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Implementation Of Fuzzy Petri Nets Using Data Mining Rules For Predicting Student Performance

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Abstract

Fuzzy Petri net models are very helpful for specifying the expert systems with imprecise description of rules. 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 construct 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 Student performance results.

Keywords:

Fuzzy Petri net;
WEKA;
Fuzzy rule base;
Classifications;
Data Mining, and Selected Attributes.

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1. Introduction

Since students are at the core of learning process, a study tailored to their motivations and strategies and factors hindering their learning are imperative as students themselves play pivotal roles in shifting their own learning and acquiring enhanced academic achievement. Analyzing students' data and information to classify students, or to create decision trees or association rules, to make better decisions or to enhance student's performance is an interesting field of research, which mainly focuses on analyzing and understanding students' educational data that indicates their educational performance, and generates specific rules, classifications, and predictions to help students in their future educational performance.

Data mining refers to extracting or "mining" knowledge from large amounts of data. Data mining techniques are used to operate on large volumes of data to discover hidden patterns and relationships helpful in decision making [1].The aim of this paper is to analyze how to evaluate progression of student performance by using fuzzy Petri nets. Here we develop a frame work and modeling approach for the classifying the progression of by student performance using Fuzzy Petri nets. In section II we discuss about the methods and materials are proposed, Section II, 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.

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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 [2,3]. 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

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 ∩ T ∩ D = O, | P | = | D |

I : P×T→{0.1} is the input function, a mapping from places to transitions

O : T×P→{0.1} is the output function, a mapping from transition to places

α: T→(0.1) is an association function, a mapping from transitions to (0.1) i.e., certainty factor

β: P→(0.1) is an association function, a mapping from places to (0.1) i.e., the truth degree

μ : P→D, is an association function, a mapping from places to proportions

2.2 Fuzzy Production Rule:

In order to [3] 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 UCI repository. It is about students of the two different schools and their information’s and grades related to their study. The data attributes include student grades, demographic, social and school related features) and it was collected by using school reports and questionnaires. In [11], the two datasets were modeled under binary/five-level classification and regression task.

DATA SET DESCRIPTION:

The data set consists of 33 conditional attributes and one decision attribute, where:

- school - student's school (binary: 'GP' - Gabriel Pereira or 'MS' - Mousinho da Silveira)
- sex - student's sex (binary: 'F' - female or 'M' - male)
- Age - student's age (numeric: from 15 to 22)
- address - student's home address type (binary: 'U' - urban or 'R' - rural)
- famsize - family size (binary: 'LE3' - less or equal to 3 or 'GT3' - greater than 3)
- P status - parent's cohabitation status (binary: 'T' - living together or 'A' - apart)
- Medu - mother's education (numeric: 0 - none, 1 - primary education (4th grade), 2 â€“ 5th to 9th grade, 3 â€“ secondary education or 4 â€“ higher education)
- Fedu - father's education (numeric: 0 - none, 1 - primary education (4th grade), 2 â€“ 5th to 9th grade, 3 â€“ secondary education or 4 â€“ higher education)
- M job - mother's job (nominal: 'teacher', 'health' care related, civil 'services' (e.g. administrative or police), 'at home' or 'other')
- F job - father's job (nominal: 'teacher', 'health' care related, civil 'services' (e.g. administrative or police), 'at home' or 'other')
- reason - reason to choose this school (nominal: close to 'home', school 'reputation', 'course' preference or 'other'
- guardian - student's guardian (nominal: 'mother', 'father' or 'other')
- Travel time - home to school travel time (numeric: 1 - <15 min., 2 - 15 to 30 min., 3 - 30 min. to 1 hour, or 4 - >1 hour)
- study time - weekly study time (numeric: 1 - <2 hours, 2 - 2 to 5 hours, 3 - 5 to 10 hours, or 4 - >10 hours)
- failures - number of past class failures (numeric: n if 1<=n<3, else 4)
- schools up - extra educational support (binary: yes or no)
- fams up - family educational support (binary: yes or no)
- paid - extra paid classes within the course subject (Math or Portuguese) (binary: yes or no)
- activities - extra-curricular activities (binary: yes or no)
- nursery - attended nursery school (binary: yes or no)
- higher - wants to take higher education (binary: yes or no)
- internet - Internet access at home (binary: yes or no)
- romantic - with a romantic relationship (binary: yes or no)
- famrel - quality of family relationships (numeric: from 1 - very bad to 5 - excellent)
- free time - free time after school (numeric: from 1 - very low to 5 - very high)
- go out - going out with friends (numeric: from 1 - very low to 5 - very high)
- Dalc - workday alcohol consumption (numeric: from 1 - very low to 5 - very high)
- Walc - weekend alcohol consumption (numeric: from 1 - very low to 5 - very high)
- health - current health status (numeric: from 1 - very bad to 5 - very good)
- absences - number of school absences (numeric: from 0 to 93)
- G1 - first period grade (numeric: from 0 to 20)
- G2 - second period grade (numeric: from 0 to 20)
- G3 - final grade (numeric: from 0 to 20, output target)
- Class:First,Second

