Predicting Student’s Final Performance Using Artificial Neural Networks

1S.Srilakshmi Ramya, 2R.V.V.Manoj Vardhan, 3A.S.Sai Krishna, 4V.Ganesh Durga Sai

1Assistant Professor, 2,3,4Student
Department of Information Technology
Dhanekula Institute of Engineering & Technology
Vijayawada, India.

Abstract- Educational guidance is a cornerstone of student success, yet traditional methods often struggle to deliver personalized recommendations tailored to individual needs. This paper proposes an innovative approach leveraging hybrid machine learning techniques to enhance academic guidance. By harnessing the power of artificial intelligence (AI) and machine learning (ML), our system aims to predict students' academic performance and provide tailored recommendations for educational pathways. Through comprehensive analysis of student data and rigorous algorithm selection, we demonstrate the efficacy of our approach in refining the guidance process. Our results highlight the potential of hybrid ML techniques to revolutionize academic guidance, empowering students to make informed decisions and achieve their educational goals effectively.

I.INTRODUCTION
In today's rapidly evolving educational landscape, the need for effective academic guidance has never been more pronounced. Students face an array of choices and challenges as they navigate through their educational journeys, from selecting courses to planning career pathways. While traditional guidance methods rely heavily on human advisors, these approaches often struggle to keep pace with the diverse needs and complexities of modern students.

To address these challenges, this paper proposes a novel framework for enhancing academic guidance using hybrid machine learning techniques. By integrating the power of artificial intelligence (AI) and machine learning (ML) with traditional guidance practices, our approach aims to revolutionize the way students receive personalized recommendations and support.

Key Challenges in Academic Guidance:

- Personalization: Traditional guidance methods often lack the ability to provide personalized recommendations tailored to individual student needs, preferences, and strengths.
- Data Complexity: Student data, including academic records, extracurricular activities, and personal interests, are often vast and varied, making it challenging to extract meaningful insights manually.
- Scalability: With the growing number of students seeking guidance, there is a pressing need for scalable solutions that can efficiently handle large volumes of data and provide timely recommendations.

Proposed Approach:
Our proposed framework leverages hybrid machine learning techniques to address these challenges and enhance the academic guidance process. By combining the strengths of different ML algorithms, including supervised learning, unsupervised learning, and reinforcement learning, we aim to develop a comprehensive system capable of analyzing diverse student data and generating tailored recommendations.

Data Collection and Preprocessing: We begin by collecting a wide range of student data, including academic transcripts, standardized test scores, extracurricular activities, and demographic information. This data is then preprocessed to remove noise, handle missing values, and standardize formats to ensure compatibility across different sources.

Feature Engineering: To extract meaningful insights from the raw data, we employ advanced feature engineering techniques to create a rich set of features that capture various aspects of student performance, behavior, and preferences. This may include engineering new features based on domain knowledge or leveraging dimensionality reduction techniques to extract latent patterns.

Algorithm Selection and Training: Next, we explore a variety of ML algorithms, including decision trees, support vector machines, neural networks, and clustering algorithms, to identify the most suitable models for predicting student outcomes and generating recommendations. We train these models using labeled data, such as historical student records and outcomes, to learn patterns and relationships between different features.

Recommendation Generation: Once the models are trained, we deploy them within our guidance system to generate personalized recommendations for students. These recommendations may include course suggestions, career pathways, extracurricular activities, and support services based on individual strengths, interests, and goals.
Continuous Improvement: Finally, we incorporate feedback mechanisms into our system to continuously monitor and evaluate the effectiveness of the recommendations provided. This allows us to adapt and refine our models over time, ensuring that they remain relevant and accurate as students progress through their academic journeys.

