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Prediction of Caesarian Possiblities with Rough Set Theory and Fuzzy Petrinet

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Abstract

The Rough set theory (RST) is a method proved its efficiency and simplicity in machine learning and successfully developing now a day's vastly and rapidly. Many extensions and hybrid algorithms are proposed so far which pavement solutions for many mining issues. In this paper the performance of RST with Fuzzy Petri Nets (FPN) is studied in the sense how it carried out in the process of data mining and predicting rules. The Rough set theory is well known for its simplicity in attribute reduction and Fuzzy Petri Nets is very much used for rule chaining mechanism. This can capture the concurrency and choices of rules. This paper experiments the caesarian data to investigate the decision making from the rules generated by LERS system of RST with the approach of FPN. The possibilities of prediction and their consequences based on the accuracy of the classifications were discussed.

Keywords: *Fuzzy Petri Nets, Rough set theory, Caesarian Data, Rule extraction, Prediction*

Introduction

Machine learning is a statistical technique that gives the computer an ability to build a model in order to learn and improve the performance of a specific task with data. This task hits the problems around supervised learning, clustering, dimensional reduction and future prediction. The algorithms made by machine learning overcome the problems and make decisions and prediction on data. The classification and regression are the task of the supervised learning where unsupervised is clustering [1].Classification is the problem of spotting a new pattern basis on the analysis of the training data and that pattern implemented by the classification known as classifier. Another important task of machine learning is dimension reduction, which involves process of attribute reduction and extraction where it reducing the number of irrelevant attributes or extracting the relevant attributes. This task is widely needed because the data analysis like classification and regression are more accurate in the reduced space and also the size of the data is large and getting complicated in this advanced world. Moreover, it improves the performance of classifier, reduces the time and space and easy to visualize in2D or 3D. The techniques like PCA, LDA, GDA, CCA etc., are been used to resolve this so far[2].

The Rough set theory has been noticed as an efficient tool in machine learning for the past decades and it has been successfully overcome the above underlined tasks in many fields [3,16]. The algorithm based on the RST called LERS system (Learning Examples fro Rough Set)becoming an evidence for it was declared as s successful application of the RST in data mining by NASA's Johnson Space Center

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adopted LERS [14] as a development tool for expert system [15]. Some institutions have made use of this helpful software about the rough sets. ROSE, ROSETTA, RSES, Rstudio [4] are the tools having the concepts of the Rough set theory and the algorithms based on that [5]. Among them ROSE tool has all the fundamentals of the Rough set theory. However, issues like too much running time, lack of current RST based algorithms, and low acceptance of big data are being found make the researchers felt lacking sometimes. In this paper, we try to figure out some issues faced by the beginners with the mentioned tool and with the concept of the Rough set theory.

Methods and Materials

RST can be described by means of lower and upper approximations. The set of granules is the universal set U and now the set is defined with respect to R where R is the equivalence relation assumed based on the knowledge prescribed in granules of U. To describe the vague part of the set X with respect to R, we need the approximations of rough set theory [6, 7].

Lower and Upper approximations

Lower approximation is the union of all elements entirely within the set with respect to R. They definitely belong to the set.

$$R_*(x) = \bigcup_{x\in U}\{R(x) : R(x) \subseteq X\} \quad (1)$$

Upper approximation is the union of elements entirely and partially belonging to the set with respect to R. i.e., they roughly are in the set.

$$R^*(x) = \bigcup_{x\in U}\{R(x) : R(x) \cap X \neq \varnothing\} \quad (2)$$

The boundary region of the set is the difference between the lower and upper approximations [8].

$$RN_R(x) = R^*(x) - R_*(x) \quad (3)$$

Quality and accuracy of approximations

The quality and accuracy of approximation can be measured using the approximations defined above [9]. The values of the calculations lies between between [0,1] and that value should not be changed while feature selection.

