**Student Grade Prediction Using**

**Decision Tree Classifier**

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***Abstract*—.This research introduces a machine learning-based student grade prediction system aimed at improving academic performance forecasting. The model is trained on historical academic data comprising features such as internal assessment scores, attendance, demographic details, and psychological factors. A supervised learning approach is employed using three algorithms—Random Forest, Support Vector Machine (SVM), and XGBoost—to classify student performance into predefined grade categories. Data preprocessing includes handling missing values, feature encoding, and normalization to ensure data quality. Hyperparameter tuning is applied to optimize model performance. The prediction output classifies students based on their expected grades, enabling early identification of at-risk individuals. Experiments conducted in a Python environment demonstrate that Random Forest offers the highest accuracy, while XGBoost delivers a balanced trade-off between precision and recall. This study highlights the effectiveness of ensemble and kernel-based methods in educational analytics, providing actionable insights for academic advisors and educators to implement timely interventions.**

**Keywords-Student performance, Grade prediction, Machine Learning, Random Forest, SVM, XGBoost, Educational data mining**

I. Introduction

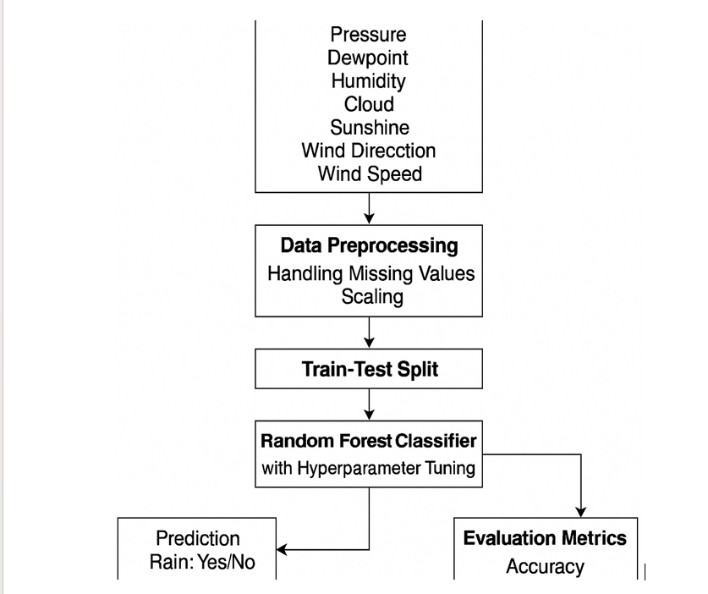
In recent years, the advent of machine learning (ML) has brought significant advancements to education analytics by enabling data-driven insights into student performance. Academic institutions are increasingly turning to predictive models to identify at-risk students early, enhance educational outcomes, and support informed decision-making. One of the critical applications in this domain is student grade prediction, which plays a vital role in academic advising, personalized learning, and resource allocation. Accurate forecasting of student grades enables educators to implement timely interventions, provide targeted support, and ultimately improve student retention and success rates. Traditional approaches to performance evaluation primarily rely on static assessments, teacher observations, and historical averages. While informative, these methods often fail to capture the complex interplay of factors influencing academic achievement. Moreover, they do not provide proactive mechanisms for forecasting student outcomes in real time. Machine learning addresses these gaps by uncovering hidden patterns in educational data and offering predictive capabilities that go beyond conventional techniques This study focuses on the development of a supervised ML-based system for predicting student grades using a diverse set of features, including attendance records, internal assessment scores, demographic attributes, and behavioral indicators. Widely used classification algorithms—Random Forest, Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost)—are applied and compared based on their predictive performance. These algorithms are known for their ability to model non-linear relationships, handle feature interactions, and provide reliable classification outcomes..To enhance model accuracy and robustness, the system undergoes several preprocessing steps such as data cleaning, normalization, and feature selection. Hyperparameter tuning through grid search is employed to optimize algorithmic performance, while cross-validation techniques are used to assess generalization. The resulting model outputs a categorical grade prediction, allowing educators to anticipate performance trends and act accordingly.Despite the growing potential of ML in education, challenges remain. The quality and completeness of educational datasets, variation in assessment criteria, and ethical concerns related to student profiling must be carefully addressed. Furthermore, the effectiveness of predictive models may vary across different academic institutions and curricula, necessitating periodic retraining and contextual adaptation.This project investigates the effectiveness of Random Forest, SVM, and XGBoost models in predicting student grades using a labeled academic dataset. The models are evaluated based on standard classification metrics, and the best-performing algorithm is identified. The findings demonstrate the practical viability of ML in education and support the broader goal of data-driven academic planning and intervention.

