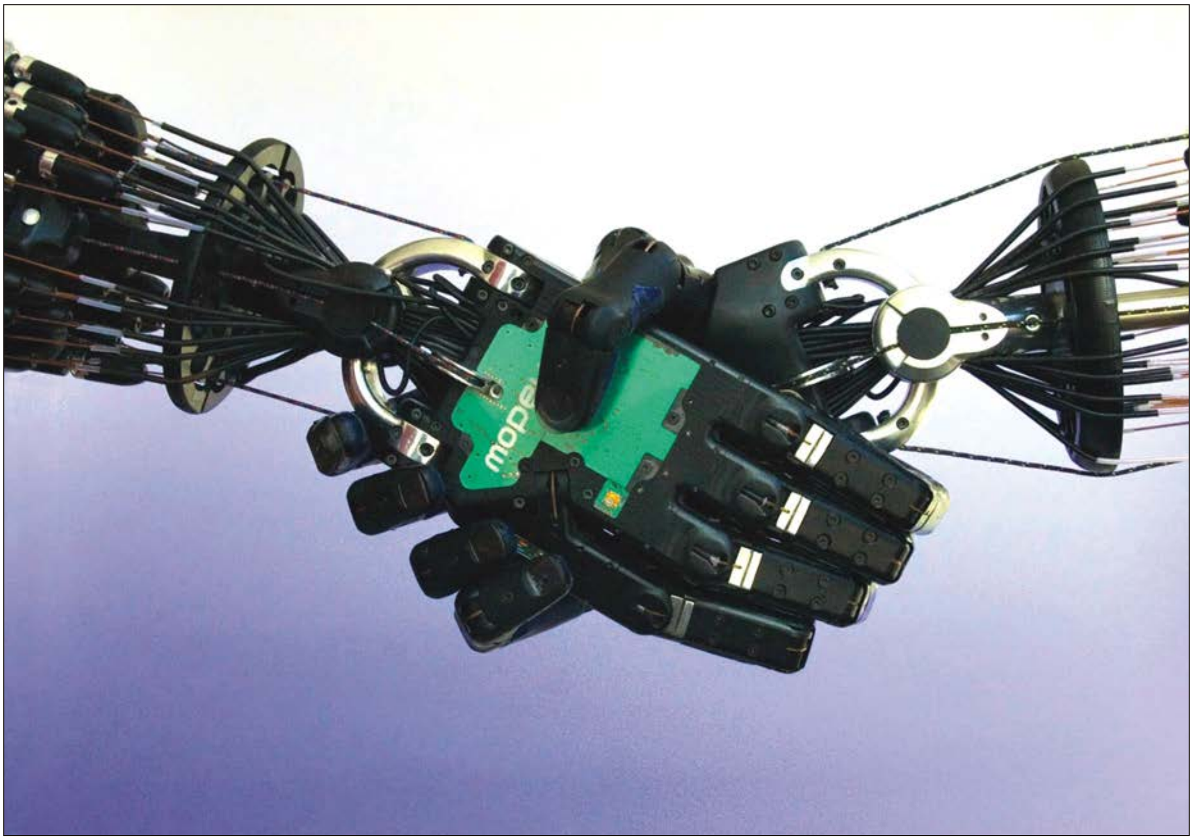

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Application of Knowledge Based System for Diagnosis of Osteoarthritis

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ABSTRACT

Osteoarthritis (OA) is a chronic condition characterized by the degeneration of cartilage in the joints. Some of the symptoms of osteoarthritis include joint pain, stiffness, swelling, bony outgrowths and grating sensation. There are many factors to diagnose osteoarthritis. To help the experts identify the possible errors, classification systems provide medical data to be examined in detail in short time. Expert system and differential artificial intelligence techniques for classification systems in medical diagnosis of arthritis are increasing gradually. The recent popularity of fuzzy expert systems, in particular fuzzy controllers, has created the need for automation of not only the process of extraction of fuzzy rules but also the process of generating the parameters of the associated fuzzy sets. The study reports the application of fuzzy logic inference system to automate the knowledge acquisition for diagnosis of osteoarthritis. These techniques are dealing with inexact and imprecise problem domains and have been demonstrated to be useful in the solution of classification problems. It addresses the issue of the application of appropriate evaluation criteria such as rule based accuracy and comprehensibility for new knowledge acquisition techniques. A system for the diagnosis of osteoarthritis and its severity using Fuzzy Logic has been designed so that the common people, who suspects little bit of pain in joints, may use this system and get the result on the diagnosis and severity of osteoarthritis which will be helpful to guide them to take proper curative measures before the severity increases.

