International Journal of Early Childhood Special Education (INT-JECSE)
DOI:10.9756/INTJECSE/V14I5.786 ISSN: 1308-5581 Vol 14, Issue 05 2022

STUDENT PERFORMANCE ANALYSIS FOR OUTCOME BASED EDUCATION

P. SNIGDHA RAO
Department of Computer Science and Engineering
VNR Vignana Jyothi Institute of Engineering and Technology

S. NAGINI, Associate Professor
Department of Computer Science and Engineering
VNR Vignana Jyothi Institute of Engineering and Technology

Devulapalli Sudheer
Assistant Professor, Department of Computer Science and Engineering
VNR Vignana Jyothi Institute of Engineering and Technology

V. S. S. BAPIRAJ
Department of Computer Science and Engineering,
VNR Vignana Jyothi Institute of Engineering and Technology

M. VIVEK VARDHAN
Department of Computer Science and Engineering,
VNR Vignana Jyothi Institute of Engineering and Technology

M. HARSHITHA
Department of Computer Science and Engineering,
VNR Vignana Jyothi Institute of Engineering and Technology

Abstract— Assuring the quality of Higher Education through assessment criteria congruent with international standards is the main intention behind Outcome Based Education. Outcome based education (OBE) is a student- centered instruction model which refers to the analysis of student performance on the basis of program outcomes, course learning outcomes, assessment matrix and rubrics for each course. This model motivates research with special emphasis on applied research that contributes to the development of society.Data analysis can assist in terms of predicting and analyzing the performance based on machine learning algorithms. This helps in incorporating students' performance with learning outcomes and program outcomes and classifying them by quality indicators which represent to what extent the goal is achieved by studying. By using different data mining algorithms, more accurate prediction and significant analysis can be carried out. The most important task taken up includes comparative analysis of students' results across batches and various regulations (latest regulation R18 proposed by AICTE has been incorporated). In addition to this, it also involves the prediction of students' marks based on ranks obtained in common entrance examination (criteria for getting admitted to engineering discipline) and the impact of academic performance on securing placements. The experimental results contain predictive analysis, data analysis and comparative analysis of student performance for an intricate analysis on the OBE based implementation. It is evident from the analysis of the achievement of 2018 batch students following the R18 regulation that success index in terms of performance is a function of competence through the realization ofoutcomes.

***Keywords*—AICTE, Comparative Analysis, Clustering, Prediction, Regression.**

I. INTRODUCTION

The most integral part of the Outcome-Based Education approach is the goal(s) or outcome(s) achieved by a student at the end of a course or a program [1-4]. Benchmarking of all academic programs was carried out by the AICTE in its quest for excellence for the sustainability of outcome based education model. This model measures the progress of a student using three parameters- Program Educational Objectives (PEOs), Program Outcomes (POs), and Course Outcomes (COs). PEOs are formulated in a broad sense. Their purpose is to focus on equipping the students to succeed professionally through the program and they are usually measured a few years after the completion of the program. On the other hand, program outcomes outline the skills to be possessed by students at the end of a program. Course outcomes refer to the criteria which measure the students' performance for each course taken throughout the duration of the program. There are different methods of teaching and learning that assist a student to reach the 'goals'. Apart from classroom teaching, group discussions, quizzes, videos, etc. also help the students in understanding the course-work better. Additionally, hands-on learning in the form of labs, course-based projects along with various e-learning platforms contributes to this. The OBE model has been in use in other countries since a relatively longer time than in India where emphasis on it has increased only recently. India has started implementing OBE at higher levels of education like diploma and undergraduate programs since 2014. Currently, for an engineering institution to be accredited by the National Board of Accreditation, the Outcome-Based Education model has to befollowed.

Educational Data Mining is a field that facilitates the application of data mining techniques in an educational context [5-6]. Data mining methods help in extracting a lot of useful information from the vast amount of data generated in an educational environment. This can in turn be utilized to suggest improvements in areas related to students' performance, teaching strategies, institutional management, etc.

DOI:10.9756/INTJECSE/V14I5.786 ISSN: 1308-5581 Vol 14, Issue 05 2022

The primary motto of this study is to analyze the impact of changes in course regulations on students' performance using parameters like examination results, attendance, placements, common entrance exam ranks, etc. Comparative analysis measures the performances of students across batches following different course structures to find out which set of students outperformed the others and the effect of varying regulations on students' results. Through prediction, students' marks are estimated by taking into account the common entrance exam ranks obtained by them. Another aspect thathas been considered is placement analysis which evaluates the ability of students to secure placements based on their academic performances. Further, the attendance of students has been utilized to compute relationships between the frequency of students attending classes and their marks as well as placements obtained. The study also includes the interrelationship between students' 12thgrade results and their undergraduateperformances.

II. LITERATURE REVIEW

There are a number of systems that have been designed and developed for student performance analysis. But most of them used basic statistical methods [7-10] like mean, standard deviation, ANOVA, t-test [11], chi-square test [12] and some utilized questionnaires and surveys for their study [15-16].

Joseph KwabinaArhinful Johnson, et. al., [17] in one of the studies, investigated the existence of a relationship between academic performance at the Senior High School and that of university. It revealed that students' previous academic performance at the High School level had almost no impact on their Grade Point Average (GPA) at the university. In conclusion, the study stated that the program taken up by a student at university played a prominent role in his/her academic performance. Certain other factors which were also considered to contribute significantly include the academic environment, the availability of academic resources, teaching empowerment, attitude of the student, and finance resources.

Chew Li Sa, et. al., [18] proposed the prediction ofstudents' performance in a course using a Student Performance Analysis System in order to help the lecturers in identifying the students who might not do well in that course. The parameters in consideration are the marks obtained by students in two previous semesters of that course. For this purpose, a predictive system has been implemented which uses the data mining technique of classification to generate rules for prediction. Classification was used in segregating students based the grade obtained.

Further, Peter Abayomi Onanuga, et. al., [19] carried outthe trend analysis of students' results in the examination in STEM subjects from 2011 to 2015. The research used Microsoft Excel as the tool for data collection and analysis. It revealed that the number of candidates who enrolled for the selected STEM subjects had constantly increased. Among all the subjects, Mathematics had the highest improvement, followed by Basic Science and then Basic Technology. The students' good performance also improved, though not in a steady manner. These findings imply that the promotion of STEM education by various governments and stakeholders has motivated students and that they have started acknowledging the part that science and technology plays in solving various problems. On the other hand, these subjects were being taught in a stand-alone manner instead of using an integrated approach.

