International Journal of Mathematical Archive-8(9), 2017, 59-66
IJMA Available online through www.ijma.info ISSN 2229 – 5046

CONSTRUCTION OF FUZZY PETRI NETS USING DATA MINING RULES FOR BREAST CANCER DATA

S. MEHER TAJ*[1], A. KUMARAVEL[2]

[1]Assistant Professor, Department of Mathematics,
AMET University, Chennai, Tamil Nadu, India.

[2]Dean, School of Computing, Bharath University, Chennai, Tamil Nadu, India.

(Received On: 01-08-17; Revised & Accepted On: 01-09-17)

ABSTRACT

Fuzzy Petri nets (FPNs) are a potential modeling technique which is used for knowledge representation and reasoning of rule-based expert systems. An expert system based on Fuzzy rule based systems are common, and specification of those systems by tools like Petri nets encourage more research work nowadays. The theme of this paper is to produce an iterative scheme using data mining techniques for extracting optimal set of rules. The best accuracies of such models are devised. The result obtained is used for generating the optimal rule base for predicting the Breast cancer results.

Keywords: *Fuzzy Petri net, WEKA, Fuzzy rule base, Fuzzy Inference System, Classifications, Data Mining, and Selected Attributes.*

1. INTRODUCTION

Breast cancer [9]is caused when abnormal tissue in the breast begins to multiply uncontrollably. These cancerous cells can travel to other locations in the body and cause further damage. The risk of developing breast cancer increases with age. The condition is most common among women over 50 who have been through the menopause. About 8 out of 10 cases of breast cancer occur in women over 50.

Data mining software is one of a number of analytical tools for analyzing data. It allows users to analyze data from many different dimensions or angles, categorize it, and review the relationships identified. Data mining has become a popular technology in current research and for medical domain applications. The aim of this paper is to analyze how to evaluate progression of disease by using fuzzy Petri nets. Here we develop a frame work and modeling approach for the classifying the progression of disease for breast cancer by using Fuzzy Petri nets. In section II we discuss about the methods and materials are proposed, Section III, we discuss about the WEKA tool, In Section IV, discusses the classification rule classifier and the various algorithms used for classification, In Section V we present the comparison of different classification techniques using WEKA from the experimental results .In section VI, we construct the fuzzy Petri nets and a conclusion is given in section VII.

2. MATERIALS AND METHODS

2.1 Fuzzy Petri Nets:

One of the most known and applicable class of Petri nets in the domain of Artificial Intelligence are fuzzy Petri nets [1,2]. They are a modification of classical Petri nets relying on interpretation of net places as logical variables with values belonging to the closed interval [0,1] of all real numbers from 0 to 1 (0 and 1 are included). The concrete values of such variables represent a truth degree of statements assigned to the variables. Net transitions are interpreted as logical implications in which input places of a transition represent premises of a given implication corresponding to the transition whereas output places of the transition represent its conclusions.

Corresponding Author: S. Meher Taj[1],*
[1]Assistant Professor, Department of Mathematics,
AMET University, Chennai, Tamil Nadu, India.

FPN structure can be defined as an 8-tuple:
FPN = {P, T, D, I, O, α, β, μ }
where,

P = {p1, p2, ..., pn} is a finite set of places
T = {t1, t2, ..., tn} is a finite set of transitions
D = {d1, d2, …, dn} is a finite set of propositions:
$P \cap T \cap D = O$, | P | = | D |
I: $P \times T \rightarrow \{0.1\}$ is the input function, a mapping from places to transitions
O: $T \times P \rightarrow \{0.1\}$ is the output function, a mapping from transition to places
α: $T \rightarrow (0.1)$ is an association function, a mapping from transitions to (0.1) i.e., certainty factor
β: $P \rightarrow (0.1)$ is an association function, a mapping from places to (0.1) i.e., the truth degree
μ : $P \rightarrow D$, is an association function, a mapping from places to proportions

2.2 Fuzzy Production Rule:

In order to [4] properly present real world knowledge, fuzzy production rules (FPRs) have been used for knowledge representation to process uncertain imprecise and ambiguous knowledge .They are usually presented in the form of a fuzzy IF THEN rule in which both the antecedent and the consequent have fuzzy concepts denoted by fuzzy sets. If the antecedent portion or consequent portion of a production rule contains AND or OR connectors, then it is called a composite fuzzy production rule.

