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Fuzzy Filtered Neural Network Approach towards Handwritten Numeral Recognition

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Abstract

This paper presents a fuzzy filtered neural network approach as an application to handwritten numerical representation. 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. The fuzzy filters with higher dimensionality improve the model recognition rate. One dimensional and two dimensional fuzzy filters are discussed and their performance is evaluated. 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: Neural Networks, Fuzzy Channels, Fuzzy Filtered Neural Networks, Genetic Algorithm

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].

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].

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]:

1) Input layer: takes input from outside sources and then these values are multiplied by the interconnecting weights of each neuron.
2) 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.
3) 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].

1) Both the concepts are concurrently used for the same task and neural nets do not change the parameters of the fuzzy logic.
2) 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.
3) The most modern approach is to treat them as a single entity rather than separate ones.

In this paper, neuro-fuzzy models have been dealt with for the application of pattern recognition. A major job in pattern recognition is to detect features. A large amount of data sets are available for training purpose for feature detection. 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. 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. Figure 1 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 remaining two middle layers are the hidden layers required for computation purpose. The activation function varies for every layer and in a particular layer all nodes have the same activation or excitatory function.

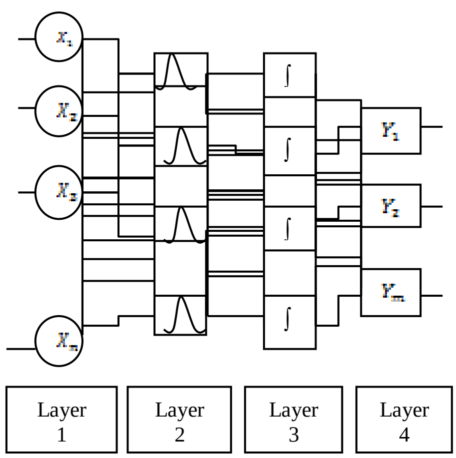

Figure 1: Fuzzy-Filtered neural network architecture

The nodes in the hidden layer function as the bell membership functions [1][2]. Mathematically this membership is represented by the equation 1. In normal neural networks structure it is difficult to understand the function of the nodes present in the hidden layer.

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

In equation 1 x_i represents the position or frequency of a physical channel, and { a_i, b_i, c_i } represent the parameter set.

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The output given by the node is normalized and can be mathematically be represented by equation 2.

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

The initial parameters of the Membership function are assigned heuristically and graphically, this assignment can be represented by Figure. 2. 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 equation 1. The graph shown in fig. 2 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.

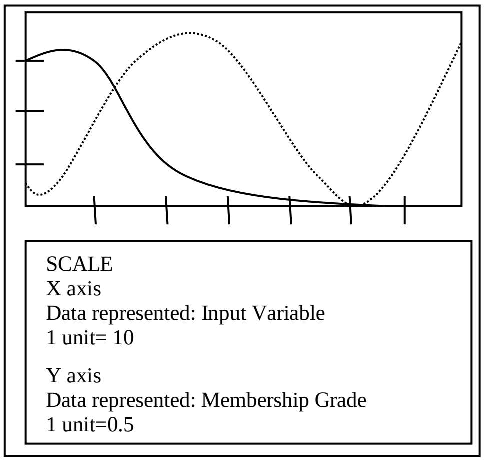

Figure 2: Initial membership function setting

RELATED WORK

The fuzzy filtered neural network architecture was applied to the real world application of handwritten numeral recognition. A training data set of images of handwritten numerals from 20 different people was used in order to train the multilayer feedforward adaptive neural network. Some part of the training set is depicted in Figure 3. 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 %, which correctly corresponds to the rate stated in [1].

