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# Personalised Learning Assistance System for Slow Learners

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**Abstract:- The Personalized Learning Assistance System (PLAS) is an innovative platform that utilizes AI/ML algorithms to cater to the diverse needs of slow learners in educational institutions. By analysing student learning behaviours, PLAS categorizes them into appropriate groups and provides tailored support. Slow learners can access the system through a dedicated portal, where they can seek assistance from their peers, available teachers, or engage with e-learning videos. The platform also features a portal for advanced learners, enabling them to mentor and guide their peers or access additional e-learning resources. Furthermore, teachers can log into the system to upload student performance data and identify those who require extra support. PLAS aims to foster an inclusive learning environment by leveraging technology to personalize the educational experience, ultimately empowering slow learners to achieve academic successthrough a comprehensive support network.**

***Keywords:-*** *Personalized Assistance System, Slow Learners, Machine Learning, Education, Adaptive Learning.*

## I. INTRODUCTION

Slow learners, within the educational context, are individuals who demonstrate a prolonged or delayed progression in acquiring academic skills compared to their peers. This term encompasses a diverse range of learners who may face challenges in comprehending and retaining information at a pace that aligns with typical developmental expectations. Notably, slow learners may exhibit varying attendance patterns, including both high attendance rates coupled with below-average academic performance, as well as low attendance rates correlating with similarly diminished scholastic achievement. This dichotomy underscores the multifaceted nature of slow learning, which can manifest irrespective of consistent classroom presence. Therefore, understanding the nuanced profiles of slow learners necessitates comprehensive assessment strategies that consider not only academic progress but also attendance patterns to tailor effective interventions and support mechanisms.

National Education Policy 2020 states: “Classroom is a combination of various students, some may be from sophisticated families, some may be from middle class and some other may be from deprived groups. In a classroom some students may be slow learners and some may be physically or mentally challenged. Teachers understand this in a right way and design activities to make all the students take part in learning process. No students are excluded from the teaching-learning process. Thus, every classroom should be inclusive. In the vision of the National Education Policy, it clearly says the high-quality education should be provided to all.”

Artificial intelligence (AI) and machine learning (ML) algorithms play a pivotal role in early detection and prediction of slow learners before major exams, facilitating proactive intervention strategies to enhance academic outcomes. Decision tree algorithms, renowned for their interpretability, analyze historical student data to identify key predictors of slow learning patterns. By leveraging features such as attendance records, quiz scores, and participation levels, decision trees delineate intricate decision paths to flag students at risk of underperformance. Furthermore, ensemble learning techniques like random forest harness the collective wisdom of multiple decision trees to enhance predictive accuracy. This amalgamation of diverse decision trees mitigates overfitting and enhances generalization capabilities, thereby furnishing more robust insights into students' learning trajectories. Multilayer perceptron (MLP) networks, a class of

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artificial neural networks, excel in modeling nonlinear relationships within data, thereby uncovering subtle correlations indicative of slow learning tendencies. Through iterative learning processes, MLPs adaptively refine their predictive models, capturing nuanced patterns that may elude conventional statistical techniques. In concert, these AI/ML algorithms empower educators with timely alerts and actionable insights, enabling targeted interventions and personalized support systems tailored to individual student needs, ultimately fostering a conducive learning environment conducive to academic success.

In today's diverse classrooms, students learn in different ways, yet some face challenges keeping up with the pace of traditional teaching methods. This project introduces a ground-breaking approach, the Personalized Learning System (PLS), designed specifically for slow learners.

Understanding the individual needs of these students is crucial. This project focuses on utilizing cutting-edge Artificial Intelligence and Machine Learning (AI/ML) technologies to predict and analyse learning patterns. By applying various algorithms to live data, the PLS aims to tailor educational experiences to suit the needs of slow learners.

The significance of this project lies in its commitment to inclusivity and fairness in education. Slow learners often struggle with conventional teaching methods, affecting their confidence and academic progress. The PLS seeks to change this by leveraging AI/ML technologies to predict learning behaviors and save data in real time. By using different algorithms, it intends to personalize learning experiences, offering adaptive materials and strategies.

