

Hybrid Intelligent System via Fuzzy Regression Analysis, Bayesian Gaussian Reasoning Model in Healthcare

Shailendra Singh Kathait, Dr. Aankita Kaur, Anubha Varshney

Abstract -In this paper, we propose the architecture of Hybrid Intelligent System with different techniques of pattern recognition and machine learning. Fuzzy Regression and Bayesian Gaussian Neural Network approach are used to build the model. Fuzzy regression deals with the uncertain, vagueness of the system. Naïve Bayesian classifier helps in building strong independent relationships whereas Gaussian classifiers correlates high dimensional data with kernel function to yield better performance of the system. A hybridized combined approach of neural network is presented in healthcare. It is due to its flexibility of modeling, and robust nature, learning ability from complex functions and the application of different algorithm for reduction of errors for a better intelligent system.

Index Terms - Hybrid Intelligent System; Neural Network (NN); Machine Learning (ML); Bayesian Gaussian Neural Network (BGNN); Pattern recognition(PR); Computational Intelligence

I. INTRODUCTION

In the recent years, Hybrid Intelligent Systems have achieved success in solving the real world complex problems. These adaptability systems must have qualities of self maintenance and information preservation etc. The objective is to carefully combine intelligent techniques together to obtain an efficient solution. Instead of using a single technology process in a system, the European Union's Fifth RTD framework program; ENUTE [1] has also used Hybrid Intelligence as one of the central topics. Hybrid Intelligent Systems are most suitable in medical applications as they provide new, effective and usable approaches for classification and discrimination tasks.

Shailendra Singh Kathait, Valiance Solutions Pvt Ltd, Noida 201301, India

Dr Aankita Kaur, Valiance Solutions Pvt Ltd, Noida-201301, India

Anubha Varshney, Valiance Solutions Pvt Ltd, Noida-201301, India, +

The main components of research in Computational Intelligence are Fuzzy set, Neural Network, Genetic

Algorithms and Evolutionary Computing, Machine learning and Data Mining. Fuzzy logic is a language which uses syntax and local semantics where one can imprint any qualitative knowledge about the problem to be solved. The main attribute of fuzzy logic is the robustness of its reasoning mechanism.

Genetic Algorithm provides a way to perform randomized global search in a solution space. It is evaluated in terms of its accuracy where problems are solved by an evolutionary process resulting in the best solution.

Machine Learning techniques are able to store or extract knowledge from large databases in an automatic computerized way. It allows development of algorithms and computer programs to learn from experience [2].

Data mining also known as KDD (Knowledge Discovery Database) is a process of extracting interesting patterns and collecting facts from a large set of data. It is a set of algorithms to find useful patterns and hidden information from huge databases [3]. Data Mining is being used in the fields like medical sciences, network data analysis etc. Medical data mining results in rapid prediction for prognosis and diagnosis of patients affected with a particular disease in a specialized medical area [4].

Among KDD techniques, Bayesian network, Classification and association techniques, neural network have emerged as important methods. Bayesian network is a fundamental technique for handling uncertainty in complex domain. Neural Networks are designed to mimic the parallel processing ability of human brain but they do not readily provide an explanation to their prediction.

Healthcare enterprises can be regarded as data rich but knowledge poor. Knowledge of any healthcare organization is confined to only few experts who acquire it through experiences in day to day medical practices.

In this paper, our aim is to design generalized hybrid architectures. It is done by choosing most suitable intelligent component theoretically and also considering the special attributes of the application under examination. We need to use technologies including computers to enhance decision making process with a clear emphasis of "improvement of quality".

II. MACHINE LEARNING AND PATTERN RECOGNITION TECHNIQUES

Databases within database management system are viewed as interrelated data whereas for Artificial Intelligence and Machine Learning they are treated as simple file structure. The systems help in analyzing data correlation and develop models within large quantities of processed data using techniques such as neural network, pattern recognition, data mining, model development and/or process optimization as a method of algorithm and data processing development.

Pattern recognition techniques such as Linear Regression, Bayesian Theory etc derive patterns in classifying and building relationship between attributes having numeric values [7] [8].

A. Decision Tree

Decision Tree algorithm searches the descriptive attribute. Those descriptive attributes are most relevant to the target attribute and for partitioning of other attributes according to conditions. Its strengths are being robust to noise and errors. Rules are then collected by following the root node to the terminating leaf node which are in the form of if-then to understand good performance even if some examples are incorrectly labeled.

It is used to build trees for predicting categorical predictor (independent) variables for classification and continuous dependent variables for regression. The decision tree having n ($\log n$) complexity can be used directly by constructing various algorithms that construct correct classification of the problem.

