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A Recommendation System for Prediction of Elective Subjects

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Abstract: Besides recommending courses which are compulsory for every student to be taken, universities as well as autonomous colleges also offer elective courses selected by the students themselves. At an undergraduate level some students find it difficult to make the choice of elective subjects. By using the information of the past courses taken by the student it is possible to guide the student about elective courses correct for him/her, based on experiences of the other students. In this paper we model the past students performance in elective in relation to other courses taken in past and recommend student on the basis of this model.
Keywords: Educational Data mining, Classification-Artificial neural network, Rapid Miner Tool.

I. INTRODUCTION

Most degree programs in universities worldwide offer elective courses in addition to compulsory courses. Elective courses are specialized courses that are based on interests or critical thinking. However selecting the right elective is of utmost importance as their grades contribute to the final degree, a wrong choice may result in poor grade. In this paper we propose a recommender system that would recommend electives to students based on the student's personal record and other past students records.
Most students find it difficult to choose the right elective for a number of reasons, especially if the electives offered are new to them. If the student takes an elective subject appropriate with his field of interest that would be better for his course of study. By analysing the courses completed by the students in the past, it is possible to categorize the student's capabilities and interest. Data mining is the extraction or mining of useful data from huge databases. The data is extracted by identifying patterns based on the nature of data the elective and compulsory courses that the past students has taken and been successful can be analysed and rules can be extracted. A recommendation system is developed in order to recommend the elective subjects to the students. In a recommendation system, it is important to analyse the data properly and determine the relationship correctly. The students are categorized according to their marks and are placed into different classes by using classification techniques. Classification is a technique of data mining. This is used to classify the data into different classes according to their categorization. The classification process divides students into multiple subsets according to a pre-determined criterion (norlida buniyamin,pauziah mohd arshad 2015). It is a two way technique i.e. Training and testing which maps data into a predefined class. It is the process of supervised learning to separate data into different class data set (taylan 2009).

II. RECOMMENDATION SYSTEM

Recommendation System (RSs) have been widely developed, implemented and accepted for various categories of application like recommendation of products (e.g., books, music, movies) and of services (e.g., restaurants, hotels, websites). In this paper a recommender system for choice of electives is proposed which provides suggestions of elective subjects to the students based on his past performance and other students experiences. Various data mining techniques have been successfully used to form recommendation systems. In general three approaches have *been commonly used to build recommendation systems.*

A. Content-Based

The system learns to recommend items that are similar to the ones that the user liked in the past. The similarity of items is calculated based on the features associated with the compared items. For example, if a user has positively rated a movie that belongs to the comedy genre, then the system can learn to recommend other movies from this genre (Perugini, Gonc¸alves, & Fox 2004).

B. Collaborative Filtering

The simplest and original implementation of this approach recommends to the active user the items that other users with similar tastes liked in the past. The similarity in taste of two users is calculated based on the similarity in the rating history of the users.

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Collaborative filtering is considered to be the most popular and widely implemented technique in RS (Herlocker, Konstan, & Riedl 2000)

C. Hybrid Recommender Systems

These RSs are based on the combination of the above mentioned techniques. A hybrid system combining techniques A and B tries to use the advantages of A to fix the disadvantages of B (Burke 2002). In this paper collaborative filtering approach is used for prediction of elective subjects.

III. RELATED WORK

Education data mining has been used in the past mainly for predicting student performances and for understanding student behaviour.(Pierre et al.) in their study they did a survey to Electrical and Computer Engineering students to collect information about effectiveness of the course. Therefore, relationships between courses may change in time according to student profile. From this the rules are extracted here, and the results obtained may not be valid for all times, and also, because of the course contents, they apply techniques only on computer engineering and similar other departments. It is observed that success in a course is closely related to student's skills (Kreber C) and also learning styles. we can represent a conclusion about a student's abilities, their skills and tendency towards a course and their success. But our aim of study is not to find how the student can be more successful but our aim is to determine relationship between courses by examining previous courses taken by the student. There are a number of studies done on determining relationships among courses by analysing the skills of the student and his previous courses. Integer programming was used t model elective course planning (Stidsen T. R, Kristiansen S., Sorensen M.) They have proposed three different solution methods. (Sanjog Ray and Anuj Sharma) discussed about course recommendation systems that help students in making choices about courses have become more relevant as the range and diversity of different elective courses available for selection have increased. They extend the concept of collaborative filtering approach to develop a course recommendation system. They proposed an approach provides student an accurate prediction of the grade they may get if they choose a particular course, which will be helpful when they decide to selecting an elective subject, as grade is an important parameter for a student while deciding on an elective subject. Experimentally evaluate the collaborative filtering approach on a real life data set and show that the proposed system is effective in terms of accuracy.(Narimel Bendakir and Esma Aimeur) proposed the RARE; a course recommender system based on association rules combines association rules together with user preference data to recommend relevant courses. The recommendation system was used on real data coming from the department of Computer Science. It analyses the past behavior of students concerning their course choices. More explicitly, it formalizes association rules that were implicit before. Those rules enable the system to predict recommendations for new students. A solution to the cold start problem, which is a central question in recommender systems, is also proposed in RARE.(Ekdahl, M., Lindström, S., Svensson) proposed Student Course Recommender system, which is an acronym for Student Course Recommender, suggests courses by using a strategy based on Bayesian Network Modelling. The Student Course Recommender network learns from the information stored about the students who have used the system. It requires the presence of enough cases in the student database. Therefore, if a user has not started or completed any courses, and is not pursuing any degree at the university, Student Course Recommender cannot give him any course recommendation. Another interesting study is done by (Sobecki J., Tomczak J. M 2011) they have used Ant colony optimization, which is commonly used in a wide range of optimization problems, and developed a course suggestion system. They have used success rate of the student in his previous courses. (Parameswaran A., Venetis P., Molina H. G. 2010) in their study of suggestion systems with an emphasis on course suggestion systems, have developed a model. In this model, course specific requirements are determined, and students who attaching these requirements are suggested the course. It makes a multi-suggestion.