Elvis Munyaradzi Ganyaupfu, et. al., [20] performed analysis to identify which of the three teaching methods- teacher-student interactive, student-centered, and teacher centered- most significantly affected students' academic performance. The technique used for this purpose was ANOVA. Using the mean scores results obtained, it was concluded that the teacher-student interactive method proved to be the most effective teaching method, followed by the student-centered method while the teacher-centered approach provided the lowest productivity among all the teaching methods. The reason for the teacher-student interactivemethod being the most effective could be that it encourages the students to be more proactive in their learning process rather than the lecturer alone providing the sources of information to thelearners.

E. O. Sodipo, et. al., [21] analyzed the various factors that affect the academic performance of students and prevent them from graduating on time at the University of Ibadan. Parameters like gender and population and techniques like chi- square test and ANOVA were used to serve this purpose. The results revealed that the gender of a student does not in any way have an impact on his/her academic performances. In addition to this, the research has found out that students perform better when the class size is small i.e. the higher the number of students, the lower the performance. Keeping thisin mind, it was recommended that the school authorities ensure that a limited set of students are admitted so that the finite amount of resources available can be utilizedefficiently.

Sarafa Adeniran Salman, et. al., [22] presented a study in order to evaluate the performance of students studying French and English languages in language and literature courses. The sources of data were the students' results along with their responses to a questionnaire. The results of the survey showed that in both the departments, that is, English and French, students performed better in language courses than in literature courses. One reason that could be associated with this difference was that some of the students

DOI:10.9756/INTJECSE/V14I5.786 ISSN: 1308-5581 Vol 14, Issue 05 2022

did not have access to textbooks owing to their poor financial status. However, the most significant explanation given by lecturers to this scenario was the lack of effort on the part of the students in reading

DOI:10.9756/INTJECSE/V14I5.786 ISSN: 1308-5581 Vol 14, Issue 05 2022

literary texts as they indulged a lot in social networking. Thus, recommendations were made to give students online assignments and also employ more faculty members in the literature department to reduce the insufficiency of lecturers.

Dr. Awoniyi Samuel Adebayo, et. al., [23] compared students' achievement in Social Studies and Integrated Sciences in the Junior Secondary School Certificate Examination in Nigeria from 2011 to 2013. This study made use of the statistical techniques, t-test and ANOVA, for the analysis. The results of students and their gender were the two parameters on which conclusions were based. The research revealed that on the whole students performed slightly betterin Social Studies when compared to Integrated Science. Also, female students did better than their male counterparts in2011, but, the performances of the both the sets of students did not differ much in 2012 and2013.

IbaanGogoZalmon, et. al., [24] evaluated students' performances in the African Senior Secondary Certificate Examination in general mathematics from 1991 to 2016. Chi- square test, mean, and percentage were the methods used and the analysis was done using the grades obtained by students. The findings indicated that the number of students increased greatly after a period of 13 years and the students had started performing better over time. These improvements could be attributed to the changes in the curriculum, novel techniques followed in mathematics, and increase in the efforts put in by the students.

Simutenda Mathews, et. al., [25] conducted a study in which the impact of using SPSS, a statistical analysissoftware, on the performances of students in hypothesis testing at Zambia Catholic University was examined. The t-test statistic for independent samples was used for this purpose. The entire set of students was divided into two groups- a control group that was taught hypothesis testing using traditional methods and an experimental group to which teaching was done using SPSS. Then, a test was conducted on these two groups in which the experimental group students performed better than the students of control group. In addition to this, in a survey administered to find the attitude of students of both the groups towards hypothesis testing, the experimental group students excelled in comparison to their counterparts. The effectiveness of SPSS was attributed to the various representations available and visualizations it possesses which improve the understanding of statistics concepts.

Mostofthesestudieshaveconsideredstudents'marksasthe only parameter to perform analysis. In reality however, the performance of students in examinations is not the only factor that governs the success of an outcome based education system. Taking this fact into consideration, we made use of additional parameters like at tendance, placements secured by students, their ranks in the common entrance exam, etc. to evaluate and in turn arrive at accurate conclusions. Also, the existing approaches have only addressed a single dimension of students' performance analysis. In the proposed study, wehave focused on analyzing the achievements of students in a full- fledged manner by including comparative analysis, prediction, placement analysis, etc.

III. METHODOLOGY

Thetechniquesusedforformulatingthemethodologyofthis study include data mining approaches like regression analysis [26-29] and clustering [30-40]. In order to obtain a proper conceptual understanding of these methods, the different ways in which they can be applied has been considered. The reason for using clustering is that it is a technique that makes it possible to segregate data into groups with similar characteristics which simplifies the analysis. Further, it is also more accurate in comparison to a manual clustering process because it divides the data based on its composition. Regression analysis has been chosen as it is capable of deriving the nature of the relationship between the parameters considered as well as the extent to which they are associated with eachother.

For comparative analysis of students' performances, the
internal examination results data of students belonging to 2015-2018 batches of the most preferred departments in a well-implemented OBE system of an engineering institution has been used. This data initially consisted of the following columns: hall-ticket number (htno), exam details (exam), month and year of examination (monyear), subject code (subcode), internal marks (intmarks), the final result stating pass or fail (result), and the final grade obtained (Grade).

htno	exam	monyear	subcode	intmarks	result	Grade
14071A05C1	I B.TECH I SEMESTER (R15) REGULAR	DECEMBER, 2015	5CS01	29	P	A
15071A0401	I B.TECH I SEMESTER (R15) REGULAR	DECEMBER, 2015	5CS01	26	P	D
15071A0402	I B.TECH I SEMESTER (R15) REGULAR	DECEMBER, 2015	5CS01	19	F	F
15071A0403	I B.TECH I SEMESTER (R15) REGULAR	DECEMBER, 2015	5CS01	39	P	A+
15071A0404	I B.TECH I SEMESTER (R15) REGULAR	DECEMBER, 2015	5CS01	40	P	A+
15071A0405	I B.TECH I SEMESTER (R15) REGULAR	DECEMBER, 2015	5CS01	23	P	B
15071A0406	I B.TECH I SEMESTER (R15) REGULAR	DECEMBER, 2015	5CS01	26	P	C
15071A0407	I B.TECH I SEMESTER (R15) REGULAR	DECEMBER, 2015	5CS01	30	P	C
15071A0408	I B.TECH I SEMESTER (R15) REGULAR	DECEMBER, 2015	5CS01	28	P	C

Fig.1 Examination results data used for analysis

From the original data, the fields that were extracted in order to perform analysis include: hall-ticket number/roll number, which specifies the year of admission and the branch a student belongs to, the subject code, which indicatesthe subject used for evaluation,the internal marks and the final grade secured by a student.

