Fuzzy based modeling for diabetic diagnostic decision support using Artificial Neural Network

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Summary
This paper investigates a variation to preliminary inquiry information obtained from patients of a diabetic and research center using fuzzy relation based model.. The proposed model is an attempt to closely replicate a physician's insight of symptom-disease associations and his approximate-reasoning for conclusion. The algorithm is evaluated on a dataset of 600 cases. The study is on people approaching diabetician with either past history of Diabetics or new case with symptoms of diabetics. Some cases are Normal patients without diabetics. The required parameters are estimated by interviewing patients. Later the parameters are modeled using a fuzzy approach and after normalization classified by Artificial neural networks as 'Close to Type 2 diabetic' or not. This result may indicate the effectiveness of proposed algorithm to optimally model the diagnostic process for small or large datasets; especially, due to its computational simplicity. Further studies on a variety of datasets in different population is required to establish such a utility.

Key words:
Fuzzy approach, diabetics, Artificial neural networks, Type 2 diabeticss

1. Introduction

To work with a live data, is a real research especially in the field of Medicine. Because of three reasons. One is to get an appointment of a doctor for an Engineering research is always very tough. The second reason is Medical Ethics have to be followed carefully as human beings are involved.And the third important reason is the study will varu with different patient group belonging to a diverse demographic, socio economic background. Diabetes in India, is a growing area of Research as Statistically the number has increased significantly in the last five years. In this paper we have put our efforts, to develop a model which can be used for classifying a Type II Diabetic patient form others. The emphasis lies in developing the Model.

In this paper a method both for constructing fuzzy membership functions from oral interviewed set of data and data of laboratory test results from patients and for forming fuzzy relationships between symptoms and diagnoses in the medical application area of type 2 diabetes is being presented. Fuzzy membership functions are generated to represent linguistic medical concepts for the data-to-symbol conversion unit of the medical knowledge-based system. Fuzzy relationships are defined for the frequency of occurrence of symptoms [1]. Efficient knowledge acquisition and representation are one of the central challenges for the successful construction and following use of medical expert and knowledge-based systems in clinical practice [2]. As medical knowledge is vague, fuzzy sets are used to deal with uncertain linguistic medical concepts such as Less, Very Less, Medium

2. Background

2.1 Diabetes Mellitus

Diabetes increases the risks of developing kidney disease, blindness, nerve damage, blood vessel damage and it contributes to heart disease [4]. Diabetes is a major health problem in both industrial and developing countries, and its incidence is rising. It is a disease in which the body does not produce or properly use insulin, the hormone that "unlocks" the cells of the body, allowing glucose to enter and fuel them [5]. Diabetes occurs when a body is unable to produce or respond properly to insulin which is needed to regulate glucose. Besides contributing to heart disease, diabetes also increases the risks of developing kidney disease, blindness, nerve damage, and blood vessel damage. Diabetes disease diagnosis via proper interpretation of the diabetes data is an important classification problem [4].

The most common form of diabetes is Type 2 diabetes [6]. This type diabetes results from insulin resistance (a condition in which the body fails to properly use insulin), combined with relative insulin deficiency. In Type 2 diabetes, either the body does not produce enough insulin or the cells ignore the insulin [7]. Although detection of diabetes is improving, about half of the patients with Type 2 diabetes are undiagnosed and the delay from disease onset to diagnosis may exceed 10 years. Thus, earlier detection of Type 2 diabetes and treatment of hyperglycaemia and related metabolic abnormalities is of vital importance.

Manuscript received April 5, 2011
Manuscript revised April 20, 2011

2.2 Neural Networks

The multilayer neural networks (MLNNs) have been successfully used in replacing conventional pattern recognition methods for the disease diagnosis systems [8] [9][10]. The back-propagation (BP) algorithm [11] is widely recognized as a powerful tool for training of the MLNNs. But, since it applies the steepest descent method to update the weights, it suffers from a slow convergence rate and often yields suboptimal solutions [12][13] A variety of related algorithms have been introduced to address that problem. A number of researchers have carried out comparative studies of MLNN training algorithms [14][15].Levenberg–Marquardt (LM) algorithm [16] used in this study provides generally faster convergence and better estimation results than other training algorithms [14][15]. On the other hand, the pervious diagnosis result of LM algorithm reported on Pima Indian diabetes disease dataset [9] was not better than the diagnosis results of other training algorithms. This can be because of that, LM algorithm converges very fast but it can cause the memorization effect when the overtraining occurs. If a neural network starts to memorize the training set, its generalization starts to decrease and its performance may not be improved for untrained test sets. Memorization of the training set can be because of the overtraining [14][15]. So, before the starting of memorization, we must determine the optimum trained neural network using the maximum accuracy value of the test data. Using the optimum trained neural network, Pima Indian diabetes disease diagnosis can be made with better accuracy. Our proposed method uses a real time dataset collected from the patients visiting Diabetes care and Research center, Tanjore, India. This paper focuses on regional people and checks the accuracy of Neural networks on fuzzified model of Questionnaire.