IV. EXTRACTING THE RULES

There are a number of methods used to extract rules from complex and huge masses of data. Artificial neural networks, fuzzy logic, genetic algorithms, data mining are well-known examples of these methods. Each method has advantages and disadvantages dependent on the areas it is used.

In course recommender system collaborative filtering approach was used. The collaborative filtering approach has divided into two types i.e. User-Based Collaborative Filtering and item-Based Collaborative Filtering. In user-based collaborative approach Similarity between the active user and every other user is calculated.Based on their similarity value with user and set of *k* users, most similar to active user is then selected. Finally, prediction for item is generated by taking the weighted average of the ratings given by the *k* similar neighbours to items. In item-based Collaborative Filtering generates predictions based on a model of item-item similarity rather than user-user similarity. In item-based collaborative filtering, first, similarities between the various items are computed. Then from the set of items rated by the target user, *k* items most similar to the target item are selected (Sanjog Ray, Anuj Sharma).

In RARE system, the two phases was developed i.e. offline phase and online phase. In offline phase they firstly classify the data and after that an association rules are generated. In classification technique they used decision tree to differentiate the subjects and students. In online phase the prediction is done on the basis of rule extracted in offline phase (Narimel Bendakir and Esma Aimeur).

V. PROPOSED PLAN

The work includes collecting the previous two years database. Analysing the collected database. After that the data cleaning and feature selection is done. After that the classification algorithm is applied to classify the data. As the classification is done on the database the classes are form then the association rule generation algorithm is applied.

A. Pre-Processing/Cleaning Of Dataset

Rapid miner studio is a code free environment for designing advanced analytical processes with machine learning, data mining, text mining, predictive analytics and business analytics. RapidMiner Studio combines technology to serve a user-friendly integration of the most recent as well as traditional data mining techniques. Defining analysis processes with RapidMiner Studio is done by drag and drop of operators, setting parameters and combining operators. Rapid miner studio contains more than 1500 operations tougher for all tasks of data analytics from data partitioning.

For our data pre-processing we have used rapid miner studio 7.4.000.There are five types of views are available for performing the process. Those are repository, process, design, result, operators. Performing any task in rapid miner tool first of all add data from repository view. In operator view all the operators are available for performing operation. In design we need to drag and drop the operator from operator view and after clicking run button the result is displayed in the result view. For pre-processing we drag data file from the repository view then drag replace missing value operator from operator view after that operator impute missing value and make connection between file and operators. After making the connection, run the process and the result is generated. The features of rapid miner tool are

1) Rapid miner has the full API support, so that it provides a extensive range of functionality and support.
2) Twenty two file formats are supported by rapid miner.
3) Many algorithms of WEKA have been present in rapid miner.
4) Full package.
5) Excel files and different databases can easy read and write by rapid miner.

After completing the pre-processing the classification algorithm is applied on the data set. For that the artificial neural network is used. In artificial neural network Multilayer perceptron model is used. we are taking multiple inputs in input string that's why multilayer perceptron model is been used. An ANN is a neural network where the main element is precisely the neuron. It is an artificial model planned to imitate the procedure of a biological neuron such that all neuron will contain as distant as possible, the same physiological and efficient individuality of biological neurons. There are several types of neural networks and each one with special characteristics, but in this work is adopted the Perceptron.

B. Multi-Layer Perceptron Algorithm

Multi-layered neural networks are basically used to deal with data-sets which has a huge number of features, particularly non-linear ones. A multilayer perceptron (MLP) is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate outputs. They are supervised networks so they require a desired response to be trained. Model of Multilayer Perceptron is recognized for providing fine results in comparison with other models related to solve classification problem. For this, the selection of the appropriate architecture (number of neurons and layers) for each specific case is an empirical problem (trial and error). MLP is composed of a minimum of three layers consisting of an input layer, one or more hidden layers and an output layer (Huey Nee Lim, Elsie Usun Francis,Mohd Yusoff Mashor 2016). The layers are fully interconnected in one direction, from the input layer toward the output layer. The number of neurons in the input and output layers are governed by the number of inputs and outputs of the pattern to be recognized. However, the number of neurons in the middle layer can be selected depending upon the application. Input patterns are exposed to the network whose output is compared to the target values to calculate the error, which is corrected in the next pass by adjusting the synaptic weights.

