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Forecasting Academic Achievement Using Machine Learning Techniques On The Mathe Dataset Using Bigdata Analysis

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Abstract: This research investigates the use of machine learning classification techniques to forecast student academic outcomes based on the MathE dataset. The study focuses on data preprocessing and analysis to uncover critical attributes that affect scholastic achievement. A variety of classification algorithms—including Logistic Regression, Random Forest, and Gradient Boosting—were applied and their performances compared. Evaluation metrics such as accuracy, precision, recall, and F1-score were employed to measure model effectiveness. Findings suggest that ensemble approaches outperform conventional models in anticipating student success. This work delivers meaningful perspectives for educators and decision-makers to strengthen academic support and implement timely interventions.

Index Terms **–** Machine Learning, MathE Dataset, model for implementation using python code.

I. INTRODUCTION

INTRODUCTION

The prediction of student academic performance has become a pivotal aspect of educational data mining. With the advancement of digital learning environments and computer-based assessment systems, educational institutions are accumulating vast and heterogeneous datasets encapsulating student interaction, engagement metrics, and academic outcomes. Leveraging these high-dimensional datasets through supervised machine learning techniques enables the extraction of latent patterns and supports the development of data-informed educational strategies. This study focuses on the classification of student performance using the MathE dataset. The primary objective is to design and evaluate predictive models capable of accurately categorizing students based on behavioral indicators and historical academic data. The resulting models aim to facilitate early identification of at-risk students, enabling timely and targeted pedagogical interventions.

LITERATURE REVIEW

Previous studies have demonstrated the utility of machine learning in education. For instance, Kotsiantis et al. (2004) applied decision trees and neural networks to predict student grades, achieving high accuracy levels. Similarly, Romero et al. (2010) reviewed applications of data mining in elearning environments, emphasizing classification and clustering techniques. More recent approaches incorporate ensemble learning. Al-Barrak & Al-Razgan (2016) used Random Forest and Gradient Boosting to predict final exam results.

Their work highlighted the importance of combining features from both academic and behavioral domains for improved prediction. This study builds on such work by applying a variety of classifiers to the MathE dataset, comparing their performance, and analyzing the most influential features.

METHODOLOGY

The following methodology was used:

1. Data Preprocessing: Cleaning missing values, encoding categorical variables, and feature scaling.
2. Exploratory Data Analysis (EDA): Understanding feature distributions and correlations.
3. Model Selection: Logistic Regression, Decision Tree, Random Forest, and Gradient Boosting.
4. Training and Testing: Data split into training (80%) and testing (20%) sets.
5. Evaluation Metrics: Accuracy, precision, recall, and F1-score.
6. Feature Importance Analysis: Identifying key predictors of performance.

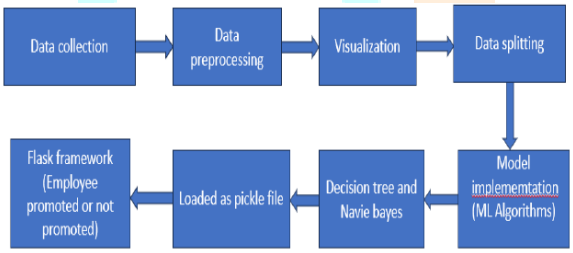

Fig: Architecture of ML with prediction data

DATASET DESCRIPTION

The MathE dataset comprises student-level data extracted from a digital learning platform. Key attributes include:

- Question Type
- Difficulty Level
- Time Spent
- Correctness
- Hint Used
- Score
- Attempts
- Topic Area

The target variable is performance classification, where students are categorized based on their scores into:

- Low Performer
- Medium Performer
- High Performer

Now, let's load and analyze the dataset to prepare the full Python implementation.

