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Robust NN based Classifiers for Handwritten Recognition of Alpha Numerals

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Abstract— Developing intelligent machines for recognizing a character is certainly not an easy task simply because a character could be printed in many possible methods. Also you will find so imperfections that are many variation of handwriting such as for example alignment, noise and angles, which will make handwritten character recognition tough to implement with a device. All these imperfections of handwritten characters may not be removed easily. This means that a single process or single machine just isn't capable of performing the method that is entire. You can accomplish it by a few processes that return some result that is desirable. This paper is about the related work for Handwritten Numeral Recognition and its Approaches.

Key words: OCR, Numeral Recognition, Supervised learning, Handwritten Recognition

I. INTRODUCTION

Handwritten recognition has enticed countless researchers across the globe. The setback of automatic recognition of handwritten text as challenged to contraption printed text is a convoluted one, exceptionally for cursive established languages. Countless researchers have given algorithms for character recognition for disparate tongues such as English, Chinese, Japanese, and Latin. Normal Optical Character Recognition (OCR) arrangement consists of the phases: preprocessing, segmentation, feature ex-traction, classifications and recognition.

The output of every single period is utilized as the input of subsequent stage. Preprocessing period consists of countless adjustment procedures for slant correction, and normalization. Countless presently counseled methods have been given for the intention of feature extraction.

Soft computing methods are generally projected to address the real globe ill-defined, imprecisely formulated setbacks, joining disparate kind of novel models of computation, such as Bayesian Classifiers, neural networks, fuzzy sets and arrangements, and Genetic Algorithms (GAs), and needing huge computation. Handwritten digit recognition is a normal example of one such problem. To recognize handwritten digits of fluctuating forms and sizes, provoked by disparate handwriting styles of disparate people, perceptual use of Cognitive skills of a human are required. Due to colossal assortments of possible requests like removing data from loaded in forms, automatic postal program identification, mail sorting arrangements, automatic reading of bank cheques etc, handwritten digit recognition is believed as a vital problem.

Handwritten Alpha Numeral Recognition is the mechanical or electronic translation of pictures of handwritten alphanumeric characters (usually seized by a scanner) into machine-editable form. Handwritten alpha numeral recognition has collection of requests in assorted fields like reading postal zip program, passport number, operative program, bank cheque, and form processing. Handwritten alphanumeric recognition is a vital constituent of character recognition system. The setback of the handwritten alpha numeral recognition is a convoluted task due to the variations amid the authors like style of including, form, stroke etc. Contrasted to the setback of printed alpha numeral recognition, the setback of handwritten alphanumeric recognition is compounded due to variations in forms sizes of handwritten characters.

Handwritten alpha numeral recognition can be differentiated into two groups i.e. Online Handwritten alpha numeral recognition and Offline Handwritten alpha numeral recognition. On-line handwritten alpha numeral recognition deals alongside automatic conversion of alpha numerals, which are composed on a distinct digitizer, tablet PC or PDA whereas a sensor picks up the pen-tip movements as well as pen-up/pen-down switching. Off-line handwritten alpha numeral recognition deals alongside a data set that is obtained from a scanned handwritten document. Nevertheless intellectual research in the earth endures, the focus on handwritten alpha numeral recognition has advanced to implementation of proven techniques. Handwritten alpha numeral recognition (using optical methods such as mirrors and lenses) and digital character recognition (using scanners and computer algorithms) were primarily believed distinct fields. Because extremely insufficient requests endure that use real optical methods, the handwritten character recognition word has nowadays been widened to contain digital picture processing as well. For extra convoluted recognition setbacks, intelligent character recognition arrangements are usually utilized that usually deals alongside the non cursive handwritings.