This project aims to revolutionize educational approaches by harnessing AI/ML techniques to understand and adapt to the unique learning styles of slow learners. Through predictive analysis and live data application, the PLS endeavours to create a supportive learning environment where every student, regardless of their pace, can thrive and succeed.

In the educational landscape of India, where the student-to-teacher ratio often poses a significant challenge, leveraging advanced learners as part of a personalized learning assistance system presents a promising avenue for addressing the diverse needs of students. With limited resources and a burgeoning student population, personalized attention becomes increasingly elusive within traditional classroom settings. However, by harnessing the expertise and proficiency of advanced learners, this system can effectively supplement the instructional process. Advanced learners, possessing a deeper understanding of academic concepts, can serve as mentors and peer tutors, offering personalized guidance and support to their peers. Through one-on-one interactions and small group sessions, they can elucidate complex topics, clarify doubts, and provide additional explanations tailored to individual learning styles. Moreover, their role extends beyond mere academic assistance; they also serve as role models, inspiring their peers through their academic achievements and fostering a culture of collaborative learning and mutual support. By harnessing the collective knowledge and expertise of both educators and advanced learners, the personalized learning assistance system not only mitigates the impact of the student-to-teacher ratio but also cultivates a dynamic and inclusive learning ecosystem conducive to academic excellence and holistic development.

## II. RELATED WORK

Govt. V.Y.T. PG Autonomous College, Durg, works on the input required to identify slow and advanced learners such as overall examination results, internal assessment scores, and observations from subject teachers. This assessment is conducted systematically, with subject teachers assessing students individually for each subject in all programs. Identification occurs after the declaration of preceding exam results, considering class performance and teacher observations. Parameters include internal assessment test scores (50%), academic performance in previous exams (25%), and teacher observations (25%), recorded on a scale of 1 to 10. A report is prepared for the entire class based on these parameters, with students scoring below 50% identified as slow learners and those scoring above 70% identified as advanced learners. This process aims to effectively cater to the learning needs of students by providing appropriate support and challenges based on their academic performance and observed abilities [1].

The Institute for Excellence in Higher Education (IEHE), Bhopal, Madhya Pradesh, aims to provide vital facilitation and encouragement to both advanced learners to excel further and slow learners to improve their performance in academic and personal domains. The policy emphasizes the development of strategies and scientific implementations by teaching departments to benefit all categories of learners, including average performers. It recognizes the need to support advanced learners with demanding and challenging opportunities while providing assistance and support to slow learners to enhance their academic and personal achievements. By addressing the diverse needs of students, the policy seeks to create a more inclusive and effective learning environment within the institute [2].

Mustafa Agaoglu et al. underscores the increasing significance of data mining applications in addressing educational and administrative challenges within higher education. While existing research predominantly focuses on modeling student performance, this paper shifts the focus towards evaluating instructors' performance through the analysis of course evaluation questionnaires. Employing four distinct classification techniques—decision tree algorithms, support vector machines, artificial neural networks, and discriminant analysis—the study compares their efficacy in modeling instructor performance based on student feedback. Results indicate that while all classifiers demonstrate high performance, the C5.0 classifier emerges as the most accurate, precise, and specific. Furthermore, the analysis of variable importance reveals the presence of irrelevant questionnaire items, emphasizing the pivotal role of student interest in determining instructor success as perceived by students. These findings underscore the efficacy and relevance of data mining

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models in enhancing course evaluation practices and advancing insights into higher education dynamics, offering valuable insights for refining measurement instruments [3].

Ijaz Khan et al. address a significant challenge faced by instructors: effectively monitoring students' academic progress in courses. They propose leveraging machine learning algorithms to identify students with unsatisfactory progress early on, allowing instructors to provide additional support promptly. Despite the abundance of student data collected by modern educational institutions, there is a need for innovative methods to utilize this data to enhance educational quality and institutional prestige. The research evaluates the effectiveness of various machine learning algorithms in predicting students at risk of poor performance and transforms the prediction model into an easily interpretable format for instructors. Decision tree algorithms are found to be most successful and are refined for practical use. The outcome of the research includes a set of proactive measures for monitoring students' performance from course inception and providing targeted support to struggling students [4].

