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A NOVEL PREDICTION MODEL FOR ACADEMIC EMOTIONAL PROGRESSION OF GRADUATES

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ABSTRACT

According to the present day necessity of the universities in anticipating the placement and career opportunities of the students, there is a need for better assessment and prediction tools based on various dimensions of the student. In this regard, Multilayer Perceptron (MLP) based prediction model is suggested to predict the job opportunities of the Undergraduate students by considering the student's Academic aspects such as Major, Discipline, Working Nature, Academic History (X and pre-university), Regularity, No. of failed courses, Degree of Intelligence, Discipline and Current GPA; Co-curricular aspects such as Project accomplishment, Certification courses, Workshops and Presentations, pre-placement training attendance, Pre-Placement Test performance, Communication Skills; Behavioral aspects such as Introvert, Extrovert, Team work attitude and other aspects such as Family background, Career objective. This system is designed to improve the accuracy in prediction of performance of the students, who are having low probability in getting a job. Thus, the outcome can be used to take few proactive measures such as conducting additional training classes and remedial counseling for enhancement of probability in getting placements. To evaluate the performance of the proposed model, collected data voluntarily from 153 final year engineering graduate students of Vignan's University, India. Prediction accuracy of Multilayer Perceptron outperforms other classification methods.

Keywords: prediction, progression, MLP, Naïve Bayes, CART, Apriori.

INTRODUCTION

Extracting knowledge from high volumes of data stored either in databases, data warehouses or in other information repositories is usually performed by Data mining. By analysing structured data, a model is built and such model is used to predict future trends or behaviours. Prediction built a model and such model used to identify class information of an unlabelled sample. Prediction can be categorized into three ways called classification, regression, and density estimation.

Classification methods like decision tree, Bayesian networks, etc. used to predict the students' behaviour in an educational environment and his/her career objective or placement performance. At present, the higher education tasks are being evaluated by the data mining methodologies. These methodologies help us to improve our understanding of the learning process where this approach focuses on identifying, extracting and evaluating variables related to the placement readiness of students. Educational Data Mining (EDM) a new emerging field which deals with data mining in higher education. It deals with developing methods to explore the different unique types of data that originate from an educational background. The huge gap in the higher education system can be filled with the help of Educational Data Mining methods.

Evaluation plays a critical role in the student's career development. The marks scored by the student and their behaviour in the classroom will decide the career of a student. Therefore, it is required to predict whether the student will be recruited or not, in a campus drive. If the prediction states that a student failed to get job then additional efforts or counselling will be offered to improve his/her behaviour, communication and few other aspects. The Prediction process includes academic aspects, behavioural aspects and few other aspects will affect the job opportunity of a student.

LITERATURE SURVEY

As many papers in this educational research focuses on learning methodologies, Pedagogic methods, and factors influencing student performance. Limited work done towards the prediction of student performance in current digitally enriched society. Ernesto Pathros Ibarra García [1] *et al*., presented a modal in which the academic performance of the newly admitted students into the engineering stream was predicted by considering socio-demographic and academic variables. Naive Bayes classifier was used to predict the academic performance which yields an accuracy of 50%.

Shaobo Huang and Ning Fang [2] presented a paper on prediction of academic performance in an introductory engineering course "Engineering Dynamics". MLR, MLP, RBF and SVM classifier are used for prediction and out of all; SVM outperformed the other models with an accuracy of 89%. But the work is limited to a single course and few factors were considered. Jui-Hsi Fu *et al*., [3] proposed a novel framework for student's performance prediction in the university based on Support Vector Regression (SVR). Big five personality model is implemented to measure student profiles by analysing students' undergraduate performance and behaviour. It was shown that there are correlations between a person's performance and personality characteristics with an accuracy of 80%. They have tested it on only 120 data samples through questionnaires.

Kamal Bunkar *et al*., [5] performed a comparative study on different decision tree algorithms for

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predicting the academic performance of the graduate students B.A of Vikram University and achieved an accuracy of 85%. Indriana Hidayah *et al*., [6] proposed a method to classify the students based on their academic performance prediction using Neuro fuzzy concept which is a combination of fuzzy's IF-THEN rules and neural networks. The data samples were collected through quizzes and questionnaires and divided into four categories as poor, satisfactory, good, and very good. They considered input parameters such as intelligence, talent, interest, and motivation and combination of three inputs (interest, talent, and motivation). Dr. Dharminder Kumar *et al*. [7] used different classification techniques to the build performance prediction model based on students' social integration, academic integration, and various emotional skills. Two algorithms (J48 and Random tree) were applied on MCA students for prediction. The algorithms were applied on only limited data samples and achieved an accuracy of 94% with random tree algorithm and 88% with J48 algorithm.