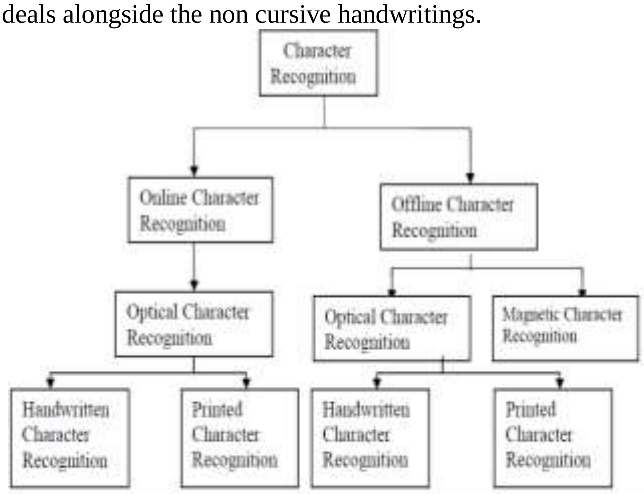

Fig. 1: Classification of Character Recognition

II. PREVIOUS WORK

In present years a little researchers have industrialized computational intellect models for precise recognition of Latin text. Many utilized an average template matching approach for knowing Latin numerals. Some suggested the use of feature vectors representing a set of momentous frontier points distances from the center of gravity (COG) of the numeral object. Many also utilized these features to derive a ideal for every single numeric digit. Some of the recent work is summarized as follows.

Jayadevan, R. et al, 2011 - In India, extra than 300 million people use Devanagari script for documentation. There has been a momentous enhancement in the research connected to the recognition of printed as well as handwritten Devanagari text in the past insufficient years. State of the fine art from 1970s of contraption printed and handwritten Devanagari optical character recognition (OCR) is debated in this paper.

Patel, D.K. et al, 2013 -The present paper deals alongside the setback of handwritten character recognition of English character. This paper presents a novel method of handwriting character recognition that exploits a compression skill of discrete wavelet change to enhance the accuracy of recognition at the pixel level, the discovering skill of manmade neural web and computational skill of Euclidean distance metric.

Sahani, S.K. et al, 2013 - This paper presents a online multi-font numeral recognition method, whose main target is to understand overlaid period numeral from video. The serving of the video construction encompassing the period text is binarized and segmented. Minimum rectangular bounding box is inserted above the remote numeral images. Euler number of numeral pictures is discovered out to primarily differentiate into three groups.

Dadong Zhao et al, - Because of its colossal contrasts in including style, context-independency and elevated recognition accuracy necessity, free handwritten digital identification is yet a extremely tough problem. Analyzing the characteristic of handwritten digits, this paper proposes a new handwritten digital identification method established on joining structural features. Given a handwritten digit, a collection of structural features of the digit encompassing conclude points, bifurcation points, horizontal lines and so on are recognized automatically and robustly by a counseled spread structural features identification algorithm and a decision tree established on those structural features are crafted to prop automatic recognition of the handwritten digit.

Kale, K.V. et al, in 2013 - Compound character recognition of Devanagari script is one of the challenging tasks as the acts are convoluted in construction and can be adjusted by including combination of two or extra characters. These compound acts occurs 12 to 15% in the Devanagari Script. The moment established methods are being prosperously requested to countless picture processing setbacks and embodies a frank instrument to produce feature descriptors whereas the Zernike moment method has a rotation invariance property that discovered to be desirable for handwritten character recognition.

Halder, C. et al, - Handwritten Bangla numeral recognition has outstanding prospects in Author Identification, Postal Automation, Bangla OCR (Optical Character Recognizer) etc. In this paper they have gave the methodical analogy of classifiers for Bangla handwritten numeral recognition. For this work they have utilized their own database (WBSUCS character database) that consists of finished 517 documents and ISI Bangla Numeral database that consists of extra than 12000 numerals.

Pirlo, G. et al, 2012 - In the earth of handwritten character recognition, picture zoning is a extensive method for feature extraction as it is rightly believed to be able to cope alongside handwritten outline variability.

Alaei, A. et al, 2012 - In present years, countless methods for the recognition of Persian/Latin handwritten documents have been counseled by researchers. To examination the promises of disparate features extraction and association methods and to furnish a new benchmark for upcoming research, in this paper a comparative discover of Persian/Latin handwritten character recognition employing disparate feature sets and classifiers is presented. Feature sets utilized in this discover are computed established on gradient, directional shackle program, shadow, under-sampled bitmap, intersection/junction/endpoint, and line-fitting information. Prop Vector Mechanisms (SVMs), Nearest Neighbour (NN), k-Nearest Neighbour (k-NN) are utilized as disparate classifiers.

