I J C T A, 9(41) 2016, pp.933-943 ISSN: 0974-5572

AN EMPIRICAL APPROACH FOR FUZZY RULES USING CLASSIFICATION AND REGRESSION TREE

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Abstract
Fuzzy logic has been extensively used in designing of medical diagnosis expert system. Fuzzy logic is adopted due to its capability of decisions making in an environment of imprecision, uncertainty and incompleteness of information. The Fuzzy based system is proposed to diagnose the Parkinson disease (PD) by measuring its level of severity using the predicted motot_updrs and total_updrs score (Unified Parkinson's Disease Rating Scale). The system is proposed to have lesser number of rules in the knowledge base, which increase the rule access rate with minimum response time thereby improving system performance. Voice dysphonia measures of PD are considered for detecting its severity level. The system consists of two phases: Knowledge based-fuzzy rule mining (FRM) and Fuzzy expert system (FES). In FRM, the regression tree is constructed using classification and regression tree (CART) method for the prediction of motor-updrs/total-updrs and this regression tree is transformed to fuzzy rules using membership functions. The second phase detects the PD with interesting fuzzy rules and report the severity level (low, medium, high, and very high) of the disease for the given subject (person).
Keywords – Parkinson disease, Fuzzy Expert system, Fuzzy rules, Classification and Regression tree, fuzzy rule mining, Dysphonia measures, updrs score.

1. INTRODUCTION

As people are getting many health problems now a day's, they are eagerly looking for good medical services. Due to increased usage of internet services, people are able and/or want to gather complete knowledge about any disease and also they want to know the correctness of their treatment. Also when a patient's case is complex and rare, doctors and medical practitioners need some expert's advice. Expert system is one of the tools used in medical field for diagnosis and prognosis of any diseases. Continual advancement in the technology leads the researchers to create an expert system for patients and non-patients.

Rule based expert system is easy to formulate and has wide(r) application for medical diagnosis task and later, machine learning techniques are used to develop knowledge based expert system. Learning systems are data-driven approaches that are derived directly from routinely monitored system operating data. They rely on the assumption that the statistical characteristics of the data are stable, unless a malfunctioning event occurs in the system. Data-driven approaches can either use

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“conventional” numerical algorithms, such as linear regression or Kalman filters, or they can use algorithms from the machine learning and data mining AI communities, such as neural networks, decision trees, and support vector machines. The limitation of this system is larger number of rules in the knowledge base which increase the memory space, reduce the rule access rate, increase the response time and hence the system performance is degraded. To overcome this limitation fuzzy logic is adopted to construct fuzzy rule and fuzzy expert system is built for diagnosis purpose. The objective of the research is to apply the concept of fuzzy logic technology to predict the severity level of PD.

The remaining part of the paper is organized as follows: Section 2 reviews related works in the area of fuzzy expert system for diagnosis and prognosis, section 3 describes source data set, CART method and basics on fuzzy logic and fuzzy expert system, section 4 presents our proposed fuzzy system based on CART method for the predicting the PD and section 5 deals with Experimental analysis. Finally the paper is concluded and our future research work is presented in section 6.

2. RELATED WORK

Ali.Adeli, Mehdi.Neshat proposed a FES for diagnosis of Heart Disease.This system examines the input fields such asresting electrocardiography (ECG), chest pain type, cholesterol, blood pressure, exercise, thallium scan, maximum heart rate etc and reports the presence of heart disease. Mamdani inference method is used and implemented in Matlab software.

Fuzzy expert system for the management of malaria (FESMM) was presented for providing decision support platform to physicians and other healthcare practitioners was designed based on clinical observations, medical diagnosis and the expert’s knowledge. The fuzzy inference method employed was the Root Sum Square (RSS). RehanaParvin et al. developed a system using fuzzy logic to diagnose the severity of heart disease of subjectstwith existing database. Oana GEMAN developed a fuzzy expert system model for the Parkinson’s disease diagnosis. In this paper, he proposed a new quantitative evaluation and analysis system for patients, in order to diagnose the Parkinson’s disease at the incipient stage.

Dr. M. Pushparani and B. Kalaivani proposed a paper that discusses about identifying the movement disorders with particular reference to Parkinson’s disease and Huntington’s disease using gait analysis. Smita S Sikchi et al. proposed a generic FESimplemented using visual basic and matlabfor diagnosis of cardiac diseases. Igodan Charles Efosa and Akwukwuma V.V.N designed Knowledge-based Fuzzy Inference System, KB-FIS for the diagnosis and detection of sepsis using Matlab’s fuzzy logic toolbox. For validating, the system was tested with the domain (medical) expert knowledge by comparing its performance with at least 10 hypothetical scenarios.

