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COMPARISON OF FEATURE EXTRACTION AND FUZZY FILTERED NEURAL NETWORK APPROACH FOR HANDWRITTEN CHARACTER RECOGNITION

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ABSTRACT

This paper presents a conventional feature extraction approach as well as a fuzzy filtered neural network approach as an application to handwritten numerical representation. First a feature extraction technique is applied for character recognition. The characters for recognition were scanned and made available offline. These scans were pre-processed and features were extracted. These extracted features were given as inputs to the neural networks and recognition thus takes place. Since , using the traditional feature extraction approch using neural networks is shown to have certain drawback , this papers aims to deal with these drawbacks and increase the efficiency of the system using fuzzy filtered neural nets for recognition. A multilayer feedforward adaptive network is used for training the model and for application of the fuzzy filters. Fuzzy filters are integrated with the neural nets for processing the physical data of the images available for the handwritten digits. The use of the fuzzy filters reduces the noise and redundancy present in the data which ultimately increases the performance of the model. This also helps in avoiding the high complexity of the neural network architecture which would otherwise be required for the same physical data. Different varieties of the fuzzy filters are integrated with the neural network separately and their performance is compared. Finally, genetic algorithm based fuzzy filtered neural networks are discussed for the application of recognition. They provide the highest recognition rate for the application.

Keywords :Feature Extraction,*Networks, *Fuzzy Channels, Fuzzy Filtered Neural Networks, Genetic algorithm

I. INTRODUCTION

It is well known today that real world problems can be computationally dealt with the help of intelligent systems. These systems can be developed by combination of multiple methodologies. Human like capabilities can only be obtained by incorporating multiple methodologies to develop one intelligent system. The techniques used exclusively will not yield as efficient results as when used together. This paper utilizes neural networks and fuzzy logic and results prove to be more efficient [16].

In an offline character recognition system, the written characters are initially captures and scanned. This scanned copy of the characters undergo processing for the recognition of the characters. There is another system called the online character recognition system where the strokes or features of the characters to be recognized are

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presented as a function of time[17].This paper deals with the offline system of character recognition. the scanned copy of the characters have to undergo several pre-processing steps before actual feature extraction can take place. These pre-processing steps are required in order to make the characters suitable for feature extraction purposes. There are many feature extraction techniques which can used like template matching, projection histograms etc. [17]. This paper uses the binarization technique for feature extraction. Neural Networks are used in the backend of the system in order to classify the characters based of the features extracted. The extracted features are sent as input to the neural network and thus classification takes place. This paper further incorporates fuzzy filters to neural network models for better performance.

A fuzzy filtered neural network is used for the application of handwritten numeral recognition. This application is a problem of feature recognition. Typical neural networks are not as efficient in feature recognition as the quantity of the features they can compute, decreases, as the number of parameters increase. Though this can be overcome by increasing the complexity of neural network architecture, it still tends to be costly in terms of architecture required and recognition rate obtained. In order to overcome this complexity issue, fuzzy filter is applied.

Fuzzy filters can be formed in different dimensions. Increasing the dimensions increases the efficiency of the model. But, this does not deal with the local optima problem due to the gradient descent problem[1]. This paper also introduce genetic algorithm based fuzzy filter which is even more flexible[9]. Finally , the paper gives a comparative analysis of the feature extraction approach and the fuzzy filtered neural network approach for recognition of handwritten characters.

II. RELATED WORK

The fuzzy filtered neural network architecture and feature extraction approach was applied to the real world application of handwritten numeral recognition. A training data set of images of handwritten numerals from 20 different people were used in order to train the multilayer feedforward adaptive neural network. Some part of the training set is depicted in Fig. 1. The dataset is self developed and is not downloaded from any openly available websites.

The dataset contains total of 1000 digits written by 20 people. Out of the 1000 numerals 600 digits are used for training purpose and the rest 400 are used for testing the model.

A three layer feedforward neural network is used and the weights of the layers in the networks are adjusted by backpropagation algorithm. After training for 250 epochs the recognition rate of the model was approximately 85 % (for the conventional feature extraction approach), which correctly corresponds to the rate stated in [18] and the recognition rate by the fuzzy filtered neural networks was found to be around 95 % .

