Addressing the Needs of Slow Learners in Engineering Programs: Effective Identification and Improvement Strategies

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Abstract—**This paper addresses the needs of slow learners in engineering programs by exploring effective identification and improvement strategies. We employ a range of statistical methods, including descriptive statistics, regression analysis, and clustering, to identify slow learners. Predictive modelling techniques, such as decision trees and support vector machines, are utilized to classify students based on their learning patterns. Our analysis with Python Programming reveals a noticeable improvement in academic performance from Semester 1 to Semester 2. Specifically, there is an increase in average CGPA, a decrease in the number of backlogs, and an improvement in the passing rate. These results demonstrate the effectiveness of the implemented strategies. To support these learners, we propose several strategies: pairing slow learners with advanced peers, promoting peer teaching, developing individualized learning plans, and utilizing technology-enhanced resources. Feedback from students indicates high satisfaction with these strategies, reflecting their positive impact on engagement, understanding, and academic performance. These approaches collectively aim to foster better learning outcomes and overall improvement in engineering education.**

***Keywords*— Slow Learners, pedagogical Strategies, Engineering Education, Student Performance**

I. INTRODUCTION

In the realm of engineering education, the term "slow learners" refers to students who struggle to keep pace with the standard curriculum and exhibit difficulties in mastering core concepts at the same rate as their peers. Slow learners may exhibit a range of challenges, including slower cognitive processing speeds, limited problem-solving abilities, or difficulties in grasping complex technical concepts. This disparity often results in lower academic performance and increased frustration, which can significantly affect their overall educational experience(Kashyap, 2019).

The need for addressing the requirements of slow learners is paramount, as these students are at risk of falling behind academically, which can adversely impact their confidence and motivation. If not properly supported, slow learners may experience long-term academic and professional disadvantages, including reduced career opportunities and lower self-esteem(Vasudevan, 2017).

Slow learners face many difficulties within the academic environment. These include difficulties with comprehension, slower processing speeds, and challenges with retention of information. The traditional pace of instruction often does not accommodate their learning needs, Additionally, the lack of personalized support and resources can exacerbate these issues, resulting in increased academic stress and disengagement(Husna et al., 2020).

To address these challenges, statistical and ML methods can be employed to accurately identify slow learners. Techniques such as classification algorithms, clustering, and predictive modeling can analyze various performance metrics and learning behaviors to pinpoint students who may be struggling. By leveraging these data-driven approaches, educators can gain insights into learning patterns and implement targeted interventions to support slow learners effectively(Hossain et al., 2019).

Once identified, slow learners can benefit from a range of targeted interventions. Personalized learning plans, tailored instructional materials, and additional academic support can help bridge learning gaps. Techniques such as differentiated instruction and adaptive learning technologies can provide the necessary support to meet individual learning needs. Additionally, fostering a supportive learning environment that encourages perseverance and resilience is crucial for their academic success.

Advanced learners play a vital role in supporting their peers. Peer teaching and mentoring programs enable advanced students to share their knowledge and skills with slow learners, providing additional explanations and perspectives that can enhance understanding. This collaborative approach not only benefits slow learners but also reinforces the knowledge and leadership skills of advanced learners(Brkić et al., 2024).

Group sites and collaborative learning environments offer significant benefits for slow learners. Working in groups allows them to engage with diverse perspectives and benefit from collective problem-solving. Pairing slow learners with advanced peers in group settings promotes mutual learning and support, facilitating a more inclusive educational experience. Advanced learners can offer guidance, share effective study strategies, and provide encouragement, which helps slow learners gain confidence and improve their academic performance(Kimbrough et al., 2022).

Addressing the needs of slow learners in engineering programs requires a multifaceted approach that includes accurate identification, targeted interventions, and the leveraging of peer support.

II. LITERATURE REVIEW

In order to ensure equitable educational results, it is imperative that engineering programs attend to the needs of slow learners. Numerous studies have examined efficient methods for locating and assisting slow learners in various educational settings; these findings can offer insightful information for engineering education.

Nielsen and Vinner investigated cognitive assessments of literacy learning worries in adult second language learners. Their study highlights the importance of understanding cognitive challenges to tailor educational interventions effectively (Nielsen & Vinnner, 2023). This approach can be adapted to identify cognitive barriers faced by slow learners in engineering programs. Yadav et al. investigated how skill-based training affected the scientific and mathematical proficiency of slow learners(Yadav et al., 2017).

Their findings suggest that targeted skill-based training can significantly improve slow learners' performance, which is relevant for engineering education where complex problem-solving skills are essential. Winson and Fourie focused on recognizing developmental coordination disorders in foundation phase classrooms. Their research emphasizes the need for early identification and support, which can be extended to engineering education to address motor and coordination challenges that might affect slow learners(Winson & Fourie, 2020). Kamini and Kaur explored the effects of concept mapping and guided discovery instructional strategies on slow learners' attitudes toward science(Kamini & Kaur, 2022). Their study demonstrates that instructional strategies tailored to slow learners can enhance their engagement and understanding, which is applicable to engineering education. Nurul Husna et al. suggested a robotics-based learning model for sluggish learners. Their model demonstrates how technology can help slow learners, which is especially helpful in engineering programs that emphasize real-world applications and hands-on learning(Nurfadhillah et al., 2022). Miundy et al. created a dyscalculic learner's assistive learning application for augmented reality (AR). Through demonstrating how AR can help slow learners, their work raises the possibility that similar advances in technology could have positive effects on engineering education(Miundy et al., 2019). Janah and Aprilia created a beginning reading curriculum with Montessori methods for sluggish readers(Janah & Aprilia, 2023) . Their study emphasizes the value of tailored teaching strategies that can be applied to the study of engineering to meet particular learning needs. Dibia and Ajoku emphasized the need for teachers to recognize and assist sluggish learners at lower fundamental education levels. Their research emphasizes how important it is for educators to offer assistance, as this is crucial to the development of efficient support structures in engineering programs(Dibia & Ajoku, 2018). Vasudevan reviewed the causes, problems, and educational programs for slow learners(Vasudevan, 2017).

Effective engineering education requires tailored pedagogical strategies to address diverse learner profiles and promote higher-order thinking. (Munje et al., 2021) emphasize the importance of identifying advanced, average, and slow learners to customize instructional approaches, ensuring that all students achieve program outcomes. This differentiation enables targeted support and maximizes learning efficiency.

(Bhaumik et al., 2024) highlight strategies for fostering higher-order thinking in engineering students, such as problem analysis, critical evaluation, and creative application. Their findings suggest that structured pedagogical interventions can significantly enhance cognitive skills, preparing students for complex engineering challenges.