Alshalaa A. Shleeg, Issmail M. Ellabib developed FIS for evaluating the risk of breast cancer. In this paper,performance of sugeno-type and mamdani-type were evaluated and and the results were compared.

3. MATERIALS AND METHODS

3.1Source Dataset

The dataset for Parkinson’s disease prediction using voice disaphonia is Oxford Parkinson’s disease dataset. The source dataset was created by Athanasios Tsanas and Max Littlle of the University of Oxford, in collaboration with 10 medical centers in the US and Intel Corporation. Linear and nonlinear regression methods were used to predict the severity of PD on the updrs scale.

This dataset is the collection of a range of biomedical voice measurements from 42 people. The voice recordings were automatically captured in the patient's homes on the weekly basis and processed appropriately in the clinic to predict the updrs score. The updrs score value was assessed at baseline (onset of trial) and after three months and 6 months.

The various attribute are:subject_id specifies the unique identification number of subject;age attribute is for holding the subject age;mupdrs is for motor_updrs score, and tupdrs for total_updrs score;the jittper, jittabs, jittrap, jittddb, jittppq5 are the variables for storing several measures of variation in fundamental frequency; shimmer, shimmdb, shimmapq3, shimmapq5, shimmapq11, and shimmdda are several measures of variation in amplitude;nhr and hnrare the two measures of ratio of noise to tonal components in voice;rpde is a nonlinear dynamical complexity measure; dfa is signal fractal scaling exponent; and ppe is a nonlinear measure of fundamental frequency variation. There are totally 5,875 voice recordings from all 42 subjects. There are around 200 recordings per patient. All subjects remained un-medicated for the six-month duration of the study.

3.2 Methods

3.2.1 Classification and Regression Tree

Classification and regression tree (CART) is a non-linear statistical regression technique used for constructing decision tree.In the process of construction of regression tree, the splitting criterion for input variable is sum of squared error (squared residual minimization algorithm) and the same algorithm is used for pruning also. The constructed tree is checked with prune parameter and the tree is displayed finally using the view function. The constructed tree gives a successively detailed mapping between the input data (16 dysphonia measures, age) and the output variable (updrs score).

3.2.2 Fuzzy logic and Fuzzy expert system

Fuzzy logic refers to logic of approximation. It is a form of knowledge representation developed by LotfiZadeh,suitable for notions that cannot be defined precisely.Fuzzy systems afford a broader, richer field of data and manipulation than traditional methods. Boolean logic assumes that every fact is either entirely true or false whereasfuzzy logic allows for varying degrees of truth. In a fuzzy system, membership function is used to map elements to real values between zero and one (inclusive).

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The FES composed of four components which include Knowledge base,Fuzzification,Inferenceengine and Defuzzification.In fuzzification, input is transformed to fuzzy using membership functions. In the inference process, fuzzy input is changed into fuzzy output using fuzzy rule set and mamdani inference method (max-min approach) is used. Finally in defuzzification, the fuzzy output of the fuzzy inference engine is converted as crisp output using centroid method. Triangular membership function is used for the input and output variable.

4. PREDICTION OF PD

The Proposed methodology is to diagnose the PD by measuring its level of severity using the predicted motot_updrs and total_updrs score. In thismethodology, there are three stages: Fuzzy partitioning, Fuzzy rule mining and Fuzzy expert system. Initially the data set attributes are partitioned to fuzzy sets and the membership function is designed for each set. In the secondstage, the interesting fuzzy rules are generated in twosteps: (a) construction of regression tress using CART method (b) Deriving fuzzy rule from the regression tree.In the thirdstage, the fuzzy expert system is designed to predict the level of severity of Parkinson disease.

4.1 Fuzzy partitioning

Attributes are partitioned to fuzzy sets using two mehods. They are equal space fuzzification and equal data point fuzzification. In the first method, fuzzy sets are symmetrical and all occupy the same range and in second method, each and every fuzzy sets have equal number of data points and are not symmetrical. To make the system more effective, attributes are partitioned to fuzzy sets using Equal data point fuzzifiaction.

The input and output variables are partitioned to fuzzy sets and the range of the fuzzy set is defined. There are 17 input variables: 16 dysphonia measures; subject age and two output variable:motor_updrs; total_updrs. The linguistic terms and its ranges of dysphonia measures and age are specified in Table1 and Table2. Table3 describes linguistic terms and its ranges formotor-updrs and total-updrs score.

