Republic of Iraq

Ministry of Higher Education

and Scientific Research

University of Babylon

College of Engineering

Handwriting Recognition By using Artificial Neural Networks

A Project

Submitted to the College of Engineering / University of Babylon Partially fulfilling the requirements for the degree of Higher Diploma of Science in Engineering / Electrical Engineering

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2022 A.D ***1443 A.H***

بِسْمِ اللهِ الرَّحْمنِ الرَّحِيمِ

﴿ نَرْفَعُ دَرَجَاتٍ مَنْ نَشَاءُ وَفَوْقَ كُلِّ ذِي عِلْمٍ عَلِيمٌ ﴾

(صَدَقَ اللهُ الْعَلِيّ الْعَظِيم)

سورة يوسف / الآية (76)

Dedication

To my family …who always give me support and love.

To my friends... who share my sadness before my joy.

To my professors …who gave me knowledge.

To the students of science ... in all parts of the world.

To all those, I dedicate this work.

Al Hasan *2022*

Acknowledgements

First of all, my praise and deepest gratitude be to Allah the compassionate, the Merciful for His assistance during the preparation of this work I would like to express my deep thanks and respect and my supervisors (Dr. Mohammed Khalid Ibrahim) I would like also to submit my thanks to all members of the (College of Engineering /Electrical Engineering Department at the University of Babylon for their cooperation. I am also thankful to all who helped me directly or indirectly to complete this work

Finally, I owe a particular appreciation and heartfelt gratitude to my family, who was always there for me and set up all of the necessary conditions for me to study without doubt.

Abstract

Convolutional Neural Network (CNN) is a computational system meant to imitate the principles by which the human brain processes and analyzes information. It is the cornerstone of artificial intelligence (AI) and is commonly utilized to tackle many issues that are difficult, if not impossible, to answer with normal algorithms. Because of their self-learning characteristics, CNNs can deliver improved outcomes as more input data becomes accessible Cross-entropy is used as a cost function in the system that will be proposed.

the scale conjugate gradient algorithm is used for training. To check how well a proposed system works, there are three important things to think about, listed from most important to least important: Receiver operating characteristics of proposed system, which actually give the classification stability result, gradient value, and percentage accuracy of proposed system. In the proposed work, EMNIST dataset was used with 10,000 examples for testing and 60,000 examples for training different techniques to pre-process an image dataset was used. These techniques are called "image processing techniques. These ways of preprocessing are used to get rid of any redundant information in the dataset, Finally, each character is fed into the neural network. In this case, an existing neural network is loaded from a .mat file and used to predict what each character is. The predicted characters are then displayed as text in a Command Window and in a .txt file. MATLABR2020a are used with windows10, CI5 Processor 2520m

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Abbreviations	Descriptions
CNN	Convolution Neural Networks
DBN	Deep Belief Network
K-NN	K-Nearest Neighbors’ Algorithm
DFFNN	Deep Forward Neural Networks
HCR	Handwritten Character Recognition
AI	Artificial Intelligence
ANN	Artificial Neural Networks
CG	Conjugate Gradient Algorithm
SCG	Scaled Conjugate Gradient Algorithm
MNIST	Modified National Institute of Standards and Technology database
EMNIST	Extended Modified National Institute of Standards and Technology database
ROC	Receiver Operating Characteristics

List Of Symbols

Symbols	Definition
$f(.)$	Activation Function
y_j	Weighted Summation
xi	Input Value
k	Number Of Kernels
x	Vector Of Scores
$\hat{\boldsymbol{s}}_{\boldsymbol{k}}$	Step Size
$\boldsymbol{\lambda}_{\boldsymbol{k}}$	Lambda Scalar
$\boldsymbol{E}_{\boldsymbol{qw}}$	Quadratic Approximation
$\tilde{\boldsymbol{w}}_{\boldsymbol{1}}$	Weight Vector
$\boldsymbol{\Delta}_{\boldsymbol{k}}$	Comparison Parameter
Erosion (Sp (i, j)	Erosion of Matrix Elements of Image
Γ	Noise Elements Matrix
•	Coordinate Logic AND Operator
R	Filter for Noise Removal
∘	Coordinate logic OR
$\boldsymbol{I}_{\boldsymbol{y}}$	Dilation Matrix

Chapter One

Introduction

1.1. Brief Introduction

Handwriting Text recognition is becoming extremely important in today's digital world Because it can be used in a variety of everyday tasks. It can be shown by the fact that in recent years, different recognition systems have been made or proposed for use in different fields where high classification efficiency is needed. Systems that can read handwritten letters and characters help people do more complicated tasks that would take a lot of time and money to do on their own. One good example is how bank checks are handled by automatic processing systems. Without automated systems for processing bank checks, the bank would have to hire a lot of people who might not be as efficient as the automated systems. Human and animal brains can learn and model relationships that aren't simple or linear by using biological neural networks [1],[2] This can be applied to handwriting recognition systems. This means that artificial neural networks can be used to create them. [3] Because people have brains, they are able to recognize various handwritten things, such as letters and characters. Handwriting letters can be seen in a variety of ways by various people because of the inherent bias in human perception [4].

Unlike humans, computers are not biased and can perform complex tasks that would take a human a long time and a lot of effort to accomplish. Knowing how people read handwriting is essential [5]. Most of what a person does when reading Handwriting is done with their eyes. The process of deciphering handwriting may appear simple, but it's more difficult than most people imagine. Even if they aren't aware of it, people can interpret what they see using the knowledge stored in their brains. Handwriting is often difficult to decipher. The complexity of visual pattern recognition only becomes apparent when attempting to build a computer system that can read handwriting[6]. Artificial neural networks are often regarded as the most effective method for developing computers that can read handwriting. When it comes to reading handwriting, neural networks can be used to create a simplified model of how the human brain functions. Using this technology, computers can read handwriting equally as well as humans, if not better than humans. When it comes to writing, there are many different styles, and some of them are difficult to decipher. Less time-consuming, but still tedious, is deciphering documents written in handwriting by various individuals [7]. Using a neural network, the suggested method can better understand and detect trends in data that would be difficult to find using other human techniques or by simply looking at the data alone [8]. Convolution Neural Networks (CNNs) can be used to develop a model that can read handwriting, characters, and sentences from an image.

1.2. Problem state

- The same handwriting characters vary in size, shape, and style from person to person, and even within the same person.
- The issue is that there's a wide range of handwriting – good and bad. This makes it tricky
- sometimes, characters look very similar, making it hard for a computer to recognize When a character has a lot of background noise it's possible that a computer program will read it as an entirely different character.

1.3. Review of Literature

Over the past three or four decades, handwriting recognition has developed into a comprehensive field with a significant influence on applications. Handwriting recognition has had some of the most important practical implications in the last decade. The successful implementation of known procedures necessitates a thorough grasp of their behavior and how well they fit into a given situation. Difficulties might develop due to the problem's inherent complexity or a technique mismatch.

D. Cruces-Álvarez ,etal (1998)[9]**,**

an approach using a neural network to categorize printed handwritten digits has been presented. A multilayer feed forward and clustered back propagation technique is used to complete the task. Kirsch masks are employed to extract special features, and neural network algorithms were utilized to classify the numerals. Utilizing a multilayer neural network has as its major objective reducing the mean square error, or cost function, between the desired and obtained results. As a result, this approach has a 9 percent rejection rate and a 1 percent mistake rate.

D. Nasien,etal(2010)[10]

Here a technique employing feed-forward neural network classifiers and freeman chain coding to recognize handwritten Latin characters is presented. Pre-processing, feature extraction, and classification are the typical three processes. The skeleton of a character was obtained using the thinning method during the preprocessing stage. This operation removes any unnecessary information while also maintaining the features of the image. They suggested a randomized technique for feature extraction before using a neural network as a classifier to categorize handwritten characters.

M. Z. Alom,etal (2017)[11]

Used the dataset CMATERdb 3.1.1 and a mix of dropout and different filters to measure how well CNN and DBN worked when Deep Learning was added. They conduct a series of tests and discover that when compared to other approaches, CNN with the Gabor feature and dropout enhances the accuracy of recognizing BANGLA digits.

S. Roy,etal (2017)[12]

A Deep Convolutional Neural Network (SL-DCNN) architecture was created using Supervised Layer Wise training. It established a new standard with a 9.67% error rate on the hard CMATERdb 3.1.3.3 handwritten Bangla isolated compound character dataset. When compared to previously established benchmarks, the model reduced mistakes by roughly 10%, which is good in the field of Bangla compound character recognition.

S. Attigeri (2018)[13]

Showed that a neural network can be used to recognize handwritten characters without needing to extract features from a scanned image. They used layers, and 100 neurons gave them an accuracy of 90.19/5.

D.S. Joshi & Y. R. Risodkar,etal (2018[14]

K-NN and Neural Network were utilized to focus on GUJARATI character recognition. In addition, they utilized image processing techniques like filtering, edge detection, and morphological alteration to achieve 78.6% accuracy on a dataset.

Y. Weng and C. Xia, (2019)[15]

Use A convolutional neural network to produce handwritten character recognition. Following several trials, they concluded that CNN models can easily classify characters. They also compared their finished model to another available mode.

R. V. K. Reddy and U. R. Babu, (2019)[16]

Recognize HINDI characters. With the aid Convolutional Neural Networks (CNNs) as well as Deep Forward Neural Networks (DFFNN). The researchers discovered that DFFNN, CNN-Adam (Adaptive Moment), and CNN-RMSprop (Root Mean Square Propagation) provide the highest level of accuracy for handwritten letters when compared to other techniques.

1.4. Research Objectives

The main goal of this investigation is to apply the neural network approach to the development of an expert system for the recognition of handwritten characters.

1. Creating a system that makes use of effective technology to recognize handwritten letters and words from photographic media in order to solve the issue of how accurate handwriting character recognition systems are; this will allow for the problem to be fixed.
2. Studying and showing the use of neural network technology to the creation of effective handwritten character recognition systems

Chapter Two

Theoretical Background

2.1. Introduction

Handwritten character recognition (HCR) is a mechanism for converting various types of documents into analyzable, editable, and searchable data. HCR's ultimate goal is to emulate human reading capabilities in such a way that the machine can read, edit, and interact with text as quickly as a human. Over the last half-century, many researchers have focused their efforts on identifying HCR, and many significant advances have been made in this field [17]. However, significant progress has been made in HCR performance in recent years, but HCR remains a difficult task due to the wide variety of handwriting styles, the presence of many similar characters, and the large number of character categories [18].

Convolutional Neural Network (CNN) is a well-known deep learning architecture inspired by the human brain's natural visual perception technique. Taking advantage of the recent exponential growth in the volume of annotated data and the rapid increases in the capabilities of graphics processing units, CNN research has quickly emerged and achieved state-of-the-art performance on a variety of tasks, including image classification, text detection, pose estimation, object tracking, action detection, visual saliency detection, scene marking, speech and natural language processing. Although there are numerous CNN architecture variants, their fundamental elements are very similar. It was made up of three types of layers: convolutional, pooling, and fully-connected. It has made significant advances in computer vision [19], and it has been implemented in the HCR to achieve excellent recognition performance [20]. As a result, the researchers are employing a variety of CNN-based models to solve HCR problems [21].

Handwriting character identification is a field of study in computer vision, artificial intelligence, and pattern recognition [22].Handwriting-recognition software can identify and recognize characters in photographs, paper documents, and other locations before converting them to electronic format or machine-encoded form. The system can use optical scanning or word recognition to read handwriting. In addition, the system might be configured to track where the pen tip moves on the screen. In other words, a system might analyze the motions of a pen tip on a screen to determine which characters are being written [23].Handwriting recognition comes in two flavors: offline and online.