B. Neural network

Artificial neural networks are modelled on the human brain for handling very complex tasks. It is a massively parallel distributed processor made up of simple processing units, for storing knowledge and making it available for use. Neural network decision process is not easily explainable in terms of rules that human experts can verify [9]. AI used in neural networks are useful in handling numerical data but not suited for decision modeling.

Neural network is executed in two stages. Stage I when neuron receives a number of inputs and is trained to perform a particular task (here encoding of neurons is from some other source of related data or derived from the original data). The input of neurons is executed via a connection (synapse) that has a weight (coefficient of connectivity). These artificial neurons are arranged on layers that carry values of the variables described. Stage II is the output derived which is the result of the problem or can be used as input to another problem. The output is deduced when the sum of the weights arranged on the layers have values greater than the threshold value. If so, the activation signal produces the output of the neuron that makes a

prediction for the task. There are different forms of Neural Network such as:

- Perceptrons (Simple Classification)
- Back propagation networks (Optimization)
- Kohonen self-organizing map (Cluster analysis)

Neural Networks are computational structures that can be trained to learn by examples using supervised learning algorithms for example: back-propagation and a training set that samples relation between input and output to perform optimization.

C. Bayesian Probability Network

Bayesian network $N(G,P)$ simply combines probabilistic knowledge of a joint probability distribution $P(V)$ by a graphical diagram of acyclic directed graph (DAG), $G=(V,E)$ such as $P(X_1=x_1 \dots X_n=x_n)$ of joint probability to each variable where $P(x_1, x_2, \dots, x_n) = \prod_{i=1}^n P(x_i | pa(X_i))$. Here, the joint probability can answer questions in probability terms but it becomes difficult as variables increase $P(x_1, x_2, x_3, x_4) = P(X_1=x_1) P(X_2=x_2) P(X_3=x_3|X_1=x_1, X_2=x_2) P(X_4=x_4|X_3=x_3) P(x_3= \text{yes} | x_1= \text{yes}, x_2= \text{yes}), P(x_3= \text{yes} | x_1= \text{yes}, x_2= \text{no}), P(x_3= \text{yes} | x_1= \text{yes}, x_2= \text{yes}), P(x_3= \text{yes} | x_1= \text{no}, x_2= \text{yes}), P(x_4= \text{yes} | x_3= \text{no}), P(x_4= \text{yes} | x_3= \text{yes})$. The challenge in Bayesian Probability Network for diagnosis is to represent domain knowledge in a network and keep it computationally tractable. Algorithms for Bayesian Probability Networks are exponential due to computational complexity in undirected loops [10]. Also there are 2^n possible combinations for n possible nodes where if a node C has two causes A and B with $P(C|A) = a$ and $P(C|B) = b$ then $P(C|A \text{ and } B) = 1 - (1-a)(1-b) = a+b-ab$ as number of input nodes. The naïve Bayesian classifiers assume independent variables of a predetermined class.

Normally to check the performance of machine learning methods the medical domains are compared with statistical logical regression approaches. Integration of machine learning methods perform better than using traditional logical regression models alone [11].

D. Gaussian Process

Gaussian Process classifiers are Bayesian Probabilistic kernel classifiers. Description of Gaussian Process can be found in Rasmussen & Williams [12]. Gaussian Process is generalization of Gaussian Probability Distribution. The process gives a prior probability to all the functions for making predictions. To estimate the output with a clear probabilistic understanding certain functions are input in the system. It is flexible in dealing with complex non linear functions to produce high performance system unlike artificial neural network in regression tasks [13].

This calls for a hybridized intelligent system which is designed as to overcome the technical problem (loss of

data, managing errors/outliers, over fitting, noisy and missing).Also, this collaborative approach helps in building the strengths and weaknesses of each system combined together to fetch better results. For example neural networks keep check on errors and outliers via back propagation gradient descent method. Bayesian method can extract conditional dependencies, maximum likelihood probabilities. Classical Statistical regression is based on probability while fuzzy regression accounts for fuzziness of the system [14].

III. FUZZY REGRESSION ANALYSIS: MEDICAL DATASETS

Medical applications due to their nature of domain are well suited for applying computational intelligence techniques in today’s healthcare environment [15] [16].Also, healthcare organizations are using these intelligent systems to improve quality of life. This can be done by improving the patient care, predicting future trends of treatments with the development of internet technologies. For a secure centralized data management solution recently cloud computing for protecting healthcare data has been introduced [17].