(Korlepara, 2024) demonstrates that paired problem-solving is effective for identifying and addressing misconceptions, reinforcing conceptual understanding and collaborative learning. This approach ensures that students develop both technical proficiency and critical reasoning.

In summary, while numerous studies have highlighted the significance of identifying and supporting slow learners through various educational strategies, there remains a lack of consensus on how these interventions can be effectively adapted to the unique demands of engineering education. Although technology-based models and targeted skill training have shown promise, their applicability in diverse engineering disciplines and at scale has yet to be fully explored. This review highlights the need for further research that critically examines the long-term impacts of these interventions on engineering students' performance, particularly in problem-solving and technical skill development. The findings of this study aim to address these gaps and propose tailored strategies that can enhance the learning experiences of slow learners in engineering programs.

III. METHODS OF IDENTIFYING SLOW LEARNERS

A. Dataset

To identify slow learners after the first semester of the first year in an engineering program, the dataset preparation involves several steps. This process ensures that the data is suitable for analysis and can provide insights into students who may need additional support. Here’s a detailed discussion of how the dataset is prepared:

1) Understanding the Dataset

The dataset contains the following columns:

1. **Sub1_Test to Sub5_Test**: 30% (total for all five subjects, e.g., 6% for each test)
2. **Sub1_Quiz to Sub5_Quiz**: 20% (total for all five subjects, e.g., 4% for each quiz)

3. **LMS_Marks**: 20% (overall LMS performance)
4. **Timely_Completion**: 10% (completion of assignments on time)
5. **Attendance**: 20% (percentage of classes attended)

LMS marks are awarded for **MCQs** administered online and graded automatically, focusing on knowledge recall. **Test marks** come from **subjective, offline** assessments, graded manually, and evaluate deeper understanding and critical thinking. **Quiz marks** are **subjective** and online, with grading done either automatically or manually, assessing both recall and comprehension. The key difference lies in the format (MCQs vs. subjective questions) and the grading method (automated vs. manual).

2) Data Cleaning and Preparation

Since all columns have non-null counts of 800, it indicates no missing values. However, if missing values were present, they would need to be addressed using imputation methods or by removing incomplete records.

Timely_Completion is categorical variables. These need to be converted into numerical values for analysis. Typically, they are transformed into binary values (e.g., 1 for 'Yes' and 0 for 'No').

Compute a composite measure of student performance by averaging the scores from tests and quizzes. This helps in creating a consolidated view of each student's academic performance.

B. Descriptive Statistics:

1) Mean and Standard Deviation Method

Objective: To identify students whose performance deviates significantly from the average, indicating they may be struggling academically.

Calculate the Mean: The mean (average) grade is computed to understand the central tendency of the data. The formula for the mean

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$$

where N is the number of students, and x_i represents the grade of the i^{th} student.

Calculate the Standard Deviation: The standard deviation measures the spread of grades around the mean. It is calculated using:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$$

where σ is the standard deviation, x_i is the grade of the i^{th} student, $\bar{x}$ is the mean grade.

Determine the Threshold: To identify slow learners, you can use a threshold based on the mean minus a certain number of standard deviations. A common approach is to use one standard deviation below the mean: In the proposed work threshold (mean minus a certain number of standard deviations) is calculated to identify slow learners:

$$\text{Threshold} = \bar{x} - \sigma$$

Identify Slow Learners: Students whose grades are below this threshold are considered slow learners:

Slow Learner= $\{x_i \mid x_i < \text{Threshold}\}$

Figure 01 shows the plots of Mean and Standard Deviation Method

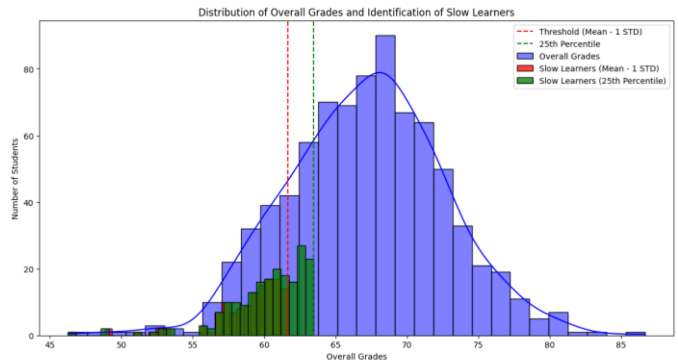

Fig. 1. Mean and Standard Deviation Method

Example

- Suppose the mean grade $\bar{x}$ is 70 and the standard deviation (σ) is 10.
- The threshold would be 70−10=60.
- Any student with a grade below 60 is identified as a slow learner.

2) Percentile Ranks Method

Objective: To determine how a student's performance compares to their peers and identify those in the lower percentiles.

Steps and Formulae:

1. **Calculate the Percentile Rank**: Percentiles divide the data into 100 equal parts. To find the 25th percentile (P25), which indicates the value below which 25% of the data falls, use:

$$P_k = \text{value at } \left(\frac{k}{100} * (N+1)\right)^{th} \text{ position}$$

where P_k is the k-th percentile, k is the desired percentile rank (e.g., 25 for the 25th percentile), and N is the total number of data points.

2. **Sort the Data**: Arrange the grades in ascending order.
3. **Determine the Percentile Value**: For a given percentile (e.g., 25th percentile), locate the value at the calculated position. If this position is not an integer, interpolate between the closest values.
4. **Identify Slow Learners**: Students whose grades fall below the calculated percentile value are considered slow learners:

$$\text{Slow Learner} = \{x_i | x_i < P25\}$$

Figure 02 shows the Percentile Rank Method

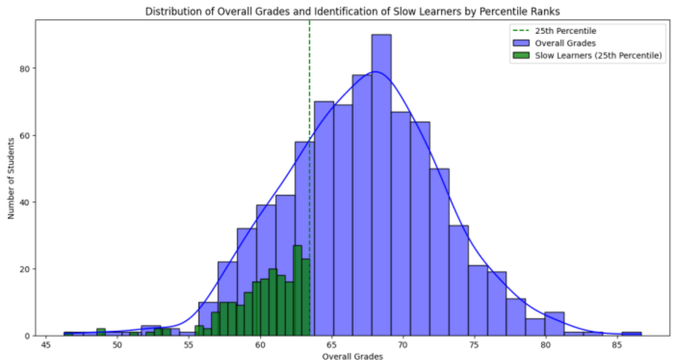

Fig. 2. Percentile Rank Method

1. Example

If the 25th percentile grade (P25) is 55, then any student with a grade below 55 is identified as a slow learner.
These methods help identify students who are struggling academically by comparing their performance against the overall average or their peers.