The accuracy of approximation is defined as

$$Accuracy related to\ one\ class = \frac{No.\ of objects belongs to lower approximation of class}{No.\ of objects belongs to upper approximation\ of\ class}$$

The quality of classification is defined as

$$Quality related to decision class = \frac{No.\ of objects correctly classified as both classes}{No.\ of objects in the universal set} \quad (5)$$

If Accuracy of approximations is equal to 1, then the set is Rough set otherwise it is a crisp set. The quality of approximations defines the number of equivalence set in the original set which holds the knowledge of the data set.

Attribute Reduction

The reduction idea of RST is to catch the relevant attributes in the information system in order to remove the unrelated attributes. The number of equivalence sets that is the quality of approximations is to be matched with every set of attributes. The attributes which are common in all set of attributes are termed as CORE. The core attributes should not be removed. If they scored equal class of approximations as the unique set then that core set is the best reduct set. And we can remove the remaining attributes other than core. If not, we should find the important attributes by the highest percentage of occurrence of attribute in the reduct sets. We should add those attributes to the core until we get the original quality of approximation. We may set the threshold value according to that.

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Rule induction

LERS, the Rough Set Learning Examples is the successful minimal algorithm used to generate decision rules in the structure of if and then rules with a perfect pattern. Pattern is the knowledge calculated by all instances regarding the set of attributes and it can identify or test any instance that belongs to that knowledge. In three approaches, it induces rules; minimum set, exhaustive set, and satisfactory set. Maximum set produces a maximum number of rules that are adequate to convey all instances. Exhaustive set uses examples to induce all rules. Satisfactory setting leads to rules that satisfy user-defined requirements. In rule induction, it is important to process numerical attribute transformation into symbolic attribute. This process of discretization may vary by algorithm. The principles of decision and their algorithms have been discussed in [10]. Decision class approximations are described as three types, i.e. minimum set, exhaustive set and satisfactory set of decision rules [11].For this study, ROSE2 [12] is a modular software system that uses the basic concepts of the rough set theory and the methods of rule finding.

Fuzzy Petri Nets:

Petri Nets (PN) is a multi-system graphical and mathematical representation method. Promising tools are available to define and discover information science processes that are described as coincidental, asynchronous, distributed, parallel, non-deterministic and/or random [20,21].Fuzzy Petri networks containing 2 kinds of nodes: Places and Transitions, where circles represent places and parallelogram represent transitions. Each place stands for an associate degree precedent or resultant and may or may not contain a token related with a degree of truth between zero and one that speaks the validity of the precedent or sequence for the amount of trust at intervals. Every transition that represents a rule is said to have an issue value of certainty between 0 and 1. The factor of certainty in rule represents the strength of the idea [23,24].

Colored Petri Net Tool:

CPN is a graphical language that helps to build simultaneous system model and analyze its properties as well. The CPN is helpful in non-deterministic and stochastic process modelling. It also offers an effective modelling system for simulating distributed and simultaneous processes with both synchronous and asynchronous communication [3].CPN model is an executable system illustration consisting of system status, events or transitions that allow the system to change its status. With the help of simulating a CPN model, it is possible to observe and investigate different scenarios and behaviour of the system. CPN is the combination of the graphical component of ordinary Petri networks and the programming language of high level.

Data Source

The UCI repository is the website providing datasets for free for the research purposes of all kind of domains [18]. For our experiment, we took the small dimension data which is caesarian dataset [19]. The amount of instances is 80 and the amount of attributes is 6 including the class attribute. The details of the attributes are described below.

Table1: Attributes description

	Attribute Name	Attribute Values
1.	Age	22,26,28,27,32,36,33,23,20,29,25,37,24,18,30,40,31,19,21,35,17,38
2.	Delivery number'	1,2,3,4

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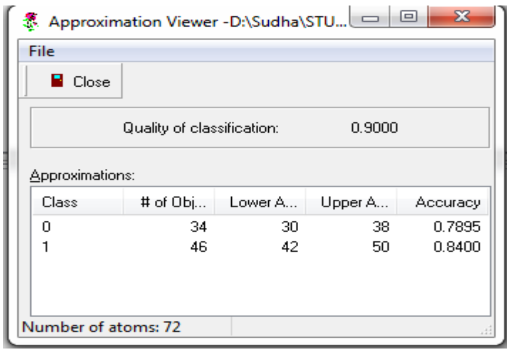
3.	'Delivery time'	{ 0,1,2 } -> {0 = timely , 1 = premature , 2 = latecomer}
4.	'Blood of Pressure	{ 2,1,0 } -> {0 = low , 1 = normal , 2 = high }
5.	'Heart Problem	{ 1,0 } -> {0 = apt, 1 = inept }
6.	Cesarean (Class)	{ 0,1 } -> {0 = No, 1 = Yes }