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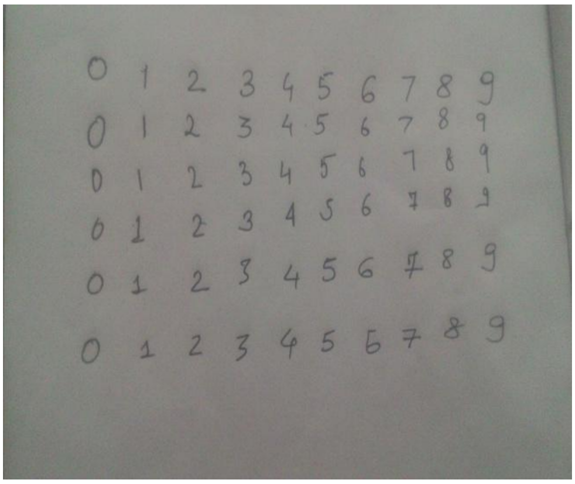

Fig. 1: Example dataset used for handwritten numeral recognition

III. FEATURE ETRACTION APPROACH

In this approach, the scanned offline copy of the character to be recognized initially undergoes pre-processing and then features are extracted from these processed characters. These features are then given as input to the neural network which performs classification of the characters based on the training data given. For example, the neural net is trained for digits. the training set will consist of digits from 0 to 9. When a scanned pre-processed digit is given for recognition to the system, the featured extracted by binarization are then compared with the existing digits in the training set of the neural networks and are then classified accordingly.

3.1 Pre-Processing

The pre-processing step involves converting the scanned image of the character into greyscale image, removal of noise present in the scan , resizing and cropping of the image. All this is done in order to make the character scan suitable for extracting features from it efficiently. If these steps are not performed then the features extracted from the character scan will not be accurate and will lead to inaccurate classification or recognition of the handwritten characters.Fig. 2depicts the character a and its pre-processed images. Fig. 2(a) depicts the original scan copy of the image of character 'd' , Fig.2(b) depicts the grayscale converted image of the character 'd' , Fig. 2(c) depicts the image where the original image is resized to a sized of 100 × 100. Further noise removal of the also takes place.

3.2 Binarization Technique

The pre-processed image undergoes an image processing technique called binarization in which the entire scanned image is to be depicted in form of only black or white pixels. The background is considered to have greater intensity and the foreground is to have lesser intensity. This means that after this technique is performed the text in this case the handwritten text is depicted by the black pixels and the background of the text is depicted by the white pixels [18].Fig. 3 shows the binary form of the character 'd' .

3.3 Feature extraction

The binarized matrix formed of the image can be used to find features of the character under study.This is an crucial step which improves efficiency and reduces the misclassification of characters by the neural networks

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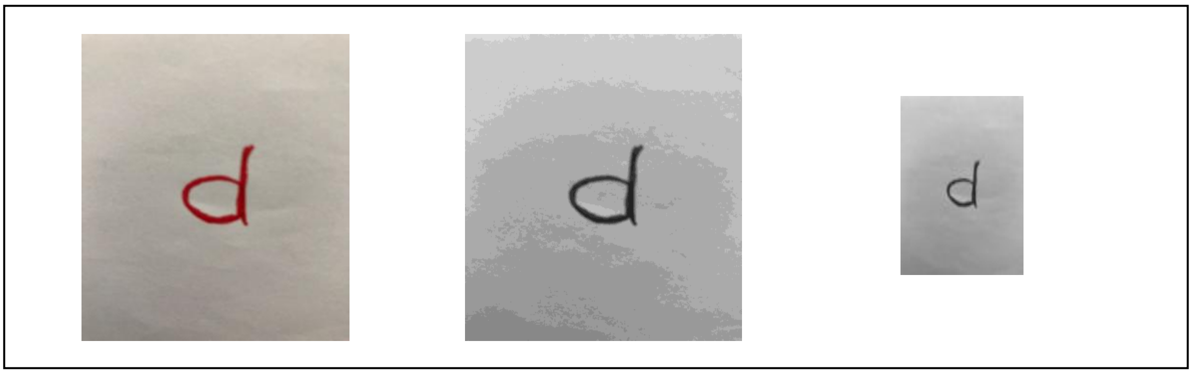
[17]. Binary forms are created for all the characters required for recognition. Column vectors are formed from the binary matrix. Each of these matrices is called feature vector for corresponding character.



