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# **GENERAL INTRODUCTION**

## **General Introduction**

One of the most important effects the field of Cognitive Science that we have in the field of Computer Science is the development of technologies that make our tools more human. A very relevant present-day field of natural interface research is handwriting recognition technology. Handwriting number recognition is a challenging problem researchers had been investigating for so long especially in the recent years. In our study, there are many fields concerned with numbers, for example, checks in banks or numbers in car plates and letters, but our main focus was on the postal code for letters.

A system for recognizing isolated digits may be as an approach to deal with such an application. In other words, to let the computer understand the Arabic numbers that are written manually by users and views them according to the computer process. Scientists and engineers with interests in image processing and pattern recognition have developed various approaches to deal with handwriting number recognition problems such as, minimum distance, decision tree and statistics.

The main objective for our system is to locate, isolate and recognize Arabic digits that exist in letters. For example, different users had their own handwriting styles. Here the main challenge is let the computer system understand these different handwriting styles and recognize them as standard writing.

We present a system that deals with such a problem. The system starts by acquiring an image of some letters that contain digits. This image is digitized using an optical device. After applying some enhancements and modifications to the digits within the image, it can be recognized by using several algorithms.

The first chapter mainly deals with the optical recognition systems and the Arabic language and its unique characteristics. In addition, some of the problems that faced us during the preparation of this work are displayed.

### **Outline**

In chapter two, we talk about letters and envelopes which are our main concern of image recognition and the Algerian postal system along side with some reviews of previous works on the same field of the image recognition process.

The third chapter gives an overview about the artificial neural network and the support vector machines, which are the methods we use to test our work.

The last chapter represents a full experiment of a the recognition process from acquiring the letter to the results obtained using Artificial Neural Network, Support Vector Machine and K-

Nearest Neighbor. Finally, this work end with a conclusion of the obtained results and the future perspectives.



# **CHAPTER 1**

## **OPTICAL CHARACTER RECOGNITION**

## **1. Introduction**

The automatic segmentation and recognition of text on scanned image documents has enabled many applications such as editing of previously printed documents and books, searching for words in that image documents etc. The off-line handwriting segmentation and recognition field arouses great interest in researchers, since there is a high level of ambiguity and complexity in such kind of image documents, and because of the necessity of Optical Character Recognition (OCR) in lots of application especially in office automation. Segmentation and Recognition of cursive handwritten text is the most difficult case in the field of OCR. Much less research has been done on the task of segmentation and recognizing of Arabic texts. The domain of handwriting in Arabic script presents unique technical challenges and has been addressed more recently than other domains due to the necessity of processing tones of previously printed Arabic books and documents. The objective of this thesis is to provide a better way to segment and recognize off-line handwritten Arabic documents. This chapter describes the concept of OCR and its importance and types. It provides an overview of OCR. This chapter also gives an overview of Arabic language and its characters and a brief history of it. Also we will talk about the letters and their history ,how it was first created ,what are made of, and it's advantages .Also we'll talk about another important compound which is the envelope and its history ,deferent sizes and what is made of .after that we will give an overview about the Algerian postal system.

## **2. Optical Character Recognition: Historical Background**

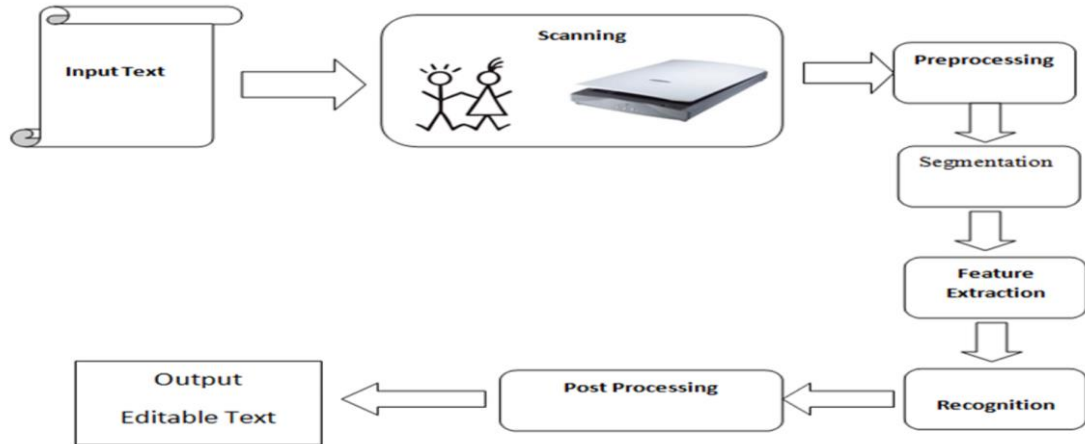
Historically, OCR has evolved in three successive ages. The early one started in 1900 when the Russian scientist Tyuring attempted to help visually handicapped people by developing an aid [7]. In 1929, Gustav Tauschek obtained a patent on OCR in Germany, followed by Handel who obtained a US patent on OCR in USA in 1933. Gustav Tauschek also invented an OCR mechanical device using templates and was granted US patent in 1935. The work done during the first stage was concentrated upon machine-printed text and upon small sets of well handwritten text and symbols. Template matching technique was used to recognize machine-printed text. For handwritten text, features of input text were extracted using primitive feature extraction techniques. These features were fed to statistical classifiers to recognize the input text. In the middle of the 1940s, the first character recognizer was developed [3]. In 1955, the first commercial system was installed at the Reader's Digest, which used OCR to input sales

reports into a computer. It converted the typewritten reports into punched cards for input into the computer in the magazine's subscription department, for help in processing the shipment of 15-20 million books a year [4]. The first Arabic character recognition research started as early as 1975 when Nazif presented his Master's thesis [14]. Due to lack of computing power, significant works were not performed until the 1980s [4]. The second development stage started in 1980 with the explosion of information technology and availability of computing power. During this stage, structural and statistical approaches were used in many systems [1]-[11]. The first passport scanners were used in the U.S. State Department. These scanners were developed by Caere Corporation in 1984 and some are still in use today. In the coming decades, the use of OCR on passports facilitates the immigration procedures in airports around the world. Since 1990s, the advanced stage started. Strong methodologies and techniques such as Neural Networks (NNs), Fuzzy set and Support Vector Machine (SVM) were invented to be used in OCR. In addition, computers and other electronic devices such as scanners, cameras and tablets become available in reasonable prices, as well as internet. The final destination of OCR is not reached especially in handwritten cursive text. Furthermore, many excellent OCR systems for Roman based scripts such as Scansoft Omnipage and Abby Fine-Reader are available in the market at reasonable prices. Lots of efforts have been done on the recognition of Latin, Indian, Chinese and Japanese characters. Unfortunately, little research has been published on the recognition of Arabic characters. This is because of the strongly cursive nature of Arabic writing and diacritic marks. In fact; the techniques applied in other languages are not directly applicable to Arabic characters without fundamental modifications [15].

### **3. Optical Character Recognition(OCR)**

Optical Character Recognition, usually abbreviated to OCR, refers to the branch of computer science that involves mechanical or electronic conversion of images of printed text or handwritten, usually scanned by a scanner or captured by a camera, into a fully machine-editable text which can be used in text processing applications such as Microsoft office Word as it had been typed through the keyboard. The automatic recognition of offline handwritten text could be applied in many areas, for instance 'form-filling' applications such as handwritten postal addresses, cheques, credit card sales slips, insurance applications, mail order forms, tax returns etc. Handwritten script, from an unconstrained population of writers and writing, is generated by using OCR applications, must subsequently be processed off-line by computers. OCR has five major stages as follows:

- Preprocessing
- Segmentation
- Feature extraction
- Training and Recognition
- Post Processing



**Figure 1. 1** :Block Diagram of OCR[17].

The printed text is a bit easy for recognition due to its constraint font, whereas recognition of handwritten character is complicated task due to the unconstrained shape variations, different writing style and different kinds of noise that breaks the strokes, primitives in the character or changes their topologies . [17]

## 4. The Model Structure

### 4.1 Preprocessing

The input of the digitizer typically contains noise due to erratic hand movements and inaccuracies in digitization of the actual input. Original documents are often dirty due to smearing and smudging of text and aging. The documents sometimes are very poor quality because of the seeping of ink from the other side of the page and general degradation of the paper or ink or both. Preprocessing is concerned with the reduction of these noises. The number and type of preprocessing algorithms employ on the scanned image depend on many factors such as paper quality, resolution of the scanned image and the layout of the text. There are many processes performed before the recognition such as: thresholding or binarization, Resize the image, converting a grayscale image into a binary black-white image .

## 4.2 Segmentation

Is a critical and important step in Arabic handwriting recognition systems. After the preprocessing stage, the systems of character recognition perform segmentation operation on the text and end with individual character or stroke before recognition stage. The goal of a segmentation process is to partition a word image into regions, each region containing an isolated character. The handwritten character segmentation process and recognition process are closely coupled, because it is difficult to segment characters without the support of recognition algorithms, unlike the problem of printed character recognition, There are three approaches for segmentation and other hybrid approaches that are combinations of these three approaches.

1. The classical approach: by using general features this approach segments the image into sequence meaningful sub-images, based on 'character like' properties.
2. Recognition based segmentation; in this approach the system depends on components match classes in its alphabet.
3. Holistic methods (or global approach), in this approach there is no need to segment words into characters, it recognizes the whole words. The connected components labeling algorithm is used in computer vision to detect connected regions in binary digital images, although color images and data with higher dimensionality can also be processed, it also called region labeling, , or region extraction, it used to extract objects from binary images by assigning a unique label to each connected region of foreground pixels. Connected component labeling works by scanning an image, pixel-by-pixel (from top to bottom and left to right) in order to identify connected pixel regions, i.e. regions of adjacent pixels which share the same set of intensity values  $V$ .

## 4.3 Feature extraction

Is the main process and the important one of the character recognition system. The definition of feature extraction is extracted from the raw data the information which is most relevant for classification purposes, in the sense of minimizing within-class pattern variability while enhancing between-class pattern variability. Features can be extracted from characters or words. Extracted features should provide uniquely relevant identification information of character class without repeat. The Arabic handwritten characters have features such as the letter's secondary components, main body, skeleton, and boundary. There are many features for every character in Arabic language, such as main body features and secondary, which are described in the next subsections.

## 5. Arabic Language

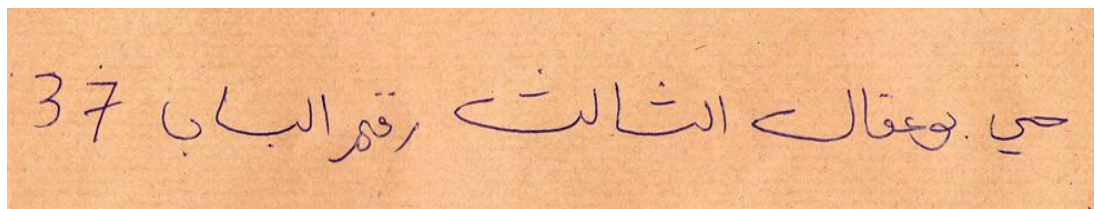
### 5.1 Introduction to Arabic Language

Arabic language is the official language for the Arab world, situated in the Middle East and North Africa Arab World consists of 22 countries. Arabic is a reference to anything connected with Arabia. Mainly, it is a reference to the Central Semitic language, thus related to and classified alongside other Semitic languages such as Hebrew and Syriac. In terms of speakers, Arabic is the largest member of the Semitic language family. It is spoken by more than 300 million people as a first language and by 300 million more as a second language in some Islamic countries. Standard Arabic is widely taught in schools, universities, and used in the offices and the media.

### 5.2 Arabic Characters

Arabic alphabet contains 28 letters. Each has between two and four shapes, and the choice of which shape to be used depends on the position of the letter within its word or sub-word. The shapes correspond to the four positions: beginning of a (sub-) word, middle of a(sub-)word, end of a(sub) word and in isolation[12] . A summary of the features of Arabic writing appears below.

1. Arabic text, both handwritten and printed, is cursive. The letters are joined together along a writing line (see Figure 1.2). This is similar to Latin ‘joinedup’ handwriting, which is also cursive, but in which the characters are easier to separate.

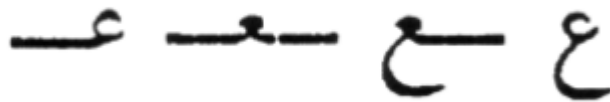


**Figure 1. 2 :**An Algerian neighborhood name written in Arabic.

2. In contrast to Latin text, Arabic is written right to left, rather than left to right. This is perhaps more significant for a human reader rather than a computer, since the computer can simply flip the images.
3. More importantly from the point of view of automated recognition, Arabic contains dots and other small marks that can change the meaning of a word, and need to be taken into

account by any computerized recognition system. Often the diacritic marks representing vowels are left out, and the word must be identified from its context.

4. The shapes of the letters differ depending on whereabouts in the word they are found. The same letter at the beginning and end of a word can have a completely different appearance as shown in Figure 1.3. Along with the dots and other marks representing vowels, this makes the effective size of the alphabet about 160 characters.



**Figure 1. 3 :** Different forms of the Arabic letter “A’in”. From left to right - beginning, middle, end, isolated. From Amin [1].

## 6. Research Problem

Lots of researches have been done in the field of recognizing typed and handwritten Latin, Chinese, and Indian characters. A few researches have been made in the recognition of Arabic characters, mainly due to the cursive nature of Arabic language. Unlike most of the other languages, both typed and hand-written Arabic characters are cursive. Furthermore, Arabic characters can take more shapes than Latin characters [3]. Another problem is the differences of Arabic fonts; i.e., a certain character in a specific font can be misrecognized as a different character in another font. In this language, some character pairs may be combined together to form another character, that is often called a ligature such as (Lam Alef لآ). Ligatures unfortunately complicate the segmentation task of any Arabic Optical Character Recognition (OCR) system. This research paper deals with the segmentation and recognition of off-line handwritten Arabic text. The problem of Arabic handwritten recognition is a result of many factors, which can be summarized as follows:

1. The research deals with off-line handwritten Recognition not On-line recognition.
2. The research studies cursive handwritten Arabic recognition for Arabic letters, which totally differ from the machine printed case.
3. The research addresses Arabic digits writing, which also totally differs from English writing in many ways (right to left for example).
5. Arabic has 28 letters, each of which can be connected in three different ways or being isolated depending on the position. Therefore, each character can have up to 4 different forms depending on its position.

## **7. Conclusion**

Chapter one offers a general introduction of the work. It discusses Optical Character Recognition, types of OCR as well as introduction to Arabic language, study focuses on developing OCR for off-line handwritten Arabic documents. Arabic language and its characters are mentioned. And also some of the problems that faced us during the preparation of this work.



**CHAPTER 2**

**LETTERS & ENVELOPES**

## **1. Introduction**

Communication is a big part of daily activities. Since the early ages when humans beings needed to contact each other, weather it was for personal reasons or political reasons there was almost only one way: sending letters. Until the beginning of the 20th century, letters were still used for communication.

In this chapter, we mainly deal with the letters and their history: how they were first created, what they are made of, and what their main advantages are. Also we will talk about another important component: the envelope and its history, different sizes and what it is made of. After that, we will give an overview on the Algerian postal system.

## **2. Letters**

### **2.1 Definition of a letter**

A letter is a written message from one party to another containing information. Letters guarantee the preservation of communication between both parties. They bring friends or relatives closer together, enrich professional relationships and provide a satisfying mean of self-expression. Letters contribute to the protection and conservation of literacy, which is the ability to write and read[26].