Let R be a set of fuzzy production rules:

R ={ R1,R2,...Rm}, and a fuzzy production rule Ri is as shown as follows
Ri: If cj then ck, (CF = μi)

IF all propositions in the antecedent dj have value true THEN the propositions in the consequent ck are true.

Where ci = {cj1, cj2,…,cjn}, represents the antecedent part which comprises of one or more Propositions connected by either “AND” or “OR” in the rule;
Dk = {ck1, ck2… ckn} represents the consequent part which comprises of one or more propositions connected by “AND” operator; μi denotes the certainty factor (CFi) of the rule Ri. Generally, FPRs are classified into four types as follows:

Type 1: IF cj , THEN ck , (CF =μ),

Type 2: IF cj1 and cj2 and …and cjn THEN ck (CF = μ),

Type 3: IF cj1 or cj2 or ...or cjn THEN ck (CF = μ),

Type 4: IF cj THEN ck1and ck2 and …and ckn (CF = μ),

FPN models are classified into 4 types of composite fuzzy production rules.

2.3 DATA SET:
In this research, we use a real dataset which was obtained from the University Medical Centre, Institute of oncology, Ljubljana, Yugoslavia [3] .They have stored as 286 instances.

DATA SET DESCRIPTION:

The data set consists of 9 conditional attributes and one decision attribute, where:

- Age :10-19, 20-29, 30-39, 40-49, 50-59, 60-69, 70-79, 80-89, 90-99.
- Menopause : lt40, ge40, premeno.
- tumor-size : 0-4, 5-9, 10-14, 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59.
- inv-nodes : 0-2, 3-5, 6-8, 9-11, 12-14, 15-17, 18-20, 21-23, 24-26, 27-29, 30-32, 33-35, 36-39.
- Node-caps : yes, no.
- Deg-malig : 1, 2, 3.
- Breast : left, right.
- Breast-quad : left-up, left-low, right-up, right-low, central.
- Irradiat : yes, no.
- Class : no-recurrence-events, recurrence-events

3. WEKA TOOL

WEKA is a collection of machine learning algorithms for data mining tasks. WEKA contains tools for data preprocessing and classification .Classification is a data mining technique used to predict group membership for data instances [5]. It is the problem of finding the model for class assignment for cross validation test. We used (Weka, 3.7.11) a learning machine tool in this work.

3.1 Association Rule Mining

Association rule[6] learning is a popular and well researched method for discovering interesting relations between variables in large databases. Many other classifications systems have been built based on association rules. In this research paper, there is an implementation of an association ruled –based classifier system in the WEKA frame work.

4. METHODOLOGY

We used different rule based classifier in this paper to evaluate the effectiveness of those classifiers in the classification problem .Figure 1 shows clearly the steps considered for our proposed method .The classifiers applied are:

4.1 JRIP Classifier:

Jrip (RIPPER) [7] is one of the most popular algorithms; it has classes that are examined in increasing size. It also includes set of rules for class is generated using reduced error Jrip (RIPPER)

4.2 Conjunctive Rule Classifier:

It is a decision-making [5] rule in which the intending buyer assigns least values for a number of factors and discards any result which does not meet the bare minimum value on all of the factors i.e. a superior performance on one factor cannot recompense for deficit on another.

4.3 NNge Classifier:

Non-Nested Generalized Exemplars [5] (NNGE) is an algorithm introduced by Brent, 1995. It performs generalization by merging exemplars, forming hyper rectangles in attribute space that represent conjunctive rules with internal disjunction. The algorithm forms a generalization each time a new example is added to the database, by joining it to its nearest neighbor of the same class.