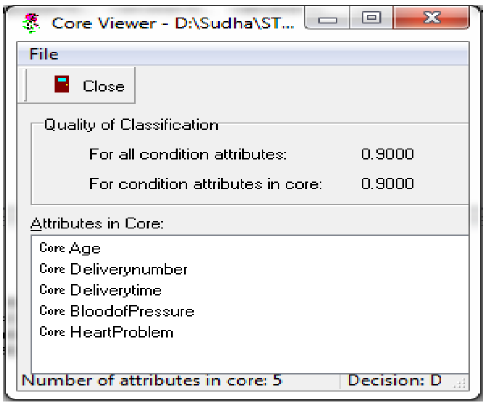
The above data was carried out for classification based on RST. For that we used the RSOE 2.2 tool which is completely constructed usingthe fundamentals of RST. Initially the RST calculated the approximations of the dataset based on the number of equivalent sets. The lower and upper approximations give the quality of classification of the dataset which should not be changed or lessened while mining. Here the quality of classification of our dataset is shown below Fig 1.

Figure 1: Quality of classification



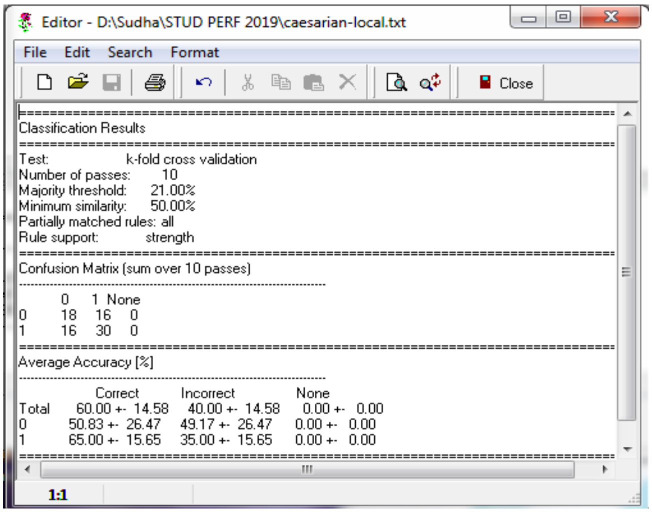
Since the dataset is having 0.9 quality of classification which is below 1, tells this dataset is a Rough set and the number of equivalence sets (atoms) is 72. Subsequently the boundary set is not empty here lead to the vagueness.

Figure 2: Core Attributes.



Based on the RST reduction concept, here the CORE attributes (Fig.2) are nothing but the entire conditional attributes and so the quality of classification is remains same for the core attribute results that the reduction must be none. That is there are no irrelevant attributes in this dataset. Then stratified 10 cross validation is done using basic minimal covering.

Figure:3 Cross Validation of Rules



The percentage of accuracy of the classification is calculated using the confusion matrix, which involves TN, TP, FN and FP. Here the accuracy is 60%, which is found by the number of appropriately classified elements over the total amount of elements. The number of correctly classified instances is 48 and incorrectly classified is 32. Using LERS, the rules generated are listed below in table 2. In that, we got 30 certain rules and 3 approximate rules.

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Table 2: Rules induced by minimal algorithm.