### **2.2 History of letters**

Historically, letters have existed from the time of ancient India, ancient Egypt and Sumer, through Rome, Greece and China, up to the present day. During the seventeenth and eighteenth centuries, letters were used to self-educate. Letters were a way to practice critical reading, self-expressive writing, polemical writing and exchange ideas with like-minded others. For some people, letters were seen as a written performance. For others, it was not only seen as a performance but also as a way of communication and a method of gaining feedback. In the ancient world, letters were written on different materials, including metal, lead, wax-coated wooden tablets, pottery fragments, animal skin, and papyrus[26].

### **2.3 The letter delivery process**

Here is how a letter gets from the sender to the recipient:

1. The sender writes a letter and places it in an envelope on which the recipient's address is written in the center front of the envelope. The sender ensures that the recipient's address includes the Zip or Postal Code (if applicable) and often includes his/her return address on the envelope.

2. The sender buys a postage stamp and attaches it to the front of the envelope on the top right corner. (For large amount mailings, postage stamps are not used: a franking machine or other methods are used to pay for the postage.
3. The sender puts the letter in a postbox.
4. The national postal service of the sender's country (e.g. Royal Mail, UK; US Postal Service, US; Australia Post in Australia; or Canada Post in Canada) empties the postbox and takes all the contents to the regional sorting office.
5. The sorting office then sorts each letter by address and postcode and delivers the letters destined for a particular area to that area's post office. Letters addressed to a different region are sent to that region's sorting office, to be sorted further.
6. The local post office dispatches the letters to their delivery personnel who delivers them to the appropriate addresses.

This whole process, depending on how far the sender is from the recipient, can take anywhere from a day to 3–4 weeks. International mail is sent via trains and airplanes to other countries[26].

### 3. Envelope

#### 3.1 Definition of the Envelope

An envelope is a common packaging item, usually made of thin flat material. It is designed to contain a flat object. Traditional envelopes are made from sheets of paper cut to one of three shapes: a rhombus, a short-arm cross, or a kite. These shapes allow for the creation of the envelope structure by folding the sheet sides around a central rectangular area. In this manner, a rectangle-faced enclosure is formed with an arrangement of four flaps on the reverse side.[25]

#### 3.2 Sizes of the envelopes

International standard ISO 269 defines several standard envelope sizes, which are designed for use with ISO 216 standard paper sizes:

Format	Dimensions (HxW mm)	Dimensions (in)	Suitable for content format
DL	110 × 220	4.33 x 8.66	1/3 A4
C7	81 x 114	3.2 x 4.5	A7 (or A6 folded in half)

C7/C6	81 x 162	3.19 x 6.4	1/3 A5
C6	114 × 162	4.5 x 6.4	A6 (or A4 folded in half twice)
C6/C5	114 × 229	4.5 x 9	1/3 A4
C5	162 × 229	6.4 x 9	A5 (or A4 folded in half once)
C4	229 × 324	9.0 x 12.8	A4
C3	324 × 458	12.8 x 18	A3
B6	125 × 176	4.9 x 6.9	C6
B5	176 × 250	6.9 x 9.8	C5
B4	250 × 353	9.8 x 13.9	C4
E4	280 × 400	11 x 15.75	B4

**Table 2. 1 :**International standard ISO 269 several standard envelope sizes[25]

### 3.3 History of envelopes

The first known envelope was nothing like the paper envelope we know of today. It can be dated back to around 3500 to 3200 B.C. in the ancient Middle East. Hollow, clay spheres were molded around financial tokens and used in private transactions. The two people who discovered these first envelopes were Jacques de Morgan, in 1901, and Roland de Mecquenem, in 1907 [25]. Paper envelopes developed in China, where paper was invented by 2nd century BC.[9] Paper envelopes, known as chihpoh, were used to store gifts of money. In the Southern

Song dynasty, the Chinese imperial court used paper envelopes to distribute monetary gifts to government officials[25].

The most famous paper-making machine was the Fourdrinier machine. The process involves taking processed pulp stock and converting it to a continuous web which is gathered as a reel. Subsequently the reel is guillotined to edges to create a large number of properly rectangular sheets. Ever since the invention of Gutenberg's press paper has been closely associated with printing.



**Figure 2. 1:** Envelope-making machines at the Post Office Savings Bank, Blythe House, West Kensington, England[25]

#### 4. Algeria Postal System

Algerie Poste (Algeria Post) is responsible for sending letters, parcels in Algeria, Africa and around the world. The routing of individual mail or companies may be followed by acknowledgment, or by express parcel is at the normal rate. Algeria Post is working with other international groups stations.



**Figure 2. 2 :**Algeria Post Logo starting from 2008[27].

Type : State-owned (government monopoly)

Industry : Postal administration

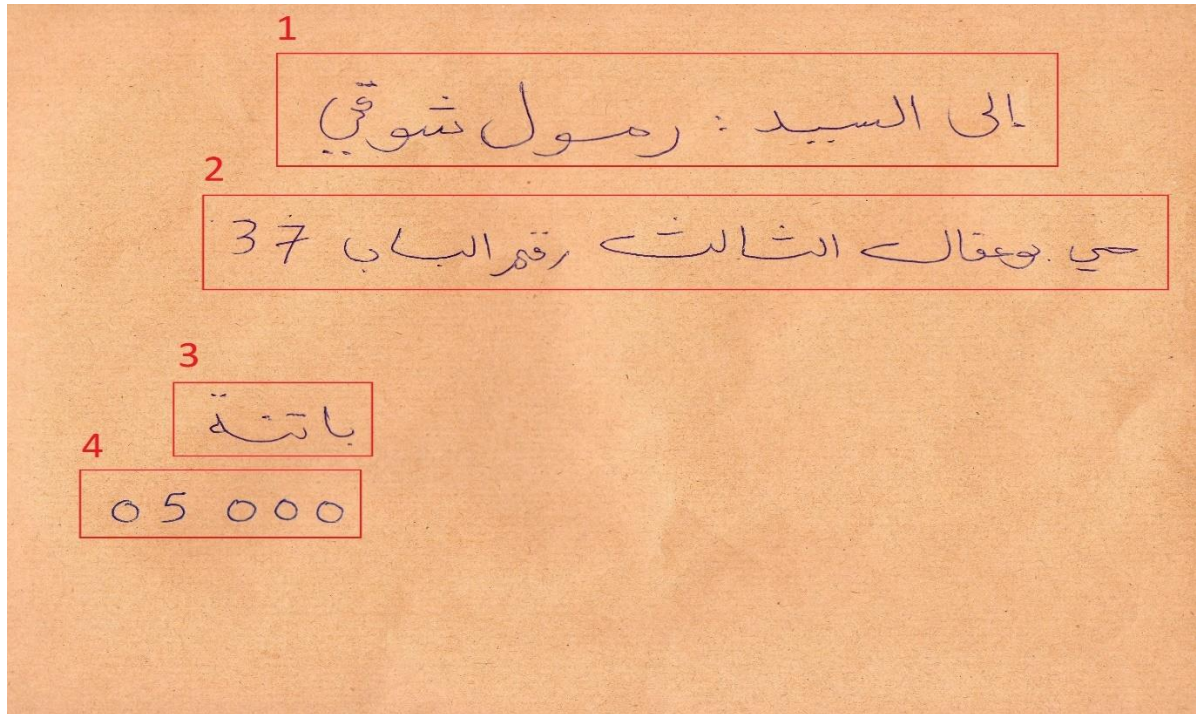
Founded : Algeria (1913)

Headquarters : Algeria

Products :First Class mail, Domestic Mail, Logistics[27].

#### 4.1 Sample of an Algerian Letter

The following images represents a backside of an Algerian letter:



**Figure 2. 3 :**An Algerian letter (backside)

- 1 : The name of the receiver
- 2 : The address of the receiver
- 3 : The state (wilaya) where the receiver lives
- 4 : The postal code

#### 4.2 List of postal codes in Algeria

In the list of postal codes of cities in Algeria, the first two numbers stand for the provincial code, postal codes of larger cities are mostly formed of the provincial code followed by a three zeros after it such as : 28000, 16000, and so on. There are also large neighborhoods in the official city limits with their own postal codes.[28]

code	Wilaya	code	Wilaya	code	Wilaya	code	Wilaya
01000	Adrar	13000	Tlemcen	25000	Constantine	37000	Tindouf
02000	Chlef	14000	Tiaret	26000	Médéa	38000	Tissemsilt
03000	Laghouat	15000	Tizi Ouzou	27000	Mostaganem	39000	El Oued
04000	Oum el-Bouaghi	16000	Algiers	28000	M'Sila	40000	Khenchela
05000	Batna	17000	Djelfa	29000	Mascara	41000	Souk Ahras
06000	Béjaïa	18000	Jijel	30000	Ouargla	42000	Tipasa
07000	Biskra	19000	Sétif	31000	Oran	43000	Mila
08000	Béchar	20000	Saïda	32000	El Bayadh	44000	Aïn Defla
09000	Blida	21000	Skikda	33000	Illizi	45000	Naama
10000	Bouira	22000	Sidi Bel Abbes	34000	Bordj Bou Arréridj	46000	Aïn Témouchent
11000	Tamanghasset	23000	Annaba	35000	Boumerdès	47000	Ghardaïa
12000	Tébessa	24000	Guelma	36000	El Taref	48000	Relizane

**Table 2. 2 :**List of Algerian states (wilaya) postal codes

## 5. Description of manual delivery systems (traditional)

The national postal service of the sender's state (wilaya) empties the postbox and takes all the contents to the regional sorting office. The sorting office then sorts each letter by address and postcode and that process happens manually. The post employees read the back of the envelope and according to the postal code the letters are sorted and grouped and then delivered to a particular area's post office.

## 6. Description of automatic delivery systems (by computer)

Now that the technology is developed using the scanners and computers, we can just pass the letters over the scanners and the computer can detect the destination of each letter automatically. This process does not take much time. In addition, it is easier and more accurate and requires less effort.

## 7. Reviews (chronological order)

The following table contains information of some of the previous works that have been done in the field of image processing and recognition systems following the chronological order of the appearance of each method :

Author	Year	Method	Evaluation/observations
Sarhan and Helalat	2007	presented [39] an Arabic character recognition system based on Artificial Neural Networks (ANN) and statistical analysis of the Arabic characters. This system uses binary images. In this system, each typed Arabic character is used as input to a simple feature extraction method, whose output is fed to an ANN that consists of two layers.	Simulation results are provided and show that the proposed system always produces a lower Mean Squared Error (MSE) and higher success rates than the current ANN solutions, especially when the contaminating noise level is low.
Al-Ma'adeed and Mohammed	2008	built a writer identification system using edge-based directional probability distribution features for Arabic words. The researchers studied the feature extraction and recognition operations on Arabic texts. To test this system, the researcher builds a new database of off-line Arabic handwriting text to be used for writer research identification. The proposed	



		database is meant to provide training and testing sets for Arabic writer identification research.	
Alkhateeb and khelifi	2009	presented a system of three stages, i.e. preprocessing, feature extraction and classification. Firstly, words are segmented from input scripts and also normalized in size. Secondly, each segmented word is divided into overlapping blocks. Absolute mean values computed for each block of segmented words constitute a feature vector. Finally, the resulting feature vectors are used to classify the words using the K nearest Neighbor classifier (KNN). The proposed system has been successfully tested on the IFN/ENIT database. Experimental results show a good recognition rate when compared with other methods. In 2010 Jeffrey Woodard <i>et al.</i> used the generative model of computer vision, along with local features represented by quantized Scale Invariant Feature Transform (SIFT) descriptors, to classify writers based on images taken from Arabic text documents. It is the first known application of the method to automated writer recognition.	This statistically based approach does not exploit spatial relationships among image features, nor does it demand explicit segmentation of linguistic units. In addition, it does not require supervised training or pre-processing. A performance of 98.0% correct Rank-1 is observed.

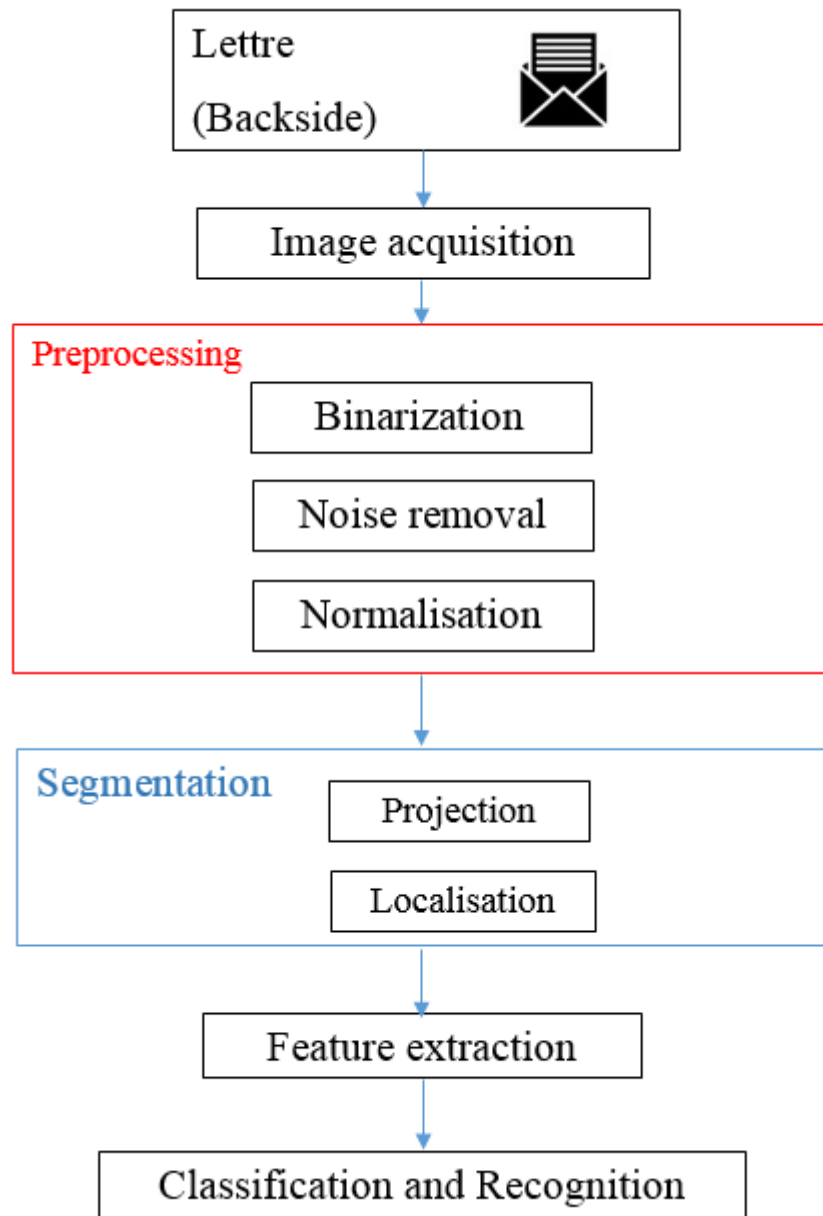
Leila <i>and</i> Maâmar		presented an off-line Multiple Classifier System (MCS) for Arabic handwriting recognition. The MCS combines two individual recognition systems based on Fuzzy ART network used for the first time in Arabic OCR, and Radial Basis Functions.	
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**Table 2. 3** :Table of reviews

Analyzing the different methods, we decided to use Neural network because Simulation results are provided and show that the proposed system always produces a lower Mean Squared Error (MSE) and higher success rates, especially when the contaminating noise level is low. We will also use the SVM.