The technique employed for evaluation is K-means clustering. K-means isrelatively faster than other clustering methods when the number of clusters (value of K) is small and is known in advance. Since the data involved in this study is one-dimensional data andit is evident that thedata points seem more separable when the data is divided into three clusters,therefore, the number of clusters is fixed to three and it is an obvious choice to opt for K-means clustering.

In comparison, each of the two batches of studentschosenforanalysisisclusteredintothreegroups-low, medium, and high (three clusters) based on the marks obtained in the internal test. In addition to this, there is further analysis performed on the set of students belonging to the lowest cluster. For this purpose, a term labeled the Batch Performance Metric (BPM), which gives the ratio of the students who passed in the final examination to those who failed is calculated, that is, the number of students obtaining grades O, A, B, C and D in the lowest cluster is divided by the count of those who got an F in the same cluster. This helps in determining if the chosen groups of students are capable of faring well in the end semester examination despite having low internal marks. Between the two selected batches of students, the group which has a higher pass/fail ratio is said to have performed better. The results obtained help the user in understanding which set of students outperformed the other and in turn in arriving at conclusions to support theanalysis.

$$\mathrm{BPM} = \frac{\text{Number of people passed in lowest cluster}}{\text{Number of people failed in lowest cluster} + 1}$$

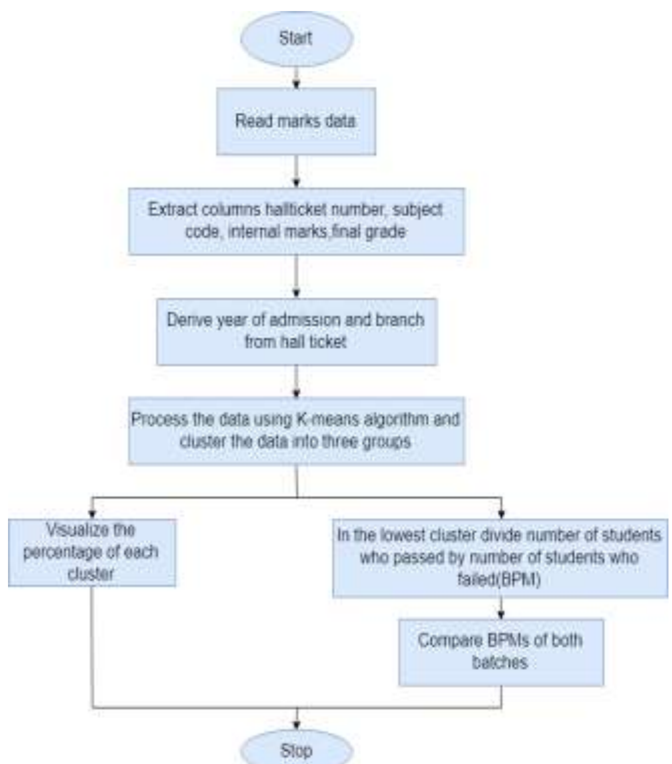


Fig. 2 Comparative Analysis Flowchart

Fig.2depicts the flowchart of Comparative Analysis where the required columns like hall ticket number, subject code, internal marks, and final grade are extracted from the data. The first few preprocessing steps involve filtering of the data based on the year of admission, the branch, and the subject that the analysis is intended to be performed on. The internal marks column is directly

DOI:10.9756/INTJECSE/V14I5.786 ISSN: 1308-5581 Vol 14, Issue 05 2022

given as input to K-means algorithm without any in place transformations on it. The results of the algorithm arevisualizedand BPM is calculated from the lowest cluster results.

In order to perform prediction, the ranks obtained by
students in the common entrance exam and internal marks of students of 2015-2017 batches belonging to the same two sought after branches as in comparative analysis have been taken into account. The students' internal marks data has been preprocessed in the same way as in comparison. The ranks data contained the following fields: hall-ticket number/roll number (htno), entrance exam rank (rank), and the category of admission (category).

htno	eamcet rank	category
15071A0501		Management
15071A0502	13515	Convener
15071A0503	2618	Convener
15071A0504		Management
15071A0505	19143	Convener
15071A0506	2868	Convener
15071A0507	4073	Convener
15071A0508		Management
15071A0509		Spot
15071A0510		Management

Fig. 3 Entrance exam ranks data before preprocessing

There are three categories of students- convener, management, and spot. The missing values shown in Fig.3 belong to the students of management and spot categories. Due to the limitation of features available in the dataset, no other imputation technique can be performed other than removal of missing values.

htno	eamcet rank	category
15071A0502	13515	Convener
15071A0503	2618	Convener
15071A0505	19143	Convener
15071A0506	2868	Convener
15071A0507	4073	Convener
15071A0512	5703	Convener
15071A0513	4654	Convener
15071A0514	2212	Convener
15071A0515	3591	Convener

Fig. 4 Entrance exam ranks data after preprocessing

Only two of the above mentioned columns have been retrieved for usage: the hall-ticket number and the entrance exam rank. The reason for utilizing these ranks as one of the criteria is to understand a student's transition between two entirely different education approaches, that is, the one adopted till 12th gradeand the one during undergraduate study. In this process, firstly, the z-scores of both the internal marks of students and their entrance exam marks have been computed.