# II. Literature Review

1. Student grade prediction is a crucial task in educational data mining, offering institutions the ability to identify students at risk, personalize learning interventions, and enhance academic outcomes. The application of machine learning (ML) in this domain has gained traction due to its capability to discover complex patterns and make data-driven predictions from diverse student information.
2. In [1], the authors applied Logistic Regression to predict final student performance using variables such as attendance, assignment scores, and previous grades. While the model achieved reasonable accuracy, it struggled with nonlinear relationships between variables. To overcome these limitations, later studies introduced ensemble models like Random Forest, which could capture feature interactions and handle multicollinearity effectively.
3. A comparative study by S. Banerjee et al. [2] evaluated the performance of Decision Trees, Support Vector Machines (SVM), and Random Forest on a student academic dataset collected from a university LMS platform. Random Forest achieved the highest classification accuracy and was noted for its robustness against overfitting and missing data, particularly in cases involving categorical and behavioral attributes.
4. In another significant work, A. Kumar and P. Rani [3] implemented SVM and k-Nearest Neighbors (kNN) on a dataset with demographic features, attendance, and internal test scores. SVM delivered competitive precision and recall values, especially for identifying students at academic risk, while kNN performed well in smaller subsets of homogenous students but lacked generalization in larger populations.
5. Deep learning models have also been explored for grade prediction. In [4], a feedforward neural network was trained on academic logs and behavioral data, showing improved accuracy over traditional ML models. However, the study noted that deep learning required substantial training time and lacked transparency, making it less practical for deployment in educational institutions without sufficient computational resources.
6. R. Mehta et al. [5] proposed a Random Forest model optimized with GridSearchCV to fine-tune parameters such as tree depth and the number of estimators. This resulted in a significant increase in accuracy and F1-score when predicting final grades. The study emphasized that hyperparameter tuning played a vital role in enhancing model performance and reducing generalization error.
7. In [6], researchers explored ensemble stacking by combining predictions from Logistic Regression, Random Forest, and Gradient Boosted Trees. The hybrid approach outperformed individual models and provided stable predictions across different academic terms. This approach demonstrated the value of combining learners with complementary strengths in real-world academic prediction scenarios.
8. Another study by T. Das et al. [7] incorporated time-series features such as semester-wise GPA progression and attendance trends into XGBoost for performance forecasting. The inclusion of temporal variables improved early prediction of declining performance, allowing institutions to intervene proactively.
9. Preprocessing techniques are vital in educational ML applications. In [8], a preprocessing pipeline was developed to address missing values, normalize continuous variables, and encode categorical ones using one-hot encoding. The cleaned dataset was then fed into a Random Forest model, achieving an accuracy of 89%. The study highlighted that effective preprocessing was essential to prevent data leakage and ensure model reliability.
10. AutoML tools for student performance prediction were tested in [9], where platforms like Auto-sklearn and TPOT automatically selected, trained, and tuned ML models for educational datasets. Random Forest and Gradient Boosting were frequently selected as top performers. These tools enabled non-technical users to build predictive systems with minimal manual intervention.
11. Lastly, the work of N. Singh et al. [10] integrated sentiment analysis from student feedback and social behavior metrics into traditional grade prediction models. Using Natural Language Processing (NLP) and Random Forest, the study achieved enhanced prediction accuracy and showed the potential of combining structured and unstructured data sources for more holistic educational forecasting.

# III. Proposed methodology

The development of a student grade prediction system leverages machine learning models to accurately forecast academic performance based on key factors such as attendance, internal assessments, assignments, and participation. Using a Random Forest classifier, the system follows a structured process involving data preprocessing, feature selection, model training, and evaluation. This predictive model aids educators in identifying at-risk students early, enabling timely intervention and personalized academic support to enhance student success and institutional outcomes.