Offline handwriting recognition entails extracting text or characters from a photograph in order to produce computer-readable letter codes[24]. It necessitates the conversion of a handwritten form into digital data. A system receives and reads a handwritten document before to transforming it to a digital representation. Online handwriting recognition, on the other hand, involves the automated recognition or conversion of characters as they were written on a customized screen [24],[25]. The technology recognizes letters and words based on pen movement. Computers interpret handwriting, photos, and documents using different approaches and strategies [26][27].

2.2. Handwriting Methods

In the field of handwriting recognition, there are two types of systems. Online and offline. Incredibly online techniques have been designed to recognize handwriting while it is being penned in real time. While offline systems do not require a time limit, online systems must be fast enough to match the writing speed. In order to lessen the impact of noise sources, more data is required. Since no specific platform is needed, these methods can be used to any paper, no matter how old it is. figure 2-1 explains the two types of handwriting systems.[17]

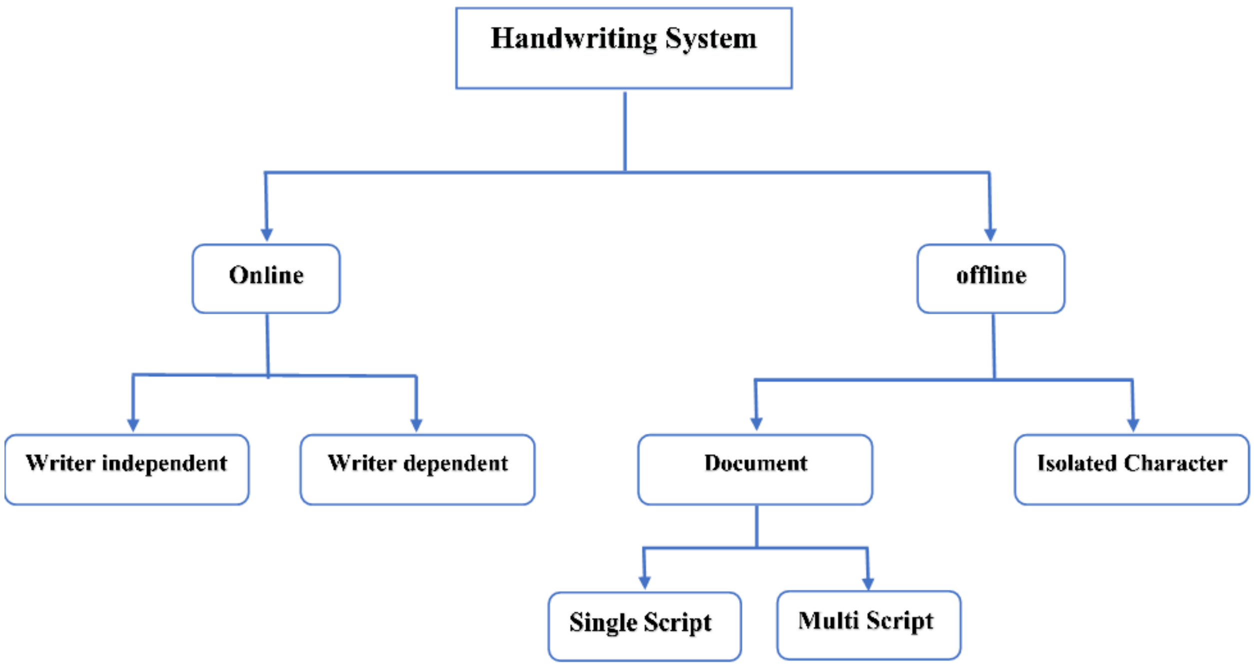

Figure 2-1 Online and Offline Handwritten Character Recognition

2.2.1. Offline

Offline handwritten character recognition technique mine the handwritten paper and it can be stored as in the form of image. Consider the scenario where one user sends a handwritten scanned digitized copy through mail to another person if the end user who have received it want to do modification in that document for further processing but it cannot be done because image doesn't allow text searching, editing and indexing. The task of identifying handwritten character in image is converted into specific format which allows reformat for further processing. It does not really require user to have operating knowledge of device and it require into online handwritten character recognition system. It can be further divided into Isolated Character Recognition and Document Recognition on the basis of how much content is stored in it.[17]

- Isolated Character Recognition: In this category image contains single character written in any script or symbol which is little easy when compared to document recognition. The system does not require segmentation of sentences as character and word is in isolation form.
- Document Recognition: Document may have multiple pages which may have multiple lines, further divided into words and characters. Offline handwritten document recognition engine requires segmentation to break apart pages to lines, lines to words, and words to character then it focusses the feature extraction and classification process. There are two types of document recognition, they are, Single script and Multi script on the basis of language script.
- Single Script: The document is written with single language script then it is very easy to identify and classify the features then it converts into ASCII equivalent.
- Multi Script: The document is written with multiple script or mixture of multiple language script then recognition engine has to deal with feature extraction and classification with all alphabets used for the document which makes challenging than single script recognition.

2.2.2. Online

In this online handwritten character recognition technique, the directional information means to identify in which direction the user wrote (left to right, right to left, top to bottom and bottom to top), From which you can get the basic information about character, unique style of writing, use of the pointing objects. Pointing object may go from left to right, right to left, top to bottom and bottom to top directional. Main function of online handwritten character recognition system is the classification process. It classifies the handwritten character and stored as ASCII code format for further processing.[17] There are two types of online handwritten character recognition system; (i) writer dependent and (ii) writer independent.

- Writer Dependent: In Writer Dependent online handwritten character recognition technique, first the end user provides the basis structures of input to recognition engine.
- Writer Independent: In Writer Independent online handwriting character recognition technique, the user can start using system without worry about underlying recognition engine.

2.3. Artificial Intelligence (AI)

The idea of computer systems interpreting handwritten characters, numbers, and phrases might be considered a human impersonation. To put it another way, a system like this may claim to use artificial intelligence to recognize handwriting in images or from any other source [30]. The concept of "artificial intelligence" refers to the capacity for robots to demonstrate rational thought [31]. The phrase refers to computers or technologies that can replicate "cognitive" processes associated with the human mind. As a result of artificial intelligence, machines may learn from their past experiences and adapt to new information (inputs) [32]. The concept of artificial intelligence encompasses a wide variety of subfields and subfields of study, such as machine learning, neural networks, and deep learning. Figure 2 -2 explain Artificial Intelligence usage

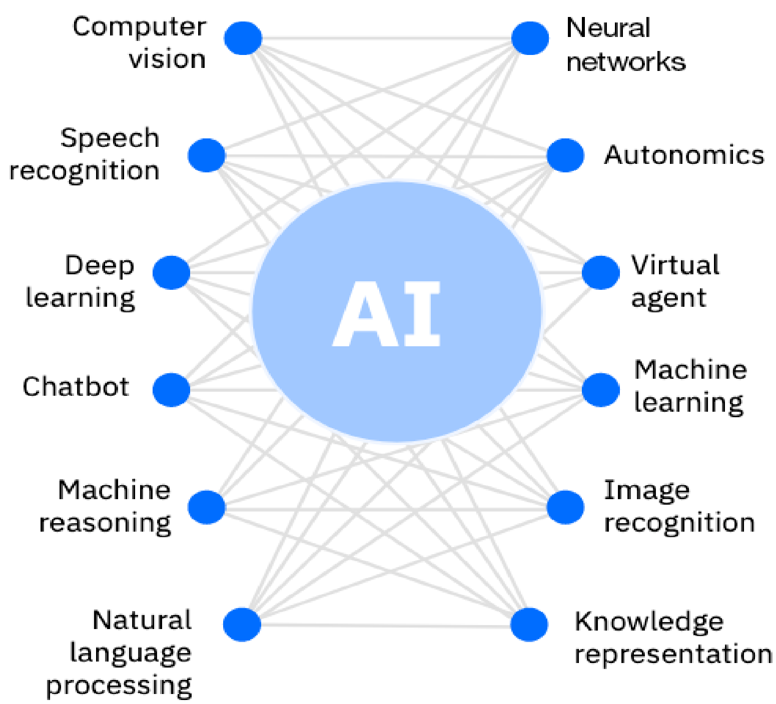

Figure 2-2 Artificial Intelligence

2.4. Artificial Neural Networks (ANN)

The term "Artificial Neural Network" (ANN) is a term used to describe information processing models or computer systems that are based on biological neural networks found in the human brain. [28]. Despite not resembling true neural systems, the systems process information like human and animal brains [29]. The networks are made up of many coupled neurons that collaborate to achieve certain task [2]. ANN imitates what it perceives in the world, like the human brain. Learning allows an ANN to accomplish tasks like data categorization or character recognition. An important aspect of learning is getting the system used to a new connection [30]. When it comes to artificial neural networks, each processor has a limited amount of local memory to operate with [31]. The processors (units) are linked by unidirectional communication channels and operate solely on local data and input received via their connections Figure 2-3 show Neural Networks architecture also equation (2-1) depicts the relative algorithm with figure (2-3)

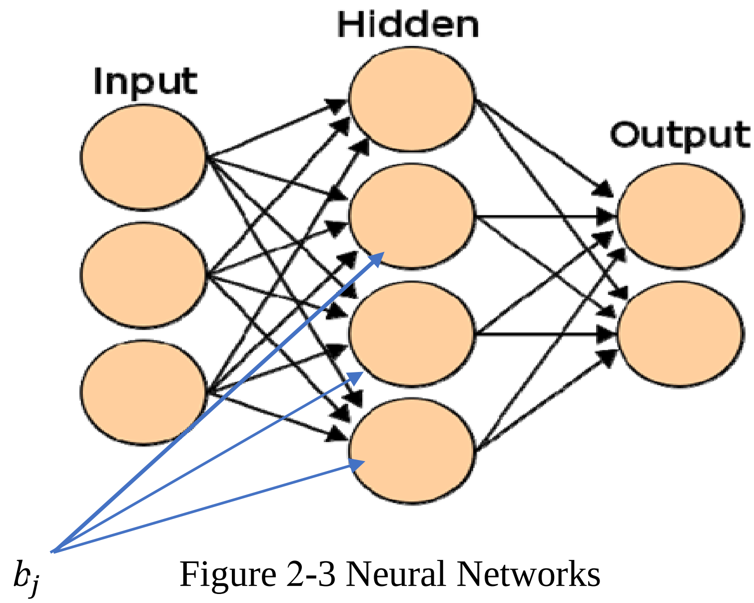

Figure 2-3 Neural Networks

where $f(.)$ is the activation function and y_j is the weighted summation. The

$$Y_j = f(y_j) = f(\sum_{i=0}^{n-1} w_{i,j} X_i + b_j) \qquad 2\text{-}1$$

output of each layer depends on the input of the previous layer and the weights between both layers. The formula may be different due to different actual connections. Usually, the functions that introduce nonlinearity to the network are calledactivation functions. Therefore, higher order items are not needed to add to the weighted sum. That’s why neural networks are used in this dissertation to recognize segmented handwritten characters.

2.5. Biological Neuron

As was said before, the biological brain system serves as the inspiration for artificial neural networks. As a consequence of this, having a grasp of the functioning of genuine neurons may help one better comprehend the workings of artificial neural networks[1]. The neurological system of the human body is divided into three stages, as shown in (Figure 2-4): neural network, receptors, and effectors. In the first stage, the receptor accepts input from the external or internal environment and transmits it to neurons [3],[1]. The neural network's second stage is to use the information it has to make a good judgement regarding the output. Electrical impulses are transformed into responses to the external environment at the last stage.