Table.1 Linguistic term and its ranges of Dysphonia measures

SI. No	Attribute name	Rep. of variable	Range			
			LOW	MEDIUM	HIGH	VERY HIGH
1	Jitter	X1	<0.03386	0.002899 to 0.06904	0.03386 to 0.1	>0.06694
2	Jittabs	X2	<0.000135	2e-006 to 0.0002673	0.0001347 0.0004	>0.000267
3	Jittrap	X3	< 0.0192	0.0003 to 0.0381	0.0192 to 0.057	>0.0381
4	Jittppq5	X4	<0.02326	0.0004 to 0.04614	0.02326 to 0.069	>0.04614
5	Jittddp	X5	< 0.05833	0.001 to 0.1157	0.05833 to 0.173	>0.1157
6	Shimmer	X6	< 0.09166	0.003 to 0.1803	0.09166 to 0.269	>0.1803
7	Shimmdb	X7	< 0.7196	0.026 to 1.413	0.7196 to 2.107	>1.413
8	Shimmapq3	X8	<0.05566	0.002 to 0.1093	0.05566 to 0.163	>0.1093
9	Shimmapq5	X9	< 0.05699	0.002 to 0.112	0.05699 to 0.167	>0.112
10	Shimmapq11	X10	<0.09399	0.003 to 0.185	0.09399 to 0.27	>0.185
11	Shimmdda	X11	<0.166	0.005 to 0.327	0.166 to 0.488	>0.327
12	Nhr	X12	<0.2498	0.0003 to 0.4995	0.2498 to 0.749	>0.4995
13	Hnr	X13	<13.73	1.66 to 25.8	13.73 to 37.88	>25.8
14	Rpde	X14	<0.4226	0.151 to 0.6944	0.4226 to 0.966	>0.6944
15	Dfa	X15	<0.6313	0.514 to 0.7487	0.6313 to 0.866	>0.7487
16	Ppe	X16	<0.2586	0.022 to 0.4954	0.2586 to 0.732	>0.4954

Table.2 Linguistic terms and its ranges of Age

Age		
INPUT FIELD	RANGE	LINGUISTIC_REPRESENTATION
X17	LOW	<52
	MEDIUM	36 to 64
	HIGH	52 to 85

Table.3 Linguistic terms and its ranges of Output variable

Motor_updrs		
INPUT FIELD	RANGE	LINGUISTIC_REPRESENTATION
Y1	LOW	<10

	MEDIUM	**6 to 25**
	HIGH	**10 to 34**
	VERY HIGH	**25 to 41**

Total_updrs		
INPUT FIELD	**RANGE**	**LINGUISTIC_REPRESENTATION**
Y2	**LOW**	**<15**
	MEDIUM	**7 to 29**
	HIGH	**15 to 39**
	VERY HIGH	**29 to 54**

4.1.1Design of membership function

The attribute values are transformed to linguistic concepts using membership functions (MF). It is a curve that defines how each point in the input space is mapped to membership value between 0 and 1. This membership values is the degree which describes to what extent the item is in the set.MF can be overlapped; every input point should belong to at least one but not more than two membership functions and two MF should not have the same point of maximum truth. A Triangular MF is used for fuzzy partitioning and can be expressed by the Eq1 where a, b and c are the co-ordinates of a triangle and x is the input value.

$$\mathbf{triangle}(x;a,b,c)=\begin{cases}0, & x\le a.\\ \dfrac{x-a}{b-a}, & a\le x\le b.\\ \dfrac{c-x}{c-b}, & b\le x\le c.\\ 0, & c\le x.\end{cases}$$

------- Eq1

As specified in Table 1, jitter(%) is partitioned into 4 fuzzy sets (Low, Medium, High and Veryhigh) and its ranges of jitter is specified in Table1. With this, the triangular MFis designed for jitter and shown in Eq 2. Similarly the triangular MF is designed for all the other input dysphonia measures, age and output updrs score (motor_updrs and total_updrs).

$$\mu_{low}(x)=\begin{Bmatrix}1 & x=0\\ (0.03386-x)\div 0.03386 & 0<x\le 0.03386\end{Bmatrix}$$

$$\mu_{medium}(x)=\begin{Bmatrix}(x-0.002899)/0.00487 & 0.002899\le x<0.03386\\ 1 & x=0.03386\\ (0.06904-x)/0.03518 & 0.03386<x\le 0.06904\end{Bmatrix}$$

$$\mu_{high}(x)=\begin{Bmatrix}(x-0.03386)/0.03518 & 0.03386<x<0.06904\\ 1 & x=0.06904\\ (0.1-x)/0.03096 & 0.06904<x\le 0.1\end{Bmatrix}$$

$$\mu_{veryhigh}(x)=\begin{Bmatrix}(x-0.06904)/0.03096 & 0.06904\le x<0.1\\ 1 & x=0.1\end{Bmatrix}$$

--------- Eq2

4.2Mining fuzzy rule

Fuzzy rules are the backbone of the Fuzzy expert system. In a fuzzy system, if there are n features and each feature is sub-divided into M fuzzy sets, then there are M^N rules. Larger the M, larger the number of fuzzy rules. The fuzzy system is not effective and efficient if all the rules are used. There are two negative effects on the system:

I. The system increases the knowledge based memory.
II. Existent of larger number of rules reduces the rules access rate.

Fuzzy rule mining extracts the interesting rule by constructing the decision tree and transforming to fuzzy rules which will be used by the inference engine of the FES. The proposed fuzzy rule mining system address the above problem.

4.2.1 Construction of decision tree

CART algorithm is implemented for the PD dataset features to construct the decision tree andtake decision regarding the updrs score for predicting the level of severity of the disease. This algorithm also useful for grouping the subjects based on their level of severity. Figure 2 is the decision tree constructed for total_updrs with one of the input dysphonia measure,jitter(%). This decision tree is used to separate the subjects based on their level of severity withjitter(%) measure alone. In similar way, the decision tree is constructed for motor_updrs/ total_uodrs with 17 input attributes to separate the subjects based on their level of severity.

4.2.2 Deriving Fuzzy rules

The interesting fuzzy rules are derived from the decision tree. Each non terminal node representscondition checking for the attribute values and the terminal node represents the predicted updrs score. Hence from this decision tree for total_updrs with jitter(%) (Figure 1), 9 rules are generated. For example if x1<0.00276036, thentotal_updrs (y2) value is 10.9851, the equivalent fuzzy rule generated is "if x1 is low then y2 is low".

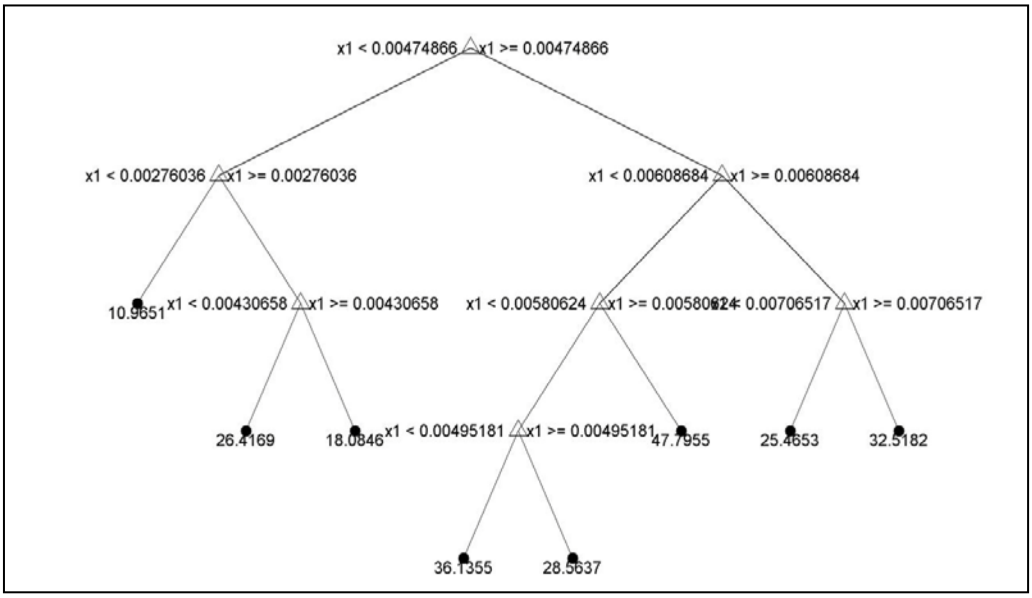

Fig.1Total_updrs with jitter(%)

In a similar way the decision tree is constructed for motor_updrs/total_updrswith all the 16 dysphonia measures and age. Then from this CART decision tree the fuzzy rules are generated in the form of IF-THEN rules.In this paper the decision tree constructed for motor_updrs which is transformed to fuzzy rules is taken as example. The total number of fuzzy rules is generated to predict the motor_updrs score is only 16.Table 4 represents the fuzzy rules for motor_updrs with 17 input measures. (16 dysphonia measures and age)

