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Ministry of Higher Education and Scientific Research
University of Babylon
College of Science for Women
Department of Computer Science

Handwritten English Numbers Recognition Based on Machine Learning

A Project

Submitted to the Council of the College of Science for Women at University of Babylon in Partial Fulfillment of the Requirements for the Degree of High Diploma in Science\ Computer Science

Submitted by

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بسم الله الرحمن الرحيم

﴿ وَلَقَدْ آتَيْنَا دَاوُودَ وَسُلَيْمَانَ عِلْمًا وَقَالَا الْحَمْدُ لِلَّهِ الَّذِي فَضَّلَنَا عَلَى كَثِيرٍ مِنْ عِبَادِهِ الْمُؤْمِنِينَ ﴾

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Dedication

To "ALLAH" my Lord, my Creator, my Dependents and my Hope.

To the messenger who reached the valley of safety and advised the nation.

To the Prophet of mercy and the light of the worlds "Prophet Muhammad peace be upon him".

To my dear father, who taught me tender without waiting for someone who always prides me … asking "ALLAH" to extend in his life to witness my superiority and success after a long wait.

To my dear mother, her invitations are the secret of my success and her tenderness.

To my dear wife, support me and he was the secret of my success and to my child (Hussein).

To my brothers and sisters who supported me all the way.

To all members of my family and friends who have spared no effortin my encouragement and support.

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Abstract

Handwriting recognition is an important issue nowadays, where handwriting can be an image, document, etc., the ability of a computer to recognize handwritten numbers is very important in more than one application such as translation, reading and number recognition applications. The proposed project provides a system that recognizes handwritten English numbers, the input data being images downloaded from a global dataset. The proposed system consists of a several stages. The first stage is the preprocessing, which includes resizing of the images to be one size (28 * 28) pixel, and then (data mapping) is applied. As for the classification stage, it relied on the use of two algorithms, the KNN algorithm and the neural network (error backpropagation). To start the process of training the selected algorithm, the data was divided into two sets, the training and the test set. Two algorithms were used for the purpose of choosing the best of it, by evaluating their performance using a number of evaluation metrics. Accuracy and Precision were used for the purpose of evaluating the performance of the algorithms. The performance of the KNN algorithm was Accuracy=0.94 and Precision=0.942 respectively when k = 4. While the best performance reached by the neural network mechanism was 0.98673333 and 0.9698, respectively, at epoch = 15. The neural network (error backpropagation) is shows the best result in the recognition stage .

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List of Abbreviations	
ANN	Artificial Neural Networks
CNN	Convolutional Neural Network
HTR	Handwriting Recognition system
KNN	K-Nearest Neighbor
LSMT	Long Short Memory Term
ML	Machine Learning
MNIST	Modified National Institute of Standards and Technology database
NN	Neural Network
OCR	Optical Character Recognition

Chapter One

General Introduction

Chapter One

General Introduction

1.1 Introduction

A handwriting recognition system (HTR) refers to the capability of a computer to accept input handwriting from a source such as printed physical documents, images, or other devices. It can take direct input from the user through writing on a touch screen and then interpret it as text [1]. A text (digits) written by hand may be found in several images, including but not limited to handwritten notes, memoranda, whiteboards, medical records, historical documents, and stylus-entered text. As a result, a comprehensive OCR(Optical Character Recognition)system has to have the capability of identifying handwritten text contained inside photographs. This emphasizes the necessity for study into the development of large-scale handwriting recognition systems that are compatible with several scripts and languages. OCR(Optical Character Recognition) refers to the use of technology to distinguish between printed and printed also text characters that are contained in digital representations of physical documents, such as scanned paper documents. Examining the text on paper and converting it into a code that a computer can read is the fundamental step in the OCR process. This code may then be used for data processing. OCR is sometimes called text recognition [2]. Note modeling is the most challenging part of constructing an HTR system; collecting enough high-quality training data in adequate quantities is the most difficult part. Many offline handwritten text recognition (HTR) systems have moved their attention to line-level recognition methodologies in recent years. For feature extraction, these algorithms use a mix of convolutional neural networks (CNN) , Long Short-Term Memory (LSTM) and recurrent neural networks. These networks are learned using Connection Temporal Classification [3].

In a way similar to that of other domains, these data-driven learning systems learn features directly from the training data, as opposed to traditional approaches that depend on manually specified features. At the same time, these methods have led to significant improvements in the accuracy of handwriting recognition on public benchmarks. Due to the high expense and complexity of gathering and labelling a large corpus of handwritten training data consisting of line images, scaling these techniques to cover additional domains or languages may be challenging. Despite these challenges, these methods have led to significant improvements in handwriting recognition accuracy.[2]

The identification of objects is quickly becoming the most searched ability in the area of machine learning. Face recognition, handwriting recognition, and other similar applications are all instances of object recognition. All these things are possible with a huge data collection of image files. The image data collection in question will include positive and negative data about the domain above. Because of this, the algorithm can categorize the unknown data more accurately. The ability to recognize handwriting is a relatively technological development that will be valuable in the 21st century. It can serve as the foundational functionality for the development of new needs. A blind person, for instance, is unable to read the newspaper unless it is available in Braille format. In this scenario, we can instruct the algorithm to identify the characters in the newspaper, save the characters as text, and then transform the text to voice. This may make life a lot easier for blind individuals, assisting many of them. The translation of languages is a potential second use for hand-write recognition technology. When working with a language that is not their native tongue, the person should snap an image of the document and submit it to an algorithm that can recognize handwriting. The characters in an image may be identified by this method, which can turn them into a text.

Afterwards, the text may be transformed into the language of the reader's choosing.[4]

1.2 Statement of the Problem

Handwriting recognition is a complex issue that has been and still is of interest to researchers and to test a system that recognizes handwriting and obtains high accuracy in identifying letters and numbers.

1.3 The Objective of Project

This project designing and implementing an approach for handwritten image recognition that is more accurate and efficient. It can recognize the numbers written by hand.

1.4 Related Works

A research was conducted on handwriting recognition in various fields, this research dealt with a comparative study with the previous work of a group of researchers and clarification of the work of each researcher, where it was found:

In (2021),Li , Minghao *et.al* , mentioned in their image "Evaluation of the feature set for offline handwriting" that handwriting recognition depends on several features extracted from the word image and that these features can be removed in several ways, there is no method that has the advantage of the proposal over others. So they suggest that the work should be in a new framework based on cooperative preparation.[5]

In (2018), Sulaiman *et.al* worked on KNN and ANN-based Recognition of Handwritten Pashto Letters using Zoning Features the system for recognizing the handwritten Pashto characters, which is a challenging task because of its difference in shape and style and between different individuals, totaling 4,488 images from 102 distinct samples for each of the 44 letters in Pashto. Therefore, the system that

was presented will be put into place. This system classifies individual characters based on zoning and then applies K-Nearest Neighbor (KNN) and Neural Network (NN) classifiers. As a result, the presented approach will be put into action. While using KNN, an overall classification accuracy of roughly 70.05 per cent will be reached, while utilizing NN will achieve 72 per cent.[6]

In (2017),Puigcerver and Joan**,** maked use of the Local Binary Pattern in their study titled "Recognition of Handwriting Numbers Using Local Bimodal Variation and K-Nearest Neighbor Classification," in which they discuss the topic (LBP). As a result, the suggested system will be put into operation, serving as the primary technique for the extraction and classification of K-NN handwriting by using the C1 model recognition system that the UNHCR uses during the general elections in Indonesia. The outcome of the test reveals an LBP difference. 89.81% was achieved by recognizing the handwritten number character in the MNIST dataset, whereas the accuracy of 70.91% was conducted by using data from model C1. The primary objective here is to cut down on the number of characteristics while simultaneously maintaining or even improving the quality of the end output, while speeding up the classification process. The results demonstrate that Bayes was correct. The net classifier is the best available classifier, having a 100% correction rate across Time, Speed, Relationships and a FAR priority of 3.13%.[7]

In (2014), Singh and Lai , created a method for recognizing digits using a neural network classifier with a single layer and combined it with principal component analysis (PCA). The developed model cuts down on the number of characteristics to reduce the required computation and correctly classifies the digit into ten groups (0 to 9). The created system comprises a backward propagation (BP) neural network, which is then trained and evaluated on the MNIST dataset of handwritten digits. The suggested method successfully achieved a high accuracy level when

tested using the MNIST 10,000 dataset. They have taken into account not only the accuracy but also the amount of time needed for training, the amount of time required for recognition, and the memory needs for the whole process. In addition to this, they have discovered the digits that were incorrectly classified by the algorithm.[8]

In (2014), Khan, et.al ,Using the Sparse Representation Classifier, a system was provided for detecting handwritten Bangla digits. The classifier assumes a test sample may be represented as a linear mixture of training samples from its native class. As a consequence, a test sample may be represented using a dictionary constructed from train samples. It is feasible to classify the test sample using its sparsest linear representation in terms of this dictionary. This representation can be effectively calculated using l1-minimization and can be used in the classification process. They used a Sparse Representation Classifier to categories the Bangla numerals, which was applied to the image zone density. Image zone density is a statistical domain feature retrieved from the character image. This result indicates that additional research is needed since it is encouraging.[9]

In(2013), Akhtar and Qureshi ,worked on a novel approach for recognizing handwritten digits. Because the handwritten digits do not all have the same size, thickness, style, location, and orientation, it will be necessary to confront various problems to find a solution to the issue of handwritten digit recognition. The distinctness and diversity of each individual's writing style impact not only using the pattern but also look for the numbers. Utilizing is how the job of categorization is completed. Therefore, the presented system will be implemented, including the KNN and SVM classifiers. Based on the test data set, obtaining a high recognition rate of 97.04 per cent overall as possible. The methodology is validated by using the well-known MNIST data set.[10]

1.5 Project Organization

The remainder of the project is structured into four chapters, the contents of which are listed below :

- **Chapter Two: (Theoretical Background)**

  This chapter presents a theoretical background of Handing Writing.

- **Chapter Three: (Proposed System Design and Implementation)**

  This chapter presents a proposed method for Design and Implementation.

- **Chapter Four: (Experimental Work and Discussion of Results)**

  This chapter presents the description of the different experiments and discusses the results and evaluations obtained from the implementation of the proposed system.

- **Chapter Five: " Conclusions and Future Works"**, The conclusions and future works will be presented in this chapter.

Chapter Two

Theoretical Background

Chapter Two

Theoretical Background

2.1 Introduction

The capability of a digital device to accept handwriting from resources like printed physical documents, images, and other devices as input is known as handwriting recognition. Additionally, it can read handwriting directly from a touch screen and translate it into text. Nowadays, various tools, including smartphones, tablets, and PDAs that use touch screens and a stylus or finger, can accept handwriting as an input. This is advantageous since it enables the user to enter text and numbers into the devices quickly. These days, there are numerous uses for handwriting recognition. To recognize handwriting, numerous techniques have been devised. Optical Character Recognition is one of the techniques (OCR). OCR will translate the images into a format that a computer can work with and interpret the text from scanned documents.

2.2 An Overview of Handwriting Recognition

Handwriting has been affected by every advancement in computer and communication technology, including word processors, fax machines, and e-mail. The role of handwriting and handwritten texts has been adjusted and reinterpreted as a result of these in-variations. Despite these technological marvels, a pen and paper are considerably more practical than a computer or mouse. Handwriting-processing computers will need to be able to read messages written in various writing styles and languages and cope with arbitrary user-defined alphabets.[11]

Handwriting can be analyzed, recognized, and interpreted in various ways. The process of turning a language represented in its spatial form of graphical marks into a symbolic representation is known as handwriting recognition.[12] Handwriting interpretation is the act of determining the meaning of a handwritten

text, such as an address. Handwriting identification refers to the procedure wherein a single writer's handwriting sample is attributed to a specific individual from among a pool of possible authors. The goal of Processing is to identify the message by isolating variances in handwriting is called handwriting recognition or interpretation. Identification and verification, on the other hand, are procedures that establish the unique characteristics of a certain author's work. Reading handwriting is a task that demands specialized expertise. One of the numerous computer-related issues sought after and investigated is how photographs can be recognized and categorized. The process by which a human may identify an image. The method of image recognition is crucial to image processing [13].

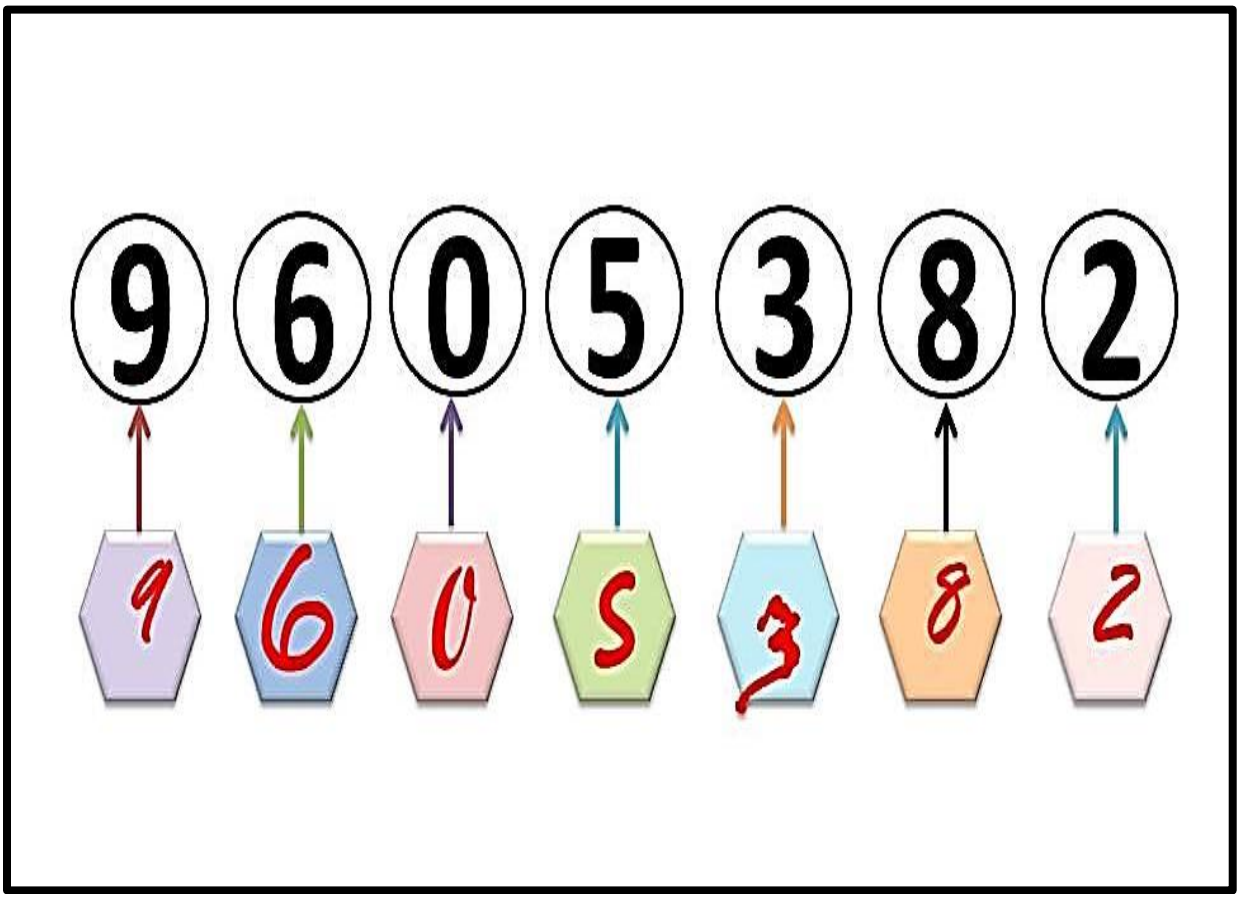


Figure (2.1): Handwriting Digits Recognition [13]