4.4 ONE R Classifier:

The One R algorithm [5] creates a single rule for each attribute of training data and then picks up the rule with the least error rate [7]. To generate a rule for an attribute, the most recurrent class for each attribute value must be established. The most recurrent class is the class that appears most frequently for that attribute value.

4.5 PART Classifier

Class for generating a [7] PART decision list. Uses separate-and-conquer. Builds a partial C4.5 decision tree in each iteration and makes the "best" leaf into a rule. In this classifier, the test option is cross validations with 10 folds. PART produces the best accuracy and also least error .Number of rules 20, time taken by 0.05 seconds.

4.6 Ridor Classification:

RIpple-Down[5] Rule learner first generates the default rule. The exceptions are generated for the default rule with the lowest (weighted) error rate. Then it generates the "best" exceptions for each exception. Thus it carries out a tree-like expansion of exceptions and its leaf has only default rule without exceptions.

4.7 Zero R Classifier:

Zero R [5]is a learner used to test the results of the other learners. Zero R chooses the most common category all the time. ZeroR learners are used to compare the results of the other learners to determine if they are useful or not, especially in the presence of one large dominating category.

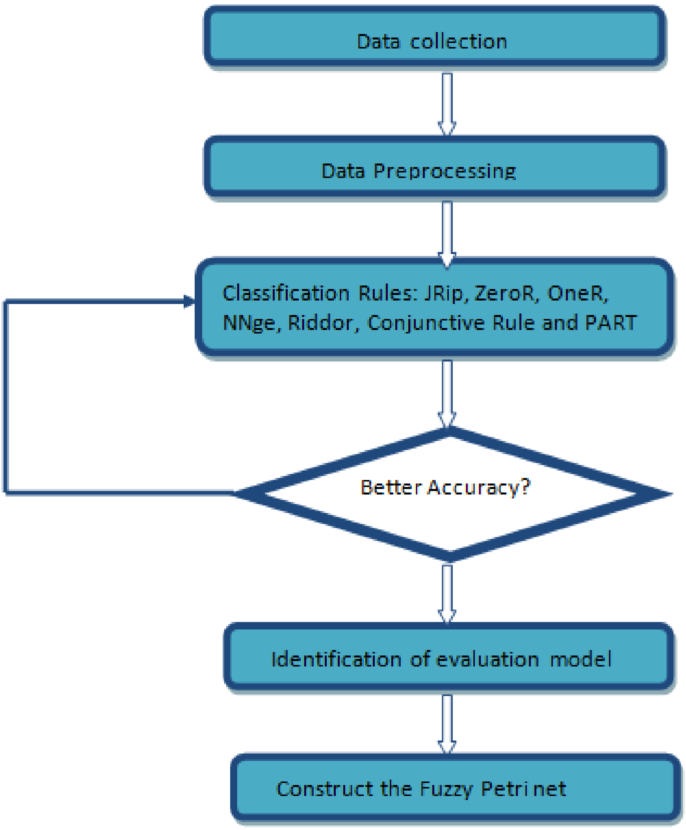

Figure-1: Main method Proposed

5. EXPERIMENTAL RESULTS:

5.1 Accuracy Measure

Classification accuracy:

It is the ability to predict categorical class labels. This is the simplest scoring measure. It calculates the proportion of correctly classified instances.

Accuracy = (Instances Correctly Classified/Total Number of Instances) *100

True positive (TP): If the instance is positive and it is classified as positive. False Negative (FP): If the instance is positive but it is classified as negative. True Negative (TN): If the instance is negative and it is classified as negative. False Positive (FP): If the instance is negative but it is classified as positive.

5.2 ROC (Receiver Operating Characteristics):

It is a plot of the true positive rate against the false positive rate. This shows the relationship between sensitivity and specificity.