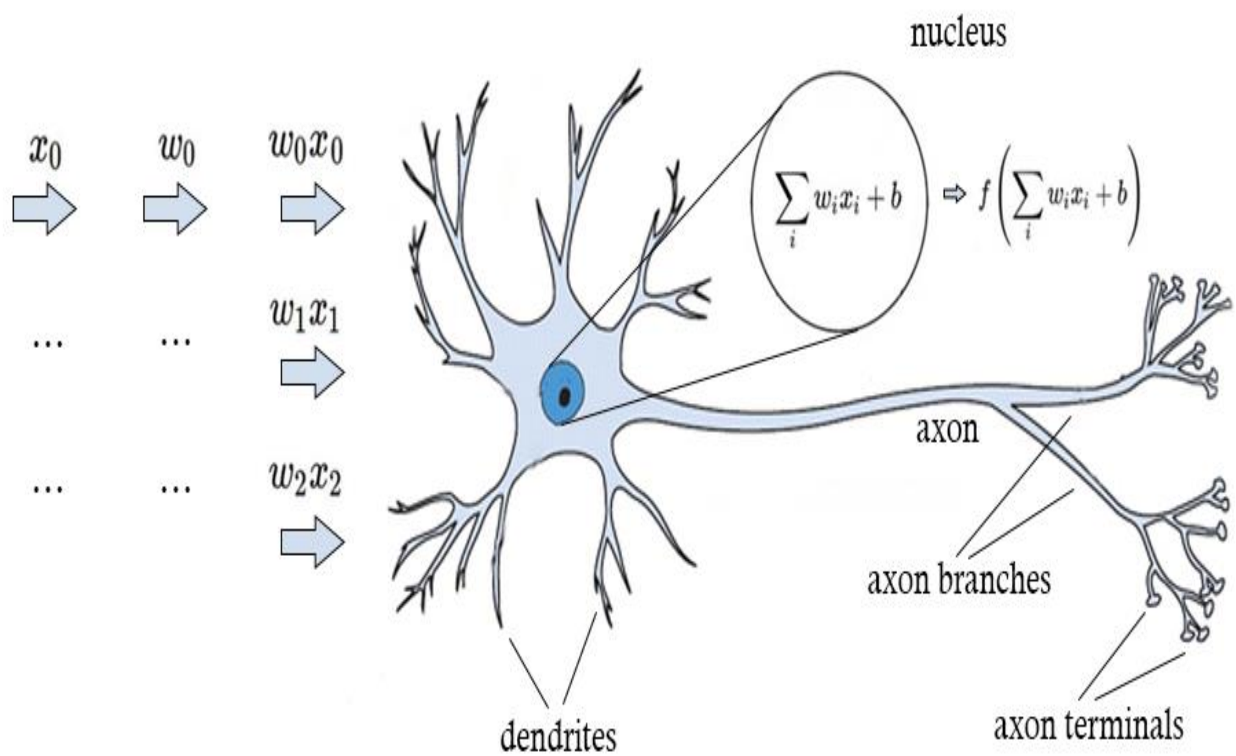

Figure 2-4 Biological Neuron

An artificial neural network is basically a smaller version of the central nervous system. Neurons are the building components of the brain. They do things like logical reasoning, cognition, and pattern recognition, just to name a few[32],[33]. In other words, it's just a basic model of a neural network system that can't do much more than a regular computer.

2.6. Convolutional Neural Network

CNN architecture mimics a human brain communication pattern of the neurons, boosted by visual cortex arrangement. Nerve cells just react to stimuli from visible spectra by observation and analysis. A range of such spectra fields overlaps to fill the whole display space. A CNN can capture the spatial dependencies inside an image to relate with the content of the image for recognition purpose. The CNN design provides a strong fit of the source image to find the distinguishing features in order to be classified. The weights, parameters and the biases involved with the transformations from original image to feature vector to know better about the nature of the image are found during the training stage [34].

In CNN, the main objective of convolution and subsampling operations is for extracting features from raw input data. In order to achieve this objective, convolution operations which are multiplications of small kernel matrices and specified areas of a two-dimensional input matrix are performed. To produce a single smaller dimensions of feature map from an input matrix, the kernel will be shifted and several multiplications will be performed from left to right and from top to bottom over specified areas of the input matrix. The equation for a convolution operation to is defined in equation (2-2) as stated in [35] as follows:

$$Q_j = f\left(\sum_{i=1}^{N} I_{i,i} * K_{i,j} + B_j\right) \qquad 2\text{-}2$$

where Q_j is an element of a single output matrix from a convolution operation. The output matrix is produced from an activation function f. First, the sum of all multiplications of kernel matrix $K_{i,j}$ and input matrix $I_{i,i}$ is computed, subsequently the bias value B_j is added to the elements of the resulting matrix.

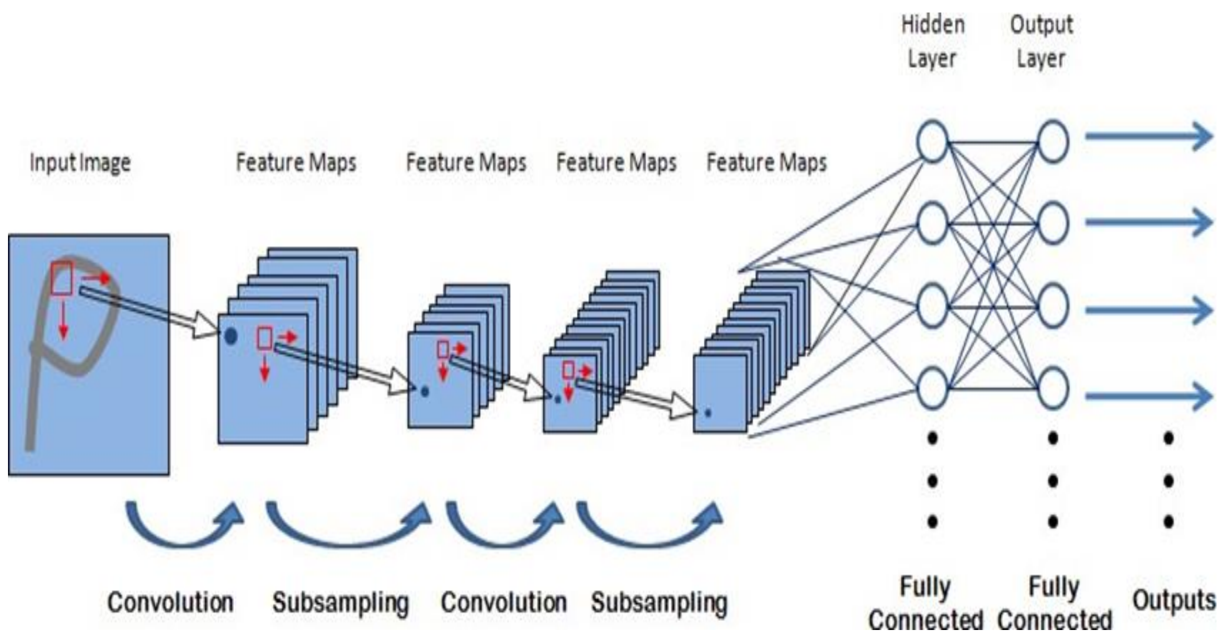

Figure 2-5 Convolutional Neural Network Architecture

Figure 2-6 depicts CNN architecture after several convolution and subsampling operations, feature maps will be flattened so that they are ready to be classified with fully-connected neural network, fully-connected neural network consists of several layers. Each layer consists of several neurons that will perform a matrix multiplication between an input matrix x_i and internal weights $w_{j,i}$ as defined in equation (2-3) as follows:

$$u_j = f\left(\sum_{i=1}^{n} w_{j,i} x_i + b_j\right) \qquad 2\text{-}3$$

where b_j is bias value, n is the number of neurons in a single layer, and f is an activation function, after processed in several layers, feature maps will be processed in the output layer. The output layer of a fully-connected neural network is a function that produces probabilities of classes $p(x)$ that the CNN input may belong.

2.7. Scaled Conjugate Gradient Algorithm (SCG)

It is possible to use affective approach in estimating the step size than the line-search technique. The idea is to estimate the term $\hat{s}_k = E''(\tilde{v}_k)\tilde{p}_k$ in CG (conjugate gradient) with a nonsymmetric approximation of the form[36]:

$$\begin{aligned} \dot{s}_k \quad &= E''(\tilde{u}_k)\tilde{p}_k \\ &\approx \frac{E'(\tilde{u}_k + \sigma_k \tilde{j}_k) - E'(\tilde{u}_k)}{\sigma_k}, 0 < \sigma_k \ll 1. \end{aligned} \qquad \text{2-4}$$

The approximation tends in the limit to the true value of $E''(\tilde{\imath}_k)\tilde{p}_k$. The calculation complexity and memory usage of $\tilde{s}_k$ are, respectively, $O(3N^2)$ and $O(N)$.If this strategy is combined with the CG approach, an algorithm directly applicable to a feedforward neural network. This slightly modified version of the original CG algorithm will also be referred to as CG.[37]

Here a combination with the model-trust region approach is done which is known from the Levenberg-Marquardt algorithm, with the conjugate gradient approach. Let us introduce a scalar λ_k in CG, which is supposed to regulate the indefiniteness of [38] $E''(w\tilde{}_k)$ This is done by setting:

$$\tilde{s}_k = \frac{E'(\tilde{w}_k + \sigma_k \tilde{p}_k) - E'(\tilde{w}_k)}{\sigma_k} + \lambda_k \tilde{p}_k, \qquad \text{2-5}$$

and adjusting λ_k in each iteration looking at the sign of δ_k, which directly reveals if $E''(\tilde{w}_k)$ is not positive definite. If $\delta_k \leq 0$, then the Hessian is not positive definite and λ_k is raised and $\tilde{s}_k$ is estimated again. If the new $\tilde{s}_k$ is renamed as $\bar{\bar{s}}_k$ and the raised λ_k as $\bar{\lambda}_k$, then $\bar{\bar{s}}_k$ is

$$\tilde{w}_k = \tilde{s}_k + \left(\bar{\lambda}_k - \lambda_k\right)\tilde{p}_k \qquad \text{2-6}$$

Assume in a given iteration that $\delta_k \leq 0$. It is possible to determine how much λ_k should be raised in order to get $\delta_k > 0$. If the new δ_k is renamed as $\bar{\delta}_k$, the

$$\begin{aligned} \vec{\delta}_k &= \tilde{p}_k^T \bar{\bar{s}}_k \\ &= \tilde{p}_k^T\left(\tilde{s}_k + \left(\bar{\lambda}_k - \lambda_k\right)\tilde{p}_k\right) = \delta_k + \left(\bar{\lambda}_k - \lambda_k\right)|\tilde{p}_k|^2 > 0 \Rightarrow \\ &\bar{\lambda}_k > \lambda_k - \frac{\delta_k}{|\tilde{p}_k|^2} \end{aligned} \qquad \text{2-7}$$

Equation (2-8) implies that if λ_k is raised with more than $-\left(\frac{\delta_k}{|\dot{p}_k|^2}\right)$, then $\bar{\delta}_k > 0$. it is clear that $\bar{\lambda}_k$ in some way should depend on λ_k, δ_k, and $|\tilde{p}_k|^2$. A reasonable choice

$$\bar{\lambda}_k = 2\left(\lambda_k - \frac{\delta_k}{|\dot{p}_k|^2}\right). \qquad \text{2-8}$$

This leads to:

$$\begin{aligned} \bar{\delta}_k &= \delta_k + \left(\bar{\lambda}_k - \lambda_k\right)|\tilde{p}_k|^2 \\ &= \delta_k + \left(2\lambda_k - 2\frac{\delta_k}{|\tilde{p}_k|^2} - \lambda_k\right)|\tilde{p}_k|^2 \\ &= -\delta_k + \lambda_k|\tilde{p}_k|^2 > 0 \end{aligned} \qquad \text{2-9}$$

The step size is given by:

$$\alpha_k = \frac{\mu_k}{\delta_k} = \frac{\mu_k}{\hat{p}_k^T\tilde{s}_k + \lambda_k|\tilde{p}_k|^2}. \qquad \text{2-10}$$

The values of λ_k directly scale the step size in such a way that the bigger λ_k is the smaller the step size, which agrees well with our intuition of the function of λ_k. The quadratic approximation E_{qw}, on which the algorithm works, may not always be a good approximation to $E(\tilde{w})$ since λ_k scales the Hessian matrix in an artificial way. A mechanism to raise and lower λ_k is needed which gives a good approximation, even when the Hessian is positive definite. Define

$$\Delta_k = \frac{E(\tilde{w}_k) - E(\tilde{w}_k + \alpha_k \tilde{p}_k)}{E(\tilde{w}_k) - E_{qw}(\alpha_k \tilde{p}_k)} = \frac{2\delta_k[E(\tilde{w}_k) - E(\tilde{w}_k + \alpha_k \tilde{p}_k)]}{\mu_k^2}. \qquad \text{2-11}$$

Here Δ_k is a measure of how well $E_{qw}(\alpha_k \tilde{p}_k)$ approximates $E(v_k + \alpha_k \tilde{p}_k)$ in the sense that the closer Δ_k is to 1, the better is the approximation. λ_k is raised and lowered following the formula

if $\Delta_k > 0.75$, then $\lambda_k = \frac{1}{4}\lambda_k$

if $\Delta_k < 0.25$, then $\lambda_k = \lambda_k + \frac{\delta_k(1-\Delta_k)}{|\tilde{p}_k|^2}$.