Rule#	IF			THEN
	Attribute	Attribute	Attribute	
Rule 1	Age = 31,23			D = 0
Rule 2	Age = 30	Delivery Number (1,3)		D = 0
Rule 3	Age = 22	BP = 2		D = 0
Rule 4	Age = 26	Delivery time = 1		D = 0
Rule 5	Age = 28	Delivery Number (1,2)		D = 0
Rule 6	Age = 18	Delivery time = 0		D = 0
Rule 7	Age = 35	Delivery Number = 1		D = 0
Rule 8	Age = 24	Delivery Number = 2		D = 0
Rule 9	Age = 27	Delivery Number = 2	Heart problem = 0	D = 0
Rule 10	Age = 25	BP = (1,2)		D = 0
Rule 11	Age = 33	Delivery Number = 3		D = 0
Rule 12	Age = 36	BP = 1		D = 0
Rule 13	Age = 20	BP = 1		D = 0
Rule 14	Age = 33	BP = 1	Delivery Number = 1	D = 0
Rule 15	Age = 26	BP = 1	Delivery Number = 1	D = 0
Rule 16	Age = 32	Deliver number = 3	Delivery time = 0& Heart problem=1	D = 0
Rule 17	(Age in{32, 21, 37, 40 17, 38	Delivery number =(1,2)		D = 1
Rule 18		Deliver number = 4		D = 1
Rule 19	Age in {27, 37, 24, 18, 28, 30, 38	Heart problem=1		D = 1
Rule 20	Age in {29, 32, 20	BP =(0,2)		D = 1
Rule 21	Age = 22	BP = 1		D = 1
Rule 22	Age = 32	Heart problem=1		D = 1
Rule 23	Age = 33	BP = 0		D = 1
Rule 24	Age = 36	Delivery time = 1		D = 1
Rule 25	Age = 35	Delivery number = 2		D = 1
Rule 26	Age = 28	Delivery number = 3		D = 1
Rule 27	Age = 26	BP = 2		D = 1
Rule 28	Age = 27	Delivery number = 1		D = 1
Rule 29	Age = 26	Delivery number = 2	Delivery time = 0	D = 1
Rule 30	Age = 26	Delivery time = 2	BP = 0	

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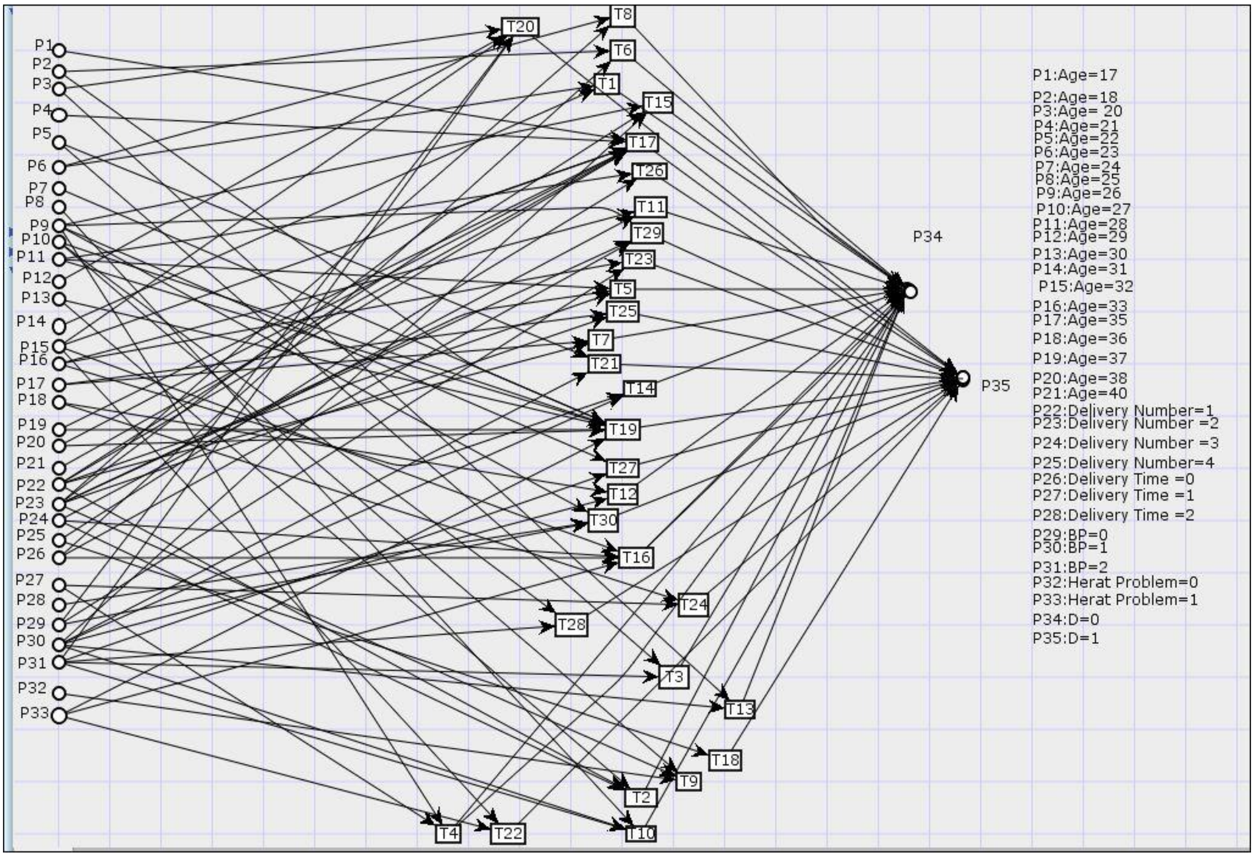
Figure: 4 CPN Tool Snapshot for caesarian data