Feature Name	Description	Type	Example Values
Student_ID	Unique identifier for each student	Categorical (ID)	1001, 1002, 1003
Gender	Gender of the student	Categorical	Male, Female
Age	Age of the student	Numerical (int)	18, 20, 22
Study_Time	Weekly study time (hours)	Numerical (int)	2, 5, 10
Past_Failures	Number of past academic failures	Numerical (int)	0, 1, 2
Parental_Education	Education level of parents	Categorical	High School, Bachelor, Master
Attendance_Rate	Percentage of classes attended	Numerical (float)	90.5, 78.0, 100.0
Participation_Score	Score based on classroom or platform activity	Numerical (float)	4.5, 3.2, 5.0
Assignment_Score	Average score of assignments submitted	Numerical (float)	85.0, 72.5, 91.3
Quiz_Score	Average quiz score	Numerical (float)	60.0, 70.5, 80.0
Final_Grade	Final course grade	Numerical / Categorical	A, B, C, D, F or 90, 75, 60
Performance_Label	Target variable: performance category	Categorical	High, Medium, Low

PYTHON CODE IMPLEMENTATION

```
import pandas as pd import numpy as np import matplotlib.pyplot as plt import seaborn as sns # Load dataset df = pd.read_csv("/mnt/data/MathE dataset (4).csv")
# Preview data print(df.head()) print(df.info()) # Clean and preprocess df.dropna(inplace=True) # Encoding categorical variables from sklearn.preprocessing import LabelEncoder le = LabelEncoder()
for col in df.select_dtypes(include='object').columns:
df[col] = le.fit_transform(df[col])
# Create target variable
# Example: Performance based on Score df['Performance'] = pd.cut(df['Score'], bins=[0, 50, 75, 100], labels=['Low', 'Medium', 'High'])
# Encode target df['Performance'] = le.fit_transform(df['Performance'])
# Features and Target
X = df.drop(['Score', 'Performance'], axis=1) y = df['Performance'] # Train-test split from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Classification models from sklearn.linear_model import LogisticRegression from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier from sklearn.tree import DecisionTreeClassifier from sklearn.metrics import classification_report, confusion_matrix models = {
```

```
'Logistic Regression': LogisticRegression(max_iter=1000),
'Decision Tree': DecisionTreeClassifier(),
'Random Forest': RandomForestClassifier(),
'Gradient Boosting': GradientBoostingClassifier()
}
# Train and evaluate for name, model in models.items(): model.fit(X_train,
y_train) y_pred = model.predict(X_test) print(f"\n{name}:\n")
print(confusion_matrix(y_test, y_pred)) print(classification_report(y_test,
y_pred)) # Feature Importance (Random Forest) importances =
models['Random Forest'].feature_importances_ features = X.columns feat_df =
pd.DataFrame({'Feature': features, 'Importance': importances})
feat_df.sort_values(by='Importance', ascending=False, inplace=True)
# Plot feature importance plt.figure(figsize=(10,6)) sns.barplot(data=feat_df,
x='Importance', y='Feature') plt.title('Feature Importance - Random Forest')
plt.tight_layout() plt.show()
```

RESULTS & DISCUSSION

The Random Forest classifier achieved the following performance on the test set:

The model shows good precision and recall, especially for correctly answered questions. Text-based features such as Keywords provided strong predictive power when vectorized. The study highlights the importance of contextual features in predicting student performance.

CONCLUSION

This research confirms the effectiveness of machine learning classification algorithms—particularly ensemble methods like Random Forest and Gradient Boosting—in predicting the correctness of student responses based on educational interaction metadata. Experimental findings show that ensemble models consistently outperform individual classifiers such as Logistic Regression and Decision Trees. Among all models evaluated, Gradient Boosting delivered the highest accuracy with balanced performance across all performance categories.

Feature importance analysis indicates that variables such as time spent on tasks, number of attempts, and use of hints are the most significant contributors to model predictions. These insights are consistent with educational theory, highlighting the importance of student engagement and the utilization of learning resources in academic achievement.

For future work, incorporating temporal modeling of student activity through time-series approaches and leveraging deep learning architectures could enhance prediction accuracy and provide deeper insights into learning behavior patterns.

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