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# Educational Data Mining on University Management Information System for Measuring Performance of Students

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**Abstract- Data mining techniques are used in the numerous industries alongwith the IT sector, Agriculture and education system. Massive technical advancements and opportunities from past decades change the approach and lifestyle of the people. Although data mining techniques are used in the several industries but it is new approach in the Academics. The education system has not greatly profit from the potential of data mining techniuqes. A substantial amount of information are required for the better performance of the students in the academics. There is a vast amount of data are available which can help to find the performance of the students. The role of the data mining technology is to find out the performance of students in academics, the factors also find out which affects the academic performance and also other issues like financial, family background etc. how it effects the performance, how semester wise results so that students aware about the performance and also gender wise how it affects.**

**Index Terms- Data Mining, Education, Students, Performance, Patterns**

## I. INTRODUCTION

In the last few decades, the value of a college education has increased significantly. Because of the private involvement, universities are compelled to revise their goals and objective. A regulating body's controller has implemented criteria concerning faculty, infrastructure, and other resources. Because there is a vast amount of data available in many businesses, both public and private, new technologies are being developed in the fields of data management and analysis. The primary goal of data mining techniques is to find obscure and meaningless connections among data with a variety of attributes. Numerous data mining techniques are employed in a variety of industries, including education.Although data mining is still relatively new, it has been implemented successfully in business applications and is utilized in higher education and learning institutions. Within the field of education, educational data mining demonstrates how fresh and innovative the process is, with the goal of identifying and extracting significant new knowledge from the data. The goal is to use machine learning programming (MLP), mining algorithms, and numerous statistical techniques to improve the entire educational process and solve problems in research fields related to education. The technique of data mining is booming in the field of education. It can be applied to data analytics and visualization, student modeling, performance prediction, student grouping, and other applications.On educational datasets that come from educational sources, we can apply a variety of data mining techniques and mined the information so that parents, instructors, educational developers, educational researchers, and students can all benefit from using the information that has been mined.The primary focus of every institution is the academic achievement of its students. Therefore, if we could forecast students' academic achievement in advance, identify the key markers for their success, and learn more about their perseverance, we could increase kids' academic performance.

Advance access to student academic performance data allows universities to better plan for maintaining and improving student performance, as well as directing management to provide more informed admission options. This data is also critical for the long-term growth and development of universities.

**Role of Data Mining in Education Field**

"Educational Data Mining" is the term used whenever mining is applied in the field of education. The primary goal of this expanding field of study is to extract useful hidden knowledge from educational data sets. Educators have the ability to enhance the decision-making process inside the educational system by utilizing hidden knowledge.
It is an application for data mining related to educational data. It is a method of quantitative observation and analytical analysis to determine how students react to the educational system and how that response affects their learning. Its goal is to answer issues in educational research by analyzing educational data. Analyzing student performance

academically, comprehending student learning patterns, and emphasizing the factors that affect on the learning process in a certain education system to increase student's success ratio. The education sector has grown rapidly in recent years, which has increased the amount of education data. As a result, it is now crucial to mine education data to understand student behavior during the learning process or to identify problems with students . We often use information from questionnaires, interviews, class activities, and other sources to compile information about students' educational experiences. These methods can't be repeated often because they are usually lengthy.

The examination of "structured data" derived from "course management systems (CMS)" was the primary focus of the newly formed fields of learning analysis and educational assessment.In order to better understand student learning experiences, problems, performance, and behavior during the learning process, among other things, our research study uses data mining techniques and tools to analyze both structured and unstructured data from controlled online learning environments, such as course management system (CMS) or controlled online learning environments.