V.O. Oladokun *et al*., [8] developed an approach to predict the performance of a student, who got admission into the Nigerian university. Factors like scores such as current courses, matriculation scores, age, gender, parent history and location have affected the performance of the student in that model. Multilayer Perceptron was used to calculate the classification accuracy over the performance of students. Behrouz Minaei *et al*., [9] presented how to classify the students' final grade based on web-based log data.

ATTRIBUTE ANALYSIS AND DISCRETIZATION

The Prediction of the job opportunities and the academic outcome of a student involves various attributes such as 10^{th}, 12^{th} and current GPA, Self discipline, current no. of backlogs, Degree of Intelligence, Attendance percentage, Family background, Career objective, Introvert, Extrovert, Team Working Attitude, Projects proficiency, Certification courses, Workshops and PPTs participation, CRT attendance, Pre Placement Test Performance, Communication Skills, Attitude.

10^{th}, 12^{th} and current GPA: The students' Marks % / Grades in 10^{th}, 12^{th} and in graduation upto current semester play a vital role in the eligibility criteria for a campus drive. These are categorized into six intervals which are labelled as O (>90%), E (>85%), A (>80%), B (>70%), C (>60%) and D (>50%).

Attendance percentage: Student's regularity in attending classes reflects his motivation towards learning. Attendance Percentage of a student is categorized into four intervals with labels as Very Regular (>=90%), Regular (>80%), moderately Regular (>70%), Irregular (<70%).

Number of Backlogs: The number of backlogs represents the students' focus and dedication towards studies. This attribute plays a vital role in the eligibility criteria for a campus drive and also has a great impact on the final grade. Number of backlogs are categorized into three classes with labels as Nil (Number of backlogs), Minimum (Number of backlogs <=3) and Maximum (Number of backlogs >3).

Degree of intelligence: The level of understanding the concepts and memorizing capabilities of a student reflect the performance of a student in the interview and also has a great impact on the final grade. This has three values Low, Average, Good.

Self-discipline: The student's behaviour in his daily life including attention and concentration in the class hours affect the performance. A student with self-discipline will always tend to be attentive and concentrated during a lecture and it is categorized as Low, Average and Good.

Family background: The family background in the aspect of educational qualification of the parents is also a considerable attribute that affect the academic and career outcome of a student. If a student's parent is at least a graduate, there is more chance that the student is well monitored and mentored towards his career goals. Family background is categorized into three classes labelled as Educated, (Professional or PG) Semi- Educated (Graduate or Less) and Illiterate.

Career objective: Career objective is a short-term goal set by a student which is to be achieved by the end of his graduation. A student with a clear career objective will always be focused and determined towards the goal. Career objective is categorized into three classes with labels as Job, Higher Studies and Business.

Introvert: Here, introvert in the sense, being shy and not interested in expressing their views. In an interview the most important element is, how expressive we are, so this attribute affects the job opportunities of a student. Introvert is categorized into three classes on a scaling from 1 to 10 with class labels as Low (<=3), Average (<=7), High (>7).

Extrovert: Here, Extrovert in the sense, being a sociable person and having the will to express his own views. In an interview, if a student is able to express his views and ideas according to the situation then it surely affects his job opportunity. Extrovert is categorized into three classes on a scaling from 1 to 10 with class labels as Low (<=3), Average (<=7), High (>7).

Team work (Group Study): Team work is the most essential requirement for a student either to work on a project during the graduation or throughout his career. Hence, this is one of the required attribute for a student to have better job opportunities. Team work is categorized into three classes with labels as Regular, Occasionally, Never (Individual Study).

Projects proficiency: It is not sure that all the projects get succeeded but a student should be able to understand about the project and gets hands on experience. This attribute of a student depicts understanding and problem solving ability of a student. Project Proficiency is categorized into three classes with labels as Poor (Less understanding), Average (Moderate understanding), and Good (Complete understanding).