Pradeep, J. et al, 2012- In this paper, an off-line handwritten English character recognition arrangement employing hybrid feature extraction method and neural web classifiers are proposed. A hybrid feature extraction method merges the diagonal and directional established features. The counseled arrangement suitably merges the salient features of the handwritten acts to enhance the recognition accuracy. Neural Web (NN) topologies, namely, back propagation neural web and radial basis purpose web are crafted to categorize the characters.

III. PROPOSED WORK

Artificial intelligence, giving machines human like abilities, has remained one of the most challenging areas of application. Giving machine the power to see, interpret and the ability to read text is one of the major tasks of AI. A lot of work has been done in this field but still the problem is not solved on its full complexity. Earlier model used is the Perceptron model in which three units are used. One is the sensory unit to receive input images, second is the association unit having features of the input and third one is response unit which consists of perceptrons to receive results in binary form. Training of perceptrons done using supervised learning model and weights are adjusted to minimize error whenever the computed output does not match target output. But this model fails due to the XOR problem. In this problem perceptron cannot handle tasks which are not linearly separable.

One of the most important methods to train neural networks is Back Propagation Algorithm. Back propagation is a systematic method of training multilayer artificial neural networks. It is built on sound mathematical base. The back propagation is a gradient descent method in which gradient of the error is calculated with respect to the weights for a given input by propagating the error backwards from output layer to hidden layer and further to input layer. This method adjusts the weights according to the error function.

As compared with BP, Genetic Algorithm is more qualified for neural networks if only the requirement of a global searching is considered. It is good at global searching (not in one direction) and it works with a population of points instead of a single point. It is a population based search algorithm and multiple optimal solutions can be captured. Another merit of Genetic Algorithm is that it is easy to be implemented by hardware. First of all, the required precision is not high. Second, if binary encoding is adopted, the results can be directly reflected to digital storage.

The basic idea of using genetic algorithm combined with back propagation algorithm for character recognition comes into mind by seeing the disadvantages of Back Propagation algorithm and advantages of Genetic algorithm. Character recognition refers to the identification of written characters. The problem can be viewed as a classification problem where we need to identify the most appropriate character the given sample matches to. If we look into the practical reality there are enumerable styles in which a character may be written.

The focus of this thesis is the recognition and verification of unconstrained Handwritten alpha numerals, with high accuracy, which is a challenging research project as these numerals are written without any constraints, (e.g., they are not all written in separate boxes, nor all written neatly, nor all using a specific type of pen). In addition, unconstrained handwritten alpha numerals have varieties of writing styles due to different backgrounds of the writers. Technically speaking, this system pursue a high recognition rate while seeking the highest reliability, which makes it practical for recognizing unconstrained Handwritten alpha numerals.

The recognition rate (*RR*) is defined as:

RR = Number of correctly recognized characters / Total number of testing characters

The reliability (RE) can be denoted as:

RE = Total number of testing characters −Number of misrecognized characters / Total number of testing characters

IV. METHODOLOGY

A. Neural Network:

The concept of Neural Networks is highly inspired by the recognition mechanism of the human brain[1,20]. The human brain is a complex, nonlinear and parallel computer, whereas the digital computer is entirely the opposite, it is a simple, linear and serial computer. The capability to organize neurons to perform computation is many times faster than a modern digital computer in existence today. Human vision is a good example for understanding this difference.

There is no universally accepted definition of neural network, but there are some architectural and fundamental elements that are the same for all neural networks.

B. Learning Process:

A key feature of Neural Networks is an iterative learning process in which data cases (rows) are presented to the network one at a time, and the weights associated with the input values are adjusted each time.

Advantages of neural networks include their high tolerance to noisy data, as well as their ability to classify patterns on which they have not been trained. If networks are trained carefully, networks can exhibit some capability for generalization beyond the training data.

The definition of the learning process implies the following sequence of events:

- The Neural Network is stimulated by an environment.
- The Neural Network undergoes changes in it parameters because of stimulation.
- The Network responds in a new way to the environment due to the changes that occurred in its internal structure.

There are numerous algorithms available and as one would expect there is no unique algorithm for designing a neural network model. The difference between the algorithms lies in formulation of how to alter the weights of the neurons and in the relations of the neurons to their environment. In the following sections some of the learning processes will be described.

