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FUZZY NEURAL NETWORK BASED EXTREME LEARNING MACHINE TECHNIQUE IN CREDIT RISK MANAGEMENT

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Abstract— Credit risk refers that a borrower will default on any type of debt by failing to make payments. Credit risk is the potential loss due to the nonperformance of a financial contract, or financial aspects of nonperformance in any contract or failing to make payments at the bank. Several approaches used to find credit risk management. In existing system Extreme Learning Machine (ELM) technique in bank loan decisions is to simplify a loan officer's job, ELMs parameters can be analytically determined rather than being tuned. SVM enable a considerably easier parameterization when compared to other learning machines like for example multi-layer perception neural networks. The existing ELM and SVM techniques also lack in the classification accuracy, speed .To improve the classification accuracy and speed of the processor training ,using fuzzy neural network. Neural networks can learn from data, but cannot be interpreted - they are black boxes to the user. Fuzzy Systems consist of interpretable linguistic rules, but they cannot learn. We use learning algorithms from the domain of neural networks to create fuzzy systems from data. The learning algorithms can learn both fuzzy sets, and fuzzy rules, and can also use prior knowledge Analysis of the credit risk at bank loan decision. Fuzzy neural network or neuro-fuzzy system is a learning machine that finds the parameters of a fuzzy system (i.e., fuzzy sets, fuzzy rules) by exploiting approximation techniques from neural networks to analysis the user details at credit risk management. Fuzzy Neural network algorithm in bank loan decisions is to simplify a loan officer's job, to control it and to achieve more efficiency and productivity.

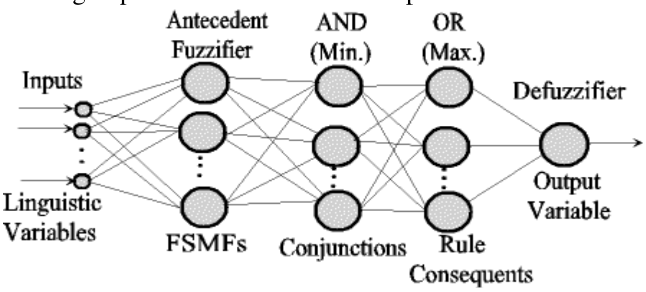
FUZZY NEURAL NETWORKS

In the case of cooperative neural fuzzy systems, both artificial neural network and fuzzy system work independently from each other. The ANN tries to learn the parameters from the fuzzy system. This can be either performed offline or online while the fuzzy system is applied. Fuzzy neural network learns fuzzy set from given training data. This is usually performed by fitting membership functions with a neural network. The fuzzy sets are then determined offline. They are then utilized to form the fuzzy system by fuzzy rules that are given (not learned) as well.

Fuzzy Logic model has advantages over the current systems based on the Altman model. The Fuzzy Logic model is easier to understand and can incorporate new knowledge easily. To illustrate, in India, since most of the knowledge is tacitly available only with the banks, this simple model can be used to generate uniformity across various branches of the same bank. Unlike the statistical models, Fuzzy Logic models are easier to interpret and they retain the experts' knowledge with them. Hence sharing of knowledge becomes easier. Since Fuzzy Logic models do not follow any distribution, one can obtain accurate ratings even with a small set of data as compared to statistical methods. Further, Fuzzy Logic models can be integrated with neural networks resulting in a better model with higher prediction accuracy. The scope of the model increases when one incorporates qualitative data the system. Furthermore, instead of using Fuzzy Logic as a standalone model, one can also use it as a module in credit rating. The problem of credit scoring i.e. rating of retail customers can be probed further as also the use of Artificial Intelligence techniques to make the model self learning.

Neural networks can learn from data, but cannot be interpreted - they are black boxes to the user. Fuzzy Systems consist of interpretable linguistic rules, but they cannot learn. We use learning algorithms from the domain of neural networks to create fuzzy systems from data. The learning algorithms can learn both fuzzy sets, and fuzzy rules, and can also use prior knowledge.