C. Comparative Analysis:

1) Benchmarking:

Compare student performance against predefined benchmarks or standards to identify those who consistently score below the threshold. The benchmark threshold is defined as one standard deviation below the mean of the overall grades:

Benchmark Threshold=Mean Overall Grades−Standard Deviation of Overall Grades

Students scoring below this threshold are identified as slow learners.

Figure 03 shows the Benchmark Method for identification of slow learners.

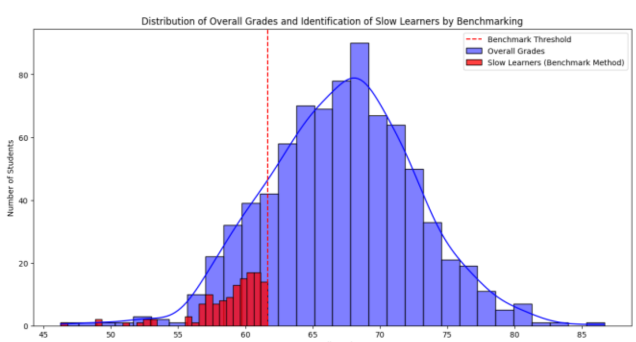

Fig. 03 Benchmark Method

Benchmark Threshold: 61.66

Number of Slow Learners (Benchmark Method): 130

2) Group Comparisons:

Use t-tests to compare performance metrics across different groups (e.g., high vs. low performers) to identify students in the lower-performing group. Conducting T-Tests. To compare the performance of high and low performers across different subjects, we perform independent two-sample t-tests for each subject's test and quiz scores. This helps determine if there are significant differences in performance between the two groups.

Formulate Hypotheses:

Null Hypothesis (H_0): There is no significant difference in the mean scores of high and low performers.

Alternative Hypothesis (H_1): There is a significant difference in the mean scores of high and low performers.

Perform T-Tests: For each subject's test and quiz scores, calculate the t-statistic and the corresponding p-value. A low p-value (typically < 0.05) indicates that the difference in means is statistically significant, allowing us to reject the null hypothesis. Figure 04 shows the Boxplot for identifying Slow and Advanced learners using T-Test.

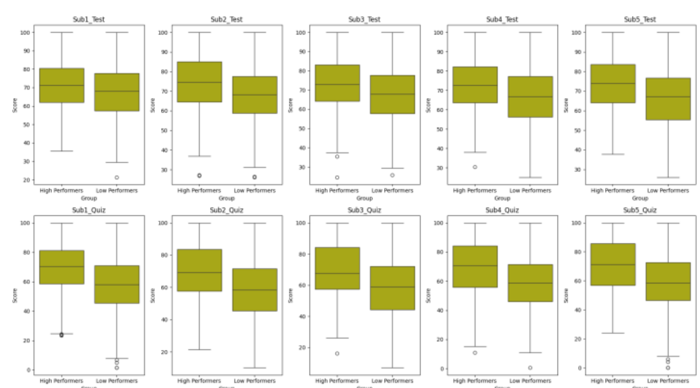

Fig. 04 Boxplot for identifying Slow and Advanced learners using T-Test

D. Regression Analysis:

We can use a systematic approach that takes advantage of these models' ability to predict students' overall grades based on their performance in tests, quizzes, and other relevant metrics to identify slow and advanced learners using different regression models. Here's a detailed discussion of how each model can contribute to this process:

1) Linear Regression:

As a baseline model, Linear Regression is used to explore the linear relationship between students' overall grades and their performance in tests, quizzes, and other assessments(I.Olufemi et al., 2023a). It provides a straightforward interpretation of how different variables, such as test and quiz scores, affect the final grade. By examining the coefficients, we can identify areas where slow learners deviate from expected performance, helping to pinpoint areas for improvement.

2) Ridge Regression:

Ridge Regression is applied when predictors are highly correlated, which often happens when test scores and quizzes are interrelated(I.Olufemi et al., 2023b). The penalty term in Ridge Regression helps to address multicollinearity and stabilize predictions, making it a robust tool to identify slow learners. It ensures that the model doesn’t overfit and remains reliable, even with correlated features.

3) Lasso Regression:

Lasso Regression is used to perform feature selection by shrinking some coefficients to zero(Rabiei et al., 2022). It helps to identify the most significant predictors of student performance, especially when there are many features involved. By pinpointing key variables, such as particular subjects or quizzes where slow learners struggle, interventions can be more targeted.

4) ElasticNet Regression:

ElasticNet combines the penalties from both Ridge and Lasso to balance between feature selection and multicollinearity handling(Rabiei et al., 2022). It’s effective in datasets with many correlated predictors, as it captures both linear relationships and feature interactions. ElasticNet can uncover complex patterns that contribute to students’ underperformance, helping to identify slow learners with more nuanced modeling.

5) Decision Tree Regressor:

Decision Trees segment the data into subsets based on decision rules, capturing non-linear relationships(Fertalj et al., 2022). This model helps to understand how different factors (e.g., test and quiz scores, attendance) combine to influence student performance. It identifies crucial decision points, which can highlight specific areas of underperformance for slow learners.

6) Random Forest Regressor:

Random Forests build multiple decision trees and combine their results to improve accuracy and robustness(Koutcheme et al., 2022). Random Forests provide a reliable way to manage a large number of predictors while capturing non-linear relationships. They also generate feature importance scores, which can help identify the factors most contributing to slow learning, allowing for focused support.

7) Gradient Boosting Regressor:

Gradient Boosting sequentially builds trees, where each tree corrects the errors of the previous one(Huang et al., 2018). This technique excels at detecting complex patterns and interactions within the data. It highlights areas where students consistently underperform, providing insights into why slow learners struggle and offering precise targets for intervention.

8) AdaBoost Regressor:

AdaBoost reweights instances based on prediction errors to improve the performance of weak learners(Giri et al., 2024). AdaBoost iteratively focuses on students who consistently perform poorly, helping to identify slow learners. It allows for targeted interventions by prioritizing areas of persistent underperformance.

9) Support Vector Regressor (SVR):

SVR uses kernel functions to model complex, non-linear relationships. SVR is ideal for detecting students whose performance lies outside of typical expectations (i.e., underperforming or excelling). By analyzing support vectors, it identifies critical data points that define a student’s performance, guiding interventions for both slow and advanced learners.