K. Hemachandran et al. delve into the transformative potential of artificial intelligence (AI) in higher education, highlighting its underutilization among professors despite its revolutionary impact on human lives. They emphasize the urgent need for implementing information bridge technology to enhance communication in classrooms and predict the future of higher education with AI. Through this research article, the authors address the current challenges faced by subject faculties and students, including changing government regulations, while exploring various arguments and hurdles surrounding AI implementation in education. They present a use case model leveraging student assessment data and generative adversarial networks (GAN) to bridge the gap between human lecturers and machines, achieving a maximum accuracy of 58% using various machine learning algorithms. The study also considers the psychological impact of AI on faculty and students, aiming to ensure a balanced integration of technology while preserving human emotions and interactions in educational settings [5].

S. Deepa et al. explore the application of data mining (DM) in education, focusing on the emerging interdisciplinary field known as educational data mining (EDM). Their research aims to enhance student performance by improving the quality of educational processes through new strategies and plans. They address the challenges of exploring unique data types from educational environments, particularly focusing on slow learner students in school education. Factors such as economy, environment, social media, psychological issues, childhood marriage, irregular attendance, and eve-teasing of girls are identified as influencing factors. The goal is to gain insights into how students learn and identify settings for improvement, utilizing data mining techniques such as the J48 algorithm to predict students at risk of not attending school. Through attribute selection and data rebalancing using cost-sensitive classification, the study aims to improve accuracy in predicting student attendance and comparing results with slow learner students' performance [6].

Sameh S. Alfere et al. delve into the burgeoning field of educational research utilizing Data Mining techniques, which has seen a rapid increase. Focusing on uncovering hidden patterns and knowledge within student performance data, their study centers on predicting student performance through classification methods, specifically modified KNN classifiers like Cosine KNN, Cubic KNN, and Weighted KNN. Utilizing a dataset from 11th-grade students in the scientific branch of Gaza Strip secondary schools, comprising 13 parameters including subject marks, average, and grade, the classifiers aim to forecast the grade a student will achieve based on their marks in two subjects. This predictive analysis holds promise for aiding school principals in early identification of students at risk of low academic achievement, enabling timely interventionand support strategies [7].

Parneet Kaur et al. focus on the application of predictive data mining models using classification algorithms to identify slow learners among students and monitor curriculum changes in educational databases. Utilizing a real-world dataset from a high school and WEKA, an Open Source Tool, they filter relevant variables and test various classification algorithms including Multilayer Perception, Naïve Bayes, SMO, J48, and REPTree. The paper compares statistics generated by these algorithms to predict accuracy and determine the best-performing classification algorithm. Additionally, a knowledge flow model among the classifiers is illustrated, emphasizing the significance of prediction and classification-based data mining algorithms in education while suggesting future research directions [8].

Ismail Celik et al. provide an overview of research examining teachers' utilization of artificial intelligence (AI) applications and machine learning methods for analyzing teacher data. Their analysis reveals numerous opportunities AI presents for teachers, including improved planning by defining students' needs and facilitating teacher familiarity with them, enhanced implementation through immediate feedback and intervention, and streamlined assessment via automated essay scoring. Moreover, the study highlights teachers' diverse roles in AI technology development, ranging from serving as models for AI algorithm training to participating in AI system accuracy checks. However, the authors also identify several challenges in implementing AI in teaching practice, offering valuable insights for the field's development [9].

