

*OPTICAL HANDWRITTEN*

RECOGNITION FOR  
ENGLISH LETTER  
LANGUAGE USING ANN  
(ARTIFICIAL NEURAL  
NETWORKS)

Supervised By: Dr. Amr Sabry Ghoneim

Faculty of Computer Science and Artificial intelligence –

Helwan Uni. CS361: Artificial Intelligence

---



## Table of Contents

<b>Abstract &amp; Motivation</b>	<b>3</b>
<b><i>INTRODUCTION</i></b>	<b>4</b>
<b>LITERATURE REVIEW</b>	<b>5</b>
<b>2. <i>HANDWRITTEN RECOGNITION SYSTEM (METHODOLOGY)</i></b>	<b>6</b>
<b>2.1 Image Acquisition</b>	<b>6</b>
<b>Pre-processing</b>	<b>6</b>
<b>Segmentation</b>	<b>6</b>
<b>Feature Extraction</b>	<b>6</b>
<b>Classification</b>	<b>6</b>
<b>Post-processing</b>	<b>6</b>
<b>3. <i>Academic publications</i></b>	<b>6</b>
<b>4. <i>INTEGRATED APPROACH TO FEATURE EXTRACTION AND CLASSIFICATION</i></b>	<b>13</b>
<b>4.1 Template Matching</b>	<b>13</b>
<b>4.2 Neural Network based classifier Neural Network (NN)</b>	<b>14</b>
<b>4.3 Feed Forward Back Propagation Neural Network Classifier</b>	<b>14</b>
<b>5. RESULTS AND DISCUSSION</b>	<b>16</b>
<b>6. CONCLUSION</b>	<b>20</b>
<b>7. Additional REFERENCE</b>	<b>21</b>

## INTRODUCTION & OVERVIEW

### Abstract & Motivation

At the beginning of the new era of AI the human beings ambitions directed them to go beyond the normal computer programs and show the real power of computer rather than accepting the normal way of high-computational power that computers have to calculate and execute given instructions; in my POV I guess it could start with *“why this electronic machine CAN not do it on its own”* and everything started at this point, but for a moment the process of making **MACHINES** thinks is not a clear one actually from the terminology - Artificial Intelligence - We can say *“we gave the computer the capability to imitate the Human intelligence”* not only the humans intelligence but their capabilities like *“vision”* we can see that in a subfield in AI called *“Computer Vision”*, the capability of *“talking”* this is applied in *“Natural language processing”* for the current project that we will discuss the usage of *“NEURAL NETWORKS”* in OCR - Optical Character Recognition - for English alphabet letters using (ANN) “Artificial Neural Networks” the main process is giving a prepared image to the computer system and tries to *PREDICT* the given letter.

---

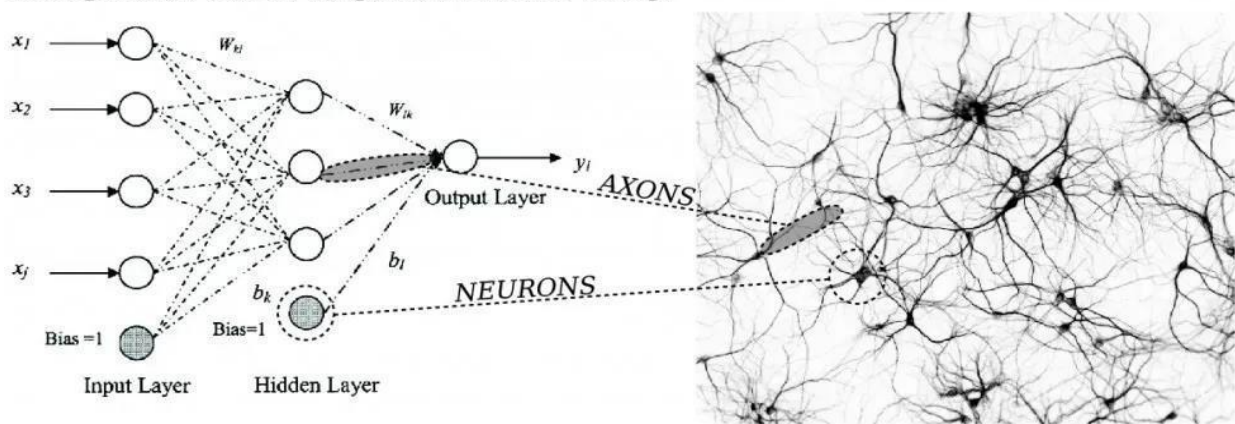
*“A year spent in artificial intelligence is enough to make  
one believe in God.” —Alan Perlis*

---

## INTRODUCTION

In this project we are trying to teach the computer or giving it the capability to visualize a given picture uploaded to the computer or recognized by the camera. In this report we will discuss the process of building the OCR model. At first we will mention the purpose of building – alphabet handwritten recognition – and the used approach; there are so many approaches related to the OCR but the approach we are following in this report is – Artificial Neural Networks (ANN) – in a brief (ANN) is an approach that relies on imitating the human neural networks. The approach was raised due to the high computational power of human neural network and the scientists decided to adopt the approach. We will discuss later why we decided to use ANN rather than the different approaches like SVM for example.

### **NEURAL NETWORK MAPPING**



(Fig.1)

in (Fig.1) we are proving the taken approach and how the neural network in humans got propagated on Artificial intelligence.