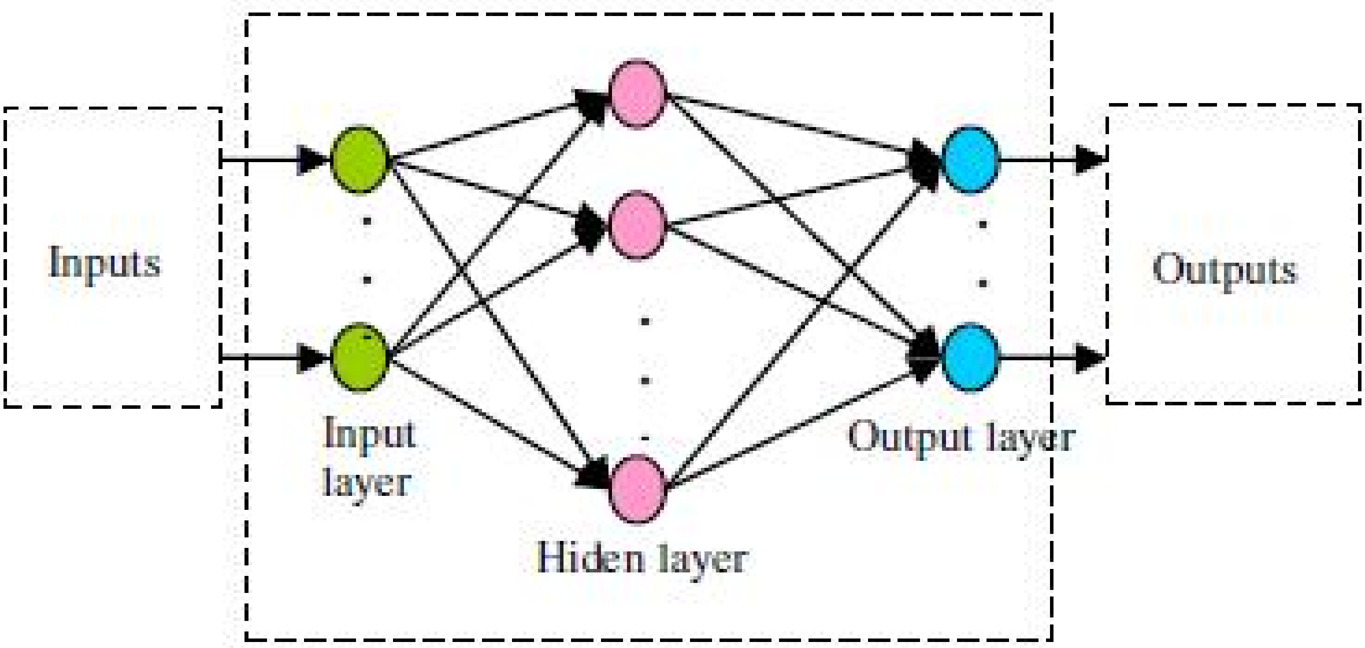

Figure 1: Multilayer Perceptron Model

C. *Association Rule Mining*

The association rule mining (ARM) has received considerable attention over the last decade. The task of ARM is to find the correlations between items in a dataset by discovering items frequently appeared together in a transactional dataset. In association rule mining the rules are form according to dataset selected.

For an active user U_a in the set of users U, the prediction problem is to predict the rating active user will give to an item I_t from the set of all items that U_a has not yet rated. The steps followed to predict the user U_a are as follows:

Step 1: Similarity between the active user U_a and every other user is calculated.

Step 2: Based on their similarity value with user U_a, set of k users, most similar to active user U_a is then selected.

Step 3: Finally, prediction for item I_t is generated by taking the weighted average of the ratings given by the k similar neighbours to item I_t

VI. IMPLEMENTATION

We performed the experimental evaluation on the anonym zed data set of 250 students and the grades they scored in 22 subjects. The dataset include two year of historical data which consist of two batches of data. Out of the total 4344 data row, training and testing is done on 586 data rows. To recommend the elective subject we use most prominent and widely used classification technique i.e. neural network. The multilayer perceptron model is used to classify the dataset into n number of groups. The groups are formed according to student score in subjects. The five groups are formed, the groups are very low, low, medium, high and very high. In very low group the student score marks between 0-20 are gathered. In low group the student score marks between 20-40 are gathered. In Medium group the student score marks between 40-60 are gathered. In High group the student score marks between 60-80 are gathered. In Very high group the student score marks between 80-100 are gathered. Each and every subject groups are formed like that.

After classification the association rules are generated according to semester wise. In association rule generation the relation between the subjects of 4^{th} semester and 5^{th} semester are generated. Likewise 5^{th} and 6^{th} semester and 6^{th} and 7^{th} semester relations are generated. As the relations are formed between the subjects of all semester the recommendation system is generated. When new student enters their marks of previous semester to predict the next semester elective the recommendation system gives recommendation to his/her.