C. Learning Paradigm:

Artificial Neural Network (ANN) is an information-processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. In Neural Networks, there are two different overall Learning paradigms. The first one is supervised learning, also known as learning with a teacher. The second one is called unsupervised learning also referred to as the learning without a teacher this project concerns working with unsupervised models and the reason for this will be elaborated in this section.

D. Supervised Learning:

In conceptual terms, the supervised learning can be seen as a teacher having knowledge of the environment derived from input-output examples. The teacher provides consultancy to the neural network telling it what is normal and abnormal traffic pattern, in the sense of what is classified as malicious and non-malicious. Basically the supervised learning operates as depicted .A portion of network connection is to be analyzed and labeled with the help of the teacher.

Afterwards the learning algorithm to generalize the rules uses the labeled training data. Finally the classifier uses the generated rules to classify new network connections and gives alert if a connection is classified

E. Unsupervised Learning:

Unlike the supervised learning, unsupervised learning does not have a teacher to tell what is a ’good’ or ’bad’ connection. It has the ability to learn from unlabeled data and create new classes automatically.

With the use of a clustering algorithm it is illustrated how unsupervised learning operates. First, the training data is clustered using the clustering algorithm. Second, the clustered weight vectors can be labeled by a given labeling process, for example by selecting a sample group of the data from a cluster and label that cluster center with the major type of the sample. Finally, the labeled weight vectors can be used to classify the network connections.

1) Transfer Functions:

Three of the most commonly used transfer functions are shown in Figure

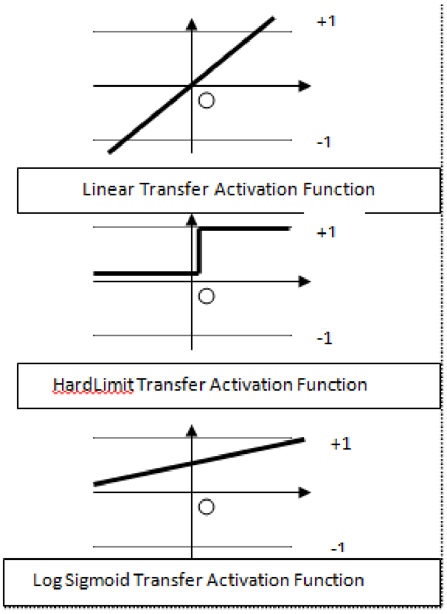

Fig. 2: Transfer Functions

Three of the most commonly used transfer functions are shown in Figure 4.2.

The hard limit transfer function shown above limits the output of the neuron to either 0, if the net input argument n is less than 0, or 1, if n is greater than or equal to 0. This is the function used for the Perceptron algorithm written in VB.NET to create neurons that make a classification decision.

There are two modes of learning: Supervised and unsupervised. Below there is a brief description of each one to determine the best one for our problem.

Steps Involved in the Numeric Recognition Process:

Initially the scanned document is divide into individual lines. These individual lines are composed of numeric digits and blank spaces. Now, these numeric digits are encapsulated in a minimum possible rectangle called glyphs. When analysed, these glyphs are made of black and white pixels comprising the shape of the numeric digits. Here, black pixel denotes 1 and the white background denotes 0.These combination of zero and one is then fetched as a input data in the neural network where the activation function is implemented on every neurons, so as to process input data. Finally, a Unicode is generated by the output neurons which resemble the designated numeric digit.

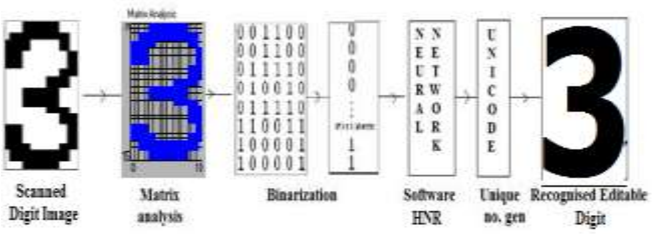

Fig 3: Steps involved in the numeric recognition process

F. Algorithm Description:

The MLP learning algorithm for two hidden layer is outlined below.

1) Initialize the network, with all weights set to random numbers between –1 and +1.
2) Present the first training pattern, and obtain the output.
3) Compare the network output with the target output.
4) Propagate the error backwards.