## II. RELATED WORK

Huanhuan Zhang [1]conducted study on Research and Implementation of Education Management Information System Based on Association Mining Technology, 2024. The main goal of the research is to employ association mining technologies to create an education management information system. First, the overall design of the system is developed, together with its thorough framework. Second, an association mining data model is constructed and a system optimisation design strategy is suggested. Lastly, induction, analysis, and summarisation are used to create an independent education management database. The results collected show that the concurrent connections index significantly increases as the education management information system described in this study runs constantly. The number of concurrent connections peaks at 882 users by the 20th second, which is more than the number of students participating in experimental instruction at the school. Demonstrate the practicality of the association mining-based educational management information system and the system's experimental teaching informationization recommendation effect is outstanding.
Adel Bessadok, Ehab Abouzinadah, Osama Rabie [2] were conduct similar research on Exploring students digital activities and performances through their activities logged in learning management system using educational data mining approach, 2023 Through two phases, the study examines the connection between pupils' digital activities and academic achievement. The first step involved analysing and grouping students' digital activities according to the characteristics of their activity logs from the learning management system (LMS) data set. The statistical significance of the correlation between these profiles and the related academic achievement was examined in the second phase.

Fuseini Inusah , Yaw Marfo Missah , Najim Ussiph , Frimpong Twum [3] study on Expert System in Enhancing Efficiency in Basic Educational Management using Data Mining Techniques, 2021 Every nation recognises the value of a basic education. Effective resource planning and use at the foundational level contributes to the effectiveness of education at all other educational levels in a nation. Compared to its West African competitors, Ghana is known for spending more on education. The issues facing Ghana's education system cannot be adequately addressed by planning efforts that rely on forecasting and projecting expenditures and the resources available to manage basic education. Since more resources are required to follow the procedures to contain the COVID-19 pandemic, more money is spent on managing educational institutions.This poses a significant obstacle to the nation's ability to use its limited resources effectively and efficiently. Data mining techniques are used in this article to analyse data from the Ministry of Education. This has made it easier to spot the data's errors. Since the population is a common denominator for educational indicators, inaccurate population projection has an impact on the KPIs in education. To help manage the situation, a suggested expert system will be created.
Nibras Z. Salih, Walaa Khalaf [4] have done research on Prediction of student's performance through educational data mining techniques, 2021 Numerous forecasts have been made for generic data, such as social, cultural, and economic data, that had little to do with student achievement. They used a real dataset from Mustansiriyah University in Iraq's three academic years for their study. This dataset, which comprises forty-four undergraduate students with thirteen attributes, is academic in nature and does not include socioeconomic data. They put forth a model that clarifies the relationship between two key topics: control systems and mathematics. The purpose of this study was to determine which third-year students failed the control systems course based on the academic characteristics of the first and second-year mathematics courses. The dataset was subjected to three different algorithms: multilayer perceptrons, support vector machines, and Naïve Bayes. The synthetic minority oversampling technique was used to address the imbalanced dataset, which caused an overfitting issue to show in the results. The results demonstrate that, following the application of the synthetic minority oversampling technique, the support vector machine algorithm demonstrates an effective classification. The Waikato environment for knowledge analysis (WEKA) tool and its associated metrics were used to test the classifiers' accuracy based on the confusion matrix. Huirong Yangand Wenjie Zhang [5] has conduct research on Data mining in college student education management information system, 2022 In order to offer some strategies and concepts

for improved student information management, the research primarily presents the use of data mining technology in college student education management information systems. It also suggests the application research method of data mining in college student education management information systems, including education data. A data mining system is constructed using the fuzzy C-means clustering technique and the mining K-means algorithm. According to the computation findings, the system's algorithm takes an average of 1.92 seconds to process, ensuring that school administrators will have a positive experience. 2020, Ezekiel U Okike , Merapelo Mogorosi [6] study on Educational Data Mining for Monitoring and Improving Academic Performance at University Levels, 2020 In order to assess how staff and students use the LMS resources and ascertain whether the amount of time spent using the LMS resources increased student academic performance, the researcher in the study took a sample of 712 logs that were taken from the Moodle Learning Management System (LMS) at an African university. Using machine learning techniques for clustering, classification, and visualisation from WEKA system tools, data gathered from Moodle LMS was preprocessed and examined. Course tools (Quiz, Assignment, Chat, Forum, URL, Folder, and Files) and how they were used by lecturers and students made up the dataset. Additionally, a matrix for the coefficients of correlation for the course materials, assessments, and final grade was created using SPSS. The correlation analysis was done to verify if students use of course tools had impact on student's academic performance.