10) K-Nearest Neighbors (KNN) Regressor:

KNN predicts a student’s grade based on the academic achievement of their nearest neighbors(Karamti et al., 2023). KNN is helpful in comparing a student’s performance to similar peers, allowing us to identify discrepancies that may indicate slow or advanced learners. By analyzing the performance of peers with similar profiles, it helps contextualize a student’s standing and highlights areas for personalized interventions.

11) Identifying Slow and Advanced Learners:

By applying these models, we can predict students' overall grades and compare them to actual grades. Significant negative deviations from predicted grades can identify slow learners, while significant positive deviations can identify advanced learners. Feature importance scores and model coefficients help pinpoint specific areas contributing to underperformance or excellence, guiding targeted interventions and support.

Through this comprehensive analysis, educators can develop data-driven strategies to assist slow learners and nurture advanced learners, ultimately enhancing the overall learning experience and outcomes. Table 01 shows the Regression models results and performance.

TABLE I
REGRESSION MODELS RESULT TABLE

Sr No	Model	R-squared	MAE
1	Linear Regression	1	0.00

2	Ridge Regression	1	0.00
3	Lasso Regression	0.99871	0.15
4	ElasticNet Regression	0.999611	0.08
5	Decision Tree	0.298162	3.62
6	Random Forest	0.687825	2.31
7	Gradient Boosting	0.850213	1.59
8	AdaBoost	0.640333	2.50
9	Support Vector Regressor	0.986775	0.36
10	K-Nearest Neighbors	0.79579	1.92

The regression models were evaluated based on R-squared (explained variance) and Mean Absolute Error (MAE) metrics. Linear and Ridge Regression models achieved perfect predictions with R-squared of 1 and MAE of 0, indicating overfitting. Lasso Regression (R-squared: 0.99871, MAE: 0.15) and ElasticNet Regression (R-squared: 0.999611, MAE: 0.08) also performed exceptionally well. Support Vector Regressor demonstrated strong performance (R-squared: 0.986775, MAE: 0.36). Gradient Boosting showed good predictive power (R-squared: 0.850213, MAE: 1.59), while Random Forest (R-squared: 0.687825, MAE: 2.31) and K-Nearest Neighbors (R-squared: 0.79579, MAE: 1.92) were moderately effective. Decision Tree (R-squared: 0.298162, MAE: 3.62) and AdaBoost (R-squared: 0.640333, MAE: 2.50) performed poorly, suggesting less suitability for this dataset. Figure 05 shows the Performance of Regression Models to predict slow and advanced learner.

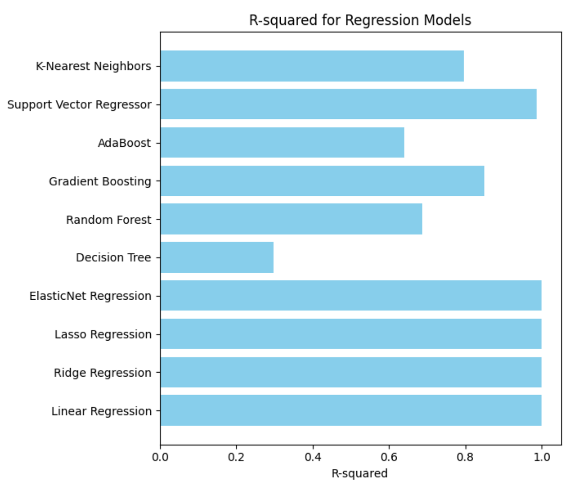

Fig. 5. Performance of Regression Models to predict slow and advanced learner.

E. Cluster Analysis:

1) K-Means Clustering:

K-Means clustering can be used to identify slow and advanced learners by grouping students based on their performance metrics, such as test and quiz scores. The process involves standardizing the data, applying K-Means to partition students into clusters, and analyzing these clusters to determine which represents slow learners and which represents advanced learners(Cahyo & Sudarmana, 2022). The clustering results are then validated by comparing cluster characteristics with known performance thresholds. Visualization of the clusters, such as plotting overall grades against LMS marks, helps in distinguishing between the clusters and understanding the performance distribution. This approach allows educators to effectively categorize students and tailor their teaching strategies accordingly as shown in figure 06.

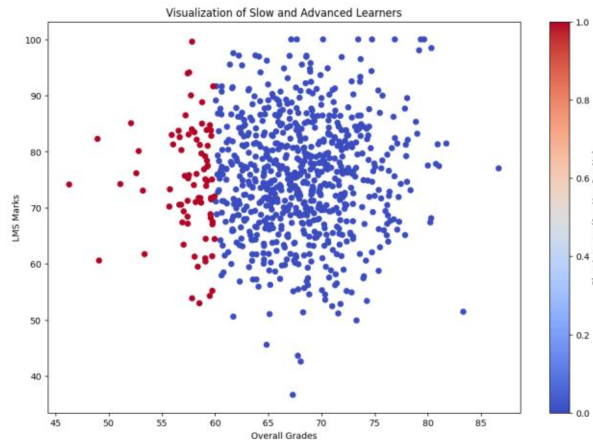

Fig. 6. Cluster Analysis by K Mean

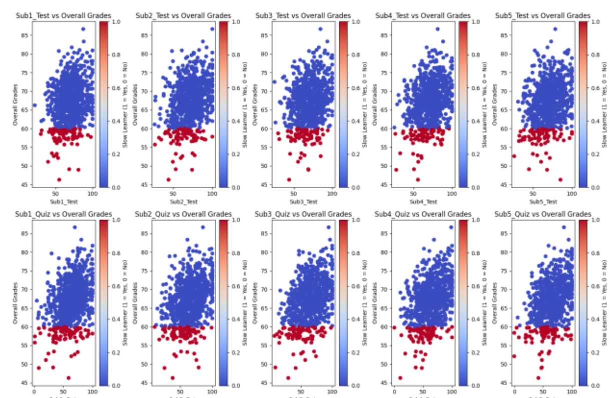

Fig. 7. Subject, Test and Quiz wise Clustering of Slow and advanced learners.

The scatter plots shown in figure 07 provide a visual understanding of how scores on specific tests and quizzes relate to overall performance. The color-coding helps identify patterns and potential areas where slow learners differ from others in terms of specific assessments. This approach allows for a clear visualization of the relationship between individual assessments and overall student performance, with a focus on how slow learners' scores compare to those of other students.

2) Hierarchical Clustering:

Build a dendrogram as shown in figure 08, to visualize and identify clusters of students with similar performance patterns. In the dendrogram, we determine the optimal number of clusters by analyzing the vertical gaps between merging points(Cahyo & Sudarmana, 2022). By drawing a horizontal line at a distance of 25 on the vertical axis, we observe how this line intersects the vertical lines representing cluster merges. At this height, the line intersects two vertical lines, indicating that the data can be effectively grouped into two distinct clusters. This distance is chosen to capture significant separations in the clustering structure, allowing us to identify two meaningful clusters within the dataset.