- Definition : Artificial neural networks (ANNs), usually simply called neural networks (NNs) or neural nets,<sup>[1]</sup> are computing systems inspired by the [biological neural networks](#) that constitute animal [brains](#)
- An ANN is based on a collection of connected units or nodes called

[artificial neurons](#), which loosely model the [neurons](#) in a biological brain. Each connection, like the [synapses](#) in a biological brain, can transmit a signal to other neurons. An artificial neuron receives signals then processes them and can signal neurons connected to it. The "signal" at a connection is a [real number](#), and the output of each neuron is computed by some non- linear function of the sum of its inputs. The connections are called *edges*. Neurons and edges typically have a [weight](#) that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold.

## LITERATURE REVIEW

Handwritten characters were a difficult task because characters are written in various ways, so they could be of different sizes, orientation, thickness and dimension. An offline HCR(English) system using neural network is presented in this report. Neural networks were good at recognizing handwritten characters a these networks are insensitive to the missing data. A Backpropagation neural network is used for classification. Experimental result of this system shows that results 93%. In this paper A neural network approach is proposed for automatic offline character recognition system. In this paper, work has been performed to recognize Devanagari characters using multilayer perceptron. Various patterns of characters were created in the matrix with the use of binary form and stored in the file. This system used the back propagation neural network for efficient recognition and neuron values were transmitted by naive bay's method in the neural network.

This paper provides review of existing works in HCR based on soft computing technique during the past decade. proposed system deals with development of grid-based method which is combination of image centroid zone and zone centroid zone of individual character or numerical image. Use of

feed forward neural network for recognition. Complete process of Devanagari character recognition works in stages as document preprocessing, segmentation, feature extraction, classification using grid-based approach followed by recognition using naive bay's. Fifty data sets, each containing 26 alphabets written by various people, are used for training the neural network and 570 different handwritten alphabetical characters are used for testing. This system performs quite well yielding higher levels of recognition accuracy compared to the systems employing the conventional horizontal and vertical methods of feature extraction.

## 2. HANDWRITTEN RECOGNITION SYSTEM (METHODOLOGY)

- 2.1 Image Acquisition
- 2.2 Pre-processing
- 2.3 Segmentation
- 2.4 Feature Extraction
- 2.5 Classification
- 2.6 Post-processing