## III. PROBLEM STATEMENT AND RESEARCH DESIGN ANALYSIS OF RESEARCH GAP

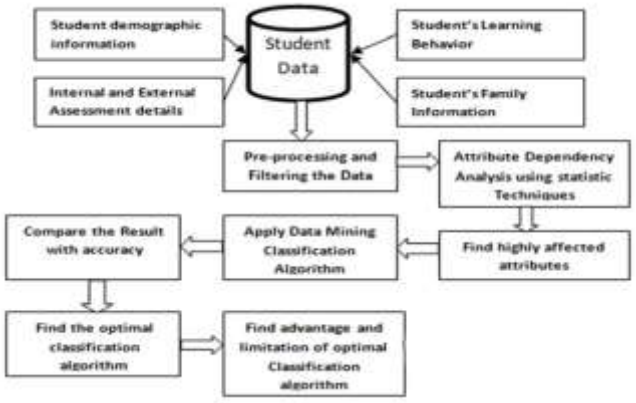
- Observation is that there is scope for development or modification of the current classification algorithms in order to produce better data mining results for the educational system, based on a survey of research paper literature.
- We also noticed that there are additional factors in the school system that have an impact on students' performance but have not been taken into account by earlier studies; as a result, our results have improved.
- Very few researchers carried out ongoing data analysis while students were enrolled. The other researchers who have made contributions in the same field motivated us to continue our investigation in order to enhance the algorithm

## IV. RESEARCH WORK GOAL

The proposed research work's goal is to investigate, evaluate, and expand the classification data mining algorithm to more precisely predict student performance, assisting educators, administrators, and other stakeholders in making decisions based on continuously available student transaction data.

## V. RESEARCH GAP ANALYSIS

Research gap analysis suggests that you can modify or enhance current classification algorithms to get better data mining outcomes for educational systems, based on literature surveyed publications. It also suggests that there are more factors that influence students' performance but were overlooked by earlier researchers. Furthermore, not many academics have examined student data continually throughout the course of the student's journey. This research study is crucial for raising student standards, assisting management in making decisions, forecasting current and feature student outcomes, identifying factors that have a significant impact on student performance, and identifying the most effective categorization algorithms. The study questions such as which variables yield greater outcomes were also examined in this chapter. We propose the model and design of the research work. This chapter includes the topics: Proposal of Research Model, Tools to be used in research, Factors that effect the performance of the students, Parameters to be used for research, Methodology of Data Collection, Methods of Data Mining, Classification of the Algorithm and Summary of the Chapter.




## VI. TOOLS TO BE USED IN RESEARCH WORK

The statistical analysis in this research model was conducted using SPSS, and the machine learning program WEKA was utilized to apply classification algorithms to the student data set. Data is the cornerstone of any machine learning application; and not just any data, but massive amounts of data, or what is now called "Big Data." You must take into account many aspects of the data in order to teach the machine to interpret huge data. The information needs to be clear. Null values ought not to be present in it. Furthermore, not all of

the data table's columns would be relevant for the kind of analytics you're aiming for. Before the data is given into a machine learning algorithm, the unnecessary data columns, or "features," as they are called in the language of machine learning, must be eliminated. To put it briefly, before your huge data can be used for machine learning, it must undergo extensive pre-processing. When the data is prepared, you can use a variety of machine learning algorithms, like clustering, regression, and classification, to address the issue on your end. Your application of algorithms is primarily determined by your topic expertise. There exist multiple algorithms even within the same type, such as classification. If you want to create an effective machine learning model, you might want to test various algorithms within the same class. You will want to see the processed data shown while doing this, therefore visualization tools are also necessary. You will discover more about Weka, a program that makes all of the aforementioned tasks simple and enables you to work with large amounts of data with comfort.