1) Correct the output layer of weights using the following formula.

$$W_{h2o} = W_{h2o} + (\eta\delta_o O_{h2})$$

Where W_{h2o} is the weight connecting hidden unit h_2 with output unit O, η is the learning rate, O_{h2} is the output at hidden unit h_2. δ_o is error given by the following.

$$\delta_o = O_o(1- O_o)(T_o - O_o)$$

2) Correct the input weights using the following formula.

$$W_{h1h2}=W_{h1h2} + (\eta\ \delta_{h2}O_{h1})$$

Where W_{h1h2} is the weight connecting two hidden layers with, Oh1 is the input at node of the second hidden layer, η is the learning rate. δ_{h2} is calculated as follows.

$$\delta_{h2} = O_{h2}(1- O_{h2})\Sigma(\delta_o W_{h2o})$$

3) Correct the input weights using the following formula.

$$W_{ih1}= W_{ih1} + (\eta\ \delta_{h1}O_i)$$

where W_{ih1} is the weight connecting node i of the input layer with node of the first hidden layer, O_i is the input at node of the hidden layer, η is the learning rate. δh_1 is calculated as follows.

$$\delta_{h1} = O_{h1}(1- O_{h1})\ \Sigma(\delta_o W_{h1h2})$$

4) Calculate the error, by taking the average difference between the target and the output vector.

5) Repeat from 2 for each pattern in the training set to complete one epoch.

6) Repeat from step 2 for a specified number of epochs, or until the error ceases to change

G. Activation Function:

If a multilayer perceptron consists of a linear activation function in all neurons, that is, a simple on-off mechanism to determine whether or not a neuron fires, then it is easily proved with linear algebra that any number of layers can be reduced to the standard two-layer input-output model. What makes a multilayer perceptron different is that each neuron uses a nonlinear activation function which was developed to model the frequency of action potentials, or firing, of biological neurons in the brain. This function is modeled in several ways, but must always be normalizable and differentiable.

The two main activation functions used in current applications are both sigmoids, and are described by hyperbolic tangent which ranges from -1 to 1, and the latter is equivalent in shape but ranges from 0 to 1. Here yi is the output of the ith node (neuron) and vi is the weighted sum of the input synapses. More specialized activation functions include radial basis functions which are used in another class of supervised neural network models.

Most common activation functions are the logistic and hyperbolic tangent sigmoid functions.

The project uses hyperbolic tangent function: $f(x) = \{2/(1+e^{-\lambda x})\}-1$ and derivative: $f'(x)=f(x)(1-f(x))$

1) Algorithm:

– Form network according to the specified topology parameters
– Initialize weight with random values
– Load trainer set files (both input numeral image and desired numeral output)
– Analyze input image and map all detected numerals into linear arrays

- Read desired output numeral from file and convert each numeral to a binary Unicode value to store separately
- For each numeral :
  - Calculate the output of the feed forward network
  - Compare with the desired output corresponding to the numeral and compute error
  - Back propagate error across each link to adjust the weights
- Move to the next numeral and repeat step 6 until all numerals are visited
- Compute the average error of all numerals.
- Repeat steps 6 and 8 until the specified number of epochs

H. Numeral Image Detection:

The process of image analysis to detect numeral symbols by examining pixels is the core part of input set preparation in both the training and testing phase. Numeric extents are recognized out of an input image file based on the color value of individual pixels, which for the limits of this project is assumed to be either black RGB (255,0,0,0) or white RGB(255,255,255,255). The input images are assumed to be in bitmap form of any resolution which can be mapped to an internal bitmap object in the Microsoft Visual Studio environment.

The procedure also assumes the input image is composed of only numeral and any other type of bounding object like a border line is not taken into consideration.

The procedure for analyzing images to detect numeral is listed in the following algorithms:

I. Detecting Individual Character:

Detection of individual Characters involves scanning numeral lines for orthogonally separable images composed of black pixels.