A. Fuzzy Regression Analysis

Fuzzy regression suits well to systems which are not well defined, uncertain, vague, and fuzzy. It helps in providing prediction of behavior of the system when the output of the system depends upon the practitioners judgments [18] and different treatment processes to be followed [19] [20] with the defined data [21] [22].Fuzzy set theory has many degree of membership (α) between 0 to 1.The membership function is associated with the fuzzy set mapping with the function. Here Fuzzy IF THEN rules are of the form: IF(x_1 is A_1 , x_2 is A_2 ... x_n is A_n) THEN (y_1 is B_1 , y_2 is B_2 ... Y_n is B_n) where x_i , y_i are values of fuzzy set A_i and B_j . Fuzzy extension is defined on extension principle [23].Fuzzy set membership is also used to estimate the missing or incomplete information.

B. Neuro-fuzzy System (FAN)

The non parametric approach of fuzzy regression named Fuzzy adaptive network is used for vague or not well defined system with the rules and reasoning of fuzzy set theory and learning ability of neural network. Fuzzy set theory is effective for solving uncertainty of the problem and network structure is suitable for many supervised learning algorithms.

Back propagation neural networks have been used for non parametric fuzzy regression where the node function is defined on fuzzy logic theory and back propagation algorithm are used to minimize the error in the system.

Different approaches of nonparametric fuzzy regression are used based on the type of network such as Regular back propagation network, fuzzified back propagation network used by Ishibuchi and Tanaka [24] [25], fuzzy radial basis function network by Cheng and Lee [26] which produces fuzzy output and tune the fuzzy connection weights automatically. The flexibility of modeling and optimization of these systems by using different functions helps in building the relationships between independent and output responses.

IV. BAYESIAN GAUSSIAN REASONING MODEL (BGNN)

Bayesian networks acts as a basis of representation of uncertain factors contributing in medical diagnosis. Also in artificial neural network the back propagation neural networks (BPNN) [27] [28] are most frequently used .It is due to the ability to build good models from example data and requirement of little knowledge of previous tasks applied into the system to solve complex problems. Recurrent[29] and radial basis function[30] neural networks are originated from BPNN as with using different functions, connections and training algorithms applied to the feed forward neural network. The use of Gaussian parameters in RBFNN (radial based function neural network) can reduce the number of training object adjusted weights and threshold errors to an extent [31]. Also the lack of self – tuning ability of the above networks make them less popular to work in on-line model based applications. The radial basis function classifiers are simple with one hidden and one output layer. The input nodes account the kernel function and output nodes gives the weighted sum of kernel functions to avoid lengthy calculations. A Gaussian function is normally taken as the kernel function where errors are minimized with gradient decent algorithm.

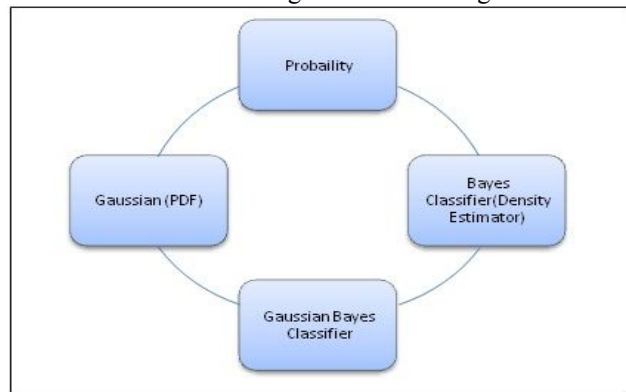


Fig.1 Bayesian Gaussian Neural Network

Bayesian Gaussian neural network (BGNN) can be a good alternative in neural network model based applications as it

saves a lot of training time by immediately setting the connection weights when the training samples are available and minimize the processing time for the adjustment of the input factors. Also, the output is an optimal solution of the a posteriori probability density function.

Case I: The Probability density distribution of Y(X) when only (X_i, Y_i) information is known -

Let (X_i, Y_i), i=1, 2...N be the training dataset where X_i is the input sample represented by m x 1 vector.

$X_i = (x_{i1}, x_{i2}, \dots, x_{im})^T$, y_i is a quantity of the sample output, N = net order [32], [34], [35]

According to Gaussian hypothesis,

$$Y \sim N(\mu_0, \sigma_0^2)$$

P(Y) is the probability density function (p.d.f).