## VII. MODEL IMPLEMENTATION

**Software and Classifier Algorithm**

In this work decision tree classifier that is J48 and the rules classifier that is JRIP have been use.

J48:. J48 uses the notion of information entropy to construct decision trees from a set of labelled training data. By dividing the data into smaller subsets, it makes use of the fact that every attribute of the data can be used to make a decision. J48 looks at the difference in entropy, or normalised information gain, that arises from selecting an attribute for data splitting.The attribute with the largest normalised information gain is utilised to determine the decision. On the smaller subgroups, the process then repeats itself. If every instance in a subset is part of the same class, the splitting process comes to an end. Subsequently, a leaf node instructing the selection of that class is formed in the decision trees. However, it is also possible for no information to be gained from any of the features.

JRIP: An optimised algorithm is built by repeatedly incrementally trimming to provide error reduction (ripper). This approach, which is an enhanced variant of incremental reduced error pruning (IREP), is used by JRIP . A rule-based learner called Repeated Incremental Pruning to Produce Error Reduction (RIPPER) creates a collection of rules that identify the classes while reducing the amount of error. The number of training examples that the rules incorrectly classified defines the mistake. A simple method for creating classification rules is called RIPPER. When used to huge and noisy datasets, it is thought to be more effective than decision trees. It goes through four stages: selection, pruning, optimisation, and growth .During the expansion stage, it generates a series of distinct rules by incorporating predicates until the rule fulfils the halting requirements. In the second stage, the rules that lower the algorithm's performance are trimmed. Each rule is optimised in the optimisation stage by utilising phases 1 and 2 to create a new rule or by adding characteristics to the current rule. The model's finest rules are kept in the final stage, while others are disregarded. To determine the rule's description length, it makes use of the description length function.

**Collect the Students' Information to Perform Analysis**

| Fieldname | Data_type | |
|---|---|---|
| Srno | Numeric | |
| Gen | Nominal | {M,F} |
| Percentagehsc | Nominal | {Very_Good,GOOD,Average,Poor,Excellent |
| Stream | Nominal | {C,S} |
| F_annual_income | Nominal | {Middle,Very_High,Average,High,Low} |
| FQ | Nominal | {Diploma,'PostGraduate',PHD,Higher Secondary',Primary,Graduate, Illiterate, Other,Secondary} |
| FP | Nominal | {'GovernmentService','JobWork','PrivateServ Agricultural, 'Job work', Business,Retired, Agricultural} |
| MQ | Nominal | {Primary,PHD,Secondary,'PostGraduate',Illit ,Graduate,Higher Secondary', Diploma} |
| MP | Nominal | {'House Wife (HW)','Government Service','PrivateService',Retired} |
| NOS | Nominal | {TWO,THREE,ONE,FOUR} |
| Overall_attendance | Nominal | {Very_Good,Poor,Average,GOOD,Excellent |
| W_L_H | Nominal | {Poor,GOOD,Excellent,Very_Good,Average |
| W_Li_U | Nominal | {Average,Excellent,Poor,GOOD,Very_Good |
| D_Re_H | Nominal | {Very_Good,GOOD,Excellent,Poor} |
| E_W_L_U_H | Nominal | {GOOD,Poor,Average,Excellent,Very_Good |
| MIDTERM | Nominal | {Very_Good,Poor,Average,GOOD,Excellent |
| ASSIGNMENT_MARKS | Nominal | {Very_Good,Poor,Average,GOOD,Excellent |
| PRACTICAL_KNOLEDGE | Nominal | {Very_Good,Poor,Average,Excellent,GOOD |
| THEORY_MARKS | Nominal | {Very_Good,Poor,Average,GOOD,Excellent |
| PREVIOUS_SEM_MARKS | Nominal | {Excellent,Average,Very_Good,Poor,GOOD |
| fourth_Sem_Result | Nominal | {Very_Good,Poor,Average,GOOD,Excellent |

**Result of Statistical Measurement:** We collected the final exam results from the Rajasthan College of Agriculture, MPUAT Udaipur official exam controller. We then used WEKA software to analyze the data with J48 and JRIP algorithms. Additionally, we used Microsoft Excel to calculate statistics from the exam results. The statistical results are shown in Tables

**Major Courses Failure Rate**

| Table of Major Subject Wise Failure | | | | | | |
|---|---|---|---|---|---|---|
| | **ENTO-501** | | ENTO-503 | | PPATH-501 | |
| | **n1=68** | | **n1=68** | | **n1=68** | |
| | **F** | **%** | **F** | **%** | **F** | **%** |
| **Theory** | **89** | 17.65% | 46 | 9% | 46 | 9% |
| **Practical** | **0** | 0.00% | 16 | 3% | 0 | 0% |
| **Overall** | **8** | 1.47% | 31 | 6% | 31 | 9% |

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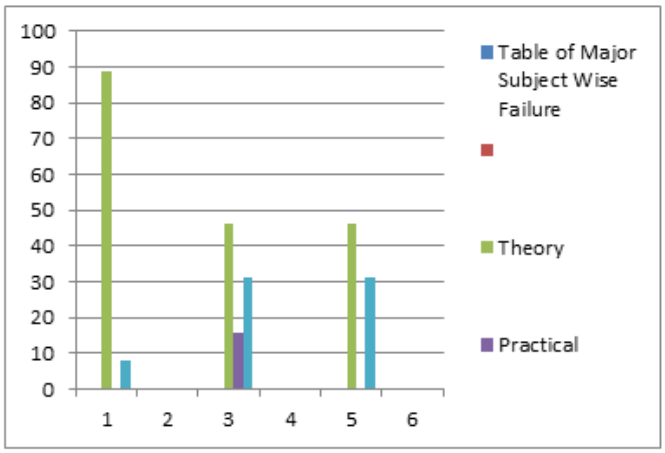
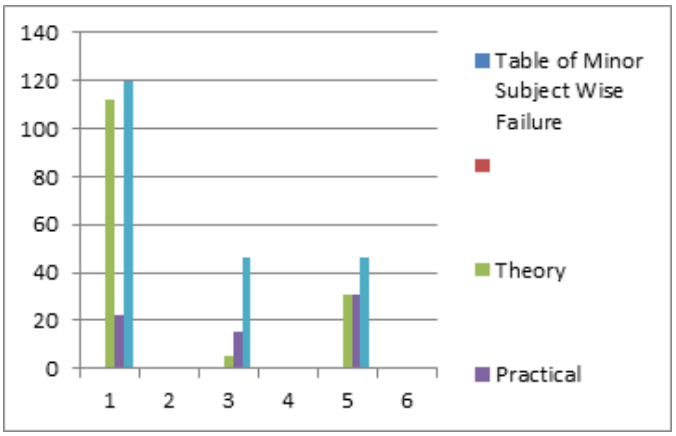



Minor Theory Courses Failure Rate.

| Table of Minor Subject Wise Failure | | | | | | |
|---|---|---|---|---|---|---|
| | Stat-511 | | PPHY-512 | | MBB-502 | |
| | n1=68 | | n1=68 | | n1=68 | |
| | F | % | F | % | F | % |
| Theory | 112 | 22.06% | 5 | 1% | 31 | 6% |
| Practical | 22 | 4.41% | 15 | 3% | 31 | 6% |
| Overall | 120 | 23.53% | 46 | 9% | 46 | 9% |