## **8. Work and methods**

There are four steps to build the isolated digits recognition system. These steps are presented on Figure.2.4 and following are their descriptions:



**Figure 2. 4 :**Flow of the work

### **8.1 Image acquisition:**

As an input, we will acquire a scanned back side of a handwritten letter. The image should have a specific format, and a determined size.

### **8.2 Preprocessing**

After getting the image, it undertakes the next phase which consists of preprocessing steps to be ready for the segmentation. The preprocessing steps are as follows :

### 8.2.1 Noise removal

It means reducing noise in an image. For on-line image processing, there is no noise to eliminate so, there is no need for the noise removal. In off-line mode, the noise may come from the writing style or from the optical device that captures the image[10].

### 8.2.2 Normalization-scaling

It standardizes the font size within the image. This problem appears clearly in handwritten text because the font size is not restricted when using handwriting.

## 8.3 Segmentation

Since the data is not isolated, we need segmentation. With regards to the isolation of digits, vertical and horizontal segmentation are applied on the image. If the letter contains more than one digit, each digit will be isolated alone.

## 8.4 Normalization scaling and translation

Handwriting produces variability in size of written digits. This leads to the need of scaling the digits size within the image to a standard size, as this may lead to better recognition accuracy. We tried to normalize the size of digits within the image in order to get better results when applying the feature extraction

## 8.5 Feature extraction

The image from the segmented stage is matched with all the digits which is preloaded into the system. In this step, the nearest match of the stored and input number is found out. Once, the matching is completed, the number with maximum matching is declared as the number present in the image. One of the known methods is the Hu Moment Invariants.

### 8.5.1 Hu's Moment Invariants

Two-dimensional (p+q)th order moments are defined as follows:

$$m_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q f(x, y) dx dy \quad (1)$$

$$p, q = 0, 1, 2, \dots$$

If the image function  $f(x, y)$  is a piecewise continuous bounded function, the moments of all orders exist and the moment sequence  $\{m_{pq}\}$  is uniquely determined by  $f(x, y)$ ; correspondingly,  $f(x, y)$  is also uniquely determined by the moment sequence  $\{m_{pq}\}$ . One should note that the moments in (1) may be invariant when  $f(x, y)$  changes by translating, rotating or scaling.[30] The invariant features can be achieved using central moments, which are defined as follows:

$$\mu_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x})^p (y - \bar{y})^q f(x, y) dx dy \quad (2)$$

$$p, q = 0, 1, 2, \dots$$

Where

$$\bar{x} = \frac{m_{10}}{m_{00}} \quad (3)$$

$$\bar{y} = \frac{m_{01}}{m_{00}} \quad (4)$$

The pixel points  $(x, y)$  are the centroid of the image  $f(x, y)$ . The centroid moments  $\mu_{pq}$  computed using the centroid of the image  $f(x, y)$  are equivalent to the  $m_{pq}$  whose center has been shifted to the centroid of the image. Therefore, the central moments are invariant to image translations. Scale invariance can be obtained by normalization. The normalized central moments are defined as follows :

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}}, \gamma = \frac{p+q+2}{2}, p + q = 2, 3, \dots \quad (5)$$

Based on normalized central moments, Hu[30] introduced seven moment invariants:

$$\phi_1 = \eta_{20} + \eta_{02} \quad (6)$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \quad (7)$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \quad (8)$$

$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \quad (9)$$

$$\phi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + 3(3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \quad (10)$$

$$\phi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] - 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \quad (11)$$

$$\phi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \quad (12)$$

The seven moment invariants are useful properties that are unchanged under image scaling, translation and rotation. [30]

## 8. Conclusion

Chapter two dealt mainly with letters and their history. It also mentioned the other important components of a message which are the envelopes, their history of creation and their

general sizes. In addition, it covered the Algerian postal system which represents our main work of the recognition of Algerian letters' postal code.

## **CHAPTER 3**

# **NEURAL NETWORK AND SUPPORT VECTOR MACHINES**

## **1. Introduction**

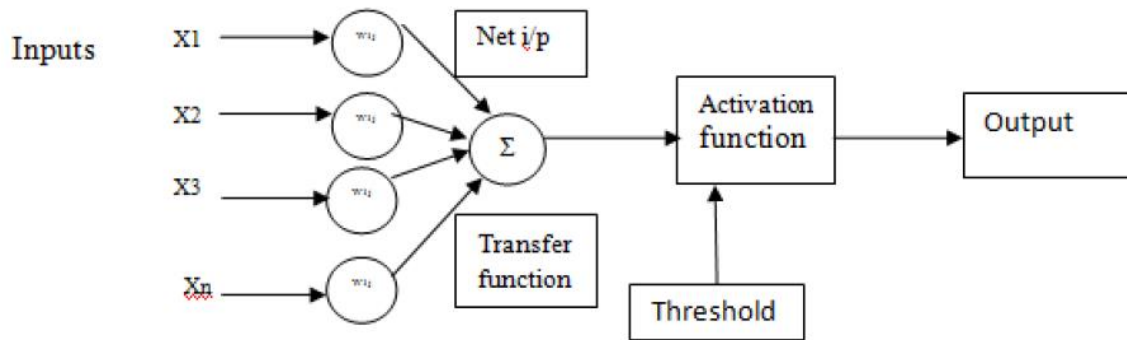
Automated Optical Character Recognition has gained impetus largely due to its application in the fields of Computer Vision, Intelligent Text Recognition applications and Text based decision-making systems. The approach taken to solve the OCR problem was based on psychology of the characters as perceived by the human beings. Thus, the geometrical features of a character and its variants were considered for recognition [5]. The solution to this problem lies in ANN, a system that can perceive and recognize a character based on its topological features such as shape, symmetry, closed or open areas, and the number of pixels. The advantage of such a system is that it can be trained on ‘samples’ and then can be used to recognize characters having a similar (not exact) feature set. The ANN used in this system gets its inputs in the form of Feature Vectors. This is to say that every feature or property is separated and assigned a numerical value. The set of these numerical values that can be used to uniquely identify each character is called its Vector. Thus, a Vector Database is utilized to train the network, so as to enable it to effectively recognize each character, based on its topological properties. To generate the Vector Database, a set of properties or features are chosen that ‘define’ the character according to the human perception. To make the system generic or open to all the variants of the OCR problem, the Vector Generation step is made to be automatic in calculations and diverse enough to increase precision. A Feature is any property of the image that can be used to identify the character, such as Curves, Closed areas, Horizontal & Vertical lines, Symmetry, Contours and Projections [6]. The higher the number of such different features available for use, the higher is the precision of the recognition. Thus, Automated Feature Extraction is another very important aspect of the OCR problem.

## **2. Artificial neural network**

Artificial neural networks have been developed as generalizations of mathematical models of biological nervous systems. A first wave of interest in neural networks emerged after the introduction of simplified neurons by McCulloch and Pitts (1943). The basic processing elements of neural networks are called artificial neurons [13] or simply neurons or nodes. In a simple mathematical model of neuron, the effects of the synapses are represented by weights connections that modulate the effect of associated input signals and the non linear characteristics exhibited by the neurons that are represented by the transfer function [29]. The neuron impulse function is calculated as the weighted sum of input signals, with the help of the



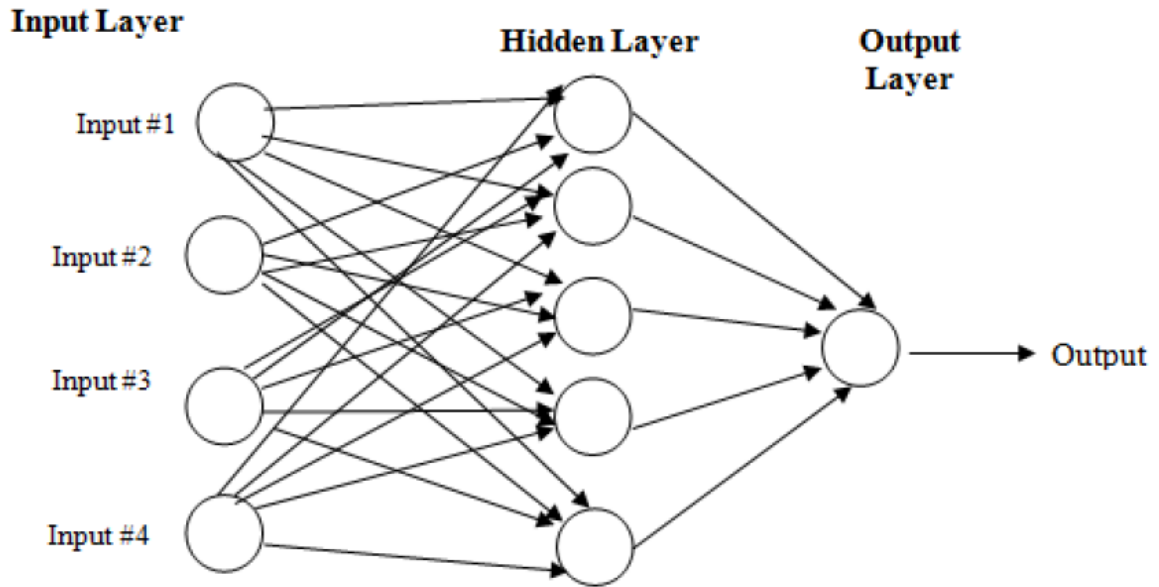
transfer function. The Learning capability of artificial neurons is achieved by adjusting the weights in accordance with the chosen learning algorithm. The artificial neural network can be trained into two main groups that are supervised and unsupervised learning. In supervised learning, the network learns by example with the help of some training algorithm and a target value is set; whereas, in the unsupervised learning, no target value is set or no example is given. Unsupervised learning is very complex and difficult to implement [20].



**Figure 3. 1 :Artificial Neural Network[2]**

### 2.1 Back Propagation Network

Back propagation, an abbreviation for ‘backward propagation of errors’, is a method used for the training of artificial neural network. From the desired or actual output, the network learns from the number of inputs, similar to the way a child learns to identify a car from group of toys. It is a supervised learning method. It requires a dataset of desired output from a set of many inputs, making up the training set. A back propagation network consists of three layers of units- input layer, hidden layer and output layer as shown in figure 3.2. These units are connected in feed forward manner with input units fully connected with units in hidden layer and units in hidden layer fully connected with units in output layer. When back propagation network is cycled, an input pattern is propagated forward to the output units through input to hidden and hidden to output weights. Back propagation is an iterative process that starts with last layer and moves backward through the layers until the first layer is reached. This algorithm is based upon Widrowhoff delta learning rule in which the weight adjustment is done through mean square error of output response to sample input. The rest of these sample patterns are repeatedly presented to the network until the error value is minimized. Weights are adjusted according to the error present in the network. [2]



**Figure 3. 2 : Back Propagation Network[2]**

### 3. Recognition Algorithm

#### 3.1 Preprocessing

Any image needs some Pre-processing, before being fed to the recognition system. The first step is the conversion of any kind of image into a Binary image (the one having pixel values as '0' & '1' only). 'Binarization' converts any image into a series of Black text written on a White background. Thus, it induces uniformity to all the input images. Other effects such as contrast and sharpness can also be easily handled once the image has been binarized. The ANN used in the system utilises 'Feature Vectors' as its input. Hence, each character is segmented out from the pre-processed image. This segmentation occurs in two phases. First, each line is separated in the input image. Then, each character is separated out in each line. It may be noted that the step of selecting out a 'Candidate Block' is required where only a part of the image contains 'text' which needs to be recognized. Segmentation can be done by calculating the edges of the character, where the sum of 'black' pixels is zero, along the periphery of the character [93]. Then, each character so separated is normalized in terms of size and focus, so as to resemble the 'templates' that have been used for training the ANN. In this way, the input samples, processed in the same way to extract Features and generate Vectors, tend to give highly precise results.

#### 3.2 Feature Extraction

Feature Extraction serves two purposes; one is to extract properties that can identify a character uniquely. The second is to extract properties that can differentiate between similar

characters. A character can be written in a variety of ways, and yet can be easily recognized correctly by a Human being. Thus, there exists a set of principles or logics that surpass all variation differences. The features used by the system work upon such properties which are close to the psychology of the characters. A set of different types of features has been used to identify the characters, in our algorithm. These include the Sum of pixels along the horizontal lines drawn at various distances along the character height. These parameters differ from one character to another based on their width profile variation along the height [93]. Considering a binary image 'I' that contains 'm' rows and 'n' columns, having a black foreground (text) and a white background, then each pixel has a value '1' or '0' depending on whether it is white or black. So, the sum of all relevant pixels at a certain object height, say  $c*m$ , ( $c$ =scale constant,  $0 < c < 1$ ), is given by,

$$Sum_{cm} = \sum_{p=1}^n I(c * m, p). \quad (13)$$

where,  $I(c*m, p)$  = Black pixel at location  $(c*m, p)$ . Similarly, a set of vertical lines drawn at various distances along the width, depicting the sum of pixels, can also serve as another feature set, as shown. Mathematically, the sum of pixels along the vertical line at a width of  $c*n$  is given by,

$$Sum_{cn} = \sum_{p=1}^m I(p, c * n). \quad (14)$$

Where,  $I(p, c*n)$  = Black pixel at location  $(p, c*n)$ . Symmetry is another parameter that can be used to reduce ambiguity among characters, such as '8' and 'B' can be differentiated based on its Horizontal Symmetry while 'I' and 'J' can be differentiated easily based on their Vertical Symmetry. It should be noted that these parameters show the 'Degree of symmetry', i.e. a decimal value between 0 (No symmetry) to 1 (Perfect symmetry), rather than 'True' or 'False'. For this, we create a matrix, say M having the first half (horizontal or vertical) part to be the mirror image of the second half. Then, the correlation is found between 'M' and 'I'. This level of correlation gives us the amount of symmetry the character has.

Another paradigm of character recognition is the number of closed areas in its shape. Characters such as 'A', 'P', 'D' and 'Q' have one closed area, while others such as 'B' and '8' have two. There also exist characters which are open, such as 'H', '7', 'C' etc. This parameter also serves to broadly classify characters based on its openness or closeness.

Comparison can be done in yet another form, namely, using the WHT coefficients. A database was created that contained the Walsh-Hadamard Transforms of each image 'template.'

Thus, each character's value is available in terms of WHT coefficients. By calculating the WHT equivalent of the input character, and calculating its correlation to each sample in the WHT database, so maintained, we are able to find the character having the highest similarity to the input character. Thus, the classification is done using transformed structure, rather than pixel-based arithmetic.

It shows the variation in the magnitude of the WHT coefficients, along the Sequence index of the coefficients. Although the whole range of coefficients was utilized for comparison, higher order coefficients (higher than 40, in the figure), having very small magnitudes can be neglected for more complex databases.

Another paradigm of character recognition is the number of closed areas in its shape. Characters such as 'A', 'P', 'D' and 'Q' have one closed area, while others such as 'B' and '8' have two. The main idea behind calculating a number of different parameters is to increase the differences among the characters, so as to make the recognition easier. Thus, the addition of parameters tends to increase the entropy of the system. Hence another parameter that was used is the 'Sum of values of the other parameters.' It should be noted that while others were primary features, i.e. calculated directly from the images, this one is a secondary parameter, i.e. calculated from primary feature values.

### 3.3 ANN Training and Classification

Before the character recognition can take place, the ANN is 'trained', so that it can develop the capability of mapping various inputs to the required outputs and effectively classify various characters. For training the ANN, we use the 'Vectors' generated by the 'Database Templates' using the above mentioned Feature Extraction techniques.