A fuzzy NN (FNN) may have 4 layers as follows: 1) the first is the input layer as in a BPNN or RBFNN that simply fans out the inputs to the next layer; 2) a hidden layer that fuzzifies the inputs, e.g., into LOW, MEDIUM, and HIGH linguistic variables as rule antecedents with a fuzzy truth for each, obtained by passing each input value through a fuzzy set membership function (FSMF) for a linguistic variable 3) a rule layer where arrows from certain fuzzifying nodes imply a consequent fuzzy variable in this layer; and 4) the defuzzification layer. Many FNNs currently use the more general 5 layers for fuzzy rules where the third is the AND (min.) layer and the fourth is the OR (max.) layer shows the general min-max FNN that allows the most general rule-based representation. Consider the rule: (A1 is LOW) AND (A2 is HIGH) => (C is LOW). The antecedents A1 and A2 propagate the minimum of their fuzzy truths to the consequent C. If (A3 is MEDIUM)AND (A4 is HIGH) => (C is LOW) also, then C takes the maximum of the two fuzzy implications as its fuzzy truth, which is fuzzy ORing of the two rules that imply (C is LOW).Thus such a FNN is a min-max (AND-OR) fuzzy rule based system conceptualized in network format. There are many variations and applications of FNNs. Rules can be built into the architecture by experts or they can be learned by training to produce known correct outputs



NNs are needed for repetitive tasks and for input-output associations for which there are no mathematical models available for the system that is to be represented. The NNs interpolate and extrapolate from known input-output pairs, and provide fast on-line computation of outputs that either could not be directly computed or would be slow to compute. They can obviously be used only in situations where there is good representative labeled data available for training the NN .

Credit Risk Management: In order to promote efficient and successful classification of loan applications, substantial research work has been carried out over the last decade. A number of classification schemes have been developed in the literature to address the problems and challenges of the classification of loan applications.

Support Vector Machine with Credit Rationing

The execution and the result of bank credit rating are closely linked with the bank's investment and loan policies which form the initial risk measurement [19]. It is an important and a shouldn't ignored issue for bankers to set up a scientific, objective and accurate credit rating model in the field of customer relationship management. In this study, two classification methods, multiple discriminate analysis (MDA), CANDISC, and support vector machine (SVM) are applied to conduct a comparative empirical analysis using real world commercial loan data set. The result comes out that SVM model has reliable high classification accuracy under feature selection and therefore is suitable for bank credit rating. Author suggests the decision-making personnel to establish a decision-making support system to assist their judgment by using the classification model.

Guo-Liang Lv et al., (2008) has been made by the study about a new model based on rough sets and support vector machines (SVM) to evaluate credit risk in commercial banks. An index system is established, and then the rough set was used to reduce the number of indexes and to make the calculation easy. The SVM was used to classify the credit risk precisely. A real case is given to test the model and the experimental results show that the model has high accuracy. The paper also compared it with the back propagation neural network (BPNN) method .The data showed that the new model based on rough sets and SVM is more precise and more efficient than the BPNN method. Those advantages proved that the new model is a more effective one for evaluating credit risk in commercial banks.

Fuzzy neural network with credit rationing

Neuro-fuzzy refers to combinations of artificial neural networks and fuzzy logic. Neuro-fuzzy was proposed by J. S. R. Jang. Neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks. Neuro-fuzzy hybridization is widely termed as Fuzzy Neural Network (FNN) or Neuro-Fuzzy System (NFS) in the literature[48]. Neuro-fuzzy system (the more popular term is used henceforth) incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The main strength of neuro-fuzzy systems is that they are universal approximators with the ability to solicit interpretable IF-THEN rules. The strength of neuro-fuzzy systems involves two contradictory requirements in fuzzy modeling: interpretability versus accuracy. In practice, one of the two properties prevails. The neuro-fuzzy in fuzzy modeling research field[49] is divided into two areas: linguistic fuzzy modeling that is focused on interpretability, mainly the Mamdani model; and precise fuzzy modeling that is focused on accuracy, mainly the Takagi-Sugeno-Kang (TSK) model. Our simple fuzzy neural network Carl G. Looney and Sergiu Dascalu[50] first thins the set of exemplar input feature vectors and then centers a Gaussian function on each remaining one and save its associated output label (target). Next, any unknown feature vector to be classified is put through each Gaussian to get the fuzzy truth that it belongs to that center. The fuzzy truths for all Gaussian centers are then maximized and the label of the winner is the class of the input feature vector. We use the knowledge in the exemplar-label pairs directly with no training, no weights, no local minima, no epochs, no defuzzification, no overtraining, and no experience needed to use it. It sets up automatically and then classifies all input feature vectors from the same population as the exemplar feature vectors. We compare our results on well known data with those of several other fuzzy neural networks, which themselves compared favorably to other neural networks. Pseudo outer-product-based fuzzy neural networks ("POPFNN") are a family of neuro-fuzzy systems that are based on the linguistic fuzzy model.

