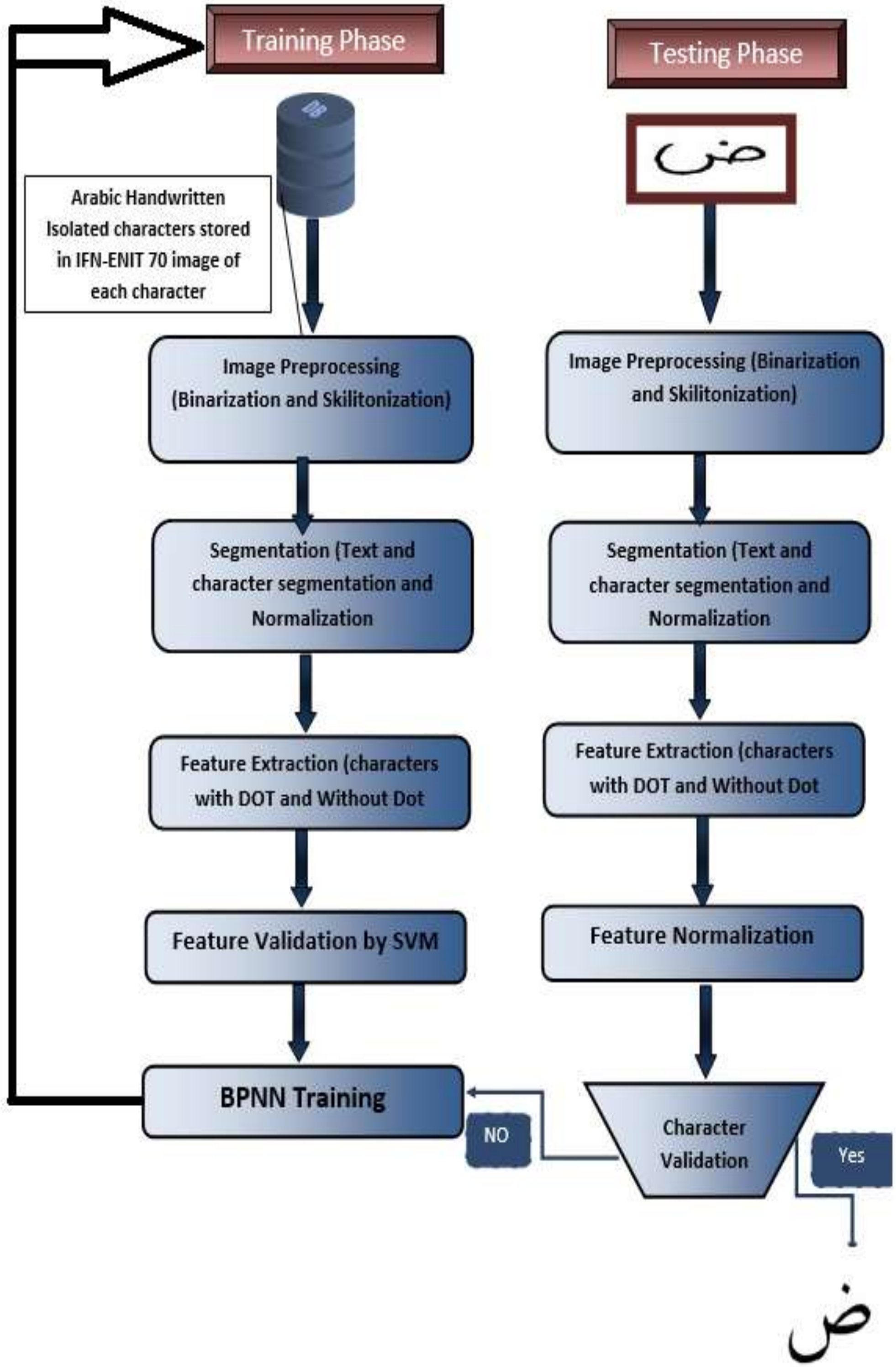


Figure 11 OCR Block Diagram

Supervised learning in general, gets its benefit by choosing training dataset as well as desired output, by already known data. In this work, SVM and NN are used.

SVM used as the binary classification scheme, due to its ability to provide high accuracy in binary classification, especially in a large dataset (Nayak, et.al., 2015). On the other hand, NN is used to apply classification between letters. BPNN is used by computing the value of a predetermined function and adjusting weights of layers in order to reduce the error rate.

3.2 DATASET

The using of IFN-ENT dataset because it consist of more than 2900 various characters that have low overall accuracy, the Arabic language contain 28 isolated characters plus the Hamza, the use of this dataset because it is reliable, realistic and the most common used in such researches (Pechwitz, et.al., 2003), the dataset is designed to cover specific shapes of Arabic characters. it contains 100 sample image for each isolated character, plus the Hamza which some researchers consider it a character, the forms will be scanned in black and white mode with low resolution of dots per inch (dpi), The images of the characters shall be converted into a binary format with small objects considered as noise and removed, the dots and marks, such as "همزة", are removed from the characters since they can affect the classification. The dots will be transfer to original location after character segmented. In this case the dots are considered as primary features to be extracted. In order to keep the originality of character image. The images of characters will not be resized and it will be used as 128x128 grid for normalization purpose. The dataset will be used in this study for training and testing. The implemented recognition system will use a free segmented dataset, which requested from IFNENIT.com, as shown in figure 12 (Lawgali, et.al., 2013).

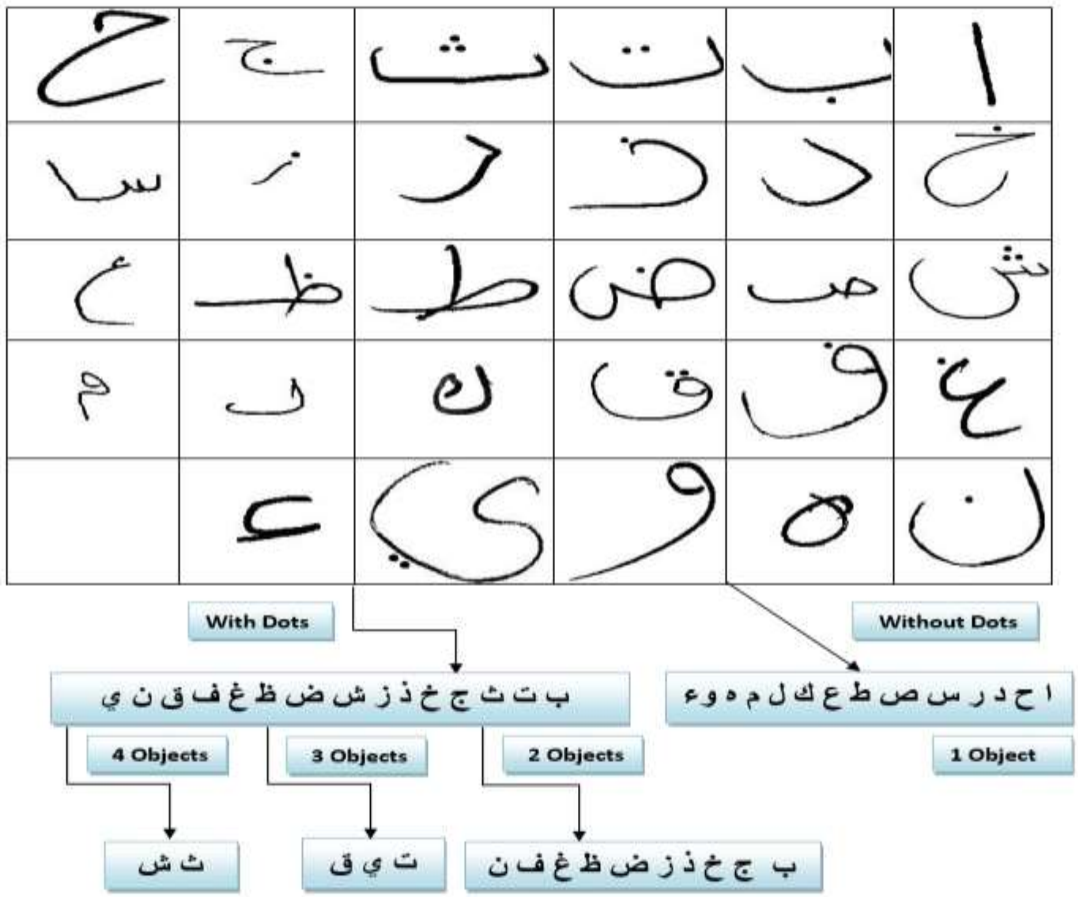


Figure 12 Sample of Arabic Character Isolated Images

3.3 Mathematical Model

During the training of the neural network, the error function can be given as illustrated by the following equation:

$$\varepsilon = \sum_{X_i \in E}(d_i - f_i)^2 \ldots\ldots\ldots (1)$$

Where; d_i: are the given desired output, and f_i: are the real output.