Classifier	Phase	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
JRIP	Cross validation	0.710	0.489	0.688	0.71 0	0.693	0.598
CONJUNCTIVE RULE	Cross validation	0.657	0.579	0.622	0.657	0.633	0.548
NNGE	Cross validation	0.650	0.535	0.634	0.650	0.641	0.558
ONE-R	Cross validation	0.657	0.573	0.624	0.657	0.635	0.542
PART	Cross validation	0.713	0.542	0.682	0.713	0.680	0.586
RIDOR	Cross validation	0.710	0.550	0.677	0.710	0.675	0.580
ZERO-R	Cross validation	0.703	0.703	0.494	0.703	0.58	0.483

Table-1: Shows the detailed accuracy by the classifiers chosen

5.3 Error Rate:

5.3.1 Mean absolute Error (MAE):

The MAE [5] measures the average magnitude of the errors in a set of forecasts, without considering their direction. It measures accuracy for continuous variables. It is a linear score which means that all the individual differences are weighted equally in the average. The formula for calculating MAE is given in equation
Shown below:

$$\text{MAE} = \left(|a_1 - c_1| + |a_2 - c_2| + ...|a_n - c_n| \right) / n$$

Assuming that the actual output is a expected output is c.

5.3.2 Root Mean –Squared Error*:*

RMSE is frequently [5] used the difference between forecast and corresponding observed values are each squared and then averaged over the sample. Finally, the square root of the average is taken. The formula for calculating RMSE is given in equation shown below

$$\sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + ...(a_n - b_n)^2}$$

The classification accuracy, mean absolute error and root mean squared error are calculated for each machine algorithm.

Classification Model	Phase	Classification-on Accuracy	Mean Absolute Error	Root Mean Squared Error	Relative absolute error	Root relative squared error	Number of Rules	Time (seconds)
JRIP	Cross validation	70.979	0.3798	0.4494	90.7822	98.3249	03	0.02
CONJUNCTIVE RULE	Cross validation	65.7343	0.4058	0.4626	96.9963	101.2185	0	0.01
NNGE	Cross validation	65.035	0.3497	0.5913	83.5656	129.3683	105	0.05
ONE-R	Cross validation	65.7343	0.3427	0.5854	81.8943	128.0681	13	0.01
PART	Cross validation	71.3287	0.3650	0.4762	87.2225	104.1825	20	0.05
RIDOR	Cross validation	70.979	0.2902	0.5387	69.3595	117.8602	03	0.01
ZERO-R	Cross validation	70.2797	0.4184	0.4571	100	100	01	0.0

Table-2: Shows the Classification Accuracy and Simulation Error

From the above table, it is observed that PART algorithm attains least error rate. Therefore PART classification algorithms performs well because it contains least error rate and also highest accuracy when compared to other algorithms [7,8]