PROPOSED METHODOLOGY

Credit risk assessment, a classification problem in nature, is a basic task in credit risk management of commercial banks whose purpose is to analyze the credit risk of banks so as to offer a decision-making ground for loan business. Hence with the rush to sanction the loans there is a lot of pressure on the assessment process to ascertain customers as “good” or “bad”. Even though it is evident for the sake of emphasis it is better to state here that neither wrongly rejecting a good customer nor accepting a bad customer is acceptable as both will affect the bottom line. Finally when there is need to grow aggressively there is a need to disburse the loans as fast as possible but at the same time giving the loan only to the right customer. In Previous approaches have used extreme learning machine and Support Vector Machine to classify the customers. It can’t be used with the huge availability of data and also the existing techniques lacks in classification accuracy, speed and robustness. Developed technique used neuro-fuzzy system to identify, learn and classify good customers and bad customers.

Despite the increase in consumer loans defaults and competition in the banking market, most of the commercial banks are reluctant to use machine learning software technologies in their decision-making routines. Generally, bank loan officers rely on traditional methods to guide them in evaluating the worthiness of loan applications. A checklist of bank rules, conventional statistical methods and personal judgment are used to evaluate loan applications. Furthermore, a loan officer’s credit decision or recommendation for loan worthiness is subjective. After some experience, these officers develop their own experiential knowledge or intuition to judge the worthiness of a loan decision. Given the absence of objectivity, such judgment is biased, ambiguous and nonlinear and humans have limited capabilities to discover useful relationships or patterns from a large volume of historical data. Generally, loan applications evaluations are based on a loan officers’ subjective assessment. Therefore, a knowledge discovery tool is needed to assist in decision making regarding the application. The complexity of loan decision tools and variation between applications is an opportunity for a neural-computing technology to provide learning capability that does not exist in other technologies.

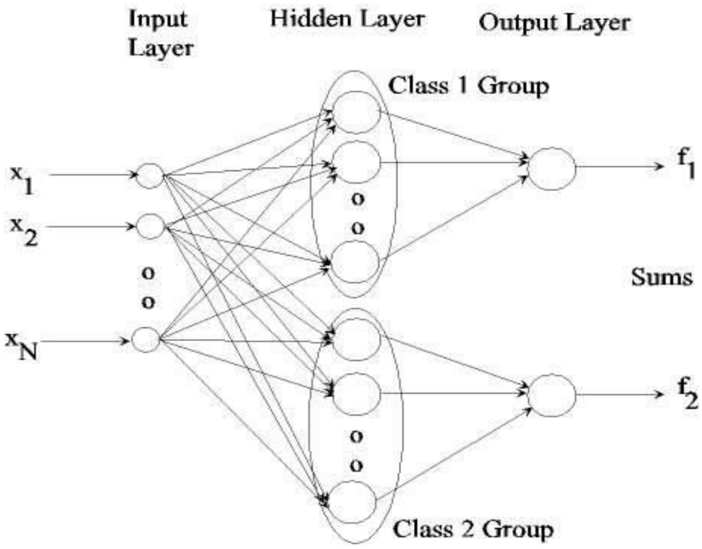
A neuro-fuzzy system based on an underlying fuzzy system is trained by means of a data-driven learning method derived from neural network theory. This heuristic only takes into account local information to cause local changes in the fundamental fuzzy system. It can be represented as a set of fuzzy rules at any time of the learning process, i.e., before, during and after. Thus the system might be initialized with or without prior knowledge in terms of fuzzy rules. The learning procedure is constrained to ensure the semantic properties of the underlying fuzzy system. A neuro-fuzzy system approximates a n-dimensional unknown function which is partly represented by training examples.

