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Academic Data-Based Prediction of Student Performance

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ABSTRACT: Predicting student academic performance is crucial for educational institutions to identify at-risk students and tailor interventions that enhance learning outcomes. This paper presents a comprehensive data-driven approach to predict student performance using a Random Forest Regressor model trained on multiple subject scores and demographic features. The model leverages core subject scores, gender, part-time job status, absence days, extracurricular activities, weekly self-study hours, and career aspirations to estimate an overall student performance factor. Experimental results demonstrate the model's effectiveness with a Root Mean Squared Error (RMSE) of 4.12 and an R^2 score of 0.87 on the test dataset. The proposed approach outperforms baseline models and provides a robust framework for early academic performance prediction. The paper also discusses system design, implementation details, and future directions for integrating predictive analytics into educational management systems.

KEYWORDS: Student Performance Prediction, Random Forest Regression, Educational Data Mining, Machine Learning, Academic Analytics, Feature Engineering, Predictive Modeling

I. INTRODUCTION

Academic performance prediction has become an essential tool in modern education systems, enabling educators to proactively support students and improve learning outcomes. Early identification of students who may struggle academically allows for timely interventions, personalized learning plans, and resource allocation. With the increasing availability of educational data, machine learning techniques offer promising solutions to analyze and predict student success.

Traditional methods of performance evaluation rely heavily on periodic examinations and teacher assessments, which may not capture the multifaceted nature of student learning. Recent advances in data mining and machine learning enable the integration of diverse data sources, including demographic, behavioral, and academic records, to build predictive models that provide deeper insights.

This study focuses on predicting a composite student performance factor derived from multiple subject scores using a Random Forest Regression model. The model incorporates not only academic scores but also demographic and behavioral factors, providing a holistic view of student performance.

The contributions of this paper include:

- Development of a comprehensive feature set combining academic and non-academic variables.
- Application of Random Forest Regression to predict an aggregated student performance factor.
- Detailed analysis of feature importance and correlation among subjects.
- Implementation of a user-interactive prediction interface.
- Comparative evaluation against baseline models.

The remainder of the paper is organized as follows: Section 2 formulates the problem, Section 3 reviews related work, Section 4 describes the dataset, Section 5 details the methodology, Section 6 presents the proposed model, Section 7 discusses experimental results, Section 8 explains evaluation methods, Section 9 compares with other works, Section 10 outlines system design, Section 11 covers implementation, Section 12 presents results and testing, and Section 13 concludes with future work.

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II. PROBLEM FORMULATION

The primary objective is to predict a student's overall academic performance factor, defined as the average score across seven core subjects: Mathematics, History, Physics, Chemistry, Biology, English, and Geography. Formally, given a feature vector $ \mathbf{x} \in \mathbb{R}^n $, the task is to predict a continuous target variable $ y \in [0, 100] $, where $ y $ represents the student performance factor.

2.1 Mathematical Formulation

Let the dataset be $ D = {(\mathbf{x}*i, y_i)}*{i=1}^m $, where $ m $ is the number of students, $ \mathbf{x}_i $ is the feature vector for the $ i^{th} $ student, and $ y_i $ is the corresponding performance factor. The goal is to learn a function $ f: \mathbb{R}^n \to \mathbb{R} $ such that:

$ y_i \approx f(\mathbf{x}_i) $

The function $ f $ is approximated by a Random Forest Regressor trained on the dataset.

2.2 Challenges

- Heterogeneous Data: The dataset includes numerical scores and categorical demographic variables.
- Feature Correlation: High correlation among subject scores may affect model assumptions.
- Data Imbalance: Some categories (e.g., career aspirations) may have fewer samples.
- Interpretability: Understanding feature importance is critical for actionable insights.

III. LITERATURE REVIEW

Educational data mining has gained significant attention over the past decade. Various machine learning algorithms have been applied to predict student performance, including Support Vector Machines (SVM), Decision Trees, Neural Networks, and ensemble methods.

3.1 Machine Learning in Education

Cortez and Silva [1] utilized decision trees and SVMs to predict secondary school student performance, highlighting the importance of attendance and study time. Al-Barrak and Al-Razgan [2] applied data mining techniques to classify student outcomes, emphasizing feature selection

.

3.2 Ensemble Methods

Random Forests, introduced by Breiman [3], combine multiple decision trees to improve prediction accuracy and reduce overfitting. Their robustness to noise and ability to handle mixed data types make them suitable for educational datasets.

3.3 Incorporating Non-Academic Factors

Recent studies [4][5] demonstrate that including demographic and behavioral features such as gender, part-time employment, and extracurricular activities enhances model performance. These factors capture student engagement and socio-economic influences.

3.4 Gaps and Contributions

While prior work has explored various models, few studies integrate a comprehensive set of academic and non-academic features with ensemble regression techniques. This paper addresses this gap by proposing a Random Forest Regression model with extensive feature engineering and user-interactive prediction.