## 4. Support Vector Machines

Support Vector Machines (SVMs) are new learning machines; and they were introduced in 1995 by Vapnik et al. In the past few years they generated a great deal of interest in the community of machine learning because of their excellent generalization in many learning problems [8], such as in handwritten digit recognition, face recognition, and novelty detection [11]. Here we only introduce some basic formulas for SVMs, and without loss of generality we consider two class classification problems. Given the training sample:

$$\{(X_i, y_i)\}, i = 1, \dots, N, y_i \in \{-1, +1\}, X_i \in R^d \quad (15)$$

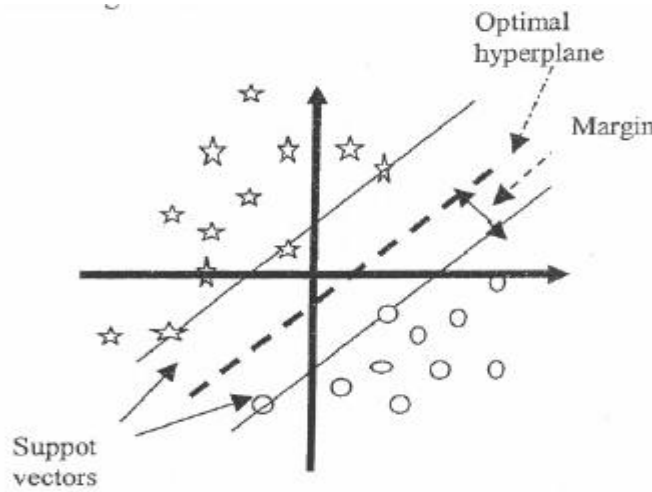
where  $X_i$  is a  $d$  dimensional training sample,  $Y_i$  is the class label for each  $X_i$ , and  $N$  is the number of training samples. Support vector machines first map the data from the input space to a very high dimensional Hilbert space  $H$  (so called feature space), using a mapping

$$\phi : R^d \rightarrow H \quad (16)$$

The mapping  $\phi$  is implemented implicitly by a kernel function  $K$  that satisfies Mercer's conditions [10]. Kernels are functions that give the inner product of each pair of vectors in the feature space, such that

$$K(X_i, X_j) = \langle \phi(X_i), \phi(X_j) \rangle, \forall X_i, X_j \in R^d \quad (17)$$

where  $(\cdot, \cdot)$  is a notation for inner product [10]. Then in the high dimensional feature space  $H$ , we try to find an optimal hyperplane by maximizing the margin between the two classes (see figure 5), and bounding the number of training errors.



**Figure 3. 3 :**Optimal hyperplane with maximum margin[15].

The decision function can be given as:

$$\begin{aligned} f(X) &= \psi(\langle W, \phi(X) \rangle - b) \\ &= \psi(\sum_{i=1}^N y_i \alpha_i \langle \phi(X_i), \phi(X) \rangle - b) \\ &= \psi(\sum_{i=1}^N y_i \alpha_i K(X_i, X) - b) \end{aligned} \quad (18)$$

Where

$$\psi(u) = \begin{cases} 1 & \text{if } u > 0 \\ -1 & \text{otherwise} \end{cases} \quad (19)$$

And

$$W = \sum_{i=1}^N y_i \alpha_i \phi(X_i) \quad (20)$$

If  $\alpha_j$  is non zero then, corresponding sample  $X_j$  is called support vector [11]. Training an SVM is to find  $\alpha_j, i = 1, \dots, N$ , which can be achieved by minimizing the following quadratic cost function.

Minimize :

$$L_D(\alpha) = \sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j K(X_i, X_j) \quad (21)$$

Subject to :

$$\begin{cases} 0 \leq \alpha_i \leq C, & i = 1, \dots, N \\ \sum_{i=1}^N \alpha_i y_i = 0 \end{cases} \quad (22)$$

where  $C$  is a parameter chosen by the user, a large  $C$  corresponds to a higher penalty allocated to the training errors. Since the kernel  $K$  is semi-positive definite, and the constraints define a convex set [10], the above optimization problem reduces to a convex quadratic programming. Therefore the solutions  $W$ , and  $b$  can be determined [8,11], and the optimal hyperplane is specified by these solutions.

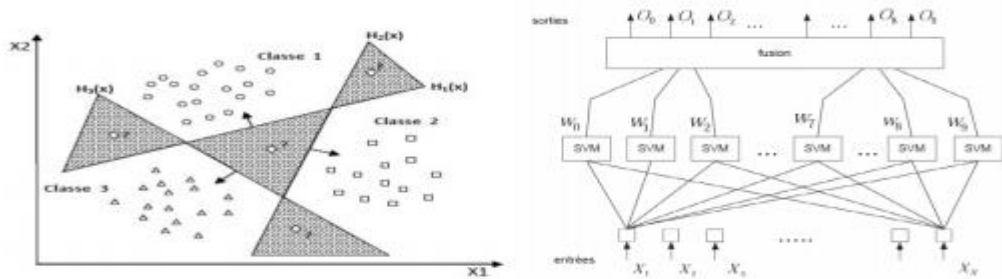
#### 4.1 Multi-class SVM

Originally, the SVM were designed primarily for 2-class problems, though several approaches to extend this algorithm to cases classes were proposed. The generalization in the multi-class cases can be done in three different ways. The first two methods are based on a multiplication of two-class classifiers while the latter offers a comprehensive resolution.

##### 4.1.1 Approach One against all(1vsR)

The most natural approach is to use this Binary discrimination method and learn functions of decision to discriminate between each class for all other (each class is opposed to all the others). It must therefore ask problems binaries. Assigning a new point to a class is through the relationship:

$$i = \text{Arg}_{1 \leq m \leq N} \text{Max}(f_m(x)) \quad (23)$$



**Figure 3. 4 :** (left) Scatter 3 classes: one approach against all (right) System Architecture Strategy A-against-all [20]

## **5. Conclusion**

In chapter three mainly introduced ANN system and the algorithm used in our work in digits recognition. We also have demonstrated the potential of Support Vector Machines in the problems of object recognition and image classification.

As we used those two methods in our work during the process of classification and recognition, the training of Artificial Neural Network and the Support Vector Machines in addition to the results obtained are detailed in chapter four.

# **CHAPTER 4**

## **EXPERIMENTAL RESULTS**



## 1. Introduction

In this study, a system for the recognition of digits is built, which may benefit the fields of postal code recognition systems. In the system concerned with isolated digits, the input is considered to be an image of a specific size and format, the image is processed and then recognized to result in edited digits. The proposed system recognizes isolated Arabic digits as the system acquires an image consisting in digits, then, the image will be processed into several phases such as image enhancement, noise removal, normalization and segmentation before recognizing the digit. A several methods will be used for the recognition phase, a feed forward back propagation algorithm will be applied for training the neural network and one against the other algorithm will be used to train the support vector machines, several groups for the k-nearest neighbor, and finally change them into a numeral text[10]. In this chapter, we display the different phases and results obtained from of applying the methods and the accuracy of the system that was proposed.

## 2. Tools and work environment

In order to undertake this work, we have used the following tools

### Microsoft office 2013

Microsoft Office 2013 is a version of Microsoft Office, a productivity suite for Microsoft Windows. It is the successor to Microsoft Office 2010 and the predecessor to Microsoft Office 2016. It includes extended file format support, user interface updates and support for touch among its new features.

#### Microsoft Word 2013:



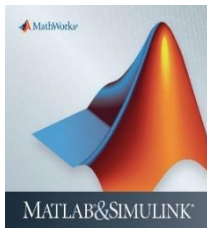
Microsoft Word is a word processor developed by Microsoft. It was first released on October 25, 1983 under the name Multi-Tool Word for Xenix systems. We used this version of MS-word for the processing of texts and creation of the theoretical part of this Research paper.[21]

#### Microsoft Power Point 2013:



Microsoft PowerPoint is a slide show presentation program currently developed by Microsoft. We used this version of MS-PowerPoint to create the slide show document that is used in the presentation.[22]

Matlab 2013:



MATLAB (matrix laboratory) is a multi-paradigm numerical computing environment and forth generation programing language. A proprietary programming language developed by MathWorks, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages including C, C++, Java, Fortran and Python. We used this version of Matlab to do all the programing part in our research.[23]

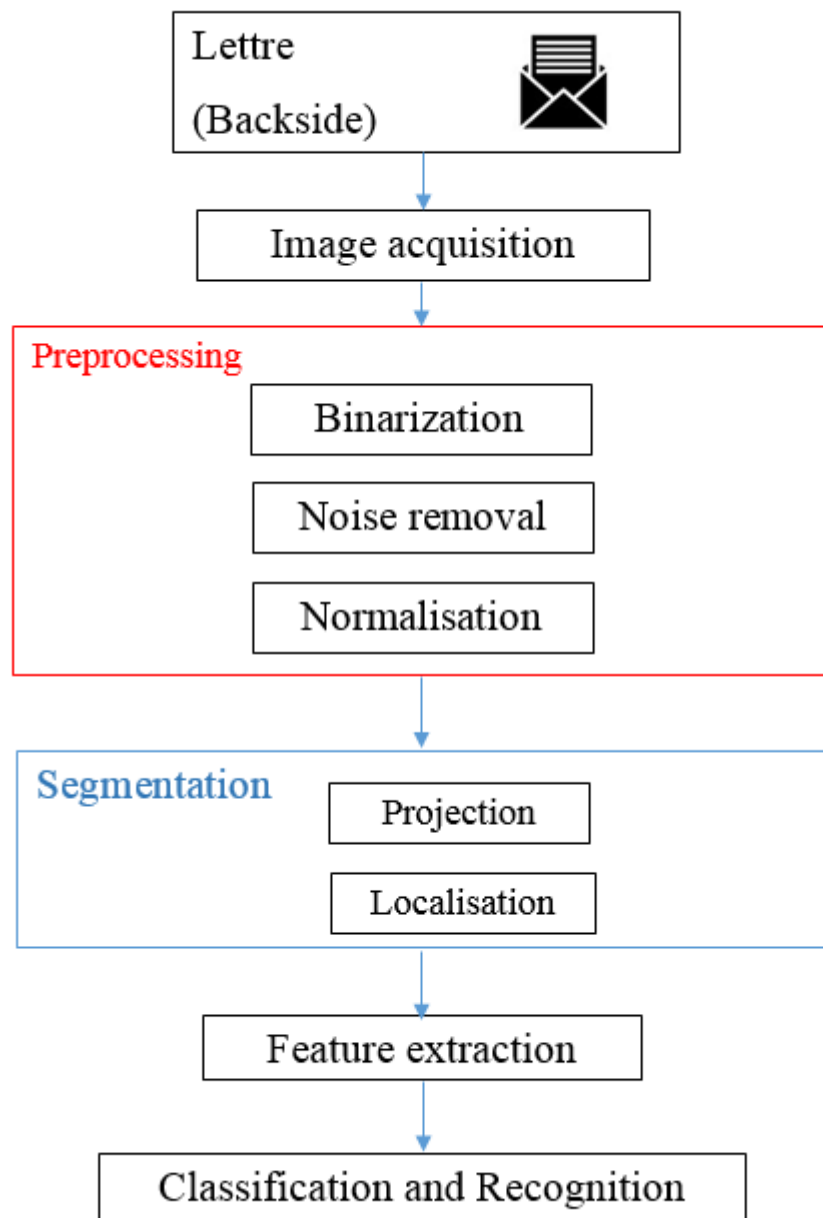
Operating System



Windows 8.1 (codenamed Blue) is an upgrade for Windows 8, a version of Windows NT, a computer operating system released by Microsoft. First unveiled and released as a public beta in June 2013. It was released to manufacturing on August 27, 2013, and reached general availability on October 17, 2013, almost a year after the retail release of its predecessor. We used this environment in our whole process to undertake our research. [24]

### **3. Description of realized system**

There are four steps to build the isolated digits recognition system. These steps are presented on Figure.4.1 and following are the descriptions of them:



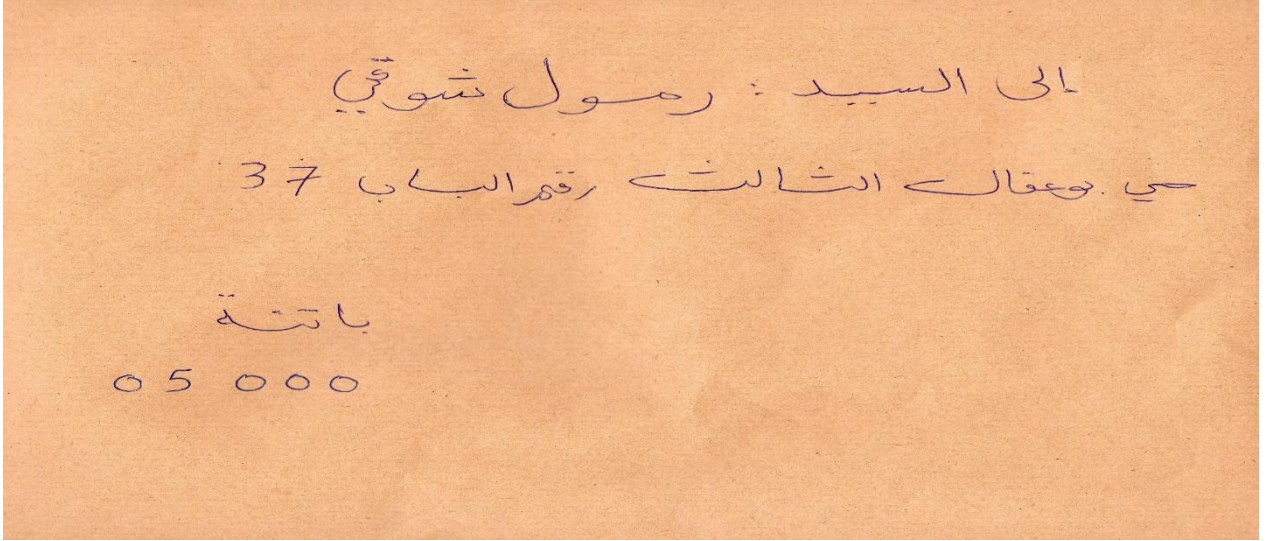
**Figure 4. 1** :Flow of the work

### 3.1 Image acquisition

As a first step in our work, we have created two types of databases. The first concern the letters and envelopes which will be used as samples to be recognized by the system. The second type was digits dedicated to train and test the neural network. For the completely scanning process, we used an Epson mark scanner model “EPSON STYLUS CX8300.”