Sangeeta. K et al. emphasize that increasing the pass percentage of students is a primary goal for educational institutions, acknowledging that a student's performance is influenced by various factors, including their learning ability. They highlight the distinction between slow learners, who require detailed explanations and resources to grasp concepts, and fast learners, who assimilate information more quickly. Given the competitive demands of the modern world, classifying students based on their learning abilities can aid in identifying slow learners who may benefit from additional support and training to improve their performance. To address

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this, the paper utilizes real-time student data from the computer science engineering department at Aditya Institute Of Technology and Management, Tekkali, Srikakulam district, to conduct experiments on the influence of cognitive attributes on academic performance. By employing classification algorithms, the study aims to categorize students into different learning groups and develop a predictive model to better understand individual differences in knowledge levels, learning preferences, and cognitive abilities [10].

Table 1 Literature Survey

| S. l | Title | Method | Accuracy |
|---|---|---|---|
| 1. | Predicting Instructor Performance Using Data Mining Techniquesin Higher Education | Decision Tree, SVM | 90% |
| 2. | An artifcial intelligence approach to monitor student performanc e and devise preventive measures | KNN, WEKA(Decision tree), ANN, Naive Bayes | Decision Tree-93% |
| 3. | Artificial Intelligence : A Universal Virtual Toolto AugmentTutoring in Higher Education | SVM, KNN, Logistic Regression (LR), Linear Discriminant Analysis (LDA), K-Nearest Neighbors (KNN), Regression Trees (CART), Naive Bayes (NB), Support Vector Machines (SVM), Random Forest (RF) | Multilayer Perception - 87.44% |
| 4. | Identificatio n of slow learners with categorizati on data mining techniques | Naïve Bayes, J48 Algorithm using SQL tool | J48 - 97% |
| 5. | Prediction of Student'sPerformance Using Modified KNN Classifiers | Fine, Medium, Coarse, Cosine KNN, Cubic KNN Classifier, Weighted KNN Classifier | Weighted KNN Classifier-94.1% |
| 6. | Classificati on and prediction based data mining algorithmsto predict slow learners ineducation sector | Decision Tree (DT), Random Forest (RF), Neural Network (NN)and Support Vector Machine (SVM) | Multi-Layer Perception-75%, Naïve Bayes-65.13%, SMO-68.42%, J48-69.73%, REPTree-67.76% |
| 7. | Classification and Prediction of Slow Learners Using Machine Learning Algorithms | CHAID, SVM, Multilayer Perception, Random Forest, REPTree, J48, SMO, Naive Bayes | CHAI-59.4% , SVM-80% , Multilayer perception-75%, RandomForest-75%, REPTree-54.4%, J48-65.8%, SMO-58.5%, Naive Bayes-55.8% |

## III. CLASSIFICATION

➢ *Three Algorithm's we chose after Thorough Literature Survey:*

- *Random Forest* is a popular and powerful **ensemble learning** method used in machine learning. It operates by constructing multiple decision trees during training and outputs the mode of the classes (classification) or average prediction (regression) of the individual trees. It's an ensemble technique that combines the predictions from several individual decision trees to generate a more accurate and robust final prediction.

**Ensemble Learning** refers to the technique of combining multiple individual models (learners) to build a stronger, more accurate model. The basic idea is that a group of weak learners can come together to form a strong learner. Ensemble methods often outperform single models because they reduce variance, increase accuracy, and mitigate overfitting by aggregating the predictions of multiple models.

- A *decision tree* is a simple yet powerful machine learning algorithm used for classification and regression tasks. It organizes data into a tree-like structure where each branch represents a decision based on features, leading to predicted outcomes at the tree's leaf nodes. It's easy to interpret, but can over fit with complex data—techniques like pruning help prevent this. Overall, decision trees are effective tools for making decisions based on data patterns.
- A *Multilayer Perceptron (MLP)* is a type of artificial neural network with layers of interconnected nodes (neurons). It's structured in an input layer, hidden layers, and an output layer. MLPs learn patterns in data by adjusting connections between neurons through a process called backpropagation. They're widely used in various fields for tasks like pattern recognition, classification, and prediction due to their ability to learn complex relationships in data.