The process of recognizing the image in image recognition will be impacted by the angle of view, lighting, and clarity of the captured image [14]. One of the most

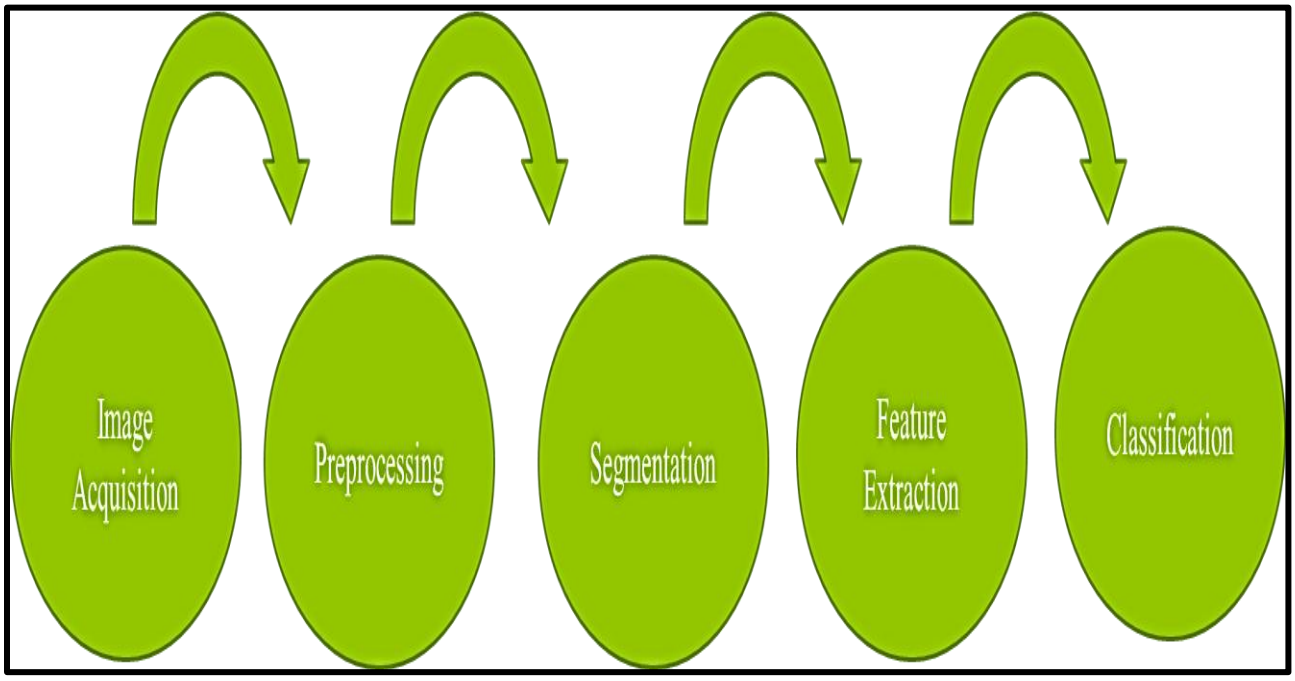
researched and sought-after topics is handwriting recognition since handwriting can help humans in tasks like post-exposure, bank check analysis, and handwritten form processing.

Every human should have a unique handwriting pattern, making image recognition for handwriting more difficult. In addition to not always being straight, handwriting occasionally has an upward and a downward slant, making it harder to recognize than computer writing, which already has a defined form [15]. There are unquestionably more variables involved in handwriting detection that might affect how well a handwriting is recognized. Because script is more likely to be misinterpreted than computer writing and is therefore more likely to have a set form, regardless of the type.

The most sought-after skill in machine learning now objects recognition. Face recognition, handwriting recognition, disease diagnosis, and other examples of object recognition are a few. All of these things are possible thanks to a sizable image data set. This image data set will include positive and negative information about that domain. This makes it easier for the algorithm to classify the unknown data. The 21st century will benefit from the new technology of handwriting recognition. It can serve as a foundational feature for the development of new requirements[15].

Processing a vast collection of paper documents, such as test scripts, is another use for handwriting recognition. The evaluation of the answer scripts can be done automatically with the aid of AI and hand-write recognition. Handwriting recognition serves as the basis case to be resolved for all of the aforementioned possibilities. One form of optical character recognition is the ability to recognize handwriting (OCR). OCR is the process of identifying text, whether printed or

written by hand. In OCR, the document is photographed as an image and then converted to the required format, such as a PDF. The character recognition algorithm is then given the file. In some situations, this can significantly reduce the amount of human interaction. Figure (1) refers to the Handwriting recognition stages[16].



Figure(2.2) : Handwriting Recognition Stages

The MNIST dataset (Modified National Institute of Standards and Technology database) [16] is a sizable collection of handwritten numbers that is frequently employed in the development of image processing systems [17] as well as other applications for training, learning, and testing in learning robots [18]. One of the most well-liked data sets in the machine deep learning areas is called MNIST. Approximate 10,000 experimental results and 60,000 images for training are both presented in the MNIST database [19].There are ten various sorts of MNIST metadata. A 28 by 28 matrices with a single pixel-specific value to each column can be used to depict images of handwritten digits.

Figure(2.3): Samples of the MNIST handwritten digits

The MNIST data, one of the most popular data used to identify handwritten numbers, is derived from the MNIST dataset, and has been created by [20].Numbers from NIST were downsized to 20 x 20 pixels and centered at 28 x 28-pixel bitmap by placing the center of gravity of the black pixel in the center of image 15.

2.3 Machine Learning

Machine learning (ML) is an AI subfield that helps computers make better predictions in the absence of explicit programming. Algorithms were trained by using machine learning that utilize existing data to make predictions about future outputs; common examples are recommended systems for online stores and search engines. They provide results that are similar to the ones entered into the search bar. There are several applications for machine learning software, such as fraud

detection, spam filtering algorithms, malware threat identification, corporate automation, and predictive maintenance.[21]

The first person to use the term machine learning in 1959 was Arthur Samuel[22]. Machine learning is an essential part of artificial intelligence, which is concerned with building and designing algorithms and mechanisms that give computers the ability to learn. It has many uses and is very important, as in the fields of medicine and engineering [23].In general, machine learning is inductive and useful learning, where it is possible to deduce and extract provisions, rules and principles of great importance from the data, where the machine learning method is close to big data mining . [24][25]

2.3.1 The Classifications of Machine Learning

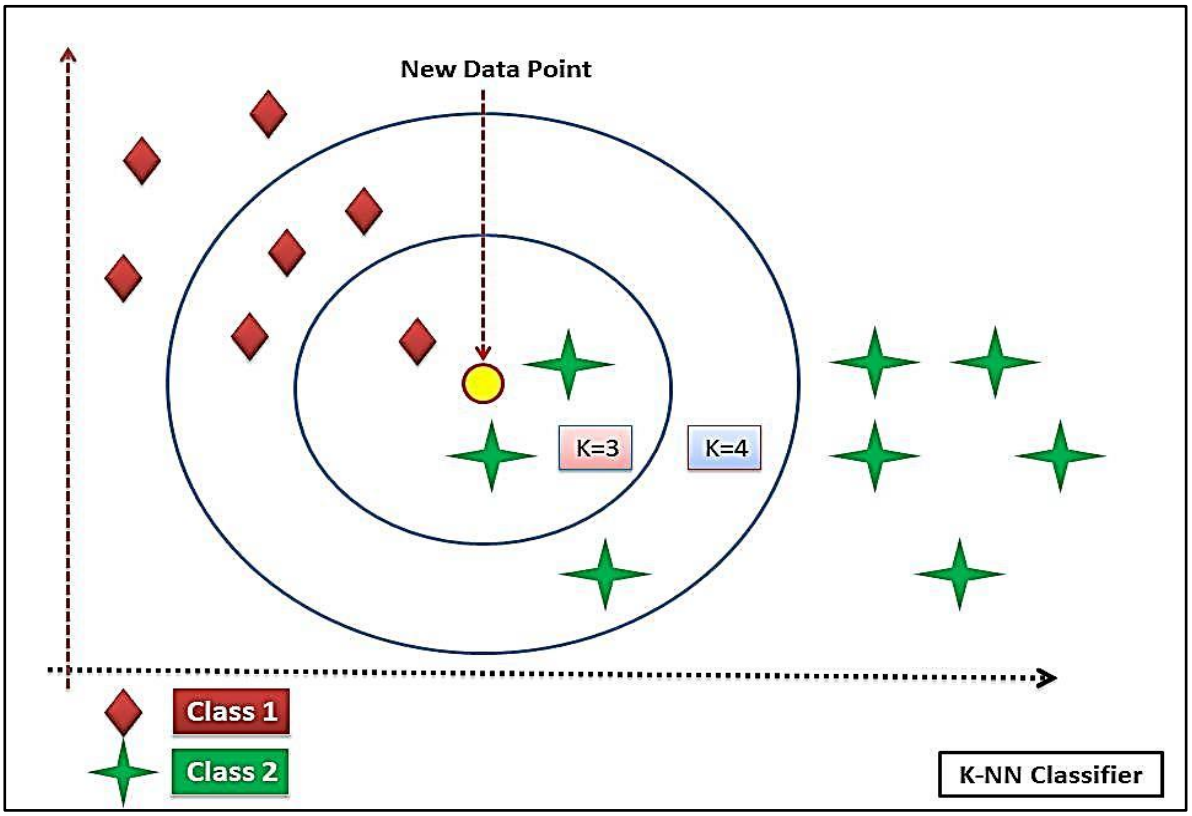
A. Supervised learning: Supervised learning Building is a mathematical model for a database that contains the desired inputs and outputs [26].

B. Unsupervised learning: Unsupervised learning algorithms are based on a set of databases that contain only the input. The algorithms learn from the test data as these algorithm depend on the commonalities between the data and reacts based on the presence or absence of such commonalities between the data. Its most prominent application is to find the probability density function[27].Semi-supervised learning is a special situation between unsupervised learning (without any labeled training data) and supervised learning (with fully labelled training data) like text document classifier .[28]

C. Reinforcement learning: Reinforcement learning uses dynamic programming techniques as it is concerned with how software agents take actions in an environment to maximize the idea of cumulative reward. Game theory, control theory, information theory, simulation-based optimization, multifactor systems, swarm intelligence, statistics, and genetic algorithms

are only few of the areas that have investigated this phenomenon. Artificial Intelligence Learning [29].

2.3.2 K-Nearest Neighbor(KNN)



Figure(2.4): KNN Classifier

Classifying instances based on the class of their nearest neighbors is a very straightforward concept: instances are grouped according to the class of their nearest neighbors. k-Nearest Neighbor (K-NN) Classification is more often known as k-Nearest Neighbor (K-NN) Classification since it is usually advantageous to consider more than one neighbor. It is sometimes called Memory-Based Classification since the training samples must be accessible at runtime, i.e. in memory. Because it is delayed until runtime, induction is considered a method of Lazy Learning. Classification is sometimes known as example-based classification

or case-based classification since it is purely reliant on training instances. Because it is a non-parametric classification method, the K-Nearest Neighbors (KNN) technique makes no assumptions about the basic dataset. It is recognized for its effectiveness and ease of use. It is a supervised learning algorithm. To estimate the category of the unlabeled data, a labeled training set containing data points separated into many groups is supplied.

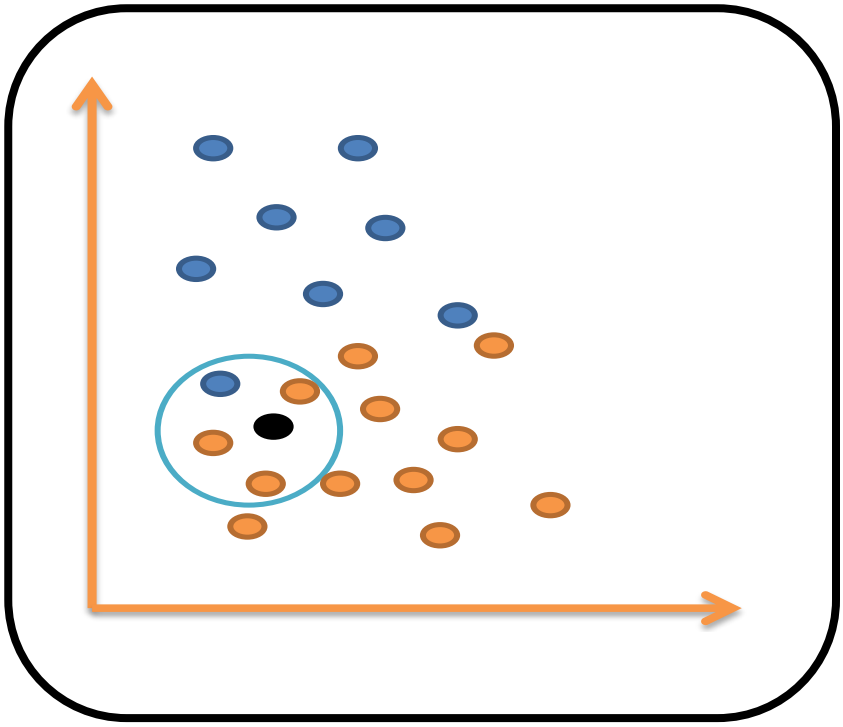
In classification, several criteria are employed to determine the dataset's category. KNN is often deployed as a classifier. It classifies data based on neighboring training examples in a particular region. This method is used owing to its rapid calculation and user-friendliness. Using the Euclidean distance, it calculates its nearest neighbors when working with continuous data. An input pattern's K closest neighbors are calculated, and the majority of nearby data decide the classification for the new input. Despite the simplicity of this classifier, the value of 'K' is essential for recognizing the unlabeled data. There are countless methods to choose "K" values, however we can simply run the classifier multiple times with different values to find which yields the best results. Due to the fact that all calculations are performed when categorizing the training data as opposed to when the data comes in the dataset, the computational complexity is somewhat increased. Lazily, the learning algorithm just stores and memorizes the training data while the dataset is being trained, rather than using the dataset. On the training dataset, there is no generalization. Consequently, the whole training basic dataset is required during the testing phase[30]. In regression, KNN anticipates continuous values. The average of the values of this value's K nearest neighbors constitutes this value. A classification algorithm is KNN. Generally speaking, classification involves two steps:

1. A classifier is built by using the training data in the first learning step.

2. A classifier evaluation.

When classifying fresh, labeled data, the closest neighbor method is used to determine what categories the data's neighbors belong to. The KNN algorithm relies on this concept throughout its computation. The KNN method lets us categorize the known tuple by fixing a certain value of K.

KNN carries out the following two processes whenever a new unlabeled tuple is discovered in the dataset: The K nearest neighbors, or the K points closest to the new data point, are examined first. Second, KNN chooses the class through which the new data must be classified using its neighbors' classes.



Figure(2.5): Neighbors' Classes

It classifies the data appropriately whenever new data is provided. It works better with a set of data that is roughly divided into groups and located in a specific area of the datagram. As a result, this algorithm provides a clearer, more accurate manner of classifying the data inputs. KNN determines the class with the most

significant number of points closest to the classification-required data point. Therefore, it is necessary to determine the Euclidean distance between the test sample and the chosen training samples[31].After collecting them, we receive a portion of the K-Nearest Neighbors to determine the training example's class. The value of K, the Euclidean distance, and the normalization of the parameters are the variables that impact KNN performance.