### 3.1.1 Envelopes dataset

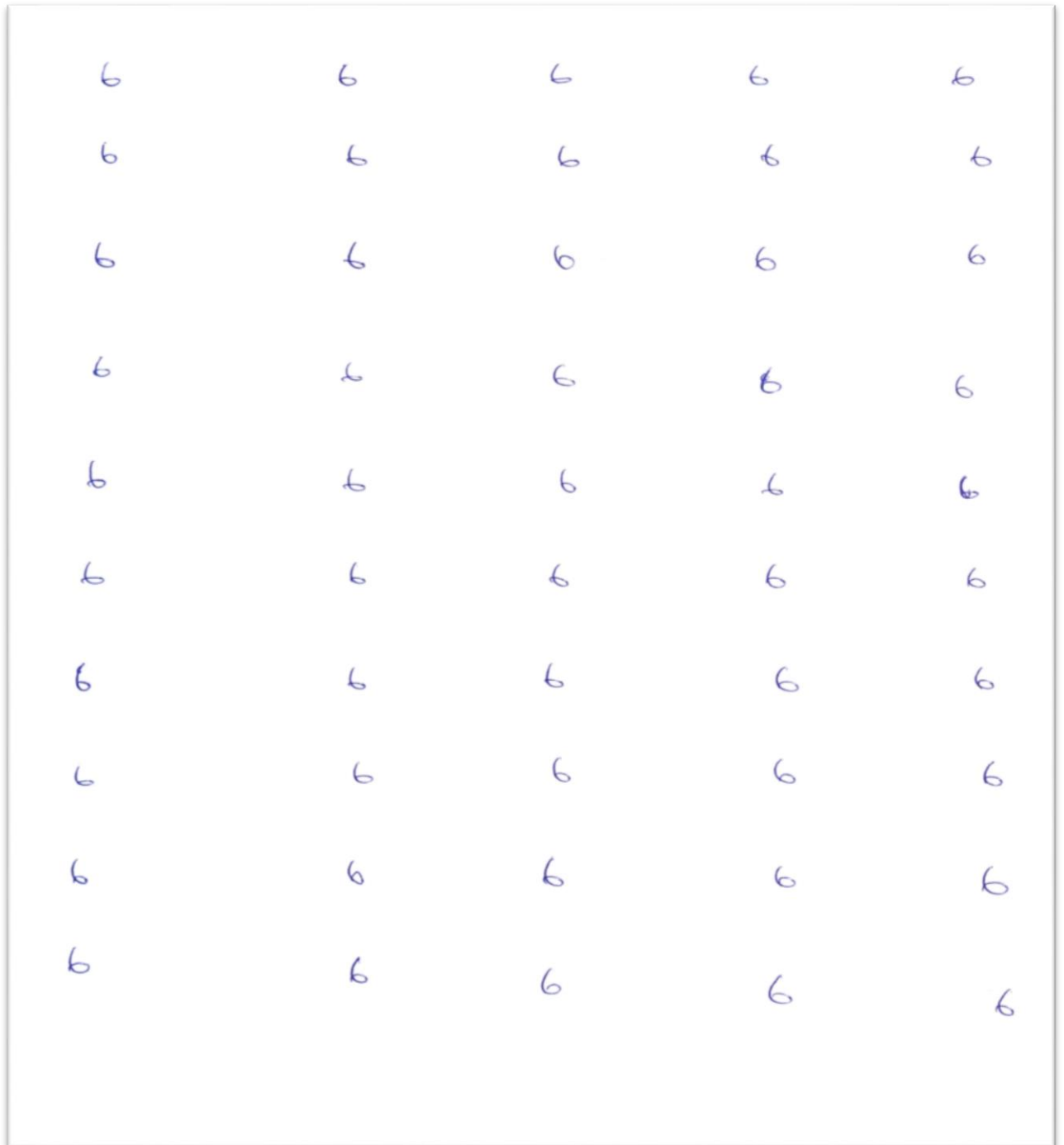
As an input, we take a scanned handwritten back side of a letter. This image should have a specific format. We use the “.bmp” format and with an undetermined size. The following figure shows some samples of those images:



**Figure 4. 2 :**Example 1 backside of a letter

### 3.1.2 Digits dataset (training/test)

Alongside with letter's database, we also created another dataset. Handwriting samples were obtained from 5 subjects. All the subjects were randomly chosen between the ages of 20 and 35. The subjects were given a piece of paper and were asked to write a list of digits from 0 to 9 in one line and repeat that action 10 times. Each time they repeat the action in different lines. All the subjects used identical pens.



**Figure 4. 3 :**Sample of the number “6”

To let the computer understand the Arabic numbers that is are written manually by users and views them according to the computer process. Here, we present a way to recognize isolated Arabic digits that exist in different applications. For example, different users have their own handwriting styles where here the main challenge falls to let the computer system understand these different handwriting styles and recognize them as standard writing. Figure 4.4 shows some examples of different user-handwritings.



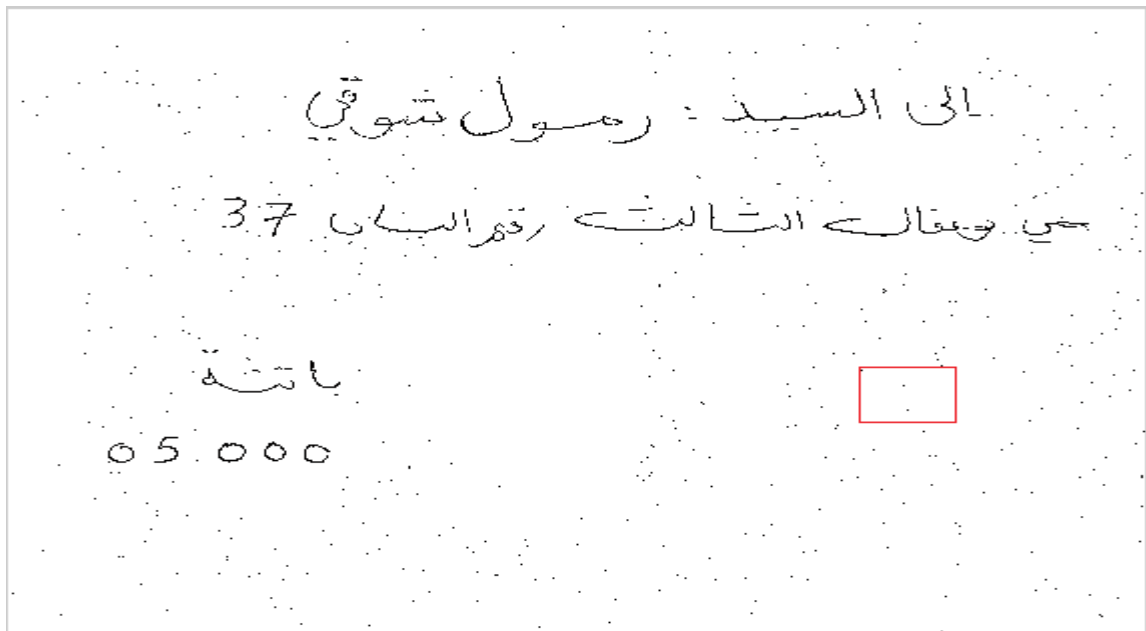
**Figure 4. 4 :**Different shapes of the number “5”

## 3.2 Preprocessing

After getting the image, it will move to the next phase, which consists in preprocessing steps prepared for the segmentation. Preprocessing itself contains several steps as follows:

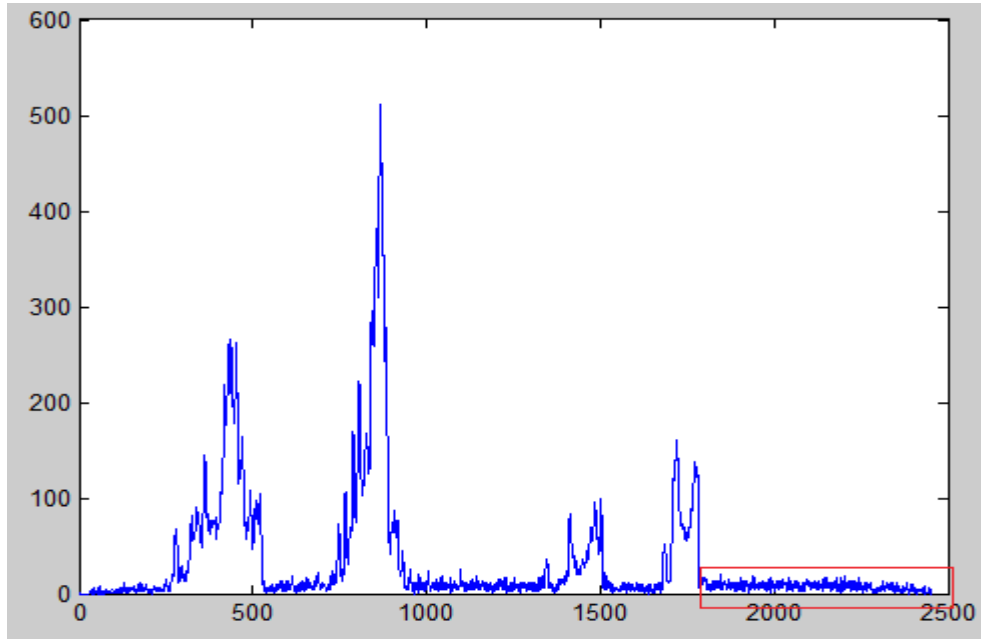
### 3.2.1 Noise removal

It is reducing noise in an image. For on-line mode there is no noise to eliminate. So, there is no need for the noise removal. In off-line mode, the noise may come from the writing style or from the optical device that captures the image [10]. We had a several examples for noise that happened after applying binairization as shown in figure [4.5]. The figure [4.6] shows a vertical vector for the images after applying the binarization.



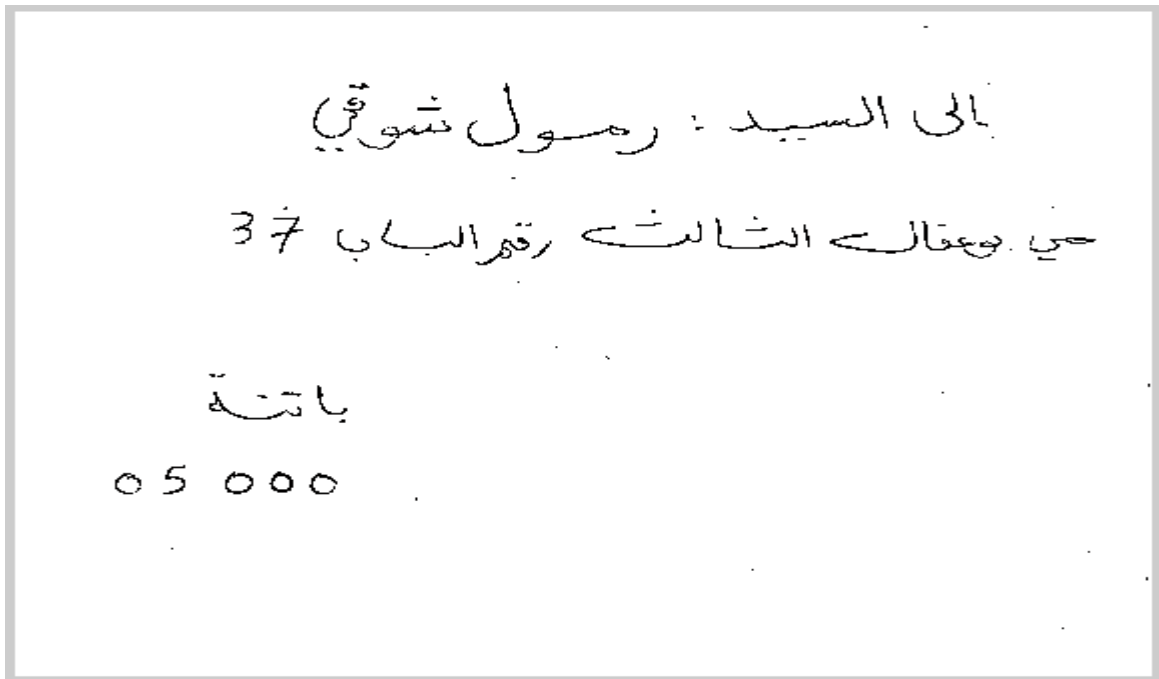
**Figure 4. 5 :**Image after applying binarization

After applying the binarization to the image due to some effects that are mentioned before, those random dots (points on the white part of the image) effects the clearance of the image and create a noise in the vector.

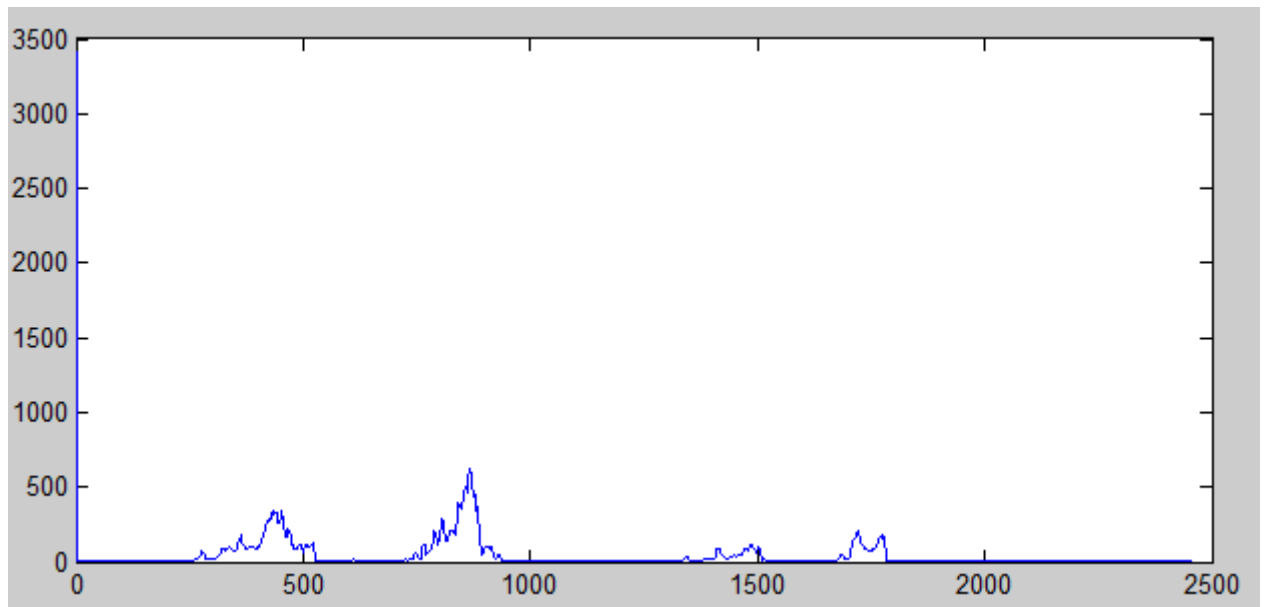


**Figure 4. 6 :**The corresponding vertical vector

With such results, we cannot detect the lines of the images. After applying the noise removal function, we could obtain much better results. We followed the “dilatation and erosion” method in order to get better results. Figure [4.7] shows the same image after applying the “dilatation and erosion” method.



**Figure 4. 7 :**Image after applying “dilatation and erosion”



**Figure 4. 8 :**The corresponding vertical vector

### 3.2.2 Normalization-scaling

It is to standardize the font size within the image. This problem clearly appears in handwritten texts, because the font size is not restricted when using handwriting. This step was applied to the second database that has the digits that we used to train in the Artificial Neural Network.