## 3. Academic publications (papers)

# 1st paper

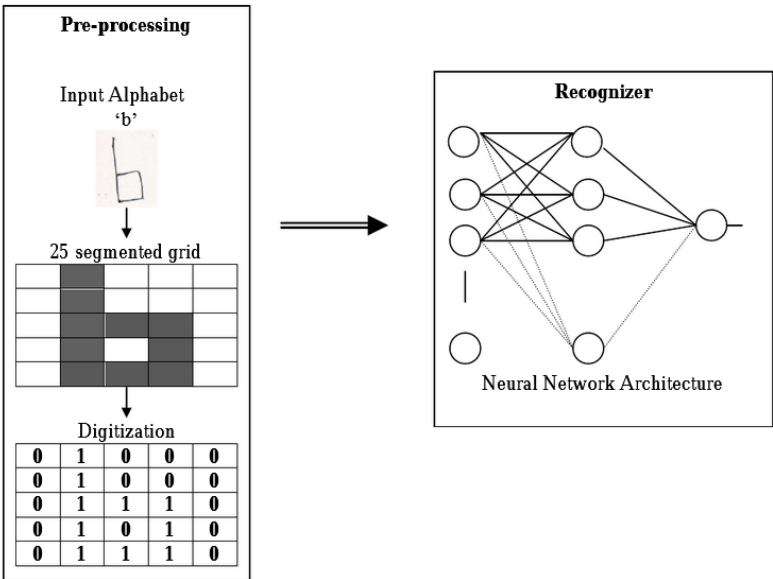


Figure 1: Two Phase Character Recognizer

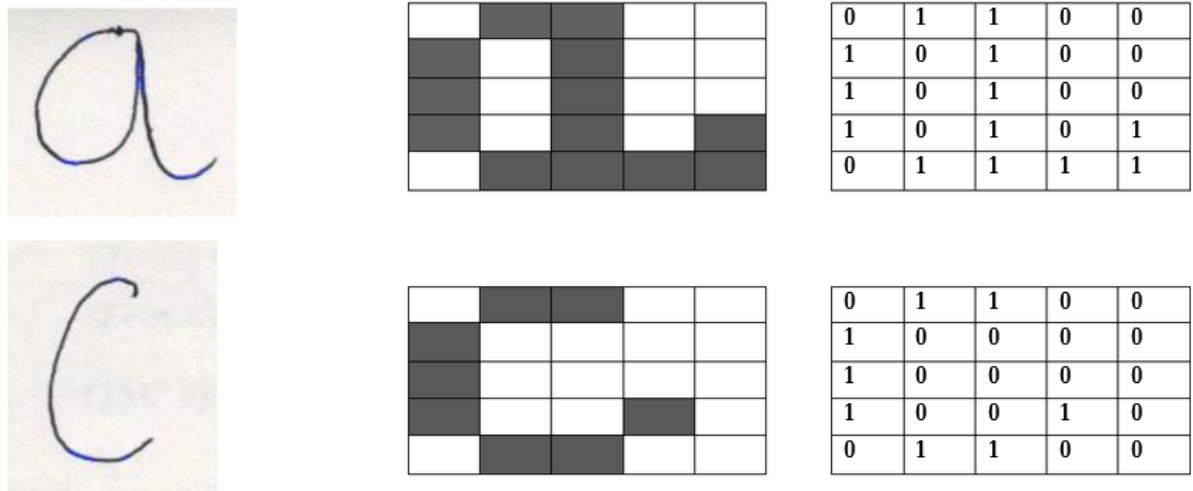


Figure 2: Example Training sets

Two phase processes are involved in the overall processing of our proposed scheme: the Pre-processing and Neural network based Recognizing tasks. The pre-processing steps handle the manipulations necessary for the preparation of the characters for feeding as input to the neural network system. First, the required character or part of characters needs to be extracted from the pictorial representation. The splitting of alphabets into 25 segment grids, scaling the segments so split to a standard size and thinning the resultant character segments to obtain skeletal patterns. The following pre-processing steps may also be required to furnish the recognition process:

- I. The alphabets can be thinned and their skeletons obtained using well-known image processing techniques, before extracting their binary forms.
- II. The scanned documents can be “cleaned” and “smoothed” with the help of image processing techniques for better performance.

paper link:

[https://www.researchgate.net/publication/224963012 Neural Networks for Handwritten English Alphabet Recognition](https://www.researchgate.net/publication/224963012_Neural_Networks_for_Handwritten_English_Alphabet_Recognition)

## # 2nd paper

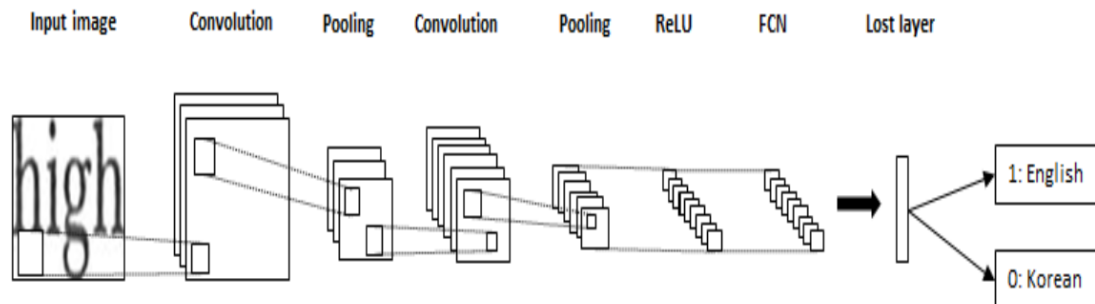


Fig. 1. Convolutional neural network

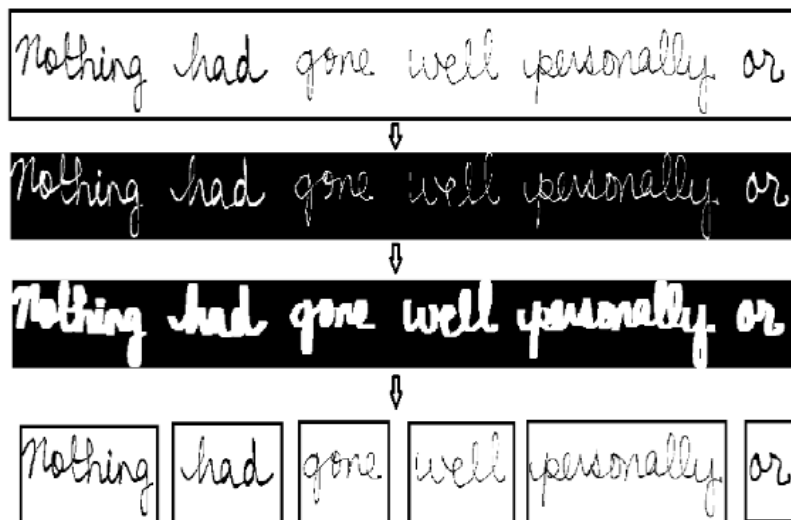


Fig. 2. Word-segmentatio procedure. From top to bottom: original image, binarized image, scanning for the same block word, and word-segmentation result.

The CNN consists of a sequence of layers, and each CNN layer transforms one activation volume to another through a differentiable function. As shown in Fig. 1, five main types of layer are applied for the creation of the CNN architecture, as follows: convolutional layer, pooling layer, rectified linear-unit layer (ReLU), fully-connected layer, and loss layer. Convolutional and pooling layers are alternately included in the low- and middle-level layers. The convolutional layers are included in the odd-numbered layers that consist of the bottom layer, and the even-numbered layers include the pooling layers. The nodes on the convolutional and pooling layers are grouped into feature maps. Each map is



connected to one or more of the maps of the previous layer. Each node on a map is connected to a small region of each of the connected maps in the previous layer. The node of the convolution layer extracts features from the input image through a convolution operation on the input nodes, and the node of the pooling layer extracts the features by selecting the maximum value among the input nodes. The convolutional layer is the core block of a CNN. The convolutional-layer parameters include a set of learnable filters. Each filter is spatially small, but they each extend through the full depth of the input volume; for instance,  $5 \times 5 \times 3$  is a typical filter on the first layer. During the forward pass, each filter is slid across the width and the height of the input volume, and the dot products between the entries of the filter and the input can be computed at any position; consequently, a two-dimensional (2D) activation map that provides the responses of that filter at every spatial position is produced. Supposedly, the network will learn the filters that become activated when they see some type of visual feature such as the edge of some orientation or the blotch of some color on the first layer; or eventually, when entire honeycomb or wheel-like patterns are seen on the higher network layers. Each of the filters in each convolutional layer will produce a separate 2D activation map and these activation maps will be stacked along the depth dimension and will produce the output volume

paper link:

<https://ijcon.accesson.kr/assets/pdf/2381/journal-13-3-38.pdf>

# 3th paper

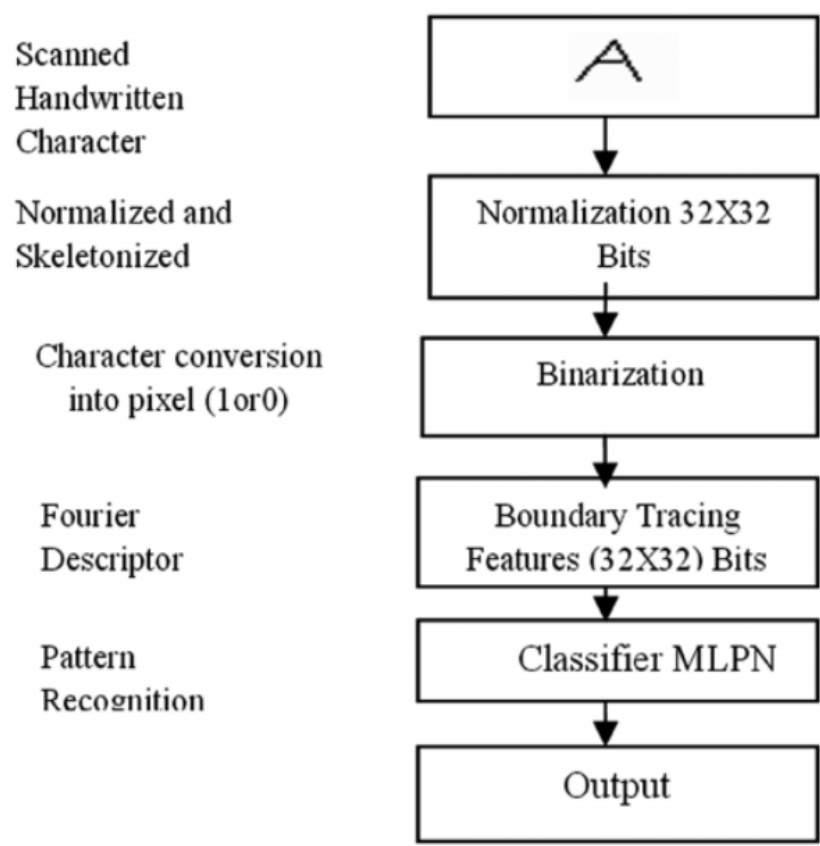


Fig. 7: A System for English Character Recognition

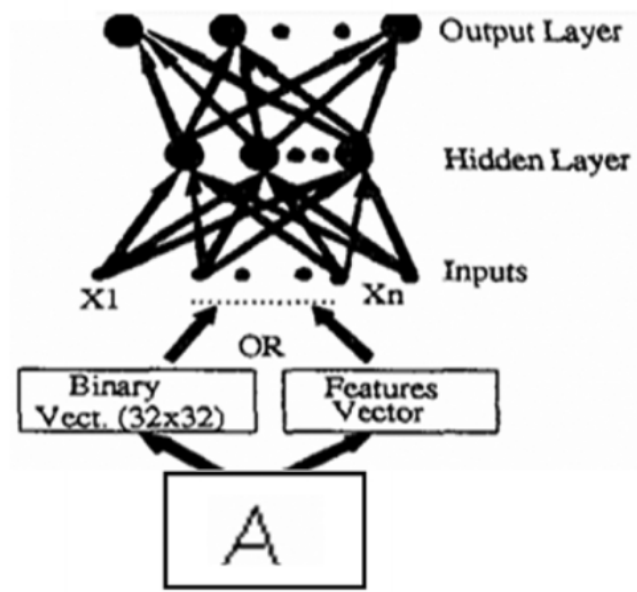


Fig. 6: Multilayer perceptron Network (MLPN)

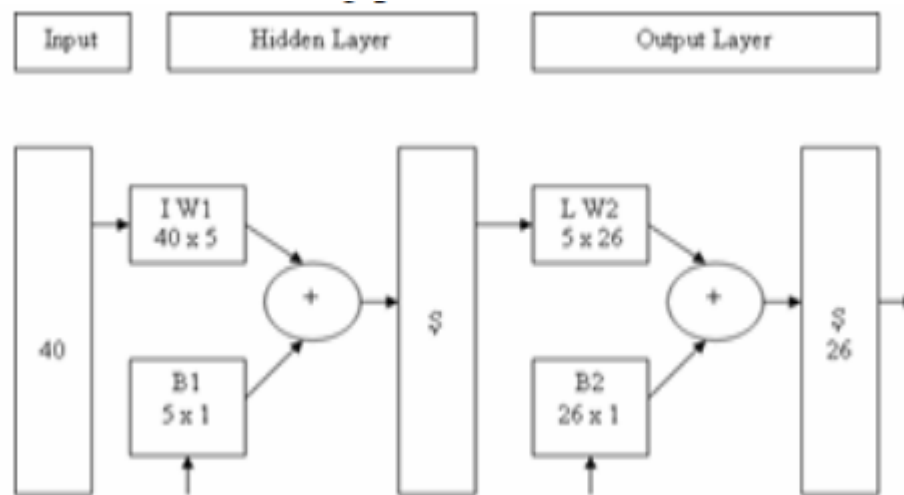
The procedure of handwritten English character recognition is as follows:

- Acquire the sample by scanning.
- Skeletonization and Normalization operations are performed.
- Apply Boundary Detection Feature Extraction technique.
- Neural network Classification.
- Recognized Character.

paper link:

<https://www.csjournals.com/IJCSC/PDF1-2/30..pdf>

# 4th paper :



**Fig 4: Neural Network Architecture**

The Character Recognition System must first be created through a few simple steps in order to prepare it for presentation into MATLAB. The matrixes of each letter of the alphabet must be created along with the network structure. In addition, one must Understand how to pull the Binary Input Code from the matrix, and how to interpret the Binary Output Code, which the computer ultimately produces.

**Character Matrixes:** A character matrix is an array of black and white pixels; the vector of 1 represented by black, and 0 by white. They are created manually by the user, in whatever size or font imaginable; in addition, multiple fonts of the same alphabet may even be used under separate training sessions [3].

**Creating a Character Matrix:** First, in order to endow a computer with the ability to recognize characters, we must first create those characters. The first thing to think about when creating a matrix is the size that will be used. Too small and all the letters may not be able to be created, especially if you want to use two different fonts. On the other hand, if the size of the matrix is very big, their may be a few problems.

Training may take more time, and results may take hours.

paper link :

[https://www.elixirpublishers.com/articles/1350124283\\_41%20\(2011\)%205587-5591.pdf](https://www.elixirpublishers.com/articles/1350124283_41%20(2011)%205587-5591.pdf)

## 4. INTEGRATED APPROACH TO FEATURE EXTRACTION AND CLASSIFICATION

During the last few decades, the field of character recognition has received a major attention from research workers in diverse disciplines such as conversion of handwritten document to an editable soft format, recognition of postal addresses for automated postal system, data and word processing, data acquisition in bank checks and processing of archived institutional records. Some methods integrate the feature extraction and classification tasks. Such methods are simpler and easier to implement. In this paper such methods are studied, and the accuracy achieved is reported.

### 4.1 Template Matching

Template matching is a simple and commonly used classification technique for character recognition. The unknown input character image is compared pixel-by-pixel with the templates of the recognizable characters. The character, whose template has the closest resemblance to the input image in terms of maximum pixel matching, is declared as the input character. In this paper, each test data was resized into an image of size 30x20 pixels. The printed character template (Times New Roman style) is saved in the database. No training is required. The test data was given as input and the recognition accuracy obtained is 54.27%. This method is simple, but recognition is poor as handwriting styles vary considerably among different people and some English characters have similar structures. Hence this method cannot be used in applications, which require high recognition rates [17].

### 3.2. Neural Network based classifier Neural Network (NN)

techniques offer a promising solution as classifiers in the handwritten character recognition system. The image after resizing is taken as an input. The classification capability of the network depends on the architecture and learning rule. The architectures considered in this paper are feed forward architecture [18-19], nearest neighborhood [20] and radial basis function architecture [21]. To evaluate the performance of the proposed method the handwritten uppercase English alphabets were collected from different individual writers. Of the 7800 samples collected, 5200 samples were used for training purpose and remaining 2600 samples were used for testing. The proposed recognition system has been implemented using Python 3.3. The recognition systems were designed using different methods but, in this report, we are only focusing on the NN classifier, and the justification will be represented using table.1

#### 3.2.1 Feed Forward Back Propagation Neural Network Classifier

The scanned image is taken as dataset/ input and feed forward architecture is used. As each image is resized into 28X28 pixels, the input layer has 600 neurons equal to the total number of pixels. The number of output neurons is based on the number of alphabets. As all the English alphabets are used, the output layer has 26 neurons. All the neurons use log sigmoid transfer functions. The back propagation algorithm with momentum and adaptive learning rate is used to obtain the parameters of the network. Two Hundred different handwritten data sets were used for training the neural network. The number of hidden layers and the number of neurons in each layer are to be obtained through trial and error. Through numerous simulations it was identified that a maximum of two hidden layers and a maximum of 100 neurons in each hidden layer would be sufficient for character recognition. Further increase in the number of neurons did not considerably improve the accuracy. This feed 103 J. Pradeep et al/ IJE TRANSACTIONS B: Applications Vol. 25, No. 2, (May 2012) 99-106 forward neural network architecture was trained for a target MSE of  $10e-8$ . After the network is

satisfactorily trained, the parameters of the trained network are fixed to enable testing. The architecture of the three-layer neural network for the handwritten recognition system is shown in Fig.5 and the network training parameters are shown in Table 1. The results obtained are shown in Table. 2.