2.4 Neural Network

Artificial Neural Networks (ANNs), commonly called neural networks (NNs) or, neural networks, are a system inspired by the biological neural networks that make up the brain [32].An artificial neural network is a mimic of the biological brain's neurons since it is composed of groups of linked nodes called artificial neurons. Any synaptic connection is capable of transmitting a signal to another cell. The synthetic neuron is capable of receiving and processing the signal. It is feasible to calculate the output of every neuron by applying a nonlinear function to the sum of its inputs. Edges are another name for connections. One kind of artificial intelligence is called a neural network, which trains computers how to process data in a manner similar to how the brain does it. Deep learning is A subset of machine learning, which is based on artificial neural networks, sometimes known as neurons, interconnected in a layered structure akin to the human brain. This method of machine learning is sometimes referred to as neural networks. Develops an adaptive method that computers may use to gain knowledge from past errors and enhance their performance over time[33]. Therefore, artificial neural networks tackle complicated tasks, such as accurately summarizing papers or identifying people in a crowd. The study of organic nerve systems formed the foundation for the creation of artificial neural networks, one of the many applications of artificial intelligence. The term "artificial neural networks" refer to

the fact that these networks have communication units that are placed inside themselves. Any additional method for these data that does not need a suggested model. Therefore, artificial neural networks have garnered the interest of a large number of researchers and scientists due to their greater adaptability in comparison to the mathematical methods used in the learning process of the data model and information storage and transmission in artificial neural networks[34].

2.4.1 Methods for Recognizing Images Artificial Neural Network (ANN)

In most situations, neurons and edges have a particular weight that adjusts themselves according to the learning level. When linked, the intensity of the signal determines whether or not there is an increase or reduction in weight. Neurons have a threshold, and the signal will only be delivered if it is strong enough to overcome the neuron's threshold. Neurons will be collected in layers.[35]

The design of artificial neural networks was similar to the design of the human brain. Neurons are a huge amount of cells that make up the human brain. It includes the neurons of the cell body in which the processing of information takes place by entering it to and from the brain (inputs and outputs). [36]

Neural systems process data for learning, conditioning, and knowledge. The most important factor for this idea is building new information structures. The architecture of the artificial neural network.

ANN systems are highly complex to give more complex and 'read' properties and analysis of complex models for data classification and forecasting. Deep learning is a branch of machine learning that focuses on the sequential learning of "Layers" of representations with increasing significance while also learning models from data. This is done in the context of deep learning.[37]

Artificial Neural Networks, often known as ANNs, are computer programs that replicate the structure and operations of the human brain. Deep learning can carry out a large number of arithmetic operations, and it can carry out many manipulations, giving it access to many learning opportunities. More than three layers of cells make up a neural network (including the input and output layers).Models referred to as "neural networks," which are structured literally, are responsible for carrying out the process of learning representations. Stacked or stacked-up layers that are put over one another.[38]

This may be accomplished by increasing the number of hidden layers as well as the number of neurons that make up each hidden layer. Counting many layers of neurons, which represent progressively more complicated systems, takes significant time and effort.[39]

2.4.2 Back propagation Neural Network

Network is the simplest method used for supervised training in neural networks. It is multi-layered and widely used, It works to adjust the values of weights and approximate the relationship between inputs and outputs and has special predictive capabilities [40].

2.4.3 Backpropagation Concept

This name was given because of the similarity of the mechanism of its access to real information, and the knowledge of the imbalance in the mechanism of work of neural networks in the body that works to transfer information by way of backpropagation towards the original source of the emergence of information because the reverse movement will lead to the truth.[41]

Backpropagation

Step #1 : input values of learning rate(μ) , Emax ,Max epoch ,moment rate($\propto$)

Step #2: Enetwork = $\emptyset$

Step #3: Compute hidden neuro activity by sigmoid function

$$hk = f(\sum_{i=1}^{ns} si \,.\, vi\ k) \qquad (2.1)$$

Step #4: Compute output neuro activity by sigmoid function

$$Oj = f(\sum_{k=1}^{nh} hk \,.\, Wkj) \qquad (2.2)$$

Step #5: Compute error of output neuros :

$$Sj = (dj - Oj)\bar{f}(nctj) \qquad (2.3)$$

Where:

$$\bar{f}(nctj) = Oj(1 - Oj)$$

Step #6: Compute error of hidden neuros:

$$Sk = \sum_{j=1}^{n0}(Sj \,.\, Wkj)\overline{f}(nctk) \qquad (2.4)$$

Where:

$$\bar{f}(nctk) = hk.(1 - hk)$$

Step #7: Adjust weight between hidden and output layer

$$\Delta Wkj^{(t+1)} = \propto \Delta Wkj^{(t)} + \mu \,.\, Sj.hk \qquad (2.5)$$

Step #8 : Adjust weight between input layer and hidden layer

$$\Delta Vik^{(t+1)} = \propto \Delta Vik^{(t)} + \mu \,.\, Sk.Si \qquad (2.6)$$

Step #9: Increase number of pattern by one

If does not reach max number of training patterns

Then return to Step 3

Else go to Step 10

Step #10:Compute MSE of network

$$MSE = \frac{1}{2}\sum_{p=1}^{p}\sum_{j=1}^{n0}(d^p j - o^p j)^2 \qquad (2.7)$$

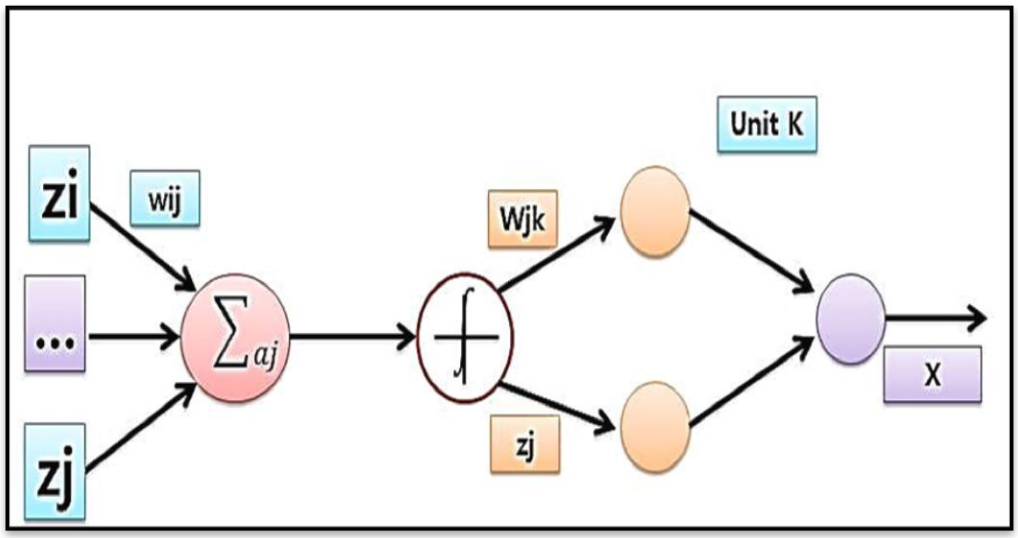
Step #11 : Test the stopping condition of the network to determine if success in their work or not

2.4.4 Backpropagation Algorithm

As it ever was, defining an error function concerning which the efficiency of the MLP is to be evaluated is required to ascertain the method by which an MLP can be taught. To assess the dataset D = (Xn, Yn), where n = 1,..., M, can employ the prediction error.

$$W = \frac{1}{2}\sum_{n=1}^{n}(Y(Xn) - Yn)^2 \qquad (2.8)$$

For simplicity, we are still addressing the scenario where the network has a single output, denoted by y', although vector outputs can easily be accommodated using the same logic.



Figure(2.6): Simple Network

We again use a gradient descent strategy to reduce the error ∑, in which weights in the network, w, are modified according to the procedure.

$$W = \sum_{i=1}^{n=j} w \ \nabla w \ \eta - w \qquad (2.9)$$

Here $\nabla_w \varepsilon(w)$ stands for the error function's gradient concerning the network's weights. The backpropagation technique makes it possible to propagate

input data backwards in the network in a straightforward and effective manner, enabling iterative updates of the weights from the input to the output. We begin by expressing the error function thus, from which we can deduce the backpropagation training algorithm.

$$En(\mathbf{w}) = 1/2\ y\hat{}(\mathbf{x}n) - yn)^2 \qquad (2.10)$$

The update rule can be used in place of the perceptron to incrementally change the weights by using one data point at a time.

$$\mathbf{W} \quad \mathbf{w} - \eta \quad {}_{w}En(\mathbf{w}): \quad \leftarrow \nabla \qquad (2.11)$$

The gradient $\nabla_w E$ still has to be determined (w). Now let's concentrate on one specific unit in the network, let's say unit j, and identify the elements of ${}_{w}E_{n}(w)$ containing the derivatives of En(w) about the weights of unit j, wij.

To adjust the weights and calculate the error rate ,When the value of k is relatively good, which represents the amount of actual activation of the output nodes, the expected output is tk, so the difference between the real output and the expected output is made by [42]:

$$\Delta \boldsymbol{k} = \boldsymbol{tk} - \boldsymbol{Ok} \qquad (2.12)$$

Backpropagation Algorithm

1- Show the main parameter of it .

2-How can update the weights (input – hidden ,hidden – output) .

3- How can compute the error .

4- Activation function used on it .

5- The states of the network success in training.

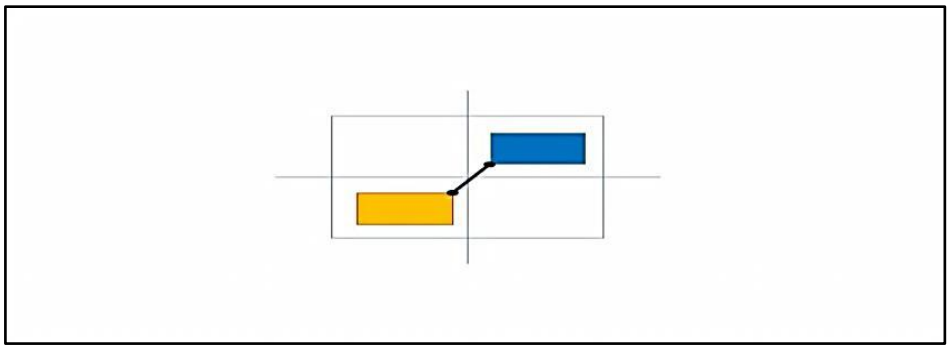
6- The states of the network fail in training.

2.5 Distance Measures

2.5.1 Euclidean distance

The normal distance between two points which can be measured using a ruler and which can be proved using the Pythagorean theorem. Distance is the sum of the squared distance between two points under the square root, Where n number of samples:

$$d(\mathrm{x},\mathrm{y}) = \sqrt{\sum_{i=1}^{n}(xi - yi)2} \qquad (2.13)$$

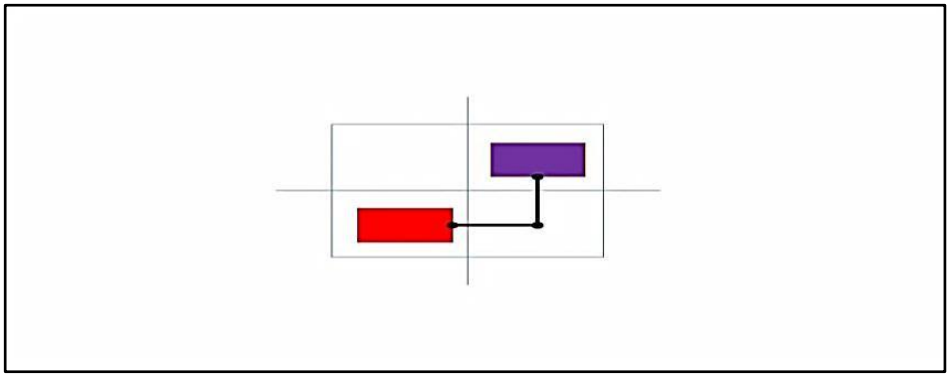


Figure(2.7): Euclidean distance

2.5.2 Manhattan Distance

Euclidean distance is the shortest distance between two points in multidimensional space. The distance between two points is the sum of the absolute differences in the Cartesian coordinates:

$$\mathrm{d} = \sum_{i=1}^{n}|xi - yi| \qquad (2.14)$$

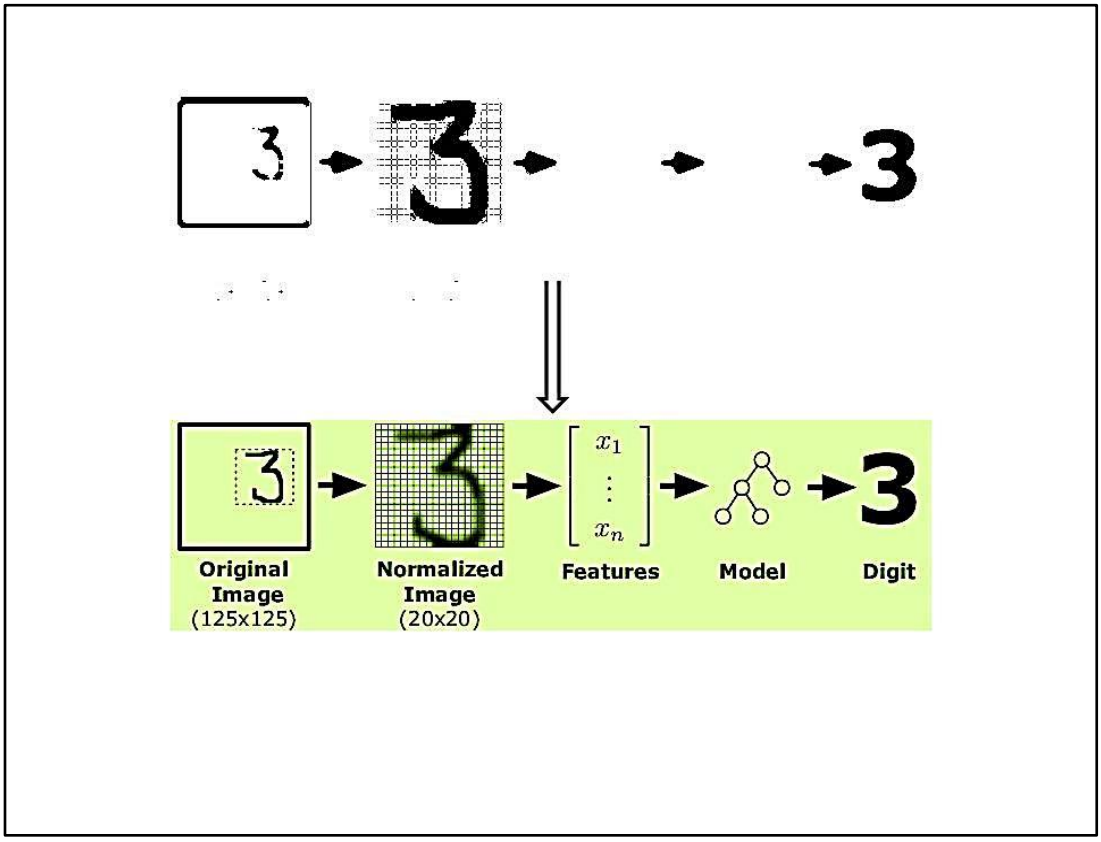


Figure(2.8): Manhattan Distance

2.6 Object Property

The ideal situation is to select k based on the data; in general, greater values of k lessen the impact of noise on classification, [43] but obscure class borders. As a result, several methods can be used to select the good k, and the nearest neighbor algorithm uses the nearest training sample (when k = 1).