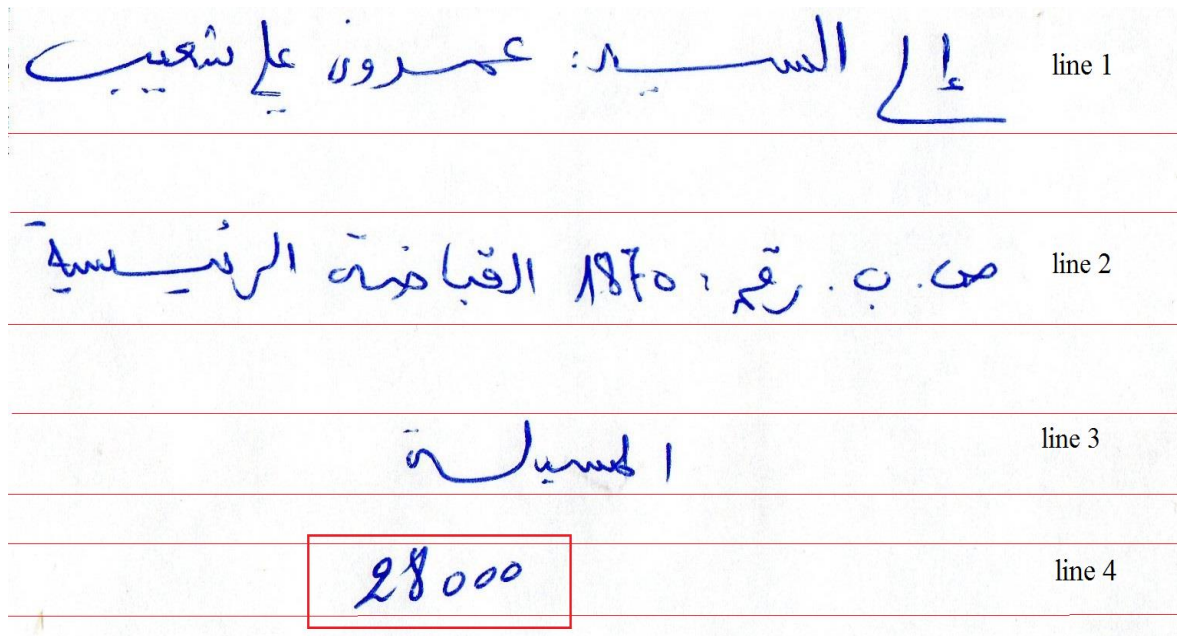
## 3.3 Segmentation

Since the data is not isolated, we need segmentation to isolate the postal code apart from the other information like the city, name and address. The segmentation phase has three main steps: the Vertical projection for text lines to detect the lines, Localization of the postal code line, and finally the Horizontal projection for postal code digits to isolate each digit alone.

### 3.3.1 Vertical projection for text lines

To apply vertical projection on the image containing more than one line, we isolate each line alone. Then, we choose the line that contains the postal code. Usually the line that contains the postal code is located in the forth line as shown in figure[4.9].

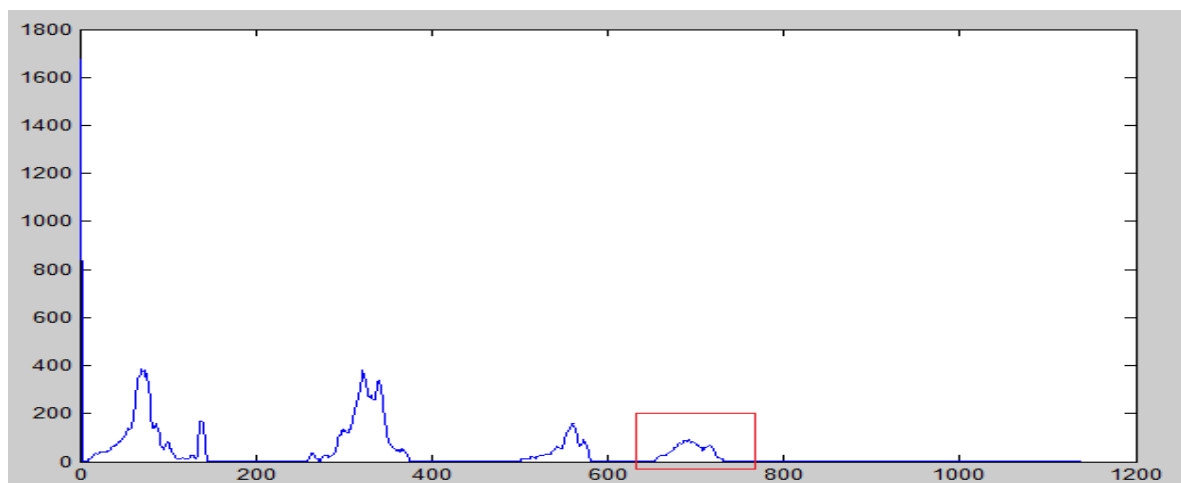




**Figure 4. 9 :**Frontside of a letter showing the four lines

### 3.3.2 Localization of the postal code line

To isolate the last line, we have to locate its corresponding range that is calculated in the vertical vector of the whole image. In that case, the last wave in the vertical vector as shown in figure [4.10] represents the corresponding vertical vector of figure[4.9].



**Figure 4. 10 :**The corresponding vertical vector

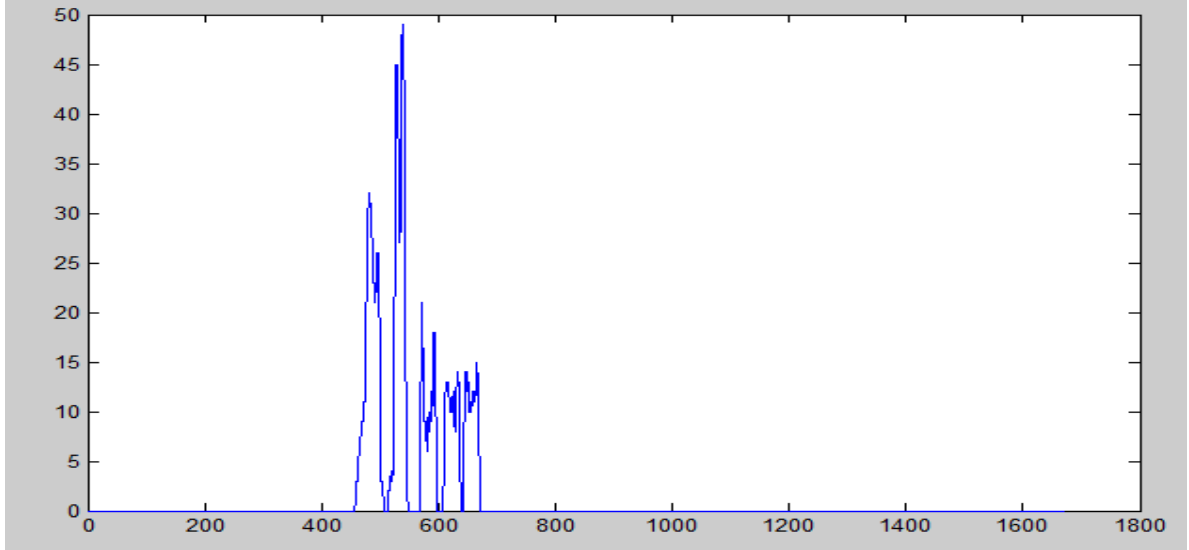
The result of applying the vertical projection is shown in figure [4.11]



**Figure 4. 11 :**The fourth line isolation

### 3.3.3 Horizontal projection for postal code digits

It is to apply a Horizontal projection on the image that corresponds to the last line which contains the postal code (figure[4.11]). In this step, we need to isolate each digit alone. To do that, we get the horizontal vector of figure [4.12]. The following figure represents the horizontal vector of figure [4.11]



**Figure 4. 12 :**The corresponding horizontal vector

Each wave represents a digit and gives us 5 waves (represents the number of the postal code digits). After applying the horizontal segmentation method, we obtain the following result:



**Figure 4. 13 :** The result

The result of segmentation phase is that we have each digit isolated.

### 3.4 Feature Extraction

Feature Extraction is used to extract relevant features for the recognition of characters. First features are computed and extracted, and then, most relevant features are selected to construct a feature vector which is used for recognition. The computation of features is based on statistical, structural, directional, moment, transformation like approaches. Feature

extraction is extracting information from raw data which is more relevant for classification purposes and that minimizes the variation within a class and maximizes the variations between classes[15]. In our work, we use the Hu's Moment Invariants method. The following table represents the results obtained after applying the Hu's Moment Invariants method on our digits dataset. The following results were applied to the first 10 digits of zeroes.

	1	2	3	4	5	6	7
1	7.0536e-04	9.4250e-09	6.3159e-14	9.3125e-08	4.8276e-24	1.5947e-16	5.4798e-26
2	7.0387e-04	9.3455e-09	5.2360e-14	9.2793e-08	4.7981e-24	1.5942e-16	6.0611e-26
3	6.9638e-04	8.2681e-09	3.6076e-14	9.2138e-08	1.9921e-24	9.6315e-17	1.0293e-26
4	7.0108e-04	9.3718e-09	5.8709e-14	9.1902e-08	4.7061e-24	1.5757e-16	7.9058e-26
5	6.9819e-04	9.1605e-09	5.7225e-14	9.1354e-08	4.5858e-24	1.5368e-16	5.5369e-26
6	6.9695e-04	9.1184e-09	5.8096e-14	9.1047e-08	4.5522e-24	1.5264e-16	4.8980e-26
7	6.9796e-04	9.2410e-09	5.0670e-14	9.1160e-08	4.6308e-24	1.5594e-16	6.6357e-26
8	6.9937e-04	9.3750e-09	6.1501e-14	9.1378e-08	4.6248e-24	1.5613e-16	9.5111e-26
9	7.0023e-04	9.0666e-09	6.0807e-14	9.2123e-08	4.6259e-24	1.5313e-16	3.2414e-26
10	7.0466e-04	9.2816e-09	6.6208e-14	9.3135e-08	4.7378e-24	1.5638e-16	3.3489e-26

**Figure 4. 14 :** Hu's Moment Invariants for 10 samples of zero digit

### 3.5 Classification and Recognition

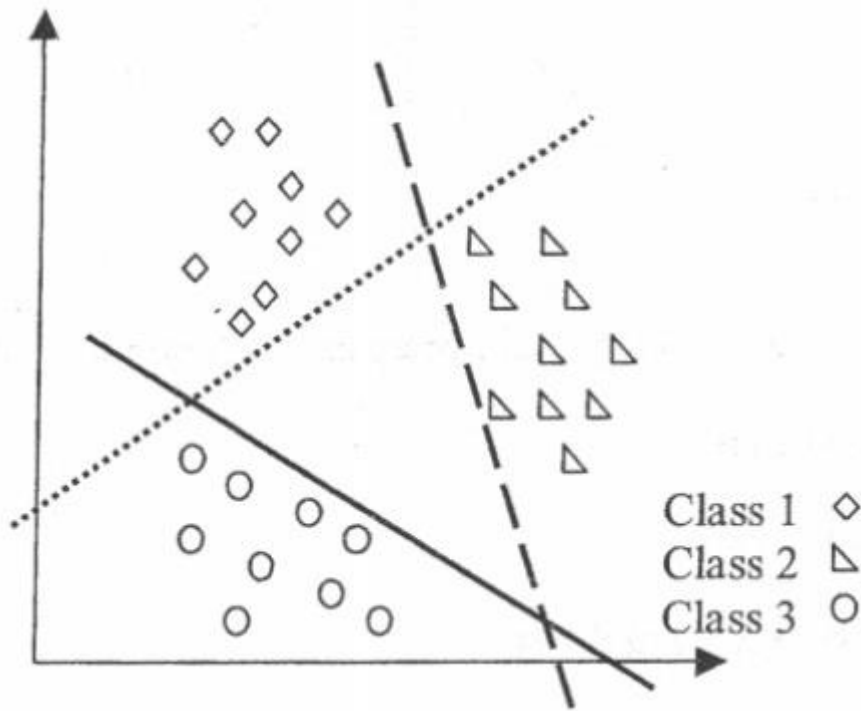
We have experimented three methods of digits recognition which are: Artificial Neural Network, Support Vector Machines, K-Nearest Neighbors.

#### 3.5.1 Artificial Neural Network initialization and training (ANN)

In order to recognize Arabic numerals given as an image to the system automatically using the intelligence of the one layered neural network. The neural network applied in the system utilizes the back propagation method. In the first step, neural network is initialized and trained with the help of back propagation network. As an input we have created a 7 input layers and as an output we created consisting in 4 output layers.

#### 3.5.2 Support Vector Machines(SVM)

Since we have 10 classes of digits, therefore we need 10 SVM classifiers or 10 hyperplanes to separate the digits from each other. For example, one classifier for digit zero (so called SVM0) will separate all the samples of zero from the other digits. This method of designing multiple SVM classifiers is called one against the others as illustrated in figure 4.14.



**Figure 4.15 :** One-against-the-others methods for a three-class problem

From the 10 outputs of the 10 SVM classifiers, we take the maximum. The SVM classifier that gives the maximum output will determine the class label for the input digit.

### 3.5.3 K-Nearest Neighbors (KNN)

In the learning phase, each numeral image is transformed to a vector by the zoning method. Then, we calculate the distance between the vector and the vector test. We choose the k-nearest neighbors from this vector test and count the numbers of these nearest neighbors in each class.

## 4 Evaluation and discussion

In this section, we present two parts, the first part concerns the digits database evaluation results, and the second part is about the letters database and postal codes recognition as well as the results of letters testing.

### 4.1 Digits database

All methods have been trained on the same training data set which contain a total of 500 isolated digits. We used different ordering for the data set in the training process. The same test of the data set has been used for testing the three methods.

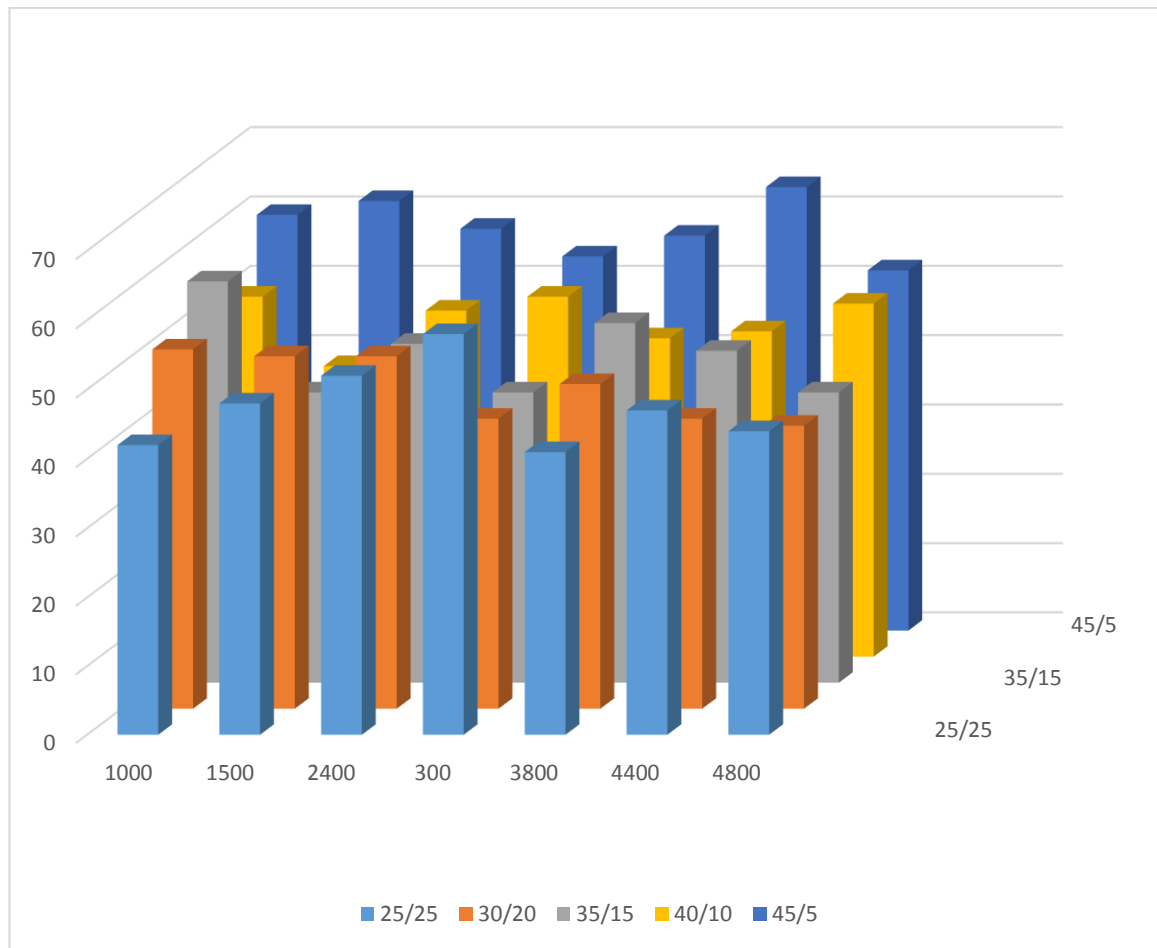
#### 4.1.1 Artificial Neural Network

Once the network has been initialized, the network is ready to train. Some issues that need to address upon training the network are: What should be the values of- learning rate, sigmoid shape, gradient, weight bias and how many values of Iterations (Epochs) are to be taken for the

training of network for a given set of inputs. Here the network learns what we have taught to it. Table 4.2 represents the results obtained after training and testing the Neural Network according to the number of hidden layers and each time we changed the number of training and test dataset. The best result we obtained was 60%.