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## IV. PROPOSED MODEL

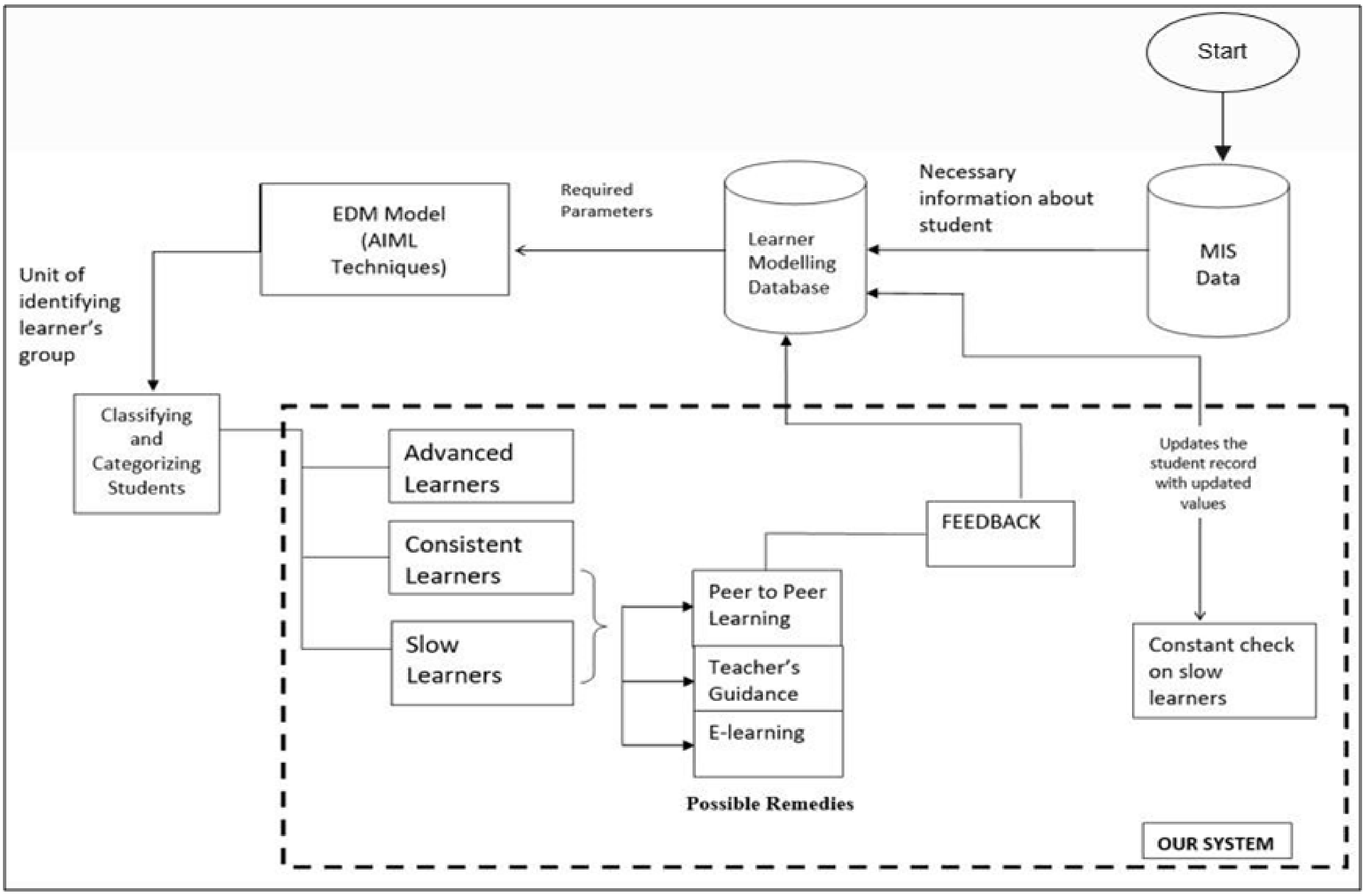


Fig 1 Detailed Design of Our Model

➢ *EDM Model*

At the heart of the learning system lies the EDM model, a sophisticated framework responsible for not only modeling the intricate learning process but also for dynamically adapting to the unique needs and preferences of individual students. Employing a diverse array of artificial intelligence (AI) and machine learning (ML) techniques such as ensemble learning and deep learning, the EDM model serves as the cornerstone of personalized learning experiences.