(a) Original character

(b) grayscale image

(c) resized image

Fig.2 Pre-Processing of a character 'd'

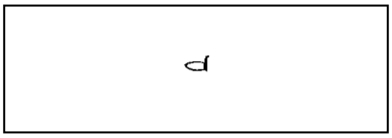


Fig. 3Binarized image

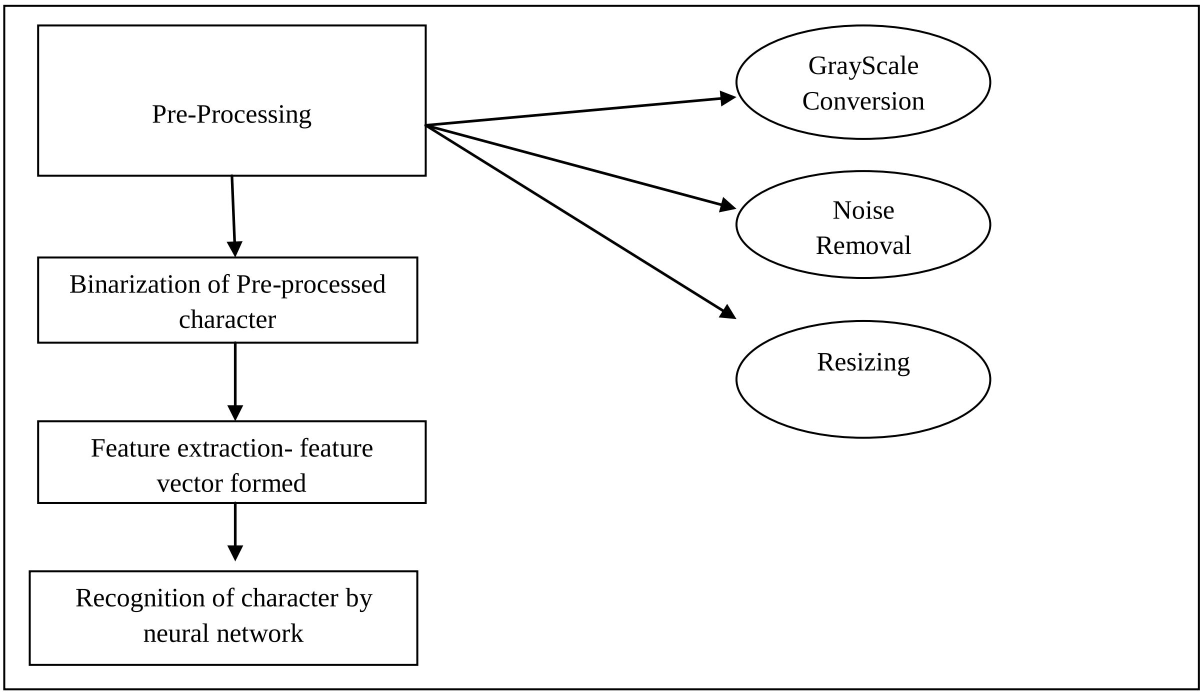


Fig. 4. Flowchart for steps involved in Handwritten character recognition using feature extraction method

3.4 Implementing using neural networks

The number of neurons present in the input layer depend upon the size of the feature vector. Backpropogation neural network are used. Transig activation function is used for hidden and output layer neurons. The number of neurons in the hidden layers are chosen in an optimal way so as to get efficient performance. A recognition

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accuracy of 85 % is obtained by these backpropogation neural networks as corresponded with the results presented in [18].More about neural networks has been discussed in the next section of the paper focussing on the fuzzy filtered neural network approach for handwritten character recognition.