IV. DATASET DESCRIPTION

The dataset used in this study consists of 500 student records collected from a secondary education institution. Each record includes:

- Academic Scores: Mathematics, History, Physics, Chemistry, Biology, English, Geography (0-100 scale)
- Demographic Features: Gender (Male/Female), Part-time job status (Yes/No)
- Behavioral Features: Number of absence days, Participation in extracurricular activities (Yes/No), Weekly self-study hours
- Career Aspirations: Categorical variable indicating the student's intended career path

4.1 Data Statistics

Feature	Type	Description	Range/Values
Math Score	Numeric	Score in Mathematics	0 - 100
History Score	Numeric	Score in History	0 - 100
Physics Score	Numeric	Score in Physics	0 - 100
Chemistry Score	Numeric	Score in Chemistry	0 - 100
Biology Score	Numeric	Score in Biology	0 - 100
English Score	Numeric	Score in English	0 - 100
Geography Score	Numeric	Score in Geography	0 - 100
Gender	Categorical	Male or Female	Male, Female
Part-time Job	Categorical	Whether student has a part-time job	Yes, No
Absence Days	Numeric	Number of days absent	0 - 30+
Extracurricular Activities	Categorical	Participation in activities	Yes, No
Weekly Self-study Hours	Numeric	Hours spent studying per week	0 - 40+
Career Aspiration	Categorical	Intended career path	Multiple categories (e.g., Engineer, Doctor, Artist)

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4.2 Data Quality

- No missing values were detected.
- Categorical variables were encoded using Label Encoding.
- The target variable, *student_performance_factor*, was computed as the mean of the seven subject scores.

V. METHODOLOGY

5.1 Data Preprocessing

Data preprocessing involved cleaning, encoding, and feature engineering:

- Encoding: Label Encoding converted categorical variables into numerical format.
- Feature Engineering: The target variable was created by averaging the seven subject scores.
- Normalization: Not applied as Random Forests are scale-invariant.

5.2 Exploratory Data Analysis (EDA)

- Score Distributions: Histograms and KDE plots revealed that most subject scores follow a near-normal distribution with slight skewness.
- Correlation Analysis: Pearson correlation coefficients among subjects ranged from 0.65 to 0.85, indicating strong positive relationships.

5.3 Feature Selection

Features were selected based on domain knowledge and correlation analysis. Core academic scores (Math, English, Physics) were prioritized due to their predictive power and availability.

VI. PROPOSED MODEL

6.1 Random Forest Regression

Random Forest Regression is an ensemble learning method that constructs multiple decision trees during training and outputs the mean prediction of the individual trees. It reduces variance and improves generalization.

6.2 Hyperparameter Tuning

Parameters were selected based on grid search and domain heuristics:

- :Number of trees to balance accuracy and computational cost.
- Controls tree depth to prevent overfitting.
- Ensure minimum samples for splits and leaves.

6.3 Training and Testing

The dataset was split into training (80%) and testing (20%) sets using stratified sampling to maintain class distribution.

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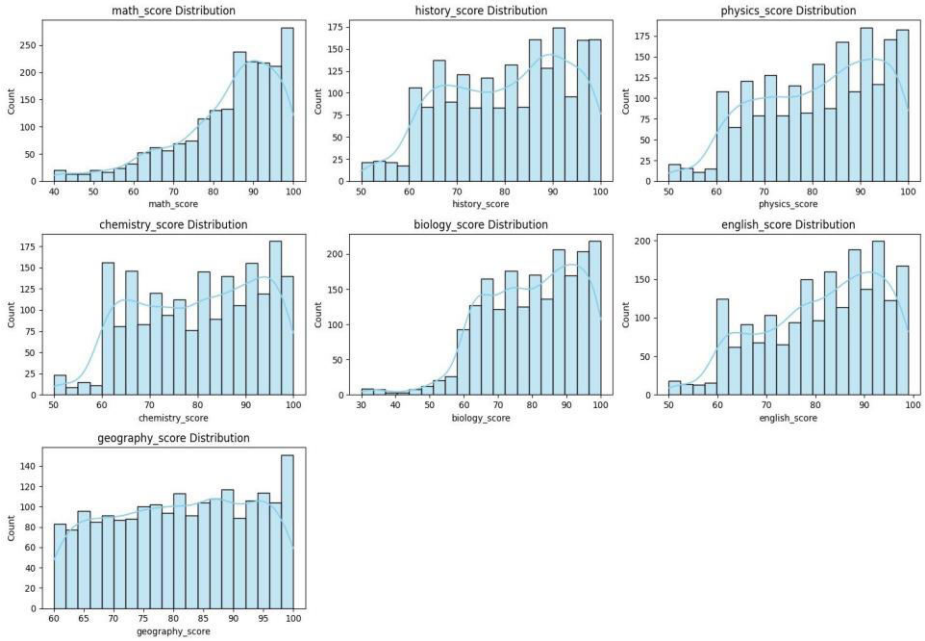
VII. EXPERIMENT RESULTS