➢ *Learner Modelling Database*

The comprehensive learner modelling database serves as a repository of invaluable information pertaining to each student. From prior knowledge and academic details to performance metrics across various subjects, this database encapsulates the essence of each learner's educational journey. Leveraging this rich dataset, the EDM model meticulously tailors learning experiences to suit the specific requirements of every student, ensuring optimal engagement and academic growth.

➢ *MIS Data*

The Management Information System (MIS) data provides invaluable insights into the overall performance and efficacy of the learning system. By analyzing this data, educators can pinpoint areas for enhancement and refinement, thereby fostering continuous improvement and innovation within the educational ecosystem.

➢ *Classifying and Categorizing Students*

Through the classifying and categorizing students module, learners are systematically grouped based on their distinct learning needs and aptitudes. This segmentation enables the EDM model to craft personalized learning pathways tailored to the unique requirements of each student, fostering a supportive and inclusive learning environment.

➢ *Advanced Learners*

Advanced learners are afforded challenging tasks and activities that stimulate their intellectual curiosity and foster their growth. Encouraged to pursue independent projects and share their expertise with peers, advanced learners serve as catalysts for knowledge dissemination and peer-to-peer learning within the classroom.

➢ *Consistent Learners*

Consistent learners benefit from activities and tasks designed to sustain and reinforce their academic progress. Through opportunities for collaborative learning and engagement with peers and educators, consistent learners are empowered to build upon their existing knowledge and skills in a supportive and nurturing environment.

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➢ *Slow Learners*

Recognizing the diverse needs of slow learners, the system provides additional support and guidance tailored to their individual learning pace. Emphasizing personalized learning experiences and opportunities for remediation, slow learners are equipped with the tools and resources necessary to overcome challenges and thrive academically.

➢ *Feedback*

A robust feedback mechanism, facilitated by the EDM model, educators, and peers, enables students to receive constructive feedback on their performance. By leveraging this feedback, students can identify areas of strength and areas for improvement, empowering them to develop effective learning strategies and achieve their full potential.

➢ *Flexibility and Scalability*

Designed with flexibility and scalability in mind, the e-learning system is poised to adapt and evolve over time. With the ability to integrate new data and cutting-edge AI and ML techniques, the system continually refines its performance, ensuring optimal outcomes for students across diverse learning environments and scales.

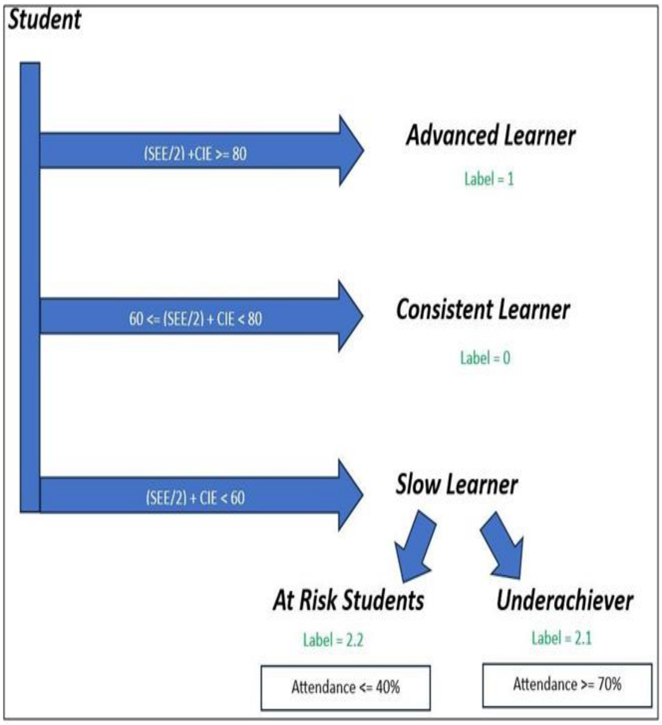


Fig 2 Student Classifying Categories

➢ *The Figure 2. Shows Three Levels of Students: Advanced Learner, Consistent Learner, and Slow Learner.*

- *Students are classified based on their SEE/2 + CIE score and attendance.*
- *Slow Learners are students with a SEE/2 + CIE score less than 60.*
- *At-Risk Students Are Slow Learners with attendance less than 40%.*
- *Underachievers are Slow Learners with attendance 70% or higher.*

The weightage division can be used to identify students who need extra support, develop personalized learning plans, and track student progress over time.