Learning algorithm is a hybrid supervised method based on gradient descent and Least-squares. Forward phase signals travel up to layer 4 and the relevant parameters are fitted by least squares .Backward phase the error signals travel backward and the premise parameters are updated as in back propagation .Mackey-Glass prediction / excellent non-linear fitting and generalization / less parameters and training time is comparable with ANN methods. Since a wide class of fuzzy controllers can be transformed into equivalent adaptive networks, ANFIS can be used for building intelligent controllers that is, controllers that can reason with simple fuzzy inference and that are able to learn from experience in the ANN style.

Fuzzy neural networks (FNN’s) are similar to the ANN’s. Let there be K classes and let
x be any feature vector from the population of interest to be recognized. The Class k exemplar feature vectors are denoted by $\mathbf{x}^{(q(k))}$ for q(k) = 1,...,Q(k). The summed functions here are not scaled and have a maximum value of unity.

$f_1(\mathbf{x}) = (1/Q(1))E_{(q1=1,Q(1))} \exp\{-\|\mathbf{x} - \mathbf{x}^{(q(1))}\|^2/(2\sigma_1^2)\}$

$f_K(\mathbf{x}) = (1/Q(K))G_{(q(K)=1,Q(K)} \exp\{-\|\mathbf{x} - \mathbf{x}^{(q(K))}\|^2/(2\ \sigma_K^2\ )\}$



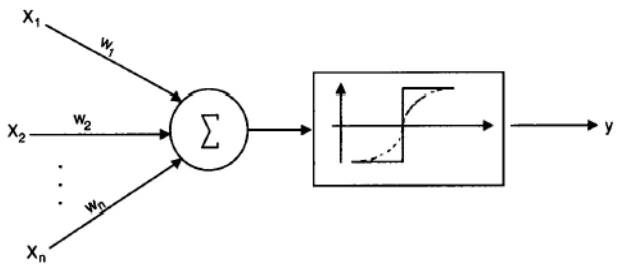
$$f_k(\mathbf{x}) = \max \{ \exp[-\|\mathbf{x} - \mathbf{x}^{(q(k))}\|^2/(2\sigma_1^2)]: 1 \le q(k) \le Q(k) \}$$

EXISTING SYSTEM

Extreme Learning Machine (ELM) technique in bank loan decisions is to simplify a loan officer’s job, to control it and to achieve more efficiency and productivity. Extreme Learning Machine (ELM) algorithm has been identified as an enabling tool for evaluating credit applications to support loan decisions and to outline some of the challenges of using ELM in the decision-making process for the banking industry. Support vector machines (SVMs) are a well-known supervised learning technique for performing binary classification. These are very accurate and generalize well to a wide range of applications.SVM separates binary classified data by a hyper-plane such that the margin width between the hyper-plane and the examples is maximized. Statistical learning theory shows that maximizing the margin width reduces the complexity of the model, consequently reducing the expected general risk of error. SVM cannot be tested against a much larger database of credit card customers than has been considered in the literature so far. SVM is tested with a polynomial kernel to determine if a non-linear polynomial decision space yields better performance than linear SVM or using the Gaussian RBF kernel. SVM performance is assessed in light of the number of support vectors required to model the data. SVM performs classification process, but it lacks in providing better results, classification accuracy is low and the processing speed is very high.

PROPOSED SYSTEM

Neural networks are good at recognizing patterns; they are not good at explaining how they reach their decisions. Fuzzy logic systems, which can reason with imprecise information, are good at explaining their decisions but they cannot automatically acquire the rules they use to make those decisions. Intelligent hybrid systems where two or more techniques are combined in a manner that overcomes individual techniques Fuzzy model of artificial neuron can be constructed by using fuzzy operations at single neuron level. Fuzzy system being represented as a network structure, making it possible to take advantage of learning algorithm inherited from ANNs.



Advantages of the proposed system

Used in multi-resolution analysis in signal processing, is used to overcome the limitations in Neural Networks.

The proposed system improves the accuracy of classification and prediction at credit card risk management.