Fig. 4 represents a flowchart representation of the steps involved in the handwritten character recognition using feature extraction by binarization technique. This method will have to deal with a complex architecture of neural networks as the neurons involved in the computation depend on the number of features. So more number of features will lead to a greater number of neurons in one particular layer. Apart from this the feature selection mechanism in this method is not very efficient and many times may lead to overfitting problem. Thus to overcome these problems fuzzy filters are introduced and incorporated in the traditional neural networks.

IV. NEURO FUZZY MODELS

The traditional artificial neural networks(ANN) obtain their functionalities from correspondence with the biological neural model. A basic ANN is made of the simple elements called the neurons. Various neurons are connected with each other to form simple neural network (NN) architecture. Each of these connections is associated with a particular numerical value known as weights [10]. These values contribute in the internal computations of the architecture and can be changed according to the required application. Architecture of a typical neural network has three layers: input layer, hidden layer and the output layer. The function served by these three layers can be described as [10][13] :

- Input layer: takes input from outside sources and then these values are multiplied by the interconnecting weights of each neuron.
- Output layer: this layer gives the least error output after computation. This layer takes the input from the input layer or the hidden layer and then applies activation function (a mathematical function like logarithmic function etc.) to the received input and gives the result as output. This computation is done in order to get the output in a particular range of values depending on the application.
- Hidden Layer: This layer is used for performing the internal computation for the system which is computing the sum of the input terms multiplied by their respective weight values.The number of hidden layers or internal computations represents the depth of the neural network. Fewer links between the input and output layers give architectures for shallow networks while more complex applications requires more number of hidden layers known as deep neural nets [11].The Neuro Fuzzy models are a combination of neural networks as well as the fuzzy logic concept. These approaches are combined in order to obtain a better mimic of the human brain. There are different approaches used for combining these two concepts [2].
- Both the concepts are concurrently used for the same task and neural nets do not change the parameters of the fuzzy logic.
- One approach is to use the neural nets to define the parameters to be used for the fuzzy sets. Once the parameters are learned by the neural network, they no longer exist.
- The most modern approach is to treat them as a single entity rather than separate ones. Filtering this physical data into fewer channels is called as fuzzy filtering. These fewer channels are known as fuzzy channels and provide overall a meaningful and required representation of the patterns under study. A model without the use of fuzzy filtered would provide similar results but at the cost of increased complexity of architecture.

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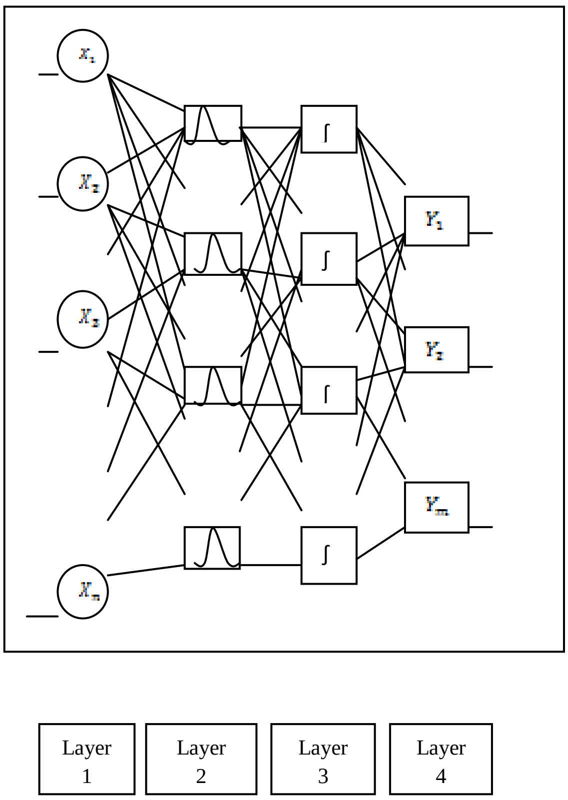
This is due to the fact that neural network models require multiple hidden layers in order to train for a large data set. Since any physical data is bound to have noise factors as well as redundancy, this use of multiple layers becomes inefficient as architecture becomes unnecessarily complex. A rather smart approach of dealing with this problem is to filter these noises and redundant values from the physical data [8].