Given: $Y_i \sim N(\mu, \sigma_i^2)$ with p.d.f p(y_i | Y = y), conditionally given Y [33]

$$P(Y) = \frac{1}{\sqrt{2\pi\sigma_0^2}} e^{-\frac{(Y-\mu_0)^2}{2\sigma_0^2}} \tag{1}$$

$$p(y_i|Y=y) = \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{-\frac{(y_i-y)^2}{2\sigma_i^2}} \tag{2}$$

from Bayes theorem

$$p(Y|y_i) = \frac{P(Y) \cdot P(y_i|Y)}{P(y_i)} \tag{3}$$

putting 1, 2 in 3

$$p(Y|y_i) = \frac{1}{2\pi\sigma_0\sigma_i} \frac{1}{P(y_i)} e^{-\frac{1}{2} \left[\frac{(Y-\mu_0)^2}{\sigma_0^2} + \frac{(y_i-Y)^2}{\sigma_i^2} \right]} \tag{4}$$

$$= c \frac{1}{\sqrt{2\pi\sigma_{0,i}}} e^{-\frac{(Y-\mu_{0,i})^2}{2\sigma_{0,i}^2}} \tag{4}$$

Where c is normalizing constant and

$$\sigma_{0,i}^{-2} = \sigma_0^{-2} + \sigma_i^{-2}$$

$$\mu_{0,i} = \sigma_{0,i}^{-2} (\sigma_0^{-2} \mu_0 + \sigma_i^{-2} y_i) \tag{5}$$

Now 4 and 5 express the posterior probability distribution of Y when only the information source (X_i, Y_i) is known.

Case II: The probability distribution Y(X) when the combined information source (X_i, Y_i) where i=1, 2,...N is known -

Here, we use the induction method and Baye's theorem, as Y_i and Y_j are conditionally independent given Y, we have

$$p(Y_i, Y_j|Y) = p(Y_i|Y) \cdot p(Y_j|Y), i \neq j$$

Using the law of mathematical induction for i=2, from Bayes theorem it follows,

$$p(Y|Y_1, Y_2) = \frac{P(Y) \cdot P(Y_1|Y) \cdot P(Y_2|Y)}{P(Y_1|Y) \cdot P(Y_2|Y)}$$

$$p(Y_1|Y) = \frac{P(Y_1) \cdot P(Y|Y_1)}{P(Y)}, p(Y_2|Y) = \frac{P(Y_2) \cdot P(Y|Y_2)}{P(Y)} \tag{6}$$

So, putting in -6 we have,

$$p(Y|Y_1, Y_2) = \frac{P(Y) \cdot P(Y_1|Y) \cdot P(Y_2|Y)}{P(Y_1|Y) \cdot P(Y_2|Y)}$$

$$= \frac{P(Y) \cdot P(Y_1) \cdot P(Y|Y_1)}{P(Y_1) \cdot P(Y)} \cdot \frac{P(Y_2) \cdot P(Y|Y_2)}{P(Y_2) \cdot P(Y)}$$

$$= K_1 \frac{P(Y|Y_1) \cdot P(Y|Y_2)}{P(Y)} \tag{7}$$

Here K_1 is a normalizing constant independent of Y.

Now suppose for i = N-1, we have

$$p(Y|Y_1, Y_2, \dots, Y_{N-1}) = K_2 \prod_{i=1}^{N-1} \frac{P(Y|Y_i)}{P(Y)} \tag{8}$$

Now when i=N, we have

$$p(Y|Y_1, Y_2, \dots, Y_N) = \frac{P(Y) \cdot P(Y_1, Y_2, \dots, Y_{N-1}, Y_N|Y)}{P(Y_1, Y_2, \dots, Y_{N-1}, Y_N)}$$

$$= \frac{P(Y) \cdot P(Y_1, Y_2, \dots, Y_{N-1}, Y_N|Y) \cdot P(Y_N|Y)}{P(Y_1, Y_2, \dots, Y_{N-1}, Y_N) \cdot P(Y_N|Y)}$$

$$= \frac{P(Y)}{P(Y_1, Y_2, \dots, Y_{N-1}, Y_N)} \cdot \frac{P(Y_N) \cdot P(Y|Y_N)}{P(Y)}$$

$$= \frac{P(Y_1, Y_2, \dots, Y_{N-1}) \cdot P(Y_N) \cdot P(Y|Y_1, Y_2, \dots, Y_{N-1}, Y_N) \cdot P(Y|Y_N)}{P(Y_1, Y_2, \dots, Y_{N-1}, Y_N) \cdot P(Y)}$$

$$= \frac{P(Y_1, Y_2, \dots, Y_{N-1}) \cdot P(Y_N)}{P(Y_1, Y_2, \dots, Y_{N-1}, Y_N) \cdot P(Y)} \cdot K_2 \frac{P(Y|Y_1) \cdot P(Y|Y_2) \cdot \dots \cdot P(Y|Y_{N-1})}{P(Y)}$$

$$= K \prod_{i=1}^N \frac{P(Y|Y_i)}{P(Y)} \tag{9}$$

Here K is the normalizing constant independent of Y. Also from 8 and 9 we get the proof.

