A Hybrid Approach of Neural Network and Level-2 Fuzzy set

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Abstract. This paper presents a new high performance algorithm for the classification problems. The structure of A Hybrid Approach of Neural Network and Level-2 Fuzzy set, including two main processes. The first process of this structure is the learning algorithm. This step applied the combination of the multilayer perceptron neural network and the level-2 fuzzy set for learning. The outputs from learning process are fed to the classification process by using the K-nearest neighbor. The classification results on standard datasets show better accuracy than other high performance Neuro-Fuzzy methods.

Keywords: Neural Network, Level-2 Fuzzy set, Neuro-Fuzzy

1 Introduction

The development of the better classification algorithm has continued interest by many researchers. Classification algorithms are applied in numerous areas of work. There are many popular classification algorithms such as neural network, decision tree and fuzzy logic. Each algorithm has different advantage and disadvantage in data classification. This paper proposes the new methodology that combines 3 algorithms including neural network, Fuzzy logic and k-nearest neighbor. The Hybrid Approach of Neural Network and Level-2 Fuzzy set result the better accuracy of classification.

The neural network is one of the best performance classification tools [1-3]. The structure is derived from the human brain. An algorithm of learning process can use the error to update the structure for better performance. Although the neural network is robust for classifying the unknown input and has good classification results. But the flaw is the structure cannot explain in natural language for human.

The fuzzy system is a technique that can deal with the uncertainty information by using the fuzzy set. However the results of fuzzy membership value also have some uncertainty information. The level-2 fuzzy set is the technique to dealing with this problem [4-8].

The evolution of neuro-fuzzy show that this algorithm can result the better performance in classification problem than many other popular algorithms. The algorithm proposed in [9-10] using fuzzification method with original information

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and divide into 3 membership functions. The results from fuzzification process that used for classification are better than using the original value. The method of dividing the membership function using incremental clustering has developed and presented in [11]. Original feature is regrouped to obtain the number of membership functions. The results are improved and confirm that the proper number of fuzzy membership functions is one thing that makes classification more effective. The algorithm proposed in [12] show another alternative neuro-fuzzy algorithm for classification. This algorithm learning the information with neural network. The error of output from neural network are retrained using mandani fuzzy method. Finally, apply the K-nearest neighbor to classification the fuzzy output. The neuro-fuzzy algorithm modified from [12] used for recognition and classification of infant cry in [13].

2 Structure of Hybrid Approach of Neural Network and Level-2 Fuzzy set

In this paper presents the new development neuro-fuzzy algorithm for classification. In Fig.1 shows overall structure of the Hybrid Approach of Neural Network and Level-2 Fuzzy set (HANN-L2F) algorithm.

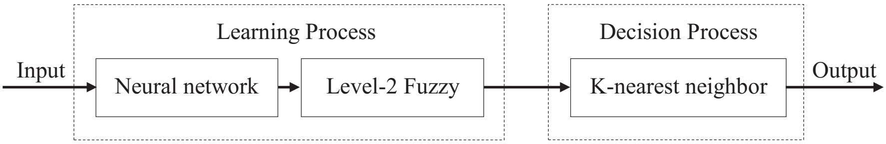

Fig. 1. Structure of Hybrid Approach of Neural Network and Level-2 Fuzzy set (HANN-L2F)

The structure including two parts that is learning process and decision process. The learning process is a combination of 2 algorithms, neural network and fuzzy system. The neural network gets input into the process for learning. After that the result will feed forward to create the level-2 fuzzy set. In the decision process of structuring, KNN is used to define the classification result.

2.1 Learning Process

The first step in this section use 3 layer neural network for learning. The outputs from neural network are preprocess by using Min-Max normalization method, before fed to fuzzification in the next step. The level-2 fuzzy set is used to handle the uncertainty of neural network results. An incremental clustering with class applied from [11] is used to find the reasonable number to create membership function. Membership values output from level-2 fuzzy set are fed to decision processes in the next step.

Neural network part. The structure from Fig.2 have three parts include input layer, hidden layer and output layer. The number of nodes in the input layer is equal to attribute size of the dataset. The number of nodes in the hidden layer is assigned to 3 nodes. Finally, output nodes in the output layer are equal to class size from data set. All weights and bias parameter are randomly initialized. The back propagation algorithm is applied in the structure.