$$z_{im} = \frac{im - \mu_{im}}{\sigma_{im}}$$

im = internal marks

DOI:10.9756/INTJECSE/V14I5.786 ISSN: 1308-5581 Vol 14, Issue 05 2022

z_{im} = z-score of internal marks

μ_{im} = mean of internal marks
σ_{im}= standard deviation of internal marks

$$z_{er} = \frac{er - \mu_{er}}{\sigma_{er}}$$

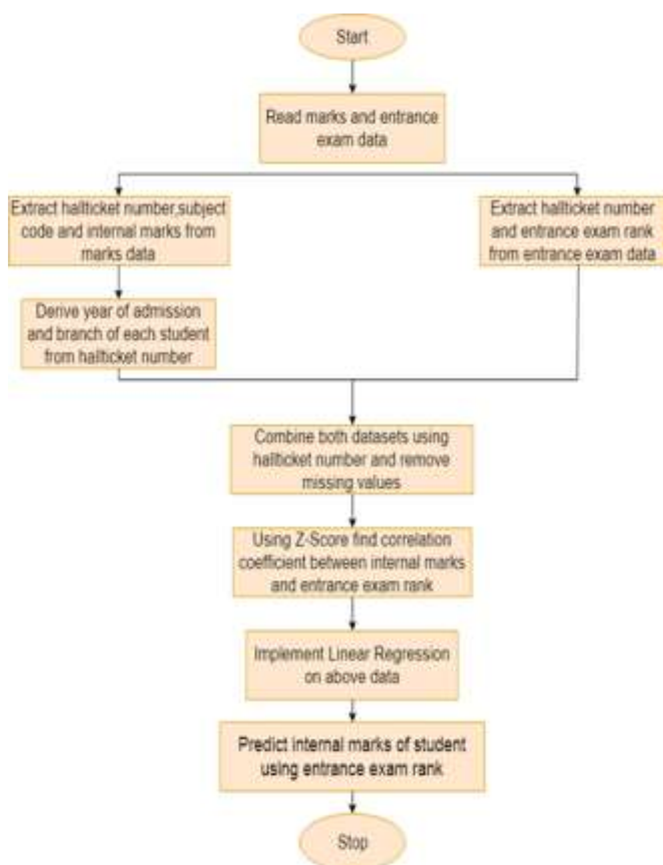
er = entrance exam ranks
z_{er} = z-score of entrance exam ranks
μ_{er} = mean of entrance exam ranks
σ_{er}= standard deviation of entrance exam ranks

Then, using these z-scores, the correlation coefficient for these two parameters has been calculated to find out the extent to which they are related.

$$r_{im,er} = \frac{\sum(z_{im} * z_{er})}{\text{Number of students in batch}}$$

$r_{im,er}$ = correlation coefficient value between internal marks and entrance exam ranks
z_{im} = z-score of internal marks
z_{er} = z-score of entrance exam ranks

Linear regression is the method that has been used to carry out prediction. It establishes a linear relationship between entrance exam ranks and the internal marks. On implementing linear regression, the rank turned out to be the independent (input) variable and internal marks, the dependent (output) variable. This implies that the internal marks are predicted using the common entrance exam ranks secured by thestudents.



DOI:10.9756/INTJECSE/V14I5.786 ISSN: 1308-5581 Vol 14, Issue 05 2022

Fig 5 Prediction Flowchart

Fig.5depicts the flowchart of Prediction where the initial preprocessing steps done on the marks datasetare the same as those of Comparative Analysis. The ranks data is also filtered by removing the missing values belonging to management and spot admission students. The next few steps involve mapping the internal marks of the students to the ranks that they obtained in the common entrance test, and the computation of Pearson's correlation coefficient between marks and ranks based on z- scores. Another preprocessing step is the normalization of marks and ranks to the same scale before feeding them to the regression model. The last step is to predict the internal marks using ranks based on the association that is formed by the regression model.

TheoutcomesgainedbyastudentintheOBEmodelare ultimately put to test when he/she is exposed to the corporate world. Thus, the analysis of placements is an integral part of this study. For this purpose, the placements data of the current outgoing batch's most preferred branch students belonging to the above mentioned institute along with their internalexamresults data is used. In the placements data provided, the name of the company a student was placed in has been replaced by the value of the package being offered. This field has been extracted along with the student's hall-ticket number/roll number (roll no) column for evaluation.

Sno	ROLL NO	Package
1	15071A0502	5
2	15071A0503	6.2
3	15071A0504	7
4	15071A0506	6.2
5	15071A0507	4
6	15071A0509	3.25
7	15071A0510	4
8	15071A0511	4
9	15071A0512	6
10	15071A0513	6

Fig. 6 Preprocessed data for placement analysis

In the analysis of placements too, the entire group of students are segregated into three clusters-low, medium, and high- based on the marks acquired and placements obtained. In each of the clusters, the highest and lowest values of packages are computed. Along with this, the mean and standard deviation of packages secured are also calculated for all the clusters. The correlation between the value of package acquired by students and their corresponding marks is found in order to understand if the students' academic performance is in tandem with their ability to obtain high payingjobs.

The frequency of a student attending classes is also considered as one of the features that have an effect on his/her performance. For this reason, attendance is one of the parameters used in this study. The attendance data of two of the most sought after branches' students during the years 2015 to 2018 is utilized to find the impact of a student's attendance on his/her performance in examinations as well as on their job- acquiring skills. The way a student has adapted to a new mode of teaching and learning is the logic behind incorporating another dimension to this study which includes the students' 12thgrade results. Using this data, an interrelationship can be established between the students' performance at two successive levels of study- undergraduate and grade 12.

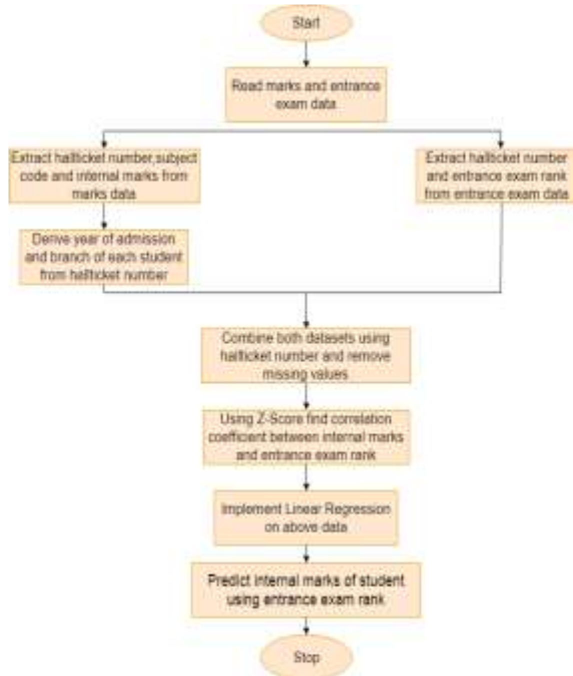
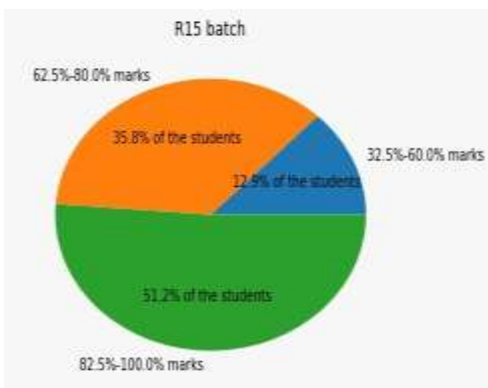


Fig. 7 Placement Analysis Flowchart

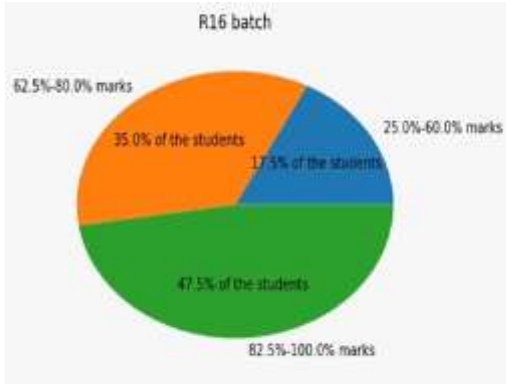
IV.RESULTS

The results obtained are presented below:
Through comparative analysis, the trend of students'performance during the years 2015 to 2018 can be observed.