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.

3.1Association 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) [6]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 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.

4.4 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.

4.5 RIDOR Classifier

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.

4.6 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.

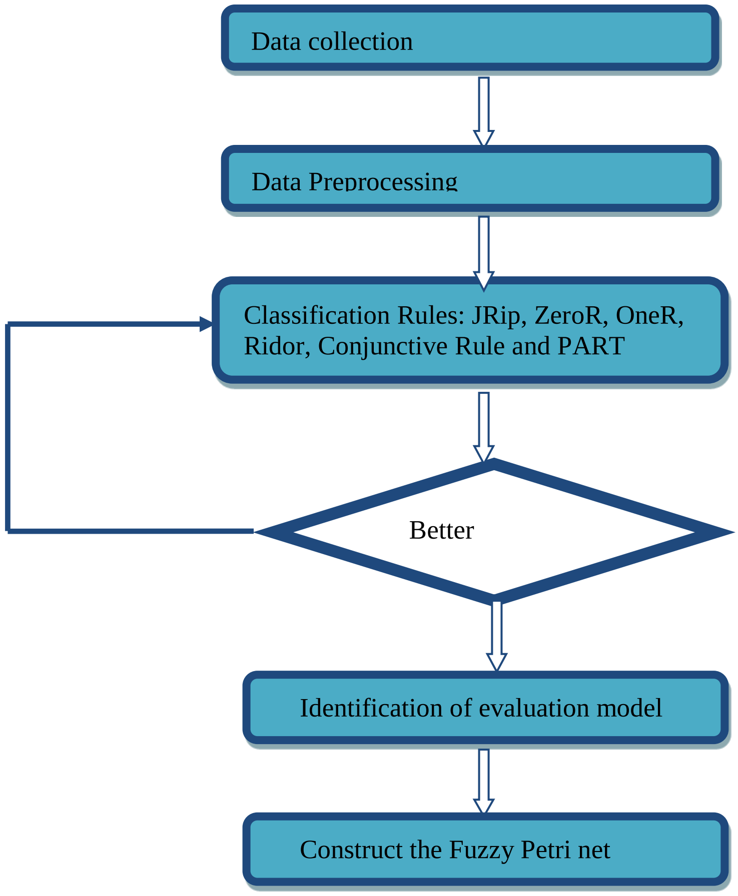

Figure: 1 Main method Proposed

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 itis 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	0.99	0.088	0.99	0.99	0.99	0.988
CONJUNCTIVE RULE	Cross validation	0.81	0.176	0.674	0.810	0.731	0.851
ONE-R	Cross validation	0.99	0.008	0.99	0.99	0.99	0.989
PART	Cross validation	0.987	0.008	0.987	0.987	0.987	0.988
RIDOR	Cross validation	0.987	0.008	0.987	0.987	0.987	0.990
ZERO-R	Cross validation	0.481	0.481	0.231	0.481	0.312	0.492