When there are irrelevant features or if the feature metrics don't match significance, the k-NN algorithm's accuracy may suffer. The accuracy of the k-NN algorithm may degrade when there are irrelevant features or the feature metrics don't match significance. It is advantageous to pick the odd number k. The bootstrap method is one of the often-used techniques for determining the best and empirically best k .[44]



Figure(2.9): Image Highlight

2.7 Components of handwriting recognition systems

Handwriting recognition systems use pattern matching to convert handwritten digits into matching text or computer commands. Batch recognition of handwritten forms is included in mainstream form sorting and processing systems.

2.7.1 Pre-processing

Preprocessing is a set of procedures applied to the scanned input image to enhance its quality and enable successful feature extraction. Pre-processing includes the following key steps:

- **Noise reduction**

  Noise reduction is the process of removing noise from a signal. Noise reduction techniques exist for audio and images. Noise reduction algorithms may distort the signal to some degree .

- **Binarization**

  Binarization is the process of transforming data features of any entity into vectors of binary numbers to make classifier algorithms more efficient.

- **Morphological Procedures**

  Morphological Procedures is the process by which a word is adjusted to conform to a certain context. To put it simply, it is the process of changing the form and function of a word to fit a context, sometimes to the extent of changing the meaning and/or grammatical function .

- **Normalization of Size**

During the process of acquiring an image, noise is added. It causes an unpredictable variation in image brightness and can occasionally be seen as image grains. The technique of removing or reducing noise from the image is known as noise removal. For the removal and reduction of noise, there are numerous

algorithms and filters. Document images can contain a variety of noises, including uniform noise, gamma noise and pepper noise. Several types of filtering techniques, such as the Gaussian and Min-Max filters approach, are used to eliminate noise. Noise from salt and pepper is eliminated using a median filter. With the aid of those holding, color or grayscale images are converted into binary images through binary. The binary techniques include Otsu's method, global thresholding, local thresholding, adaptive those holding, etc. Preprocessing also employs morphological techniques. Common morphological operations that affect character size in images include dilation and erosion. Dilation is the pixel-wise enlargement of character boundaries. Erosion is the gradual disappearance of pixels around a character's outline. To "skeletonize" an image of text is to reduce it to a representation using just one pixel. The method of normalization is used to narrow the range of pixel intensity values found in an image. The preprocessing technique known as size normalization enlarges the character image to a standard size. The preprocessing of character images also includes skew detection and rectification. The image is given skew during document scanning. Skew angle is the angle made by the image's text lines for their horizontal axis. Before processing, skew detection seeks to align an image's text. The Hough transform method and the projection profile approach are two frequently employed skew removal strategies.

- **Segmentation**

The segmentation method separates each number from the image of a handwritten character. Implicit and explicit segmentation are the two types of segmentation. While words are directly predicted using implicit segmentation which does not break them down into individual letters words are broken down into individual characters using explicit segmentation. Several methods may be used in the segmentation process, including threshold-based, edge-based, region-

based, clustering, and others. The many stages of segmentation include line segmentation, word segmentation, and character segmentation. Line segmentation is accomplished by the use of the horizontal projection profile approach. It identifies the breaks in continuity between the lines. The process of segmenting words involves applying the vertical projection profile method to the lines that have been split. Finally, connected component labelling isolates the characters from these words.

- **Feature Extraction**

Because the technique that involves the extraction of features is the most significant and decisive one, the precision of the classification is dependent on the quality of the extracted features. The following are the three primary categories that are used to classify feature extraction methods:

a) Statistical characteristics.
b) The growth of the Series and global change
c) Architectural Elements.

As a statistical distribution of points, statistical characteristics reflect the character image. Statistical feature extraction employs several approaches, including zoning, crossing and distance computations, projections, etc. In addition to the Fourier transform, Gabor transforms, Wavelets, Moments, and the Karhunen-Loeve Expansion are used in the global transformation and series expansion procedures. The character's geometrical and topological traits serve as the foundation for the character's structural characteristics. In our designs, structural elements include loops, curves, lines, T-points, crossings, aspect ratios, strokes and their orientations, and deflection between two or more points.

- **Classification**

The decision-making component of any recognition system is classification. Analyzed are various classification strategies used by character recognition systems. The most often used classifiers are the Support Vector Machine (SVM) classifier, the Artificial Neural Network classifier, and the Nearest Neighbor classifier. After comparing the input vector with the previously stored pattern, the classifiers output the best match. Character recognition can be successfully applied using a variety of pattern classification techniques. The classification algorithms used by handwritten character recognition systems may be categorized as statistical methods, ANN structural approaches, or multiple classifier methods. Each of these categories is broken further into subcategories. For a single recognition system, the input feature vectors for statistical methods, ANN, and SVM should have the same dimension. The classification outcomes of various classifiers are merged in multiple classifier methods to rank the classes.

2.8 Evaluation Measures

Evaluation measures helps us to estimate how well our model is trained and it is important to pick a matric that matches overall goal for the system. There are some command evaluation measures include confusion matrix , Precision and accuracy .Therefor, we must be know:

- There are basic definitions must be know:

  - Positive : The label / class/ category of interest .

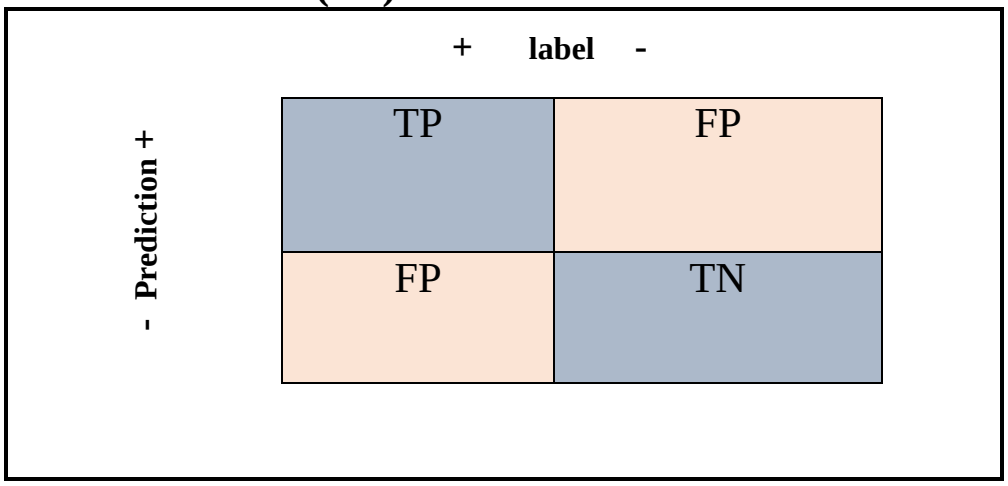
  - Negative : Not the label we are looking for .

    - True Positive (TP) : predicted positive , actually positive .
    - False positive (FP) : predicted positive , actually false.
    - True Negative (TN) :predicted Negative , actually Negative .
    - False Negative (FN) :predicted Negative , actually positive .

2.8.1 Confusion Matrix

The confusion matrix, also called (error matrix) ,It is a summary table used to evaluate the performance of the classification model, i.e. a table used to describe the performance of model that contains a set of data whose true values are known [45]. As shown in the following table:

Table (2.1): Confusion Matrix



2.8.2 Accuracy (A)

Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations . As a result, the goal of accuracy is make the fewest number of mistakes[45]. The accuracy is calculated as follow :

$$\text{Accuracy} = TP + TN / TP + TN + FP + FN \qquad (2.15)$$

$$\text{Accuracy} = \frac{\text{number of classified correct}}{number\ of\ samples} \qquad (2.16)$$

Accuracy is calculated by dividing the number of samples subject to correct classification by the total number of samples[45].

2.8.3 Precision (P)

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations . As a result, the goal of precision is minimize mistakes in guessing positive labels[45] .The precision is calculated as follow :

$$\text{Precision} = TP / TP + FP . \quad (2.17)$$

Chapter Three

Proposed System Design and Implementation

Chapter Three

Proposed System Design and Implementation

3.1 Introduction

The use of mobile phones, cameras and social networking sites is the hallmark of this era. The camera has become the most used device daily. Recognizing handwriting images is a necessity to use this type of image in translation, correspondence, reading image messages, and others.

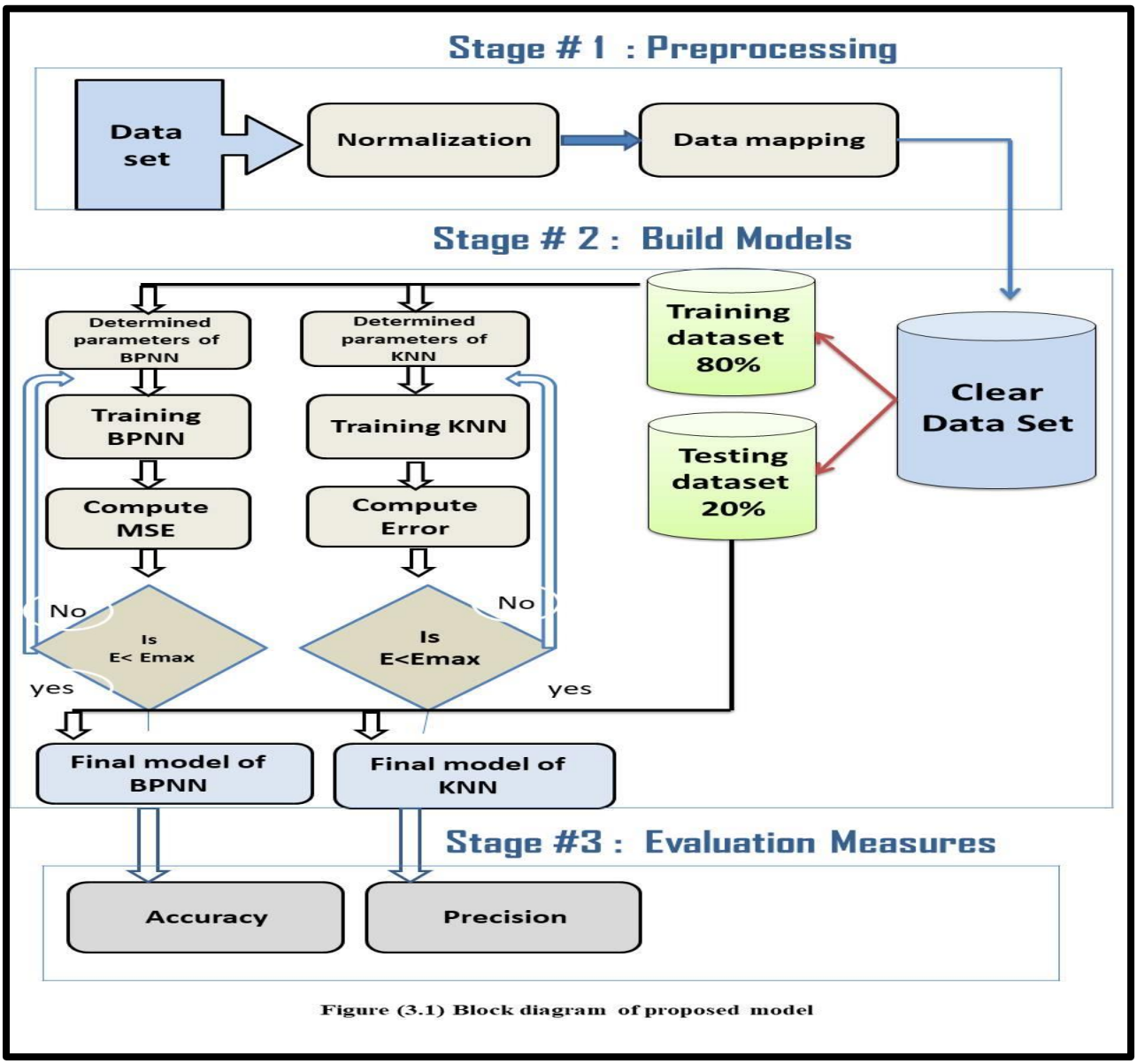


Figure (3.1) Block diagram of proposed model

The third chapter provides an in-depth analysis of how the proposed system for recognizing handwriting in images works, and the below figure (3.1) represents a proposed model.

3.2 The Suggested System

The Suggested system includes a set of steps that will be clarified in the following paragraphs:

3.2.1 Data Acquisition

In order to construct the MNIST database, binary representations of handwritten integers taken from MNIST's Dataset 3 and other were used. The suggested system's handwriting recognition method relied on this dataset to function. A training set and a test set were created from this data in order to assess the efficacy of the algorithms' training procedure. Listed below are some representative images from the dataset utilized by the proposed model.

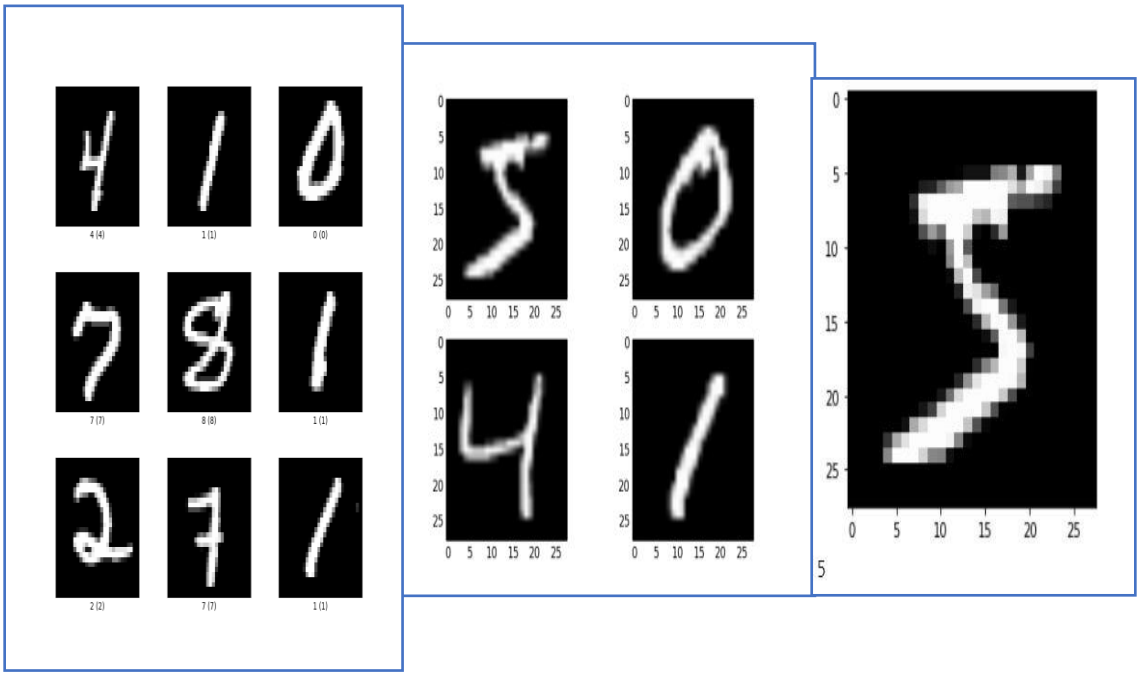


Figure (3.2): Samples of Dataset

3.2.2 Preprocessing

Preprocessing is very necessary on the data set to prepare it for the primary processing, which is the classification process. The pre-processing is done on handwriting images by normalizing the dataset pixel.

Data Mapping

The MNIST dataset contains grayscale images, and the range of values for each pixel in those images is between 0 and 255, including both boundary values. To convert the pixel values to a scale from 0.0 to 1.0, we multiply them by 0.99 / 255 and then added 0.01. Because of this, the 0 values don't get counted as inputs, which means they don't have the potential to prohibit weight updates using the procedure below.