TABLE 1. Feedforward Neural Network Training Parameters

Feedforward Neural Network Parameters	
Input nodes	600
Hidden layers	2
Hidden layers nodes	100
each Output nodes	26(alphabets)
Training epochs	9
Training algorithm	Gradient descent with momentum training and adaptive learning
	Performance function Mean Square Error (MSE)
Training goal achieved	10e-8

TABLE 2. Performance Comparison of Different Classifiers

Enrollment in local colleges, 2005

Classifier	Number of Correctly Recognized alphabet	Recognition Rate in %
Template Matching	1411	54.27
Feed Forward NN	2448	94.15
Nearest Neighbor NN	2244	86.96
Radial basis function NN	2245	89.42

As observable in the previous table the NN Classifier got the highest recognition capability in contrast with the other algorithms, and for more we will provide extra table and charts to demonstrate the detailed results.

**TABLE 3.** Summary of the results achieved by the proposed methods

Classifier	No of alphabets with recognition rate greater than 90%	Alphabets with a recognition rate greater than 90%
Template Matching	2	U, L
Feed Forward NN	23	A,B,C,F,G,I,J,K,L,M,N,O, P,Q,R,S,T,U,V,W,X,Y,Z
Nearest neighbour NN	8	C,D,L,O,P,T,U,W
Radial basis function NN	14	A,C,F,G,L,N,P,S,T,U,V,W, Y,Z

## 5. RESULTS AND DISCUSSION

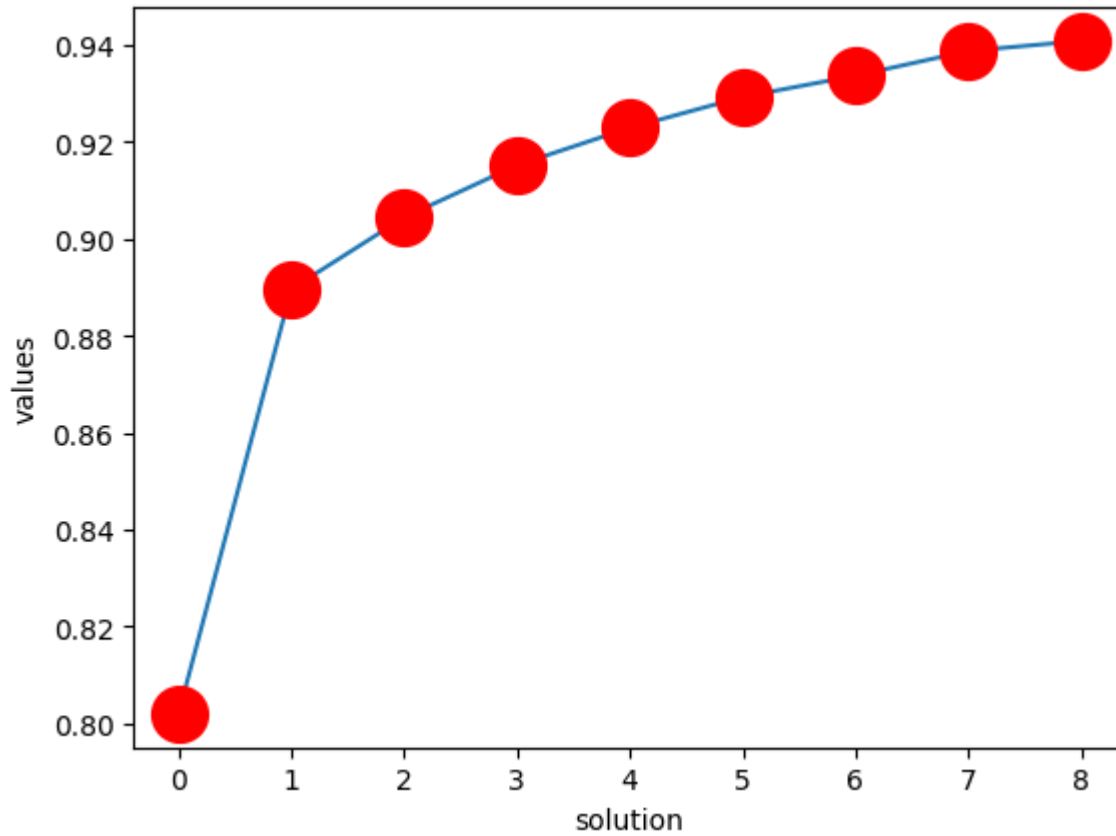
The experimental results obtained in recognizing the handwritten English characters using four different classifiers are summarized in Table.2. The recognition accuracy obtained for the template matching method and the NN methods are also summarized in Table 2. The results in Table 2 indicate the superior recognition accuracy of Feedforward Neural network as compared to other classifiers. Using a number of handwritten tests data the confusion matrix was obtained for the four different classifiers. This was to investigate the recognition accuracy for each alphabet. This parameter is important as any written text would have a varied number of each alphabet. If the classifier has more than 90% recognition rate for each alphabet, then the overall worst case recognition rate would be almost constant irrespective of the data. Table 3 reports the number of alphabets having recognition rate less than 90% and the alphabets are also listed. It is seen from Table 3 that template matching has a poor recognition rate for 24 alphabets and hence has very poor recognition accuracy. Among the NN based classifiers the Feed forward neural network recognizes 23 alphabets with over 90% accuracy and is the best classifier.



The classification accuracy of the Feedforward NN is shown separately for each alphabet in Fig. 7. The maximum number of misclassifications occurs for the letter D which is misclassified 16 times for every 100 presentations (84% recognition).