3. Data Preparation

When taking dataset of patients, Questionnaire and Interview methods are followed to speed up the process of diagnosis. Moreover, when taking a fairly long term measurement, a reasonable estimation method from the roughly observed level data is very effective. With the expert opinion, the First stage data set for Interviewing/Questionnaire was prepared in the local regional language for the convenience of the patients. Initial trial was made for analyzing the non crisp way of answering of patients like Rarely I get shoulder pain, More or Less , 5 to 6 times a day, Frequently, Very rarely etc. Care was taken not to miss any answer as it is the preliminary stage of diagnosis. Data set was collected from Diabetic Care and Research Centre, Sivapreethi hospital, Tanjore, Tamilnadu. Data Preparaton and Data collection was done for the year 2010 -2011.
The dataset contains 600 samples and two classes.
Class 1 : normal
Class 2 : Type 2 Diabetes

All samples have 10 features
Feature 1 : Polyurea
Feature 2 : Poludipsea
Feature 3 : Polyurea
Feature 4: Nocturia
Feature 5 : Tiredness
Feature 6: Giddiness
Feature 7 : Sleeplessness
Feature 8 : Non healing ulcer
Feature 9 : Itching
Feature 10 : Shoulder pain

This is the preliminary and essential reqirement for type 2 diaetes mellitus

4. Data Modelling

Understanding data is very important. The perception of a person who looks into the data and the perception of a person who is going to utilize the data forms major role in successful formulation of a Data Model. The data prepared are carefully modeled into 5 more stages for further analysis.
Stage 1:{ General Symptoms }
Stage 2:{ Symptoms of Complication }
Stage 3:{ Past History }
Stage 4: { Feminine questions }
Stage 5:{ Physical Eamination }
Stage 6:{Test measurements }
In this study emphasis is given in fuzzifying the first stage or preliminary stage of input features.

4.1 Fuzzyification of Stage 1

Stage 1 again can be divided into 2 sub stages. Substage 1 deals with 3 P's namely Polyurea, polydipsea, Polyphagia and Nocturia[Urination during night]. The non crisp values are fuzzified as given in the table 1 below. The fuzzy terms and the values are given after discussion with experts in this field.

Table 1: Fuzzy features of sub stage 1 of Stage 1 in Type 2 Diabetes

Feature 1:Polyurea – Increased frequency of Urination		
Less frequent	0 to 5 times	Per day
Frequent	4 to 10 times	Per day
More frequent	More than 9 times	Per day
Feature 2: Polydipsea – Increased frequency of Thirst		
Less thirsty	Drinking 0 to 4 times	Per day
Thirsty	3 to 7 times	Per day
More thirsty	6 to 14 times	Per day
Feature 3 : Polyphagia - Increased hunger		
Less hungry	Eating 1 to 3 times	Per day
Hungry	2 to 5 times	Per day
More hungry	4 to 10 times	Per day
Feature 4: Nocturia – Night Urination		
Less frequent	0 to 3 times	Per night
Frequent	2 to 5 times	Per night
More frequent	More than 4 times	Per night

Table 2: Fuzzy features of sub stage 2 of Stage 1 in Type 2 Diabetes

Feature 5:Tiredness
Rarely
Often
More Often
Feature 6: Giddiness
Rarely
Often
Very often
Feature 7: Sleeplessness
Rarely
Often
Very often
Feature 8: Non healing ulcer
Less
More
Very much
Feature 9 : Itching
Rarely
Often
Very often
Feature 10: Shoulder pain
Rarely
Often
Very often

5. Results and Discussion

The table bekow shows the sample vector for the first 10 patints P1, P2, …P10 with symptoms S1, S2, …S10.

Table 3: Patient vs Symptom matix

	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**S10**
P1	0	8	0	0	0	0	0	0	0	0
P2	9	12	6	3	3	0	0	0	0	3
P3	0	0	0	0	0	0	0	3	0	0
P4	11	12	7	3	3	3	0	0	0	0
P5	0	0	0	2	0	0	0	2	0	0
P6	9	10	6	2	3	0	0	0	0	0
P7	10	10	0	5	0	0	0	0	0	0
P8	0	0	0	0	0	0	0	0	0	0
P9	0	8	5	3	3	2	0	4	4	4
P10	0	8	0	0	0	0	0	0	4	0

The above values are normalized and the new values are as in the table 4 below.