Algorithm 3.1: Data Mapping

Input: Input Image .

Output: Mapping Image .

Begin

Step1:read input image that is grayscale and its pixels are (0- 255).

Step 2: applying the Formula

$$Map.value = (X*(0.99/255) + 0.01) \quad (3.1)$$

End

End Data Mapping

3.2.3 Classification

In the classification stage, two algorithms will be applied to identify handwriting images, which are ANN and KNN, where the images will be entered after mapping for values. Algorithms' starting points are two sets of data: the

training set and the test set. The data was divided by (80%-20%), where 80% of the data will be dedicated to the training phase, while the testing phase of the model will be 20%.

3.2.3.1 K-Nearest Neighbor

K-NN, algorithm is considered to be one of the more straightforward approaches to machine learning. Despite its apparent simplicity, it has shown to be highly useful in resolving numerous classification and regression issues, including those in the fields of image analysis and character recognition.

The key idea behind the nearest neighbor classification approach is identifying a subset regard training samples which consider most similar to a modern instance which been classed. These adjacent samples will be used to establish the label for the newly generated sample. The number of neighbors to be discovered in k-nearest neighbor classifiers is a user-defined parameter that is kept constant. Another kind is the method for discovering neighbors based on a radius. These methods take into account all samples within a certain radius; therefore, the number of neighbors varies depending on the local density of points. The distance may be measured in any metric system; however, the traditional Euclidean distance is the one most often employed. Since they simply "remember" all of their training data, techniques based on neighbors are known as non-generalizing methods in machine learning. Neighbors of the mystery sample may vote on how to categorize it, and chosen by majority vote.

Algorithm 3.2: K-Nearest Neighbor

Input : MNSIT Dataset.

Output : Recognition English number handwritten

Initialization : K=0 .

Step #1 : For i=1 to Tns // Tns = Total Number of Sample in Dataset

Step #2 : Compute Euclidence Distance as equation ($d(\mathrm{x},\mathrm{y}) = \sqrt{\sum_{i=1}^{n}(xi - yi)2}$) .

Step #3 : Sort Samples based on values of distance .

Step #4 : Take a first k of rows of the saved array.

Step #5 : Identify the dominant class in the row.

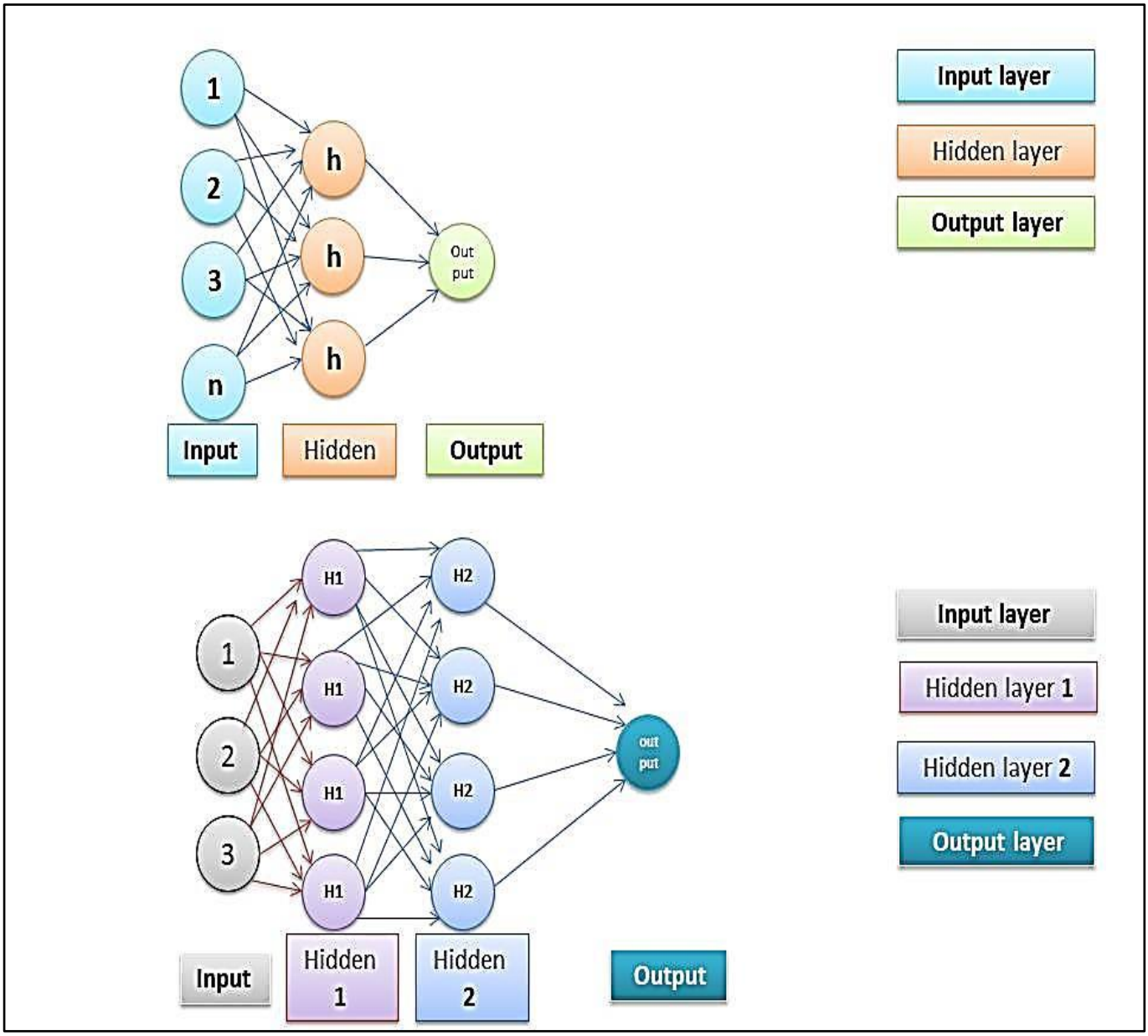
Step #6: Provide the expected class.

End K-Nearest Neighbor

3.2.3.2 Error Backpropagation of the Neural Networks

A backpropagation neural, which a feedforward neural with several layers and has a significant user base, is by a significant margin the neural network that has the most extensive use. In addition, supervised training of multilayer neural networks is both one of the most straightforward ways and one of the most flexible methods. Backpropagation only succeeds when weight values are set inward. It is possible to make it even more general so that it can function well with data that wasn't included in the training set (predictive abilities).

Training and testing are the two stages that will typically make up a Backpropagation network.



Figure(3.3): Simple Neural Network and Deep Learning Neural Network

When training a network, it is "shown" (or fed) a number of examples of inputs and their corresponding classifications.

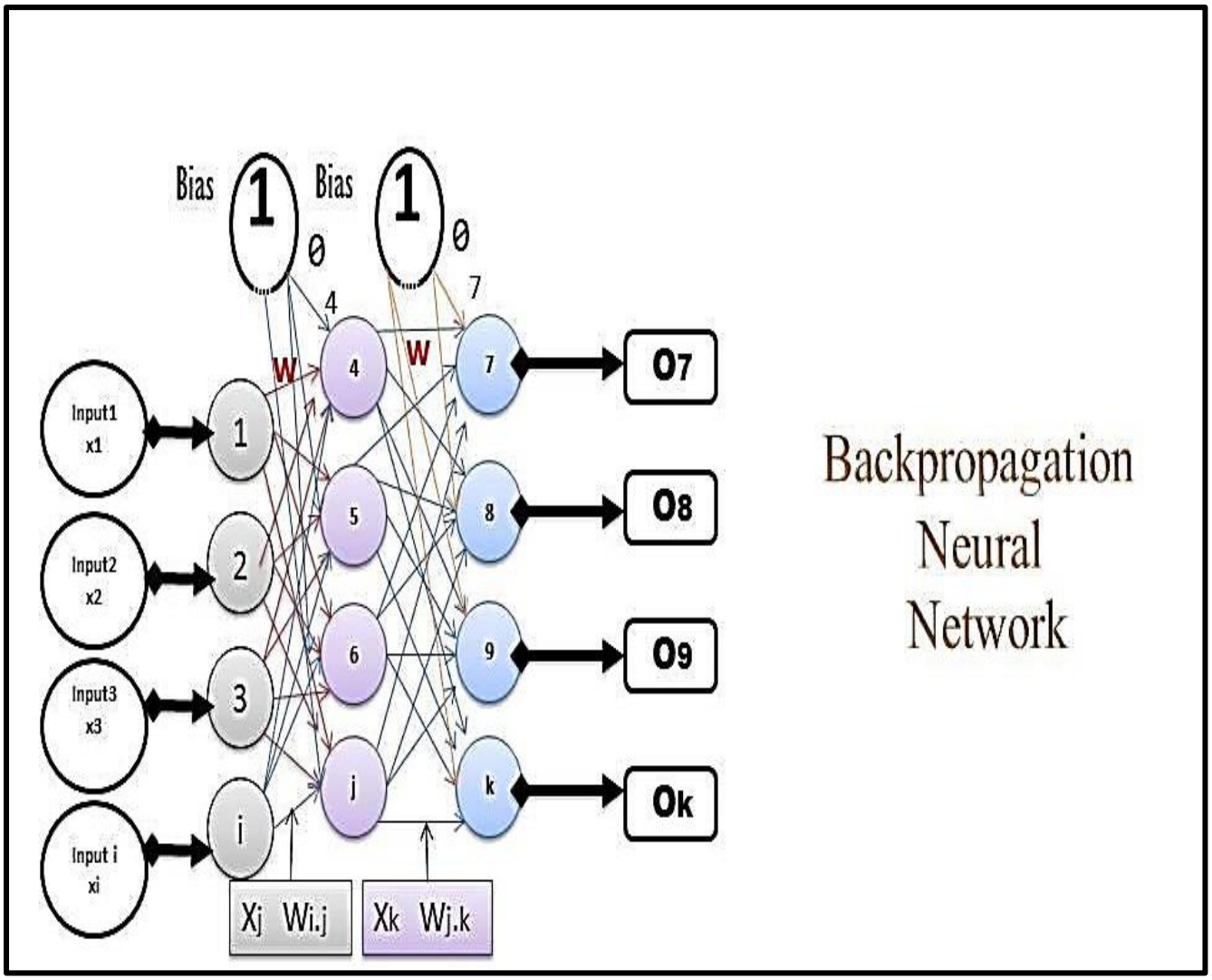


Figure (3.4): Backpropagation Neural Network

Training and testing are the two processes that generally make up the Backpropagation network. During the training phase of the process, the network is "shown" several examples of inputs as well as the appropriate classifications. The Backpropagation algorithm will be described in the following :

Algorithm 3.3: Backpropagation Neural Network

Input : MNIST Dataset; L;

Output: Recognition English number, handwritten ;

Assign all network inputs and output

Initialize all weights with small random numbers, typically between -1 and 1

repeat

for every pattern in the training set Present the pattern to the network

// Propagated the input forward through the network:

for each layer in the network

for every node in the layer

1. Calculate the weight sum of the inputs to the node

2. Add the threshold to the sum

3. Calculate the activation for the node

end

end

// Propagate the errors backward through the network

for every node in the output layer

calculate the error signal

end

for all hidden layers

for every node in the layer

1. Calculate the node's signal error

2. Update each node's weight in the network

end

end

// Calculate Global Error

Calculate the Error Function

end

while ((maximum number of iterations < than specified) AND

(Error Function is > than specified))21.End of Backpropagation

End BPNN

3.5 System Evaluation

The performance of the two algorithms will be evaluated using different metrics to compare their performance. Therefore will be used for evaluation:

1- The accuracy of our model's predictions gives us an overall image of how much we can depend on those predictions. This measure does not consider the differences between different error classifications and types.

2- Precision, sometimes called the Positive Predictive Value (PPV), is the proportion of correct predictions to all correct predictions made by a model. It's useful for datasets when the distribution is abnormally turn or unequal. The falser positives the model makes, the less accurate it will be.

3- A confusion matrix, also known as an error matrix, is a table that compares the actual classifications in a test set to the predictions made by a model. The table can be used to determine the types of errors being made and the number predictions made by the model. This matrix describes how well a classification model performed on test data for which the actual values were already known. It is a matrix with the dimensions n by n, where n is the total number of classes. After generating predictions based on the tested data, one may produce this matrix.

Chapter Four

Experimental Work and Discussion of Results

Chapter Four

Experimental Work and Discussion of Results

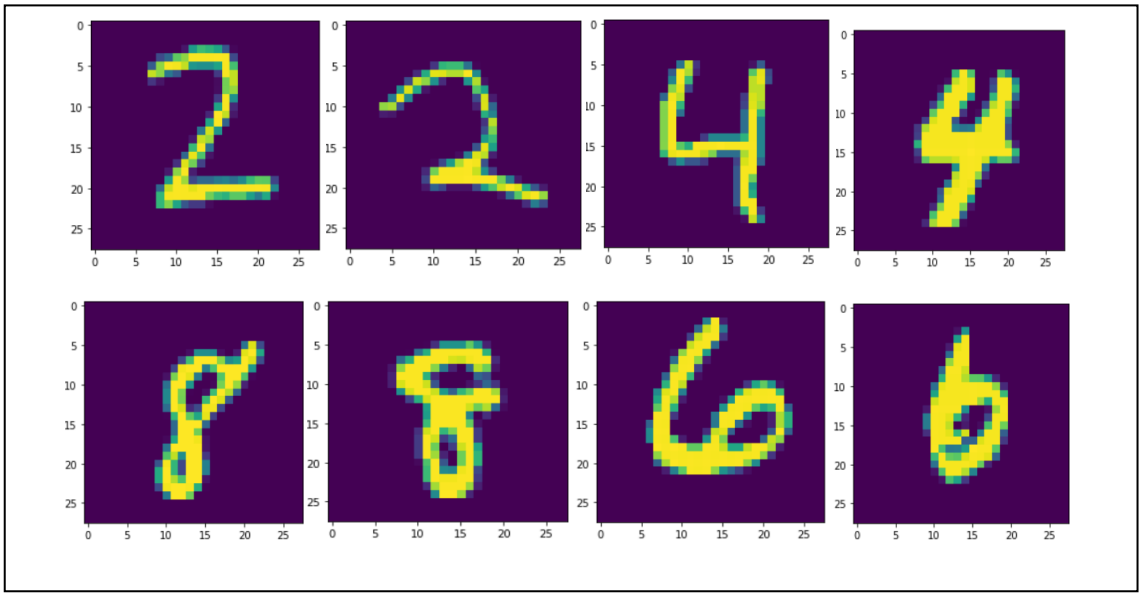
4.1 Introduction

This chapter discusses the experimental work and results. Python 3 have been used to simulate the suggested system. The proposed systems are used to categories handwritten pictures.

4.2 Dataset

Follow the link "http://yann.lecun.com/exdb/mnist/" to get entry to the MNIST handwritten digit database. There are a total of 60,000 instances for training and 10,000 for testing in the database. From the MNIST, you may get a sample of a larger collection. The image is now centered on the specified number sizes. The source aspect ratio of black and white (binary-level) MNIST images has been preserved as it has been reduced to fit a 20 x 20 pixel square.

The anti-aliasing method that the normalization algorithm employs produces images with greyscale levels as a consequence of the algorithm's usage of it. By determining the center of gravity of the pixels and then translating the image, we were able to center the images inside a 28x28 area. This allowed the images to be shown in the exact same location in each of the 28x28 areas—figure (4.1) samples from the dataset.