The fuzzy Neural Networks approximates a function performs better than ELM,SVM

Training Algorithm

A supervised learning system that performs classification is known as a learner or, more commonly, a classifier. The classifier is first fed training data in which each item is already labeled with the correct label or class. This data is used to train the learning algorithm, which creates models that can then be used to label/classify similar data.

If there are N samples (x_i, t_i), where $x_i = [x_{i1}, x_{i2} \ldots x_{in}]^T$ R^n and $t_i = [t_{i1}, t_{i2}, \ldots, t_{im}]^T$ R^n, then the standard SLFN with N hidden neurons and activation function g(x) is defined as:

$$\sum_{i=1}^{\tilde{N}} \beta_i \, g(w_i \cdot x_j + b_i) = 0_j, j = 1, \ldots \ldots, N.,$$

where $w_i = [w_{i1}, w_{i2}, \ldots, w_{in}]^T$ represents the weight vector that links the ith hidden neuron and the input neurons, $\beta_i = [\beta_{i1}, \beta^{i2}, \ldots, \beta^{im}]^T$ represents weight vector that links the ith neuron and the output neurons, and b_i represents the threshold of the ith hidden neuron.

The "." in $w_i \cdot x_j$ indicates the inner product of w_i and x_j. The SLFN try to reduce the difference between o_j and t_j. This can be given as:

$$\sum_{i=1}^{\tilde{N}} \beta_i \, g(w_i \cdot x_j + b_i) = t_j, j = 1, \ldots \ldots, N.,$$

or, more in a matrix format as H ß = T, where

$$H(a_1, \ldots, a_{\tilde{N}}, b_i, \ldots, b_{\tilde{N}}, x_1, \ldots, x_N) = \begin{bmatrix} g(w_1, x_1 + b_1) & \cdots & g(w_g, x_g + b_g) \\ \vdots & \ddots & \vdots \\ g(w_1, x_1 + b_1) & \cdots & g(w_g, x_g + b_g) \end{bmatrix}_{N * \tilde{N}}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N} * m} \quad \text{and} \quad T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}_{N * m}$$

The matrix H is the hidden layer output matrix of the neural network. If the number of neurons in the hidden layer is equal to the number of samples, then H is square and invertible. Otherwise, the system of equations requires to be solved by numerical methods, concretely by solving

$$min_{\beta} \; ||H\beta - T||$$

The result that reduces the norm of this least squares equation is

$$\hat{\beta} = H^{+}T$$

where $H^{\dagger}$ is known as Moore-Penrose generalized inverse. The most significant properties of this result are:

Minimum training error. Smallest norm of weights and best generalization performance. The minimum norm least-square solution of Hβ = T is unique, and is

$$\hat{\beta} = H^{+}T$$

The ELM algorithm works as follows:

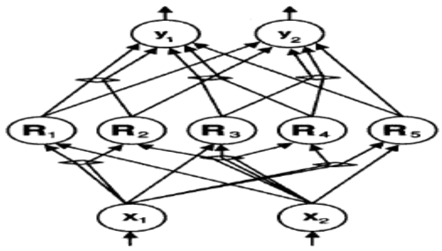
Give a training set $N = \{(x_1, t_1) | x_1 \in R^n, t_1 \in R^m, 1 = 1 \ldots \ldots N\}_t$

activation function g(x) and hidden neuron $\tilde{N}$, do the following

- Assigning random value to the input weight w_i and the bias $b_i, i = 1, \dots \dots \dots . \tilde{N}$
- Find the hidden layer output matrix H.
- Find the output weight β, using $\hat{\beta} = H^{+}T$, where β, H and T are defined in the same way they were defined in the SLFN specification above.

Neuro fuzzy system

Supervised learning in FNN consists in modifying their connection weights in a such a manner that an error measure is progressively reduced Its performance should remain acceptable when it is presented with new data .In this fuzzy neural system independent variables are fuzzified (if they are crisp variables) and their membership functions are determined at the input unit and appropriate rules are generated before they are introduced for the activation of the hidden layer. Also, the network outputs produced in the output layer are simply returned as constants or linear combinations of weighted rules which is the ultimate output. This typically adds two units (layers) to the structure. The iteration process takes place between the fuzzification and the defuzzification layers. In this process, appropriate weights are estimated for each rule to determine its impact on the final output.