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:

MAE = $(|a_1 - c_1| + |a_2 - c_2| + ...|a_n - c_n|)/n$

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	98.9873	0.0133	0.0821	3.1967	17.9952	3	0.03
CONJUNCTIVE RULE	Cross validation	81.0127	0.1820	0.3013	43.6083	66.0511	1	0.01
ONE-R	Cross validation	98.9873	0.0086	0.0822	1.6212	18.0115	3	0.03
PART	Cross validation	98.7342	0.0137	0.0857	3.2929	19.0041	3	0.05
RIDOR	Cross validation	98.7342	0.0084	0.0919	2.0265	20.1375	4	0.05
ZERO-R	Cross validation	48.1013	0.4164	0.4562	100	100	0	0.0

Table: 2 Shows the Classification Accuracy and Simulation Error

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

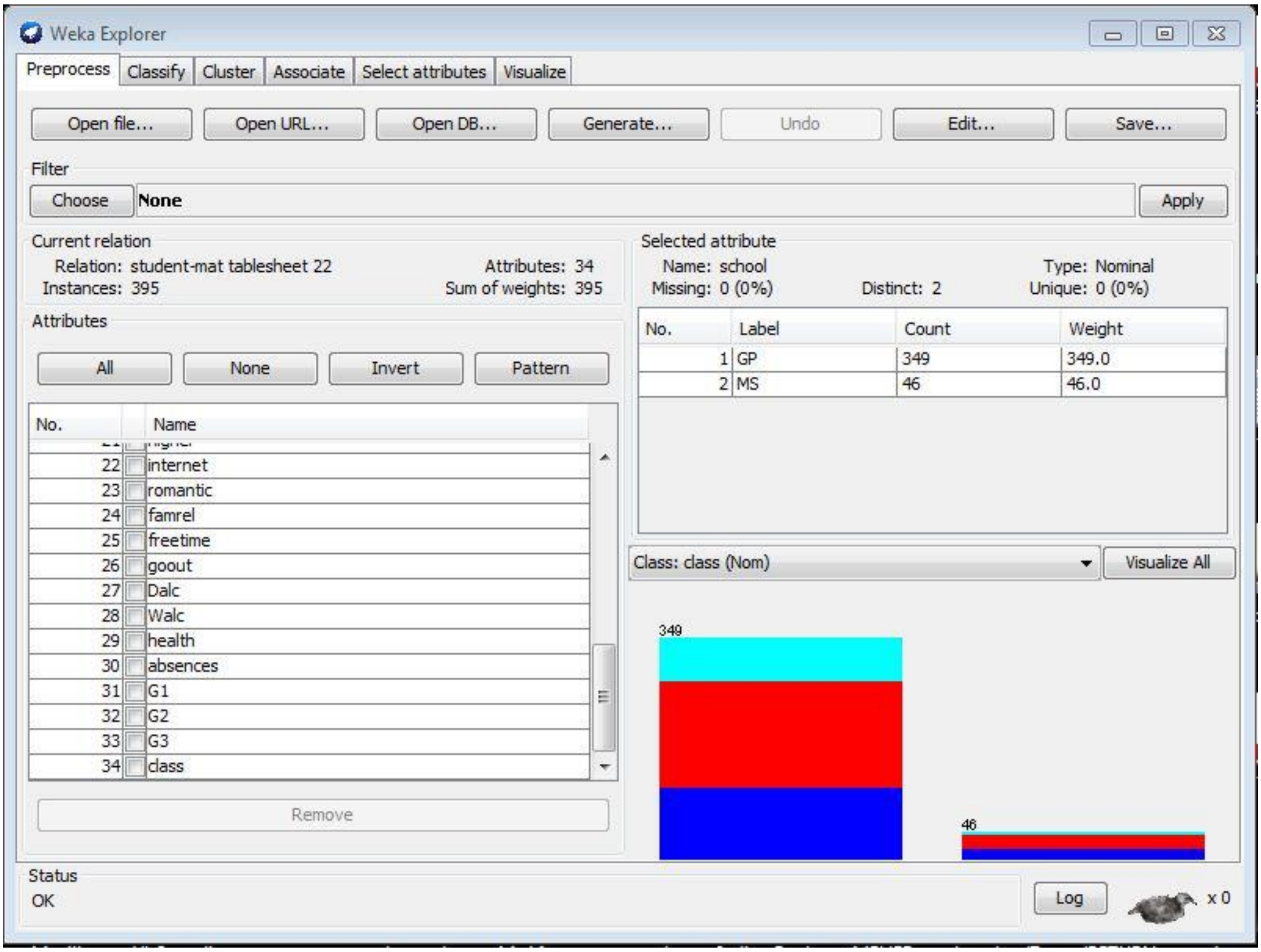

Table: 3 Print Screen of WEKA 3.6 Environment

Table: 4 Classifier Output of the RIDOR Model

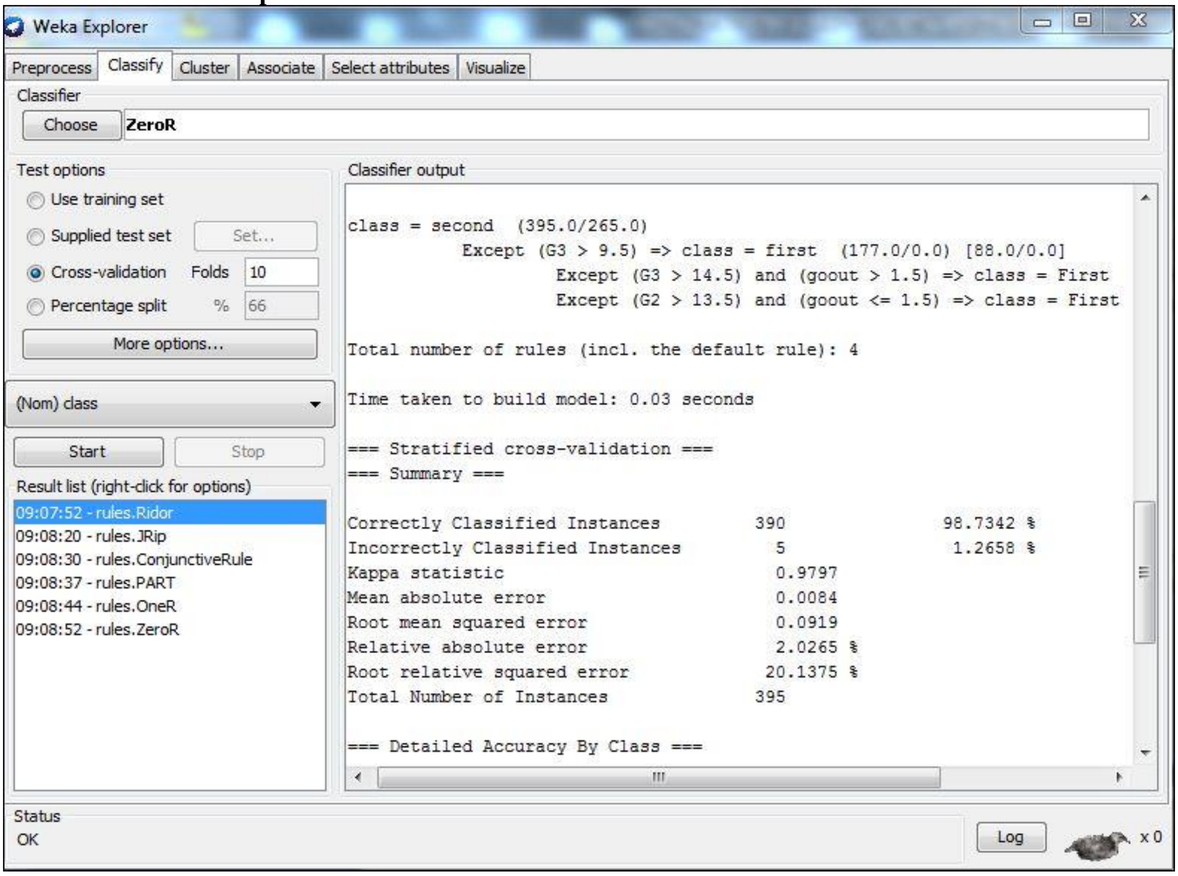

Table: 4 Classifier Output of the RIDOR Model

6 Construction of Fuzzy petri net:

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

R1: Class = second (395.0/265.0)
R2: Except (G3 > 9.5) => class = first (177.0/0.0) [88.0/0.0]
R3: Except (G3 > 14.5) and (go out > 1.5) => class = First (45.0/0.0) [23.0/0.0]
R4: Except (G2 > 13.5) and (go out <= 1.5) => class = First (4.0/1.0) [1.0/0.0]