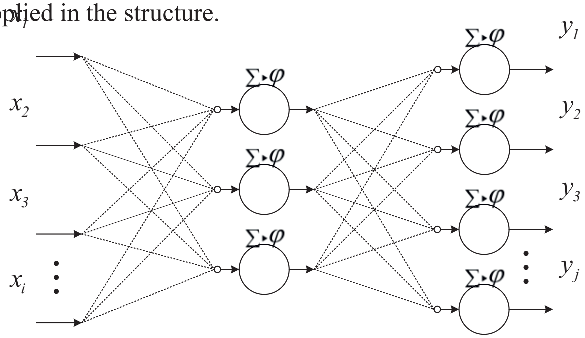

Fig. 2. Structure of Neural Network in Learning Process

Every nodes use log sigmoid as activation function. The output from each node calculate by

$$y_j = 1/\left(1+e^{-v_j}\right) \tag{1}$$

where
$$v_j = \sum_i w_{ij}x_i + b_i \tag{2}$$

In equation (1) and (2), j is represents the node in each layer and i is represents the number of input feature relevant to the considered node. In (2) w_{ij} is all weight parameters in the considered layer. The back propagation algorithm is used to update the structure parameters from learning process by using the value of undesired output error. This error will be used to find the gradient for update weights and bias can be defined as

$$e_j = d_j - y_j \tag{3}$$

In the equation (3), d is the desired output. The gradients used for update weights and biases for output layer and the hidden layer are displayed in equation (4) and (5) respectively. These equations are as follows

$$\delta_j(n) = e_j(n)\varphi_j'(v_j) \tag{4}$$

$$\delta_j(n) = \varphi_j'(v_j)\sum_i \delta_i w_{ij} \tag{5}$$

The weights are updated by

$$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n) \tag{6}$$

where $$\Delta w_{ij}(n) = \eta \delta_j(n) y_j(n) \tag{7}$$

Before the outputs are sent to create fuzzy membership value, the data are normalized. Although classify by neural network results a good performance, but does not mean the values are desired. The Min-Max normalization is used for preprocess output as

$$y_j' = \left(\left(y_j - b \right) / \left(a - b \right) \right) \left(a' - b' \right) + b' \tag{8}$$

In (8) y_j' is the normalized output, y_j is the neural network original output. The maximum and minimum value of feature is a and b respectively. The new maximum and new minimum value of feature is a' and b'.

Level-2 Fuzzy set part. This step uses the level-2 fuzzy set to transfer normalized data from the previous section to fuzzy value. The structure of this part is displayed in Fig. 3.

Fig. 3. Structure of Level-2 Fuzzy set process

In order to consider the uncertainty of classification results from neural network, the gaussian membership function is applied. The incremental clustering use class is applied to determine the level-1 membership function number. The incremental clustering use class algorithm is as follows.

1. **Assume** [x_i , c_i , c_i'] where x_i is input , c_i is original class and c_i' is new class.
2. Sort rows by x_i
3. Assign $class \leftarrow 1$, Let c_1' equal to $class$.
4. **For** $i \leftarrow 2$ to n
5.   **If** c_i is equal c_{i-1}
6. $c_i \leftarrow class$
7.   **Else**
8. $class \leftarrow class + 1$
9. $c_i \leftarrow class$
10.   **End if**
11. **End for**

The fuzzification process of level-1 fuzzy set used y'' as input of the gaussian membership function. The membership value of the level-1 fuzzy set is as follows

$$\alpha_k = \left(u_{\alpha(k)}\left(y_k''\right) / y_k''\right) \tag{9}$$

where
$$u_\alpha\left(y''\right) = e^{\left(\left(y''-c\right)^2/2\sigma^2\right)} \tag{10}$$

Where y'' is the input, c is mean and σ is standard deviation. From (10) is the fuzzy set equation. Assign α_k is membership fuzzy set. The example of the class scatter plot and membership function graphs of Seeds dataset from level-1 fuzzy process is displayed in Fig.4.

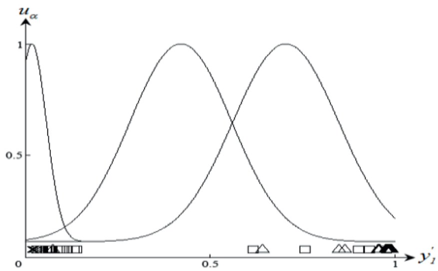

Fig. 4. Example of the scatter plot and membership function graphs of class in Seeds dataset

The seeds dataset in Fig. 4 has 3 classes the different symbols represent to each class. Between each class has interrupted with class. The uncertainty is clearly observing since between each class has interrupted with other classes. The level-2 fuzzy set is applied to handle this uncertainty problem. The results from level-1 Fuzzy set are re-fuzzification using gaussian membership function. The example of the level-2 fuzzy set is demonstrated in Fig 5.