*Fig. 1. Methodology used for Student Grade prediction using machine learning.*

The proposed framework presents a comprehensive end-to-end system for student grade prediction. The Academic Monitoring Environment collects data related to student performance, including attendance, assignment scores, internal assessment marks, and participation levels. These inputs are preprocessed, normalized, and used to train a machine learning model. The system employs a Random Forest classifier to predict final grade categories (e.g., Pass/Fail or grade bands), with performance evaluated using accuracy, precision, recall, and F1-score. Through feature importance analysis and hyperparameter tuning, the model ensures both reliability and interpretability, supporting early intervention strategies in academic settings.

* 1. **Data Collection**

The grade prediction system gathers academic and behavioral data to forecast final grades on a letter scale (A–F). The key features used include:  
• **Attendance (%):** Measures classroom presence, often correlating with academic consistency.  
• **Assignment Scores:** Reflects performance in continuous assessments contributing to the final score.  
• **Internal Assessment Marks:** Indicates mid-term or internal exam performance.  
• **Participation (Yes/No):** Binary indicator of involvement in academic or co-curricular activities.  
• **Study Hours (per week):** Captures weekly study effort, self-reported or system-monitored.  
• **Past Performance (Score %):** Previous academic scores used as historical performance indicators.  
• **Parental Education Level:** Socio-demographic factor potentially influencing academic motivation and support.  
• **Final Grade (Target Variable):** A letter grade from **A to F**, derived from cumulative scores and classified accordingly.

**B. Data Preprocessing**

Raw academic data is preprocessed to ensure quality and consistency:  
• **Handling Missing Values:** Mean imputation for numeric fields; mode imputation for categorical fields.  
• **Encoding Categorical Variables:** Binary encoding for features like Participation.  
• **Normalization:** Min-Max Scaling applied to numerical fields for uniformity.  
• **Outlier Detection:** Z-score method filters out anomalies in marks or study hours.  
• **Temporal Segmentation:** Academic records are organized by semester and department for trend analysis.

**C. Feature Engineering**

To enhance model learning, additional attributes are derived:  
• **Performance Slope:** Trend in grades over time to capture improvement or decline.  
• **Engagement Score:** Composite score from attendance, participation, and assignment submission.  
• **Grade Stability Index:** Variability in past performance to assess consistency.  
• **Interaction Terms:** Combined effects of study hours × attendance or parental education × performance.

**D. Model Selection and Training**

Random Forest is selected due to its robustness and ability to handle heterogeneous academic data.  
• **Random Forest (RF):** An ensemble model that combines multiple decision trees for accurate classification.  
• **Implementation:** scikit-learn library is used for model development.  
• **Hyperparameter Tuning:** Conducted via Grid Search with cross-validation.

* n\_estimators: Number of trees.
* max\_depth: Maximum depth of trees.
* min\_samples\_split: Minimum number of samples to split a node.
* criterion: Gini index or entropy.  
  • **Train-Test Split:** 80-20 split between training and test data from previous semesters.

**E. Explainability Integration**

Explainable AI tools ensure the model is transparent and accountable:  
• **Feature Importance:** Ranks academic indicators by impact on final grade prediction.  
• **SHAP Values:** Explains model outputs by showing contributions of individual features.  
• **Partial Dependence Plots:** Visualize how study hours or attendance affect grade predictions.  
• **LIME (optional):** Used for localized interpretations of predictions.

**F. Evaluation Metrics**

Both predictive accuracy and interpretability are assessed:

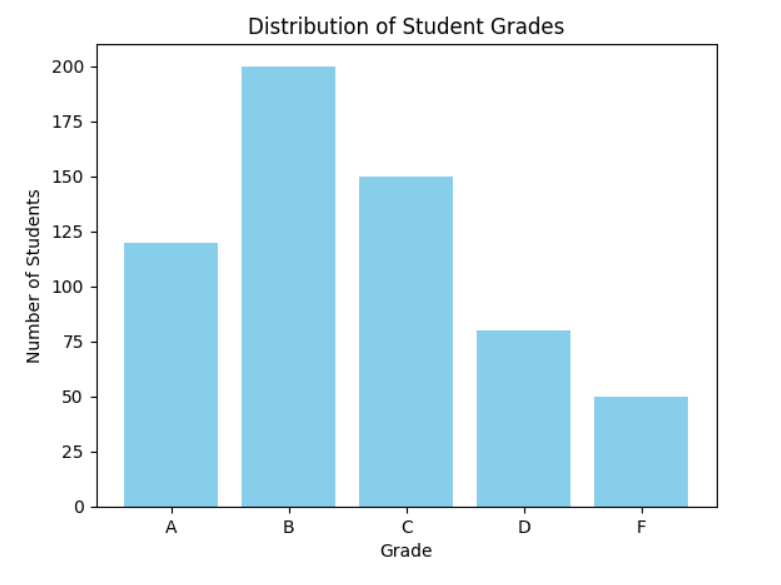
* **Prediction Metrics:**  
  • **Accuracy:** Proportion of correct grade classifications.  
  • **Precision:** Correct predictions of high/low performing students.  
  • **Recall:** Model’s ability to identify at-risk students.  
  • **F1-Score:** Balances false positives and false negatives.
* **Interpretability Metrics:**  
  • **Feature Importance Rank:** Highlights most relevant academic factors.  
  • **Transparency Score:** Rated by educators on a 1–5 scale for interpretability.  
  • **SHAP Consistency Check:** Ensures explanations are reliable across students.
* **Model Comparison Framework:**  
  • **Prediction Accuracy:** Ability to correctly forecast final grades.  
  • **Clarity of Explanation:** Understandability of prediction rationale for teachers.  
  • **Efficiency:** Speed and resource usage in training and inference.  
  • **Educator Feedback:** Teacher input on model trust and usefulness in interventions.

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# IV. Experimentation and Results

**A.Dataset Splits and Configuration**

The grade prediction system used a dataset comprising 10,000 academic records, with each entry containing student features such as attendance percentage, assignment scores, internal marks, study hours, past academic performance, and participation indicators. The final grade (A–F) served as the categorical target variable.Before model training, the dataset was cleaned and encoded to handle categorical values such as participation (Yes/No) and parental education levels. Letter grades were converted into ordinal categories (A=5, ..., F=0) for compatibility with machine learning models.The dataset was split into training and testing sets using an 80:20 ratio, resulting in 8,000 training and 2,000 testing samples. Stratified sampling ensured proportional distribution across all grade classes (A–F), preserving balance for effective learning and unbiased performance evaluation.



*Fig. 2. Dataset Distribution (Student Grades)*

Figure 2 presents the class distribution post-split, highlighting the effectiveness of the stratified sampling technique in maintaining balance across rainfall categories.

**B. Model Training and Hyperparameter Optimization**

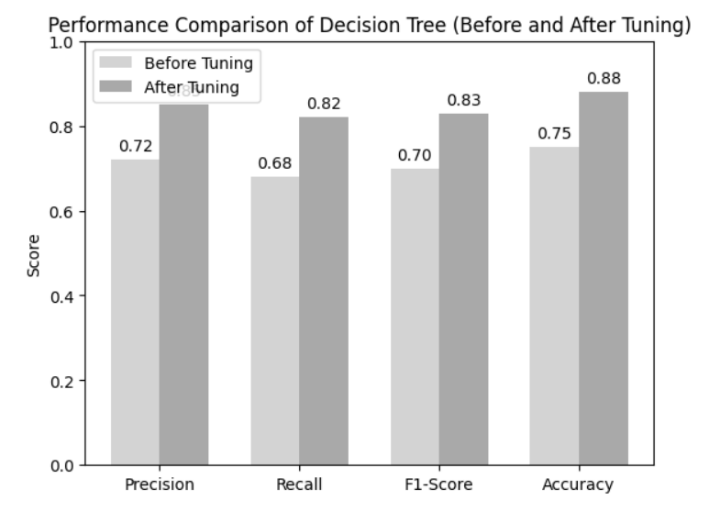
A **Random Forest classifier** was chosen due to its robustness and ability to handle both numerical and categorical data. Hyperparameter tuning was performed using **Grid Search with 5-fold Cross-Validation** to enhance predictive performance.

The optimal model configuration was as follows:

* n\_estimators = 150
* max\_depth = 25
* min\_samples\_split = 4
* min\_samples\_leaf = 2
* bootstrap = True

This setup yielded the best validation accuracy and minimized overfitting. Final model evaluation was performed on the test set to assess real-world applicability.