	Training	250	300	350	400	450
	test	250	200	150	100	50
Number of hidden layers						
20		42%	54%	46%	46%	53%
40		42%	50%	46%	42%	56%
60		46%	50%	52%	48%	60%
80		50%	48%	50%	40%	56%
120		48%	58%	42%	54%	52%
160		50%	46%	48%	48%	48%
220		52%	48%	48%	46%	60%
280		42%	52%	48%	44%	50%

**Table 4. 1 :**The neural network training statistics



**Figure 4. 16 :ANN training histogram**

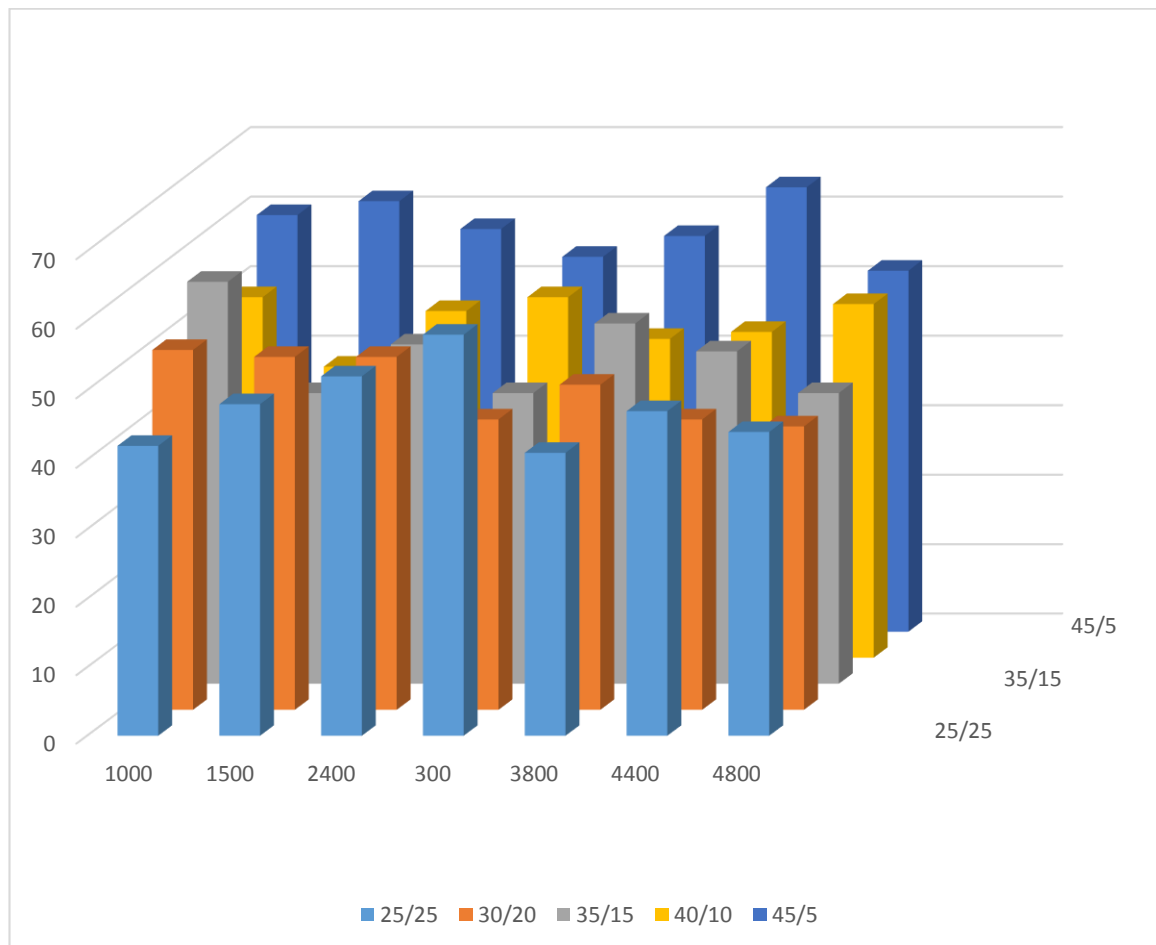
#### 4.1.2 Support Vector Machines

In Table 4.3 and Table 4.4, the numbers shows the correct recognition of the multiple SVM classifier. In table 4.3, we fixed the value of the “BoxConstraint” variable and changed the “sigma” variable, whereas in table 4.4 we fixed the sigma’ variable and gave several values to the ‘BoxConstraint’ variable. As we observe our highest rate was 64% in both tables.

For this table, we fixed the BoxConstraint variable and gave it the value 4400.

	Training	250	300	350	400	450
	Test	250	200	150	100	50
<b>Parameters</b>						
<b>Sigma= 2.7</b>		45%	50%	52%	51%	56%
<b>Sigma= 6.9</b>		46%	51%	50%	50%	64%
<b>Sigma= 20.5,</b>		45%	51%	52%	50%	60%
<b>Sigma= 18.9</b>		43%	48%	48%	51%	62%
<b>Sigma= 15.9</b>		44%	42%	44%	43%	58%
<b>Sigma= 10.0</b>		45%	51%	48%	49%	54%
<b>Sigma= 8.1</b>		44%	47%	45%	51%	60%

**Table 4. 2 :Statistics of training SVM**

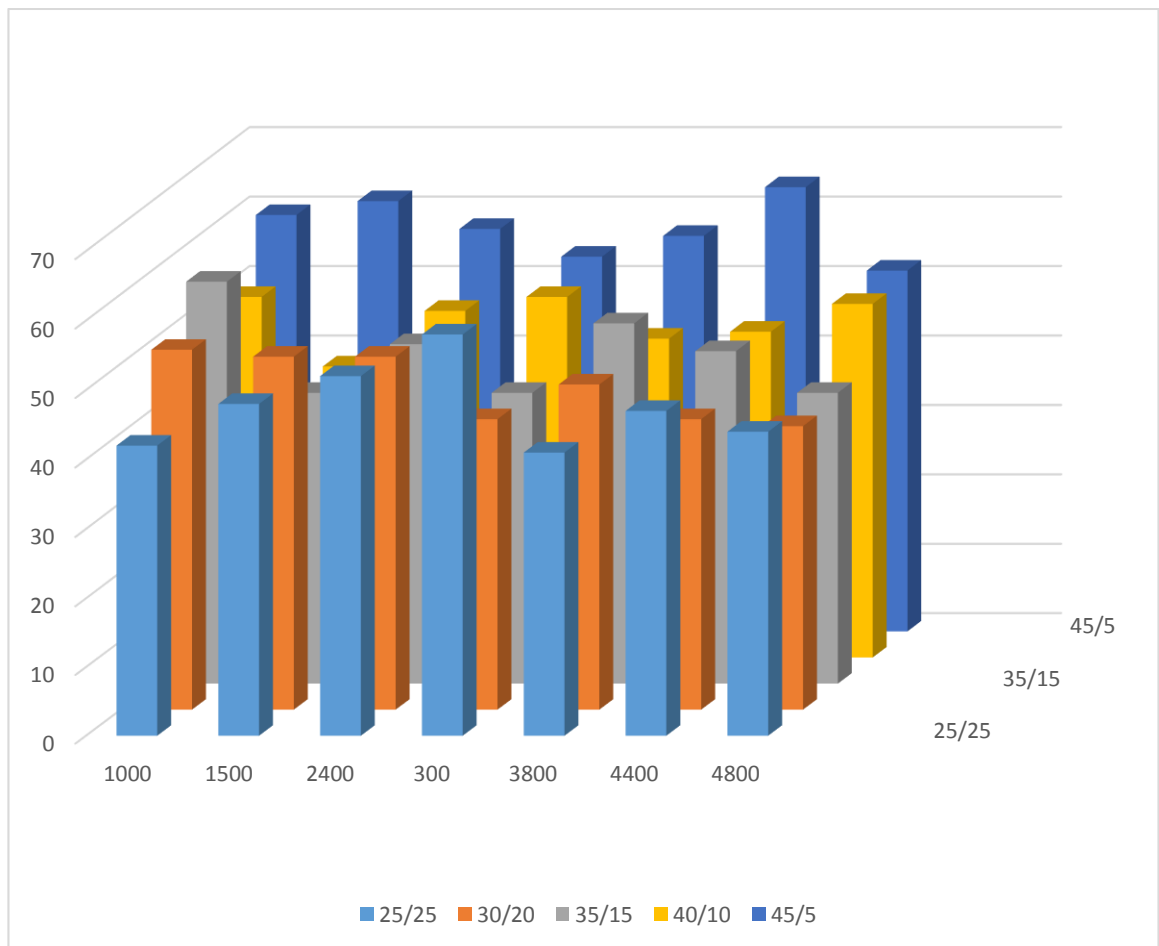


**Figure 4. 17 :SVM training histogram with BoxConstraint=2.9**

For this table, we fixed Sigma variable and gave it the value 2.9

	Training	250	300	350	400	450
	Test	250	200	150	100	50
<b>Parameters</b>						
<b>BoxConstraint = 1000</b>		42%	52%	58%	52%	60%
<b>BoxConstraint = 1500</b>		48%	51%	42%	42%	62%
<b>BoxConstraint = 2400</b>		52%	51%	49%	50%	58%
<b>BoxConstraint = 3000</b>		58%	42%	42%	52%	54%
<b>BoxConstraint = 3800</b>		41%	47%	52%	46%	57%
<b>BoxConstraint = 4400</b>		47%	42%	48%	47%	64%
<b>BoxConstraint = 4800</b>		44%	41%	42%	51%	52%

**Table 4. 3** :Statistics of training SVM method (2)



**Figure 4. 18** :SVM training histogram with sigma=2.9

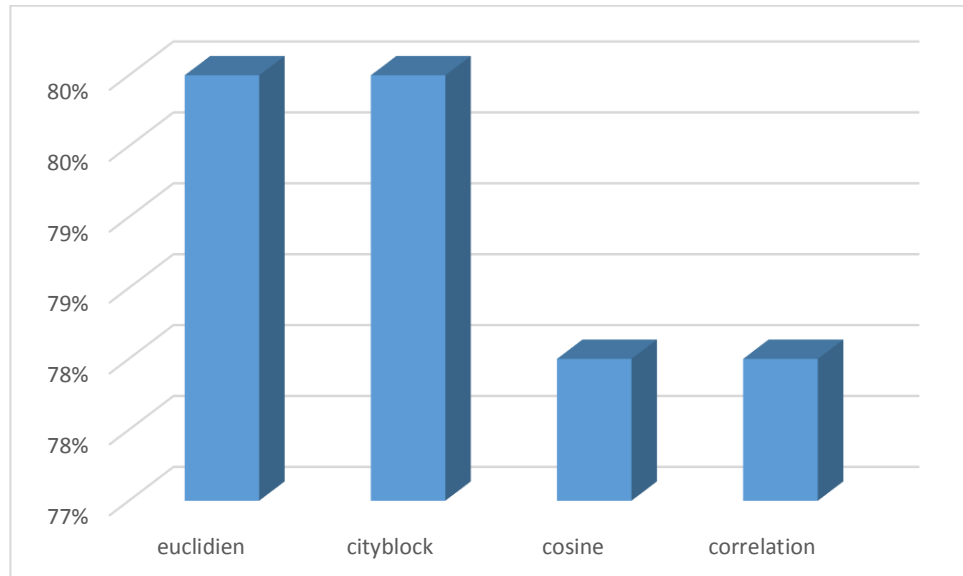


#### 4.1.3 K-Nearest Neighbor

The recognition will be assigned to the class that is most represented. The following table 4.5 represents the training of KNN and each time we changed the distance.

Distance	euclidean	cityblock	cosine	correlation
<b>Result obtained</b>	80%	80%	78%	78%

**Table 4. 4 :KNN training statistics**



**Figure 4. 19 :KNN training histogram**

#### 4.2 Interpretation

For the three methods, we have obtained the following results

1. For ANN: the best result obtained among the tested parameters was 60% when used with both 60 and 220 hidden layers.
2. For SVM: the best result obtained among the tested parameters was 64% and that result was obtained for Sigma=2.9 and BoxConstraint=4400.
3. For KNN : the best result obtained was for both groups Euclidean and Cityblock with 80% recognition rate.

By analyzing the obtained results, we can say that the best method for recognition rate is KNN with the highest recognition rate.

#### 4.3 Code postal Recognition

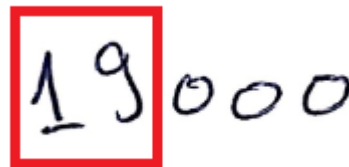
We had created a test database that consists of several letters, this time we asked 5 subjects to write a frontside of letters but with different destinations in order to test our system accuracy. The images extracted from the segmented stage are matched with all the numbers which are

preloaded into the system. In this step, the nearest match of the stored and input number is found out. Once, the matching is completed, the number with a maximum matching is declared as the number present in the image. We have tested 10 images as shown in figure 4.14.

<p>الى السيد : د. معش صالح حي ليشتار عمارة رقم ٥٦ تيليف ١ ٤ ٥ ٥ ٥</p>	<p>الى السيد : عبد الله عبد الرحيم حي 365 مسلك الحريات تيليف ١ ٨ ٥ ٥ ٥</p>	<p>الى السيد : علاء اسماء حي باسما جراح عمارة رقم ٢٤ الجزائر ١ ٦ ٥ ٥ ٥</p>
<p>الى السيد : فزات مولود حي النجاح بلدية عمارة تيليف ١ ٥ ٥ ٥ ٥</p>	<p>الى السيد : عمر ونا عبد الحق حي الاشمل عمارة رقم ١٤ بلج بومسراج ٣ ٤ ٥ ٥ ٥</p>	<p>الى السيد : يوركنة الحاج عابد حي النضمة، الدائرة 65 عنوداية ٤ 7 ٥ ٥ ٥</p>
<p>الى السيد : سعدكي عبد الكريم حي حمام السخنة مسكليف ١ 9 ٥ ٥ ٥</p>	<p>الى السيد : بوضوف علي حي سيدي مبارك قسنطينة ٢ ٥ ٥ ٥ ٥</p>	<p>الى السيدة : سالمى هيثام حي الورود عمارة ٥٤ رقم 1٥ سكليف ١ 9 ٥ ٥ ٥</p>

**Figure 4. 20 :**Sample of test letters database

As our work is mainly concerned with Algeria's 48 wilayas, and in order to make the process of recognition even easier, we eliminated the three right digits which are always zeroes in the case of wilayas ( see chapter 2 section 4) which only gives us the two digits to the left as shown in figure 4.15.