Figuer (4.1):Samples from dataset

There must be a balance with many of examples for any class that must be close or equal so that the training process for any model is successful and there are no high differences in the number of instances, which leads to shortcomings in the process of the training. The following figure refers to many examples in Classes in the dataset.

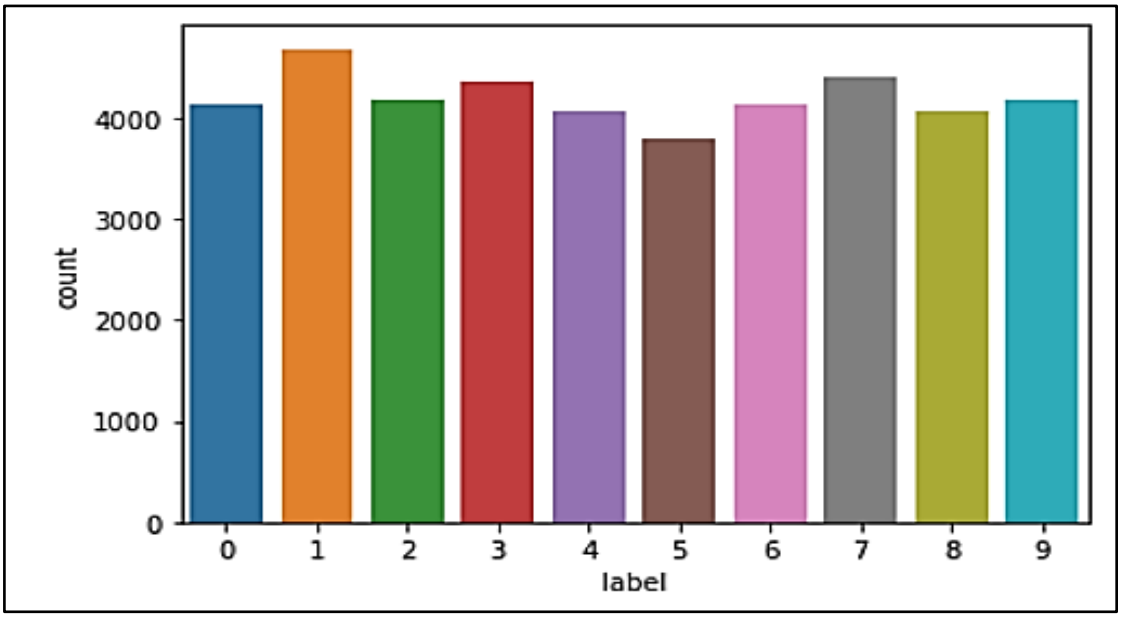


Figure (4.2) :Visualizing Many Classes in Dataset

4.3 Pre-processing (Data Mapping)

The stage of pre-processing include the image pixel values were matched according to equation (3.1), which converts the pixel values in the image according to the period [0.01, 1], and this step is essential for preparing the data in a way that suits the inputs required in the classification stage. Figure (4.3) shows the pixels of the image after the mapping stage.

```
[[0.01 0.01 0.01 ... 0.01 0.01 0.01]
 [0.01 0.01 0.01 ... 0.01 0.01 0.01]
 [0.01 0.01 0.01 ... 0.01 0.01 0.01]
 ...
 [0.01 0.01 0.01 ... 0.01 0.01 0.01]
 [0.01 0.01 0.01 ... 0.01 0.01 0.01]
 [0.01 0.01 0.01 ... 0.01 0.01 0.01]]
```

Figure (4.3): Pixels of Image after Mapping Stage

The following figure shows the representation of the label for each class in the form of a diagonal matrix.

```
label:  0  representation as diagonal matrix.:  [1 0 0 0 0 0 0 0 0 0]
label:  1  representation as diagonal matrix.:  [0 1 0 0 0 0 0 0 0 0]
label:  2  representation as diagonal matrix.:  [0 0 1 0 0 0 0 0 0 0]
label:  3  representation as diagonal matrix.:  [0 0 0 1 0 0 0 0 0 0]
label:  4  representation as diagonal matrix.:  [0 0 0 0 1 0 0 0 0 0]
label:  5  representation as diagonal matrix.:  [0 0 0 0 0 1 0 0 0 0]
label:  6  representation as diagonal matrix.:  [0 0 0 0 0 0 1 0 0 0]
label:  7  representation as diagonal matrix.:  [0 0 0 0 0 0 0 1 0 0]
label:  8  representation as diagonal matrix.:  [0 0 0 0 0 0 0 0 1 0]
label:  9  representation as diagonal matrix.:  [0 0 0 0 0 0 0 0 0 1]
```

Figure (4.4): Labels Representation as a Diagonal Matrix

4.4 Classification

The proposed system performs the process of classifying handwriting. Recognizing and classifying handwriting images is essential in many applications, such as writing recognition, text translation, text correction and other electronic applications. In the proposed system, identification or classification was carried out after the initial processing using KNN and BPNN. The training process of the two models was carried out after performing the method of segmenting the data set as follows:

- Splitting dataset

  The dataset was divided into two sets. The first group represents the training set, which was 60,000 instants, and the test set was 10,000 instants, as the total sum of the dataset was 70,000 instants.

4.4.1 K Neighbor Classifier

A sample that has to be categorized is the basis for the K neighbors Classifier, which considers the sample's k closest neighbors. The user chooses an integer value for the variable denoted by the letter k. This is the classifier used most of the time by both algorithms. To find out the best or optimal value of "K", the principle of "trial and error" will be applied by applying the model with a set of trials and comparison on the accuracy that is calculated after applying KNN models with different "K" values. By plotting the precision with the number of K values in the graph, it is possible to find out the differences and choose the best value for K .

The performance of the KNN model is shown in Figure (4.5) with various values for "K." Since the high value of model accuracy was "0.94", the "4" parameter value is the one that provides the best results.

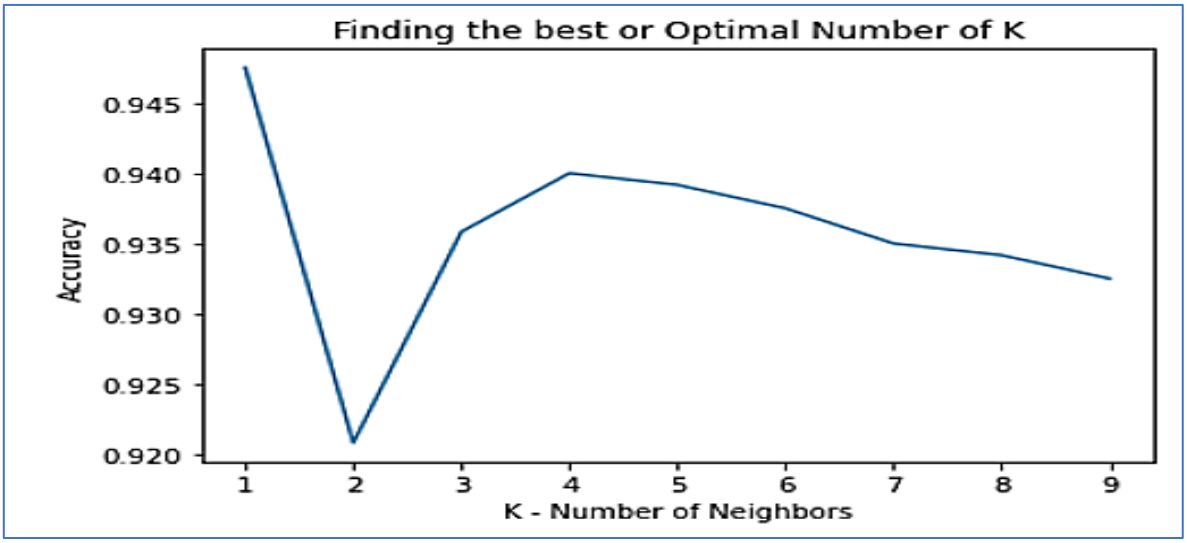


Figure (4.5) : K Value and Accuracy of Model

The following table represents a comparison between the precision and accuracy values with the change in the importance of the number of neighbors (K), where the best value for accuracy and precision appears when the value of (k) is 4.

Table (4.1) :Values of K, Accuracy and Precision

K	Accuracy	Precision
1	0.9475	0.948
2	0.9208333	0.925
3	0.9358333	0.938
4	0.94	0.942
5	0.9391666	0.942
6	0.9375	0.940
7	0.935	0.938
8	0.9341666	0.937
9	0.9325	0.936

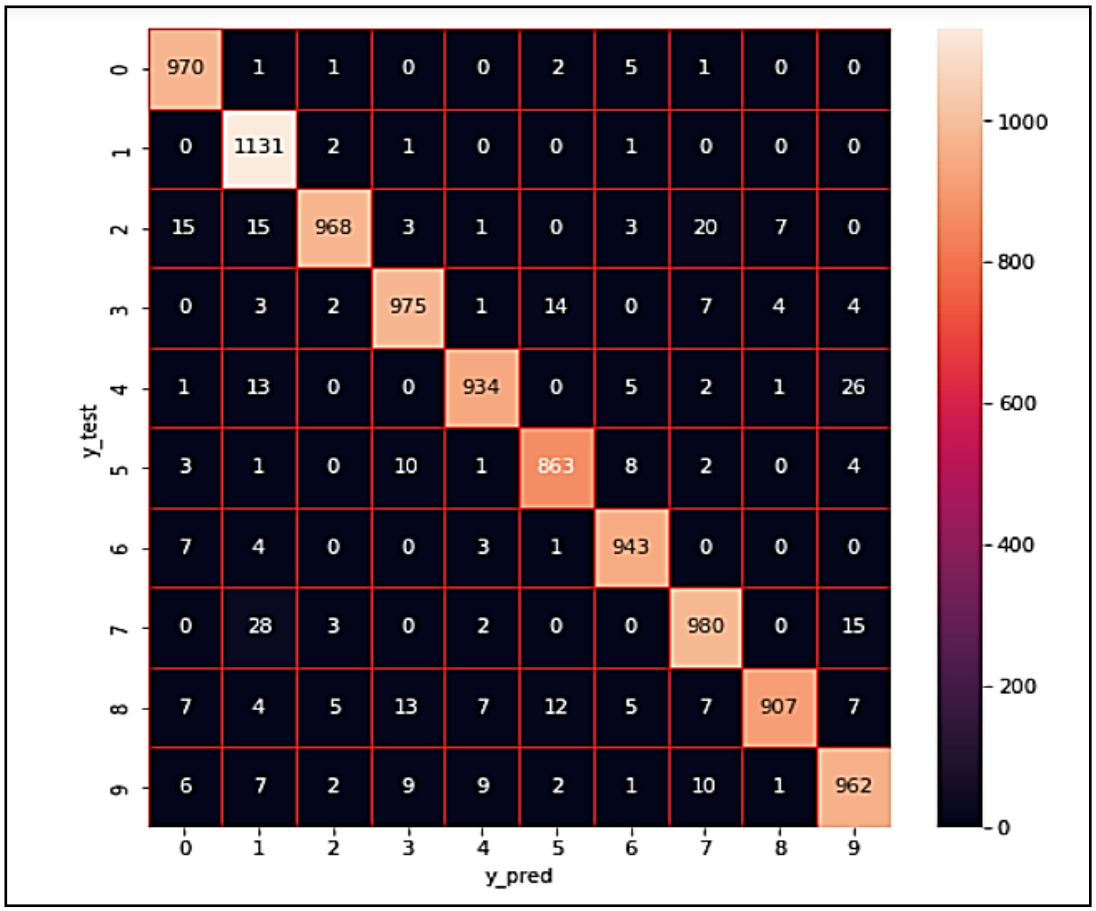


Figure (4.6) : Confusion Matrix

Confusion is a matrix that is represented in the following form. It represents the testing phase of the model and its final results when the accuracy is (94) in the training phase, but in the testing phase, it is (96). The confusion matrix represents the performance of the final model. Figure(4.6) displays the confusion matrix that was used .

4.4.2 Backpropagation Classifier

The size of the image input to the neural network with dimensions (28, 28), meaning that the input layer represents (784) neurons, one hidden layer was chosen to make the classification process more accurate, and the output layer was only (10) with the various classes in the data set. Many epochs were chosen on the rule of “trial and error” to obtain the model's highest accuracy. The training process

searches for optimal or better weights to obtain the highest accuracy. After getting the highest accuracy in the training phase, the network weights are stored and the test set is entered, representing 10% of the total data.

Table (4.2) Epoch, Accuracy and Precision

Epoch	Accuracy	Precision
2	0.934	0.933
3	0.952	0.947
5	0.968	0.962
7	0.974	0.964
10	0.981	0.969
15	0.986	0.969

Figure (4.7) represents the epoch number with the model's accuracy where that optimal number of epochs is 15, and the accuracy reached to 0.986. This means accuracy of the model is increased when the no. Epoch is increased.

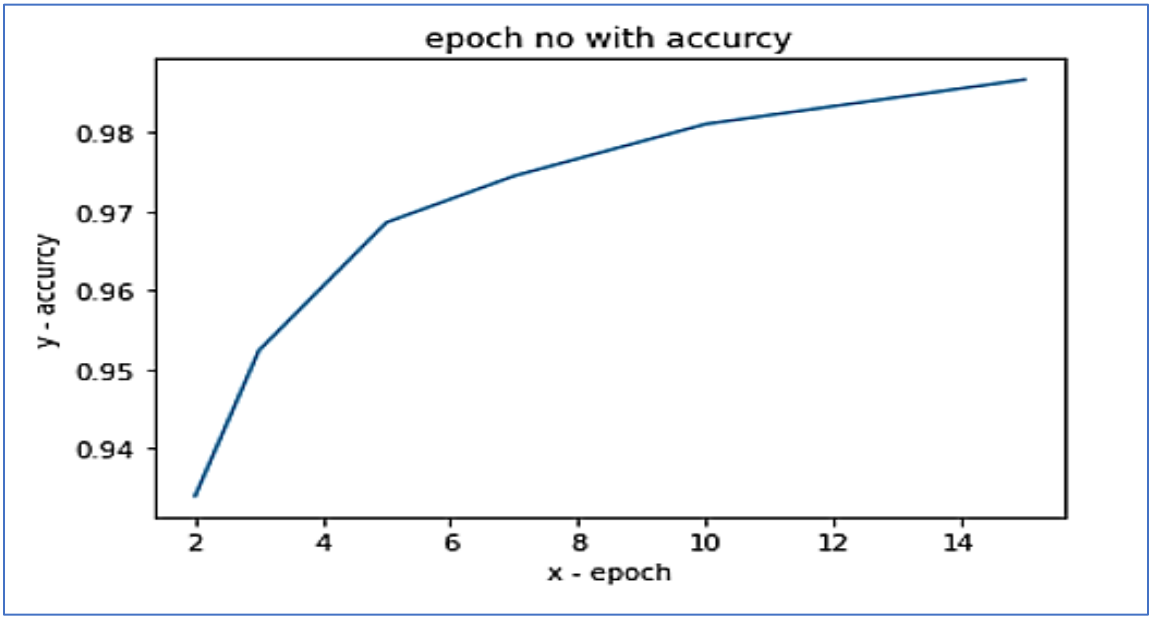


Figure (4.7): Represents epoch number with accuracy

When the epoch was 2, the confusion matrix of the model's performance is shown in figure (4.8), and the accuracy was found to be 0.93401666**.**