Key words: Osteoarthritis, fuzzy expert systems, mamdani type fis, artificial intelligence, arthritis

INTRODUCTION

Osteoarthritis (OA) is a chronic condition characterized by the degeneration of cartilage in the joints. The breakdown of these tissues eventually leads to pain and joint stiffness (Lawrence *et al.*, 1998; Felson, 1990). Obesity is a known risk factor for the development and progression of osteoarthritis (Losina *et al.*, 2011). Aging, injury, hormonal disorders, repetitive stressful joint use and genetics are the other causes of osteoarthritis. Some of the symptoms of osteoarthritis include joint pain, stiffness, swelling, bony outgrowths and grating sensation. Delay in the detection of osteoarthritis may allow higher risk of disease severity. There are many factors to diagnose osteoarthritis. The evaluation of data collected from patients and decisions of experts are very important in diagnosing osteoarthritis (Polat and Gunes, 2007). To help the experts identify the possible errors, classification systems provide medical data to be examined in detail in short time. Expert system and differential artificial intelligence techniques for classification systems in medical diagnosis of arthritis are increasing gradually (Polat *et al.*, 2008).

The advantage of classification systems over other approaches is that they can produce accurate results in situations where data is imperfect and noisy. They do not require add-on mechanisms for dealing with imperfect data because they have an inherent ability to deal with uncertainty. The recent popularity of fuzzy expert systems, in particular fuzzy controllers, has created the need for automation of not only the process of extraction of fuzzy rules but also the process of generating the parameters of the associated fuzzy sets.

The present study reports the application of fuzzy logic inference system to automate the knowledge acquisition for diagnosis of osteoarthritis. These techniques are dealing with inexact and imprecise problem domains and have been demonstrated to be useful in the solution of classification problems. It addresses the issue of the application of appropriate evaluation criteria such as rule based accuracy and comprehensibility for new knowledge acquisition techniques.

MATERIALS AND METHODS

Fuzzy Logic Controller (FLC) is a control system based on Zadeh's fuzzy set theory (Zadeh, 1965). FLC is a potential tool for dealing with uncertainty and imprecision. Thus, the knowledge of a doctor for the diagnosis of osteoarthritis can be modeled using an FLC (Mamdani and Assilian, 1975). The performance of an FLC depends on its knowledge base which consists of a data base and a rule base. It is observed that the performance of an FLC mainly depends on its rule base and optimizing the membership function distributions stored in the data base in a fine tuning process (Pratihar *et al*., 1999).

Creation of fuzzy set: In order to develop a fuzzy set for osteoarthritis, data is important. The data is sign and symptoms of patients, laboratory tests, medical reports, etc. The data regarding osteoarthritis was collected from Stanmore Garden Hospital, Valparai, Coimbatore, Tamil Nadu, India. Eight symptoms were finalized as the inputs for diagnosing the osteoarthritis and type of osteoarthritis (hip or knee) by consulting the doctor and analyzing the data of the 30 patients. The symptoms are:

- Pain (hip/knee)
- Morning stiffness on knee joints
- Grating sensation on knee joints
- Bony tenderness of knee
- No detectable warmth on knee joints
- Bony outgrowths on the hip joints
- Joint space narrowing in the hip region
- C Reactive protein (CRP) test