Set of training data pairs ($\mathbf{x}_k$, d_k) for k=1,2..n $\mathbf{w}^{t+1}=\mathbf{w}^t + \Delta\mathbf{w}^t$, where weight change is a given function of difference between the target response *d* and calculated node output y $\Delta\mathbf{w}^t=F(|d^t-y^t|)$ Three-layer feedforward network (no cycles in the network and no connections exist between layer n and layer n+j, with j>1 input variables / hidden layer - fuzzy rules / output variables Hidden and output units use *t*-norms and *t*-conorms as aggregation functions The fuzzy sets are encoded as fuzzy connection weights and fuzzy inputs The input units are labelled $x_1..x_n$, hidden rule units are called $R_1 \dots R_k$ and the output units are denoted as y_1 y_m Each connection is weighted with a fuzzy set and is labelled with a linguistic term Connection coming from the same input unit and having same label are weighted by the same common weight (shared weight). The same holds for the connections that lead to the same output unit There is no pair of rules with identical antecedents.

STRUCTURE OF LEARNING ALGORITHM

. Select the next training pattern (s, t) from the training set.

2. For each input unit x_i find the membership function $\mu_{ji}^{(i)}$ Such that

$$\mu_{ji}^{(i)}(s_i) = \max_{j\in\{1,\dots,p_i\}} \{\mu_j^{(i)}(s_i)\}$$

3. If there is no rule R with weights $W(x_1, R) = \mu_{ji}^{(i)}, \dots \dots \dots , w(x_n, R) = \mu_{jn}^{(i)}$

Then create the node and connect it to all the output nodes.

4.for each connection from the new rule node to the output node find the suitable fuzzy weight $v_{ji}^{(i)}$ using the membership function assigned to the output units y_i such that

$$v_{ji}^{(i)}(t_i) = \max_{j\in\{1,\dots,q_i\}} \{v_j^{(i)}(t_i)\}$$

$v_{ji}^{(i)}(t_v) \geq 0.5$ .if the fuzzy set is not defined then create a new one $v_{new}^{(i)}(t_i)$ for the output variable V_i and set $W(R,y_i)= v_{new}^{(i)}$

5.If there are more training samples then stop otherwise go to step1

6. Evaluate the rule base and change the rule conclusion if appropriate

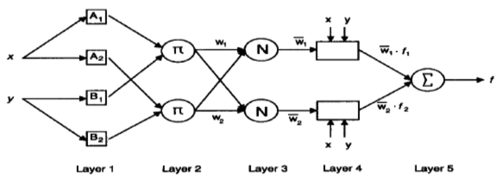
Training algorithm

Adaptive Network-based Fuzzy Inference System. Neuro-fuzzy system that can identify parameters by using supervised learning methods. Sugeno-type fuzzy system with learning capabilities. Nodes have the same function for a given layer but are different from one layer to the next.

If x is A_1 then AND y is B_1 then $f_1 = p_1 x + q_1 y + r_1$

If x is A_2 then AND y is B_2 then $f_2 = p_2 x + q_2 y + r_2$

$$f = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} = \overline{w_1} + \overline{w_2}$$



Learning algorithm is a hybrid supervised method based on gradient descent and Least-squares. Forward phase signals travel up to layer 4 and the relevant parameters are fitted by

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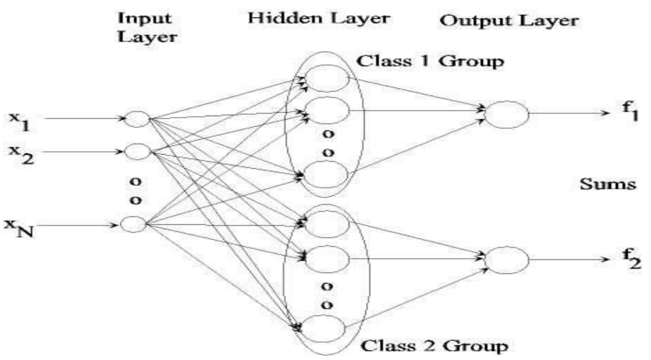

Classification Accuracy

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