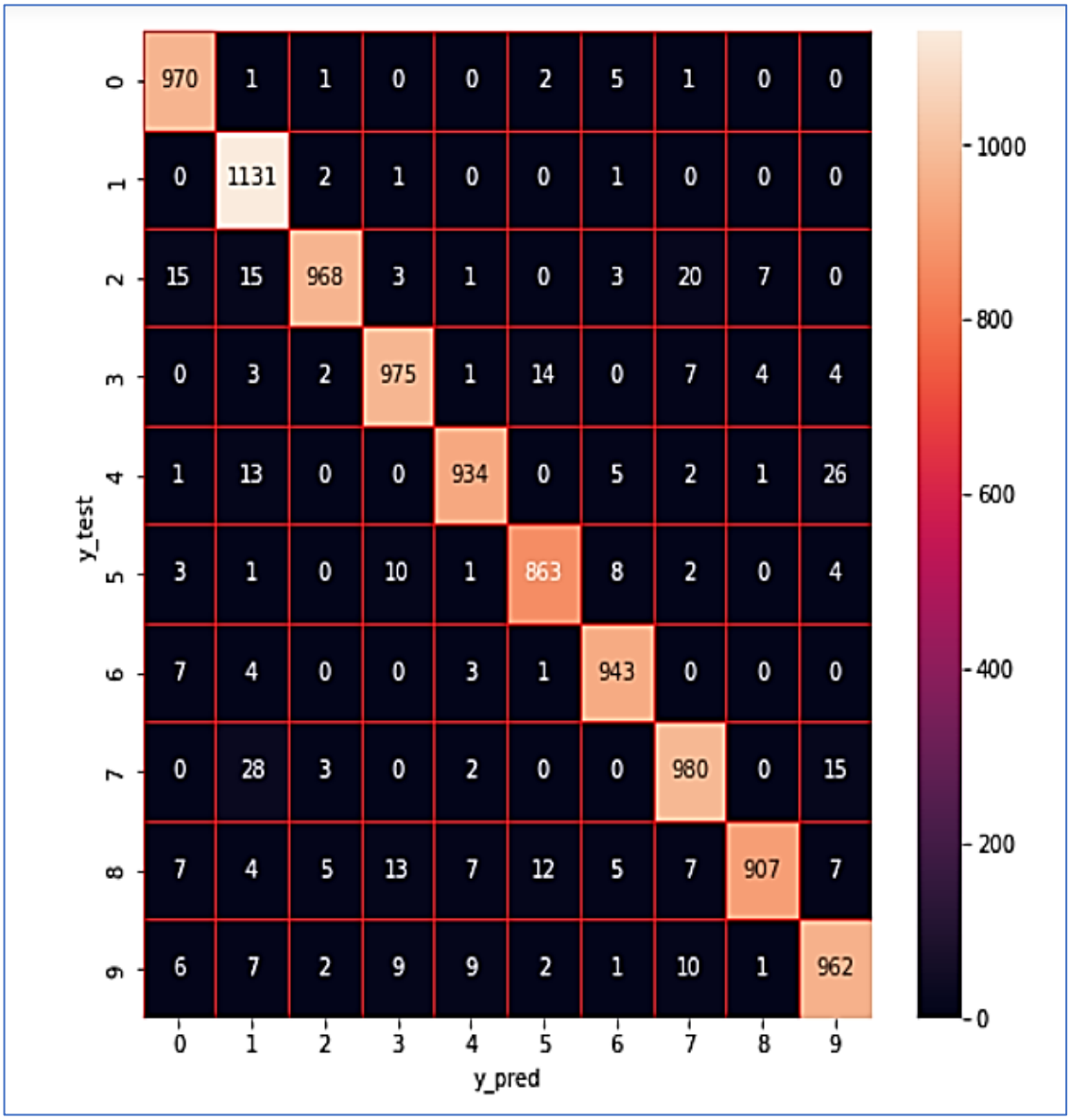


Figure (4.8): Confusion Matrix with Epoch=2, Accuracy=0.934

The confusion matrix of the model's performance at the time when the epoch was three and the accuracy was 0.95243333 ,It is explained in the figure (4.9) .

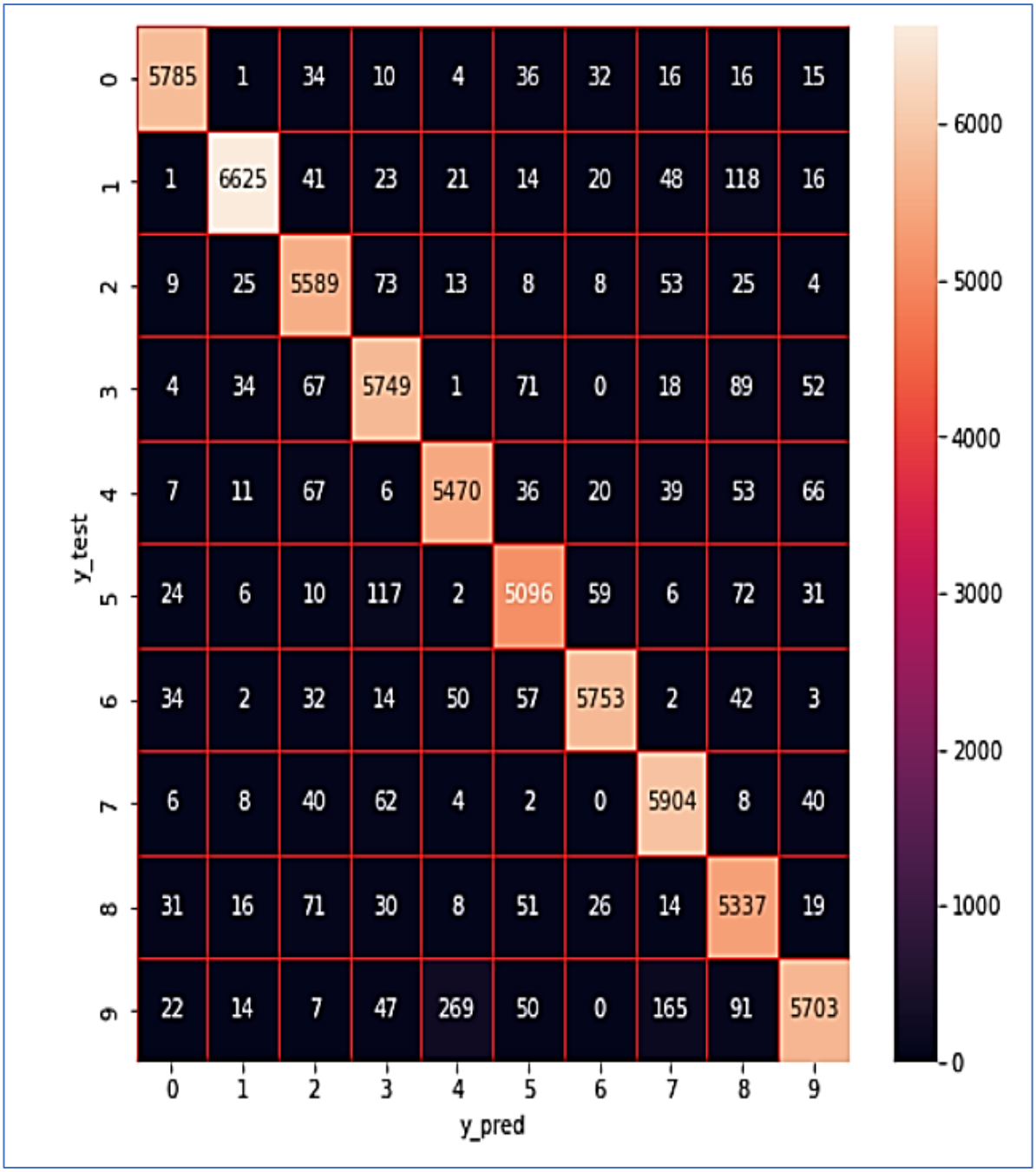


Figure (4.9): With Epoch=3, Accuracy=0.952

The confusion matrix of the model's performance at the time when the epoch was five and the accuracy was 0.96865555 ,It is explained in the figure (4.10).

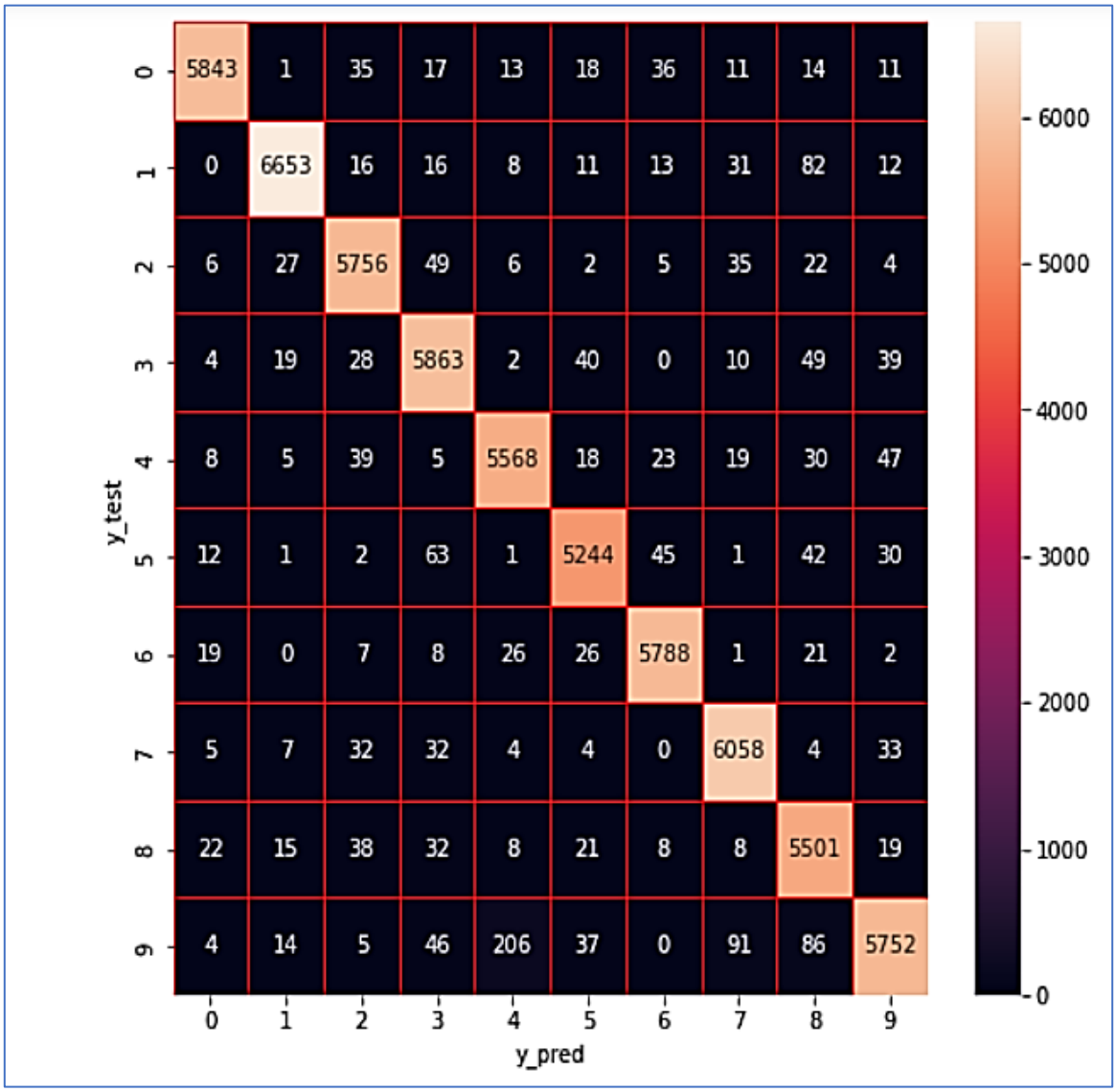


Figure (4.10) : With Epoch=5, Accuracy=0.968

The confusion matrix of the model's performance at the time when the epoch was s even and the accuracy was 0.97453333 ,It is explained in the figure (4.11).

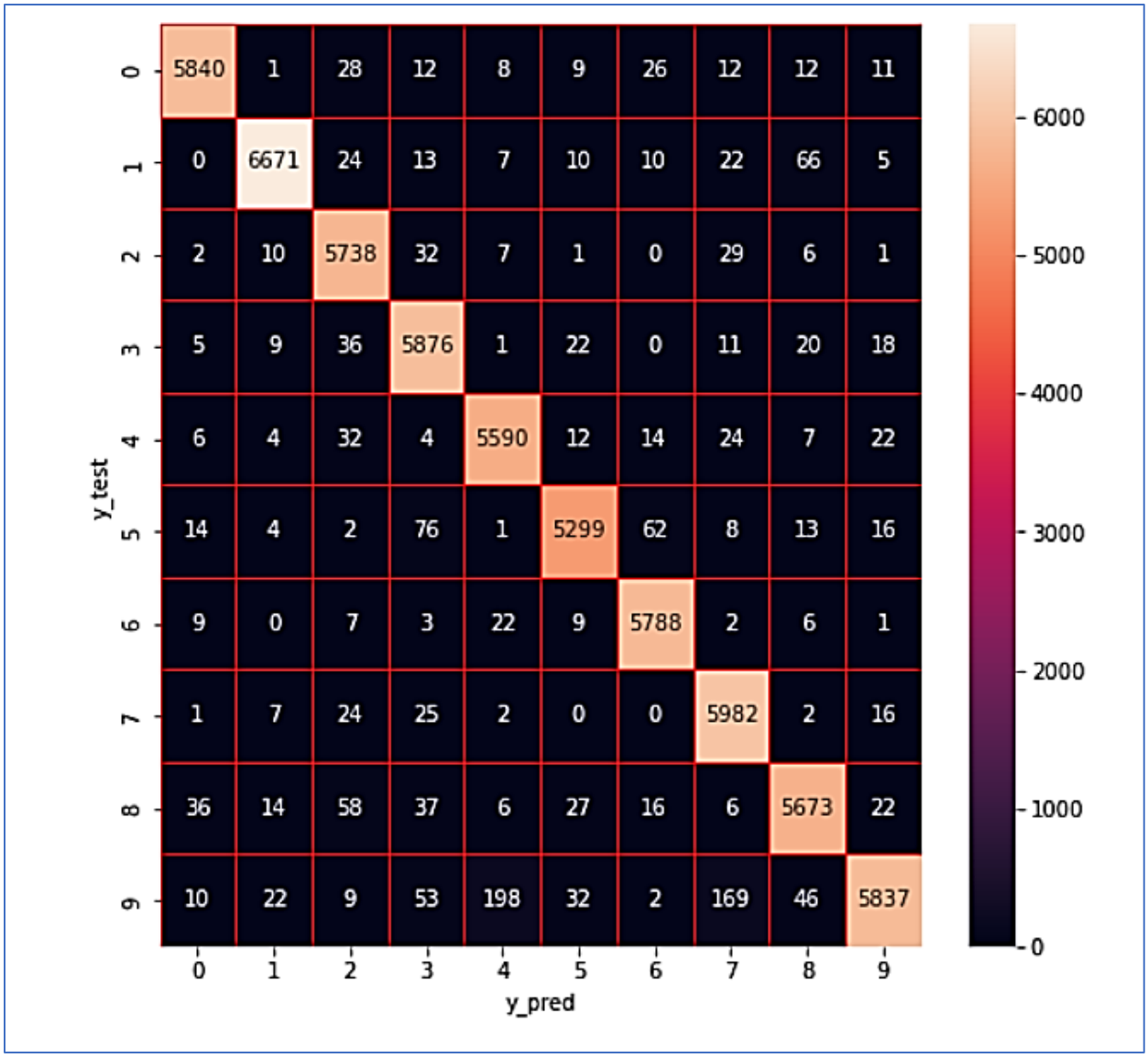


Figure (4.11) : With Epoch=7, Accuracy=0.974

The confusion matrix of the model's performance at the time when the epoch was 10 and the accuracy was 0.98111111, It is explained in the figure (4.12).