The value of ε mainly depends on the values of the weight.

The gradient descent: minimizing the value of the error through moving the network weights along the decreasing slope of error. The main idea is to perform the training process by adjusting the values of the weights using sheared method in order to reach the minimum value of the error gradient. Now, the assigning of W_i^j by equation 2:

$$W_i^j \leftarrow W_i^j + c_i^j \delta_i^j X^{j-1} \ldots\ldots\ldots (2)$$

Will be performed, where;

W_i^j: weight of the i^{th} sigmoid in the j^{th} layer.

c_i^j: learning rate constant of the i^{th}sigmoid in the j^{th} layer.

X^{j-1}: system input, which is also the previous layer output.

δ_i^j: the network output sensitivity to the change in the input of the system.

The sensitivity of the network can be given as illustrated in the following equation:

$$\delta_i^j = (d - f)\frac{\partial f}{\partial s_i^j} = -\frac{1}{2}\frac{\partial \varepsilon}{\partial s_i^j} \ldots\ldots (3)$$

when $\delta_i^j = \delta^k$, for the output layer

$$\delta_i^j = \delta^k = (d - f)\frac{\partial f}{\partial \delta^k} \ldots\ldots (4)$$

From equation (4) $\delta_i^j = (d - f)f(1 - f)$

So, $W^k < -W^k + c^k(d-f)f(1-f)X^{k-1}$ …….. (5)

While for the hidden layers,$\delta^k = (d-f)f(1-f)$ so;

$\delta_i^j = f_i^j(1-f_i^j)\sum_{l=1}^{m_{j+1}} w_{il}^{j+1}$……. (6)

And the weight equation for the output layer is gain in equation 7:

$w_{ij}(t+1) - w_{ij}(t) = \eta\Delta_i(t)z_j(t) = \eta\big(d_i(t) - y_i(t)\big)g'\big(a_i(t)\big)z_j(t)$……. (7)

When η: Learning rate

$g'\big(a_i(t)\big)$: activation function

$d_i(t)$: desired or target output

$y_i(t)$: real output

$z_j(t)$: Output from the previous layer

$w_{ij}(t+1)$: Adjusted value of the weights

The Weights for the hidden layers in equation (8-10) are concluded from the previous equations (1-7):

$v_{ij}(t+1) - v_{ij}(t) = \eta\delta_i(t)x_j(t) = \eta g'\big(u_i(t)\big)x_j(t)\sum_k \Delta_k(t)\,w_{ki}$…. (8)

$\Delta_i(t) = \big(d_i(t) - y_i(t)\big)g'\big(a_i(t)\big)$……. (9)

$\delta_i(t) = g'\big(u_i(t)\big)\sum_k \Delta_k(t)\,w_{ki}$……. (10)

These equations (8-10), are used to calculate the values of the weights on the links between neurons by selecting random values of the weights and then adjusting them based on the error value (Rojas, 1996).

Back propagation is a multi-layer feed forward, managed learning network based on gradient drop learning law. This back propagation neural network gives a computationally competent technique for altering the weights in feed ahead network, by differentiable start function units, to learn a teaching set of input-output data. The gradient drop technique purpose is to reduce the whole squared error of the output calculated by the net. The intent is to teach the network to attain balance among the capability to react properly to the input patterns that are utilized for teaching and the capability to give a high-quality reply to the input that are alike (Zheng, et.al., 2015)

A classic back propagation network with Multi-layer, feed-forward supervised learning is shown in the Figure 13. Here learning procedure in Back propagation needs couples of input and goal vectors. The output vector ‘o ‘is contrasted with goal vector ’t ‘. In case of dissimilarity of ‘o’ and ‘t‘vectors, the weights are adjusted to reduce the dissimilarity. At first arbitrary weights and thresholds are allocated to the network, so that the output of the network is 1 precisely, when the output of all units in the first layer is 1 (Anthony, et.al., 2009). These weights are updated each iteration with the intention of reducing the mean square error among the output vector and the goal vector, (Han, et.al., 2009).

A number of hidden units: If the start function can differ with the function, then it can be seen that an n-input, output function needs at most 2n+1 hidden unit. If an additional number of hidden layers is present, then the computation for the δ’s are replicated for every extra concealed layer present, summing all the δ’s for units present in the preceding layer that is fed into the present layer for which δ is being computed.

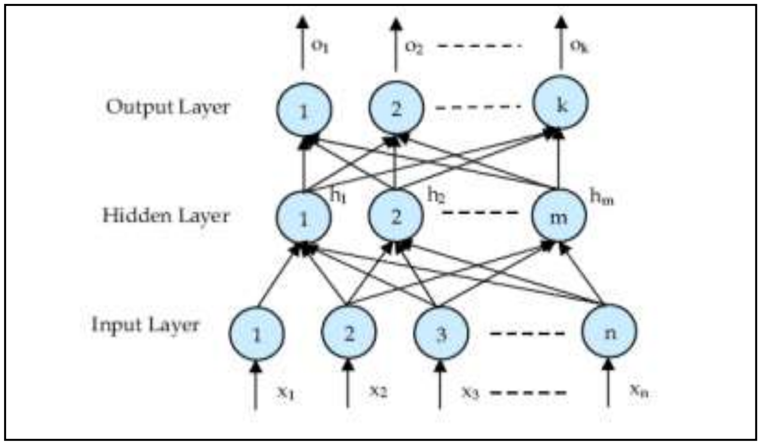


Figure 13 Basic Block of Back propagation neural network

On the other hand, the given training data for characters dataset{X1 ... Xn} that are vectors in some space X ⊆ Rd. where Xi ∈ {−1, 1}, in their simplest form, SVMs has hyperplanes that separate the training data (data points) by a maximal margin, all vectors lying on one side of the hyperplane are labeled as −1, and all vectors lying on the other side are labeled as +1, the separating vector which is given by F(x,w,b) = sign(w. x - b)

plus-plane = { x : w . x + b = +1 }Predict Class = +1 X+ zone

minus-plane = { x : w . x + b = -1 } Predict Class = -1 X- zone

the space between X+&X-zone is called M=margin width

Let X+be the closest plus-plane-point to X- ……….i

X+ = X- + α w …………………………….ii

|X+ - X- | = M…………….…………….iii

From (i), (ii) and (iii) are concludes that M as follows

w. (X - + α w) + b = 1 =>w. X - + b + α w .w = 1 =>-1 + α w .w = 1 => $\alpha = \dfrac{2}{\mathbf{w.w}}$

M = |X+ - X- | =| α w |=> $\alpha \,|\, \mathbf{w} \,| = \alpha\sqrt{\mathbf{w.w}}$ => $=> \dfrac{2\sqrt{\mathbf{w.w}}}{\mathbf{w.w}} => M = \dfrac{2}{\sqrt{\mathbf{w.w}}}$

Which mean the hyperplanes that are touched by the maximal radius hyper sphere correspond to the support vectors and that the radius of the hyper sphere is the margin of the linear SVM, which is useful in determining the training error and complexity term, as shown in Figure 14 (Tong, et.al., 2002).