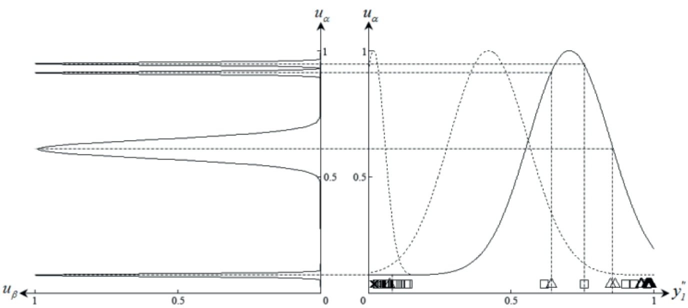

Fig. 5. Example clustering results and membership graph of the Level-2 fuzzy set.

The membership value of level-2 fuzzy set is defined by

$$\beta_k = \left(u_{\beta(k)}\left(u_{\alpha(k)}\right) / u_{\alpha(k)}\right) \tag{11}$$

From equation (11) β is a finally training set from learning process. This value is used to classification in decision process. The $u_{\alpha(k)}$ is the membership value of level-1 fuzzy, which use to calculate the value of the level-2 fuzzy set.

2.2 Decision Process

The k-nearest neighbor is applied with the membership value from level-2 fuzzy to identify the class of classification process. The euclidean distance is used as distance function as displayed

$$d = \sqrt{\sum (p_i - q_i)^2} \tag{12}$$

After finishing the training process, 10 percent of training sample is randomly selected. The decision process is applied to these samples to find the best k of each data set. The best k equal to k from the training fuzzy set is used in the decision process of testing sample.

3 Experimental and Result

The performance measure results for algorithm in this paper. Using 10 datasets from UCI [14]. Each dataset has different in feature and details. The propose HANN-L2F is verified the performance by comparing the classification result with the popular neural network and the 2 high accuracy algorithms of neuro-fuzzy [10-11].

3.1 Experimental result

The experimental results displayed in table 1 compare the results from HANN-L2F with the popular classification algorithm neural network.

Table 1. The result from the propose HANN-L2F compare with Neural network

Dataset	Average Accuracy of 10-fold cross validation	
	Neural Network	HANN-L2F
Breast Cancer	96.77	**97.23**
Glass	61.38	**68.78**
Pima	76.23	**78.31**
Seeds	90.48	**93.33**
Zoo	96.09	**98.09**
Average	84.19	**87.15**

The neural network that used in the experiment has the same structure as the one used in our proposed neural network. The experimental results displayed in table 2 compare with NF[10] and ENF[11], those have verified their high performance with other algorithms. Accuracy displayed in both tables are the average 10-fold cross validation. Table 1, result from all 5 datasets show the higher accuracy of HANN-L2F than neural network those have the same structure.

Table 2. The result from HANN-L2F compare with Neuro-fuzzy[10] and ENF[11]

Dataset	Average Accuracy of 10-fold cross validation		
	NF[10]	ENF[11]	HANN-L2F
Hayes	61.26	74.23	**78.13**
Iris	96.00	96.67	**98.67**
Liver	67.91	65.54	**74.86**
Vote	95.18	95.18	**97.27**
Wine	95.49	97.19	**97.78**
Average	83.17	85.76	**89.34**

The algorithm NF[10] and ENF[11] verify their high performance comparing with the other popular classification algorithm. The classification results in table 2 show that our propose algorithm HANN-L2F has better accuracy than NF and ENF in all datasets. The accuracy of Hayes and Liver are drastic improve by our propose classification algorithm.

4 Conclusion

The Hybrid Approach of Neural Network and Level-2 Fuzzy set show higher classification accuracy. This algorithm used key feature from neural network and level-2 fuzzy system for learning and then used k-nearest neighbor for classification. The experimental results show that Hybrid Approach of Neural Network and Level-2 Fuzzy set can deal with uncertainty output from neural network to improve the accuracy.

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