Table 2 Weightage Division as a Parameter

| **Parameters** | **Weightage in %** |
|---|---|
| Attendance | 25% |
| Academics: (Class Test, IA's, CTA, CIE) | 50% |
| Preceding result(SEE) | 25% |

The weightage division shown in above table allocates different weights to different factors that influence a student's performance, such as academics, attendance, and behaviour. This helps identify students who need extra support and tailor interventions to their specific needs. It also allows for tracking progress over time to evaluate the effectiveness of the interventions.

The Slow Learner Assistance Portal is designed for both educators and students offers a sophisticated interface optimized for educational management. Upon authentication, students gain access to a curated list of courses corresponding to their enrollment. Within this interface, students navigate to their chosen subject, initiating a streamlined educational journey.

Students who are slow learners in their selected subject are seamlessly directed to an interface offering tailored support options. These include peer-to-peer engagement for collaborative learning opportunities, scheduled meetings with educators for targeted remediation sessions, and access to a repository of e-learning materials designed to augment comprehension and retention.

Students who are advanced learners in their selected subject also have access to e-learning resources, ensuring a comprehensive educational experience that caters to diverse proficiency levels.

For educators, the portal streamlines the assessment and tracking process. Through an intuitive interface, educators can directly upload marks of the whole class onto the platform. Upon submission, educators have the option to generate a downloadable report. This report categorizes student performance based on predefined metrics, facilitating informed decision-making and personalized intervention strategies.

## V. RESULTS

In conducting a comparative study of three machine learning algorithms—random forest, decision tree, and multilayer perceptron (MLP)—across varying epochs and train-test divisions, our aim was to ascertain the optimal configuration for predicting student performance and

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identifying slow learners within an educational context. We systematically evaluated each algorithm's performance across different epoch counts, ranging from 20 to 100, while also varying the train-test division ratios at 60-40, 70-30, and 80-20. Each configuration underwent rigorous testing through three trial runs to ensure robustness and reliability of the results, as shown in the below mentioned table.

Table 3 Comparative Study between the Models

**Random Forest**

| Random Forest | Trial 1 | Trial 2 | Trial 3 | Average |
|---|---|---|---|---|
| 60-40 | 86.67% | 80% | 80% | 82.22% |
| 70-30 | 72.73% | 77.27% | 77.27% | 75.75% |
| 80-20 | 100% | 100% | 100% | ***100%*** |

**Decision Tree**

| Decision Tree | Trial 1 | Trial 2 | Trial 3 | Average |
|---|---|---|---|---|
| 60-40 | 70% | 70% | 70% | 70% |
| 70-30 | 63.64% | 63.64% | 63.64% | 63.64% |
| 80-20 | 80% | 80% | 80% | ***80%*** |

**Multilayer Perception(Epochs: 100)**

| Multilayer Perception | Trial 1 | Trial 2 | Trial 3 | Average |
|---|---|---|---|---|
| 60-40 | 73.33% | 76.67% | 76.67% | 75.56% |
| 70-30 | 72.73% | 72.73% | 72.73% | 72.73% |
| 80-20 | 93.33% | 93.33% | 93.33% | ***93.33%*** |

Across all epochs and train-test division ratios, random forest consistently demonstrated superior predictive accuracy compared to decision tree and MLP. Notably, the random forest algorithm yielded the highest accuracy rates when trained and tested with an 80-20 split, indicating its efficacy in handling larger training datasets while maintaining generalization capabilities.