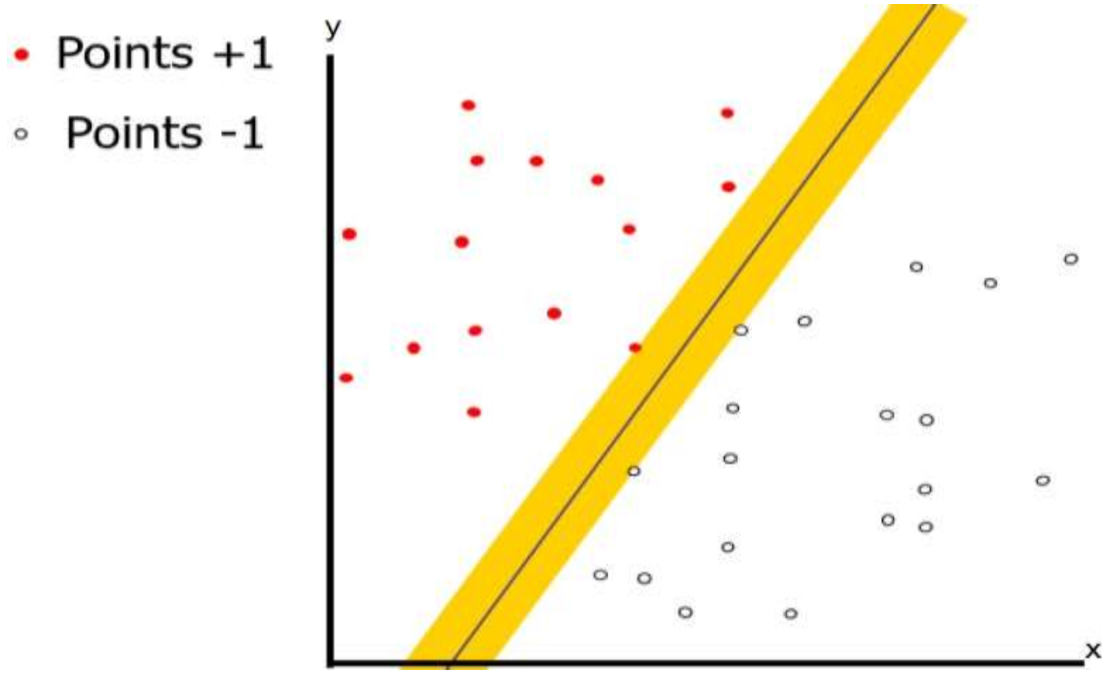


Figure 14 Linear SVM example

3.4 Work Flow

The sequence of images manufacturing, administrative, or other processes through the OCR, which is considered as a piece of work passes from initiation to completion. Flowcharts are useful tools for visualizing the process and parameters in order to understand the steps of workflow. The proposed method is represented in figure 15. Segmentation is used by IFN-ENIT, some pre-processing can be used to smoothen the data. Then, features extraction are achieved using wavelet and curvelet methods.

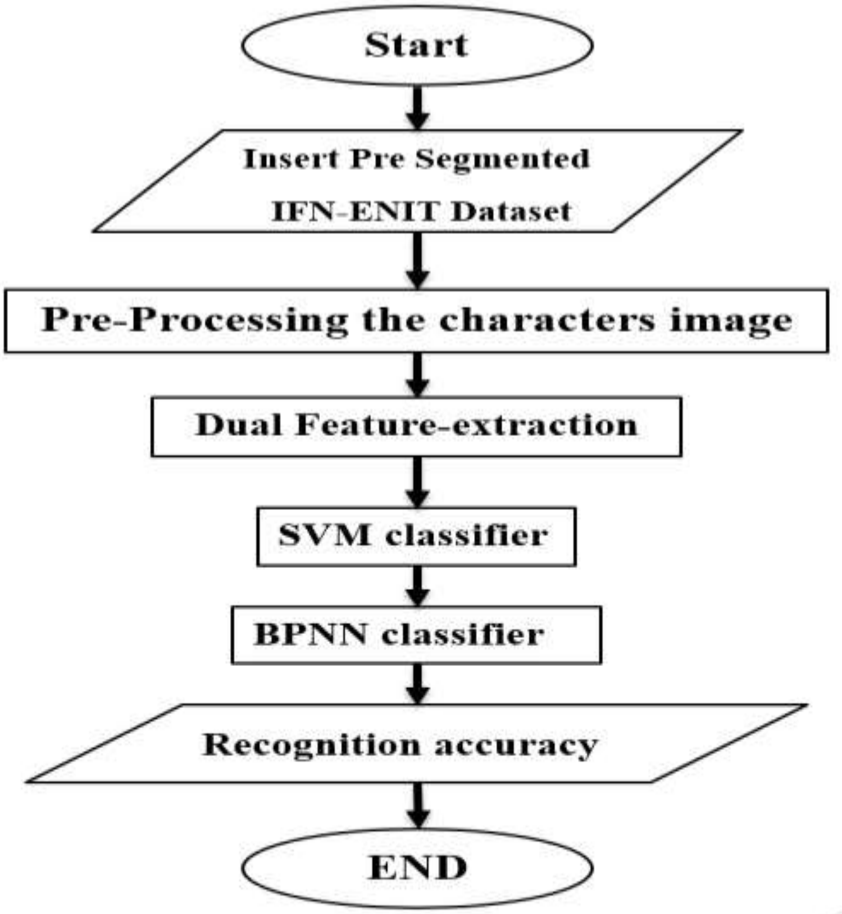


Figure 15 Flow work

The next step, SVM is used to split all letters into two groups; letters with dot(s) and letters without dost(s), using binary classification in which the image is being logically divided into 4 equal parts (quadrants) and apply morphological commands to predict the number of objects and its respective area. These will show how features are extracted to train the SVM in order to classify characters in the two groups.

This step is applied by searching on how many object in the image, since any letter without dot(s), will be count as one object. Finally, BPNN is used to detect the errors occurs in the previous classifier, detection of the character and compute the overall accuracy for letters.

3.4.1 Segmentation

Reaching the best recognition depends on finding the appropriate segmentation method/model. The key models are estimated baseline, line segmentation, thinning foreground, dots extraction and no character segmentation. Segment the character from the background is done by ref (x) in this steps.

1. **Line Segmentation**: this method aims at separating the whole image of text into lines by locating the lower and upper bound of each text line. The only problem in this process is where some of the dots are determined in line segments that are separate, as shown in figure 16 (Said, et.al., 2012). To ensure that the problem is solved, after extracting the text from image in all lines, the following steps are conducted.

- Finding the highest height of the line in the image, which is the last upper pixel.
- Any height of line which is smaller than half the height of line in the image is considered as sub-line.
  - If a subline is found, it is merged with the line which is closest to it.

Figure 16 Line segmentation model: Source (Al-Ani, et.al., 2014)

2. **Estimate Baseline**: Arabic printed or handwritten scripts consists of letters connected to each other and is cursive, with a baseline which is an imaginary line. In Arabic characters, dots are imaginary lines positioned, in the middle, above or under them. It is important to detect baseline because it determines the position of dots in Arabic characters (Rejean, et.al., 2000). Figure 17 explains the extraction using baseline where baseline corresponds the horizontal line with the maximum Neighborhood Foreground Pixel Density (NFPD) through each line, NFPD is the density of connected pixels that have positive value (+1) (Bansal, et.al., 2014).

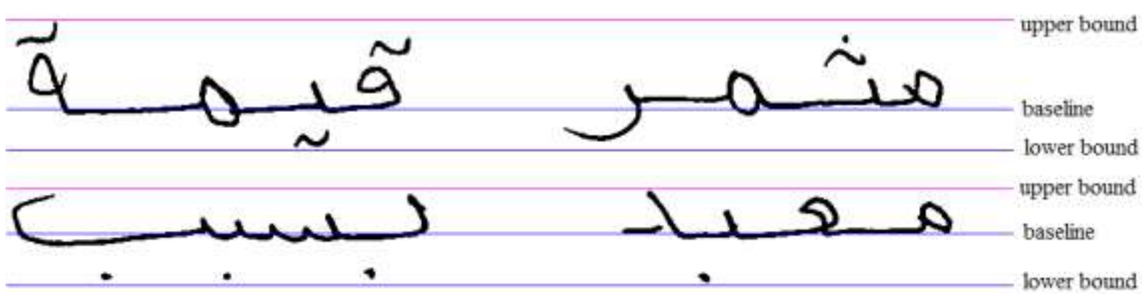


Figure 17 Estimate Baseline Extraction Model; Source (Al-Ani, et.al., 2014)

3. **Extraction of Dots**: the number of Arabic characters that contains dots are fifteen ('Nuqta'). Dots below or above the central part are used to distinguish characters that seem similar in Arabic Characters. For instance, "Thaa" (ث) and "Baa" (ب) have similar character bodies which are characterized by 3 dots above and one dot below to distinguish the characters (Rejean, et.al., 2000). After every single dot is separated from text image, search for a triple and double dots begins by scanning the text image, as shown in figure 18.
4. **Character Segmentation**: in this model, an operation is used to decompose sequence of a character of an image into individual symbols of an image (Osman, 2013). The process of segmentation is applied to the words that have been thinned, which pass by the extraction of dots from segmentation of line as shown in the figure 18