1) Algorithm:

- Start at the first numeral line top and first x-component
- Scan up to image width on the same y-component

a) if black pixel is detected register y as top of the first line

b) if not continue to the next pixel

- Start at the top of the numeral found and first x-component, pixel(0, numeral _top)
- Scan up to the line bottom on the same x-component

c) if black pixel found register x as the left of the numeral

d) if not continue to the next pixel

e) if no black pixels are found increment x and reset y to scan the next vertical line

- Start at the left of the numeral found and top of the current line, pixel(numeral _left, line_top)
- Scan up to the width of the image on the same x-component

f) if no black pixel are found register x-1 as right of the symbol

g) if a black pixel is found increment x and reset y to scan the next vertical line

- Start at the bottom of the current line and left of the numeral, pixel(numeral _left,line_bottom)
- Scan up to the right of the numeral on the same y-component

h) If a black pixel is found register y as the bottom of the numeral

i) If no black pixels are found decrement y and reset x to scan the next vertical line

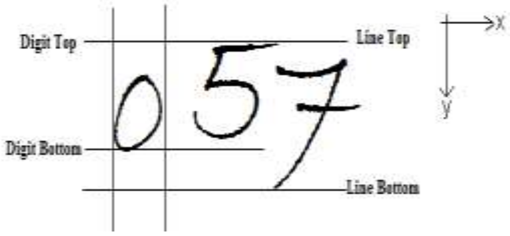

Fig. 4: Line and Digit Boundary Detection

From the procedure followed and the above figure it is obvious that the detected numeral bound might not be the actual bound for the numeral in question. This is an issue that arises with the height and bottom alignment irregularity that exists with handwritten alpha numeral. Thus a line top does not necessarily mean top of all numerals and a line bottom might not mean bottom of all numerals as well. Hence a confirmation of top and bottom for the numeral is needed.

An optional confirmation algorithm implemented in the project is:

1) Start at the top of the current line and left of the numeral
2) Scan up to the right of the numeral.

- If a black pixels is detected register y as the confirmed top.
- If not continue to the next pixel.
- If no black pixels are found increment y and reset x to scan the next horizontal line.

J. Characters to Image Matrix Mapping:

The next step is to map the numeral image into a corresponding two dimensional binary matrix. An important issue to consider here will be deciding the size of the matrix. If all the pixels of the numeral are mapped into the matrix, one would definitely be able to acquire all the distinguishing pixel features of the numeral and minimize overlap with other numeral. However this strategy would imply maintaining and processing a very large matrix (up to 1500 elements for a 100x150 pixel image).

Hence a reasonable tradeoff is needed in order to minimize processing time which will not significantly affect the separability of the patterns. The project employed a sampling strategy which would map the numeral image into a 10x15 binary matrix with only 150 elements. Since the height and width of individual images vary, an adaptive sampling algorithm was implemented. The algorithm is listed below:

1) *Algorithm:*

a) For the width (initially 20 elements wide)
- Map the first (0,y) and last (width ,y) pixel components directly to the first (0,y) and last (20,y) elements of the matrix
- Map the middle pixel component (width/2,y) to the 10th matrix element
- subdivide further divisions and map accordingly to the matrix

b) For the height (initially 30 elements high)
- Map the first x,(0) and last (x ,height) pixel components directly to the first (x,0) and last (x,30) elements of the matrix
- Map the middle pixel component (x ,height/2) to the 15th matrix element
- Subdivide further divisions and map accordingly to the matrix

c) Further reduce the matrix to 10x15 by sampling by a factor of 2 on both the width and the height

Fig. 5: Mapping numeric images onto a binary matrix

In order to be able to feed the matrix data to the network (which is of a single dimension) the matrix must first be linearized to a single dimension. This is accomplished with a simple routine with the following algorithm:
- Start with the first matrix element (0,0)
- Increment x keeping y constant up to the matrix width
  - Map each element to an element of a linear array (increment array index)
  - If matrix width is reached reset x, increment y
- Repeat up to the matrix height (x ,y)=(width, height)

Hence the linear array is our input vector for the MLP Network.

In a training phase all such numerals from the trainer set image file are mapped into their own linear array and as a whole constitute an input space.

The trainer set would also contain a file of numeral strings that directly correspond to the input symbol images to serve as the desired output of the training. A sample mini trainer set is shown below:

K. *Training:*

Once the network has been initialized and the training input space prepared the network is ready to be trained. Some issues that need to be addressed upon training the network are:
- How chaotic is the input space? A chaotic input varies randomly and in extreme range without any predictable flow among its members.
- How complex are the patterns for which we train the network? Complex patterns are usually characterized by feature overlap and high data size.

What should be used for the values of:
- Learning rate
- How many Iterations (Epochs) are needed to train the network for a given number of input sets?
- What error threshold value must be used to compare against in order to prematurely stop iterations if the need arises?