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VII. SYSTEM ARCHITECTURE

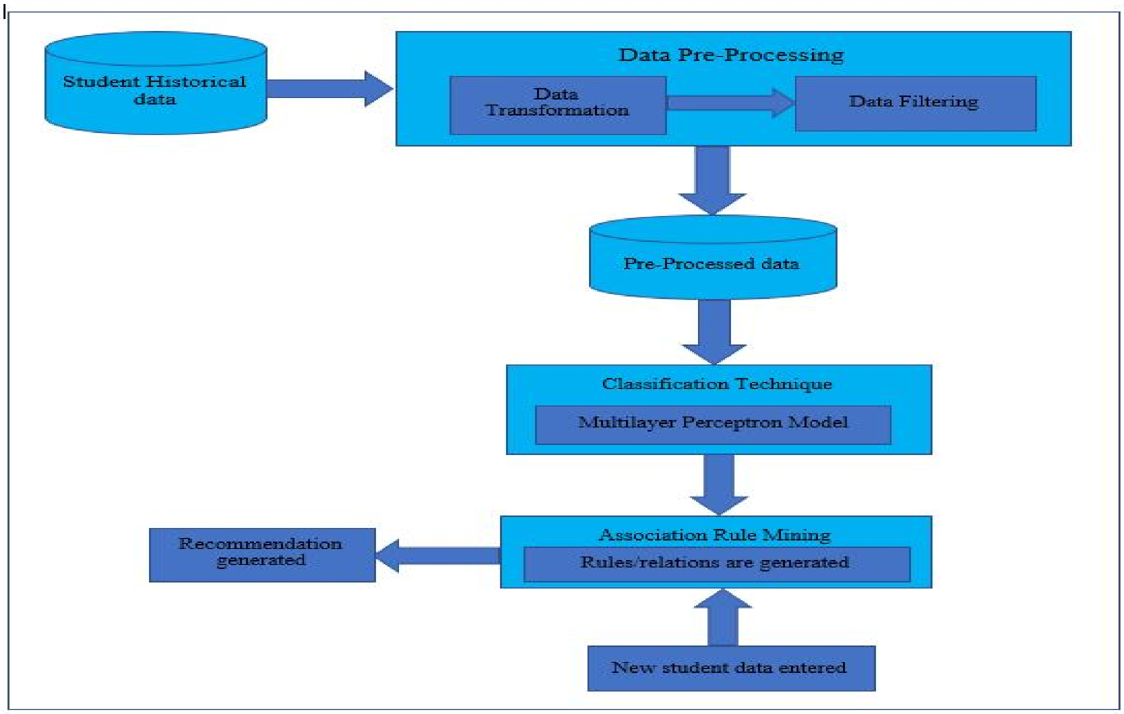
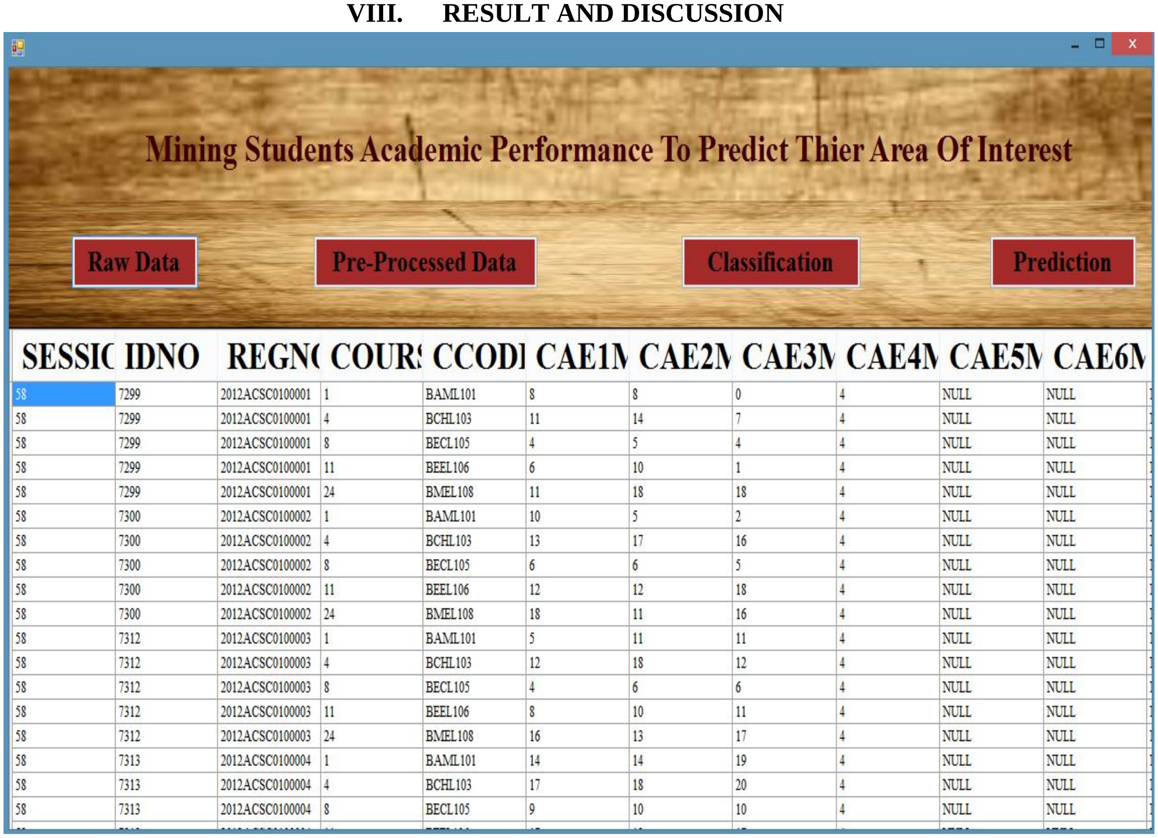


Figure 2: System Architecture

VIII. RESULT AND DISCUSSION



SESSIC	IDNO	REGN(	COUR!	CCODI	CAE1N	CAE2N	CAE3N	CAE4N	CAE5N	CAE6N
58	7299	2012ACSC0100001	1	BAML101	8	8	0	4	NULL	NULL
58	7299	2012ACSC0100001	4	BCHL103	11	14	7	4	NULL	NULL
58	7299	2012ACSC0100001	8	BECL105	4	5	4	4	NULL	NULL
58	7299	2012ACSC0100001	11	BEEL106	6	10	1	4	NULL	NULL
58	7299	2012ACSC0100001	24	BMEL108	11	18	18	4	NULL	NULL
58	7300	2012ACSC0100002	1	BAML101	10	5	2	4	NULL	NULL
58	7300	2012ACSC0100002	4	BCHL103	13	17	16	4	NULL	NULL
58	7300	2012ACSC0100002	8	BECL105	6	6	5	4	NULL	NULL
58	7300	2012ACSC0100002	11	BEEL106	12	12	18	4	NULL	NULL
58	7300	2012ACSC0100002	24	BMEL108	18	11	16	4	NULL	NULL
58	7312	2012ACSC0100003	1	BAML101	5	11	11	4	NULL	NULL
58	7312	2012ACSC0100003	4	BCHL103	12	18	12	4	NULL	NULL
58	7312	2012ACSC0100003	8	BECL105	4	6	6	4	NULL	NULL
58	7312	2012ACSC0100003	11	BEEL106	8	10	11	4	NULL	NULL
58	7312	2012ACSC0100003	24	BMEL108	16	13	17	4	NULL	NULL
58	7313	2012ACSC0100004	1	BAML101	14	14	19	4	NULL	NULL
58	7313	2012ACSC0100004	4	BCHL103	17	18	20	4	NULL	NULL
58	7313	2012ACSC0100004	8	BECL105	9	10	10	4	NULL	NULL

Figure 3: Raw dataset

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In raw dataset we collected the data of graduation completed students which contain their session no, ID no., registration number course code , TAE Marks, CAE marks and Total marks.