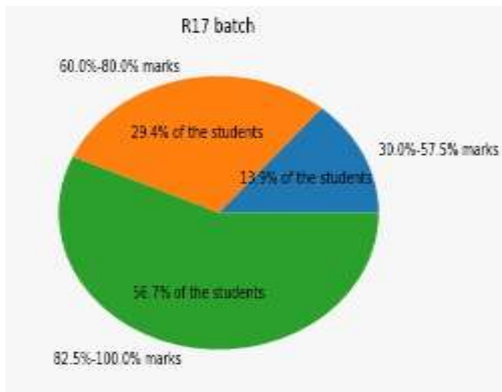


8 (a)

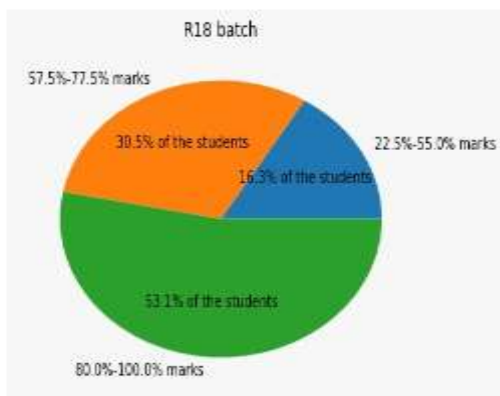
International Journal of Early Childhood Special Education (INT-JECSE)
DOI:10.9756/INTJECSE/V14I5.786 ISSN: 1308-5581 Vol 14, Issue 05 2022



8 (b)



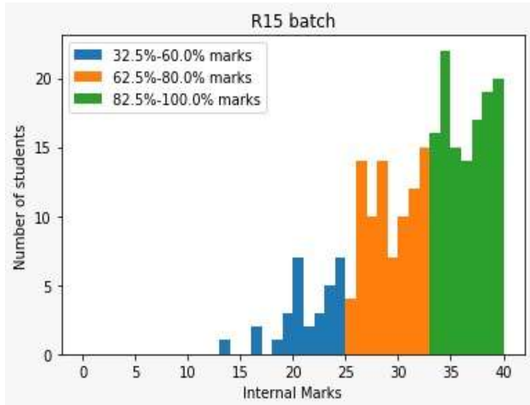
8 (c)



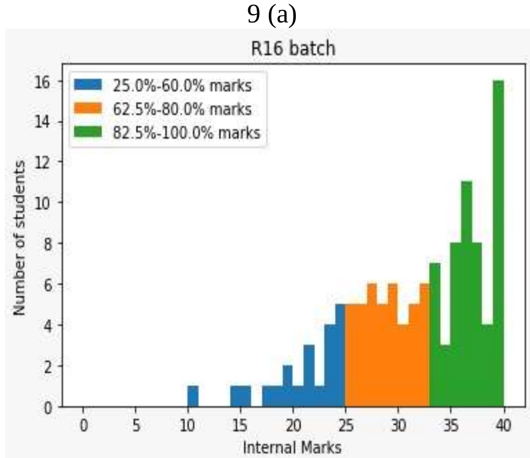
8 (d)

Fig. 8Cluster based pie-chart representations of performances of 2015, 2016, 2017 and 2018 batches of preferred department 1 in subject 1

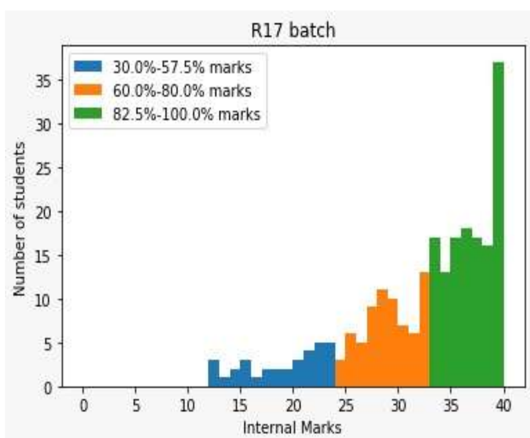
DOI:10.9756/INTJECSE/V14I5.786 ISSN: 1308-5581 Vol 14, Issue 05 2022



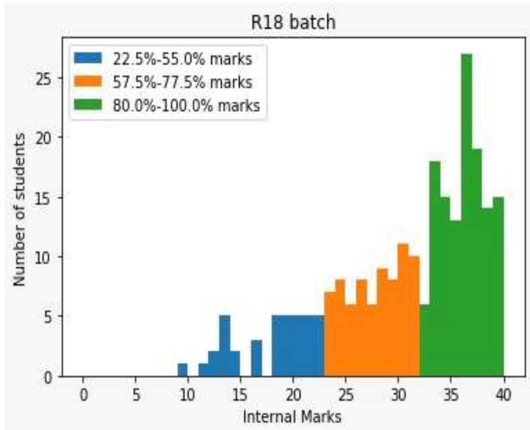
9 (a)



9 (b)



9 (c)



9 (d)

Fig. 9 Cluster based histogram representations of performances of 2015, 2016, 2017 and 2018 batches of preferred department 1 in subject 1

The clear separation between the clusters justifies the selection of ‘K’ value i.e., the number of clusters in K- means algorithm.

Year	Branch	Subject	Pass (cluster 0)	Fail (cluster 0)	BPM
R15	Preferred branch 1	Subject 1	26	5	4.33
R16	Preferred branch 1	Subject 1	19	2	6.33
R17	Preferred branch 1	Subject 1	30	3	7.5
R15	Preferred branch 2	Subject 1	31	17	1.72
R16	Preferred branch 2	Subject 1	21	6	3
R17	Preferred branch 2	Subject 1	46	2	15.33
R18	Preferred branch 2	Subject 1	39	0	39
R15	Preferred branch 1	Subject 2	49	1	24.5
R16	Preferred branch 1	Subject 2	10	4	2
R17	Preferred branch 1	Subject 2	37	4	7.4
R15	Preferred branch 2	Subject 2	18	9	1.8
R16	Preferred branch 2	Subject 2	26	6	3.71
R17	Preferred branch 2	Subject 2	24	7	3

Fig. 10 BPM for sample data

From the above table (Fig. 10), it is evident that the students of 2018 batch have a significantly higher value of BPM than all the other batches. This implies that the students of 2018 batch did exceedingly well when compared to all their seniors, that is, the students of 2015, 2016 and 2017 batches. Thus, it can be concluded that the modified AICTE methodologies resulted in an improvement in the students’ performance. This could be attributed to the lowering of the workload in terms of theoretical subjects and increasing the amount of hands-on experiencegained.

In another part of comparative analysis, a threshold value is used for internal marks, which is set at 75 percent. Further, based on the entrance exam ranks secured, students aredivided into convener and management categories. The convenerquota students are further segregated based on the value of ranks obtained. The main aim of this analysis is to calculate the number of students who fall above and below the threshold value of marks.

Year	Branch	Percentage of students above 75%		
		Ranks below 5000	Ranks below 10000	Management
R15	Preferred branch1	88.31%	82.69%	60.64%
R15	Preferred branch2	74.29%	74%	55.56%
R16	Preferred branch1	79.07%	83.02%	54.55%

DOI:10.9756/INTJECSE/V14I5.786 ISSN: 1308-5581 Vol 14, Issue 05 2022

R16	Preferred branch2	90.24%	85.71%	67.16%
R17	Preferred branch2	73.61%	75.49%	46.15%

Fig. 11Percentage of students scoring above threshold value category-wise

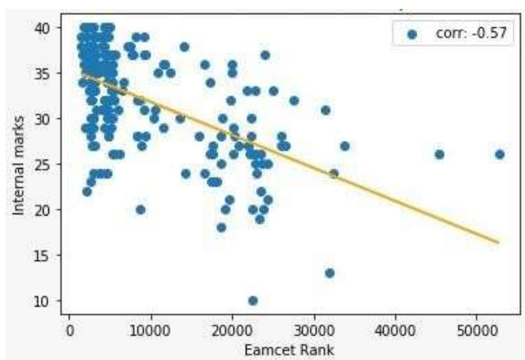
The above table reveals that in majority of the cases in almost every category, the percentage of students scoring more than the threshold value in subject1 is higher than the ones who score below it. For instance, in the R15 batch, the percentage of students who scored more than the threshold value i.e., 75%,and secured ranks below 5000(i.e., category 1) is 88.31 which is higher than the ones who scored below it. There is just one exception to this observation- that of the R17 batch's management category. This implies that the students' ranks in the common entrance examination do not have a significant impact on their performance in internalexaminations.

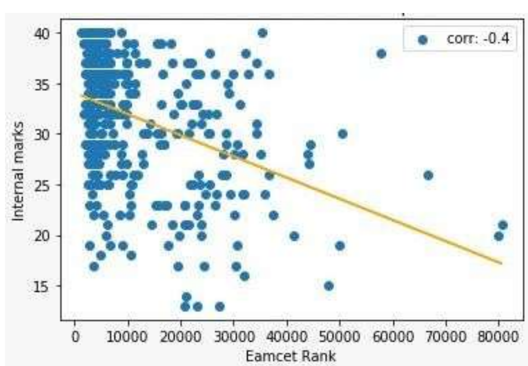
As is evident from the above observation, prediction depicts a weak negative correlation between the two parameters considered, that is, students' common entrance test ranks and the marks scored in their internal examination. This suggests that there are cases where a student gets good internal marks despite having an average rank and that the entrance exam rank alone cannot be used for predicting students' performance.

Branch	Correlation coefficient
Preferred branch 1	-0.57
Preferred branch 2	-0.4

Fig. 12 Branch-wise correlation coefficient between entrance exam ranks and internal marks combined for all batches

13 (a)





13 (b)

Fig. 13Common entrance exam ranks vs Marks plots for preferred branch 1 (a) and preferred branch 2 (b) students

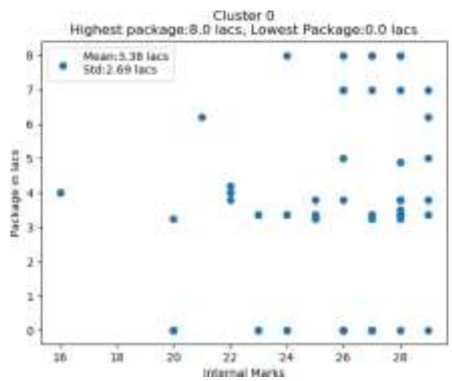
In the analysis of placements, the students are divided into three clusters based on the internal marks scored and value of

DOI:10.9756/INTJECSE/V14I5.786 ISSN: 1308-5581 Vol 14, Issue 05 2022

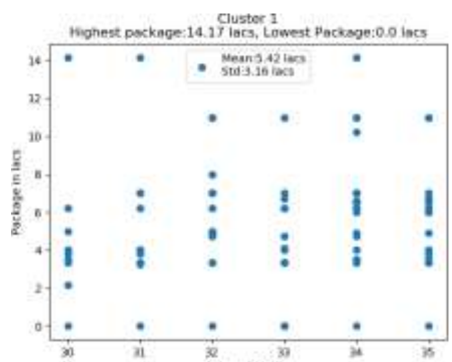
packages secured. For each cluster, the highest package, lowest package, mean, andstandard deviation are computed. The lowest value of package obtained in each cluster, that is, 0.0 lakhs, refers to the unplaced students. This evaluation yields a note worthy result. It can be observed that there is a direct relationship between the internal marks obtained by students and the value of package secured by them. This is evident from the steady increase in the mean value of package acquired with an increase in the students' marks. Thus, it can be stated that the students' who perform well academically also possess the capability to obtain a high valuepackage.