The complexity of the individual pattern data is also another issue in character recognition. Each symbol has large number of distinct features that need to be accounted for order to correctly recognize it.

Elimination of some features might result in pattern overlap and the minimum amount of data required makes it one of the most complex classes of input space in pattern recognition.

Other than the known issues mentioned, the other numeric parameters of the network are determined in real time. They also vary greatly from one implementation to another according to the number of input symbols fed and the network topology. For the purpose of this project the parameters used are:
- Learning rate =0.15
- Number of Epochs = 300
- Mean error threshold value = 0.0002

V. Results and Analysis

Increasing the number of iterations has generally a positive proportionality relation to the performance of the network. However in certain cases further increasing the number of epochs has an adverse effect of introducing more number of wrong recognitions. This partially can be attributed to the high value of learning rate parameter as the network approaches its optimal limits and further weight updates result in bypassing the optimal state.

With further iterations the network will try to swing back to the desired state and back again continuously, with a good chance of missing the optimal state at the final epoch. This phenomenon is known as over learning.

The size of the input states is also another direct factor influencing the performance. It is natural that the more number of input symbol set the network is required to be trained for the more it is susceptible for error. Usually the complex and large sized input sets require a large topology network with more number of iterations.

For the above maximum set number of 90 symbols the optimal topology reached was one hidden layer of 250 neurons.

Learning rate parameter variation also affects the network performance for a given limit of iterations. The less the value of this parameter, the lower the value with which the network updates its weights. This intuitively implies that it will be less likely to face the over learning difficulty discussed above since it will be updating its links slowly and in a more refined manner. But unfortunately this would also imply more number of iterations is required to reach its optimal state. Thus a trade of is needed in order to optimize the overall network performance. The value optimal decided upon for the learning parameter is 0.50.