- A multiple layer feedforward adaptive network is used for the implementation of the fuzzy filters. Fig. 5 depicts the architecture of a fuzzy filtered neural network [7]. The fuzzy filtered neural network's given architecture consists of four layers. Layer 1 is the input layer while layer 2 is the output layer. The input has been denoted by x_1 , x_2 and so on while the outputs are denoted by y_1 , y_2 and so on. The remain two middle layers are the hidden layers required for computation purpose. The activation function varies for every layers and in a particular layer all nodes have the same activation or excitatory function.
- The nodes in the hidden layer function as the bell membership functions[1][2]. Mathematically this membership is represented by the (1). In normal neural networks structure it is difficult to understand the function of the nodes present in the hidden layer.

$$\mu_A(x_i) = \frac{1}{1+\left|\frac{x_i-c_i}{a_i}\right|^{2b_i}} (1)$$

n (1) x_i represents the position or frequency of a physical channel, and { a_i, b_i, c_i } represent the parameter set. The output given by the node is normalized and can be mathematically be represented by (2).

$$Node\ Output = \frac{\sum_i \mu_A(x_i) f(x_i)}{\sum_i \mu_A(x_i)} \quad (2)$$



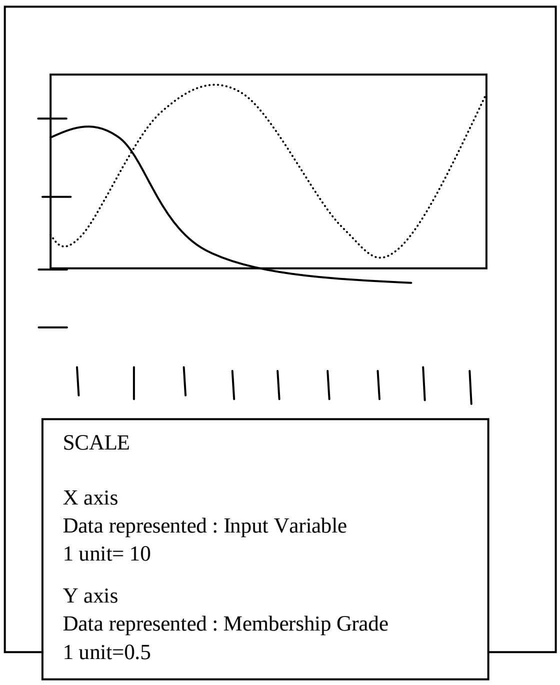


Fig. 5: Fuzzy-Filtered neural network architecture.Fig.6: Initial Membership function setting.

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The initial parameters of the Membership function are assigned heuristically and graphically, this assignment can be represented by. The input range for this graphical representation is assumed to be 0 to 60. This range can vary according to be application in this the neuro-fuzzy networks are being applied to.

All the datasets can be grouped together in different sets (fuzzy sets) having similar characteristic. For example , if we deal with an application involving one of the features as color of an object , different fuzzy sets can be formed based on the different colors. Each of these fuzzy sets will have their own membership function depending on their color and other parameters given by (1). The graph shown in fig. 6 gives two membership grades for two different fuzzy sets against the input parameters. The graphs obtained are different in nature because of the difference in the characteristics of each of the fuzzy sets.

4.1 Experimental Results and Discussion

The images are preprocessed to fit a 32 × 32 matrix and left aligned. These images are then given as input to the fuzzy filters. A fuzzy filter is a robust input-output model which is invariably unrelated to fluctuations in the input signal frequency or redundant values of the provided input [3]. Since a fuzzy filter is used for feature filtering, the system does not have considerable false positives making it a reliable system. The system described in [14] also provides the advantage of no false positives but on the other hand it also has an disadvantage of not incorporating all the important feature points [14] which is not the case in the system described in this paper. All important features are filtered and used for training along with saving the system from the problem of overfitting (on inclusion of too many features the neural network tends to behave more generalized rather than specialized for a particular application).

A one dimensional fuzzy filtered increased the recognition rate of the model to an accuracy of 90 %. For even better results we increase the dimensionality of the fuzzy filters (from n dimension to n+1 dimension) by projecting it according to (3).

$$\mu_B(a, b) = \mu_A(a) \quad (3)$$

In (3) ,μ_A ,μ_B represent the membership functions of n+1 and n dimensional membership function respectively.