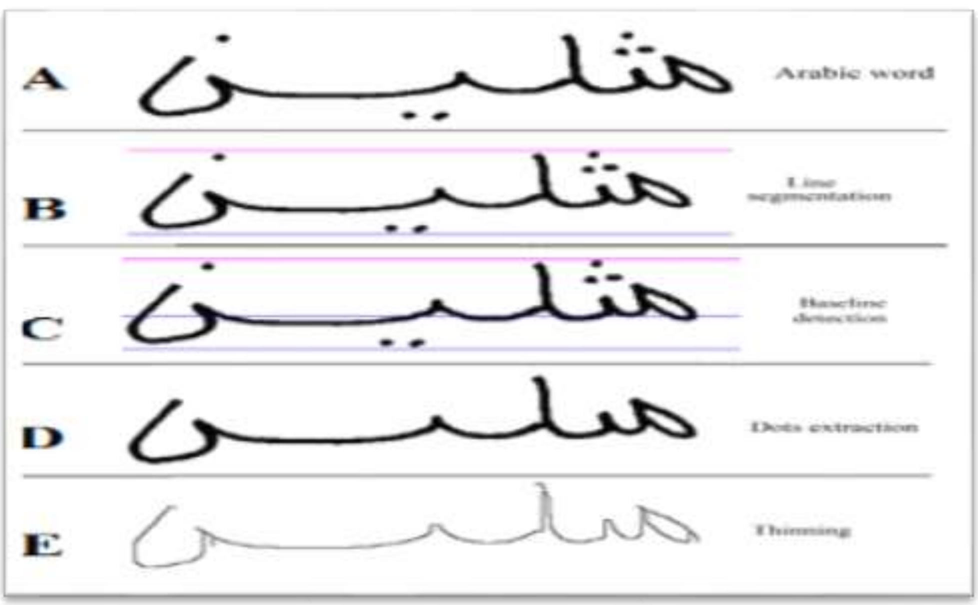


Figure 18 Extraction using character segmentation Model; Source (Al-Ani, et.al., 2014)

Ideally, the character segmentation depends on identifying the ending and starting of sub-words/words and identifying the point of segmentation among the characters in the sub-words/words (Aouadi, et.al., 2016). The segmented dataset are downloaded from IFN-ENIT. The segmentation process is no longer required, because there are many kinds of researches about IFN-ENIT segmentation that already reach a high accuracy segmentation result, the choice of using pre-segmented dataset is to focus on recognition accuracy instead of segmentation process, the used Isolated Arabic dataset achieved 90.8% accuracy of segmentation.

3.4.2 Preprocessing

The images in the dataset are clear and without noise, either way the system will be going to include Thinning as noise reduction. Thinning: this is a process used to simplify the shape of text and reduces the data amount required for handling in order to come up with connected character Skelton of the image input. In a real time system the need to remove noise from the images is required, even if the noise is barely observed. Median filter will be included in the system, since images in the original dataset have different sizes. As a preprocessing step in this system. The normalization of the size is required for all the images by changing their block size. The given dataset image come in one size of grid, which is 128×128 grid. The normalize technique changes the available block size into another by cutting the edges (Blob). This process compares the level of similarity and differences in the processing data (mostly images or kinds of visual data). Blob detection was used to obtain zones of interest for additional processing. The process of rotating the normalized data to enhance the alignment of character and facilitate the capture of visual data is called skew correction. Binarization is the process of changing available data before normalization into binary matrix which can be understood by the computers (machine language). In general, noise filtering, smoothing, binarization, skew-correction and normalization should be done in this pre-processing step. (Sadri, et.al., 2003).

The Optical Character recognition (OCR) objective is to convert the text into digital image using computer vision. There are two categories of automatic handwriting recognition, these are the online and offline recognition. Handwriting recognition using the online method is easier than the offline because the script temporal information is available (AL-Zawaideh, 2012). One of the most challenging task is recognition of Arabic handwriting character (Plamondon, et.al., 2000).

3.4.3 Feature Selection and Extraction

After the data has been prepared, the proposed system will extract designated features for each of the character groups defined by the feature extraction techniques. Since Arabic letters are considered cursive letters, so the most appropriate method to use in order to extract the main features of the training dataset would be curvelets and wavelets feature. The determination of the importance of each feature by considering how the performance is influenced without that feature is needed. If removing a feature deteriorates the classification performance, the feature is considered important (Chang, et.al., 2008), with curvelet and wavelet based feature extraction (Separated) is the best way to achieve a high overall accuracy rate. Based on object-counting which is basically a pixels boundary detection and extraction in morphological operation. Considering that the number of feature extractions is not important, but the quality of retrieving of each one is, because it may not correspond with the classifiers, and for that a training of the system in which feature extraction is suitable is in demand for the scanned character in this system.

3.4.3.1 Curvelet and Wavelet

Both DWT and curvelet are used to detect the feature components in images. Wavelet features are used due to its performance of finding low and high pixels density frequency in the letter and detect in which region of area the dots going to be. It is performed on rows first then on columns, H and L denote high-pass and low-pass channels respectively. The DWT divided the image logically into four parts LL, LH, HL and HH, each one represents a quarter part of the image, to locate the features of dots (Hiremath, et.al., 2015). On the other hand, curvelet is used to study the shape, main body and the direction of each continuity of the character. The structuring element consists of a pattern specified as the coordinates of a number of discrete points relative to some origin. The following steps clear the feature classification:

- Grid coordinates are used to represent the element as a small image on a square grid in IFN-ENIT, the grid is represented in 128×128 pixels.
- In each case (character image) the origin is marked by a ring around that point, the origin does not have to be in the center of the structuring element (character foreground pixels).
- One of the reasons that the accuracy is lowered that the grid is not modified, so the structuring is done by translating the structuring element to various points in the input image, and examining the intersection between the translated kernels coordinates and the input image coordinates. The basic effect of the operator on a binary image is to isolate the boundaries of regions of foreground pixels.

- The operator takes two pieces of data as inputs, the first is the image which is to be trained, The second is a set of coordinate points known as a structuring element which is the testing image (also called the desire output image).
- The SVM takes these two pieces and calculate the difference between them, then put the predicted value according to the calculation.

3.4.4 Classifier Design

After optimal feature subset is selected, a classifier can be designed using several approaches, the first approach is not the simplest way but the most accurate one. Linear SVM it consists of supervised models with associated learning algorithms that analyze data used for classification and analysis which is based on the concept of similarity. Linear SVM deals with the separable classes, the ANN manages weighted hubs (nodes) automatically by figuring and calculating the error term for the yield units by using the difference that gives the error.

3.4.5 SVM Classification

Classification is a general process related to categorization, the process in which main body and objects are recognized, differentiated, and understood. In the case of isolated Arabic handwritten characters, SVM classification object is to split the characters with dots and characters without dots from each other. This makes the NN process easier to recognize them as shown later on in chapter 4. The difference between characters with dots from characters without dots, lead to a major reduce in the error rate on some characters within the dual stage classifiers. By other means the probability of characters similarity with the same shape will be reduced, when increasing the categorization by object-counting feature of those letters according to their main body shape and its location, as well as to their object (dots).

3.4.6 Backward Propagation of Errors BPNN

BPNN algorithm can be explained in the following steps:

- The error term that is concluded from the output can be measured by the difference of nodes weights that generate the error.
- The error term will be saved as a value and return backward from the output layer to the first step after input (first hidden layer).
- Within each layer, the system will compare and calculate the current layer weights with the desired output weights, trying to reduce the gap between them.

After using SVM, the output of SVM comes in two groups, each group contains mini-small groups of letters, after that, each group is entered to BPNN in order to apply and compute accuracy. Training the system by initializing the network with random weights, the random weights are assigned from the NN to break the symmetry and this makes the neural network learn faster (Rojas, 2013). Symmetry is a type of invariance: the property that something does not change under a set of transformations. The process starts from the last layer which is called the output layer heading to the first one (input layer), comparing the network random weights with the actual output weights this process is called (error function), then modify or adjust the layers one by one heading to the source and calculate real value to random weights (weights updating) until the input weights are nearly the same of desire weights, mixing ANN with SVM reduce the probability of classification error. The optimization is not a single or standalone step, it is combined with several parts of the ANN process, in preprocessing. Optimization ensures that the input pattern that is taken from the background has the best quality, in optimization the feature extraction deals with each character in a different way just like (س) and (ن), the human brain can recognize the characters easily, so let’s take a look at (س) and (ن), in figure 19.

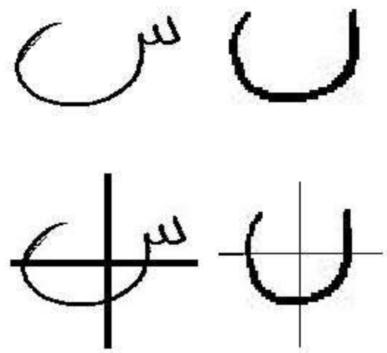


Figure 19 Seen and Noon characters

The wavelet has a limitation in this case because it will split the image into several parts (theoretical), then somehow the Siin (س) look just like the noon (ن) from respective of view except the top right angle, however the problem can be reduced by curvelet feature extraction, and for that the suggestion of using dual extraction method are required so it can reduce the defects while extracting the characters, dual stage of classifiers-feature extraction that reduce the error rate which is generated from the difference between them. The most proper technique for the proposed work is back propagation algorithm which effectively solved the problem between classifiers (Werbos, 1975). The purpose of using BPNN in this study because it is more suitable with SVM classifier, because the SVM reduce the vanishing gradient problem. ANN uses multiple characteristics in the analysis of one’s handwriting, these characteristics change in use from one kind to another, these characteristics are collected using sensitive technologies, like digitizing tablets, (Wadhawan, et.al., 2015), identification process is performed by verifying the error distance between ANN classification and SVM classification, that should take more time, the proposed work results show a minimum error rate as shown in chapter four, so identification process is not really necessary.