Certification courses: Certification courses in technical domain will be a great asset for a student to get

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placement and also depicts whether the student is motivated towards his career or not. A student who has technical certifications will have a high priority in the selection of candidates in placement interviews. Certification courses have two categories with class labels as Yes (At least two), and No.

Workshops and conferences participation: A student who actively participates in workshops and conferences will enhance the knowledge about the latest technologies and tools. Participation in Presentation of conference papers improves the presentation skills of the student. So, these attributes affect the career opportunities of a student. Workshops and Conference participation is categorized into three with class labels as Poor, Fair (More than 3 programs), and Good (More than 6 programs).

Pre-placement training attendance: Pre-Placement Training is conducted for training the students to improve the skills required in the aspect of career. The student's willingness in attending these classes shows the level of interest towards his career. CRT attendance is categorized into four with class labels as Poor (<50%), Average (<70%), Good (<80%), and Very Good (>80%).

Pre-placement test performance: Pre-Placement test is conducted for assessing the preparation levels of a student. If a student is having good score in these tests, then student is more likely to get placed in the campus drive. This is categorized into four with class labels as Poor (<50%), Average (<70%), Good (<80%), and Very Good (>80%).

Communication skills: Communication skills deal with listening, speaking, reading and writing capabilities of a student. If a student is good at communication skills then scope is more to get succeeded in the career. Communication skills are categorized into four with class labels as Poor, Average, Good, and Very Good.

The detailed architecture of the proposed method is shown in Figure-1. About 153 graduate students' data has collected and then pre-processing techniques are applied on the dataset for cleansing. Data pre-processing is vital for the knowledge retrieval. In the next step, the attributes with distinct values are identified and removed and then the attributes which are irrelevant and weakly relevant are identified and those are eliminated. In the training phase, 80 students' information is used to build a model, and then the performance of the model is computed on the test dataset of 73 samples with the use of the knowledge database. In the pre-processing stage, 80 students of Vignan University data will be used as training set to build a model. The attributes like Registered Number, Name and Mail ID's have distinct values and those attributes will not provide any knowledge hence those attributes have to be removed. To maintain the data as consistency, data pre-processing is necessary.

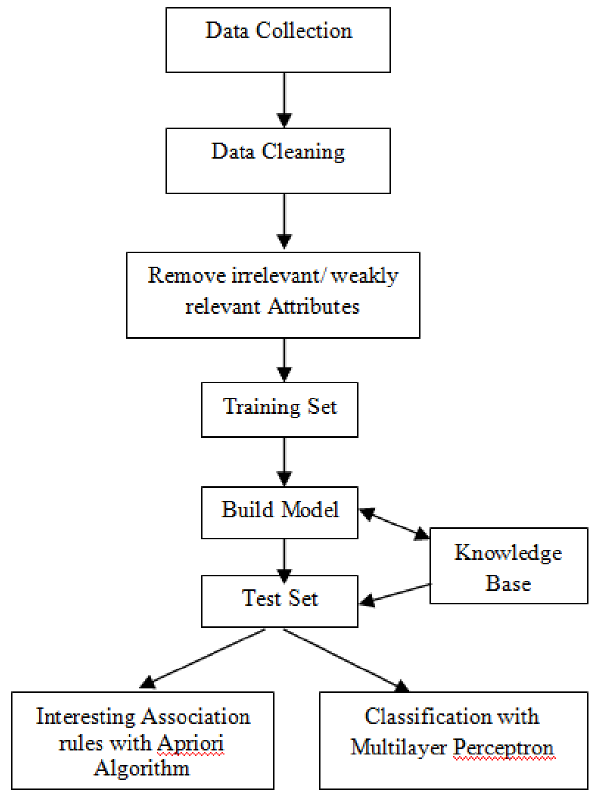

Figure-1. Detailed architecture of proposed method.

Multilayer Perceptron is a most familiarized classifier used to provide class labels to the test samples. The generic architecture of MLP is shown in Figure-2. The Learning process of Multilayer Perceptron is as follows:

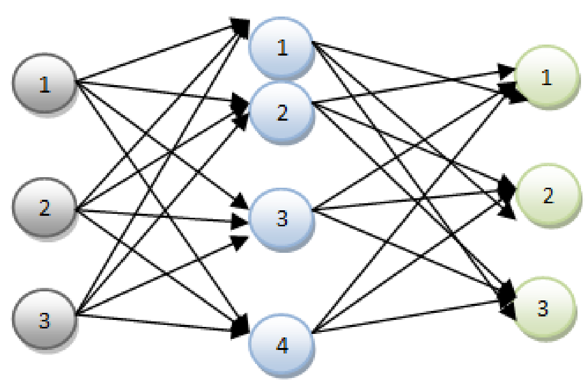

Figure-2. Generic architecture of multilayer perceptron.

a) The network is initialized with random weights which range from -1 to 1.
b) The preliminary training pattern is set and output is found.
c) Now, the network output is compared with the obtained target output and the error gets propagated

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backwards. The weights of the output layer are corrected using the formula

$W_{ho} = W_{ho} + (\alpha\, \delta_o\, o_h)$

Here W_{ho} is the weight of the connection between the hidden unit h and the output unit o, α is the e learning rate and o_h is the output obtained at the hidden unit, h

$\delta_O = o_o (1-o_o)(t_o-o_o)$

Here o_o is the output obtained at node o in the output layer, t_o is the target output

$W_{ih}=W_{ih}+ (\alpha\, \delta_h\, o_i)$

Here W_{ih} is the weight of the connection between the node i in the input layer and node h in the hidden layer, o_h is the input given at node i in the input layer, α is the learning rate δ_h computed is as follows.

$$\delta_h = o_h\,(1 - o_h) \Sigma\, \delta_o W_{ho}$$

d) The error is defined as average difference among the target and the output vector. For example, we can use the following function. Here p is the total number of units present in the output layer.

$$err = \frac{\sqrt{\sum_{o=1}^{p}(t_o - o_o)^2}}{p}$$

e) To complete one epoch, for each training pattern, repeat the process from step 2.
f) To avoid the network from being influenced by the sequence of the data, mix up the training set randomly.
g) The whole process is repeated from step 2 until the error is found to change.

EXPERIMENTAL RESULTS AND DISCUSSIONS

The application which is proposed is applied on a dataset of 73 students of IV year CSE, Vignan University with tuples. The Multilayer Perceptron is compared with Naïve Bayes and J48. The proposed application has addressed three specific objectives called Placement opportunities, Career objective and B. Tech GPA. Experimental results of each objective are shown below.

Placement opportunities

Table-1 shows the Confusion matrix which is generated using J48 algorithm. It provides accuracy of 90.41% by classifying 66 data records correctly out of 73.

Table-1. Confusion matrix by J48.

	Class A	Class B
Class A	52	4
Class B	3	14

Table-2 shows the Confusion matrix which is generated using Naïve Bayes algorithm. It has achieved of 93.15% of accuracy by classifying 68 data records correctly out of 73.

Table-2. Confusion matrix by Naïve Bayes.

	Class A	Class B
Class A	52	4
Class B	1	16

Table-3 shows the Confusion matrix which is generated using Multilayer Perceptron algorithm. It gained accuracy of 100% by classifying 73 data records correctly out of 73.

Table-3. Confusion matrix by Multilayer Perceptron.

	Class A	Class B
Class A	56	0
Class B	0	17

Comparative study of classification accuracies of different classification algorithms is shown in Figure-3. Multi Layer Perceptron has yielded the best classification rate.

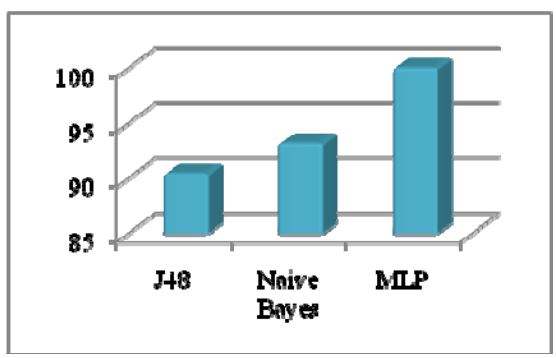

Figure-3. Comparative study of classification accuracies.

Table-4. Comparison between various classification methods.

Method	TP Rate	FP Rate	Precision	Recall	F Measure	ROC Area
J48	0.904	0.152	0.906	0.90	0.905	0.956
Naive Bayes	0.932	0.062	0.939	0.93	0.933	0.982
MLP	1.0	0.0	1.0	1.0	1.0	1.0

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The accuracy by class in detail for all classification methods are represented in the form of TP Rate, FP Rate, Precision, Recall, F-Measure, and ROC Area in Table-4.

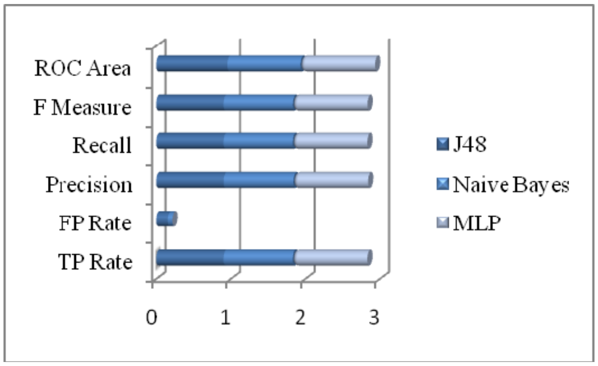

Figure-4. Comparative study of various classification methods.

Career objective

Career objective is a short-term or long-term goal set by a student and which is to be achieved after the end of his graduation. A student with a clear targeted career objective will always be focused and determined towards the goal. Career objective is categorized into three classes with labels as Job, Higher Studies, and Business. Table-5 shows the Confusion matrix which is generated using J48 algorithm. It provides accuracy of 83.56% by classifying 61 data records correctly out of 73.

Table-5. Confusion matrix by J48.

	Class A	Class B	Class C
Class A	49	2	0
Class B	7	12	0
Class C	3	0	0

Table 5.2.2 shows the Confusion matrix which is generated using Naïve Bayes algorithm. It provides accuracy of 79.45% by classifying 58 data records correctly out of 73.

Table-6. Confusion matrix by Naïve Bayes.

	Class A	Class B	Class C
Class A	47	3	1
Class B	8	11	0
Class C	3	0	0

Table-7 shows the Confusion matrix which is generated using Multilayer Perceptron algorithm. It provides accuracy of 98.63% by classifying 72 data records correctly out of 73.

Table-7. Confusion matrix by Multilayer Perceptron.

	Class A	Class B	Class C
Class A	51	0	0
Class B	1	18	0
Class C	0	0	3

Correctly classified records using different classification algorithms are represented below.

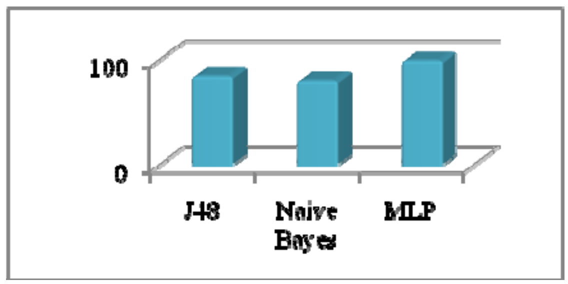

Figure-5. Comparative study of different classification methods in career objective aspect.

The accuracy by class in detail for all classification methods are represented in the form of TP Rate, FP Rate, Precision, Recall, F-Measure, and ROC Area in Table-8.

Table-8. Comparison between various classification methods.

Method	TP Rate	FP Rate	Precision	Recall	F Measure	ROC Area
J48	0.836	0.327	0.803	0.836	0.812	0.84
Naive Bayes	0.795	0.364	0.771	0.795	0.776	0.982
MLP	0.986	0.032	0.987	0.986	0.986	0.964

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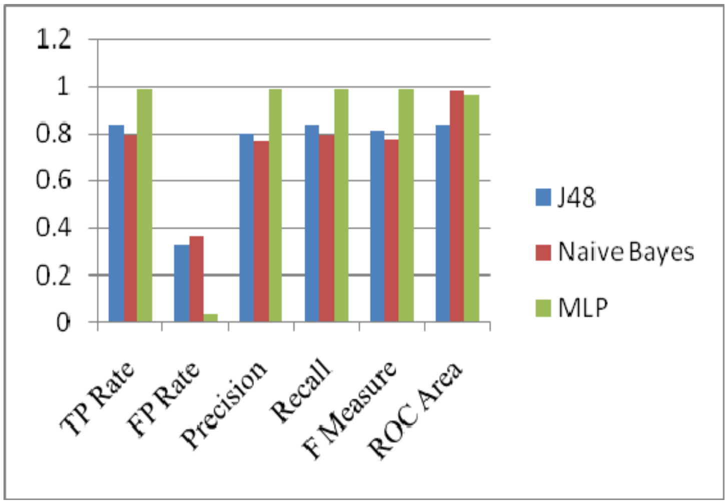

Figure-6. Comparative study of various classification methods in career objective aspect.