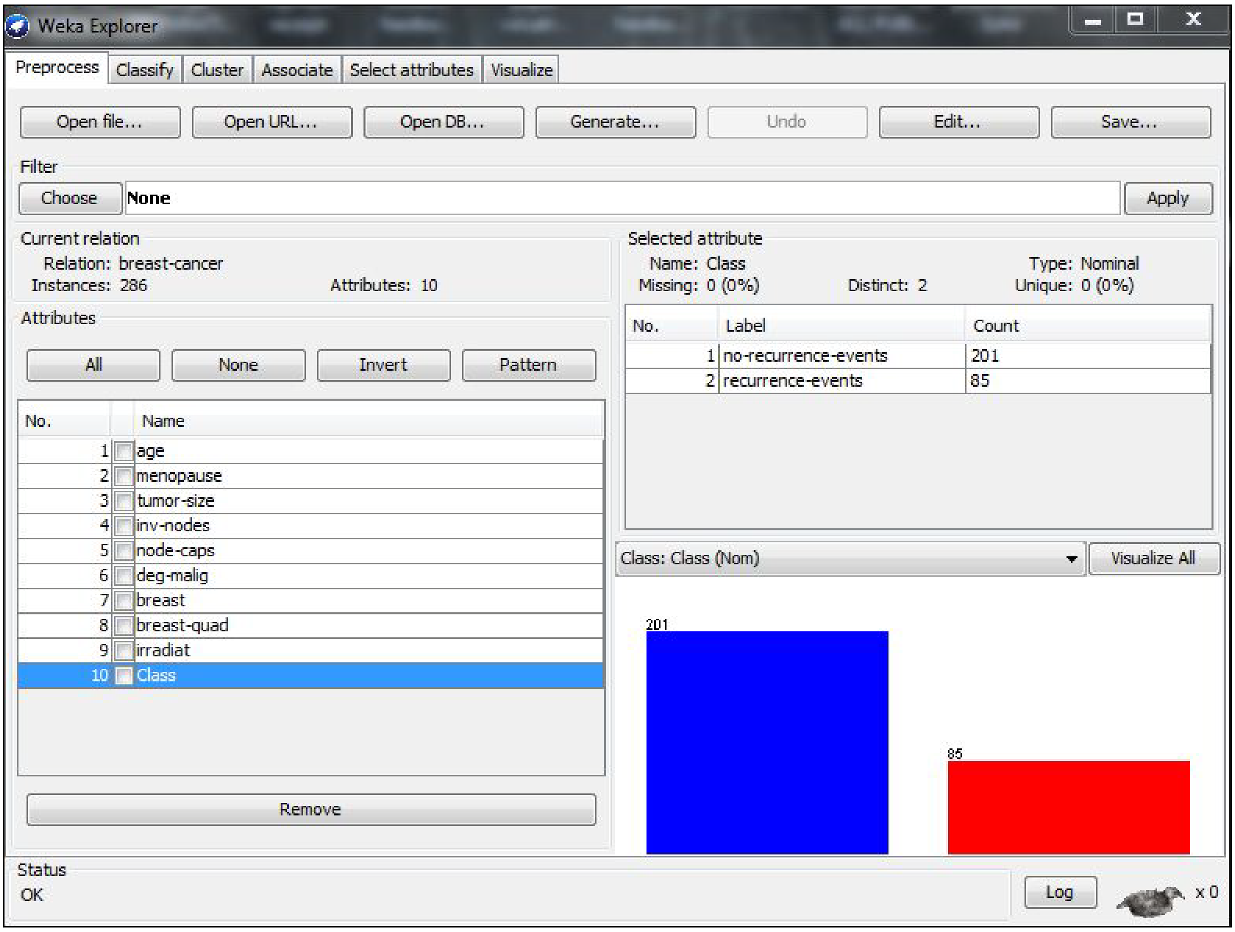

Table-3: Print Screen of WEKA 3.6 Environment

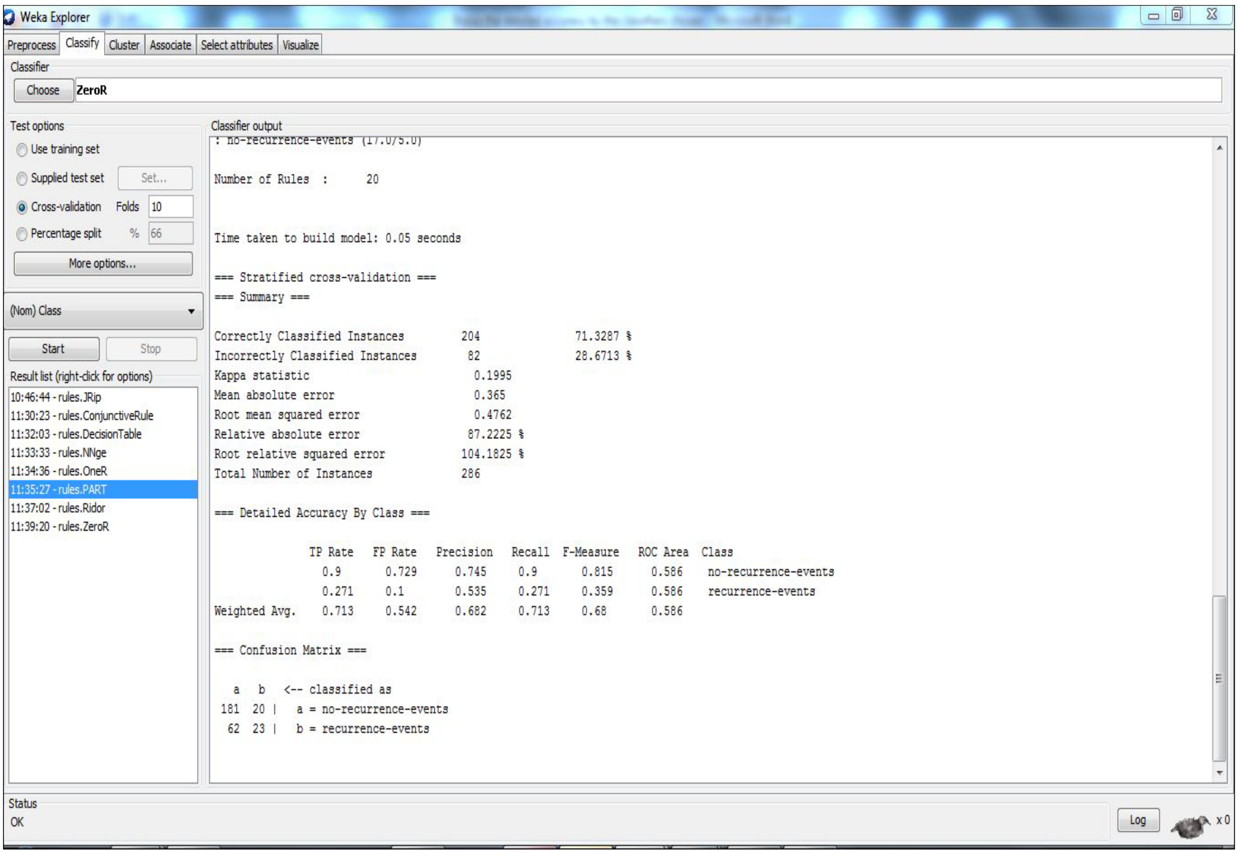

Table-4: Classifier Output of the PART Model

6. CONSTRUCTION OF FUZZY PETRI NET

The above tables show that we need to identify, PART Classifier produces the better accuracy and also gives the minimum error. Using WEKA tool, PART Classifier are generate the following twenty rules:

R1: node-caps = no AND inv-nodes = 0-2 AND tumor-size = 10-14: no-recurrence- events (26.0)
R2 : node-caps = no AND inv-nodes = 0-2 AND deg-malig = 1: no-recurrence- events (53.56/10.56)
R3: deg-malig = 2 AND inv-nodes = 0-2 AND breast-quad = left_low: no recurrence-events (33.0/8.0)
R4 : deg-malig = 2 AND inv-nodes = 0-2 AND breast-quad = left_up: no recurrence-events (27.0/4.0)
R5 : deg-malig = 2 AND tumor-size = 20-24 AND irradiat = no: no-recurrence-events (11.0/2.0)
R6: deg-malig = 2 AND tumor-size = 25-29: no-recurrence-events (9.0/3.0)