Chapter Four: Implementation and Results

4.1 Overview

In this chapter Arabic letter recognition system model is constructed using MATLAB2014A, using SVM and neural networks. In order to guarantee the main objective of this thesis by analyzing the main concepts and the performance of Arabic letter recognition system to obtain results and compare them.

4.2 Implementation Steps

Here in this chapter, details implementation steps with the final result is being revealed, listed here an overview of what will go through this chapter:

- **Data Base loading**: the dataset character images used as a total 2928 for both training and testing is loaded. The images used for testing is 439 image, for validation is 439 and the images used for training is 2049. The flow chart (Figure 20) shows the numbers of images used, all the characters are loaded within one database, and no real separation is applied.

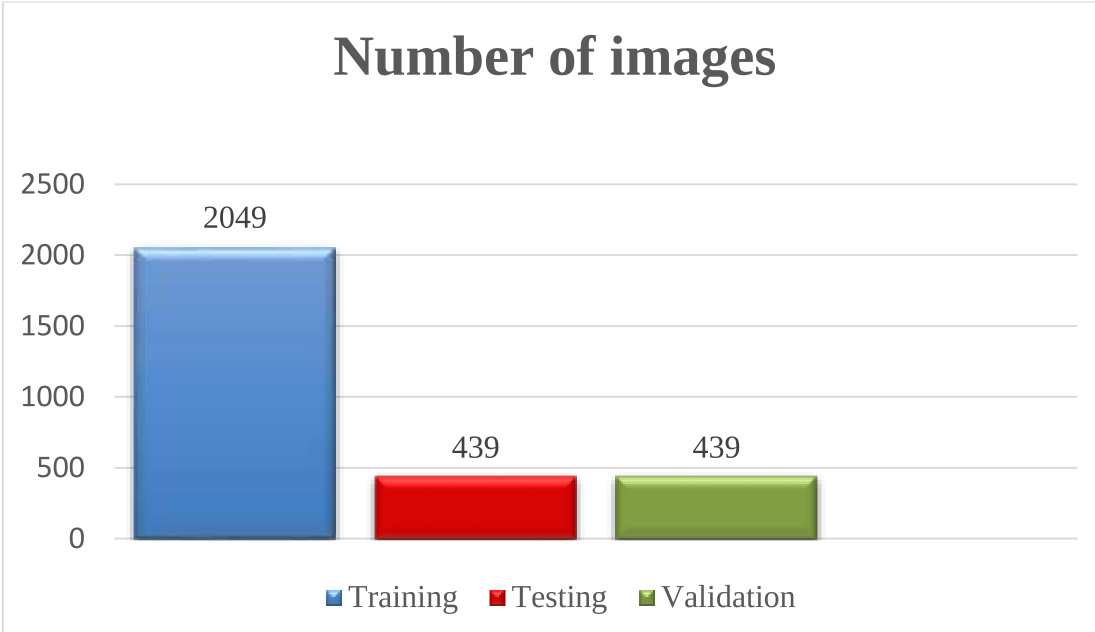


Figure 20 Number of images used in this system

- **Data Set Classification**: classify dataset each letter in a specific table cell.
- **Image Storing**: both the training and testing images is being saved as different variables
- **Feature Extraction**: curvelet and wavelet feature extraction are applied to recognize isolated characters shapes –as described in the previous chapter and stored in the temporary database.
- **SVM**: the images variables are being entered into a binary SVM, to classify them into two groups, with and without dots to decrease the number of classified groups and though enhance the accuracy.
- **Neural Network**: Apply training images to get neural network recognition learning using back propagation method in order to get optimum weights at specific mean square error.

4.3 Hardware Specification

For this system a Personal computer has been used as a working area for installation and implementation with the following specification:

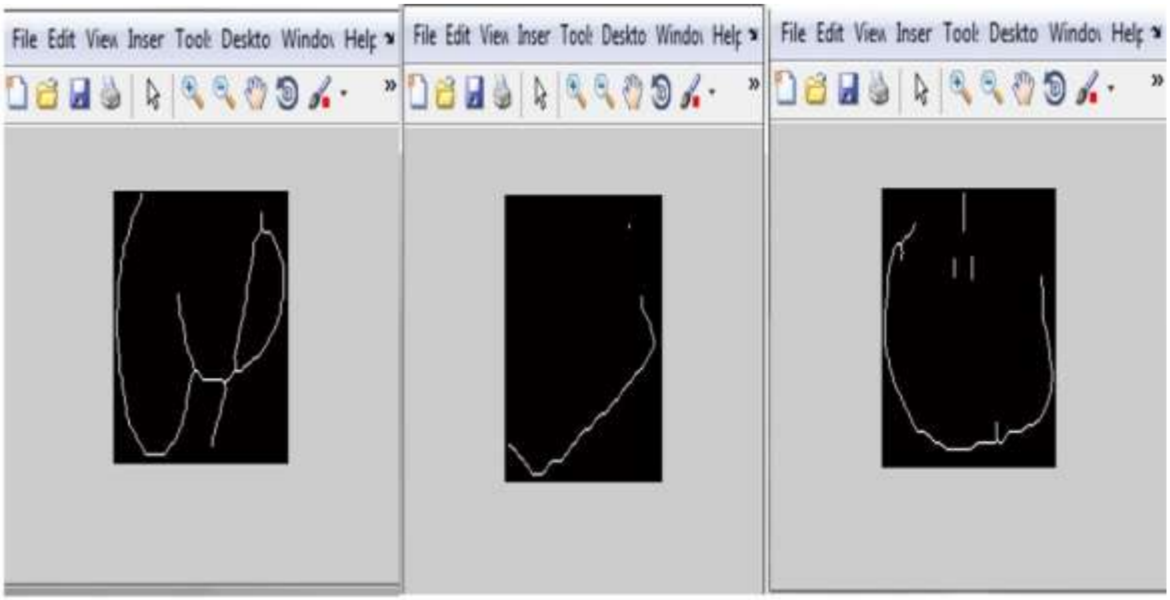
- Windows 8.1 64 bit.
- Processor :Intel Core I7-4720 HQ @ 2.6 GHz
- RAM: 16 GB Ram DDR4.
- GPU: NIVIDIA 960 GTXM.

4.4 Feature Extraction

In the implementation, the emphasis on certain feature extraction characteristics is increased because the characters are complex. All features are used to increase the recognition and accuracy of the character shape. The steps of extraction as following:

First of all, binarize the image of the character, this step is used to find what we call in image processing area –region of interest- which is the portion of the image that of interest for further processing.

After that, each letter is presented and main features are extracted, different arrangements occurred depending on the number of objects in each image and its location, for example, any letter without dot(s) counted as one object, while there are letters with two or three or four objects. Figure 21, is an example of a letter with single, two and four objects.



One Object Two Objects Four Objects

Figure 21 Feature Extraction object counting

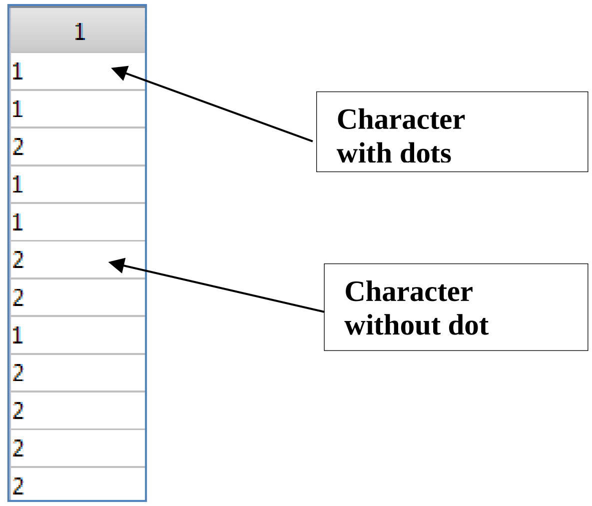
4.5 SVM Stage

This stage is used to classify dataset into two groups with and without dots, binary SVM is used in order to apply the classification, the output of each group is indexed with margin value {-1,+1}. The following scripts explain SVM work in MATLAB

```
SVMModel = fitcsvm(X,group);
[pred,score] = predict(SVMModel,X);
```

Table 3 shows the result after recognition by SVM to classify the objects where 1 represents character with dot/s and 2 represent character without dots.