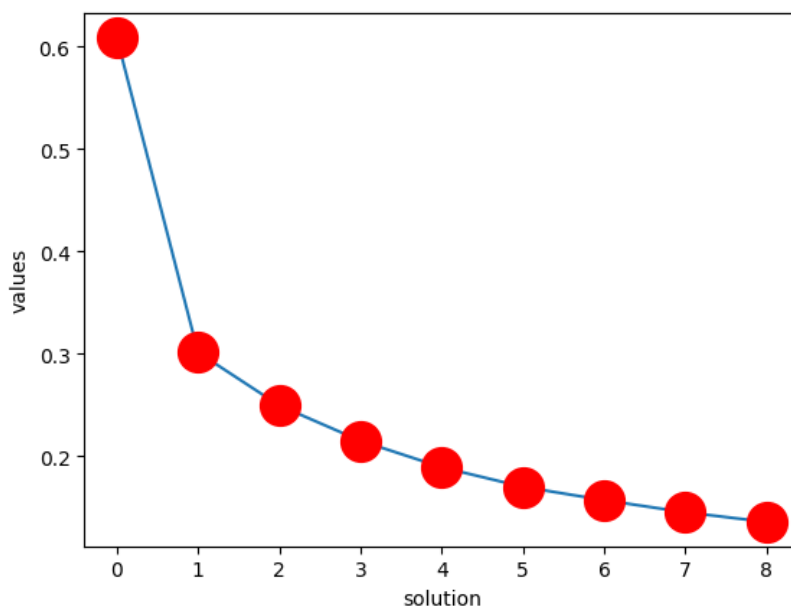
All the other alphabets have better recognition accuracy.

acc\_val , acc :

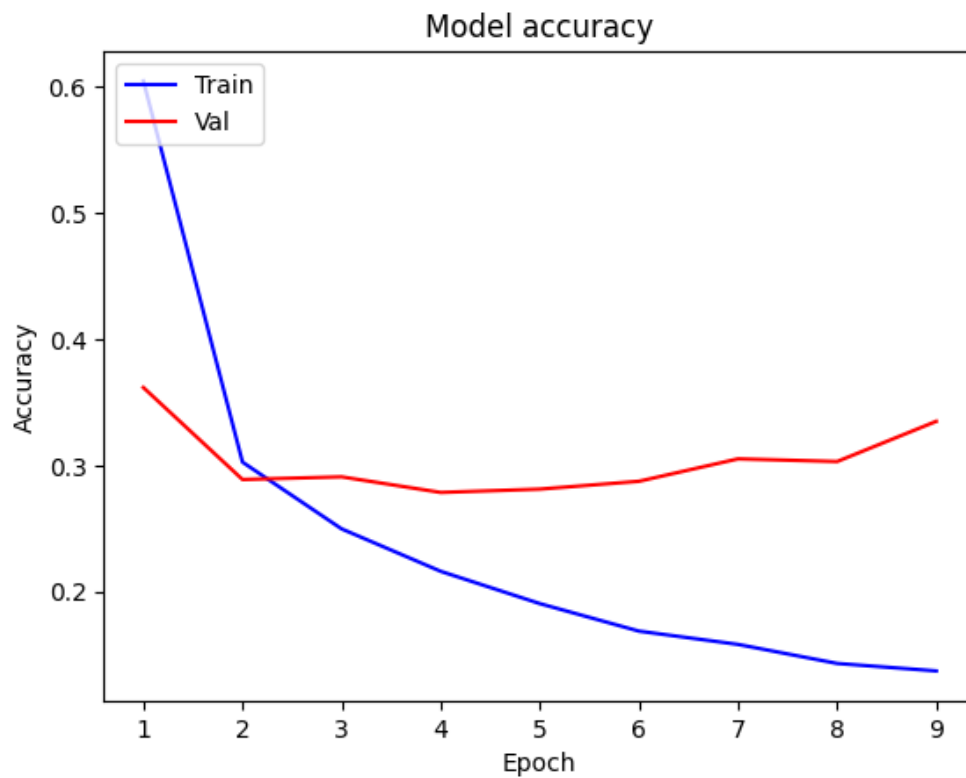
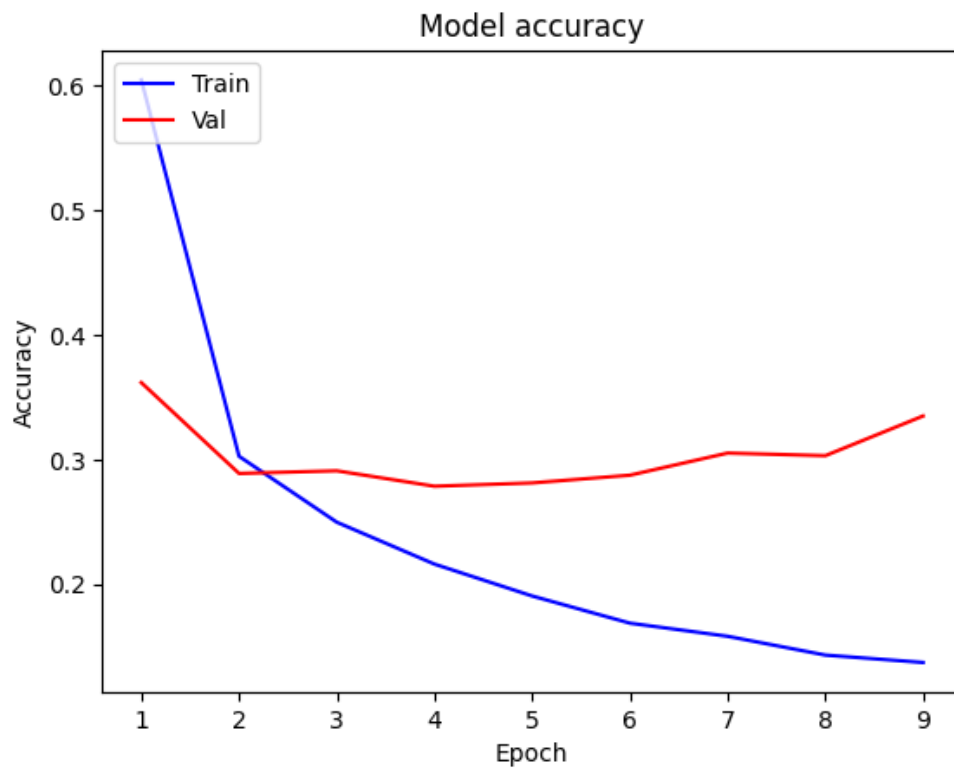