The data from 30 patients were selected for analysis which supports the severity, different types and conditions in osteoarthritis, out of which 53.33% (16 out of 30 patients) of them had knee osteoarthritis and 23.33% (7 out of 30 patients) of them had hip osteoarthritis. 23.33% (7 out of 30 patients) of the patients had no osteoarthritis. The analysis of osteoarthritis symptoms from 30 patients shows that 56.7% (17 out of 30 patients) of them had knee pain, 23.33% (7 out of 30 patients) of them had hip pain and 20% (6 out of 30 patients) of them had no pain. 46.7% (14 out of 30 patients) of the patients had maximum morning stiffness for more than 30 minutes, 13.3% (4 out of 30 patients) of them had less stiffness and 40% (12 out of 30 patients) of them didn't have morning stiffness. Grating sensation of joints was present in 63.3% (19 out of 30 patients) of the patients and 36.7% (11 out of 30 patients) of the patients didn't have grating sensation. 43.3% (13 out of 30 patients) of the patients had the problem of bony tenderness while 56.7% (17 out of 30 patients) of them didn't have this problem. 43.3% (13 out of 30 patients) of the patients felt no warmth to the touch where 56.7% (17 out of 30 patients) of the patients had no such problem. Presence of bony outgrowths on x-rays occurred in 40% (12 out of 30 patients) of the patients and 60% (18 out of 30 patients) of the patients had no bony outgrowths. 53.33% (16 out of 30 patients) of the patients had the presence of joint space narrowing on x-rays while the rest 46.7% (14 out of 30 patients) didn't have joint space narrowing.

Analysis of C Reactive Protein (CRP) levels from 30 patients, shows that 56.7% (17 out of 30 patients) of them had average CRP levels (less than 3 mg L^{-1}) and 43.35%(13 out of 30 patients) of them had high CRP levels (greater than 3 mg L^{-1}). The above eight symptoms that are mostly used for the diagnosis of osteoarthritis were used as an input in fuzzy inference system.

Algorithm for the fuzzy inference system for diagnosis of osteoarthritis: For the eight symptoms, eight input variables and one output variable OA-type was created using the fuzzy logic tool box of MATLAB (7.0). The eight input variables are crucial and mainly considered for the detection and diagnosis of osteoarthritis. The input variables Grating Sensation (GS), Bony Tenderness (BT), Detectable Warmth (DW), Bony Outgrowths (BO), Joint Space Narrowing (JN) and C Reactive Protein (CRP) are divided into two membership functions (no and yes). The input variable Morning Stiffness (MS) is divided into max, min and no membership functions. The input variable pain is divided into no, hip and knee membership functions. The membership functions for eight input variables are shown in Table 1-8. The membership function

Table 1: Membership function for input variable 'PAIN'

Membership function	Type	Parameters
No	Trapmf	(-0.36 -0.04 0.025 0.2)
Hip	Trimf	(0.15 0.375 0.6)
Knee	Trapmf	(0.55 0.7 1 1)

The membership function 'No' denotes absence of hip or knee pain. The membership functions 'Hip and Knee' denotes the presence of hip pain and knee pain, respectively

Table 2: Membership function for input variable morning stiffness (MS)

Membership function	Type	Parameters
No	Trapmf	(-36 -4 3 25)
Min	Trimf	(20 42.5 60)
Max	Trapmf	(55 64.2 100.2 133)

The membership function 'No' denotes the absence of morning stiffness in knees. The membership function 'Min' denotes a minimum presence of morning stiffness in knees. Max membership function denotes the maximum presence of morning stiffness in knees

Table 3: Membership function for input variable grating sensation (GS)

Membership function	Type	Parameters
No	Trimf	(0 0.15 0.3)
Yes	Trimf	(0.25 0.625 1)

The No membership function denotes the absence of grating sensation in knees and the membership function 'Yes' denotes the presence of grating sensation in knees

Table 4: Membership function for input variable 'Bony Tenderness (BT)'

Membership function	Type	Parameters
No	Trimf	(0 0.3 0.6)
Yes	Trimf	(0.5 0.75 1)

'No' membership function denotes the absence of bony tenderness in knees. The membership function 'Yes' denotes the presence of bony tenderness in knees

Table 5: Membership function for input variable detectable warmth (DW)

Membership function	Type	Parameters
No	Trimf	(0 0.3 0.6)
Yes	Trimf	(0.5 0.725 1)

The membership function 'No' denotes the absence of detectable warmth in knees and the membership function 'Yes' denotes the presence of detectable warmth in knees

Table 6: Membership function for input variable bony outgrowths (BO)

Membership function	Type	Parameters
No	Trimf	(0 30 60)
Yes	Trimf	(50 72.5 100)

No membership function denotes the absence of bony outgrowths in hip joints. The membership function 'Yes' denotes the presence of bony outgrowths in hip joints