Now, the p.d.f of equation 4 in equation 9

$$p(Y|Y_1, Y_2, \dots, Y_N) = C_2 \frac{\frac{1}{\sqrt{2\pi\sigma_{0,i}}} e^{-\frac{(Y-\mu_{0,i})^2}{2\sigma_{0,i}^2}}}{\left(\frac{1}{\sqrt{2\pi\sigma_{0,i}}}\right)^{N-1} \frac{1}{e^{-\frac{(N-1)(Y-\mu_{0,i})^2}{2\sigma_{0,i}^2}}}}$$

Here C_2 is a normalizing constant independent of Y. As σ_0^2 is very large so keeping the numerator part

$$p(Y|Y_1, Y_2, \dots, Y_N) = C_3 \frac{1}{\sqrt{2\pi\sigma_0}} \cdot \prod_{i=1}^N \frac{1}{\sigma_i} e^{-\frac{(Y-\mu_0)^2}{2\sigma_0^2}}$$

Here $\sigma_{0,i}^{-2} \approx \sigma_i^{-2}$, $\mu_{0,i} \approx \mu_0$ under gaussian hypothesis

$$p(Y|Y_1, Y_2, \dots, Y_N) = C_4 \frac{1}{\sqrt{2\pi\sigma_0}} e^{-\frac{(Y-\mu_0)^2}{2\sigma_0^2}}$$

where C_4 is normalizing constant independent of Y and y'

$$\text{where } y'(N) = \sigma(N)^2 \cdot \sum_{i=1}^N \sigma_{i-1} y_i$$

$$\sigma(N)^{-2} = \sum_{i=1}^N \sigma_{i-1}^{-2}$$

- 10

$$(x-x_1)^T D (x-x_0)$$

Assume that $\sigma_{i-1}^2 = \sigma_0^2 \cdot e$

- 11

D is the input threshold matrix. Therefore, equation 10 and 11 constitute the Bayesian Gaussian reasoning model. The model based application plays important role in optimization, diagnosis of treatment to adapt to practical process.

V. SOME APPLICATIONS OF OTHER HYBRID SYSTEMS: HEALTHCARE

Hybrid combinations are capable of describing reasoning and providing intelligent approach in medical applications. The following are the hybrid schemes that combine more than two techniques which help in solving medical diagnostic problems in the healthcare:

A. Neuro-fuzzy hybrids

Neural network and fuzzy logic both deal with uncertainty of complex system. Neural network models the complex non linear relationships, minimize the errors in predefined classes through processing of training nodes may take some time. Fuzzy logic modifies the vague inputs and outputs as fuzzy sets which increase the flexibility of the system to work in uncertain condition. In [36] [37] medical applications, this kind of hybrid intelligence can be found. A combination of neural networks and fuzzy logic develop an adaptive control system for arterial blood pressure using nitroprusside drug [38].

B. Neuro-genetic hybrids

Neural network design is problem specific. Genetic Network Programming (GNP) is an evolutionary approach for optimization techniques. It uses directed graphs, consists of start node, processing nodes and judgment nodes. Here, judgment nodes are of IF THEN type while processing nodes are the action/processing part. The concept of reusability of nodes defines a compact structure of the graph. The past history of the node transaction affects the current node of memory function [39]. In the graph structure of GNP the nodes are predefined. For example: the evolutionary artificial neural network approach for breast cancer diagnosis was presented [40].

C. Machine learning- fuzzy logic hybrids

Fuzzy logic is used to model vague, uncertain decision attributes. Machine learning re-processes these attributes

before the actual classification and diagnosis tasks. A hybrid intelligent system as above is used for diagnosis of coronary stenosis [41].

D. Other Intelligent hybrids

These systems are combination of other intelligent techniques with standard mathematical methods used in specific situations which perform better in evaluation of complex domain applications.

A case based neural network and its use in medical domain is presented in [42]. A hierarchical neural network structure and intelligent decision fusion has been developed by an adaptive medical image visualization system [43].

VI. CONCLUSION

The purpose of using a hybrid intelligent system approach is to make possible use of more complex intelligent architectures by collaboratively combining more than one intelligent technique. A hybridized combined approach of neural network with Bayesian classifier and Gaussian classifier is presented for healthcare medical applications to enhance the performance of the system.

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