The formula for $\Delta_k < 0.25$ increases lambda such that the new step size is equal to the minimum to a quadratic polynomial fitted to $E'(\tilde{w}_k)^T \tilde{p}_k, E(\tilde{w}_k)$, and $E(\tilde{w}_k + \alpha_k \tilde{p}_k\ )$ [39]. The SCG algorithm is as shown below.

1 Choose weight vector $\tilde{w}_1$ and scalars $0 < \sigma \leq 10^{-4}$, $0 < \lambda_1 \leq 10^{-6}, \bar{\lambda}_1 = 0$. Set $\tilde{p}_1 = \tilde{r}_1 = -E'(\tilde{w}_1), k = 1$ and success = true.

2 If success = true, then calculate second order information:

$\sigma_k = \frac{\sigma}{|\tilde{p}_k|}$,

$$\tilde{s}_k = \frac{\left(E'(\tilde{w}_k + \sigma_k \tilde{p}_k) - E'(\tilde{w}_k)\right)}{\sigma_k}$$

$\delta_k = \tilde{p}_k^T \tilde{s}_k$.

3 Scale δ_k: $\delta_k = \delta_k + \left(\lambda_k - \bar{\lambda}_k\right)|\tilde{p}_k|^2$.

4 If $\delta_k \leq 0$ then make the Hessian matrix positive definite:

$$\bar{\lambda}_k = 2\left(\lambda_k - \frac{\delta_k}{|\tilde{p}_k|^2}\right)$$
$$\delta_k = -\delta_k + \lambda_k|\tilde{p}_k|^2$$
$$\lambda_k = \bar{\lambda}_k.$$

5 Calculate step size:

$$\mu_k = \tilde{p}_k^T \tilde{r}_k,$$
$$\alpha_k = \frac{\mu_k}{\delta_k}.$$

6 Calculate the comparison parameter:

$$\Delta_k = \frac{2\delta_k[E(\tilde{w}_k) - E(\tilde{w}_k + \alpha_k\tilde{p}_k)]}{\mu_k^2}. \quad 2\text{-}12$$

7 If $\Delta_k \geq 0$ then a successful reduction in error can be made:

8 If $\Delta_k < 0.25$, then increase the scale parameter:

$$\lambda_k = \lambda_k + \left(\frac{\delta_k(1 - \Delta_k)}{|\tilde{p}_k|^2}\right) \quad 2\text{-}13$$

9 If the steepest descent direction $\tilde{r}_k \neq \tilde{0}$, then set $k = k + 1$ and go to 2 else terminate and return $\tilde{w}_{k+1}$ as the desired minimum.

The value of σ should be as small as possible, taking the machine precision into account. When σ is kept small ($\leq 10^{-4}$), experiments indicate that the value of σ is not critical for the performance of SCG.

2.8. Noise Removal

For noise reduction, according to equation (2-13) the image I has been defined as a matrix, which consist of binary elements of the original image (decimal matrix elements of image I must be convert to binary elements). Since binary conversion effects on all matrix elements, image noise pixels have been also converted under this conversion[40]. Now, to separate noise of image by using equation (2 -13)

$$S(i,j) = \sum_{p=0}^{B-1} 2^p \left(S_p(i,j)\right) \quad i = 1,2,\ldots,M \; j = 1,2,\ldots,N \qquad 2\text{-}14$$

$$\mathrm{Erosion(I)} = \sum_{p=0}^{n-1} 2^p \, \mathrm{Erosion}\left(\mathrm{S}_p(\mathrm{i},\mathrm{j})\right) \quad \mathrm{i} = 1,2,\ldots,\mathrm{M} \; \mathrm{j} = 1,2,\ldots,\mathrm{N} \qquad 2\text{-}15$$

Where Erosion (Sp (i, j)) is the erosion of matrix elements of image I. The erosion operation on an image is equal to the coordinate logic AND operator. Thus equation (2-14) can be considered as the coordinate logic AND operation on all matrix elements of original image. In the proposed model the AND operation has been operated on original matrix elements and elements of matrix Γ. Matrix Γ has been defined as $\Gamma = [1 \;\; 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 0]$ using several simulations. After AND operation, matrix IΓ is expressed as[40]:

$$I_r = \sum_{p=0}^{n-1} 2^p \Gamma \quad \bullet S_p(i,j) \quad i = 1,2,\ldots,M \; j = 1,2,\ldots,N \qquad 2\text{-}16$$

Where • is the coordinate logic AND operator and Γ is noise elements matrix. Since noise recognition and extraction is performed by the AND operator, thus noise removal can also be obtained by forming a filter which consists of this operator. The proposed filter for noise removal is presented as:

$$\mathrm{R} = \left[\mathrm{I}_\gamma(\mathrm{i},\mathrm{j}) \bullet \; \mathrm{I}(\mathrm{i}+1,\mathrm{j}) \bullet \; \mathrm{I_r}(\mathrm{i},\mathrm{j}+1)\right] \circ \left[\mathrm{I}_\gamma(\mathrm{i},\mathrm{j}) \bullet \; \mathrm{I}(\mathrm{i},\mathrm{j}-1) \bullet \; \mathrm{I}_\gamma(\mathrm{i},\mathrm{j}+1)\right] \qquad 2\text{-}17$$

Where ∘ and • are coordinate logic OR, AND operators, respectively. I γ is Dilation matrix of Sp(i,j) which is expressed as:

$$I_y = \text{Dilation(I)} = \sum_{p=0}^{n-1} 2^p \text{ Dilation}\left(S_p(i,j)\right) \qquad \text{2-18}$$
$$i = 1,2,\ldots.,M \; j = 1,2,\ldots.,N$$

2.9. Dataset

EMNIST [57] dataset which is very similar to the MNIST dataset is selected, and the quantity, category, and exception of the dataset are processed accordingly. Finally, the network model is trained and tested on this dataset. EMNIST is known as MNIST. However, the accuracy of most network models in the MNIST dataset is excellent, so on this basis, the EMNIST dataset is launched, and the image size and interface of this dataset are like MNIST. As the EMNIST dataset is a preprocessed dataset that can be directly used in the network model, there is no need for normalization, centralization, binarization, refinement, and other operations. As the EMNIST dataset is a foreign dataset, its character writing mode is different from the traditional Chinese writing mode. They usually like to use the connecting pen, and these data are not filtered, so the dataset contains some abnormal data that is difficult to be recognized, as shown in figure 2-7. According to the causes of data exceptions, abnormal data can be roughly divided into the following types [57]:

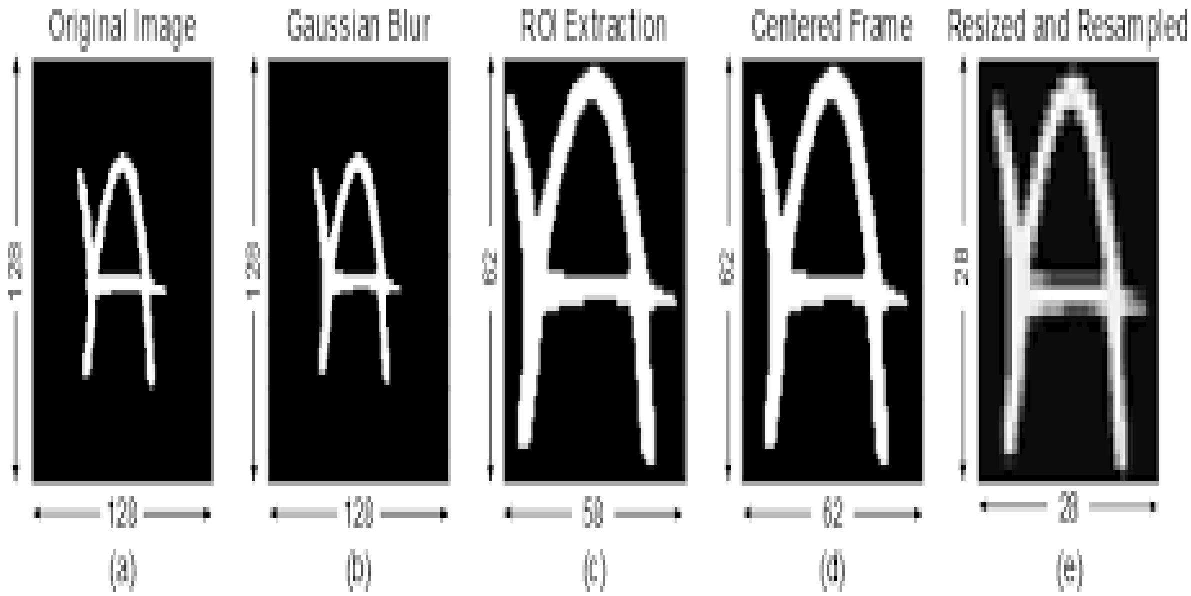

Figure 2-6 Abnormal data in the Dataset

1. The writing character is too small or the connecting pen makes it unrecognizable, which affects the recognition accuracy.
2. The strokes of writing characters are too vague to be recognized, resulting in the unknown shape of the characters.
3. Due to different writing habits, the characters seem so similar to other types of characters.
4. The differences between different characters are too small to distinguish. These abnormal data will affect the experimental accuracy and cause unnecessary errors. In order to avoid the affection of abnormal data.

Chapter Three

Proposed Handwriting System

3.1. Introduction

Handwritten character recognition will be implemented in this chapter. The premise of this project is based on the application of contemporary neural network techniques for recognition in order to accomplish effective hand-character recognition using MATLAB. The suggested system makes use of a data set that will be integrated in the implemented code. To accomplish this job, an ANN system is constructed and trained in MATLAB using a suitable dataset to recognize various kinds of handwritten letters and deliver accurate text recognition to a test input the system Procedure is shown in Figure 3-2.

3.2. Design and Architecture

In this section will talk about the architecture and design of the neural network-based system for recognizing handwritten characters was suggested before. Input pre-processing, convolutional neural networks (CNN), and output components are all part of the system that is being suggested, as depicted in figure (3-1) and figure (3-2).