Table 3 Score Results of SVM



Finally, accuracy of classification of groups can be computed as shown in the following script

```
%////////// evaluating accuracy ///////////////////////////

matched=0;
unmatched=0;
for i=1:length(pred)
    if(pred{i}==group{i})
        matched=matched+1;
    else
        unmatched=unmatched + 1;
    end
end

accuracy=(matched/(matched + unmatched)) * 100;
display(strcat('SVM accuracy:',num2str(accuracy),'%'));
```

The results of training SVM classifier is shown in figure 22

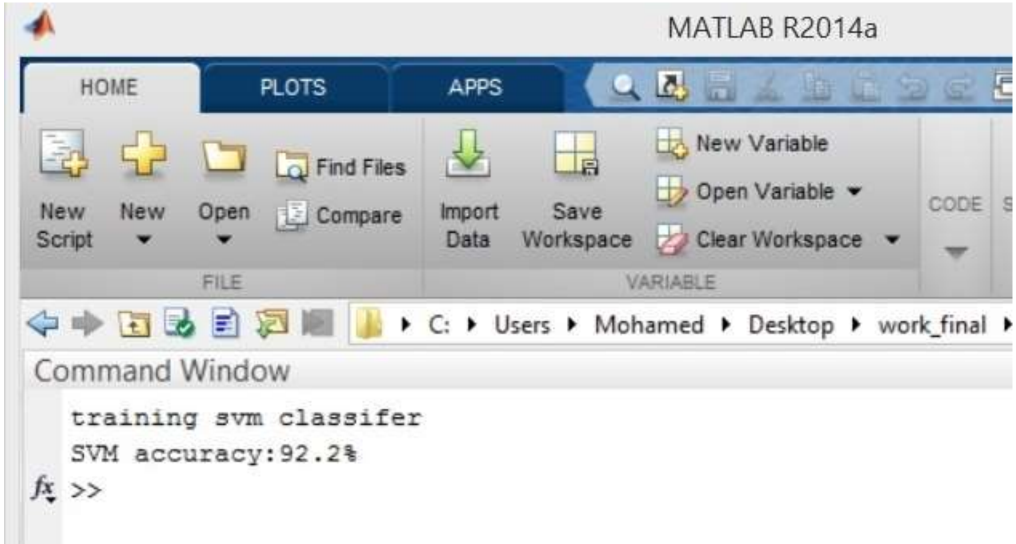


Figure 22 System accuracy percentage

Hereafter the illustration of the accuracy of each letter separately that proceeds out of this step. As shown by using confusion matrix the achieved results is so promising where the achieved total accuracy is (92.2%), some characters reach up to (99%) recognition rate, others not that good result like Miim (م) as shown in table 4.

Table 4 Hybrid proposed system SVM fed to BPNN

Accuracy percentage%	Character Name	Accuracy percentage%	Character Name	Accuracy percentage%	Character Name
96%	(Kaaf)ك	**98%**	(Zaay)ز	**97%**	(Alif) ا
84%	(Laam)ل	**98%**	(Siin)س	**90%**	(Baa) ب
80%	(Miim)م	**98%**	(Shiin)ش	**80%**	(Taa) ت
90%	(Nuun)ن	**89%**	(Saad)ص	**%96**	(Thaa) ث
99%	(Haa)ه	**98%**	(Daad)ض	**98%**	(Jiim) ج
96%	(Waaw)و	**85%**	(TAA) ط	**87%**	(Haa) ح

85%	(Yaa)ي	**92%**	(Dhaa) ظ	**90%**	(Khaa)خ
88%	(Hamza)ء	**99%**	(Ayn)ع	**99%**	(Daal)د
		82%	(Ghayn)غ	**98%**	(Dhall) ذ
		90%	(Faa)ف	**95%**	(Raa) ر
		99%	(Qaaf)ق		

4.6 Neural Network (NN) Stage

In this stage neural network using back-propagation are implemented to detect each letter and recognize it to one of the available categories. The BPNN will randomize the weights for the whole network as a start, in the training case, the process of making the training inputs to network and calculate output is necessary to compare it later with the target data weights. Second step is to back-propagate through the network and check the weights for all the available layers starting with output layer, back to input layer. In each layer the NN system in Matlab should compare network output with correct output (target). It also calculates the error function or the observed error, then adapt the weights in current layer to modify the state of the NN, until the hidden layer and output layer are similar, in other words, when the tuning set error stops improving, the updating of the weights is no longer required because it will provide the same previous weights.

The following script explain the training of NN, as shown 70% of dataset is used for training, while 15% for testing and 15% for validation.

```
%//////////// training the networks /////////////
hiddenLayerSize = 10;
net_1 = patternnet(hiddenLayerSize);

net_1.divideParam.trainRatio = 70/100;
net_1.divideParam.valRatio = 15/100;
net_1.divideParam.testRatio = 15/100;
net_1.trainFcn = 'trainscg';
```

This is an essential step that will be used as a way to improve the ability of the neural network to recognize the Arabic letters. In general, the neural network consists of input layer, hidden layer and output layer. In each layer there are a set of neurons, each one of these neurons is connected to all neurons in the next layer. There are features that are essential to recognize the isolated Arabic letters. At each line between the neurons is the weight value, the main idea of the training lies in giving these weights random values at the first time and then adjust their values to minimize the error function between the real output and the desired output. An important idea is when increasing the number of epochs, which is how much loop the training of the neural network is performed, and then better results will be achieved.

NN-tool is shown in Figure 23, NN consists of an input, output, and ten hidden layers. Also in this step, the algorithm and the progress of the Arabic letter recognition are demonstrated. NN-tool demonstrates the progress of the Arabic letter recognition, the performance in neural network Matlab is cross-Entropy value to epoch term, the cross-Entropy is an error measurement, the epoch is a measure of the quantity of times that all of the training vectors are used once to update the weights. In other meaning all the nodes in the layers are checked and adjusted according to the desired output one time at least and all of the training samples pass through the learning algorithm. The NN performance in this code is equal to 0.0527. The gradient algorithm is an optimization algorithm used to find a local minimum of that function, the detector goes to the negative of the gradient of the function at the present point, the number one represents the local maximum of that function. In addition to that, the min-gradient is equal to 0.00501.NN-tool shows the values for the optimized learning that occurred at epochs 54.

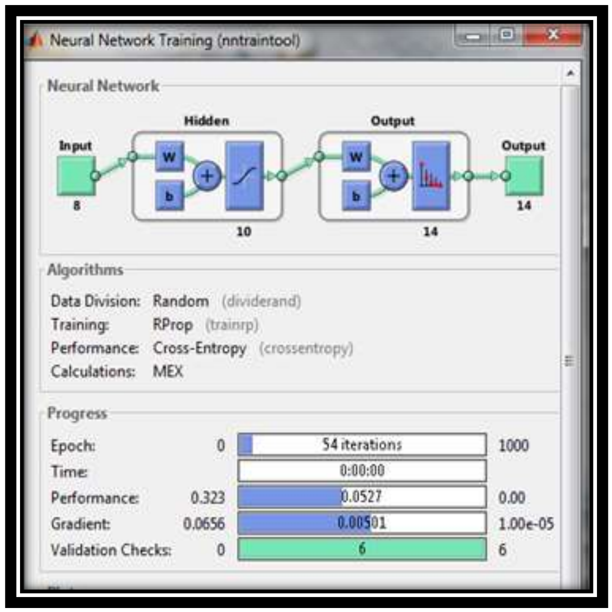


Figure 23 Neural Network Tool

The result of NN-tool is shown in Fig 24, clearly the optimized learning occurred at epochs 54, cross entropy around 0.1 which is the point that connect training, testing and validation.