R7: node-caps = no AND tumor-size = 20-24 AND inv-nodes = 0-2: no-recurrence events (10.27/2.27)
R8 : deg-malig = 1: no-recurrence-events (4.18/1.18)
R9 : deg-malig = 2 AND tumor-size = 0-4: no-recurrence-events (4.0/1.0)
R10: deg-malig = 2 AND tumor-size = 35-39: no-recurrence-events (4.0)
R11. tumor-size = 20-24: recurrence-events (8.0/2.0)
R12: deg-malig = 2 AND tumor-size = 30-34 AND irradiat = no: no-recurrence- events (9.0/2.0)
R13: tumor-size = 40-44 AND breast-quad = left_up: no-recurrence-events (5.0)
R14: node-caps = yes AND breast-quad = left_low AND deg-malig = 3: recurrence-events (12.43/2.43)
R15: tumor-size = 30-34: recurrence-events (29.58/10.58)
R16: tumor-size = 25-29 AND breast = left: recurrence-events (8.0/1.0)
R17: tumor-size = 15-19: no-recurrence-events (7.0/1.0)
R18: tumor-size = 25-29 AND menopause = ge40: no-recurrence-events (4.0)
R19: tumor-size = 35-39 AND menopause = premeno: recurrence-events (4.0/1.0)
R20: no-recurrence-events (17.0/5.0)