Table.4 Fuzzy IF-THEN Rules for Motor_updrs

SI.NO	Attributes (16) of Dysphonia measures and age (17th)																	Output Motor-updrs
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	Y1
1	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L
2	M	M	M	M	M	M	M	M	M	M	M	M	M	M	M	M	M	M
3	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H
4	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	H	VH
5	L	L	L	L	L	L	L	L	L	L	M	M	M	M	M	M	M	L
6	L	L	L	L	L	L	L	L	L	L	H	H	H	H	H	H	H	L
7	L	L	L	L	L	L	L	L	L	L	VH	VH	VH	VH	VH	VH	L	L
8	M	M	M	M	M	M	M	M	M	M	L	L	L	L	L	L	L	M
9	M	M	M	M	M	M	M	M	M	M	H	H	H	H	H	H	H	M
10	M	M	M	M	M	M	M	M	M	M	VH	VH	VH	VH	VH	VH	M	M
11	H	H	H	H	H	H	H	H	H	H	L	L	L	L	L	L	L	H
12	H	H	H	H	H	H	H	H	H	H	M	M	M	M	M	M	H	H
13	H	H	H	H	H	H	H	H	H	H	VH	VH	VH	VH	VH	VH	H	H
14	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	L	L	L	L	L	L	L	VH
15	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	M	M	M	M	M	M	H	VH
16	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	H	H	H	H	H	H	H	VH

4.3Fuzzy Expert System

The FES is implemented using Fuzzy inference system Toolbox (FIS toolbox), Matlab 2011. In the fuzzification process, all the input attribute values of a given subject are fuzzified to produce fuzzy input. In the mamdaniinference process, the truth degree of the rule is calculated using max-min method. Then this truth degree is converted to crisp output using centroid method (defuzzification).

5. EXPERIMENTAL ANALYSIS

Implementation is performed using statistical Analysis Toolbox and Fuzzy Logic Toolbox in Matlab 2011.CART method in statistical Analysis toolbox is used.Figure 2 is the FIS editor for motor_updrs with dysphonia measures in fuzzy logic. Figure 3 is the fuzzy rule viewer for predicted motor_updrs.