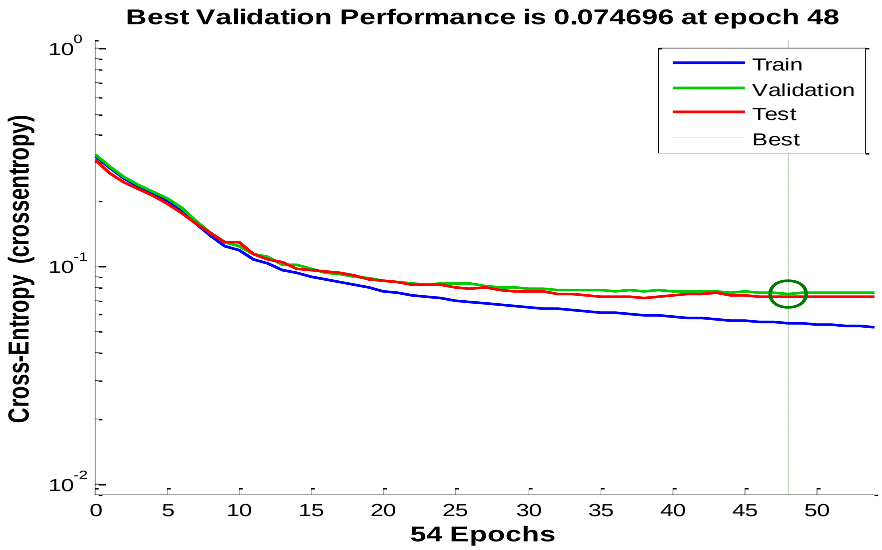


Figure 24 NN-Tool Result

4.7 Measurements of the Results

After compiling NN-tool. Overall accuracy of each letter is computed, there are two main groups in this work, and each group contains many sub-groups. The group that contain the characters with dots are divided according to the number of object and directions of that object. The group that contain the characters without dots are randomly divided, because the system depend on object-counting technique. Which mean only characters with dots will be highly categorize. Verification and validation techniques applied throughout the recognition process enable the matlab to find errors before they can set back the project. Most system design errors are introduced in the original specification, but they aren't found until the test phase are applied. The following scripts shows the accuracy computed for each group and for each letter category.

predict_1 = round(net_1(inputs_1));
figure(1)
plotconfusion(predict_1,outputs_1);
[net_2,tr] = trainrp(net_2,inputs_2,outputs_2);
predict_2 = round(net_2(inputs_2));
figure(2)
plotconfusion(predict_2,outputs_2);
[net_1,tr] = trainrp(net_1,inputs_1,outputs_1);

Maximum accuracy of letters can be reached up to 99% while some letters are difficult to recognize, because it recognizes in the wrong group in SVM-stage previously. As shown in table 5, the character (ق) has the highest recognition rate, because the two dots, character continuity and domestic long-bending (Curved inwards) make it the most recognizable character, where the character (ه) has the lowest one.

Table 5 NN Single classifier Character Recognition

Accuracy percentage%	Character Name	Accuracy percentage%	Character Name	Accuracy percentage%	Character Name
99%	(Qaaf)ق	**98%**	(Zaay)ز	**68%**	(Alif) ا
64%	(Kaaf)ك	**98%**	(Siin)س	**86%**	(Baa) ب
74%	(Laam)ل	**69%**	(Shiin)ش	**78%**	(Taa) ت
70%	(Miim)م	**89%**	(Saad)ص	**59%**	(Thaa) ث
71%	(Nuun)ن	**98%**	(Daad)ض	**66%**	(Jiim) ج
56%	(Haa)ه	**85%**	(TAA) ط	**75%**	(Haa) ح
96%	(Waaw)و	**92%**	(Dhaa) ظ	**90%**	(Khaa)خ
85%	(Yaa)ي	**99%**	(Ayn)ع	**99%**	(Daal)د
88%	(Hamza)ء	**82%**	(Ghayn)غ	**98%**	(Dhall) ذ
		76%	(Faa)ف	**65%**	(Raa) ر

Table 6, shows the worst cases in recognition of the isolated characters in this system, the worst case among them is **Haa (ه)** in both single and Hybrid classifiers, the reason for that is the lack of feature extraction that extracts and detect the holes, **Zaay** (ز) is second rated case as worst character , because it has similarly structure element as character Laam (ل), the instance represent the character image that have classification error form the 439 test set .

Table 6 worst cases classification errors in isolated character

No	Letter	Instance/439-Error rate%	Often mistaken for
1	Haa (ه)	24 -1.7%	و
2	Zaay (ز)	20 -1.4%	ل
3	Alif (ا)	17 -1.2%	و
4	Thaa (ث)	17 -1.2%	ش
5	Sheen (ش)	15 -1.0%	ث
6	Faa (ف)	14 -0.9%	ز

The chosen characters above are the characters that reach 0.9 error rate, since the error rate percentage equals (100%-recognition percentage) for the hybrid proposed system the overall error rate reach as (7.8%), and there is much more characters in the neural network as a single classifier that reach up to (28.05%) error rate.

4.8 Summary between AHCR System and other OCRs

This section purposes a comparison between AHOCR systems that have been Built and implemented to reach satisfied result according to the used dataset sample, all the authors used an IFN-ENIT dataset for training and testing as shown in table 7, however each one of them used different dataset sample, techniques, and classifiers, which leads to differences in results, the dataset that was taken from IFN-ENIT website comes in different forms and samples according to the link the website gives (when opened it appears as a compressed folder), and sometimes the authors choice is different in (complete word) cases.

Table 7 Summary of this system and other AOCR Based on IFN-ENIT

Authors	Classifier	DATASET Sample	Recognition rate (%)	
			Single Classifier	Multi classifier
(Mowlaei, et.al., 2002)	Haar wavelet	32 isolated Faresi/ Arabic 279 postal address	97.24%	-----
(Maddouri, et.al., 2002)	NN combining global and local vision modeling	30 sample 70 words	97%	-----
(Bouchareb, et.al., 2008)	PCA & SVM	1000 isolated character	-------	96%
Proposed system (2016)	SVM /BPNN	2928 isolated characters	81.75%	92.2%
(Dupre, 2003)	Hybrid HMM /ANN	Not mention	-------	87.40%
(Al-HAJJ, et.al., 2007)	HMM/MLP	not mention	86.5 %	90.96%
(Shanbehzadeh, et.al., 2007)	Vector Quantization	3000 isolated characters	85.59%	------
(AlKhateeb, et.al., 2011)	HMM/re-ranking	500 word	-------	84.09%
(Dehghani, et.al., 2001)	Semi continuous one dimensional HMM	17000 character	65%	-------

As shown in figure 25, the proposed system has achieved an excellence accuracy result compared with others, proportion to the used dataset samples. The difference in extracting the features, classification methods and type of dataset samples: word, characters, and document.

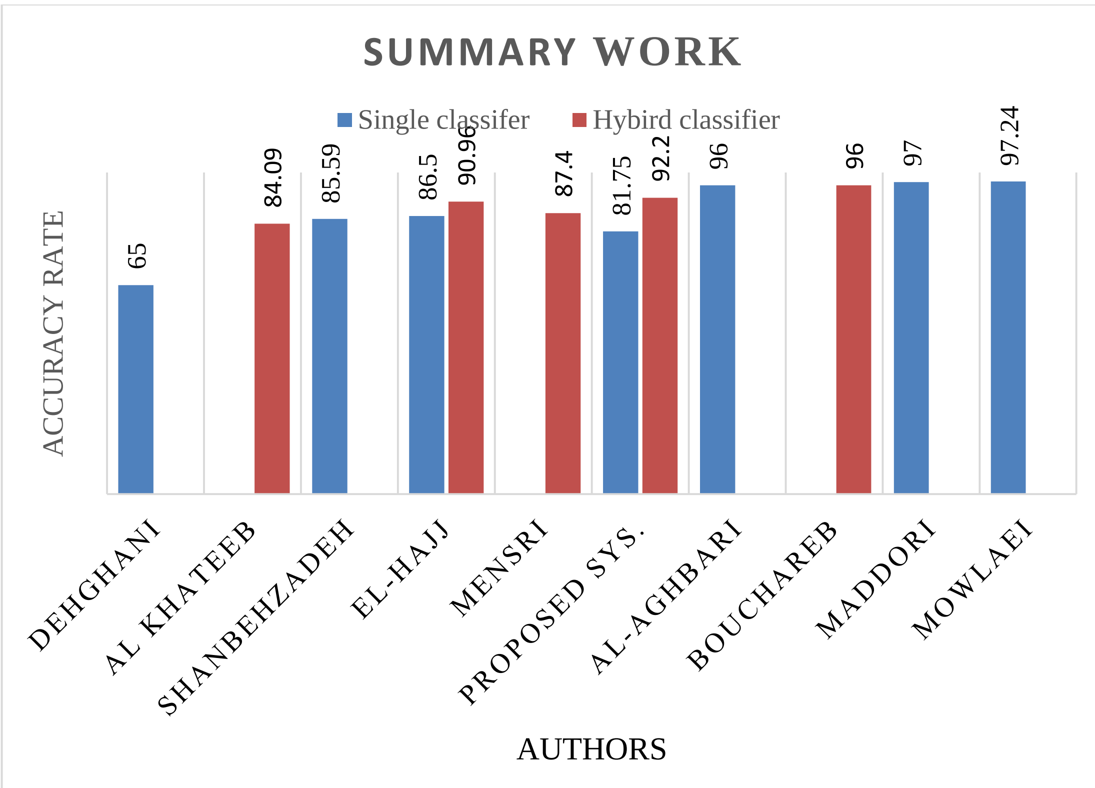


Figure 25 Summary work based on IFN-ENIT dataset

The single Neural Network classifier has a low overall accuracy, as shown in figure 26, the reason of that is the NN cannot deal with the proposed features-extraction together, as well the categorization of the characters take more time and resource to assign the character to its group.