Specifically, upon conducting three trials for random forest with 80-20 train-test division, we observed a discernible trend towards improved accuracy with increasing epoch counts. While the initial trial at 20 epochs yielded respectable accuracy, the subsequent trials at 50 and 100 epochs exhibited notable enhancements in predictive performance. This trend underscores the importance of sufficient epoch counts in facilitating convergence and refining the model's predictive capacity over successive iterations.

Conversely, decision tree and MLP algorithms, while demonstrating commendable performance, consistently fell short of random forest's accuracy levels across all epoch counts and train-test division ratios. Despite variations in epoch counts and train-test splits, decision tree and MLP algorithms exhibited relatively stable performance, albeit with lower accuracy rates compared to random forest.


| Roll No. | USN | Name | Total Marks | Label |
|---|---|---|---|---|
| 101 | 2SD15CS002 | ABHISHEKKUMAR | 75.5 | Consistent Student |
| 102 | 2SD15CS003 | ABHISHEKSMASTI | 80.5 | Advanced Learner |
| 103 | 2SD15CS005 | AISHWARYA | 87.5 | Advanced Learner |
| 104 | 2SD15CS006 | AKASHR | 71.0 | Consistent Student |
| 105 | 2SD15CS007 | AKHEELSAJJAN | 74.0 | Consistent Student |
| 106 | 2SD15CS008 | AKSHATASHARANNAVAR | 75.0 | Consistent Student |
| 107 | 2SD15CS009 | AMANVERMA | 55.0 | At Risk |
| 108 | 2SD15CS011 | AMRUTHAMALLELA | 76.5 | Consistent Student |
| 109 | 2SD15CS012 | ANANTARAJPUPADHYE | 65.0 | Consistent Student |
| 110 | 2SD15CS013 | ANIRUDHKULKARNI | 74.0 | Consistent Student |
| 111 | 2SD15CS014 | ANKURSHUKLA | 74.5 | Consistent Student |
| 112 | 2SD15CS015 | ANUPGINAMDAR | 67.0 | Consistent Student |
| 113 | 2SD15CS016 | ANURAGDEVOOR | 73.5 | Consistent Student |
| 114 | 2SD15CS018 | ARAVINDAN | 64.0 | Consistent Student |
| 115 | 2SD15CS019 | ASHAA | 74.0 | Consistent Student |
| 116 | 2SD15CS020 | ATULKUMAR | 72.5 | Consistent Student |
| 117 | 2SD15CS021 | AVINASHKUMARBHARTI | 65.5 | Consistent Student |
| 118 | 2SD15CS022 | BSHARATHKUMAR | 66.5 | Consistent Student |
| 119 | 2SD15CS023 | BASAVARAJRAJASHEKHARPATIL | 77.0 | Consistent Student |
| 120 | 2SD15CS024 | BHAGYASUBRAYABHAT | 87.0 | Advanced Learner |
| 121 | 2SD15CS025 | BHAGYAVATIHATTI | 76.5 | Consistent Student |
| 122 | 2SD15CS026 | BHARATHIMH | 74.0 | Consistent Student |

Fig 3 An Example of Student Classified into Categories by Our Model

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## VI. CONCLUSION

The challenges faced by educational institutions in addressing the needs of slow learners underscore the necessity for a personalized assistance system. Such a system, capable of dynamically adapting to the specific requirements of slow learners, holds immense potential to enhance their learning outcomes. The objectives outlined, including the identification and classification of students, comparative analysis of machine learning models, provision of personalized learning plans, and continuous progress monitoring, form a comprehensive approach towards addressing this critical need. Through a thorough literature survey and comparative analysis, the groundwork has been laid for the development of an effective personalized assistance system. System development, focusing on building a secure database and user-friendly interface, and implementing predictive algorithms as the backend, is crucial for the successful execution of personalized learning and remedial suggestions. Furthermore, the establishment of assessment metrics and continuous feedback loops ensures the ongoing refinement and improvement of the system, ultimately contributing to a more inclusive and effective educational environment for slow learners.

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