The membership function for a particular data is associated with the mean and deviations within points of that dataset [12]. Membership functions of a multiple dimensional fuzzy filters can either be composite or non-composite.

1) A composite membership function (for a two dimensional fuzzy filter) is a combination of two one dimensional fuzzy filters which are joined together by union or multiplication (intersection).

2) A non-composite membership function is one which cannot be decomposed into simple functions.

Assuming that a composite membership function is given in (4). The graphs obtained for the membership function after union of two functions is shown in Fig. 8 and the membership function obtained after intersection of two functions is shown in Fig. 9. The graphs shown in fig. 7-10 are obtained using MATLAB version 7.9.0.529(R2009b).

$$f(x, y) = e^{-(y-6)^2} . e^{-(\frac{x}{2}-\frac{3}{2})^2} \quad (4)$$

The above function can be decomposed into the given two functions in (5) and (6):

$$f(x, y) = e^{-(y-6)^2} \quad (5)$$

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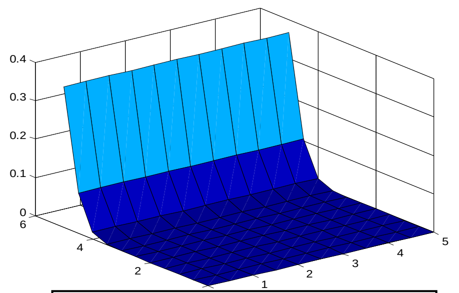
$$f(x,y) = e^{-\left(\frac{x}{2}-\frac{3}{2}\right)^2} \quad (6)$$

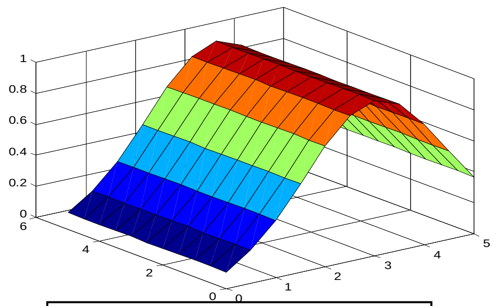
(5) is graphically represented in Fig. 7(i) and (6) is graphically represented in Fig.7(ii).

An example of the non-composite membership function can be given by (7) and graphically depicted by Fig. 10:

$$f(x,y) = (|x|.|y-6|+1)^{-2.5} \quad (7)$$



(i) For (5).



(ii) For (5).

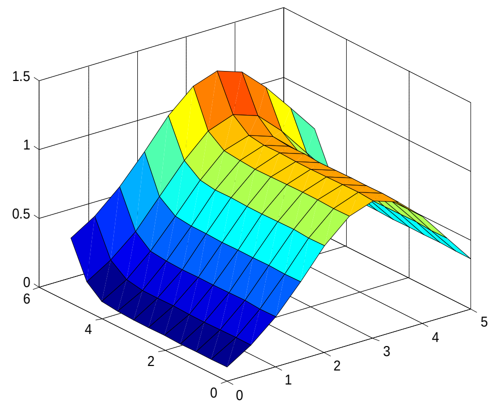


Fig. 8 : Plot for composite membership function after union of two membership functions.

Fig. 7 : Two membership functions

Two membership functions can be combined to get a two dimensional fuzzy filter or altogether a different function can be formed for the formation of the 2-D filter. A general architecture of a 2-D fuzzy filter is shown in Fig. 11[9]. In Fig. 11 two types of parameters are used X and Y as input. It is a 5 layer architecture where layer1 is the input layer and layer 5 is the output layer while the other three layers are the hidden layers. The membership function is applied at the layer 1. Layer 2 is the multiplication layer [15]. Its output is the multiplication of all the incoming signals from the membership function layer (layer 1). Layer 3 is the normalization layer [15]. In this layer the ratio of the multiplied value of each node to the sum of the overall multiplied value is found. Layer 4 is the defuzzyfication layer [15] which gives the weighted output for each node. Layer 5 gives the sum of all the weighted outputs.

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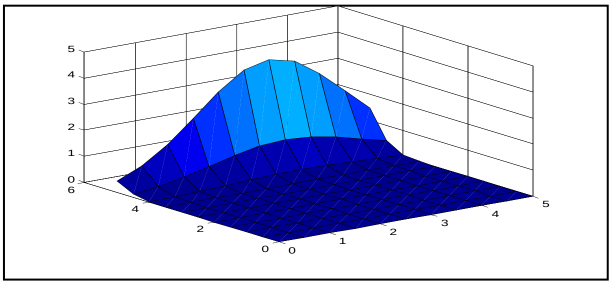

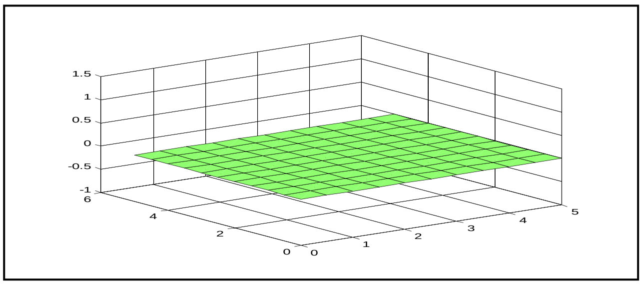

Fig.9 : Plot for composite membership function after intersection of two membership function **Fig.10: Plot for a non-composite function given by (7).**

When two dimensional fuzzy filters were applied to the physical data of the images of the handwritten digits, the neural nets showed an output accuracy of 92%, which corresponds to the efficiency stated in [1]. Even though the performance of the model has significantly increased,however, there is a limitation in the use of these one dimensional and two dimension fuzzy filters viz. that the location of these filters in the architecture of the model remains limited. This is due to the fact that for learning gradient descent algorithm is used and this algorithm cannot overcome the problem of local optima [1] . Due this limited adaptability, the applicability of these type of fuzzy filters is restrained. Another type of fuzzy filters can be used in order to overcome this limitation, it is the fuzzy filter based on genetic algorithm. The genetic algorithm based fuzzy filter is delineated in the next section of the paper.

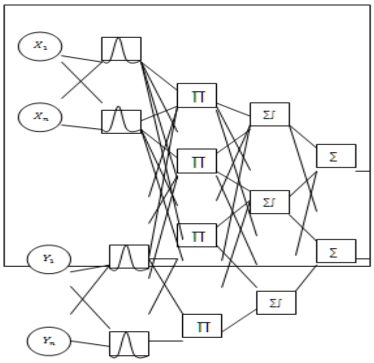

Fig.11 : Architecture for 2-D fuzzy filter.

4.3 Genetic algorithm based fuzzy filter

Genetic algorithms (GAs) make use of the concept of natural selection and evolutionary process [6]. They were first proposed by John Holland in the university of Michigan in 1975 [4]. Genetic algorithm is a survival of the fittest algorithm which works well as an optimization algorithm. The steps involved in a genetic based concept are:

- Selection: two random parameters are selected in order to begin the process.
- Reproduction: the selected parameters are then reproduced i.e. combined in different ways to prude a different parameter .The parameter which promises better stability is selected for further computations. This is also called crossover.
- Mutation: this method is applied in order to increase the diversity of the parameters chosen and escape the criteria of local optima [5].

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The flowchart for the steps involved in the genetic algorithm is clearly depicted in Fig. 12. As the flowchart in Fig.11 depicts initially the dataset of parameters need to be established. Parameters will be chosen from this dataset for crossover and reproduce new sets of parameters; hence the dataset needs to be exhaustive. An evaluation is performed on the parameters existing in the dataset to find whether the application needs are met by the existing parameter sets. If the needs are met then the algorithm is aborted, else parameters are selected for crossover and reproduced together (new parameter sets are formed). This algorithm is applied to the fuzzy filters in my application. GAs was employed in order to define rectangular regions, where each rectangular region is supposed to depict one individual digit. These regions do not duplicate regions for other digits. The aim is to map a digit to its particular rectangular region for recognition purpose. Evaluation function employed for the selection process of the GA is given by the (8) [1]:

$$\sum_n \sum_r \frac{b(r)}{w(r^2)\times z} \times 10 + \sum_{other\,digits} \sum_n \sum_r \frac{w(r)}{b(r^2)\times z} \quad (8)$$

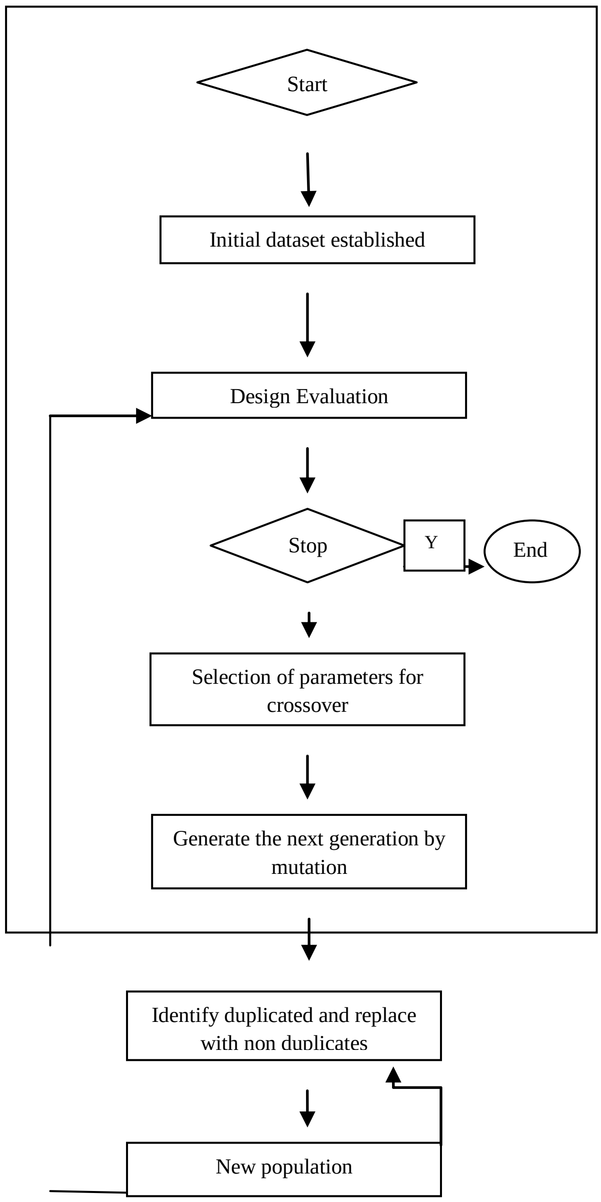

Fig. 12: Genetic Algorithm Flowchart

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In (8), n represents a numeral, r stands for a region, b(r) and w(r) is the number of black pixels and white pixels in a region respectively, z is the total number of overlapped pixels in the rectangle represented by the numeral. The introduction of 'z' in the (8) is done in order to prevent rectangle of different digits from overlapping. Greater overlapping leads to higher chances of misclassification. The rectangles are then fuzzified using the Gaussian function (creation of a membership function).

These GA generated fuzzy filters are then integrated with the neural model for the classification process of the handwritten numerals. This process provided the best classification accuracy as compared to the normal neural network model as well as the models integrated with the 1-D and 2-D fuzzy filters. The recognition rate of GA based fuzzy filtered neural network model for handwritten numeral recognition was found to be 95%.

V. CONCLUSION

Two models for recognition of handwritten numerals were developed and compared. First the traditional feature extraction method was developed which provided a recognition rate of approximately 85%. The binarization technique was used to extract the features from the scan of the character to be recognized. The feature vectors formed were given to the neural networks as input and recognition was performed. It was found that this simple method of using feature extraction along with neural networks has few complications which could be dealt with by adding the concept of fuzzy filters to the traditional neural networks. Incorporation of Fuzzy filters in the basic feedforward neural network model lead to increase in the classification accuracy and overall recognition rate. Classification of the numerals with a normal neural network model gave an recognition rate of 85% while by integrating it with fuzzy filters it could be increased to 95%. Various dimensions of filters applied in front of the neural network gives different efficiency rates. The best accuracy and optimization was provided by the genetic algorithm based fuzzy filtered neural network model.

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