B.Tech GPA

The student's % of Marks in graduation up to current semester plays a vital role in the eligibility criteria for a campus drive. B. Tech GPA has discretized into six intervals and which are labelled as O (>90%), E (>85%), A (>80%), B (>70%), C (>60%) and D (>50%). Table-9 shows the Confusion matrix which is generated using J48 algorithm. It provides accuracy of 79.45% by classifying 58 data records correctly out of 73.

Table-9. Confusion matrix by J48.

	Class A	Class B	Class O	Class E	Class C	Class D
Class A	14	5	1	0	0	0
Class B	1	31	0	0	0	0
Class O	0	0	3	1	0	0
Class E	2	4	0	3	0	0
Class C	0	1	0	0	2	0
Class D	0	0	0	0	0	4

Table 5.3.2 shows the Confusion matrix which is generated using Naïve Bayes algorithm. It provides accuracy of 68.49% by classifying 50 data records correctly out of 73.

Table-10. Confusion matrix by Naïve Bayes.

	Class A	Class B	Class O	Class E	Class C	Class D
Class A	15	5	0	0	0	0
Class B	7	23	1	1	0	0
Class O	3	0	1	0	0	0
Class E	3	1	0	5	0	0
Class C	0	2	0	0	1	0
Class D	0	0	0	0	0	5

Table 5.3.3 shows the Confusion matrix which is generated using Multilayer Perceptron algorithm. It provides accuracy of 100% by classifying 73 data records correctly out of 73.

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Table-11. Confusion matrix by Multilayer Perceptron.

	Class A	Class B	Class O	Class E	Class C	Class D
Class A	20	0	0	0	0	0
Class B	0	32	0	0	0	0
Class O	0	0	4	0	0	0
Class E	0	0	0	9	0	0
Class C	0	0	0	0	3	0
Class D	0	0	0	0	0	5

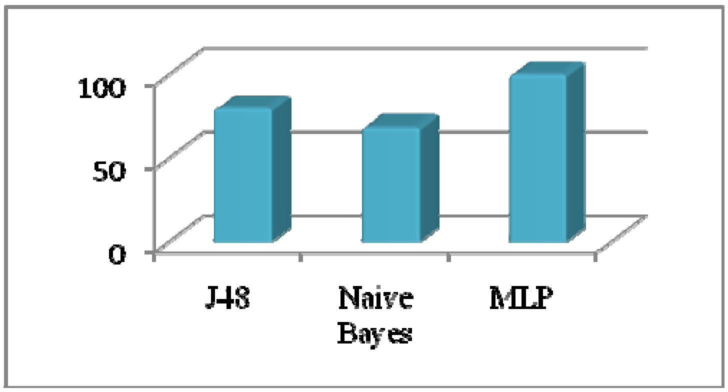

Figure-7. Classification accuracy with different methods.

Accuracy of each class with all classification methods are represented in the form of TP Rate, FP Rate, Precision, Recall, F-Measure, and ROC Area in Table 5.3.4.

Table-12. Comparison between various classification methods.

Method	TP Rate	FP Rate	Precision	Recall	F Measure	ROC Area
J48	0.795	0.125	0.8	0.795	0.779	0.935
Naive Bayes	0.685	0.155	0.712	0685	0.681	0.906
MLP	1	0	1	1	1	1

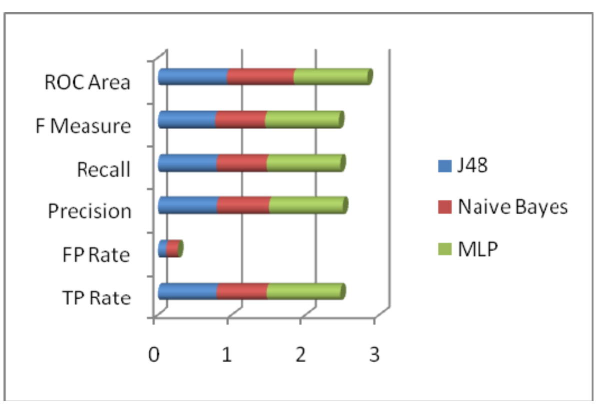

Figure-8. Detailed accuracy chart of classification methods.