Table 7: Membership function for input variable 'Joint Space Narrowing (JN)'

Membership function	Type	Parameters
No	Trimf	(0 25 50)
Yes	Trimf	(45 72.5 100)

The membership function 'No' denotes the absence of joint space narrowing in hip region and the membership function 'Yes' denotes the presence of joint space narrowing in hip region

Table 8: Membership function for input variable C Reactive protein (CRP)

Membership function	Type	Parameters
No	Trimf	(0 1.5 3)
Yes	Trimf	(2.75 6.375 10)

The membership function 'No' denotes the normal CRP levels. The membership function 'Yes' denotes abnormal CRP levels

Table 9: Membership function for output variable OA-type

Membership function	Type	Parameters
No	Trapmf	(0 7.5 15)
Hip	Trimf	(15 22.5 30)
Knee	Trapmf	(30 37.5 45

The membership function 'No' denotes the absence of osteoarthritis. The membership function 'Hip' denotes the presence of hip osteoarthritis. The membership function knee denotes the presence of knee osteoarthritis

plot for output variable OA-type is shown is Table 9. We used Mamdani-type FIS to develop the diagnostic framework.

Based on the descriptions of the input and output variables 33 rules were constructed by selecting an item in each input and output variable box and one Connection (AND). None was chosen as one of the variable qualities to exclude any of the variables from a given rule. The weight was specified to unity (1). Table 10 shows the rule base for the osteoarthritis inference system.

Table 10: Rule base for osteoarthritis inference system

PAIN	MS	GS	BT	DW	BO	JN	CRP	OA-type
Knee	Max	Yes	Yes	Yes	None	None	None	KOA
Knee	Max	Yes	Yes	None	None	None	None	KOA
Knee	None	Yes	Yes	Yes	None	None	None	KOA
Knee	Max	None	Yes	Yes	None	None	None	KOA
Knee	Max	Yes	None	Yes	None	None	None	KOA
Knee	Min	Yes	Yes	Yes	None	None	None	KOA
Knee	Min	Yes	Yes	None	None	None	None	KOA
Knee	Min	None	Yes	Yes	None	None	None	KOA
Knee	Min	Yes	None	Yes	None	None	None	KOA
Hip	None	None	None	None	Yes	Yes	None	HOA
Hip	None	None	None	None	Yes	None	Yes	HOA
Hip	None	None	None	None	None	Yes	Yes	HOA
Hip	None	None	None	None	Yes	Yes	Yes	HOA
No	None	None	None	None	None	None	None	NOA
Knee	Max	Yes	None	None	None	None	None	KOA
Knee	Max	None	Yes	None	None	None	None	KOA
Knee	Max	None	None	Yes	None	None	None	KOA
Knee	Min	Yes	None	None	None	None	None	KOA
Knee	Min	None	Yes	None	None	None	None	KOA
Knee	Min	None	None	Yes	None	None	None	KOA
Knee	None	Yes	Yes	None	None	None	None	KOA
Knee	None	Yes	None	Yes	None	None	None	KOA
Knee	None	None	Yes	Yes	None	None	None	KOA
Hip	None	None	None	None	No	No	No	NOA
Hip	None	None	None	None	Yes	No	No	NOA
Hip	None	None	None	None	No	Yes	No	NOA
Hip	None	None	None	None	No	No	Yes	NOA
Knee	Max	No	No	No	None	None	None	NOA
Knee	Min	No	No	No	None	None	None	NOA
Knee	No	Yes	No	No	None	None	None	NOA
Knee	No	No	Yes	No	None	None	None	NOA
Knee	No	No	No	Yes	None	None	None	NOA
Knee	No	No	No	No	None	None	None	NOA

PAIN-knee pain or hip Pain, MS-Morning Stiffness, GS-Grating Sensation, BT-Body Tenderness, DW-Detectable Warmth, BO-Bony Outgrowths, JN-Joint space narrowing, CRP-C-Reactive Protein, OA-type-OsteoArthritis type, KOA-Knee OsteoArthritis, HOA-Hip OsteoArthritis, NOA- No OsteoArthritis, Max-Maximum, Min-Minimum

RESULTS AND DISCUSSION

In a fuzzy logic system, it may not be necessary to evaluate every possible input combination, since some symptoms of osteoarthritis may rarely or never occur. By making this type of fuzzy logic system, fewer rules can be evaluated, thereby simplifying the processing logic and perhaps even improving the performance of fuzzy logic system. The inputs are combined logically using the AND operator to produce the output values for all expected inputs. The active conclusions are then combined into a logical sum for each membership function. All that remains is to combine these logical sums in a defuzzification process to produce the crisp output. The fuzzy outputs for all rules are finally aggregated to one fuzzy set. To obtain a crisp decision from this fuzzy output, we have to defuzzify the fuzzy set.