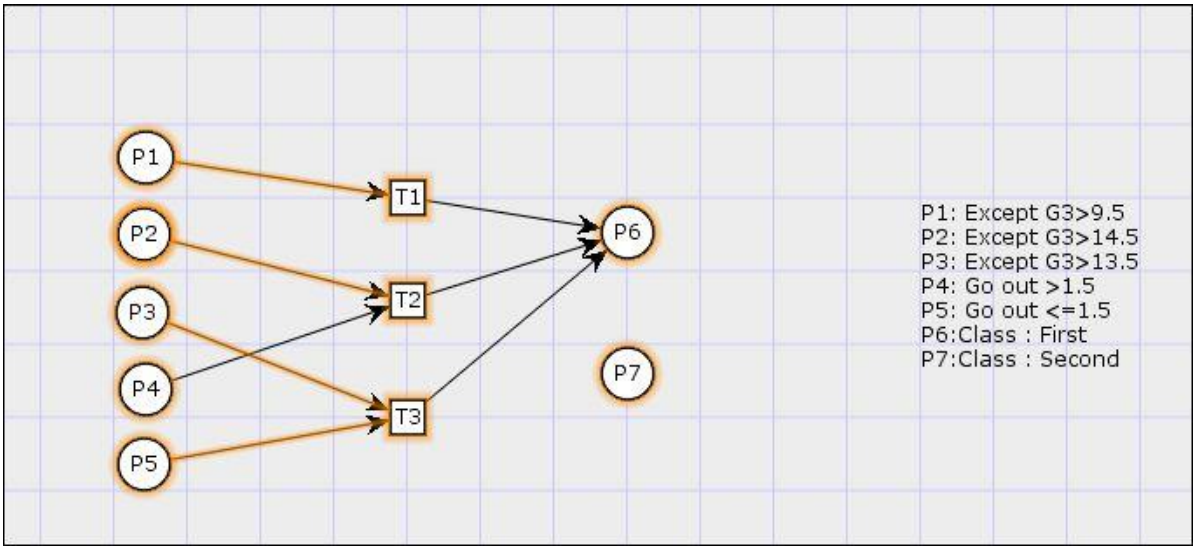

Figure: 2 CPN Tool Snapshot for execution of RIDOR Classifier Rules

The corresponding Fuzzy Petri net model is illustrated in Fig. 2. In the Fuzzy Petri net model [7, 10], according to the proportions dedicated to each place, transitions 1 to3 respectively represent rules 1 to 4.

1. 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, RIDOR classifier produces the better accuracy and the lowest error in MAE and RMSE. In RIDOR classifier, a number of rules are 4 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.

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