Cluster	Highest Package (LPA)	Lowest Package (LPA)	Mean	Standard Deviation
Low	8	0	3.38	2.69
Medium	14.17	0	5.42	3.16
High	14.17	0	6.05	2.75

Fig. 14Cluster-wise representation of packages obtained

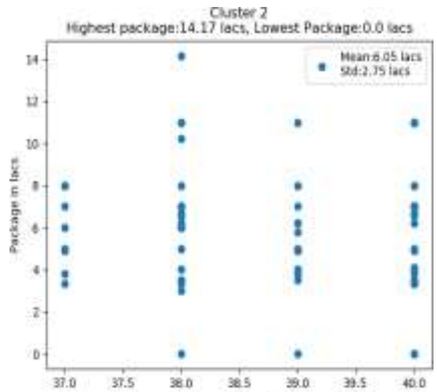


15 (a)



15 (b)

DOI:10.9756/INTJECSE/V14I5.786 ISSN: 1308-5581 Vol 14, Issue 05 2022



15 (c)

Fig. 15 Clustering analysis based on placements and marks obtained by 2015 batch students belonging to preferred department 1

The influence of attendance on a student's performance in examinations as well as on placements is almost insignificant. Using the value of correlation coefficients of these two analyses, which are less than 0.5, it can be deduced that they are both almost negligibly correlated with attendance, that is, there are a significant number of cases where a student obtains a high value package and performs well academically despite his/her frequency of attending classes being relatively low.

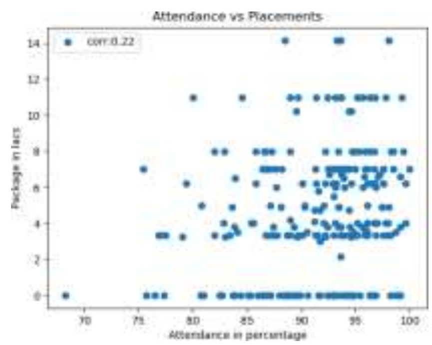


Fig. 16 Correlation between attendance and placements of2015 batch students belonging to preferred department1

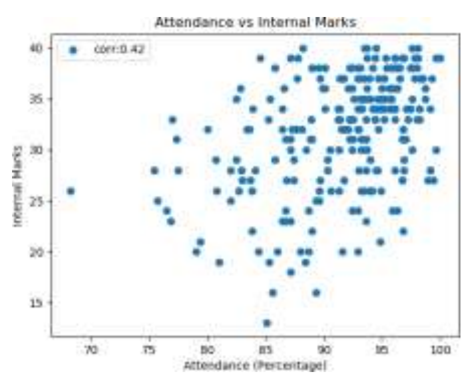


Fig. 17 Correlation between attendance and internal marks of2015 batch students belonging to preferred department1

Finally, the relationship between students' 12th grade marks and their internal marks is also observed to be inconsequential. The value of the correlation coefficient indicates that there is a weak positive correlation between them, that is, while some students who perform well in their 12th grade also do well in their undergraduate study, there are also students whose internal marks are high despite an average performance during their 12th.

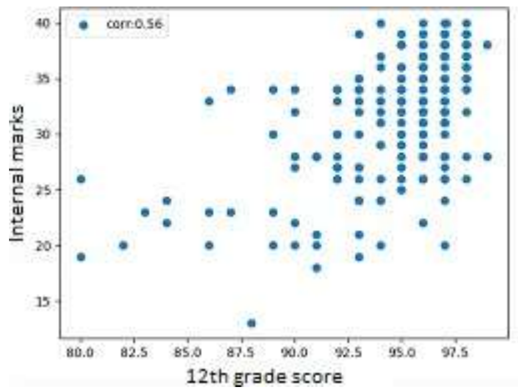


Fig. 18 Correlation between the 12thgrade and internal marks of 2015 batch students belonging to preferred department 1

V. CONCLUSION

The main intention of this study is to assist the lecturers in analyzing, predicting and keeping track of students' progress throughout the course of the program. It will also serve as a motivation for students to compete with each other and perform better. The research reveals that the changes in the curriculum brought about by AICTE resulted in an enhanced performance of 2018 batch students when compared to the previous batches. This suggests that the pragmatic approach employed for teaching the 2018 batch students has been effective and the practical knowledge gained from it has enabled them to excel even at theory exams. In addition to this, the performance of students in placements could be directly correlated with their academic performance. This means that students who obtain good grades in examinations also have better chances of securing higher pay packages in comparison to their underperforming counterparts.

Another dimension of this study, prediction, depicted a weak negative correlation between the two parameters considered,that is, students' marks and their common entrance exam ranks. This strengthens the fact that the Outcome Based Education model is entirely different from the learning methodologies used for engineering entrance exams and that the ranks in this examination cannot be used as the sole deciding factor in predicting students' performance during their undergraduate study. The difference between the two models of education was further evident from the almost negligible correlation between the students' marks in engineering and their 12thgrade performance. The frequency of students' attending classes, that is, their attendance also did not have a considerable impact on their performance in examinations as well as placements. Despite the fact that these analyses were carried out using the data pertaining to the two most soughtafter branches and two of the most fundamental subjects in engineering, the trends observed in students' performancesin other subjects and in other departmentswere also thesame.

VI.FUTURE SCOPE

In future this research can be extended to include analysis of students' performance using additional knowledge obtained through online courses, coursebased projects, usage of gadgets for academic purposes, etc. The productivity of AICTE's new methodologies like the mandatory internship, virtual laboratories, design thinking courses, etc. on the 2018 batch students' placement process can also be evaluated.If these factors prove to be effective, similar approaches can be put into place for future batches of students. In addition to this, comparative analysis of placements belonging to various batches as well as different branches can be done. This can be used to understand which batch of students possesses better skills to secure placements. A deeper analysis could help in figuring out the reasons for the improved performance of a particular set of students and in accurately assessing the skillset required for students to obtain betterplacements.