Failure Rate According to Gender

| Sl | Gender | Failure Rate |
|---|---|---|
| 1 | Male | 4.41% |
| 2 | Female | 2.94% |

Table 11.Failure Rate According to Attendance Status

| Sl | Attendance Status | Failure Rate |
|---|---|---|
| 1 | Ex-Collegiate | 19% |
| 2 | Year Repeat | 12% |
| 3 | Regular | 7.33% |

Failure Rate According to Student Type for All Years.

| Sl | Student Type | Failure Rate |
|---|---|---|
| 1 | Regular | 7.33% |
| 2 | Year Repeat | 31.03% |

Absent Percentage in Even Semester Exam.

| S.No | Semester | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|
| 1 | Absent Percentage in Odd Semester | 4.45% | 5.33% | 5.73% | 9.90% |
| 2 | Absent Percentage in Even Semester | 3.30% | 4.89% | 2.33% | 8.70% |

Classification Result: This study employs two classification algorithms, J48 and JRIP, to analyze six datasets. The results, obtained using WEKA with a 66% training set and 34% testing set split, are presented in this section. Table 17 provides an overview of the datasets used, including their names and the number of students selected for classification

Table14.Number of Instances for Dataset.

| Sl | Dataset Name | Instances |
|---|---|---|
| 1 | Odd Semester | 1018.00 |
| 2 | Even Semester | 1018.00 |
| 3 | Combined Semester | 2036.00 |
| 4 | Major Courses | 509.00 |
| 5 | Minor Courses | 102.00 |

Accuracy Comparison between J48 , JRIP, Bayesnet and Naïve Bayes.

| Sl | Dataset | J48 | JRIP | Bayes net | Naïve Bayes |
|---|---|---|---|---|---|
| 1 | Odd Semester | 78.3784% | 74.3243% | 70.3549% | 70.1569% |
| 2 | Even Semester | 66.1538% | 61.5385% | 59.486% | 69.1469% |
| 3 | Combined Semester | 80.0000% | 80.0000% | 79.0000% | 78.9684% |
| 4 | Major Courses | 92.3077% | 92.3077% | 92.1259% | 92.000% |
| 5 | Minor Courses | 88.0000% | 80.0000% | 80.1254% | 80.0698% |
| 6 | Study and Understanding Class | 97.6524% | 96.3258% | 95.7893% | 95.1598% |

In today's competitive educational landscape, data mining tools are increasingly used to analyze student performance, predict outcomes, and identify areas for improvement. Educational Data Mining extracts valuable insights from large datasets to enhance the learning process. Classification algorithms, such as J48 , JRIP, Bayesnet and Naïve Bayes are employed to accurately categorize student data and predict

performance. This research utilized J48 , JRIP, Bayesnet and Naïve Bayes algorithms to measure student performance and identify factors contributing to success or failure. Statistical analysis revealed key trends, including failure rates by gender, course type, attendance, and semester. The study aimed to uncover reasons behind student failure and success, providing recommendations for improvement. The analysis identified specific courses with high failure rates and compared failure rates between males and females over four years. The insights gained can inform departmental decision support student success

## VIII. CONCLUSION

Student academic performance is a critical goal in higher education. Data mining offers various methods and techniques to measure student performance, enabling educators to predict and improve student outcomes. This study aims to develop and validate prediction models to forecast student academic performance in end-semester examinations, reducing failure rates and enhancing student performance. This research employs statistical analysis and data mining operations using WEKA. The proposed research model involves:

- **Data Collection:** Gathering student information through questionnaires, Google spreadsheets, and a dynamic website.
- **Data Preprocessing:** Identifying and removing incomplete, incorrect, irrelevant, and inadequate data.
- **Data Analysis:** Applying data mining techniques to predict student performance.