The corresponding Fuzzy Petri net model is illustrated in Fig. 2. In the Fuzzy Petri net model [9, 10], according to the proportions dedicated to each place, transitions 1 to19 respectively represent rules 1 to20.

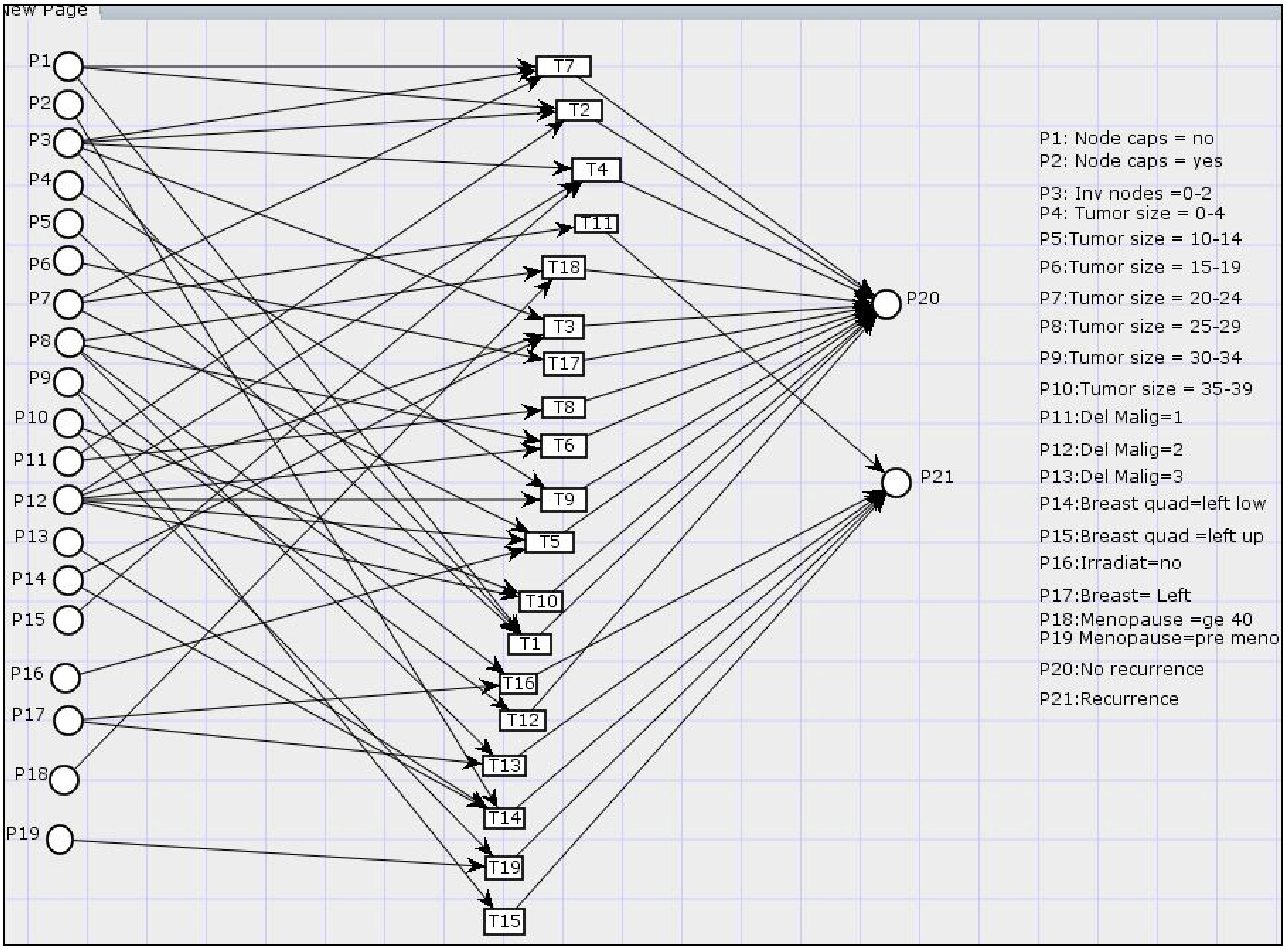

Figure-2: CPN Tool Snapshot for execution of Part Classifier Rules

7. CONCLUSION

This work is performed using Machine learning tool, to predict the effectiveness of all the rule based classifiers. Classification Accuracy is used as a measure for the performances of various algorithms. Comparisons among classifiers are based on the accuracy, Mean Absolute Error and Root Mean squared values also considered. Comparisons among classifier based on the correctly classified instances are shown in Table 2. Based on the results, PART classifier produces the better accuracy and the lowest error in MAE and RMSE. In PART classifier, a number of rules are 20 is given above. Some parameters for tuned for better results, for the purpose of comparing the Classification accuracy obtained with the same number of rules.

ACKNOWLEDGEMENT

The first author would like to thank the management of AMET University for their support and encouragement for this research study.

REFERENCES

1. Looney, C.G.: "Fuzzy Petri Nets for Rule-Based Decision-making. IEEE Trans. Syst., Man, Cybernetics, 18-1, 1988, pp178-183, .
2. Murata, T. "Petri Nets: Properties, Analysis and Applications". Proc. of the IEEE, Vol.77, April 1989, pp. 541-580.