SESSIONNO	REGNO	Subjects	CAE1MARK	CAE2MARK	CAE3MARK	TOTAL_MARKS
64	2012ACSC0100001	Graph Theory & Combinatorics	13	15	14	44
64	2012ACSC0100001	Theory of Computation	12	9	13	66
64	2012ACSC0100001	System Programming	9	13	13	66
64	2012ACSC0100001	Data Communication	8	12	6	66
64	2012ACSC0100001	Object Oriented Programming Throu...	12	15	13	70
64	2012ACSC0100002	Graph Theory & Combinatorics	14	17	19	42
64	2012ACSC0100002	Theory of Computation	13	14	15	39
64	2012ACSC0100002	System Programming	10	14	17	62
64	2012ACSC0100002	Data Communication	11	18	14	72
64	2012ACSC0100002	Object Oriented Programming Throu...	13	15	18	50
64	2012ACSC0100003	Graph Theory & Combinatorics	11	19	13	48
64	2012ACSC0100003	Theory of Computation	17	10	11	58
64	2012ACSC0100003	System Programming	13	15	13	20
64	2012ACSC0100003	Data Communication	15	12	9	74
64	2012ACSC0100003	Object Oriented Programming Throu...	11	11	12	57
64	2012ACSC0100004	Graph Theory & Combinatorics	18	20	19	63
64	2012ACSC0100004	Theory of Computation	16	18	16	70
64	2012ACSC0100004	System Programming	13	17	16	57
64	2012ACSC0100004	Data Communication	11	16	18	41
64	2012ACSC0100004	Object Oriented Programming Throu...	15	14	18	70
64	2012ACSC0100005	Graph Theory & Combinatorics	14	16	17	22
64	2012ACSC0100005	Theory of Computation	10	10	15	23
64	2012ACSC0100005	System Programming	10	10	18	25

Figure 4: Pre-Processed data

The pre-processing is done by using the rapid miner tool. In pre-processing unwanted data, noise data, null values are removing and finally important features are taken for further process.

```
C:\Users\Neha\Documents\Visual Studio 2012\Projects\login\login\bin\Debug\login.vshost.exe
<Common Subjects>==>                                                           <Output>
Total No of Students between 0 to 20 Marks =13

2012ACSC0100022   | Computer Networks                        |18          | 0.588291078015468 very Low
2012ACSC0100024   | Computer Networks                        |18          | 0.588291078015468 very Low
2012ACSC0100025   | Computer Networks                        |18          | 0.588291078015468 very Low
2012ACSC0100066   | Computer Networks                        |18          | 0.588291078015468 very Low
2012ACSC0100076   | Computer Networks                        |18          | 0.588291078015468 very Low
2012ACSC0101100   | Computer Networks                        |18          | 0.588291078015468 very Low
2012ACSC0101103   | Computer Networks                        |18          | 0.588291078015468 very Low
2012ACSC0101106   | Computer Networks                        |18          | 0.588291078015468 very Low
2012ACSC0101110   | Computer Networks                        |18          | 0.588291078015468 very Low
2012ACSC0111053   | Computer Networks                        |18          | 0.588291078015468 very Low
2012ACSC0111056   | Computer Networks                        |18          | 0.588291078015468 very Low
2012ACSC0111060   | Computer Networks                        |18          | 0.588291078015468 very Low
2012ACSC0111121   | Computer Networks                        |18          | 0.588291078015468 very Low
Total No of Students between 20 to 40 Marks =44

2012ACSC0100002   | Computer Networks                        |34          | 0.650851851909814 Low
2012ACSC0100003   | Computer Networks                        |23          | 0.650851851909814 Low
2012ACSC0100004   | Computer Networks                        |39          | 0.650851851909814 Low
2012ACSC0100007   | Computer Networks                        |35          | 0.650851851909814 Low
2012ACSC0100008   | Computer Networks                        |32          | 0.650851851909814 Low
2012ACSC0100009   | Computer Networks                        |39          | 0.650851851909814 Low
2012ACSC0100010   | Computer Networks                        |29          | 0.650851851909814 Low
2012ACSC0100011   | Computer Networks                        |31          | 0.650851851909814 Low
2012ACSC0100012   | Computer Networks                        |26          | 0.650851851909814 Low
2012ACSC0100013   | Computer Networks                        |25          | 0.650851851909814 Low
2012ACSC0100014   | Computer Networks                        |26          | 0.650851851909814 Low
2012ACSC0100018   | Computer Networks                        |36          | 0.650851851909814 Low
2012ACSC0100019   | Computer Networks                        |33          | 0.650851851909814 Low
2012ACSC0100027   | Computer Networks                        |33          | 0.650851851909814 Low
2012ACSC0100032   | Computer Networks                        |36          | 0.650851851909814 Low
2012ACSC0100033   | Computer Networks                        |35          | 0.650851851909814 Low
2012ACSC0100058   | Computer Networks                        |24          | 0.650851851909814 Low
2012ACSC0100067   | Computer Networks                        |31          | 0.650851851909814 Low
2012ACSC0100080   | Computer Networks                        |39          | 0.650851851909814 Low
2012ACSC0100085   | Computer Networks                        |36          | 0.650851851909814 Low
2012ACSC0101088   | Computer Networks                        |28          | 0.650851851909814 Low
2012ACSC0101089   | Computer Networks                        |39          | 0.650851851909814 Low
2012ACSC0101090   | Computer Networks                        |34          | 0.650851851909814 Low
2012ACSC0101095   | Computer Networks                        |37          | 0.650851851909814 Low
2012ACSC0101098   | Computer Networks                        |34          | 0.650851851909814 Low
2012ACSC0101099   | Computer Networks                        |26          | 0.650851851909814 Low
2012ACSC0101101   | Computer Networks                        |36          | 0.650851851909814 Low
2012ACSC0101105   | Computer Networks                        |21          | 0.650851851909814 Low
2012ACSC0101122   | Computer Networks                        |37          | 0.650851851909814 Low
2012ACSC0101124   | Computer Networks                        |30          | 0.650851851909814 Low
2012ACSC0108093   | Computer Networks                        |38          | 0.650851851909814 Low
2012ACSC0111029   | Computer Networks                        |38          | 0.650851851909814 Low
2012ACSC0111031   | Computer Networks                        |35          | 0.650851851909814 Low
2012ACSC0111038   | Computer Networks                        |26          | 0.650851851909814 Low
2012ACSC0111040   | Computer Networks                        |37          | 0.650851851909814 Low
2012ACSC0111046   | Computer Networks                        |35          | 0.650851851909814 Low
```

Figure 5: Classified Data

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In classification, the data is classified into different groups. The subject wise groups are formed.