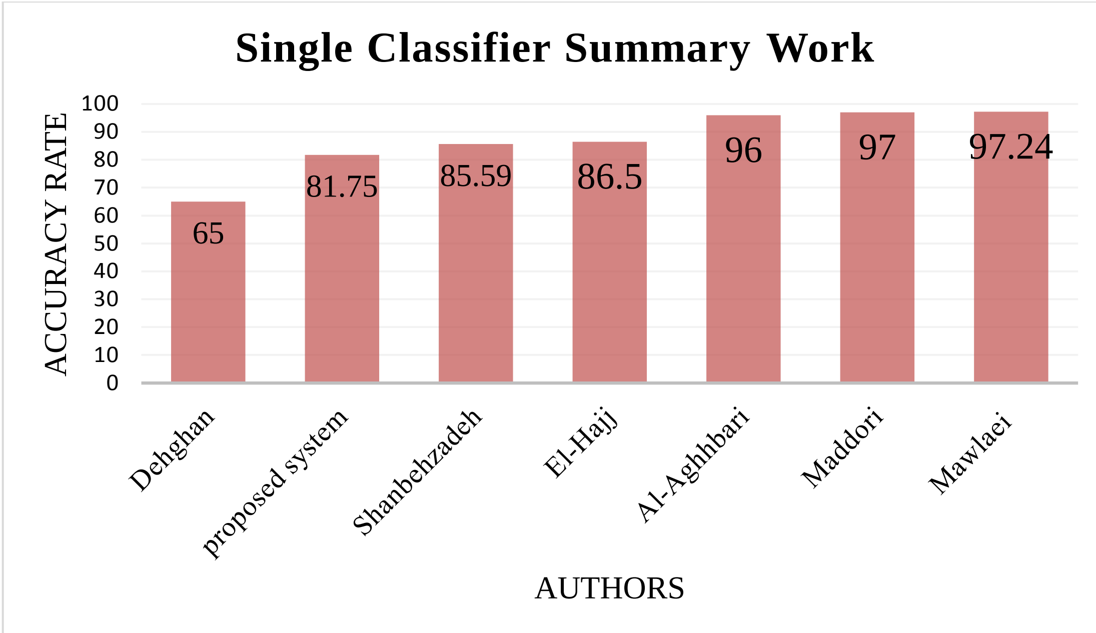


Figure 26 Single Classifier Summary Work

As shown in figure 27 The Hybrid approached solve this particular problem by using the SVM classifier as categorization process which remarkably increased the recognition rate.

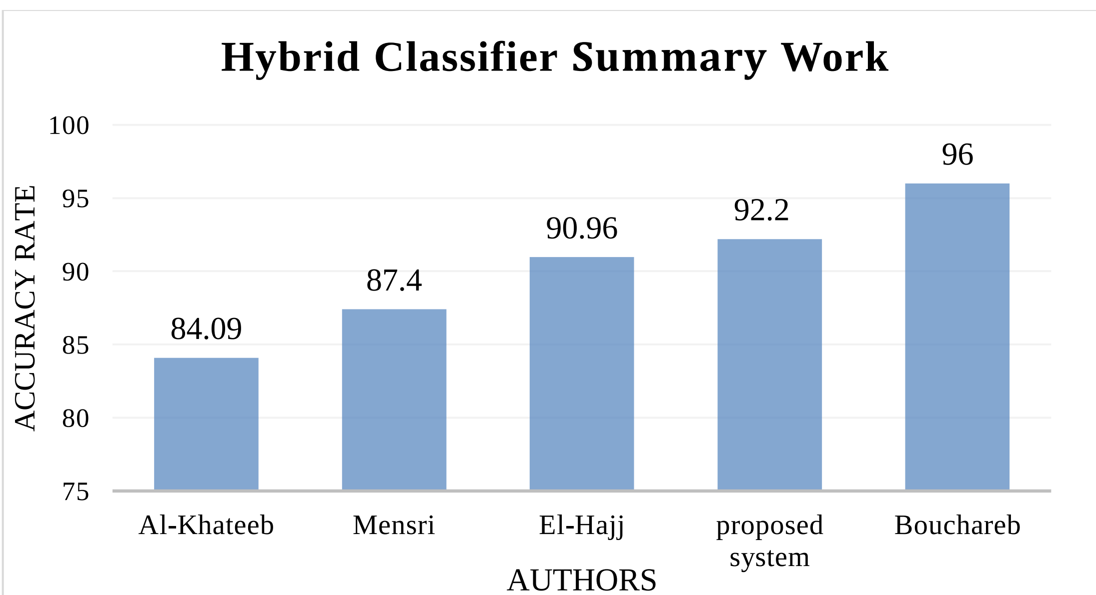


Figure 27 Hybrid Classifier Summary Work

Chapter Five: Conclusions and Future Work

5.1 Conclusions

In this thesis, the process of Arabic Letters recognition based on using both the neural network with support vector machine technique is proposed. This process starts with dividing known Arabic Letters images dataset into two databases, applying the feature extraction technique on each dataset.

The developed algorithm can be used in order to overcome the main restrictions of using the traditional NN algorithms, which depends on one classifier only. SVM-NN can provide high accuracy with low time processing especially with a huge dataset. SVM classifier provides accuracy up to 92.2% by dividing the whole dataset into two groups for decreasing processing time for NN stage. The probability of error tends to be zero as the categorization of characters increases.

Results show that there is a match between both the recognition rate and the success values of the algorithm and the resultant maximum recognition rate is 99% using confusion matrix scheme. Despite of the computational complexity of this system, the classifier is suitable for real time applications because the run time is acceptable.

5.2 Recommendations and Future Work

For this thesis, the researcher can recommend the following ideas:

- In future, many solutions can be used in order to overcome the disadvantages that face this project, for example, some enhancement steps can be done on the algorithm to decrease its complexity as well as develop the accuracy of the model in addition to the efficiency of the retrieval.

- Another environment of the database also can be used which is the online database environment that permits the addition and removal of images in order to use the database in easy and simple way than that used with the offline database.
- Further theoretical analysis is needed to find further optimality in choosing the number of layers, in addition to the number of neurons per layer using the back propagation neural network.
- Since the handwritten Arabic characters word and sentences are required, the recommendation is to use the proposed system in the recognition of such characters, the capability of achieving a higher recognition rate could be done.
- The expectation of a higher recognition accuracy from this system for printed characters since it is smoother and well defined.
- The real-time system has a limitation in such system, building a pre-extracted features database from the characters, which is provided via cloud could accelerate this particular process.

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Appendices

Appendix (A): Registration form for IFN-ENIT - database

***IFN/ENIT*- database**

DATABASE OF HANDWRITTEN ARABIC WORDS

REGISTRATION FORM for NON-COMMERIAL USE ONLY

Procedure:

1. Please fill this form carefully. (*) *In case of student registration: Please push your professor/supervisor to register.*
2. Print this form. Please use the printing function of your browser.
3. Please fax the signed form to us.
4. We send to you necessary details for download per e-mail in the next days.

first NAME: Sadeq

TITEL & last NAME (*): Prof. Dr. AlHamouz

INSTITUTION:
The Faculty of Information Technology
Middle East University, Amman, Jordan

postal ADDRESS:
P.O.Box 383, Amman 11831, Jordan

e-mail (*): shamouz@meu.edu.jo

I note that the data is supplied with no guarantee of accuracy or usability. The authors can't guarantee to maintain the *IFN/ENIT*-database, but would be interested in hearing of any comments or results that you have.

I will use the *IFN/ENIT*-database for non-commerical research only.

DATE Saturday, August 06, 2016

SIGNATURE - SadeqHamouz Mohamed

fax number: +49-531-391-8218

Please choose one of the following download possibilities:

- Download as ISO-CD-IMAGE (Version 2.0) **OR**
- Download as ZIP-ARCHIVE (Version 2.0)
- Download **Set e** (Update from version 1.0 to 2.0)

MEU

Appendix (B): IFN-ENIT Dataset PDF sample page

Appendix (C): IFN-ENIT Dataset Random Characters image samples