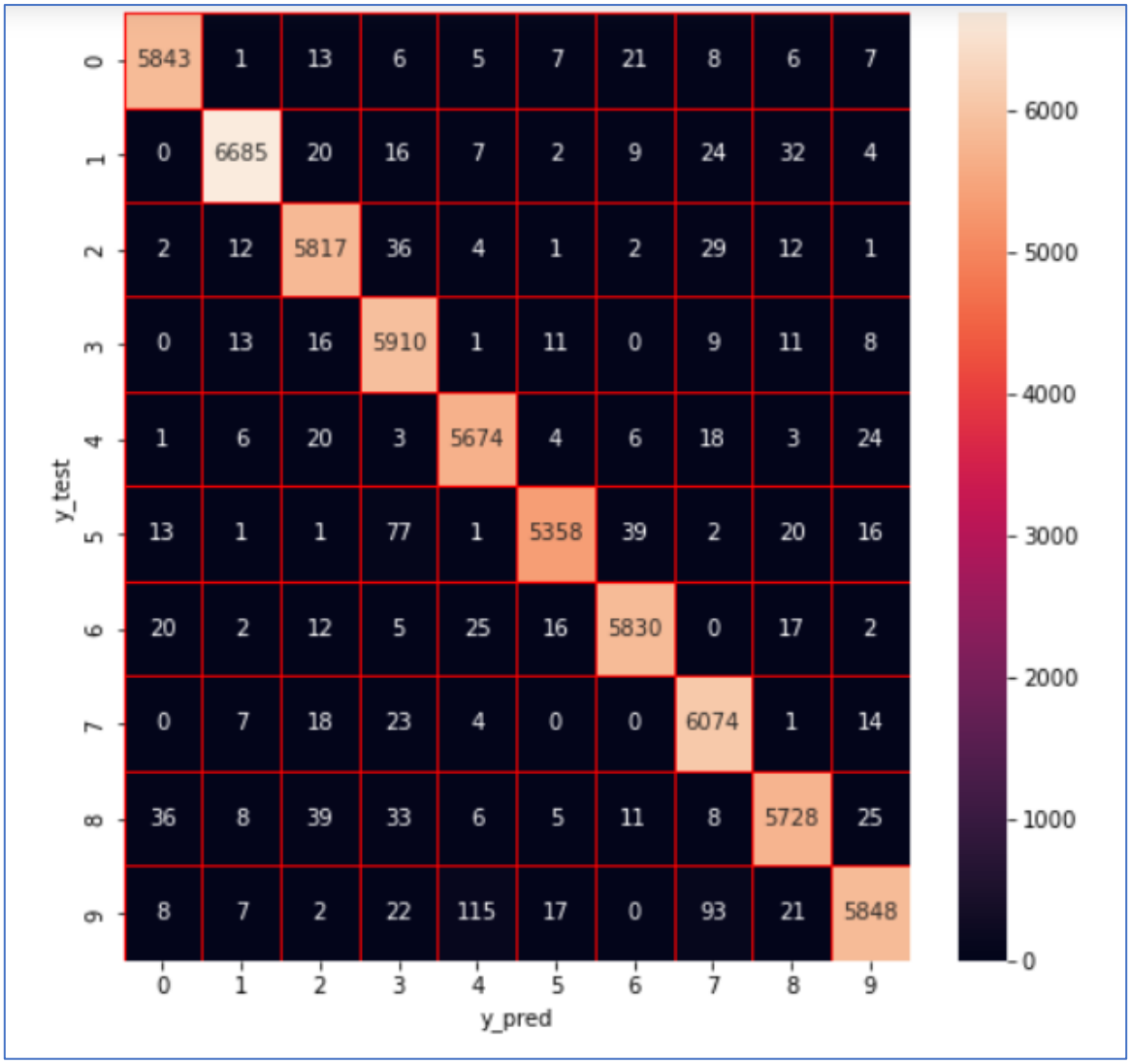


Figure (4.12) : With Epoch=10, Accuracy=0.981

The confusion matrix of the model's performance at the time when the epoch was 15 and the accuracy was 0.98673333 ,It is explained in the figure (4.13).

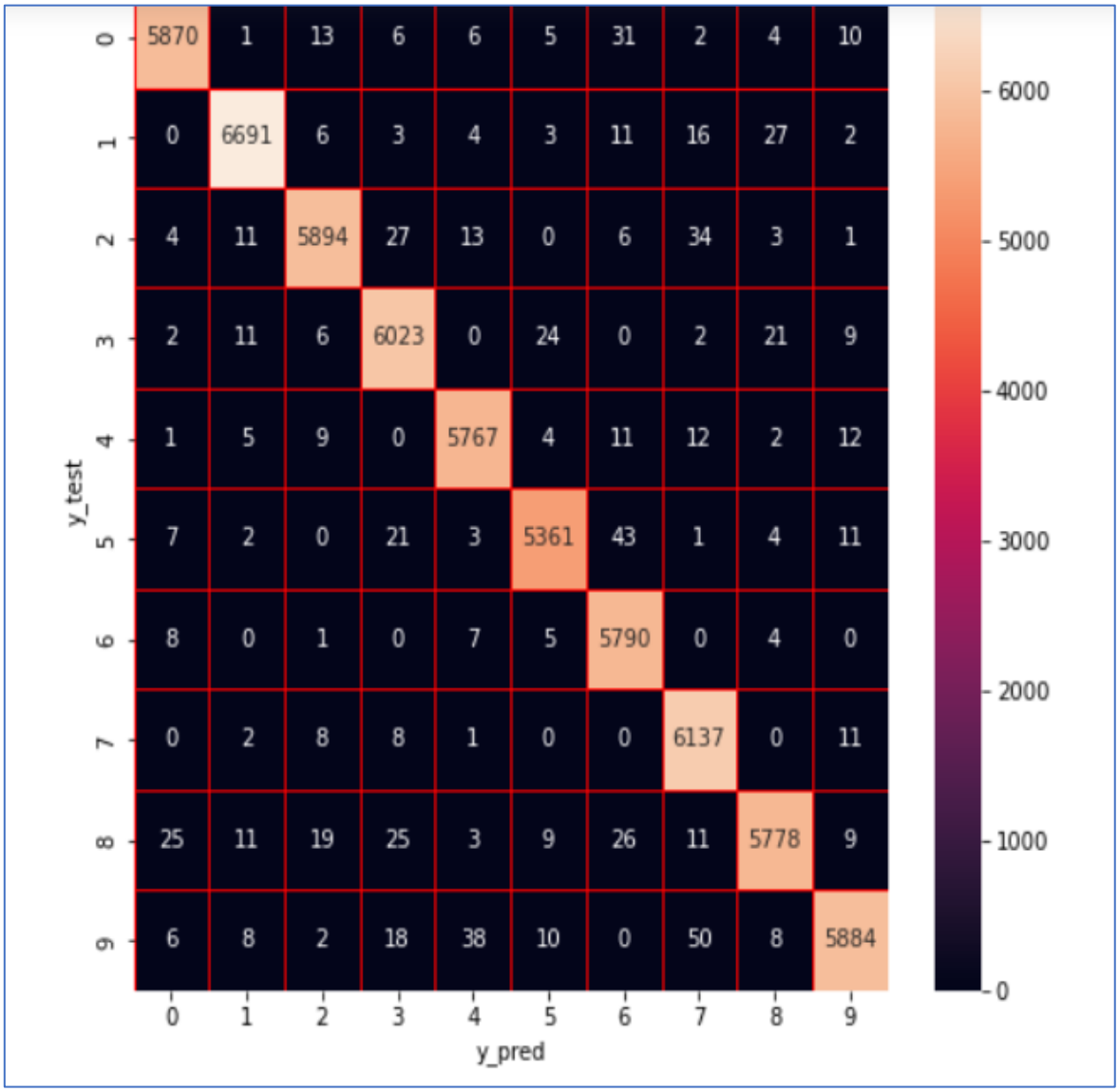


Figure (4.13) : Epoch=15, Accuracy= 0.986

4.5 Evaluation of Model

When comparing the performance of the two models used in the proposed system, which are KNN and backpropagation, according to the evaluation metrics, which is the value of accuracy and precision, the performance of backpropagation was the best as shown in the following figure .

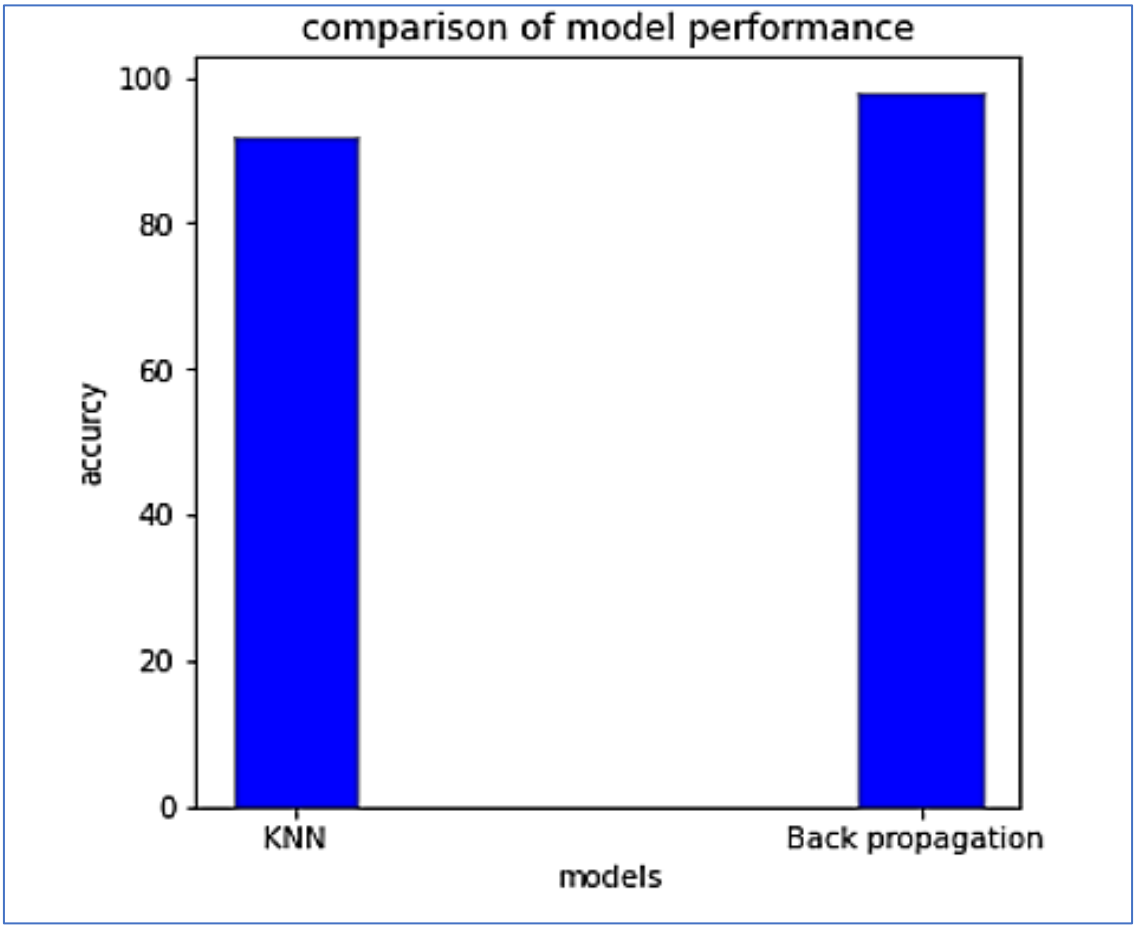


Figure (4.14) : Comparison of model

Chapter Five

Conclusion and Future Works

Chapter Five

Conclusion and Future Works

5.1 Introduction

In the last chapter, the conclusions reached through the experiments and results of this work will be presented, and a set of future work will be proposed that can be accomplished along the lines of the proposed system.

5.2 Conclusions

1. The accuracy and precision indicators show an accurate description of the performance of the algorithms that were employed in the proposed system. The two indicators described the performance of the first algorithm (KNN), which gave results (0.94 and 0.942), respectively. As for the performance of the (PBNN) algorithm, the description of its performance according to the two indicators was (0.98673333 0.9698) respectively.
2. The first model used in the proposed system, which is (KNN), contains a sensitive parameter that affects the accuracy obtained by the model, which is the number of neighbours. The optimum number of neighbours was determined by the principle of trial and error. The optimal number was (4) and the accuracy was (94).
3. In the second model used in the proposed system, which is (BPNN), there is a set of influential parameters that were set during the training process. The number of epochs is one of the parameters affecting the performance of the model, so focus on it and conduct a number of epochs for the purpose of reaching the optimal number of epochs, which gives the highest accuracy which was (15) and the accuracy reached (0.98673333).

4. The proposed system has given very good results in terms of accuracy and precision, it is reliable in recognizing the image of handwriting completely, it can be applied to numbers and letters as well.

5.3 Future Works

The suggestions for future works can be summarized as follows:

1. An image of a word can be used instead of a letter for the purpose of handwriting word recognition.
2. Using deep learning techniques to extract attributes from images, for example, the CNN method
3. The images are obtained from a camera that is known at the beginning of the system, from which the images are taken, processed and recognized.

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الخلاصة

يعد التعرف على خط اليد قضية مهمة في الوقت الحاضر ، حيث يمكن أن تكون الكتابة اليدوية عبارة عن صورة أو مستند وما إلى ذلك ، تعد قدرة الكمبيوتر على التعرف على الأرقام المكتوبة بخط اليد مهمة جدًا في أكثر من تطبيق مثل تطبيقات الترجمة والقراءة والتعرف على الأرقام. يوفر المشروع المقترح نظامًا يتعرف على الأرقام الإنجليزية المكتوبة بخط اليد ، تم الحصول على بيانات الإدخال من منوعات البيانات عالمية. يتكون النظام المقترح من عدد من المراحل. المرحلة الأولى هي المعالجة المسبقة ، والتي تتضمن تغيير حجم الصور لتكون بحجم واحد (28 * 28) بكسلات ، ثم يتم تطبيق خطوة (تعيين البيانات). أما بالنسبة لمرحلة التصنيف فقد تم استخدام خوارزميتين هما خوارزمية KNNوالشبكة العصبية (BPNN). لبدء عملية تدريب الخوارزميات المختارة ، تم تقسيم البيانات إلى مجموعتين ، مجموعة التدريب ومجموعة الاختبار. ممثلة لغرض اختيار الأفضل من خلال تقييم أدائها باستخدام عدد من مقاييس التصنيف. تم استخدام الدقة والدقة لغرض تقييم أداء الخوارزميات. كان أداء خوارزمية KNN 0.942, 0.94, على التوالي عند k = 4 ,بينما كان أفضل أداء وصلت إليه آلية الشبكة العصبية 0.986 , 0.9698 , على التوالي في epoch = 15 , وضح الشبكة العصبية (خطأ الانتشار الخلفي) أن أفضل نتيجة. في مرحلة التعرف على خط اليد .

جمهورية العراق
وزارة التعليم العالي والبحث العلمي
جامعة بابل كلية العلوم للبنات
قسم علوم الحاسوب

تمييز الارقام الانكليزية المكتوبة يدويا" باستخدام تعلم الالة

بحث
مقدم الى مجلس كلية العلوم للبنات في جامعة بابل كجزء من متطلبات الحصول على درجة الدبلوم العالي في العلوم / علوم الحاسوب

من قبل
علي عبد الكريم سلمان اليساري

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