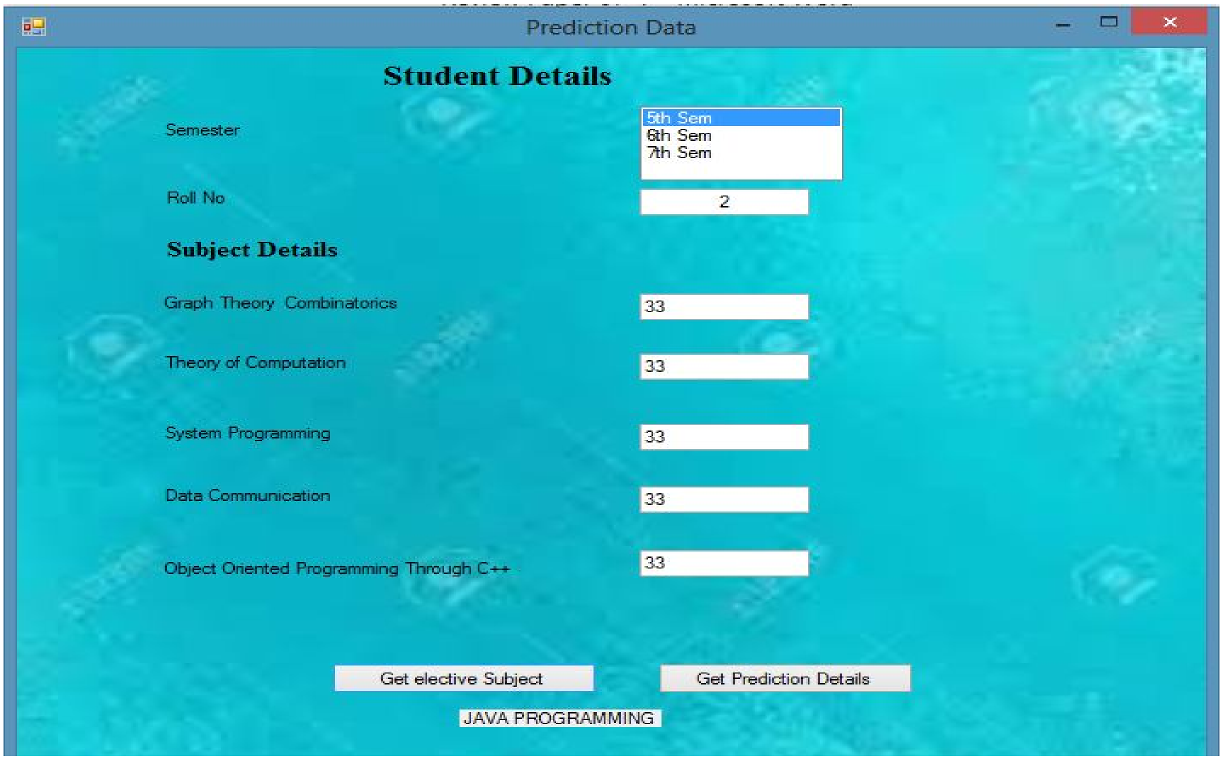
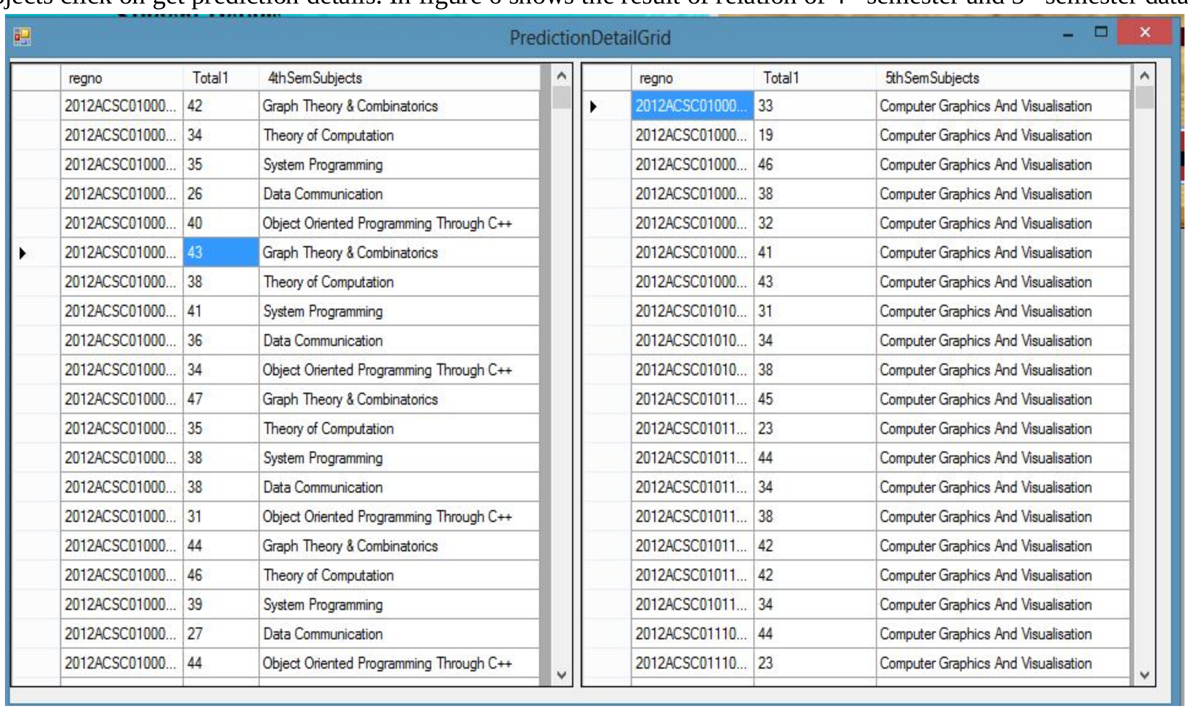