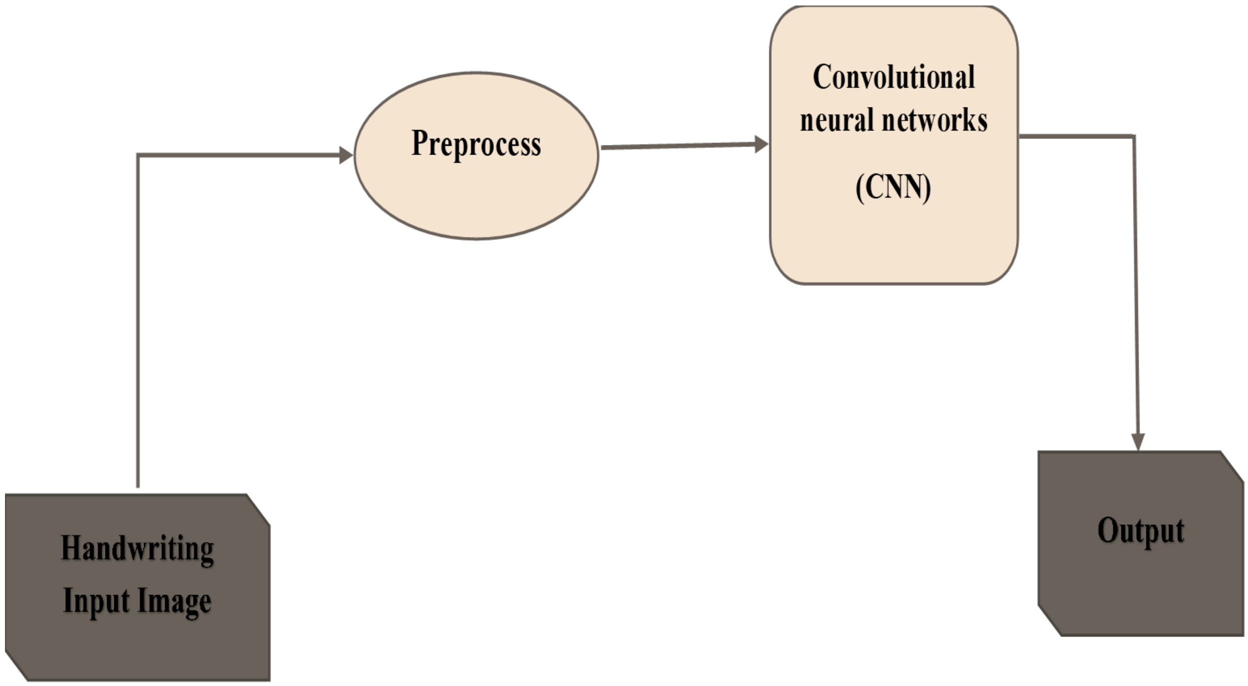

Figure 3-1 Design and Architecture

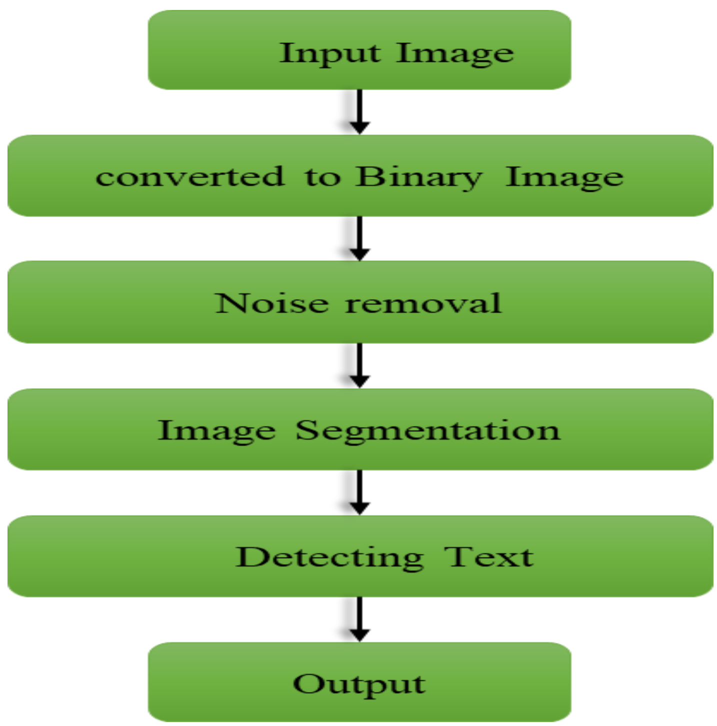

Figure 3-2 System Procedure

3.3. Image enhancement techniques

By the reduction of noise, boosting contrast, image blurring, and conveying more information, image attributes may be changed to make it more acceptable and to improve image quality. As a consequence, the processing of an image in such a way that the end output is superior to the original image and offers improved input for automated image processing algorithms is known as image post-processing.

3.3.1. Input Image

This step involves entering a picture and loading it into the workspace. And it preprocesses the input picture so that the neural network can process it more easily.

3.3.2. Binarization

This technique is used to convert a grayscale image into a monochromatic one, which reduces the amount of information contained within the image by transforming it from discrete grayscale forms into a binary one

3.3.3. Noise Removal

Images have the potential to be tainted by a wide variety of enticing noises. As a result, noise removal is required to improve image quality. separate noise by using equation 2-15 in chapter two

3.3.4. Image Segmentation

In image analysis and interpretation, picture segmentation is a crucial stage. Picture segmentation is a difficult and active study subject in image processing because to the effect of the complex backdrop, the diversity of object properties, and the noise the process of image segmentation results in the production of a set of contours that are extracted from the picture or a collection of regions that encompass the whole image. In terms of some characteristic or computed attribute, such as color, intensity, or texture, the pixels in an area are all comparable the system procedure is.

- The system starts by finding the number of rows and columns in the input image.
- Then it creates a new image with these dimensions, which is preprocessed to reduce the error.
- Then it creates a new image with these dimensions, which is preprocessed to reduce the error.
- Each character then separated and preprocessed in the same way that the E-MNIST dataset.

3.3.5. Detecting Text

In this step the system feed this image matrix into the neural network and get an output from it. the net function takes in an input and outputs a matrix of numbers that represent how much each pixel contributed to the final result. - In order for this system to work, reshape desired input is needed so that it has 784 rows and 1 column (the number of pixels).

3.3.6. Converting Handwriting Character

- In the first part of the system, load an image of a handwritten text. The image is then converted to grayscale The function rgb2gray is used to convert an RGB color space value into a grayscale value where each pixel has equal luminance or brightness levels of 0-255 and finally converted to binary
- . The binary image is cleaned up, and the characters in the image are segmented.

- Then, each character is resized and padded so that it has the same format as images in the EMNIST dataset, which was used to train the neural network.
- the system starts by loading the images into a matrix of 784 rows and 1 column, The first image is loaded into the first row, and so on.
- Next, it reshapes the input to be in a matrix of size 784 x 1. Then it feeds this input to net which outputs an output matrix that has one column for each pixel in the input image.
- Finally, each character is fed into the pretrained neural network These techniques result 97.8% accuracy by the use of different predicted characters, which are then displayed as text in a command window and in a.txt file.

Chapter Four

Results and Discussion

4.1. Introduction

In this chapter the result of the designed system will be illustrated. The following steps will be taken to show the simulation of MATLAB code to get the desired recognition character. Three images had been tested to show the performance of the implemented code

4.2. Network Parameters

The input character is first pre-processed using the mentioned techniques and the required characteristics are extracted. All these characteristics are fed into Neural Network and this input matrix is compared with target matrix. Target matrix contains the samples created for testing purpose. Later the required changes are made and the output matrix finally recognizes and prints the output the training procedure is done by MATLAB program as shown in figure (4-1) also the NN used here is CNN as depicted is figure (4-2)

- Test set: 10,000 examples
- Training set: 60,000 examples
- input nodes: 784
- Hidden nodes: 150
- Output nodes: 46
- Training algorithm: Scaled conjugate gradient training.
- Training goal achieved: 0.000001
- Total Training epochs: 206

- Time elapsed: 06.08 Min
- Best Validation performance: 0.0170 at epoch 200.

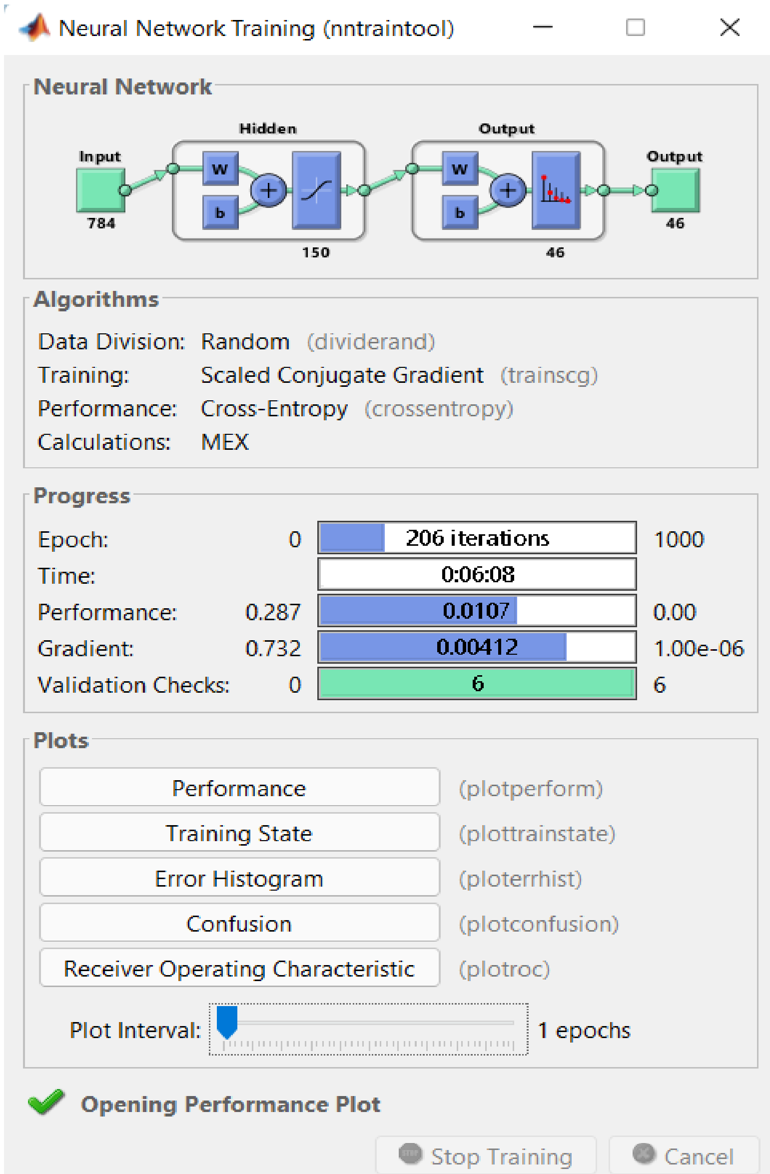

Figure 4-1 Neural Network training session

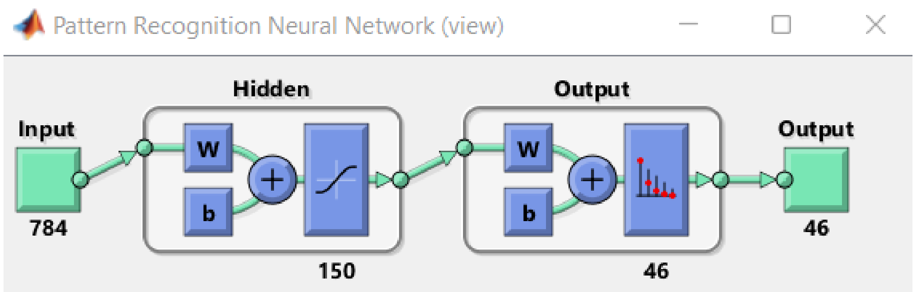

Figure 4-2 Stacked Layers of CNN

4.3. Performance Parameter

The performance parameter displays the system's accuracy in terms of parameters such as receiver operation characteristics, gradient, validation, and accuracy percentage. The following is a definition for them:

4.4. Receiver operating Characteristics (ROC)

Receiver Operating Characteristics (ROC) or ROC curves are graphical representations of the performance of a classifier, whether it properly classifies all classes. In order to derive the curve, comparing the real positive rate to the false positive rate is necessary. In machine learning, the true rate is sometimes referred to as exact classification or the probability of detection. The fallout or chance of false categorization is also known as the false rate. As demonstrated in Figure 4-3, a ROC curve can be produced by graphing the detection probability against the fallout probability. This method's predictive potential can be best gauged by looking at how far it is away from the random guess line on each side of that corner's upper left corner. If the outcome falls below a certain line, the procedure is no better than a guess made at random. The stability of our proposed system is also shown by the ROC curve. ROC curve demonstrates the following things:

1. It shows the tradeoff between false positive rate and true positive rate.

2. Closer the curve to the top and left-hand corner, the proposed system will be more accurate in result.
3. Closer the curve to the bottom and right-hand corner, less accurate result will be gotten.
4. Area under the ROC curve is a measure of test accuracy

46 ROC curves are shown in Figure 4- 3. In order to get an accurate reading, you need to look at the curve's underside. Area 1 is a great place to test. Testing accuracy is 97.8% with our proposed method. Testing accuracy can be viewed using the ROC curve. All 46 classes are found to fall between a value of 0.97 and a value of 1.