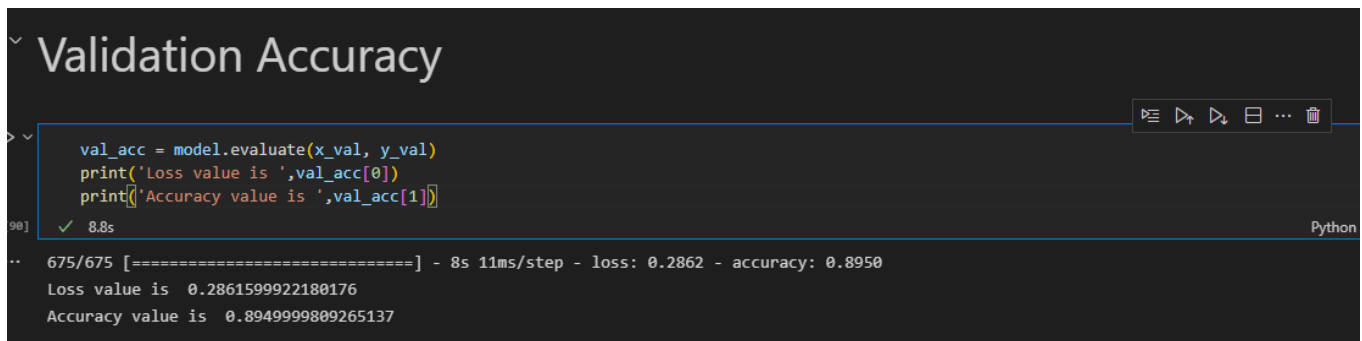
the ratio of the training model = 94.1 accuracy value that model gained from training = 89.6

loss & loss value :



loss that happened in a model 0.137 , the loss value which happened in predict phase in a model = 0.334





The screenshot shows a Jupyter Notebook interface with a dark theme. The title of the notebook is 'Validation Accuracy'. The code cell contains the following Python code:

```
val_acc = model.evaluate(x_val, y_val)
print('Loss value is ',val_acc[0])
print('Accuracy value is ',val_acc[1])
```

The output of the code cell is as follows:

```
✓ 8.8s
675/675 [=====] - 8s 11ms/step - loss: 0.2862 - accuracy: 0.8950
Loss value is  0.2861599922180176
Accuracy value is  0.8949999809265137
```

## 6. CONCLUSION

An off-line handwritten character recognition system with four different classifiers namely, template matching, Feedforward NN, radial basis function NN and nearest neighbor NN for recognizing handwritten English alphabets has been described in this paper. The feature extraction and classification tasks are performed together as a single process in the proposed system unlike in typical handwritten recognition systems in which these tasks are carried out in two different stages. As a result, the proposed system is found to be less complex and allows faster recognition of characters. All the different classifiers have been trained with 200 sets of data and extensively tested. Experimental results show that the feed forward neural network is distinctly superior to the other classifiers in recognizing the handwritten English alphabets. carried out to identify the recognition rates for each letter of alphabet. This would help to estimate the recognition rate irrespective of the handwritten content. It was identified that the Feedforward NN outperformed the remaining classifiers.

The proposed system will find useful applications in recognizing the handwritten names, reading documents and conversion of any handwritten document into structural text form. Further improvements may be possible with a more complex Feedforward NN architecture, but this would also increase the computation complexity. Therefore, combination of a standard feature extraction technique with Feedforward NN may provide better solutions.

## 7. Additional Resources

- <https://ieeexplore.ieee.org/document/6195348>
- [https://www.researchgate.net/publication/342281588\\_Handwritten\\_Character\\_Recognition\\_using\\_Neural\\_Networks\\_forBanking\\_Applications](https://www.researchgate.net/publication/342281588_Handwritten_Character_Recognition_using_Neural_Networks_forBanking_Applications)
- <https://iopscience.iop.org/article/10.1088/1742-6596/1918/4/042152/pdf>

202000436	شريف شعبان محمود عبد الغفار
202000661	كريم اشرف السيد جبريل
202000257	حبيبہ عبد الغني سيد
202000005	إبراهيم عصام محمود عبد الرحمن
202000884	مريم محمد سليمان
202000472	ضحى حسانين محمد الصاوي