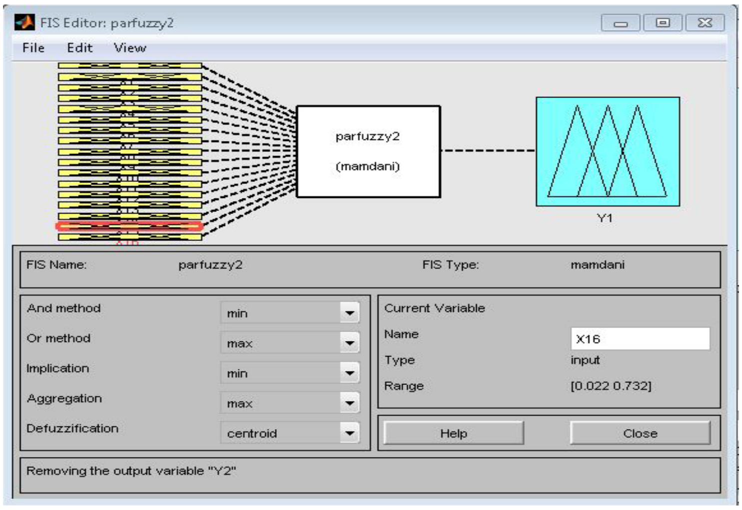

Fig.2FIS editor for motor_updrs

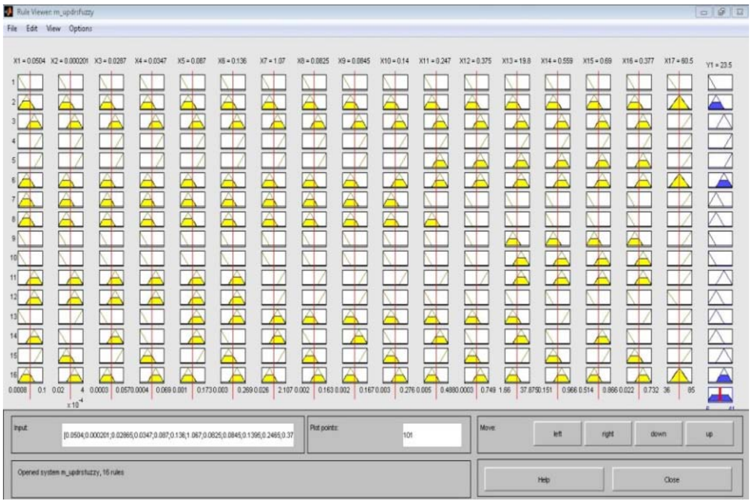

Fig.3Fuzzy rule viewer for motor_updrs

To evaluate the proposed methodology, all the 41 subjects of PD dataset are checked for the level of severity of PD by predicting the motor-updrs score. Table 5 shows the subject_indexof subjects with PD, which is grouped as low, medium, high, and very-high by measuring the severity using motor_updrs with 16 dysphonia measures.

From this Table 5 we analyzed that subject 1, 5, 21, 28, 35, 37, 39, 41, 3, 6, 17, 25, 31, 33 are predicted as more-affected because they comes under very high level of severity. Subjects 29, 34, 36, 8, 13, 26, 30, 38, 42 are under the high level of severity. Subjects 2, 4, 7, 9, 10, 11, 12, 14, 15, 19, 23, 24, 40 are in medium level of severity and the subjects 16, 18, 20, 22, 27, 32 are in low severity level.

Table.5 List of subjects and their Level of severity

SI NO	Level of Severity	Subject Index of people with PD
1	LOW	16, 18, 20, 22, 27, 32
2	MEDIUM	2, 4, 7, 9, 10, 11, 12, 14, 15, 19, 23, 24, 40

3	**HIGH**	**8, 13, 26, 29, 30, 34, 36, 38, 42**
4	**VERY HIGH**	**1, 3, 5, 6, 17, 21, 25, 28, 31, 33, 35, 37, 39, 41**

Figure 4 shows the bar graph for severity level of PD for the subjects. There are 6 subjects under low level of severity, 13 subjects come under medium level of severity, 9 under high level of severity and 14 under very-high level of severity.

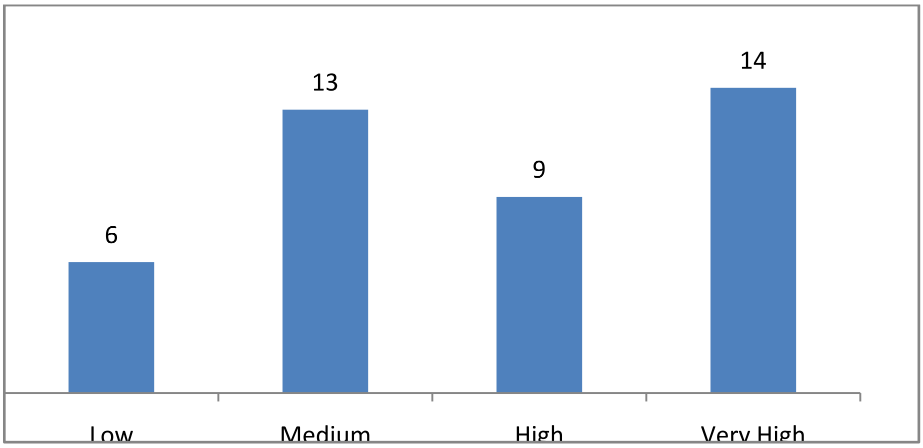

Fig.4 Severity level of PD

CONCLUSION

The aim of this paper is to design a system that would assist physicians to diagnose PD more quickly and effectively. Fuzzy rules are the backbone of the FES. The FES is not effective and efficient if there are many numbers of rules. In this paper, anFRM based on CART method is introduced to enhance the compactness of FES. In FRM, the regression tree is constructed with the input attributes (dysphonia measures and age) to predict the motor-updrs score and then the fuzzy rule are derived from this regression tree. Thus FES diagnoses the PD by predicting the level of severity with motor-updrs using 16 fuzzy rules only. With lesser number of rules, two negative effects of fuzzy systemare addressed. Hence the system performance is definitely improved. It is observed that more number of subjects come under medium and very high severity level of PD.

The efficacy of the expert system is evaluated not only with the no. of rules, but also with no. of attribute tested to derive the final conclusion. In this paper all the 17 input attributes are tested to derive the conclusion. The correlation between the attributes is evaluated. It is not necessary to test both the input attributes when they are highly correlated. One of the attribute should be skipped in the prediction of updrs value. Hence determining the subset of dysphonia measures which will not have the highly correlated features could be considered for future work.

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