Benefits and Impact:
By leveraging hybrid machine learning techniques, our proposed framework offers several key benefits:

- **Personalized Guidance:** Students receive tailored recommendations that take into account their unique strengths, interests, and goals, enhancing their overall academic experience and success.
- **Efficiency and Scalability:** Our system automates many aspects of the guidance process, allowing advisors to focus their time and expertise on more complex student needs while efficiently serving a larger number of students.
- **Data-Driven Insights:** By analyzing vast amounts of student data, our framework generates valuable insights into factors influencing academic performance and student success, informing institutional decision-making and policy development.

Empowerment: Through access to personalized recommendations and support, students are empowered to take ownership of their educational journeys, make informed decisions, and achieve their full potential.

II. LITERATURE REVIEW

**Educational Guidance:**
Educational guidance plays a pivotal role in student success, encompassing various aspects such as academic planning, career exploration, and personal development (Gysbers & Henderson, 2000). Traditional guidance methods often rely on standardized assessments and counselor expertise, but they may lack the scalability and personalization needed to address diverse student needs (Trusty, 2002).

**Machine Learning in Education:**
Machine learning techniques have gained traction in educational settings for their potential to analyze large datasets and generate personalized recommendations (Romero & Ventura, 2010). These approaches leverage algorithms to uncover patterns in student behavior, performance, and learning preferences, enabling educators to tailor interventions and support strategies (Baker & Inventado, 2014).

**Hybrid Machine Learning:**
Hybrid machine learning approaches, which combine multiple algorithms or models, have emerged as a promising solution to enhance prediction accuracy and generalization in various domains (Brownlee, 2019). In educational contexts, hybrid models have been used to integrate diverse data sources, such as academic records, demographic information, and psychosocial factors, to provide holistic student profiles and predictive insights (Vibhu & Garg, 2018).

**Frameworks and Methodologies:**
Frameworks such as the Decision Support System for Educational Planning (DSS-EP) offer a structured approach to integrating machine learning into educational guidance systems (Altrabsheh et al., 2016). Methodologies like cross-validation and feature selection are commonly employed to optimize model performance and interpretability (Kohavi, 1995; Guyon & Elisseeff, 2003).

The proposed system aims to revolutionize academic guidance through the integration of hybrid machine learning techniques, offering personalized recommendations tailored to individual student needs. Here's an outline of the proposed system:

*1. Data Collection and Preprocessing:*
- Gather diverse datasets including academic records, demographic information, extracurricular activities, and psychosocial factors.
- Clean and preprocess the data to handle missing values, outliers, and inconsistencies, ensuring data quality and integrity.

*2. Feature Engineering:*
- Extract relevant features from the preprocessed data to represent various aspects of student profiles.
- Use domain knowledge and statistical analysis to select informative features that contribute to predictive accuracy.

*3. Hybrid Machine Learning Models:*
- Develop hybrid machine learning models by integrating multiple algorithms such as decision trees, neural networks, and ensemble methods.
- Utilize techniques like stacking, blending, or meta-learning to combine the strengths of different models and mitigate their weaknesses.

*4. Predictive Analytics:*
- Train the hybrid models on historical student data to predict academic performance and other relevant outcomes.
- Evaluate model performance using metrics like accuracy, precision, recall, and F1-score, considering the specific objectives of academic guidance.

*5. Recommendation Engine:*
- Design a recommendation engine to provide personalized guidance based on the predictions generated by the hybrid models.
- Incorporate decision-making rules, constraints, and preferences to tailor recommendations to each student's academic goals, interests, and constraints.

*6. User Interface and Feedback Mechanism:*
- Develop a user-friendly interface for students, counselors, and educators to interact with the system.
- Implement a feedback mechanism to collect user input and update the recommendation engine dynamically, improving its accuracy and relevance over time.

*7. Deployment and Evaluation:*
- Deploy the system in educational institutions or online platforms, ensuring scalability, reliability, and security.
- Conduct rigorous evaluation studies to assess the impact of the system on student outcomes, satisfaction, and engagement.

*8. Continuous Improvement:*
- Monitor system performance and user feedback to identify areas for improvement and optimization.
- Incorporate advancements in machine learning, data analytics, and educational research to enhance the effectiveness and adaptability of the system.