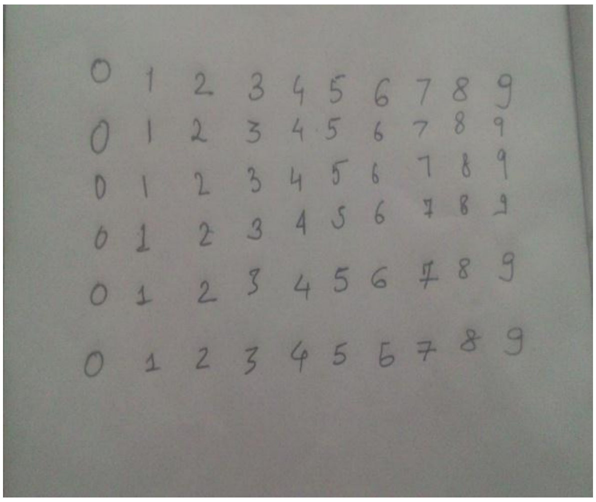

Figure 3: Example dataset used for handwritten numeral recognition

Due to networks complex structure, the model does not achieve any more than the 85 % accuracy. For further improvement of the model, the fuzzy filters are applied to the network which is discussed in the next section of the paper.

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 a 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 equation 3.

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

In the above equation 3, μ_A, μ_B represent the membership

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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.

Assume that a composite membership function is given by the equation 4. The graphs obtained for the membership function after union of two functions is shown in Figure 5 and the membership function obtained after intersection of two functions is shown in Figure 6. The graphs shown in fig. 4-7 are obtained using MATLAB version 7.9.0.529(R2009b).

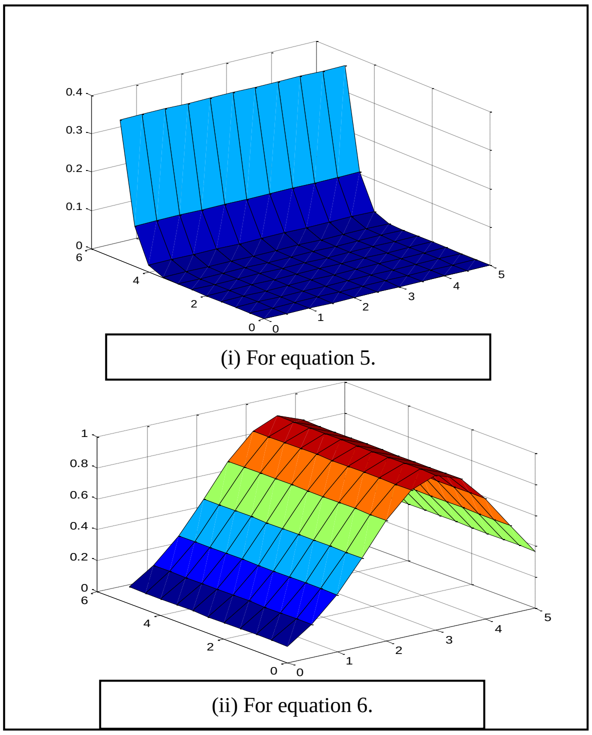
$$f(x,y) = e^{-(y-6)^2} . e^{-\left(\frac{x}{2}-\frac{3}{2}\right)^2} \qquad (4)$$

The above function can be decomposed into the given two functions in equations 5 and 6.

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

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

Equation 5 is graphically represented in Figure 4(i) and equation 6 is graphically represented in Figure 4(ii).



(i) For equation 5.

(ii) For equation 6.

Figure 4: Plots for 2 different membership functions.

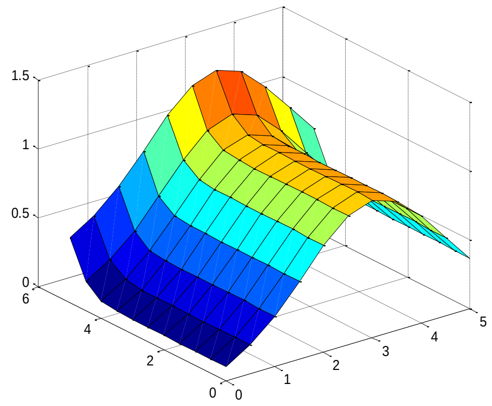


Figure 5: Plot for composite membership function after union of two membership functions.

An example of the non-composite membership function can be given by equation 7 and graphically depicted by Figure. 7.

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

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 Figure 8[9]. In Figure 8 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.

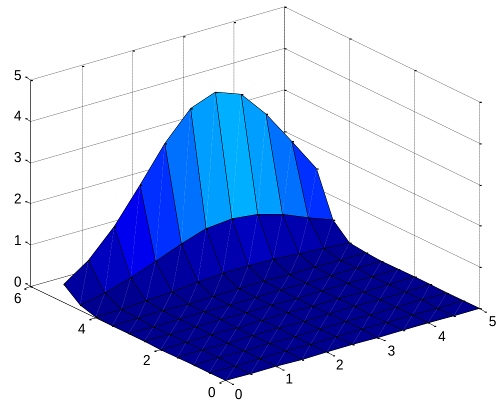


Figure 6: Plot for composite membership function after intersection of two membership functions.

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

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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.

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 types 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.

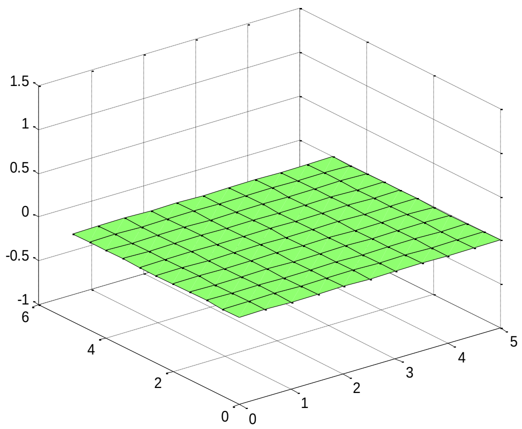

Figure 7: Plot for a non-composite function given by equation

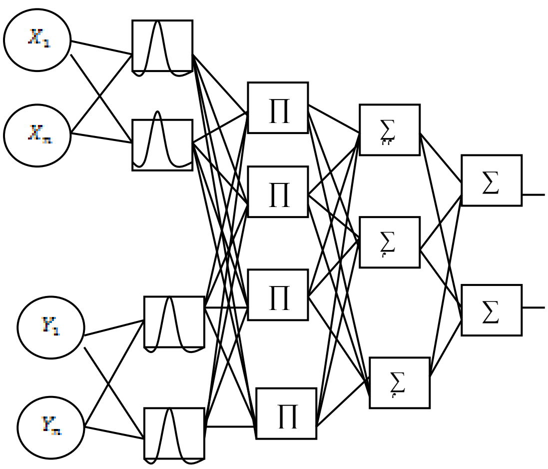

Figure 8: Architecture for 2-D fuzzy filter

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:

1) Selection: two random parameters are selected in order to begin the process.
2) 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.
3) Mutation: this method is applied in order to increase the diversity of the parameters chosen and escape the criteria of local optima [5].

The flowchart for the steps involved in the genetic algorithm is clearly depicted in Figure 9. As the flowchart in Figure 9 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. Genetic Algorithms were 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 [1] employed for the selection process of the GA is given by the equation 8.

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

In equation 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 equation 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%.

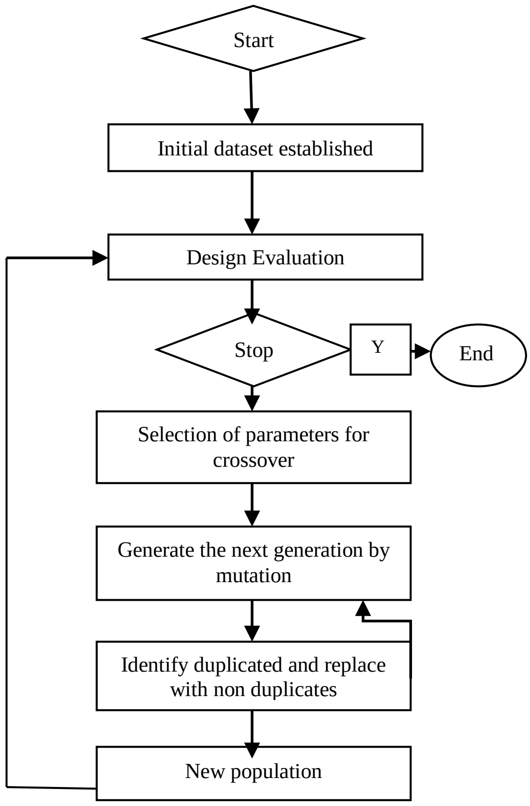

Figure 9: Genetic Algorithm Flowchart

CONCLUSION

A model for recognition of handwritten numerals was developed. 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 a 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.

REFERENCES

[1]. J. -S.R. Jang, C. -T. Sun, E. Mizutani, “Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence”, Pearson Education Pte. Ltd., Delhi, India, 1997.

[2]. Chokri Slim, "Neuro-Fuzzy Network based on Extended Kalman Filtering for Financial Time Series", World Academy of Science, Engineering and Technology, vol. 22, pp. 134-139, 2006.

[3]. Mohit Kumar, Kerstin Thurow, Norbert Stoll, Regina Stoll, "Fuzzy Filtering: A Mathematical Theory and Applications in Life Science", Fuzzy Systems, Ahmad Taher Azar (Ed.), ISBN: 978-953-7619-92-3, InTech, 2010.

[4]. J.H. Holland, “Adaption in natural and artificial systems”, University of Michigan press, Michigan, 1975.

[5]. M Ranjani, P Murugesan, "Modeling of Genetic Algorithm based Fuzzy Logic Controller for Quasi-Resonant Converter fed Drive", International Journal of Conceptions on Electrical and Electronics Engineering Vol. 1, Issue 1, Oct 2013.

[6]. Lior Rokach, "Genetic Algorithm-based Feature Set Partitioning for Classification Problems", Department of Information System Engineering Ben-Gurion University of the Negev.

[7]. DezhiLi, WilsonWang, FathyIsmail, "Enhanced fuzzy-filtered neural networks for material fatigue prognosis", Applied Soft Computing, Elsevier, Vol. 13, Issue 1, pp. 283-291, January 2013.

[8]. JyhShing, R.Jang, “Fuzzy Modelling using Generalized neural networks and Kalman filter algorithm", Proceedings of AAAI-91, 1991.

[9]. Chuen-Tsai Sun, Tsuey-Yuh Shuai , Guang-Liang Dai, "Using Fuzzy Filters as Feature Detectors", IEEE, pp. 406-410, 1994

[10]. Laurene Fausett, Fundamentals of Neural Networks Architecture, Algorithms and Applications, 2011.

[11]. Schmidhuber J., "Deep Learning in neural networks: An overview", Neural Networks, Elsevier Ltd, Vol. 61, pp. 85-117, January 01, 2015

[12]. Chi-Yuan Yeh, Wen-Hau Roger Jeng, Shie-Jue Lee, "DataBased System Modeling Using a Type-2 Fuzzy Neural Network With a Hybrid Learning Algorithm", IEEE Transactions on Neural Networks , Vol. 22, Issue 12, pp. 2296-2309, Dec. 2011.

[13]. Wilbert Sibanda, Philip Pretorius, "Artificial Neural Networks- A Review of Applications of Neural Networks in the Modeling of HIV Epidemic", International Journal of Computer Applications, Vol. 44, Issue 16, April 2012.

[14]. Divya Sharma, “Recognition of Handwritten Devanagari Script Using Soft Computing”, Computer science and engineering department, Thapar university, Patiala, June 2009.

International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 18 (2017) pp. 7115-7121

[15]. K. Ramesh, A. P. Kesarkar, J. Bhate, M. Venkat Ratnam, and A. Jayaraman, "Adaptive neuro-fuzzy inference system for temperature and humidity profile retrieval from microwave radiometer observations", Atmospheric Measurement Techniques Journal, Vol. 8, pp. 369–384, January 2015.

[16]. Satwanti Devi, Sanjay Kumar, Govind Singh Kushwaha, "An adaptive neuro fuzzy inference system for prediction of anxiety of students", 2016 Eighth International Conference on Advanced Computational Intelligence (ICACI), IEEE, Chiang Mai, pp. 7-13, 2016.