Table 4: Normalised Patient vs Symptom matrix

	S1	**S2**	**S3**	**S4**	**S5**
P1	0	0.6666	0	0	0
P2	0.8181	1	0.8571	0.6	1
P3	0	0	0	0	0
P4	1	1	1	0.6	1
P5	0	0	0	0.3333	0
P6	0.8181	0.8333	0.8571	0.3333	1
P7	0.9090	0.8333	0	1	0
P8	0	0	0	0	0
P9	0	0.6666	0.7142	0.6	1
P10	0	0.6666	0	0	0

	S6	**S7**	**S8**	**S9**	**S10**
P1	0	0	0	0	0
P2	0	0	0	0	0.75
P3	0	0	0.75	0	0
P4	1	0	0	0	0
P5	0	0	0.5	0	0
P6	0	0	0	0	0
P7	0	0	0	0	0
P8	0	0	0	0	0
P9	0.6666	0	1	1	1
P10	0	0	0	1	0

The output vector after normalization is {1,0.67, 0.67, 0.67, 0.67, 0.67, 0.67, 0.67, 0.67, 0.67}
Among the first 10 patients, only a single case in non diabetic and the other 9 case are diabetic. This number changes and in our data set of 600 samples, 330 are type 2 diabetic and 270 are non diabetic. The backprogaton algorithm of neural networks is used for classification. The model of network is as in Figure 1 below. The network has 10 input features Polyurea, Polydipsia, Polyphagia, Nocturia, Tiredness, Giddiness, Sleeplessness, Nonhealing ulcer, Itching, Shoulder pain indiacted as 1..10. The architecture has a single hidden layer with 2 neurons I and II. The output layer is a single layer with 2 output neurons A and B.

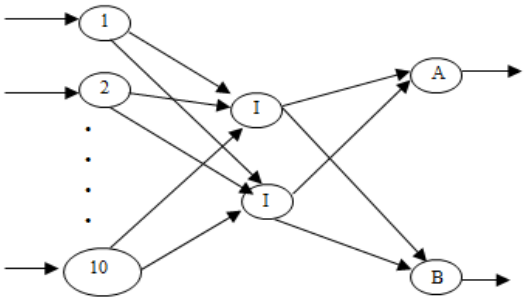

Figure 1: Backpropagation Neural Network

The table 5 below given the different measures of accuracy during the training period and testing period. Classification accuracy is better during Testing time. Training time is 00:00:00.015.

Table 5: Measures of Accuracy

Measures of Accuracy	Training	Testing
Classification Accuracy	82.9%	83.3%
Sum of Squares error	9.357	3.876
Incorrect predictions	17.1%	16.7%

The Receiver Operating Characteristic curve (ROC) for the classification is as shown in Figure 2. It gives a view on sensitivity and specificity, which are the important terms in medical diagnosis. In ideal cases, as sensitivity increases, there is little decrease in specificity, until very high levels of sensitivity are reached. The sensitivity of a test is the probability that the test is positive when given to a group of patients with the disease. The specificity of a test is the probability that the test will be negative among patients who do not have the disease The table 6 gives an example for calculation of sensitivity and specificity values.

Table 6: Parmaters for calculation of Sensitivity and Specificity

	Disease Present	No Disease
Test Positive	P	Q
Test Negative	R	S

Sensitivity = P/(P+R)
Specificity = S/(Q+S)
Positive Predictive Value = P/(P+Q)
Negative Predictive Value = S/(R+S)

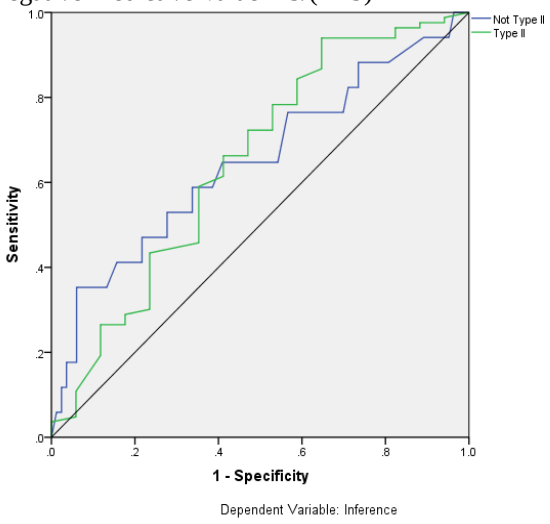

Fig 2: Sensitivity vs Specificity

6. Conclusion

In this paper we have combined Fuzzy modeling and artificial neural network architecture. The method as it models the realistic or linguistic way of the patient is proven to be highly efficient with good accuracy. Further, as it works on the real-time dataset, it can assist the diabetolgist as a support for classification and further analysis. The features collected in stage 1 are not enough to classify Type 2 diabetes patient from others. Further stages are required to be analyzed for further improvement.

Acknowledgment

The authors would like to express their cordial thanks to Dr. T.Gurumoorthy, Professor, Diabetology, Tanjore Medical College, Tanjore, India for his valuable advice.

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