The Apriori algorithm

Apriori Algorithm is a significant for mining frequent item sets from Boolean association rules. It is the most familiar and useful algorithm for Association Rule Mining.

Algorithm

a) Input: {Transactional database, Minimum support count}
b) Output: {Interesting association rules}
c) Identify the frequent itemsets: Itemsets that satisfy the minimum support count

- An itemset is said to be frequent iff all of its subsets are frequent. i.e., $\{I_1, I_2\}$ is a frequent itemset, only if both $\{I_1\}$ and $\{I_2\}$ are frequent
- Recursively find all frequent itemsets of level from 1 to k (k-itemset)

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d) Generate Association rules based on identified frequent itemsets.

Apriori algorithm has evaluated on the dataset and following frequent association rules are identified with the highest confidence values.

- Attitude=Good Placed=Yes 46 ==> No. Of backlogs=Nil 46 conf:(1)
- Placed=Yes 56 ==> No. Of backlogs=Nil 55 conf:(0.98)
- Self Discipline=Good Placed=Yes 45 ==> No. Of backlogs=Nil 44 conf:(0.98)
- Communication Skills=Good 56 ==> No. Of backlogs=Nil 53 conf:(0.95)
- Attitude=Good 56 ==> No. Of backlogs=Nil 53 conf:(0.95)
- Self Discipline=Good Attitude=Good 49 ==> No. Of backlogs=Nil 46 conf:(0.94)
- Self Discipline=Good 55 ==> No. Of backlogs=Nil 51 conf:(0.93)
- Extrovert=Average 52 ==> No. Of backlogs=Nil 48 conf:(0.92)
- Career Objective=Job 51 ==> No. Of backlogs=Nil 47 conf:(0.92)
- Family Background=Semi- Educated 48 ==> No. Of backlogs=Nil 44 conf:(0.92)

Based on predictive Apriori algorithm the following interested association rules are found with Interesting classified association rules with Predictive Apriori are as follows:

- Attitude=Good Placed=Yes 46 ==> No. Of backlogs=Nil 46 acc:(0.9826)
- Communication Skills=Good Placed=Yes 43 ==> No. Of backlogs=Nil 43 acc:(0.98139)
- Introvert=Low 32 ==> No. Of backlogs=Nil Placed=Yes 32 acc:(0.97495)
- Certification Courses=Yes Placed=Yes 31 ==> No. Of backlogs=Nil 31 acc:(0.97413)
- CRT online Test performance=Good Placed=Yes 31 ==> No. Of backlogs=Nil 31 acc:(0.97413)
- Degree of Intelligence=Average 30 ==> No. Of backlogs=Nil 30 acc:(0.97325)
- Communication Skills=Good; Attitude=Good; Career Objective=Job; 30 => Self Discipline=Good 30 acc:(0.97325)
- Attitude=Good Career Objective=Job Placed=Yes 30 => Self Discipline=Good No. Of backlogs=Nil 30 acc:(0.97325)
- Project Proficiency=Average Placed=Yes 27 ==> No. Of backlogs=Nil 27 acc:(0.97025)
- Attendance Percentage=Regular Placed=Yes 26 ==> No. Of backlogs=Nil 26 acc:(0.9691)

CONCLUSIONS

In the present days, all the Universities are following Outcome based education to maintain quality in education. On student aspect Placement, Career Objective and GPA are the three main outcomes to rank the University. In this regard, it is very essential to anticipate the progress of students in advance. Academic, Emotional and other attributes will affect the student career. Attributes like No. of backlogs, Self Discipline, Degree of Intelligence, Attendance, GPA and CRT performance have shown great impact on the career of the student. Counseling System taken a vital role in all-round development of the student. In the proposed method, attributes with distinct values are removed and irrelevant or weakly irrelevant attributes are identified and those are removed. 80 graduate students information is used to build a model, remaining 73 students' information is classified using Multilayer Perceptron and proposed method outperforms other classification methods.