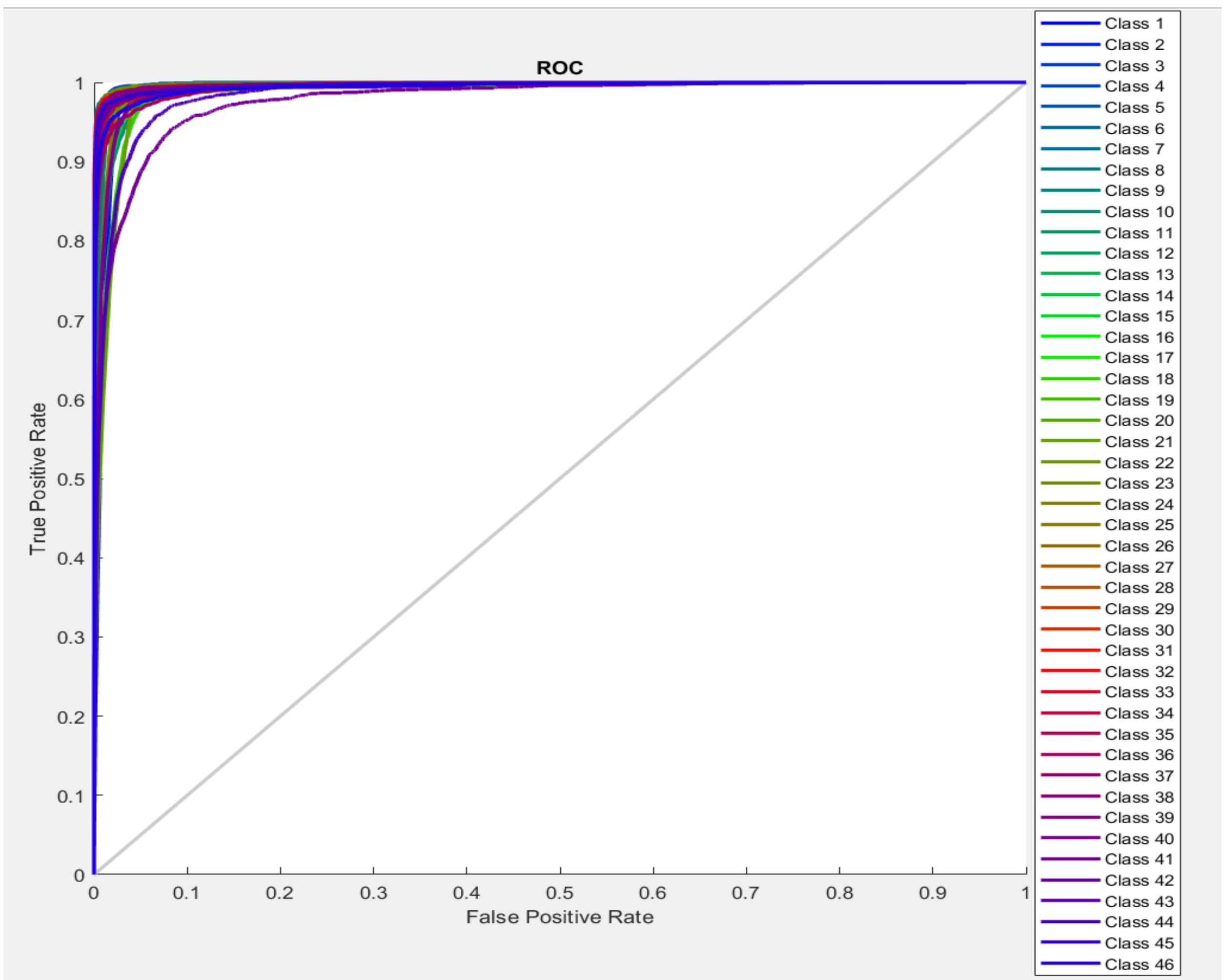

Figure 4-3 ROC Characteristics

4.5. Cross Entropy versus number of Epochs

Use cross-entropy error to evaluate neural network quality rather than mean square error when using neural networks for classification and prediction. The cross-entropy cost function is defined as follows[41]:

$$C = \frac{-1}{n} \sum_{x} [y \ln a + (1-y) \ln(1-a)] \qquad 4\text{-}1$$

Figure 4- 4. This test line is below the validation line, this indicate that the pattern is matched properly. There is no mismatch in our proposed system

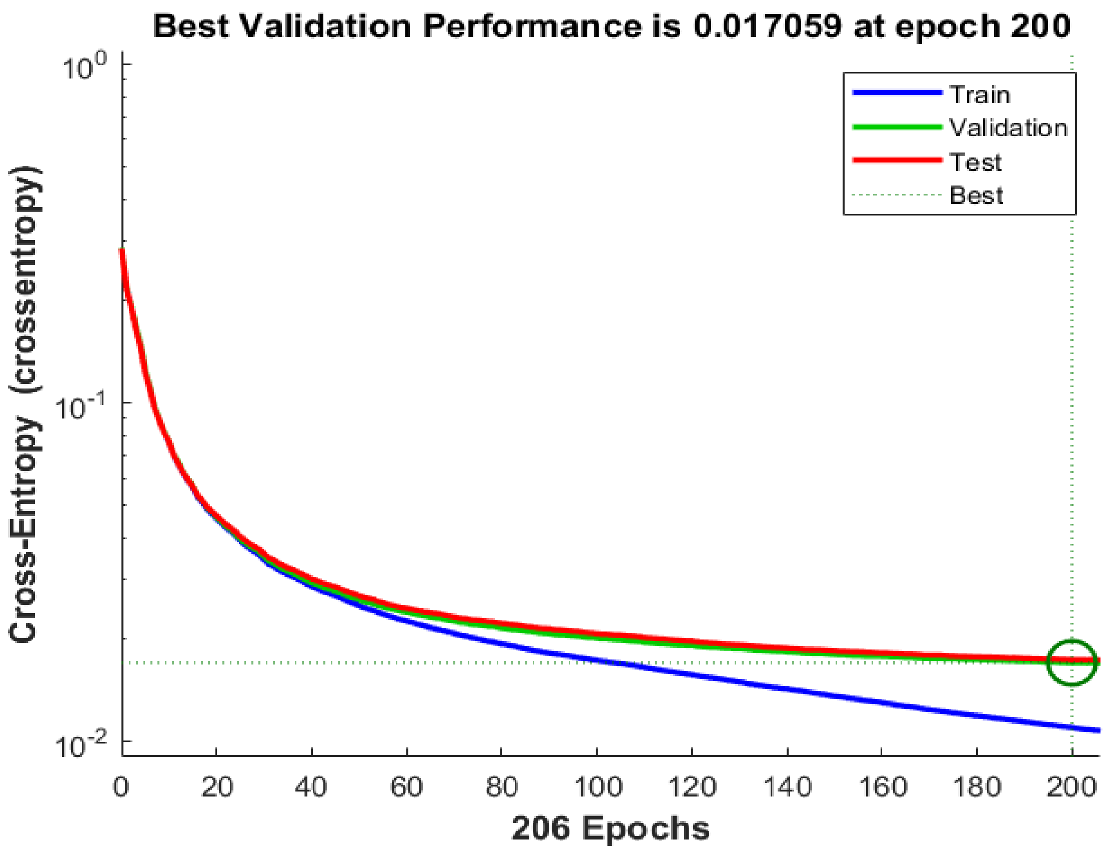

Figure 4-4 Cross-Entropy versus Number of Epochs

In training network, 206 iterations were used. From Figure 4- 4 it is shown that our network gives best validation performance at epochs 200.

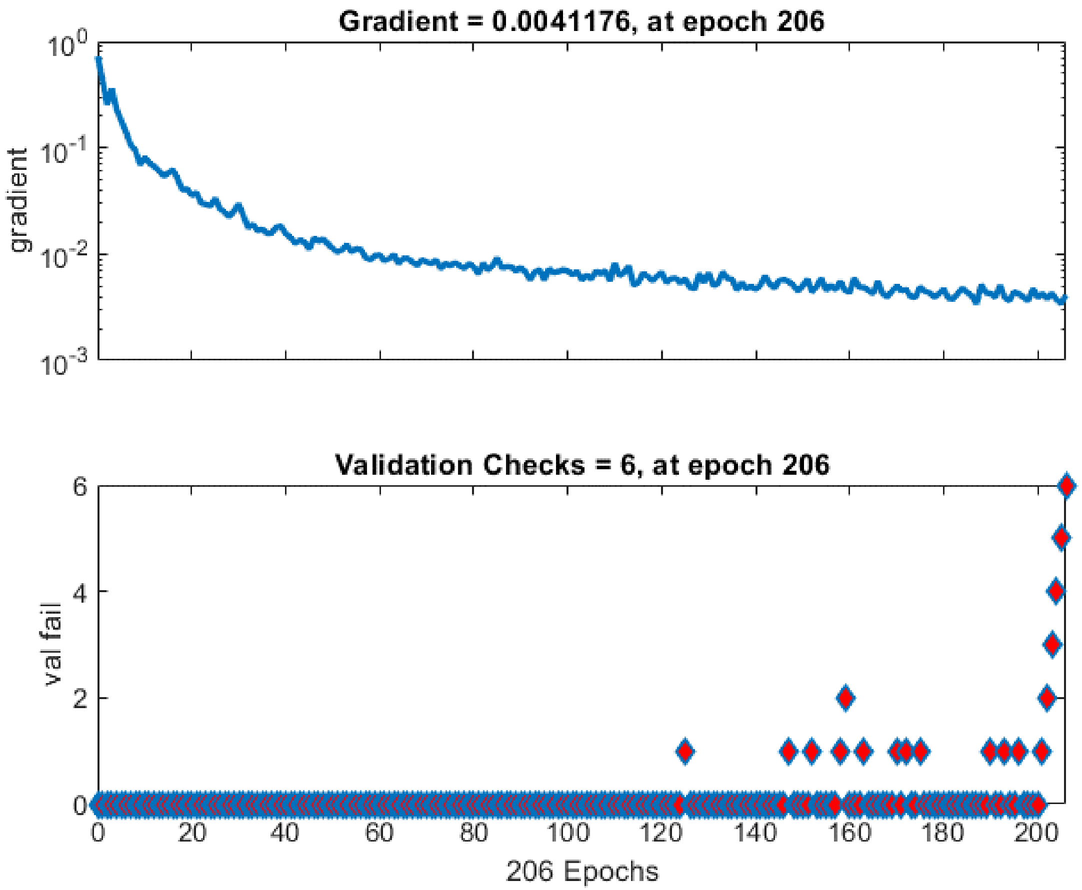

Figure 4-5 Gradient Vs Epochs

Gradient refers to the change in error energy when compared to the weight of the synapses. Training the training dataset requires the scale conjugate gradient algorithm. When developing a neural network, it is important to find the error function or cost function with the least amount of effort. Costs for our proposed work will be calculated using cross entropy.