In Figure.4, the Petri net template, transitions 1 to 30 reflect rules 1 to 30 in the implemented rule above, according to the quantities allocated to each place, and firing each transition ensures that the corresponding rule is fulfilled.

Discussion

The first 16 certain rules are bounded to the class 0 and remaining bounded to class 1. The decisions can be made between the rules since they were executed by FPN and the FPN chart represents that all rules well fired without break seems the grouped rules and gives some précised decisions to predict the possibilities of Caesarian. The list of possibilities is listed in the following table 3.

The set of rules represented a model by FPN, which can be used to characterize the uncertainty. The FPN model varies with expert knowledge beside with some parameters and more instances to create appropriate model to determine the risk factors about the instances [25]. The predicted possibilities help to provide suitable treatment to the ward of maternity to avoid the risks of life.

Table 3: Predictions from the decision rules.

#Decisions	Age	Delivery number	Delivery Time	Blood Pressure	Heart Problem	Caesarian
1.	18 - 36	1 or 2 or 3	Timely or premature	Normal	-	No
2.	27 - 32	2	-	-	Apt	No
3.	32 - 33	3	Timely	-	No	No
4.	17 - 40	1 or 2	-		inept	Yes
5.	20 – 40	-	-	Low or high	-	Yes

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6.	26 - 40	-	Premature or late	-	-	Yes
7.	28 - 40	3	-	-	-	Yes

Form the above table, we can notice that if the instance has inept heart problem or BP or Premature or late delivery time or under third time delivery then it causes Caesarian. Also if having normal BP or timely delivery time and no heart problem results in normal delivery. When an instance comes under any of these factors has to given proper treatment with the displayed factors where as the absent factors in the decision table may take as in the positive manner.

Conclusion

In this paper, the concept of Rough set theory has been investigated through an experiment on small dimension data and established the connection of Petri net's behavior for implementing the decision rules. The experiment reveals that rules generated by LERS can be executed by FPN and the decision making from the rules is constructive and effective with the transition nets of rules by Fuzzy Petri Nets. For case, the possibilities of caesarian cases can be predicted with the help of these decision rules reducted and finalized in the discussion. This study has to be taken over to the high dimensional data to figure out the facts of efficiency of this combination in diagnosing purposes.

References

[1]. Ian H.Witten and Eibe Frank , Data Mining: Practical Machine Learning Tools and Techniques, Second Edition, Elseiver, pp 62-82.

[2]. C. Ding, X. He, H. Zha, H.D. Simon, Adaptive Dimension Reduction for Clustering High Dimensional Data, Proceedings of International Conference on Data Mining, 2002

[3]. Pawlak.Z, Rough Sets and Intelligent Data Analysis, Information Sciences, Vol147, no. 1, pp. 1-12, 2002.

[4]. Abbas, Z. and Burney, A. (2016) A Survey of Software Packages Used for Rough Set Analysis. *Journal of Computer and Communications*, **4**, 10-18.