REFERENCES

[1] Ernesto Pathros Ibarra García, Pablo Medina Mora. 2011. Model Prediction of Academic Performance for First Year Students. Proceedings of 10th Mexican International Conference on Artificial Intelligence. pp. 169-174.

[2] Shaobo Huang and Ning Fang. 2011. Work in Progress - Prediction of Students' Academic Performance in an Introductory Engineering Course. Proceedings of 41st ASEE/IEEE Frontiers in Education Conference, S4D-1 pp. S4D1-S4D3.

[3] Jui-Hsi Fu, Jui Hung Chang, Yueh-Min Huang, Han-Chieh Chao. 2012. A Support Vector Regression-based Prediction of Students' School Performance. Proceedings of International Symposium on Computer, Consumer and Control. pp. 84-87.

[4] Kamal Bunkar, Rajesh Bunkar, Umesh Kumar Singh, Bhupendra Pandya. 2012. Data Mining: Prediction for Performance Improvement of Graduate Students using Classification. pp. 1-5.

[5] Indriana Hidayah, Adhistya Erna Permanasari, Ning Ratwastuti. 2013. Student Classification for Academic Performance Prediction using Neuro Fuzzy in a Conventional Classroom. pp. 1-6.

[6] Pauziah Mohd Arsad, Norlida Buniyamin, amalul-lail Ab Manan. 2013. A Neural Network Students' Performance Prediction Model. Proc. of the IEEE International Conference on Smart Instrumentation, Measurement and Applications. pp. 1-5.

[7] Tripti Mishra, Dharminder Kumar, Sangeeta Gupta. 2014. Mining Students' Data for Performance Prediction. Proceedings of Fourth International Conference on Advanced Computing and Communication Technologies. pp. 255-262.

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[8] V.O. Oladokun, A.T. Adebanjo, and O.E. Charles-Owaba. 2008. Predicting Students' Academic Performance using Artificial Neural Network: A Case Study of an Engineering Course. The Pacific Journal of Science and Technology. 9(1): 72-79.

[9] Behrouz Minaei-Bidgoli, Deborah A. Kashy, Gerd Kortemeyer, William F. Punch. 2003. Predicting Student Performance: An Application of Data Mining Methods with the Educational Web-Based System Lon-Capa. Proceedings of 33rd ASEE/IEEE Frontiers in Education Conference. pp. 1-6.

[10] Pauziah Mohd Arsad, Norlida Buniyamin, Jamalul-lail Ab Manan. 2014. Neural Network and Linear Regression Methods for Prediction of Students' Academic Achievement. Proceedings of Global Engineering Education Conference. pp. 916-921.

[11] Behrouz Minaei-Bidgoli, Deborah A. Kashy, Gerd Kortemeyer, William F. Punch. 2003. Predicting student performance:An Application of data mining methods with the educational web-based system Lon-Capa. 37th ASEE/IEEE Frontiers in Education Conference. IEEE.

[12] Naeimeh Delaware. 2005. Application of Enhanced Analysis Model for Data Mining Processes in Higher Educational System. 6th International Conference on Information Technology Based Higher Education and Training, pp. F4B/1-F4B/6.

[13] K V Krishna Kishore, S Venkatramaphanikumar S, Alekhya. 2014. Prediction of Student Academic Progression: A Case Study on Vignan University. Proceedings of International Conference on Computer Communication and Informatics. pp. 1-6.

[14] Nguyen, Nguyen T., Paul Janecek and Peter Haddawy. 2007. A Comparative Analysis of Techniques for Predicting Academic Performance. In Proceedings of the 37th ASEE/IEEE Frontiers in Education Conference. pp. 7-12.

[15] Muslihah W, Yuhanim Y, Norshahriah W, Mohd Rizal M, Nor Fatimah A and Hoo Y. S. 2009. Predicting NDUM Student's Academic Performance Using Data Mining Techniques. In Proceedings of Second International Conference on Computer and Electrical Engineering. pp. 359-363.

[16] Brijesh kumar Baradwaj and Saurabh Pal. 2011. Mining educational data to Analyze student's performance. International Journal of Advanced Computer Science and Applications. 2(6): 63-69.

[17] Surjeet kumar and Saurabh Pal. 2012. Data Mining: A Prediction for Performance Improvement of Engineering Students using Classification. World of Computer Science and Information Technology Journal (WCSIT). 2(2): 51-56.