**Figure 4. 21 :**Postal code for wilaya of Setif

#### 4.4 Letters test result

##### 4.4.1 Matlab GUI

A user interface (UI) is a graphical display in one or more windows containing controls, called components, that enable a user to perform interactive tasks. The user does not have to

create a script or type commands at the command line to accomplish the tasks. Unlike coding programs to accomplish tasks, the user does not need to understand the details of how the tasks are performed. UI components can include menus, toolbars, push buttons, radio buttons, list boxes, and sliders just to name a few. UIs created using MATLAB® tools can also perform any type of computation, read and write data files, communicate with other UIs, and display data as tables or as plots.

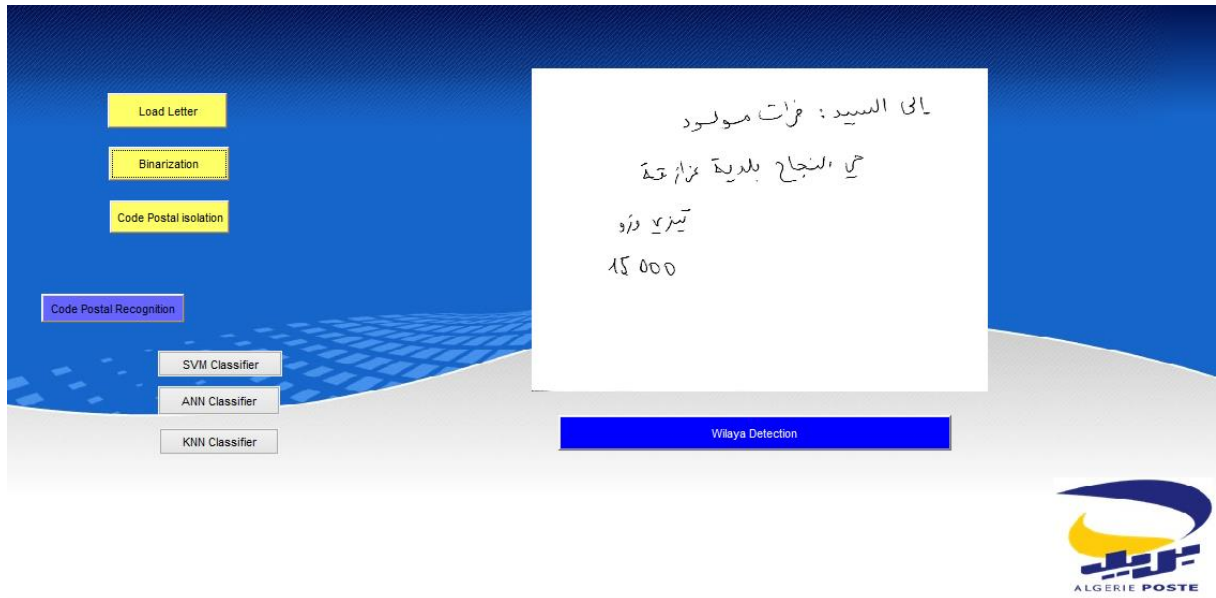
The following figure illustrates our system interface that we created using Matlab guide :



**Figure 4. 22 :** The application interface

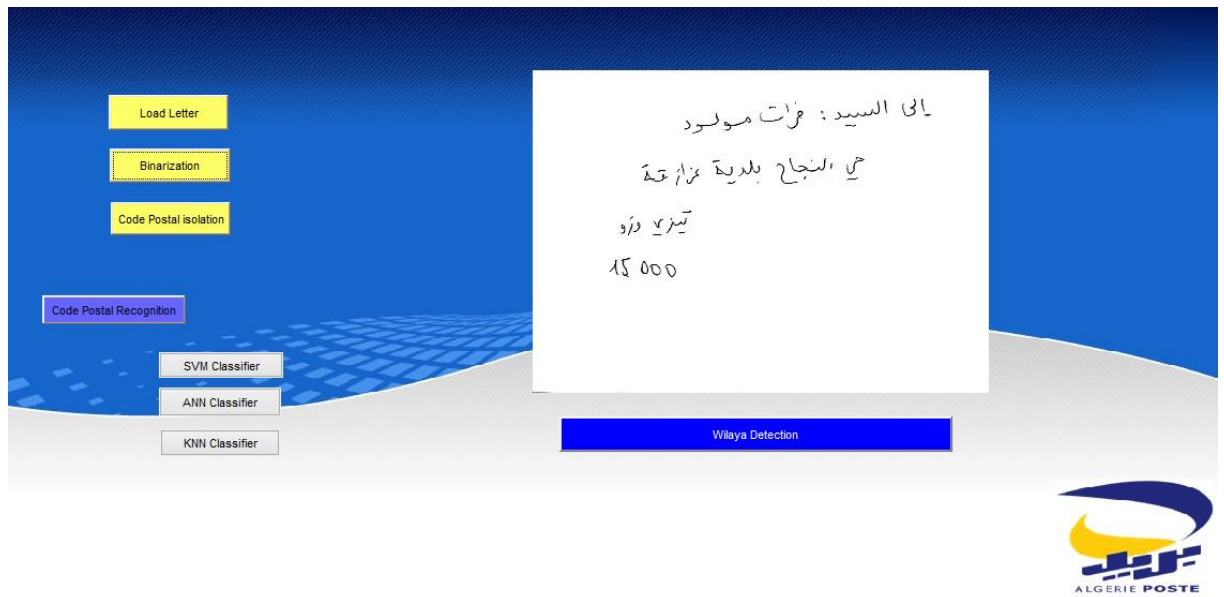
We have 7 main buttons, each one activates a certain function as described below :

**Load Letter :** pushing this button allows to choose which letter to display, The result of pressing the button is shown in figure 4.23



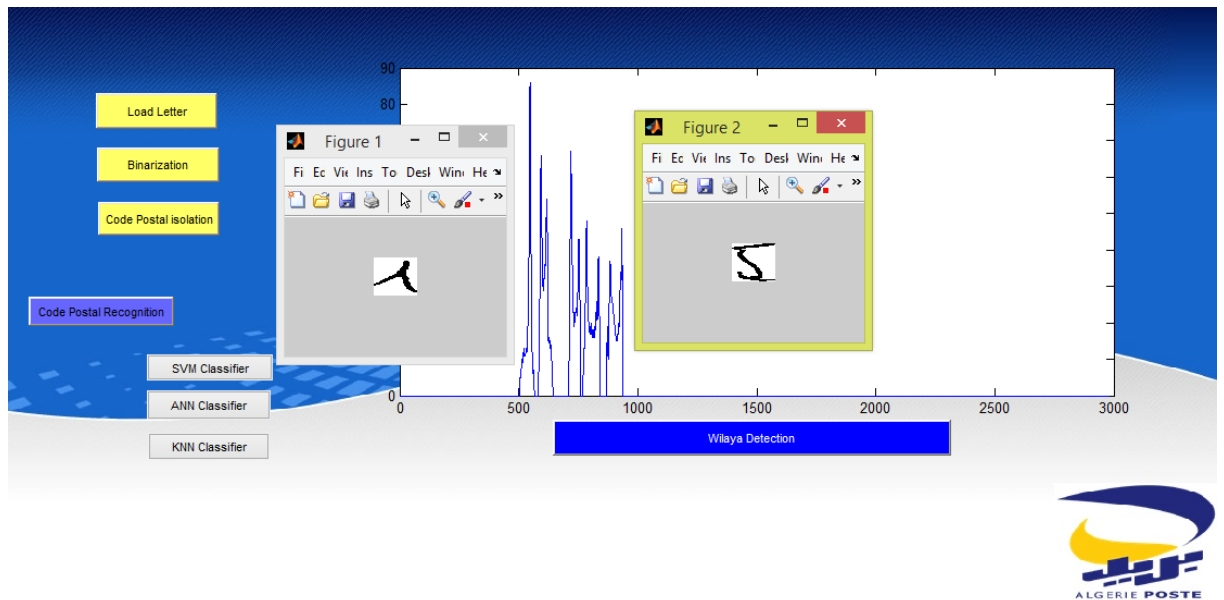
**Figure 4. 23 :** Loading a letter

Binarization : this button applies the binarization step to the loaded letter, as shown in figure 4.24



**Figure 4. 24 :** Applying binarization to the letter

Postal code isolation : this button locates the postal code digits and displays the first two digits separately .Figure 4.25 shows this step's results



**Figure 4. 25 :** Postal code isolation

Postal code recognition : this step applies classification to our located digits.in this step we have three options :

Using the SVM classifier : applies the SVM method recognition.

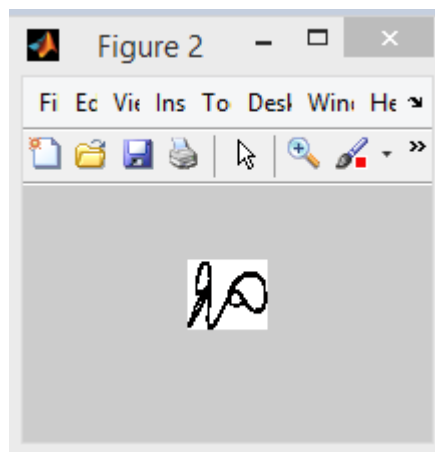
Using the ANN classifier : applies the ANN method recognition.

Using the KNN classifier : applies the KNN method recognition.

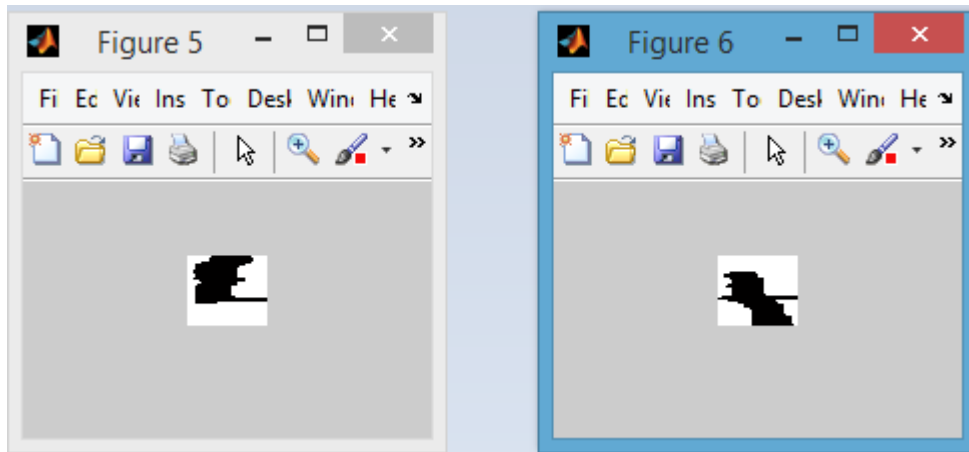
Wilaya detection : this button shows the recognized Wilaya by our system.

## 4.2 The obtained results

Our system succeeded in localizing the postal code digits with a rate of 97% , Some digits couldn't be localized due to the way they were written, Whereas others attached together our system recognized them as one part, The figures below shows those two cases



**Figure 4. 26 :** Two digits attached : “2”and “0”



**Figure 4. 27 :** A separated digit "4"

## 5 Conclusion

The present work deals with the recognition of postal code by using SVM, ANN and KNN. The K-nearest neighbor technique has been adopted to recognize handwritten numerals and yields 80% of accuracy. The ANN classifier technique has been applied to recognize the digits in the postal code, which produces 58% of the result. In addition, SVM is found equivalent to the postal code, based on this the postal letters are sorted. The experimental results reveal that KNN approach yields fast and accurate result with good precision of 80%. The test set, however, contains a significant number of imperfectly segmented characters as well as some garbage images, thus making it a good test set for recognition. The results were satisfying with the image processing and the system training .



## **GENERAL CONCLUSION**



## General Conclusion

We developed a system for Arabic handwritten digits recognition. We efficiently chose a segmentation method to fit our demands. Our system successfully designs and implement a neural network which efficiently works without demands, the support machine vector implementation was success and did recognize digits, whereas K-nearest neighbor classifier had the highest recognition rate. In addition, the system is able to understand the Arabic numbers that were manually written by the user.

The achieved results demonstrates that the ANN based system has shown promising results despite the fact of being trained only on a single set of templates. number of nearest neighbor is increased when using the KNN classifier also the recognition rate is increase. The system has its advantages such as Less Time Complexity, Very Small Database and High- Adaptability to untrained inputs, with only a small number of features to calculate as compared to other methods, Yet, the system has a large scope for further developments, The system performance can be further increased by:

- 1) increasing the DATABASE used for training the ANN,SVM and KNN so as to enable it to recognize stylized fonts also.
- 2) using better algorithms for training the ANN, SVM and KNN so as to decrease the Time complexity while handling larger databases.
- 3) using a better Feature Extraction techniques so as to increase the precision of results.
- 4) increase the DATABASE used for wilaya recognition, so our system will be able to detect more than just the 48 wilaya of Algeria.
- 5) fuse the recognition techniques in order to get better results and increase the rate of recognition

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**ملخص -** تم إنشاء نظام معتمد على ثلاث مصنفات. الشبكة العصبية الخلفية نشر مع طبقة واحدة خفية، مصنف شعاع الدعم الآلي، و مصنف ن-أقرب جار و هذا قصد انشاء نظام التعرف على أرقام الرموز البريدية مستخدمين طريقة عزوم هو. تم تدريب النظام وتقييمه على عدة أشكال مختلفة من نماذج خط اليد المقدمة من طرف المشاركين من الذكور والإناث. اثبتت تجارب اختبار ان تأثير حجم على دقة التعرف، بالإضافة لتأثير أسلوب الكتابة اليدوية على الدقة. وأظهرت النتائج أن أسلوب الكتابة اليدوية قد تتفاوت وتؤثر على دقة التعرف التي تسلط الضوء على بعض المشاكل مع ترميز الأرقام النظم.

**الكلمات المفتاحية:** الشبكة العصبية، شعاع الدعم الآلي، ن-أقرب جار، عزوم هو، الرموز البريدية، نظام التعرف.

**Abstract** — A three based classifiers system was created. A back-propagation neural network with one hidden layer , a support Vector machine classifier, and K- nearest Neighbor classifier were used to create an adaptive postal code digits recognition system by using the Hu moments invariants feature extraction method. The system was trained and evaluated through different forms of handwriting samples provided by both male and female participants. Experiments tested, the effect of the size set on the recognition accuracy, and the effect of handwriting style on the recognition accuracy. Results showed that the handwriting style of the subjects had varying and drastic effects on the recognition accuracy which allowed to identify some of the problems with the system digits encoding.

**Keywords :** KNN, SVM, ANN, Hu moments ,code postal, recognition system.

**Résumé-** Un système basé sur trois classificateurs a été créé. Un réseau neuronal back-propagation avec une seule couche cachée, et une machine à vecteurs de support classificateur, et des plus proches voisins de classificateurs k ont été utilisés pour créer un système adaptatif de reconnaissance de chiffres du code postal, en utilisant la méthode d'extraction des caractéristiques des moments de Hu. Le système a été formé et évalué à travers les différentes formes d'échantillons d'écriture fournies par les deux participants masculins et féminins. Les expériences ont testé, l'effet de la taille indiquée sur la précision de la reconnaissance, et l'effet du style d'écriture sur la précision de la reconnaissance. Les résultats ont montré que le style d'écriture des sujets avait des effets drastiques et variables sur la précision de la reconnaissance qui a permis d'identifier certains des problèmes avec l'encodage des chiffres du système.

**Les mots clés :** RNA, MVS, KNN , les moments de Hu, code postal, système de reconnaissance