Figure 6: Final Predicted Elective Shown here

In this new student has to entered the marks of their previous semester and click on get elective button. For finding the relation between subjects click on get prediction details. In figure 6 shows the result of relation of 4th semester and 5th semester data.



regno	Total1	4thSemSubjects
2012ACSC01000...	42	Graph Theory & Combinatorics
2012ACSC01000...	34	Theory of Computation
2012ACSC01000...	35	System Programming
2012ACSC01000...	26	Data Communication
2012ACSC01000...	40	Object Oriented Programming Through C++
2012ACSC01000...	43	Graph Theory & Combinatorics
2012ACSC01000...	38	Theory of Computation
2012ACSC01000...	41	System Programming
2012ACSC01000...	36	Data Communication
2012ACSC01000...	34	Object Oriented Programming Through C++
2012ACSC01000...	47	Graph Theory & Combinatorics
2012ACSC01000...	35	Theory of Computation
2012ACSC01000...	38	System Programming
2012ACSC01000...	38	Data Communication
2012ACSC01000...	31	Object Oriented Programming Through C++
2012ACSC01000...	44	Graph Theory & Combinatorics
2012ACSC01000...	46	Theory of Computation
2012ACSC01000...	39	System Programming
2012ACSC01000...	27	Data Communication
2012ACSC01000...	44	Object Oriented Programming Through C++

regno	Total1	5thSemSubjects
2012ACSC01000...	33	Computer Graphics And Visualisation
2012ACSC01000...	19	Computer Graphics And Visualisation
2012ACSC01000...	46	Computer Graphics And Visualisation
2012ACSC01000...	38	Computer Graphics And Visualisation
2012ACSC01000...	32	Computer Graphics And Visualisation
2012ACSC01000...	41	Computer Graphics And Visualisation
2012ACSC01000...	43	Computer Graphics And Visualisation
2012ACSC01010...	31	Computer Graphics And Visualisation
2012ACSC01010...	34	Computer Graphics And Visualisation
2012ACSC01010...	38	Computer Graphics And Visualisation
2012ACSC01011...	45	Computer Graphics And Visualisation
2012ACSC01011...	23	Computer Graphics And Visualisation
2012ACSC01011...	44	Computer Graphics And Visualisation
2012ACSC01011...	34	Computer Graphics And Visualisation
2012ACSC01011...	38	Computer Graphics And Visualisation
2012ACSC01011...	42	Computer Graphics And Visualisation
2012ACSC01011...	42	Computer Graphics And Visualisation
2012ACSC01011...	34	Computer Graphics And Visualisation
2012ACSC01110...	44	Computer Graphics And Visualisation
2012ACSC01110...	23	Computer Graphics And Visualisation

Figure 7: Relation between 4th semester and 5th semester

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IX. CONCLUSION

This paper present the recommendation system for recommending elective subjects based on the neural network and association rule. This system works on real database coming from the university or colleges. It analyses the past behaviour of students concerning their elective subject choices. More explicitly, it formalizes association rules that were implicit before. These rules enable the system to predict recommendations for new students. When new students enter their marks the elective subject is predicted by the recommendation system.

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REFERENCES

[1] Ana Ktona, Denada Xhaja, Ilia Ninka, "Extracting Relationships Between Students'Academic Performance and Their Area of Interest Using Data Mining Techniques" in IEEE 2014 pp 6-11.

[2] Bo Guo, Rui Zhang, Guang Xu, Chuangming Shi and Li Yang,"Predicting Students Performance in Educational Data Mining" IEEE 2015 pp 125-128.

[3] Alan Cheah Kah Hoe, Mohd Sharifuddin Ahmad, Tan Chin Hooi, Mohana Shanmugam, Saraswathy Shamini Gunasekaran, Zaihisma Che Cob, Ammuthavali Ramasamy,"Analyzing Students Records to Identify Patterns of Students' Performance" UNITEN Grant Scheme No.: J510050264 pp544-547.

[4] Norlida Buniyamin, Usamah bin Mat, Pauziah Mohd Arshad,"Educational Data Mining for Prediction and Classification of Engineering Students Achievement" in IEEE 2015 Pp 49-53.

[5] Usamah bin Mat, Norlida Buniyamin, Pauziah Mohd Arsad, RosniAbu Kassim,"An Overview of Using Academic Analytics to Predict and Improve Students' Achievement: A Proposed Proactive Intelligent Intervention" in IEEE 2013 Pp 126-130.

[6] Huey Nee Lim1, Elsie Usun Francis,Rosline Hassan,"Classification of Bone Marrow Acute Leukemia Cells using Multilayer Perceptron Network" in IEEE 2016 Pp 486-490.

[7] Ms.Tismy Devasia ,Ms.Vinushree T P , Mr.Vinayak Hegde,"Prediction of Students Performance using Educational Data Mining" in International Journal ofInnovative Research in Science, Engineering and Technology, vol 3,Special iss 3, March 2014,pp 25-30.

[8] Kin Fun Li, David Rusk and Fred Song, "Predicting Student Academic Performance" Seventh International Conference on Complex, Intelligent, and Software Intensive Systems 2013, pp27-33.

[9] Sumit Garg, Arvind K. Sharma, "Comparative Analysis of Data Mining Techniques on Educational Dataset" , International Journal of Computer Application 2013, Pp 1-5.

[10] Taylan, O., Karagözoğlu, Bahattin "An adaptive neuro-fuzzy model for prediction of student's academic performance." Computers& Industrial Engineering 2009 pp- 732-741.