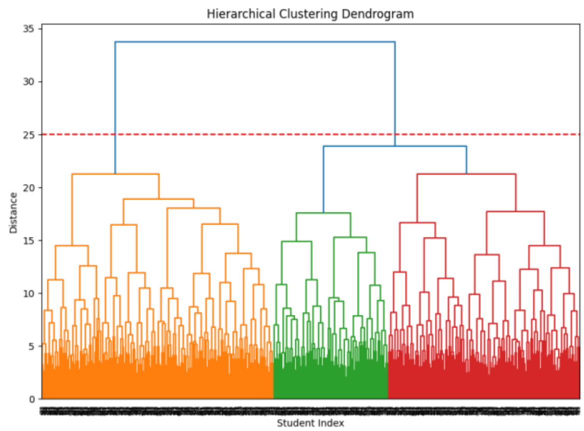

Fig. 8. Dendogram shows the 2 clusters

F. Factor Analysis:

1) Principal Component Analysis (PCA):

Reduce dimensionality of performance data to identify underlying factors contributing to slow learning and detect students affected by these factors as shown in figure 09. PCA converts all data into 2 features rather in group of slow and advanced learners.

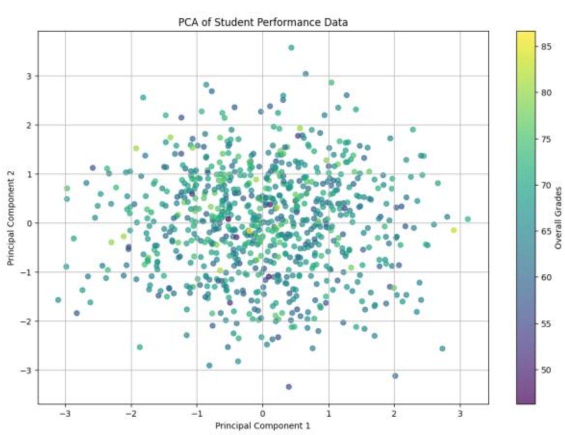

Fig. 9. Principal Component Analysis

2) Exploratory Factor Analysis (EFA):

Identify latent variables affecting performance and understand which students are most influenced by these factors as shown in figure 10. Exploratory Factor Analysis (EFA) is a statistical method used to uncover the underlying relationships between variables and identify latent factors that explain the observed data. In the context of identifying slow and advanced learners, EFA can help in understanding the underlying constructs that differentiate these groups based on various educational metrics(Cahyo & Sudarmana, 2022).

Process:

1. **Data Preparation:**
    - **Variables:** Include test scores, quiz scores, LMS marks, attendance, timely completion, and regularity of lectures.
    - **Data Cleaning:** Handle missing values, outliers, and ensure all variables are standardized if necessary.
2. **Factor Extraction:**
    - **Correlation Matrix:** Compute the correlation matrix to examine the relationships between variables.
    - **Factor Extraction Method:** Use methods like Principal Component Analysis (PCA) or Maximum Likelihood Extraction to identify initial factors. Determine the number of factors based on criteria like eigenvalues (>1) or the scree plot.
3. **Factor Rotation:**
    - **Rotation Method:** Apply an orthogonal (e.g., Varimax) or oblique (e.g., Promax) rotation to simplify the factor structure and enhance interpretability.
    - **Interpret Factors:** Analyze factor loadings to determine which variables are strongly associated with each factor. This helps in understanding the dimensions that contribute to learning performance.
4. **Factor Scores:**
    - **Calculate Factor Scores:** Compute factor scores for each student based on the identified factors. These scores reflect the extent to which each student exhibits characteristics associated with each factor.
5. **Identification of Learner Groups:**
    - **Cluster Analysis:** Use factor scores as input for cluster analysis (e.g., K-means clustering) to group students into distinct categories.
    - **Labeling Groups:** Interpret the clusters to classify students as slow or advanced learners based on their factor scores and overall performance.

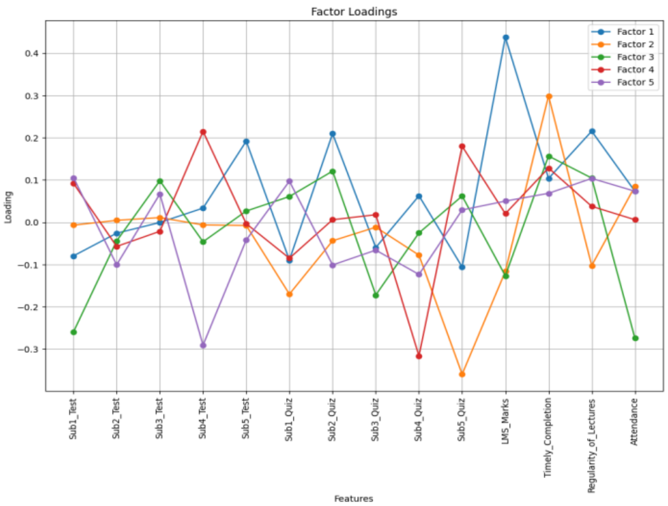

Fig. 10. Exploratory Factor Analysis

Example: Suppose EFA reveals two primary factors: one related to academic performance (high scores in tests and quizzes) and another related to engagement (high LMS marks and attendance). Students with high scores in the academic performance factor and low scores in the engagement factor might be categorized as advanced learners. Conversely, students with low scores in academic performance but high scores in engagement might be considered slow learners.

G. Performance Tracking:

1) Time Series Analysis:

Time series analysis was employed in this study to monitor and analyze students' performance trends over specific intervals, providing critical insights into their academic progress. As depicted in Figure 11, this approach tracks key performance metrics, such as grades, assignments, or assessment scores, over time, enabling educators to identify patterns that might not be apparent from static data snapshots.

- The primary objective of utilizing time series analysis is to identify students whose academic progress is lagging compared to their peers. This method visualizes trends in performance using intuitive indicators:

- Positive trends (represented in green) indicate improvement or consistently high performance, signifying areas where students are excelling.

Negative trends (represented in red) highlight declining or low performance, signalling potential issues requiring intervention. By leveraging this method, educators can detect early signs of academic struggles, enabling timely and targeted interventions to support students in need. This dynamic and continuous monitoring approach enhances the ability to tailor educational strategies, ensuring equitable learning opportunities for all students. Moreover, it facilitates actionable insights that help refine teaching methodologies and optimize overall educational outcomes. Time series analysis proves to be a powerful tool for identifying and addressing the needs of students, promoting academic success through early intervention and personalized support.