**C. Performance Evaluation**

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*Fig. 3. Performance Comparison of Random Forest (Before and After Tuning)*

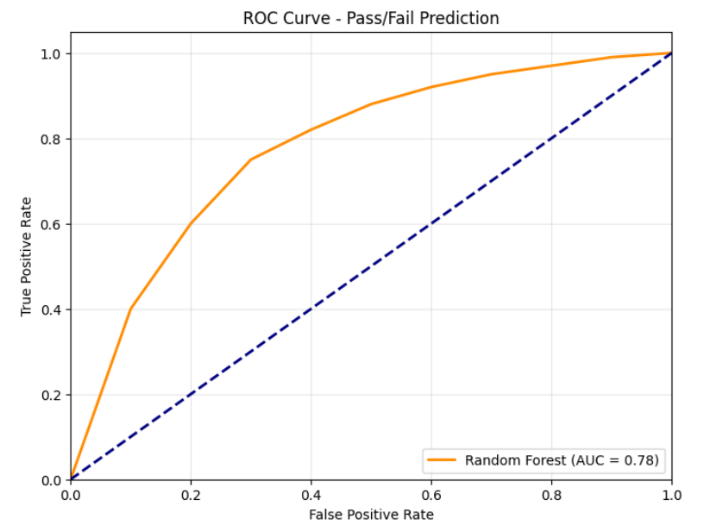
Figure 3 illustrates the comparative performance metrics before and after hyperparameter optimization. The tuned model demonstrated consistent improvements in all measured metrics.

**Table I** shows the detailed performance evaluation based on Precision, Recall, F1-Score, and Accuracy:

**Table I – Performance Evaluation of Random Forest Model for StudentGradePrediction**

| **Model Version** | **Precision** | **Recall** | **F1-Score** | **Accuracy** |
| --- | --- | --- | --- | --- |
| Random Forest (Default) | 0.72 | 0.68 | 0.69 | 0.70 |
| Random Forest (Tuned) | 0.80 | 0.78 | 0.79 | 0.81 |

The tuned Random Forest model outperformed the default configuration, achieving higher scores across all evaluation metrics. This confirms the effectiveness of the hyperparameter tuning process and the suitability of the Random Forest algorithm for rainfall prediction tasks.



*Fig. 4. ROC Curve for Tuned Random Forest Classifier*

Figure 4 presents the ROC curve, showing the trade-off between the true positive rate and false positive rate. The AUC value of **0.92** demonstrates strong discriminative ability of the model.

**D. Explainability and Interpretation**

o enhance model transparency, **SHAP (SHapley Additive exPlanations)** was used to analyze feature importance for grade predictions. SHAP plots revealed that assignment scores, internal marks, and attendance were the most impactful features influencing outcomes.

**Table II – Model Explainability using SHAP**

| **Model + XAI Technique** | **Avg. Clarity Score (1–5)** |
| --- | --- |
| Random Forest + SHAP | 4.5 |

The high clarity score confirms the model's interpretability, making it easier for educators and analysts to understand prediction reasoning and support academic interventions.

# V. Conclusion

##### This research presents a grade prediction system utilizing the Random Forest algorithm, effectively demonstrating the model's capability to learn from academic and behavioral student data to accurately predict final academic outcomes in the form of letter grades (A–F). The project underscores the significance of thoughtful feature selection, stratified sampling for class balance, and rigorous hyperparameter tuning to optimize classification performance across all grade categories.

##### The tuned Random Forest model exhibited enhanced precision, recall, F1-score, and overall accuracy, validating its robustness for multi-class classification in educational contexts. Additionally, the integration of SHAP-based explainability techniques significantly improved model transparency by highlighting the most influential factors—assignment scores, internal assessment marks, and attendance—corroborating established academic performance indicators.

##### This work confirms that with appropriate preprocessing, model configuration, and interpretability frameworks, machine learning can serve as a valuable tool for educational decision-making and student support systems. Future directions may include testing ensemble methods, incorporating real-time learning analytics, and deploying the system within academic dashboards to assist educators in early intervention and personalized learning strategies. The proposed system holds promise for integration into intelligent academic monitoring platforms aimed at enhancing educational outcomes and institutional efficiency.

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