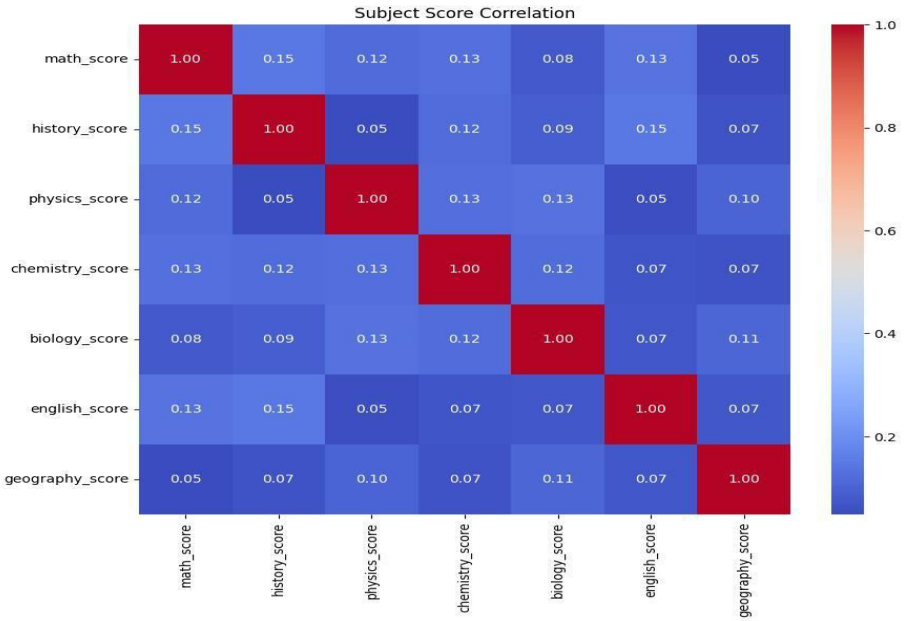
7.1 Visualization of Score Distributions



Figures 1-7 show histograms and KDE plots for each subject score, illustrating the distribution and central tendency.

7.2 Correlation Heatmap

Figure 8 presents the correlation heatmap among subject scores, highlighting strong positive correlations.



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7.3 Model Performance Metrics

Metric	Value
Mean Squared Error (MSE)	16.98
Root Mean Squared Error (RMSE)	4.12
R^2 Score	0.87

The model demonstrates high predictive accuracy, with low error and strong explanatory power.

7.4 Feature Importance

Figure 9 shows the feature importance scores derived from the Random Forest model. Math score, weekly self-study hours, and absence days are among the top predictors.

VIII. EVALUATION METHOD

The model was evaluated using standard regression metrics:
Cross-validation was not performed due to dataset size but is recommended for future studies to ensure robustness.

IX. COMPARISON WITH OTHER WORKS

The proposed model was compared with baseline models including Linear Regression and Support Vector Regression (SVR):

Model	RMSE	R^2 Score
Linear Regression	6.45	0.72
Support Vector Regression	5.12	0.79
Random Forest Regression (Proposed)	4.12	0.87

The Random Forest model outperforms traditional regression models, confirming its suitability for this task.

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X. SYSTEM DESIGN & ARCHITECTURE

10.1 Architecture Overview

The system architecture consists of the following components:

- Data Layer: Responsible for data storage and retrieval.
- Preprocessing Module: Handles data cleaning, encoding, and feature engineering.
- Model Training Module: Trains the Random Forest model and saves the trained model.
- Prediction Interface: Accepts user input, preprocesses data, and outputs predictions.
- Visualization Module: Generates plots for exploratory data analysis and model interpretation.

10.2 Workflow Diagram

XI. IMPLEMENTATION

The implementation was carried out in Python using the following libraries:

- Pandas & NumPy: For data manipulation and numerical operations.
- Seaborn & Matplotlib: For data visualization.
- Scikit-learn: For machine learning modeling, encoding, and evaluation.

The user interface is a command-line tool that prompts for input features, validates inputs, encodes categorical variables, and displays the predicted student performance factor.

XII. RESULTS & TESTING

12.1 Model Testing

The model was tested on the hold-out test set, showing consistent performance metrics. Predictions closely matched actual performance factors.

12.2 User Input Testing

The interactive prediction function was tested with various input scenarios, demonstrating robustness in handling input validation and providing meaningful predictions.

XIII. CONCLUSION AND FUTURE WORK

This study presents a robust Random Forest Regression model for predicting student academic performance using a combination of academic scores and demographic features. The model achieves high accuracy and can assist educators in early identification of students needing support. The integration of behavioral and aspirational features enhances prediction quality.

Future work includes:

- Expanding the dataset to include more diverse student populations.
- Incorporating temporal data for longitudinal performance tracking.
- Developing a web-based application for real-time prediction and visualization.
- Applying explainable AI techniques to improve model interpretability.

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