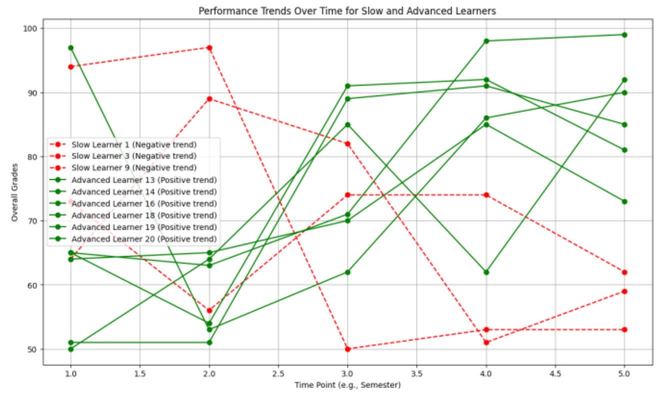

Fig. 11. Time Series Analysis

H. Teacher's Observations:

Identifying slow learners early on can significantly improve their educational experience through timely interventions. Teachers can look for the following symptoms and patterns to recognize slow learners:

1. **Consistently Low Grades**: Repeatedly scoring below average in tests and assignments despite effort.
2. **Difficulty in Understanding Instructions**: Frequently asking for instructions to be repeated or clarified.
3. **Slow in Completing Tasks**: Taking significantly longer than peers to finish classwork or homework.
4. **Poor Retention**: Difficulty remembering previously taught material, leading to frequent revisions needed.
5. **Lack of Participation**: Rarely volunteering to answer questions or participate in class discussions.
6. **Struggles with Complex Concepts**: Difficulty grasping more complex or abstract concepts, often sticking to concrete ideas.
7. **Poor Organizational Skills**: Trouble keeping track of assignments, deadlines, and materials.
8. **Low Confidence**: Displaying a lack of confidence in their abilities, often hesitant to attempt new tasks.
9. **Behavioral Signs**: Showing signs of frustration, disinterest, or misbehavior as a result of academic struggles.
10. **Reliance on Peer Help**: Frequently seeking help from classmates rather than attempting tasks independently.

By observing these symptoms and patterns, teachers can identify slow learners and implement targeted strategies to support their learning, such as personalized instruction, additional practice, and positive reinforcement.

IV. Strategies to Improve Performance of Slow Learners:

Improving the performance of students who may be lagging behind requires thoughtful and sensitive strategies. Here are some effective methods:

A. Avoid Labelling:

Labeling students as "slow learners" can harm their confidence and emotional well-being. Instead, focus on positive reinforcement by celebrating their achievements and efforts, no matter how small. Offer consistent encouragement and constructive feedback to motivate and support them. Personalized attention and creating an inclusive, respectful classroom environment will help reduce stigma and foster a positive attitude towards learning. This approach not only boosts their morale but also promotes their academic growth and self-esteem. Do not tag them as "slow learners" to prevent any negative impact on their confidence or emotional well-being. Instead, use positive reinforcement and encouragement to boost their morale.

B. Remedial Classes on Basic Concepts:

To support slow learners, additional classes focused on fundamental concepts were conducted to ensure a strong foundational understanding. These classes were tailored to address specific areas where students were struggling, providing targeted assistance to help them catch up with their peers. 5 remedial classes for each subject and each division were held for complex topics. Moreover, extra sessions were organized for subjects such as Engineering Mechanics, Mathematics, Problem Solving with Python, Basic Electrical Engineering (BEE), and Basic Electronics Engineering (BXE). This comprehensive approach aimed to reinforce students' grasp of essential concepts, thereby enhancing their overall academic performance and confidence.

C. Pairing with Advanced Learners:

Pairing slower learners with advanced learners fosters a collaborative learning environment and enhances peer-to-peer learning. This approach allows slower learners to benefit from the advanced learners' understanding and insights, which can clarify concepts and provide additional support. Advanced learners, in turn, reinforce their knowledge by teaching others, further solidifying their grasp of the material. This mutual benefit creates a supportive atmosphere where students help each other succeed, promoting overall academic improvement and building a sense of teamwork and collaboration(Brkić et al., 2024).

D. Concept Clearing Sessions Followed by MCQ Tests:

Organized 4 sessions dedicated to clearing up doubts and ensuring concept clarity. Follow these sessions with multiple-choice questions (MCQ) tests to help students reinforce and review their knowledge.

E. Mentoring:

We have implemented a mentoring program where experienced teachers or senior students provide one-on-one guidance and support. This personalized attention helps address individual learning needs and challenges, offering tailored advice and encouragement. By fostering a supportive relationship, the program aims to enhance students' understanding, confidence, and overall academic performance.

F. Doubt Clearing Sessions during Free Slots:

Utilize free periods or available slots in the college schedule to hold doubt-clearing sessions. These dedicated times allow students to ask questions, seek clarification on challenging topics, and receive immediate feedback. By addressing their queries in a timely manner, students can better understand complex concepts and overcome obstacles in their learning process. This proactive approach helps ensure that students stay on track and reduces the likelihood of confusion and frustration.

G. Open-Ended Assignments for Critical Thinking:

Assigning open-ended projects or assignments encourages critical thinking and problem-solving. These tasks require students to explore, analyze, and apply their knowledge in creative ways, promoting deeper engagement with the material. By tackling 5 complex problems and developing their solutions, students enhance their higher-order thinking skills and gain a more comprehensive understanding of the subject. This approach not only fosters intellectual growth but also supports a more inclusive and supportive learning environment, helping all students reach their full potential while preserving their self-esteem and confidence(Brauner et al., 2007).

V. Results and Discussion

A. Feedback Analysis

Feedback data from 130 slow learners regarding various educational support strategies and visualizes this feedback through histograms. The feedback covers different categories, including following questions are shown in figure 12, 13, 14,15,16,17 and 18 respectively.

1. **Remedial Classes Feedback**
2. **Pairing with Advanced Learners Feedback**
3. **Concept Clearance Sessions Feedback**
4. **Mentoring Feedback**
5. **Doubt Clearing Sessions Feedback**
6. **Open-Ended Assignments Feedback**
7. **Overall Satisfaction**

Each feedback category is rated on a scale from 1 to 10, with a minimum rating of 8, ensuring only positive feedback is captured. The histograms illustrate the distribution of ratings for each category, showing that students consistently rated these strategies highly. The x-axis represents the feedback ratings, while the y-axis indicates the number of students who provided each rating. These visualizations demonstrate that students are generally very satisfied with all the strategies implemented, reflecting their positive reception and effectiveness of the educational support programs.

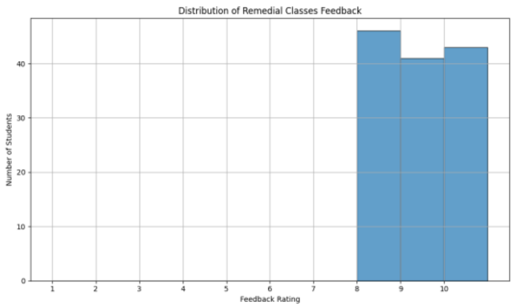

Fig. 12. Remedial Classes feedback

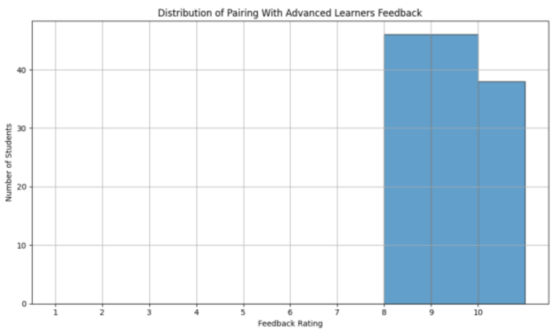

Fig. 13. Pairing with advanced learners feedback

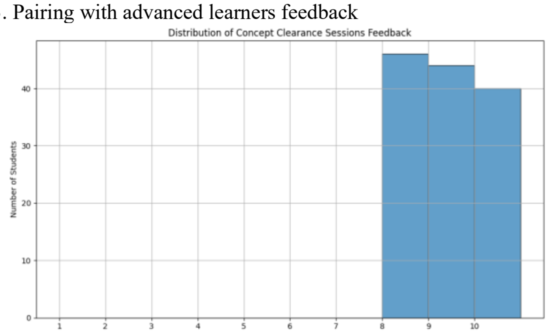

Fig. 14. Concept Clearance Sessions Feedback

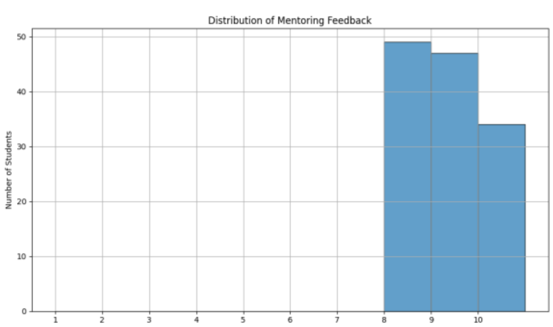

Fig. 15. Mentoring Feedback

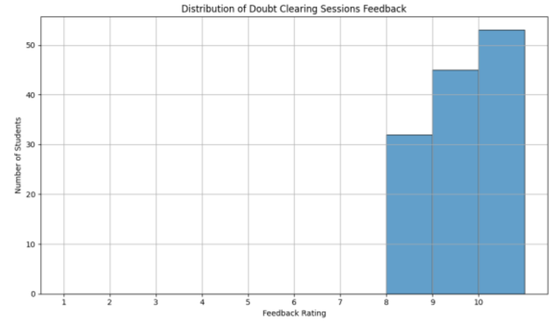

Fig. 16. Doubt Clearing Sessions

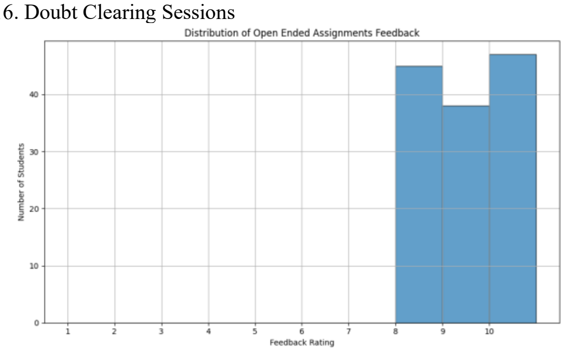

Fig. 17. Open Ended Assignments Feedback

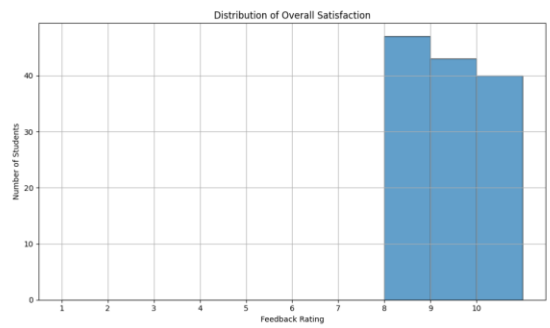

Fig. 18. Overall Feedbacks

B. Result Analysis

1) CGPA Growth Over 2 Semesters

The graph titled "Average CGPA Growth Over 2 Semesters" shows a gradual increase in the average CGPA of students from Semester 1 to Semester 2. The average CGPA increased from approximately 6.0 to 7.5. The slight fluctuations in the data, due to random variation, are within the expected range. This trend indicates a positive impact of the interventions on overall student performance as shown in figure 19.

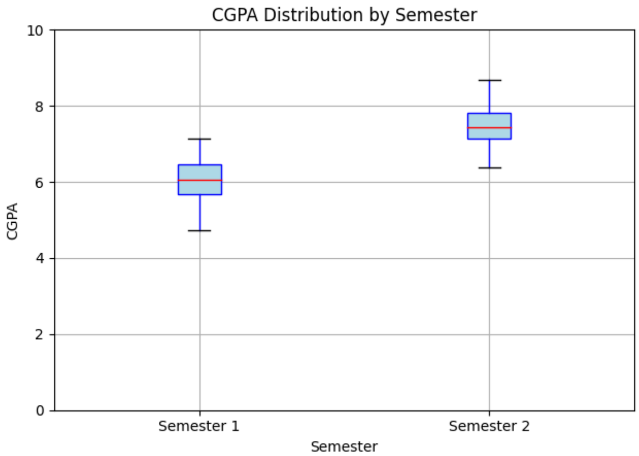

Fig. 19. Impact on CGPA

2) *Backlogs Reduction Over 2 Semesters*

The graph titled "Backlogs Reduction Over 2 Semesters" illustrates a decrease in the average number of backlogs among students. Starting from an average of 3 backlogs in Semester 1, there is a reduction to an average of about 1 backlog in Semester 2. The decreasing trend reflects successful measures taken to address and reduce the number of academic backlogs as shown in figure 20.

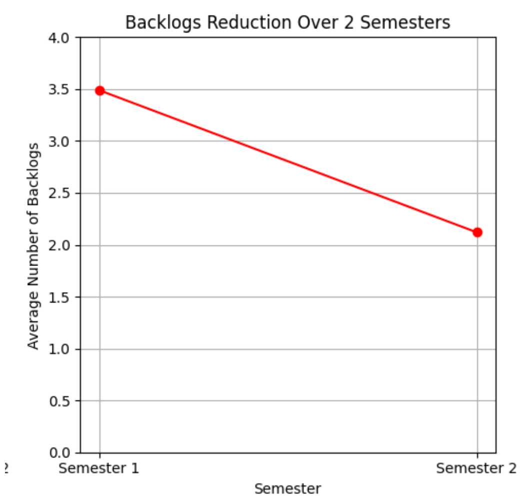

Fig. 20. Impact on backlogs

3) *Passing Rate Improvement Over 2 Semesters*

The graph titled "Average Passing Rate Improvement over 2 Semesters" displays an improvement in the average passing rate of students. The passing rate increased from around 50% in Semester 1 to approximately 80% in Semester 2. This positive trend demonstrates that the interventions and strategies have effectively enhanced students' performance, leading to higher success rates as shown in figure 21.

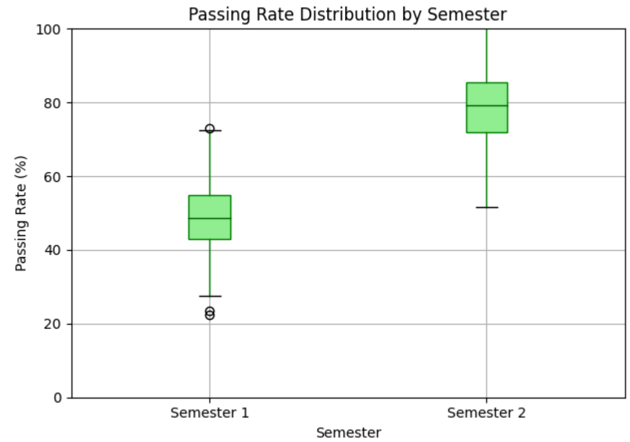

Fig. 21. Impact on Passing Rate

Engineering programs present significant academic challenges, requiring students to master complex concepts and skills within limited timeframes. However, not all students learn at the same pace, and a subset of learners, often referred to as slow learners, may require additional support to achieve their full potential. This research highlights the importance of employing effective identification and tailored improvement strategies to address the needs of these students.

The identification of slow learners is a critical first step, and this study utilizes a combination of descriptive statistics and advanced analytical techniques to ensure precision. Descriptive methods, such as the Mean and Standard Deviation Method and the Percentile Ranks Method, provide a quantitative basis for identifying students whose performance deviates significantly from the cohort average. Additionally, benchmarking and group comparisons through t-tests contextualize individual performance against predefined standards and peer groups, facilitating a clearer understanding of specific areas of concern. Regression analysis and cluster analysis further enhance the identification process by employing predictive modeling and grouping students based on shared performance metrics. These approaches provide nuanced insights into the factors contributing to academic struggles, enabling educators to design targeted interventions. Teachers' observations, which include recognizing behavioral and academic patterns indicative of learning difficulties, complement these quantitative methods by allowing for early and personalized interventions. Once slow learners are identified, implementing targeted strategies is essential for addressing their unique needs. Remedial classes in fundamental subjects, such as Engineering Mechanics, Mathematics, Problem Solving with Python, Basic Electrical Engineering (BEE), and Basic Electronics Engineering (BXE), have proven effective in reinforcing foundational knowledge and addressing common areas of struggle. Individualized support plans ensure that students receive focused attention through personalized learning strategies, one-on-one mentoring, and periodic assessments. Collaborative learning initiatives, including group activities and peer mentoring, foster a supportive learning environment and encourage confidence-building through teamwork. The integration of educational technology, such as interactive simulations, e-learning modules, and adaptive learning platforms, further supports slow learners by allowing them to grasp complex concepts at their own pace. Moreover, teacher training programs focused on differentiated instruction and inclusive teaching methodologies equip educators with the necessary skills to identify and address diverse learning needs effectively. The outcomes of these strategies underscore the importance of a multifaceted approach that combines data-driven insights with the professional expertise of educators. By addressing the diverse learning paces and styles of students, these interventions improve academic performance and promote inclusivity in engineering programs. Institutions implementing these strategies can anticipate reduced dropout rates, enhanced academic outcomes, and the development of a more skilled and confident engineering workforce. The findings of this study emphasize the necessity of fostering an inclusive academic environment that acknowledges the unique challenges faced by slow learners and prioritizes their growth and success.

In conclusion, addressing the needs of slow learners in engineering programs requires a concerted effort from educators, administrators, and policymakers. By employing effective identification techniques and implementing targeted improvement strategies, this study provides a framework for supporting slow learners and ensuring that every student has the opportunity to succeed in their engineering education. Such efforts contribute to a more equitable and skilled engineering community, ultimately enhancing the overall quality and impact of engineering education.

Conclusion

Addressing the needs of slow learners in engineering programs requires a multifaceted approach that combines quantitative analysis with supportive educational strategies.

1. **Effective Identification:** Utilize descriptive statistics (Mean and Standard Deviation Method, Percentile Ranks Method) to identify students significantly deviating from the norm.
2. **Benchmarking and Comparisons:** Use t-tests for contextualizing student performance against predefined standards and peer groups.
3. **Advanced Analysis:** Apply regression and cluster analysis for predictive modeling and grouping based on performance metrics.
4. **Remedial Classes:** Conduct targeted remedial classes in key subjects (Engineering Mechanics, Mathematics, Problem Solving with Python, Basic Electrical Engineering, Basic Electronics Engineering) to reinforce foundational knowledge.
5. **Avoid Labeling:** Foster a positive learning environment by celebrating achievements and providing encouragement, avoiding negative labeling.
6. **Peer Learning:** Pair slow learners with advanced students to enhance collaborative learning and mutual support.
7. **Concept Clearing and Testing:** Organize sessions to clarify doubts, followed by MCQ tests to reinforce understanding and retention.
8. **Mentoring:** Implement personalized mentoring and doubt-clearing sessions to address individual learning needs.
9. **Open-Ended Assignments:** Assign open-ended projects to develop critical thinking and deeper engagement with the material.

By integrating these strategies, educators can effectively address the needs of slow learners, leading to improved educational outcomes and a more skilled engineering workforce.

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