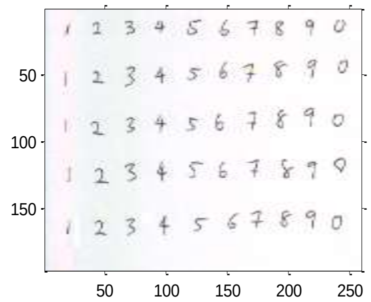

Fig. 6: Handwritten Digits taken for Segmentation Process

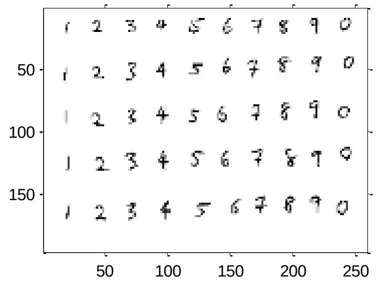

Fig 6: Binary Image output after Segmentation Process

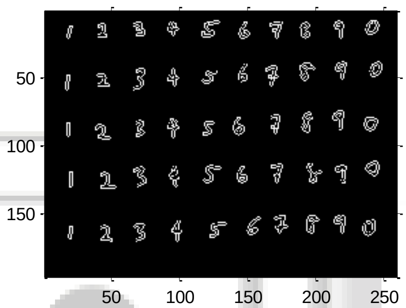

Fig 7: Binary Image Edge detection

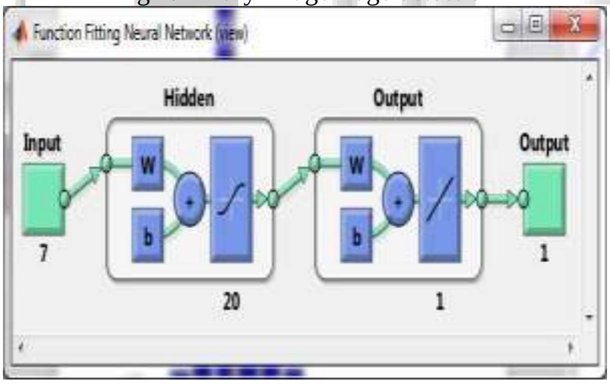

Fig. 8: ANN training For IDS using Levenberg-Marquet Algorithm

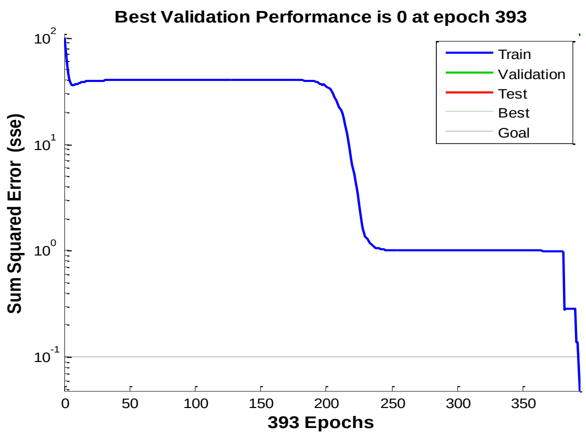

Fig. 9: Performance Check

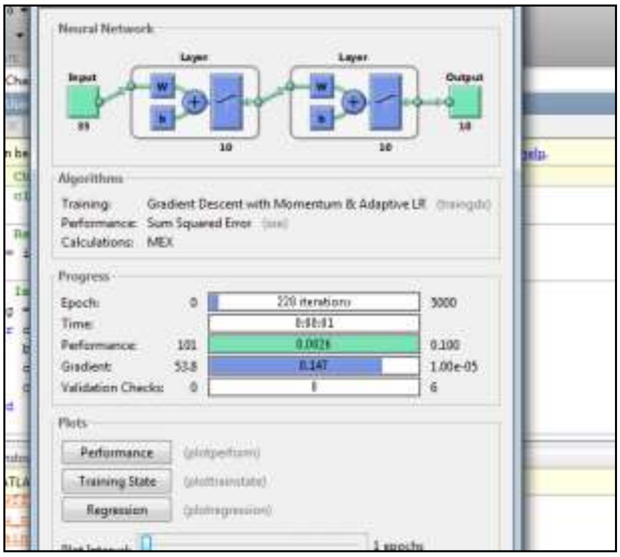

Fig 9: ANN Validation Performances

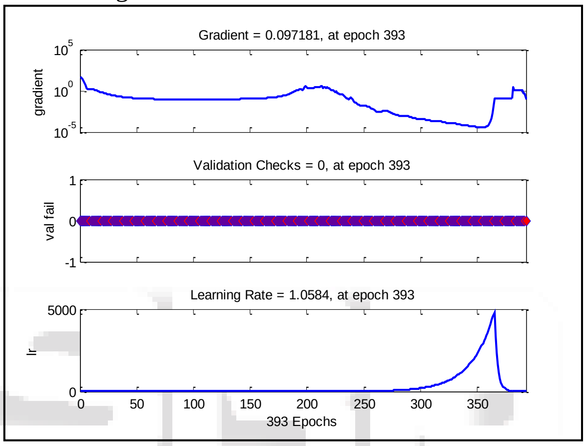

Fig. 10: Gradient, Validation Check, Learning Rate

VI. CONCLUSIONS AND FUTURE SCOPE

The proposed method for the Multiscript Handwritten Recognition using multilayer perception algorithm showed the remarkable enhancement in the performance when two hidden layers are used. If the accuracy of the results is a critical factor for an numeral recognition application, then the network having many hidden layers should be used but if training time is a critical factor then the network having single hidden layer (with sufficient number of hidden units) should be used. The number of hidden layers is proportional to the number of epochs. This means that as the number of hidden layers is increased, the training process of the network slows down because of additional branching of weight adjustment. However, the training of the network is more accurate if more hidden layers are used. This accuracy is achieved at the cost of network training time. It has been found in Handwritten Recognition that recognition of numeral in multisript is very difficult task. Following are main reasons for difficulty in recognition of multiscript alpha numeral.

Colored multiscript numeric recognition can be carried out in spite of the- black color and white color. Some multiscript symbols are similar in shape (like 7 in English and 6 in Urdu). Over the past three decades, many different methods have been explored by a large number of scientists to recognize characters. A variety of approaches have been proposed and tested by researchers in different parts of the world, including statistical methods, structural and syntactic methods and neural networks. No Handwritten Recognition is more than 99% accurate till date. The recognition accuracy of the neural networks proposed here can be further improved. The number of numeral set used for training is reasonably low and the accuracy of the network can be increased by taking more training character sets. This approach of recognition is used for recognition of multiscript numeral only.

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