4.6. Error Histogram

Error histogram is the histogram of the errors between target values and predicted values after training a feedforward neural network. As these error values indicates how predicted values differing from the target values, hence these can be negative. Bins are the number of vertical bars that are observing on the Figure. The total error range is divided into 20 smaller bins here. Y-axis represents the number of samples from your dataset, which lies in a particular bin. the height of that bin for training dataset lies below but near to 40 and validation and test dataset lies between 50 and 60. It means that many samples from different datasets have an error lies in that following range. Zero error line corresponding to the zero-error value on the error axis the error histogram is shown in figure (4-6)

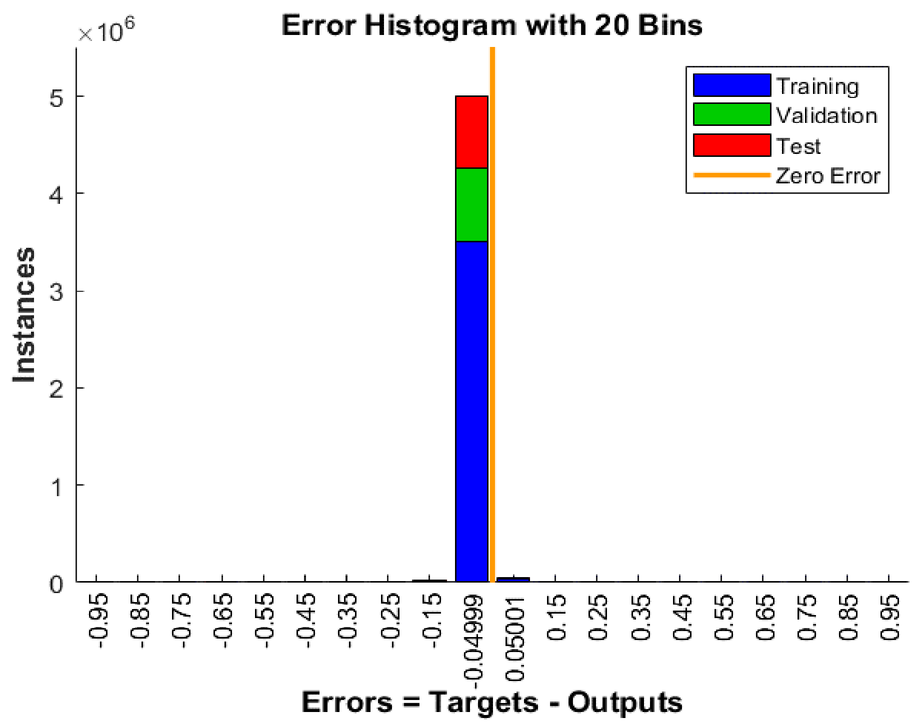

Figure 4-6 Error Histogram

4.7. Results with Capital letters

The system is a handwritten character recognition system that uses a convolutional neural network. In the first part of the system, loads an image of a line of handwritten text. The image is then converted to grayscale, then converted to binary. The binary image is cleaned up, and the characters in the image are segmented. Then, each character is resized and padded so that it has the same format as images in the EMNIST dataset, which was used to train the neural network. Finally, each character is fed into the neural network. In this case, an existing neural network is loaded from a .mat file and used to predict what each character is. The predicted characters are then displayed as text in a Command Window and in a .txt file. Three images had been tested to show the performance of the implemented code figure 4-7 shows the capital letters image with noise the procedure maintained can be depicted in figures (4-8….4-11) the same procedure of the proposed handwriting system that applied to the capital letters are done on the examples that have mixed and small letters. The result of testing those images can be shown in figure (4-12…4-21)