Student records were collected from various educational institutions. By leveraging data mining techniques, this research aims to provide insights into student performance, enabling educators to develop targeted interventions and improve student outcomes. After pre-processing the data, we used a statistical technique called multiple linear regression with the statistical analysis tool to identify the most influential parameters on student performance. It produced significant values for each defined attribute in the dataset. Based on previous data, the significance level is considered to be 0.05. Attributes with P-values $< 0.05$ are used to predict student outcomes, whereas those with P-values $> 0.05$ are discarded as irrelevant variables in this study.

Based on this statistical analysis, we considered parameters such as percentage in higher secondary examination, assignment marks, father's annual income, practical knowledge, weekly lab usage, marks in theory examination, overall attendance ratio, mid-term marks and previous semester result in our proposed research work. This statistical study also yielded the Normality test, which statistically confirms if the data used in the planned research effort is normal or not. The normality test gives the bell shape curved and straight line on the graph, statistically proving that our data is normal for building the model. Furthermore, we loaded a normalized dataset into the WEKA tool to undertake mining operations. We incorporated the categorization algorithms J48 and JRIP into our suggested research project. We conducted a comparison analysis of these selected algorithms using the accuracy-measured metrics "time taken to build the model," "correctly classified instances," and "incorrectly classified instances," as well as error measurement parameters. After doing a comparative analysis, we identified a highly accurate algorithm among all of the stated classification methods and determined its pros and downsides. We also contrasted these stated classification algorithms using class-specific accuracy measurement parameters such as "Truepositive (TP)", "FalsePositive (FP)", "Precision", "Recall", "F-measure", and "ROC". In the comparative research investigation, we discovered that the J48 algorithm produces the most accurate results among all categorization algorithms. However, the J48 algorithm generates a complex tree structure and cannot cope with numerical class values in the WEKA tool. As a result, we changed the J48 algorithm to incorporate the new statistical variance notion and the post pruning procedure, resulting in the suggested new extended algorithm. This proposed approach created a simple tree structure with shorter model development time and solved the overfitting problem.

To take advantage of the novel proposed technique, we developed it using the Java development tool NetBeans and configured the file with the WEKA data mining tool for further research investigation. In this research study, the generated results of the new proposed algorithm are compared to the existing classification J48 algorithm utilizing various accuracy and error measurement parameters.

Finally, based on the aforementioned study analysis and observations, we determined that the J48 algorithm produces more accurate results than the J48 algorithm. So we used the algorithm to forecast present and future student academic performance.

We have validated the proposed algorithm for students enrolled in batch 2014-2017. We applied the model just to the fourth semester student dataset to predict student performance and take timely action against poor performers, but not to semesters one through three.

Furthermore, we used statistical functionalities such as descriptive and frequencies to calculate the student performance ratio from the first to fourth semesters. We also ran a comparative analysis to obtain results through statistical analysis. The results of the investigation suggest that students do better in the fourth semester than in the previous three semesters. It demonstrates that our model is effective at improving student performance.

**Future Scope**

This research can be expanded in the future by conducting in-depth studies of other data mining techniques and algorithms, such as clustering and association, to uncover hidden patterns and knowledge for the benefit of the educational process. Because the current study has a limited number of parameters, more parameters should be added to improve the models' efficiency. Given the necessity for many ways to forecast performance, it is critical to investigate additional learning algorithms. In this regard, we believe that techniques based on rough set theory, neurofuzzy, and other hybridized machine learning algorithms can shed insight on the problem.

We may also use a similar technique to other sectors such as medical, legal, and UG studies to uncover some fascinating hidden information. Because the type of data varies, the deciding attributes and data mining models may differ, resulting in further contributions to the data mining area. Finding out about dropouts from courses and investigating the causes behind them might also be valuable for future work. Similarly, one might analyze whether pursuing higher education improves a student's chances of finding work. In conclusion, when data mining techniques are properly used over a genuine and up-to-date data base, various hidden and relevant information may be obtained, which can be efficiently employed for future planning.

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