[5]. T. Slimani, "Application of Rough Set Theory in Data Mining," International Journal of Computer Science & Network Solutions, vol. 1, no. 3, pp. 1-10, 2013.

[6]. Grzymala-Busse, J.W. &Stefanowski, J., Three Discretization Methods for Rule Induction. International Journal of Intelligent Systems, 16, 2001, 29-38.

[7]. Pawlak.Z, Rough Set Theory and ItsApplıcations To Data Analysis, CyberneticsandSystems:AnInternationaljournal, Vol 29, no. 7, pp. 661-688, 1998.

[8]. Pawlak.Z, Rough Set Theory and ItsApplıcations To Data Analysis, CyberneticsandSystems:AnInternationaljournal, Vol 29, no. 7, pp. 661-688, 1998.

[9]. Maciocha, A and Kisielnicki, J. "Intellectual Capital and Corporate Performance" The Electronic Journal of Knowledge Management Volume 9 Issue 3 (271-283) 2008.

[10]. Zdzislaw Pawlak, Rough Sets and Decision Algorithms, W. Ziarko and Y. Yao (Eds.): RSCTC 2000, LNAI 2005, pp. 30-45, 2001**.**

[11]. Polkowski L. &Skowron, A. (Eds.), Rough Sets in Data Mining and Knowledge Discovery, Vol.1, PhysicaVerlag, 500-529, 1998.

[12]. ROSE Software <http://idss.cs.put.poznan.pl/site/rose.html>

[13]. **WEKA:**https://sourceforge.net/projects/weka/

[14]. Grzymala-Busse JW. LERS A system for learning from examples based on rough sets. In: Slowinski R, editor. Intelligent decision support handbook of applications and advances of the rough sets theory. Kluwer Academic Publishers 1992. P3_18.

[15]. Grzymala-Busse, J.W.: Rough Set Theory with Applications to Data Mining. Real World Applications of Computational Intelligence. Springer, Heidelberg, 2004.

[16]. Mienko R., Stefanowski, J., Taumi, K.&Vanderpooten, D., Discovery-Oriented Induction of Decision Rules. Cahier du Lamsade, No.141, Université Paris Dauphine, 1996.

[17]. Almarabeh, H., Analysis of Students' Performance by Using Different Data Mining Classifiers. I.J. Modern Education and Computer Science, 2017. **9**(8): p. 9-15.

[18]. UCI: https://archive.ics.uci.edu/ml/datasets/Caesarian+Section+Classification+Dataset

[19]. Amin, Muhammad & Ali, Amir. (2018). Performance Evaluation of Supervised Machine Learning Classifiers for Predicting Healthcare Operational Decisions. Copyrights © Wavy AI Research Foundation.

[20]. Shen, V.R.L., 2006. Knowledge representation using high-level fuzzy Petri nets. IEEE T. Syst. Man Cy. A, 36(6): 1220-1227.

[21]. He, X., W.C. Chu, H. Yang and S.J.H. Yang, 1999. A new approach to verify rule-based systems using petri nets. Proceeding of 23th IEEE Annual International Computer Software and Applications Conference (COMPSAC'99), pp: 462-467.

[22]. Kouzehgar,M., M.A.Badamchizadeh and S. Khanmohammadi, 2011. Fuzzy Petri nets for human behavior verification and validation. Int. J. Adv. Comput. Sci. Appl., 2(12): 106-114.

[23]. Jenitha.G Shenbaga Ezhi, Kumaravel.A, 2017,A Study On Fuzzy Cognitive Mapping On Real Time Situation, International Journal Of Engineering, Science And - Volume 6(8): 123-127.

[24]. Jenitha.G and Kumaravel.A,2017,An Instance of Reinforcement Learning Based On Fuzzy Cognitive Maps,International Journal of Computational and Applied Mathematics. 12(1):200-207

[25]. Milinkovic, S., Markovic, M., Veskovic, S., Ivic, M., Pavlovic, N., 2013. A fuzzy Petri net model to estimate train delays. Simulat. Model. Pract. Theory 33, 144– 157