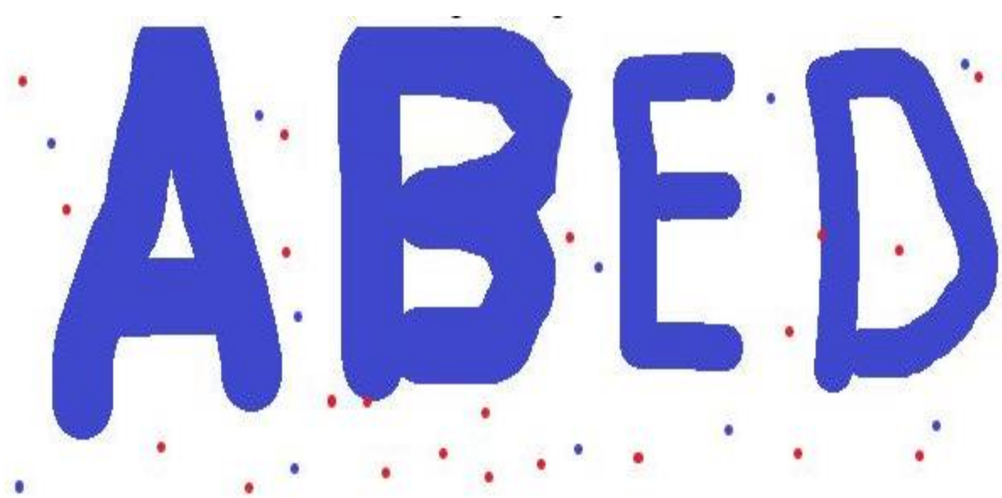

Figure 4-7 Capital litter original image

Figure 4-8 Capital letter Convert to gray scale

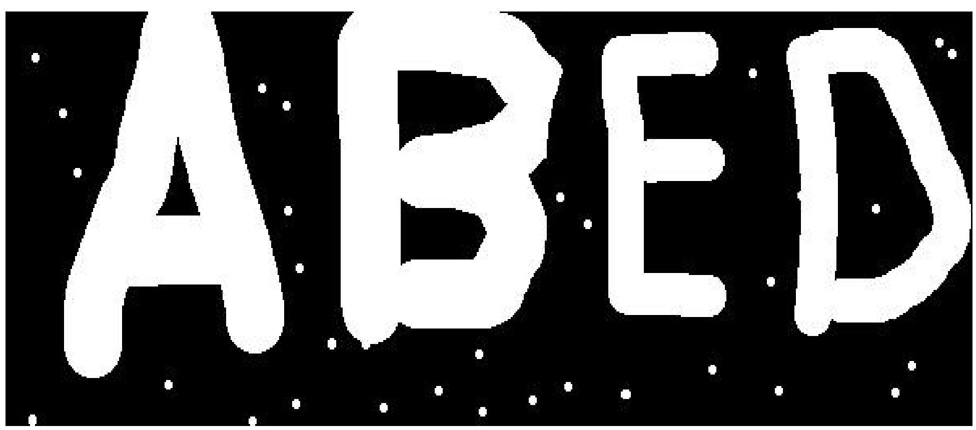

Figure 4-9 Capital letter Binary image

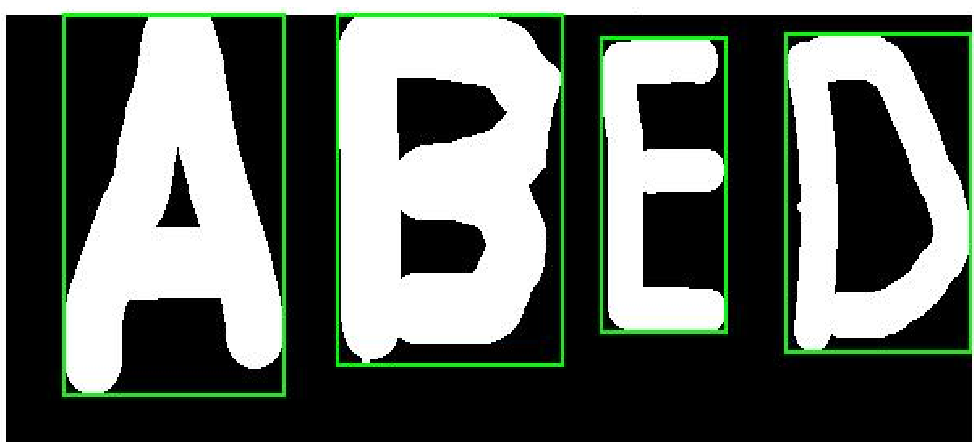

Figure 4-10 Capital letter Segmented image

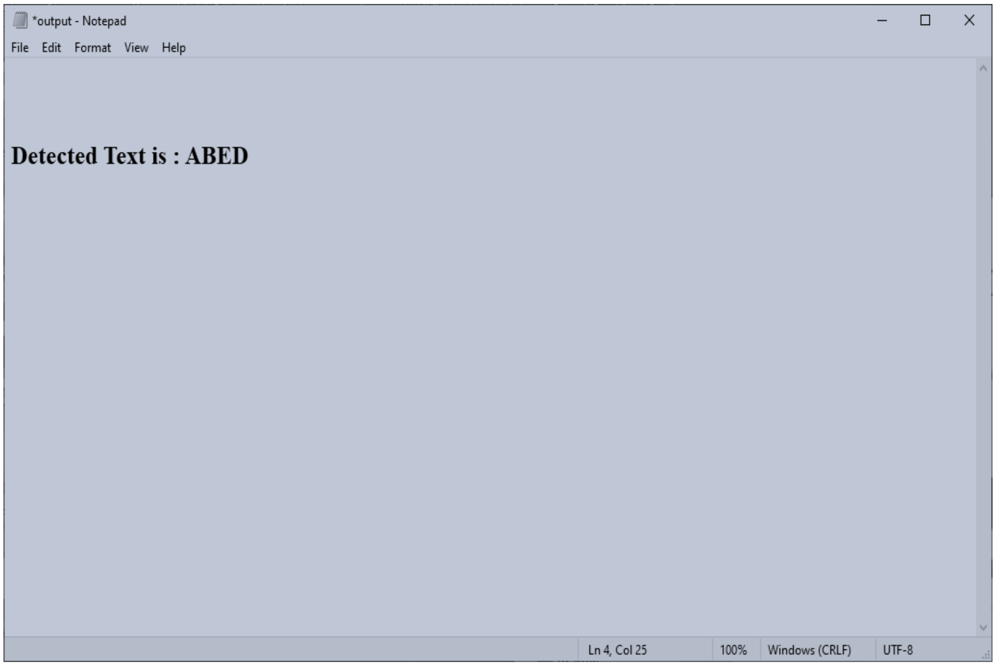

Figure 4-11 Capital letter Detected text

Figure 4-12 Mixed letter original image

Figure 4-13Mixed letter gray scale image

Figure 4-14 Mixed letter binary image

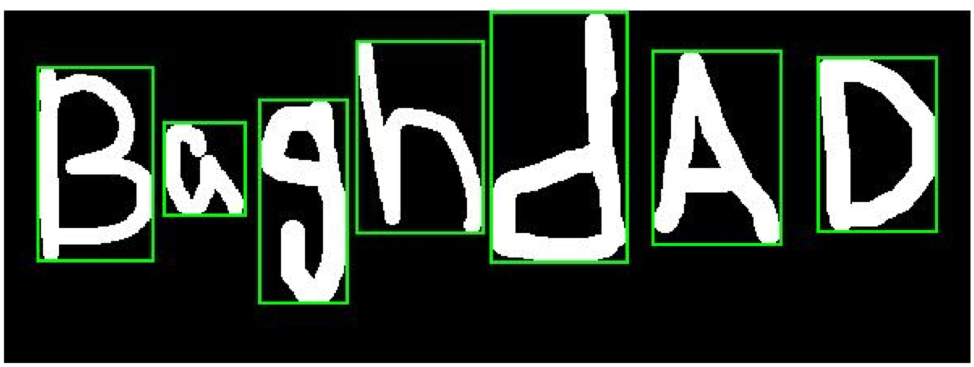

Figure 4-15 Mixed letter segmented image

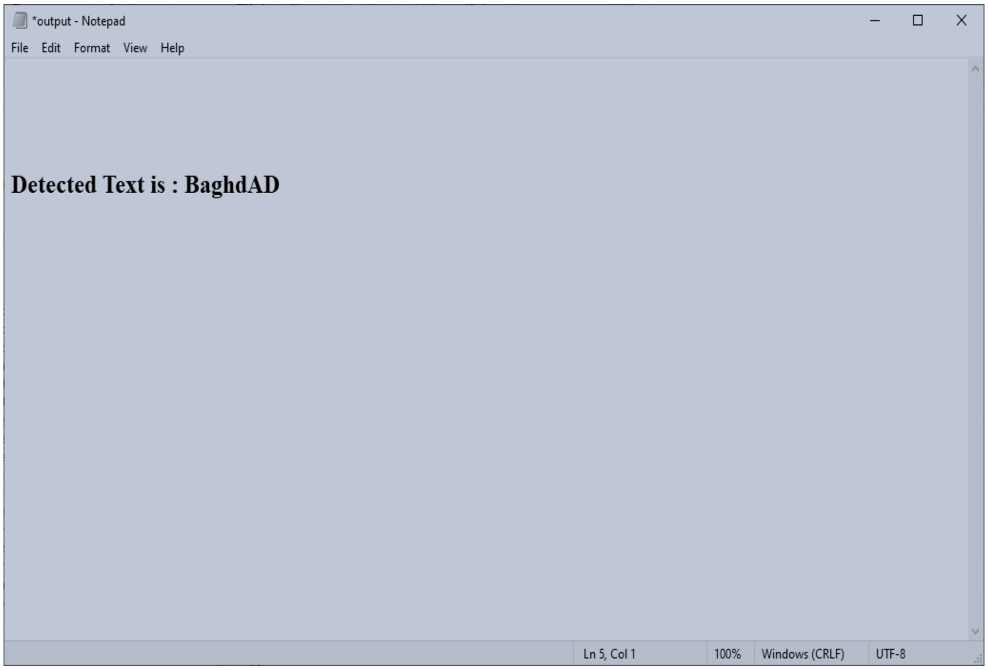

Figure 4-16 Mixed letter Detected Text

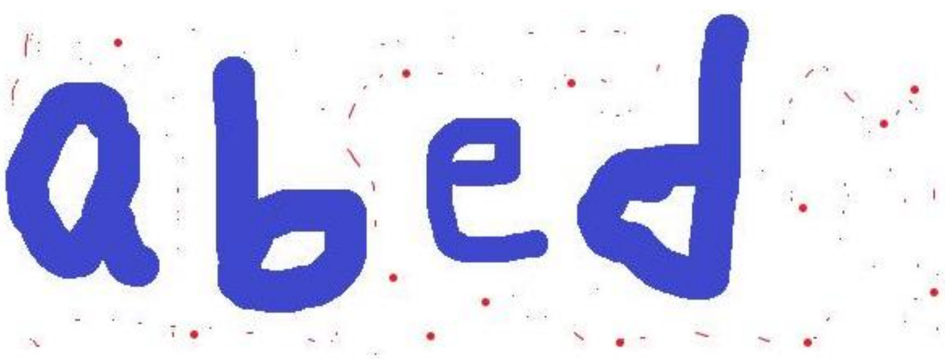

Figure 4-17 Small letter original image

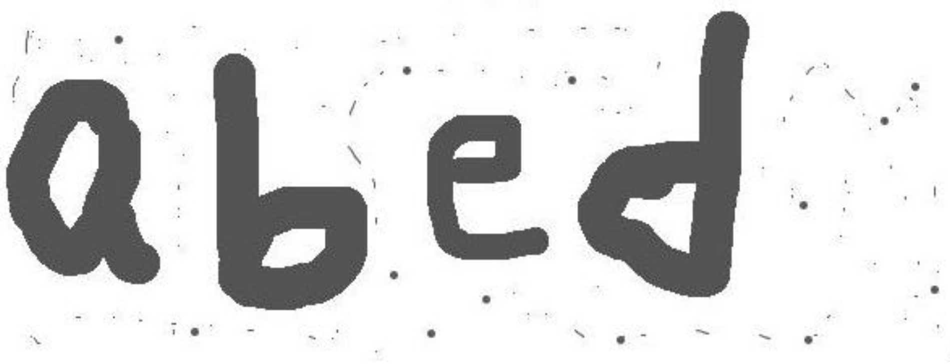

Figure 4-18 Small letter Gray scaled image

Figure 4-19 Small letter binary image

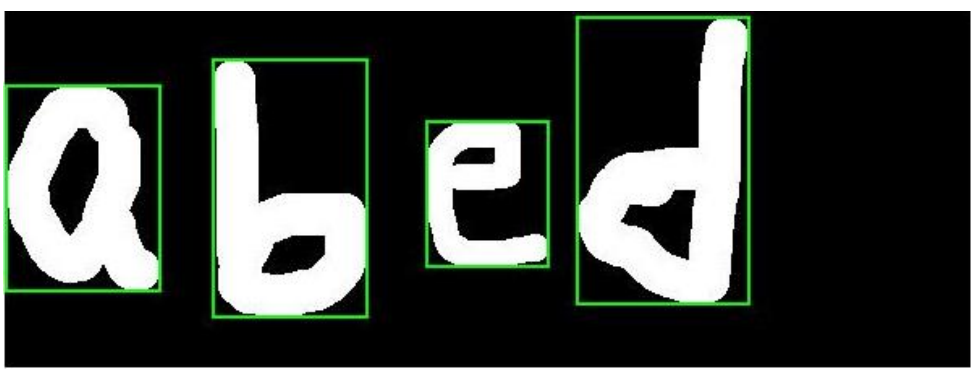

Figure 4-20 Small letter segmented image

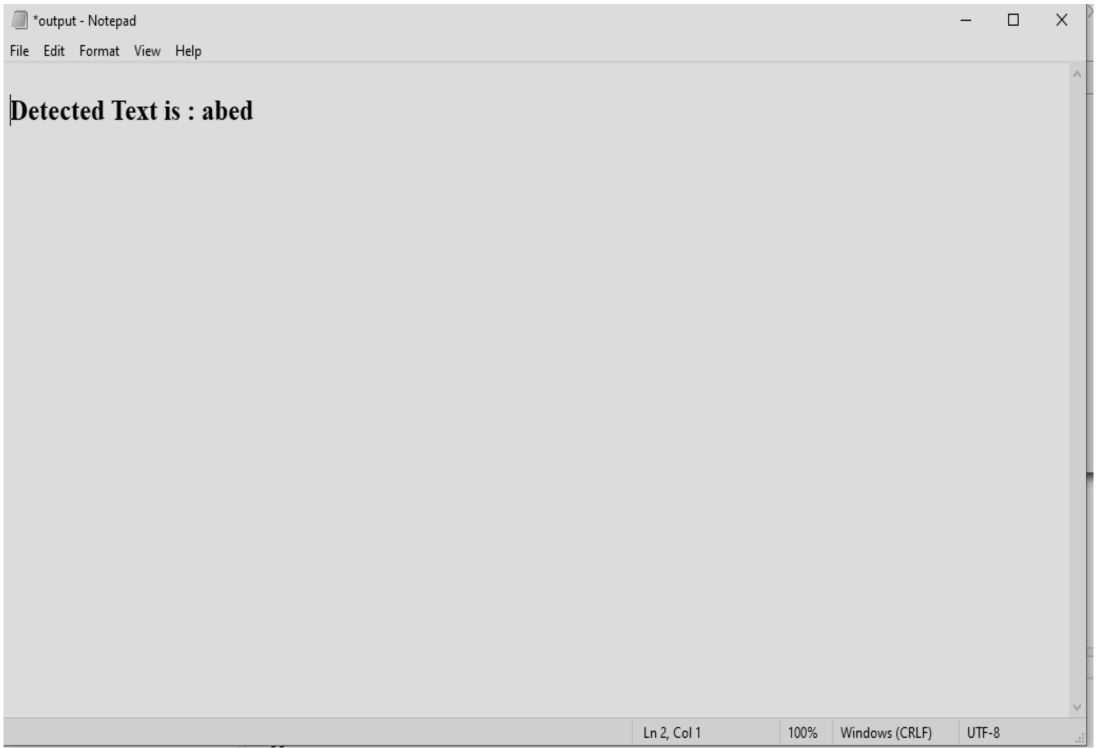

Figure 4-21 Small letter Detected Text

4.8. Discussion

The technology employs a convolutional neural network to recognize handwritten characters.

- load an image of a handwritten text is the first part of the system.
- The image is then converted to grayscale and finally converted to binary.
- The binary image is cleaned up, and the characters in the image are segmented. Then, each character is resized and padded so that it has the same format as images in the EMNIST dataset of handwritten character, has a training set of 60,000 examples, and a test set of 10,000 examples. It is a subset of a larger set available from NIST. The character has been size-normalized and centered in a fixed-size image.28*28 pixel for each image.

Chapter Five

Conclusion and Future Works

5.1. Conclusion

- This project presented a new system for handwritten text recognition based on an improved artificial neural network. CNN neural network was used because (CNN) is modern method in handwriting recognition task specialized for image processing.
- The scaled conjugate gradient algorithm was used for training significantly accelerates the training process and gives accurate results.
- Cross entropy cost function was used because One of the most common loss functions used for training neural networks Using cross entropy can measure the error (or difference) between two probability distributions
- The EMNIST datasets provide a new classification benchmark that contains more image samples, more output classes, a more varied classification task, this therefore represents a new and modern performance benchmark for the current generation of classification and learning systems.

5.2. Future Work

The main goal of the current study, which was to recognize English handwritten words with high accuracy, was met. There is, however, some related work that might be continued. The following are some ideas for future work:

- Try to recognize the character for long sentence
- Try to translate the recognized word to the langue that the user understands

- A new character dataset can be created which includes most overlapping character combinations and labeled as multiple characters
- A segmentation method can be developed such that it can use recognition accuracy of the proposed work for assessing its segmentation accuracy and use it for training itself.

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الخلاصة

الشبكة العصبية الاصطناعية (CNN) هي نظام كمبيوتر يحاول العمل بالطريقة التي تعالج بها أدمغتنا المعلومات وتحللها. إنه أساس الذكاء الاصطناعي (AI) وغالبًا ما يستخدم لحل المشكلات التي يصعب أو يستحيل حلها باستخدام الخوارزميات العادية. نظرًا لأن شبكات CNN يمكن أن تتعلم من تلقاء نفسها فمع توفر المزيد من بيانات الإدخال يمكنها تقديم نتائج أفضل. يتم استخدام الانتروبيا المتقاطعة كدالة تكلفة في النظام الذي نقترحه لهذا المشروع.

نستخدم خوارزمية مقياس التدرج المترافق (SCG) لتدريب الشبكة العصبية (CNN) للتحقق من مدى جودة عمل النظام المقترح، هناك أشياء مهمة يجب التفكير فيها، مدرجة من الأكثر أهمية إلى الأقل أهمية: خصائص تشغيل جهاز الاستقبال للنظام المقترح، والتي تعطي في الواقع نتيجة استقرار التصنيف (ROC) وقيمة التدرج ودقة النسبة المئوية للنظام المقترح اما فيما يخص الية العمل فقد تم استخدام مجموعة بيانات EMNIST مع 10,000 مثال للاختبار و60,000 مثال لتدريب تقنيات مختلفة على المعالجة المسبقة لمجموعة بيانات الصورة. وذلك بواسطة برنامج الماتلاب (MATLAB R2020a) مع نظام (Windows10) ومعالج (core i5 2520m)

جمهورية العراق
وزارة التعليم العالي والبحث العلمي
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تمييز خط اليد باستخدام الشبكات العصبية الاصطناعية

بحث

مقدم الى كلية الهندسة في جامعة بابل كجزء من متطلبات نيل درجة الدبلوم العالي في الهندسة / الهندسة الكهربائية.

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1443 هـ ***2022 م***