3. Zwitter. M and Soklic .M, University Medical Centre, Institute of oncology, Ljubljana, Yugoslavia.1988.
4. Hu-Chen Liu,Long Liu,Qing-Loian Lin, and Nan Liu"Knowledge Acquisition and representation using Fuzzy Evidential Reasoning and Dynamic Adaptive Fuzzy Petri Nets "IEEE Trans on Cybernetics,43(3), 2013,pp1059-1071.
5. C.Lakshmi Devasena, T.Sumathi, V.V. Gomathi and M.Hemalatha, "Effectiveness Evaluation of Rule Based Classifiers forthe Classification of Iris Data Set, Bonfring International Journal of Man Machine Interface, Vol – 1, special issue, 2011.
6. Shilpa Dhanjibhai Serasiya, Neeraj Chaudhary, "Simulation of various classifications results using WEKA" International Journal of Recent Technology and Engineering (IJRTE), , Volume -1, Issue -3, 2012.
7. Meher Taj.S and Kumaravel. "A Fuzzy Petri Nets Construction For Predicting The Bank-Deposit Profiles" International Journal Of Engineering Sciences & Research Technology, 5(2), 2016, pp 320-327.
8. A.Kumaravel and Pradeepa.R, "Efficient Molecule Reduction For Drug Design by Intelligent Search methods" International Journal of Pharma and Bio Sciences, 4(2) 2013, pp 1023 -1029.
9. Shweta Kharya "Using Data Mining Techniques For Diagnosis and Prognosis Of Cancer Disease" International Journal of Computer Science, Engineering and Information Technology (IJCSEIT), 2(2), 2012, pp.55-66.

Source of support: Nil, Conflict of interest: None Declared.