Defuzzification of the output: Defuzzification is the process of transforming a fuzzy output of a fuzzy inference system into a crisp output. The input for the defuzzification process is a fuzzy set (fuzzy outputs for individual rules) and the final desired output is a single number. The most popular defuzzification method called the centroid calculation was used here which returns the center of area under the curve.

The centroid defuzzification technique can be expressed as:

$$x^* = \frac{\int \mu_i(x)\,x\,dx}{\int \mu_i(x)\,dx}$$

where, x^* is the defuzzified output, $\mu_i(x)$ is the aggregated membership function and x is the output variable in the sense of osteoarthritis.

Validation of the osteoarthritis fuzzy inference system: The performance of the developed fuzzy inference system was validated by comparing the diagnosis results provided by the fuzzy inference system with the diagnosis supplied by a clinical expert.

From the results, the manually constructed FLC was found to be correct when compared with the field data output. It happened because the rule base of the constructed FLC was designed after a careful study of the effects of different inputs on the output, i.e., grade of the disease. Based on the output of the FLC which is expressed on a scale of 0-45, decision can be taken on the severity of osteoarthritis for a particular set of input symptoms. Table 11 shows the validation data and the generated output by the Fuzzy Inference System. Figure 1-3 displays the rule viewer for osteoarthritis inference system showing the output as knee osteoarthritis, hip osteoarthritis and no osteoarthritis for validation data sets.

Validation data set 1 satisfies rules 7, 18, 19 and 21. Validation data set 2 satisfies rule 12 and validation data set 3 satisfies rule 24, hence, patient 3 is having no osteoarthritis symptoms where as patient 1 and 2 are at higher risk factor of knee and hip respectively which was also justified by the doctors. The severity of disease calculation error value was minimum of 9% between calculated value and diagnosed value; hence the accuracy was measured as 91%. The rule viewer clearly shows which rules are active and the influence of membership functions in the final output. In Fig. 1-3 the nine plots in each row represents the antecedent and consequent of the each rule, with the rule numbers displayed on the left of each row. There are 298 plots nested in a single figure window. Each rule is a row of plots and each column is a variable. The first eight columns of plots (the yellow plots) show the membership functions referenced by the antecedent, or the if-part of each rule. The ninth column of plots (the blue plots) shows the membership functions referenced by the consequent, or the then-part of each rule. The plots which are blank

Table 11: Validation data set of osteoarthritis

PAIN	MS	GS	BT	DW	BO	JN	CRP	OA-type
0.747	50.0	0.500	0.717	0.152	50.0	17.4	1.40	37.5
0.399	90.6	0.129	0.283	0.152	27.5	79.2	6.91	22.5
0.500	31.7	0.399	0.283	0.152	27.5	21.9	2.42	7.51

PAIN-knee pain or hip Pain, MS-Morning Stiffness, GS-Grating Sensation, BT-Body Tenderness, DW-Detectable Warmth, BO-Bony Outgrowths, JN-Joint space narrowing, CRP-C-Reactive Protein, OA-type-OsteoArthritis type