VII. REFERENCS

[1]. Joshi NeetiDattuprasad And Priyanka Sharma (2018) – "Analysis of Student Performance Using Machine Learning Approaches For Outcome Based Education", IJCA,Volume 13 – Issue1.
[2]. OriahAkir, Tang Howe Eng and SenianMalie (2012) – "Teaching and learning enhancement through outcome-based education structure and technology e-learning support", Procedia - Social and Behavioral Sciences.
[3]. Boud, D and Feletti, G (1999)- "The challenge of problem-based learning", Kogan Page.
[4]. Hesson, M. and Shad, K.F. (2007)- "A student-centered learning model," American Journal of Applied Sciences.
[5]. P. Guleria, M. Arora, and M. Sood- "Increasing quality of education using educational data mining".
[6]. C.Romero, S.Ventura (2007)- "Educational data mining: A survey from 1995 to 2005", Expert Systems with Applications, Volume 33, Issue 1.
[7]. Adeyemi, T.O. (2011)- "A comparative study of students' academic performance in public examinations in secondary

schools in Ondo and Ekiti States, Nigeria", Journal of Economic Theory.
[8]. Collins, A. and Robert J. (2004)- "Enhancing Student Learning Through Innovative Teaching and Technology Strategies", Kogan Page
[9]. Zulfiqar Ali, S Bala Bhaskar (2016)- "Basic statistical tools in research and data analysis", Indian J Anaesth.
[10]. Laura Pagani, Chiara Seghieri- "A Statistical Analysis of Teaching Effectiveness from Students' Point of View".
[11]. Obioma, G (2009)- "The predictive validity of public examination: A case study of Nigeria", A paper presented at the 33rd Annual Conference of International Association of Educational Assessment (IAEA) held in Baku.
[12]. Clarke, G.M. and Dcooke (1998)- "A Basic Course in Statistics. Third Edition. Internet: Performance of Students in Nigeria Education."
[13]. Azwa Abdul Aziz, Nur Hafieza Ismail, Fadhilah Ahmad (2013)- "Mining Students Academin Performance", Journal of Theoretical and Applied Information Technology, Volume 53, No 3.
[14]. Bharati Kharade and Kishor Wagh, PhD (2016)- "Data AnalyticsinEducationalManagementSystem",International Journal of ComputerApplications.
[15]. A.O. Akanbi (2003)- "Trend in Physics Education in Secondary School in Kwara State", Lafiagi Journal of Science Education.
[16]. Onofrio Rosario Battaglia, Benedetto Di Paola,Claudio Fazio-"ClusterAnalysisofEducationalData:anExampleof Quantitative Study on the answers to anOpen-Ended Questionnaire".
[17]. Joseph KwabinaArhinful Johnson, Frederick Narkwa Anderson (2015) - "Statistical Exploration of Academic Performance of Students in some Selected Programmes of the University of Cape Coast", IISTE, Volume 5, Issue 1.
[18]. Chew Li Sa, DayangHananibt.Abang Ibrahim, Emmy Dahliana Hossain (2014) - "Student Performance Analysis System (SPAS)", ICT4M.
[19]. Peter Abayomi Onanuga, Adewale O. Saka (2018) – "Trend Analysis of Students' Academic Performance", ICASE, Volume 29, Issue 2.
[20]. Elvis Munyaradzi Ganyaupfu (2013) - "Teaching Methods and Students' Academic Performance", IJHSSI, Volume 2, Issue 9.
[21]. Sodipo, E. O., Sodipo, A. A. and Adepoju, K. A. (2015) – "Statistical Analysis Of Students' Academic Performance In Nigeria Universities: A Case Study Of The University Of Ibadan, Nigeria", IJRAMR, Volume 2, Issue 2.
[22]. Sarafa Adeniran Salman, Thomas Akanbi Balogun (2015) – "A Comparative Study of Students' Academic Performance in Language and Literature Courses: English and French Languages in Focus", APJEAS, Volume 2, Issue 2.
[23]. Dr. Awoniyi Samuel Adebayo, AwoniyiTinuola Dorcas (2015) – "Comparative Analysis Of Students' Scores In Social Studies And Integrated Science At Junior Secondary School Certificate Examination In Edu Local Government Area Of Kwara State, Nigeria", ESJ, Volume 11, Issue 1.
[24]. Zalmon, IbaanGogo and Wonu, Nduka (2017) – "Comparative Analysis Of Student Mathematics Achievement In West African Senior Secondary Certificate Examination In Nigeria", EJRRES, Volume 5, Issue 1.
[25]. Simutenda Mathews, Allan Musonda (2018) – "The Effect of Instruction with SPSS on Students' Achievement and Attitude towards Hypothesis Testing: A Case of Zambia Catholic University", IJSR, Volume 7, Issue 6.
[26]. Oyerinde O. D. and Chia P. A.(2017) - "Predicting Students' Academic Performances – A Learning Analytics Approach using Multiple Linear Regression", International Journal of Computer Applications (0975 – 8887), Volume 157 – No 4.
[27]. Gibbs Y. Kanyongo, Janine Certo, Brown I. Launcelot (2006)- "Using regression analysis to establish the relationship between home environment and reading achievement: A case of Zimbabwe", International Education Journal.
[28]. Cody S. Ding (2006) – "Using Regression Mixture Analysis in Educational Research", Practical Assessment, Research & Evaluation, Volume 11, Number 11.
[29]. Shaobo Huang, Ning Fang- "Regression Models of Predicting Student Academic Performance in an Engineering Dynamics Course".
[30]. Y.Park, J.H. Yu, and I.H.Jo- "Clustering blended learning courses by online behavior data: A case study in a Korean higher education institute".
[31]. Dhara Patel, Ruchi Modi, Ketan Sarvakar (2014)- "A Comparative Study of Clustering Data Mining: Techniques and Research Challenges", IJTEMAS, Volume 3, Issue 9.
[32]. S.R.Pande , Ms. S.S.Sambare and V.M.Thakre (2012)- "Data Clustering Using Data Mining Techniques", International Journal of Advanced Research in Computer and Communication Engineering, Volume 1, Issue 8,
[33]. Amandeep Kaur Mann and Navneet Kaur(2013)- "Review Paper on Clustering Techniques", Global Journalof Computer Science and Technology,Volume 13,Issue5.
[34]. Santi Setyaningsih (2012)- "Using Cluster Analysis Study to Examine the Successful Performance Entrepreneur in Indonesia",

ICSMED.
[35]. Mythili S and Madhiya E (2014)- "An Analysis on Clustering Algorithms in Data Mining", IJCSMC, Volume 3, Issue 1.
[36]. Sudhir Singh and Nasib Singh Gill (2013)- "Analysis And Study Of K-Means Clustering Algorithm", IJERT, Volume 2, Issue 7.
[37]. Dr. S.P.Singh, Ms. Asmita Yadav(2013)- "Study of K- Means and Enhanced K-Means Clustering Algorithm", International Journal of Advanced Research in Computer Science, Volume 4, Number 10.
[38]Lei Bao, Edward F. Redish (2006)- "Model analysis: Representing and assessing the dynamics of student learning".
[39] A.K.Jain, M.N.Murthy, P.J. Flynn- "Data clustering: A review".
[40] P. Indira Priya, Dr. D. K. Ghosh (2013)- "A Survey on Different Clustering Algorithms in Data Mining Technique", IJMER, Volume 3, Issue1.