[11] Mohd Arshad, P., N. Buniyamin, Ab Manan J"Neural Network and Linear Regression Methods for Prediction of Students Academic Achievement"2014 IEEE Global Engineering Education Conference (EDUCON), Istanbul, Trukey, IEEE.

[12] Baker, R. S. J. D., Kalina Yacef"The State of Educational Data Mining in 2009: A Review and Future Visions." Journal of Educational Data Mining pp- 3-16.

[13] Mat, U., Norlida Buniyamin, P. Mohd Arshad, R. A. Kassim" An Overview of Using Academic Analytics to Predict and Improve Students' Achievement: A Proposed Proactive Intelligent Intervention" IEEE 5th International Conference on Engineering Education (2013 ICEED), Selangor, Malaysia, , IEEE 2014.

[14] Zhang Y, e. a." Using data mining to improve student retention in HE: a case study."Proc.12th Int. Conf. on Enterprise Information Systems, 2009

[15] Dekker, G., Pechenizkiy, M., and Vleeshouwers J" Predicting students drop out: A case study."Proceedings of the 2nd International Conference on Educational Data Mining, 2009 ,pp- 41-50.

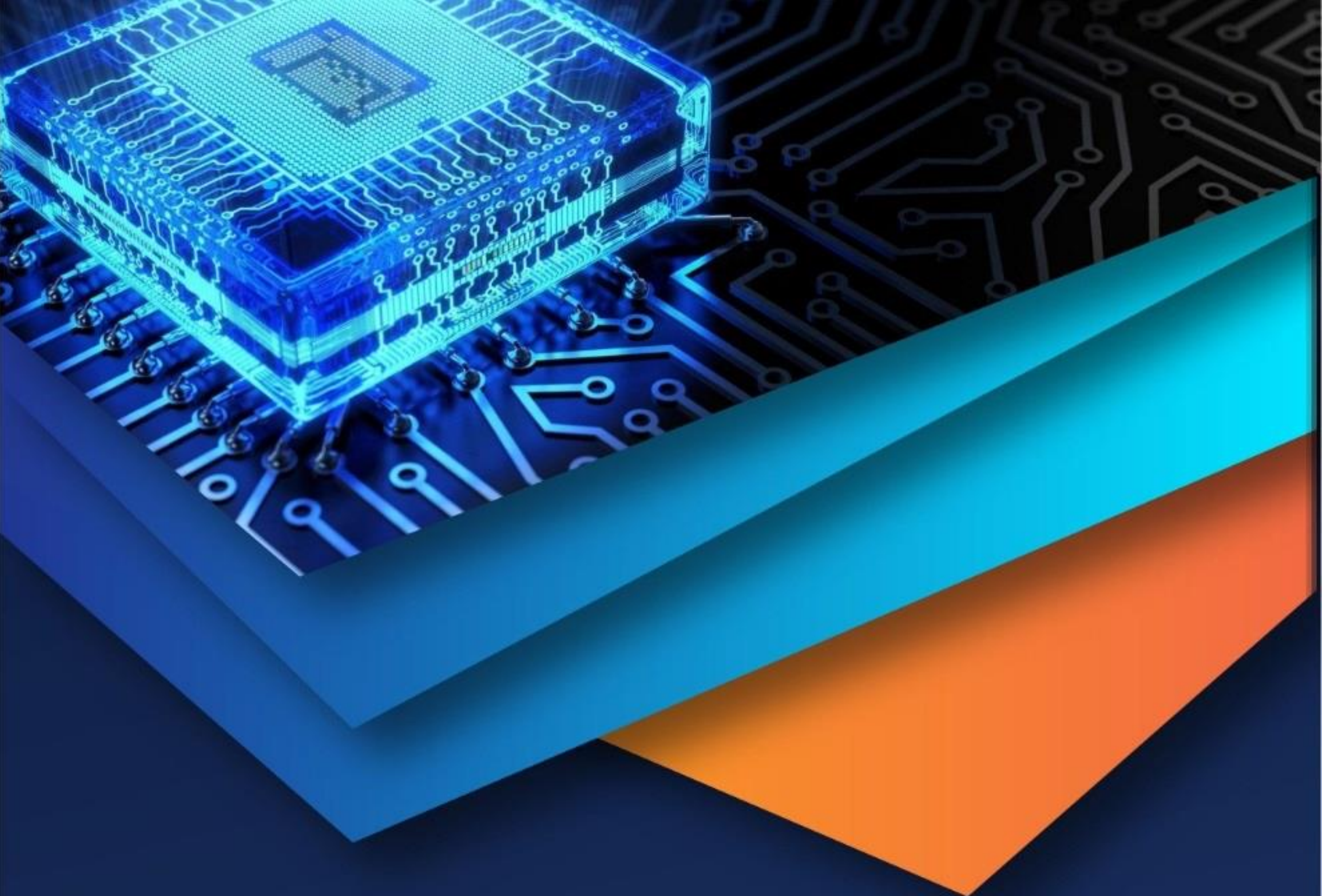
[16] Ritu Sharma, Mr. Shiv Kumar, Mr. Rohit Maheshwari,"Comparative Analysis of Classification Techniques in Data Mining Using Different Datasets" in IJCSMC, Vol. 4, Issue. 12, December 2015, pg.125 – 134.

[17] Sanjog Ray and Anuj Sharma," A Collaborative Filtering Based Approach for Recommending Elective Courses" ,ICISTM 2011 © Springer-Verlag Berlin Heidelberg 2011, pp- 30–339.

[18] Narimel Bendakir and Esma Aimeur," Using Association Rules for Course Recommendation", American Association for Artificial Intelligence 2006, pp-1-10.

[19] Francesco Ricci , Lior Rokach , Bracha Shapira ,Paul B. Kantor," Recommender Systems Handbook" , Springer New York Dordrecht Heidelberg London 2010, pp-1-845.

[20] Bendakir N., Aimeur E., Using association rules for course recommendation, American Association for Artificial Intelligence, 2006 , pp-1-900.



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45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

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