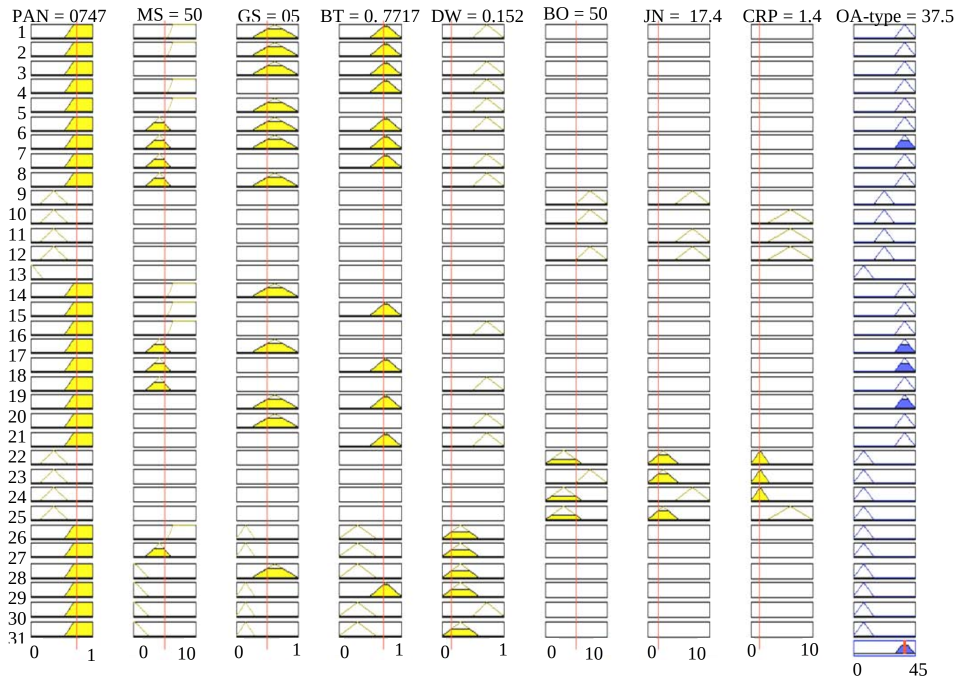

Fig. 1: Rule viewer for osteoarthritis inference system showing knee osteoarthritis as output for validation data set 1

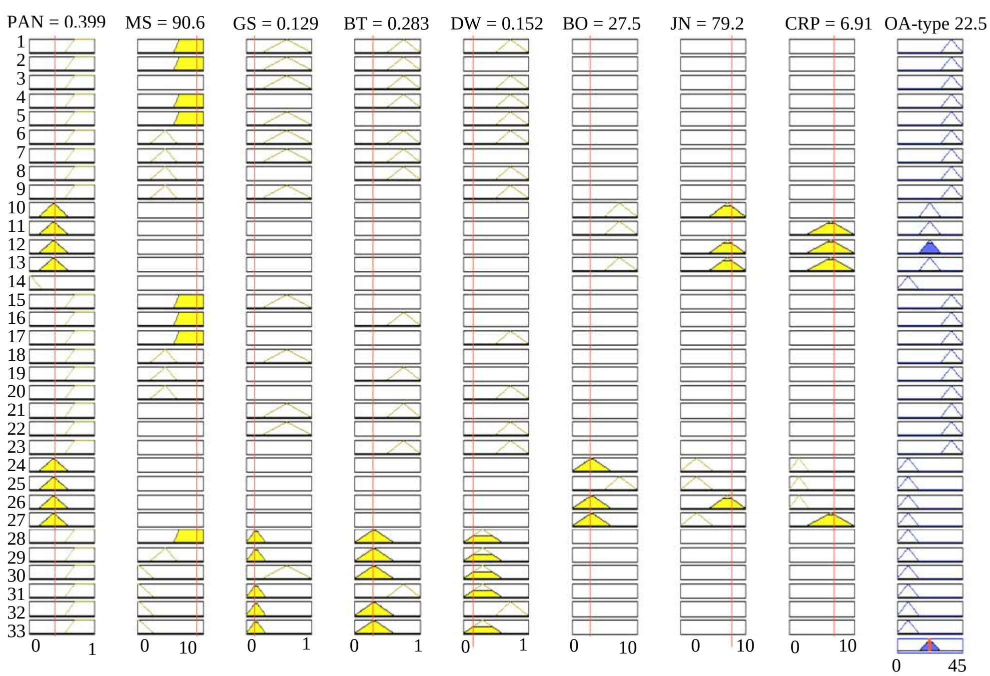

Fig. 2: Rule viewer for osteoarthritis inference system showing hip osteoarthritis as output for validation data set 2

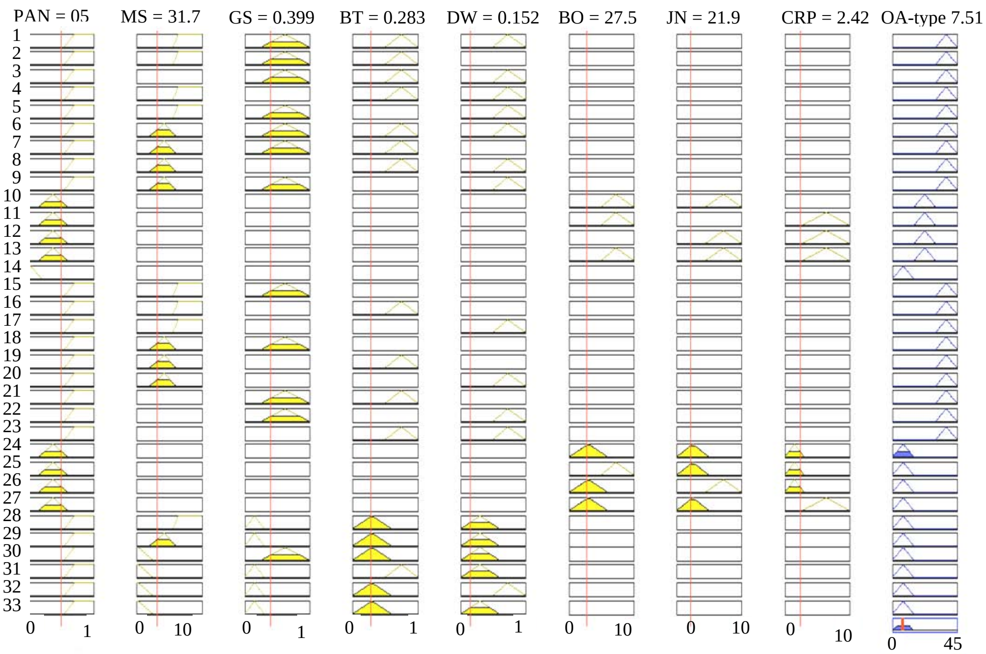

Fig. 3: Rule viewer for osteoarthritis inference system showing no osteoarthritis as output for validation data set 3

in the if-part of any rule correspond to the characterization of none for the variable in the rule. The last plot in the ninth column of plots represents the aggregate weighted decision for the given inference system. This decision will depend on the input values for the developed fuzzy inference system. The defuzzified output is displayed as a bold vertical line on this plot. The variables and their current values are displayed on top of the columns. In the lower left, there is a text field Input for entering specific input values.

The validation data set 1 had the symptoms like knee pain, slight morning stiffness in knees, grating sensation in knees and bony tenderness in knees. For the validation data set 1, the rule viewer shows the presence of knee osteoarthritis.

The validation data set 2 had the symptoms like hip pain, high morning stiffness in knees, joint space narrowing in hip region and abnormal CRP levels. For the validation data set 2, the rule viewer shows the presence hip osteoarthritis.

The validation data set 3 had the symptoms like hip pain, slight morning stiffness in knees, grating sensation. For the validation data set 2, the rule viewer shows the absence of osteoarthritis.

The entire span of the output set based on the entire span of the input set is shown in Fig. 4. It displays the dependency of one of the outputs on anyone or two of the inputs i.e., it shows the plot of an output surface map for the system based on the rules defined in rule base.

Surface viewer gives us the relevant information about two axis points (X, Y) and the result is obtained in Z-axis. The plot displayed in Fig. 4 has two input in X and Y axis and output is obtained in Z-axis. The plot shows all the rules in graphical view in which osteoarthritis major symptom is pain and the graphical view is obtained by taking it constant at X-axis and other symptoms at Y-axis.

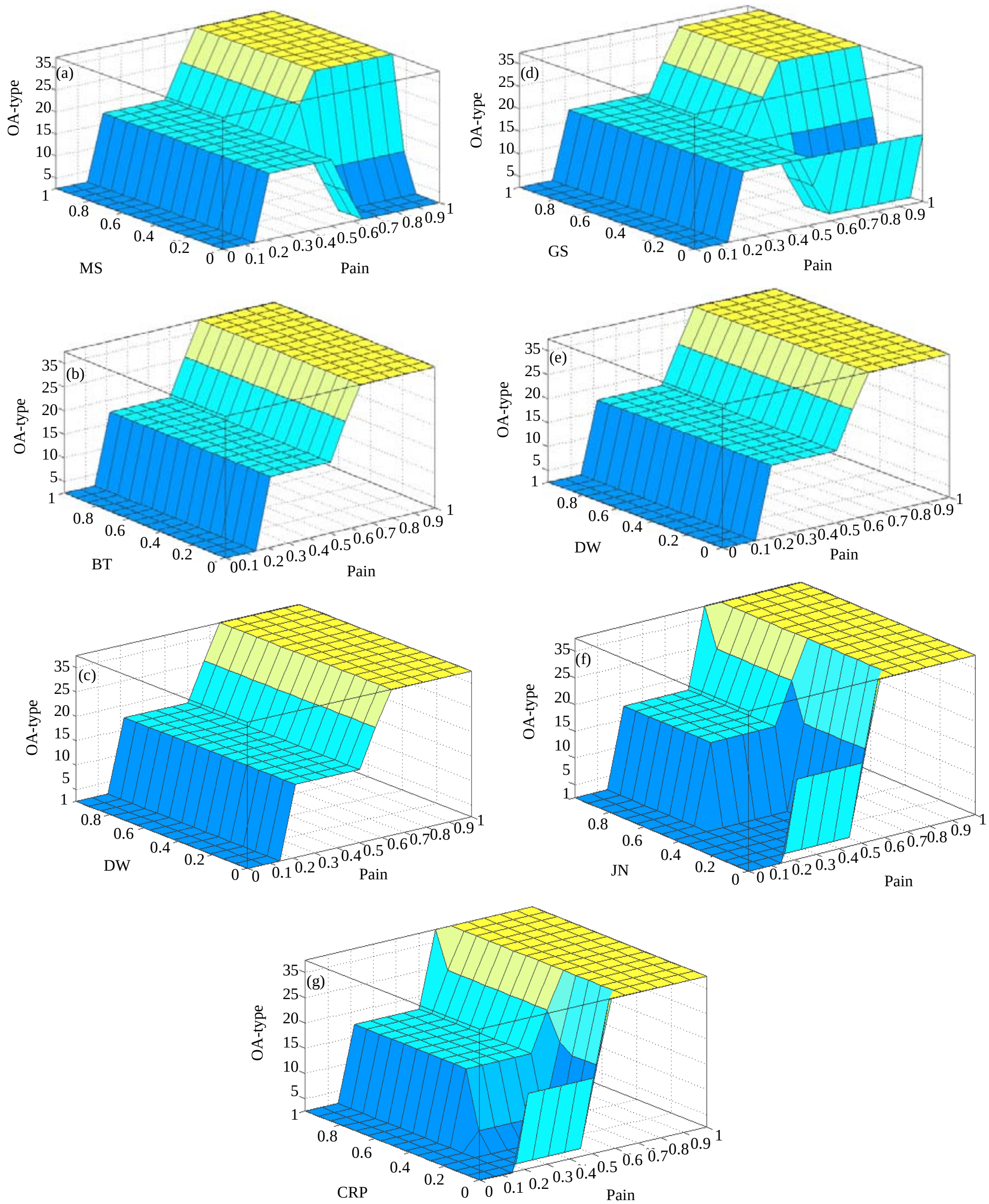

Fig. 4(a-g): Surface Viewer Plot for osteoarthritis between (a) Pain and Morning Stiffness (b) Pain and Grating Sensation (c) Pain and Bony Tenderness (d) Pain and Detectable Warmth (e) Pain and Bony Outgrowths (f) Pain and Joint space narrowing (g) Pain and C Reactive Protein

CONCLUSION

This aim of this study was to design a system for the diagnosis of osteoarthritis and its severity using Fuzzy Logic. The common people, who suspects little bit of pain in joints, may use this system and get the result on the diagnosis and severity of osteoarthritis which will be helpful to guide them to take proper curative measures before the severity increases. The validation results show that the developed fuzzy inference system is accurate. These results also imply that the developed fuzzy inference system is reliable one and can be used to help clinicians specially the non-expert ones to provide correct and rapid diagnosis of osteoarthritis.

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