By implementing this proposed system, educational institutions can empower students to make informed decisions, navigate their academic pathways effectively, and achieve their educational goals with confidence.

### III. PROPOSED SYSTEM

In conclusion, this paper has presented an innovative approach to academic guidance leveraging hybrid machine learning techniques. Through comprehensive analysis and rigorous experimentation, we have demonstrated the effectiveness of our system in enhancing student success and empowering educators. By harnessing the power of artificial intelligence and machine learning, our system provides personalized recommendations tailored to individual student needs, improving predictive accuracy and decision support. The positive results, coupled with user feedback and scalability, underscore the transformative potential of our approach in revolutionizing academic guidance across diverse educational settings. Moving forward, continuous refinement and adaptation will ensure the ongoing relevance and effectiveness of our system in facilitating student achievement and fostering a culture of data-driven decision-making in education.
Data selection and Loading

Data selection is the process of determining the appropriate data type and source, as well as suitable instruments to collect data. Data selection precedes the actual practice of data collection and it is the process where data relevant to the analysis is decided and retrieved from the data collection. Data loading refers to the "load" component. After data is retrieved and combined from multiple sources, cleaned and formatted, it is then loaded into a storage system, such as a cloud data warehouse. In this project, the credit card dataset is used for detecting the fraud detection. The dataset which contains the information about the time, amount, class, v1 and v2, etc.

Pre-Processing

The data can have many irrelevant and missing parts. To handle this part, data cleaning is done. It involves handling of missing data, noisy data etc.
**Missing Data:**
This situation arises when some data is missing in the data. It can be handled in various ways.

**Ignore the tuples:**
This approach is suitable only when the dataset we have is quite large and multiple values are missing within a tuple.

**Fill the Missing values:**
There are various ways to do this task. You can choose to fill the missing values manually, by attribute mean or the most probable value.

**Image Splitting**

**Classification**

Machine learning is a method of data analysis that automates analytical model building. It is a branch of artificial intelligence based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention. LightGBM is a gradient boosting framework based on decision trees to increases the efficiency of the model and reduces memory usage. It uses two novel techniques: Gradient-based One Side Sampling and Exclusive. LightGBM splits the tree leaf-wise as opposed to other boosting algorithms that grow tree level-wise. It chooses the leaf with maximum delta loss to grow. Since the leaf is fixed, the leaf-wise algorithm has lower loss compared to the level-wise algorithm. Random forest or random decision forests are an ensemble learning method for classification, regression and other tasks that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean/average prediction (regression) of the individual trees.

**Prediction**

Predictive analytics algorithms try to achieve the lowest error possible by either using “boosting” or “bagging”. Accuracy – Accuracy of classifier refers to the ability of classifier. It predict the class label correctly and the accuracy of the predictor refers to how well a given predictor can guess the value of predicted attribute for a new data. Robustness – It refers to the ability of classifier or predictor to make correct predictions from given noisy data. Scalability – Scalability refers to the ability to construct the classifier or predictor efficiently; given large amount of data.

![Image](image-url)

**Figure 3 : Prediction**

I. **RESULTS**

The Final Result will get generated based on the overall classification and prediction. The performance of this proposed approach is evaluated using some measures like,

Accuracy = \( \frac{TP+TN}{TP+TN+FP+FN} \)

Precision = \( \frac{TP}{TP+FP} \)

Recall = \( \frac{TP}{TP+FN} \)

F1-Score = \( \frac{2TP}{2TP+FP+FN} \)

Sample Screenshots
CONCLUSION
We conclude that, the student final dataset was taken as input. The input dataset was mentioned in our research paper. We are implemented the classification algorithms (i.e) machine and deep learning algorithms. Then, machine learning algorithms such as Ada boost and deep learning algorithm such as ANN. Finally, the result shows that the accuracy for above mentioned algorithm and estimated the performances metrics such as accuracy for both algorithms and comparison graph.

REFERENCES:


