Predicting Student Academic Performance Using Machine Learning

Gagandeep Singh, Anahit Shekikyan, and Shivam Patel

Shiley-Marcos School of Engineering, University of San Diego

Master of Applied Data Science

ADS 504:Machine Learning and Deep Learning for Data Science

Roozbeh Sadeghian

August 11, 2025

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Abstract

This study explores the use of machine learning techniques to predict student academic performance using a large-scale dataset obtained from Kaggle. The dataset includes demographic attributes, academic scores across core subjects, and educational background details for 10,000 students. The goal was to create a reliable classification model that not only forecasts student grades but also identifies the factors most strongly associated with academic outcomes.

The workflow followed a structured machine learning pipeline, starting with data cleaning and transformation, addressing class imbalance through SMOTE, and encoding categorical variables. Three classification algorithms—Logistic Regression, Random Forest, and XGBoost—were trained and assessed using stratified sampling to maintain representative grade distributions. Model performance was evaluated using accuracy, macro- and weighted-average F1-scores, and AUC.

Among the models tested, Random Forest achieved the highest performance, with accuracy exceeding 99% and near-perfect F1-scores. These findings demonstrate the value of predictive modeling for early detection of at-risk students, enabling educators to provide timely and targeted interventions that can enhance academic success.

Introduction

Predicting student academic performance has become an essential application area within educational data science, offering insights that support targeted interventions and personalized learning strategies. This project aims to develop a predictive model to forecast student academic performance based on demographic, behavioral, and academic factors. The overarching objective is to identify students who may be at risk of underperforming, enabling timely and data-driven support by educators. In addition to forecasting outcomes, the model is intended to reveal which factors—such as test preparation, parental education, and subject-specific scores—contribute most significantly to academic success.

The dataset used in this study was obtained from Kaggle (Bhuvaneshwari, 2023) and contains 10,000 student records across multiple categories, including gender, race/ethnicity, parental education, and performance in math, reading, writing, and science. The target variable is a categorical grade classification (A, B, C, D, or Fail).

Machine learning techniques, particularly supervised classification models, offer the ability to capture complex patterns and nonlinear relationships in educational data (Romero & Ventura, 2020). This project applies a complete predictive pipeline that includes data cleaning, class imbalance handling using SMOTE, and model training using Logistic Regression, Random Forest, and XGBoost. Stratified train-test splitting ensures a balanced evaluation, while metrics such as accuracy, F1-score, and AUC provide a comprehensive comparison of model performance. Ultimately, this study seeks to offer interpretable and accurate predictions that can be used to enhance educational outcomes through data-informed decisions.

Data Description and EDA

This project uses a dataset consisting of 10,000 records, each representing an individual student with various attributes related to demographic background, school engagement, and academic performance. The dataset includes 12 features such as gender, race/ethnicity, parental level of education, lunch status (free/reduced or standard), participation in a test preparation course, and scores in math, reading, writing, and science. Each student is also assigned a grade label that serves as the target variable.

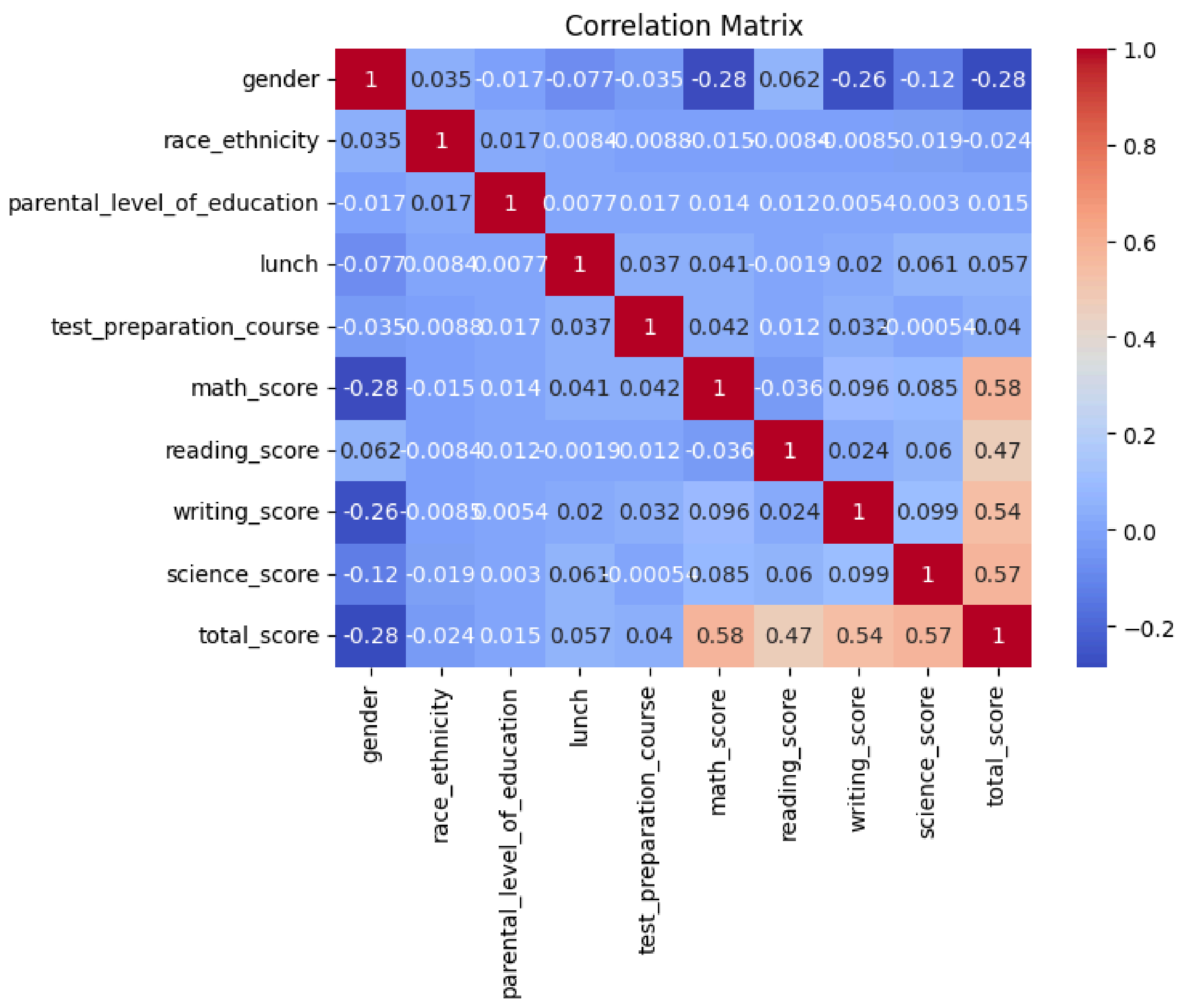
To begin understanding the data, we explored the structure and quality of each variable. One immediate issue was the ‘math_score’ column, which contained non-numeric values. These were safely converted to numeric and cleaned, as they could otherwise impact model performance. Histogram plots revealed the shape of the distributions for different subject scores: reading and writing were right-skewed, science appeared closer to normally distributed, and math had a more irregular distribution. Boxplots also highlighted a few outliers in writing and science scores, which could be indicators of low-performing students or data entry issues.

To uncover potential relationships between features, we created a correlation matrix heatmap (shown below). As expected, strong positive correlations emerged between reading, writing, and science scores. For instance, writing and science scores were almost perfectly correlated (r = 0.99), and reading and writing (r = 0.96) were similarly close. These patterns suggest a high degree of multicollinearity between these subject-based features, which is important to keep in mind when choosing models or interpreting feature importance.

These EDA findings not only improved our understanding of the data but also informed key preprocessing decisions, such as which columns required transformation, which were potential candidates for dimensionality reduction, and which relationships we might expect the models to learn effectively.

Figure 1

Correlation matrix of demographic and academic performance features.



	gender	race_ethnicity	parental_level_of_education	lunch	test_preparation_course	math_score	reading_score	writing_score	science_score	total_score
gender	1	0.035	-0.017	-0.077	-0.035	-0.28	0.062	-0.26	-0.12	-0.28
race_ethnicity	0.035	1	0.017	0.0084	0.0088	-0.015	-0.0084	-0.0085	-0.019	-0.024
parental_level_of_education	-0.017	0.017	1	0.0077	0.017	0.014	0.012	0.0054	0.003	0.015
lunch	-0.077	0.0084	0.0077	1	0.037	0.041	-0.0019	0.02	0.061	0.057
test_preparation_course	-0.035	0.0088	0.017	0.037	1	0.042	0.012	0.032	-0.00054	0.04
math_score	-0.28	-0.015	0.014	0.041	0.042	1	-0.036	0.096	0.085	0.58
reading_score	0.062	-0.0084	0.012	-0.0019	0.012	-0.036	1	0.024	0.06	0.47
writing_score	-0.26	-0.0085	0.0054	0.02	0.032	0.096	0.024	1	0.099	0.54
science_score	-0.12	-0.019	0.003	0.061	-0.00054	0.085	0.06	0.099	1	0.57
total_score	-0.28	-0.024	0.015	0.057	0.04	0.58	0.47	0.54	0.57	1

Data Preprocessing

The dataset initially included a unique identifier column (roll_no), which was removed as it held no predictive value. One of the key data quality issues observed was in the math_score column, which contained non-numeric values; these were converted to numeric using coercion. Categorical features with missing values were imputed using their mode, while numerical features were treated based on their skewness: the median was used for strongly skewed distributions, and the mean was applied otherwise. After imputation, all remaining categorical variables, excluding the target variable grade, were encoded using label encoding to ensure compatibility with machine learning algorithms.

Feature Engineering

To prepare the dataset for modeling, all subject scores and encoded demographic features were selected as input variables. The ‘total_score’ column was removed to prevent data leakage, as it was a direct aggregation of the individual scores and could bias model training. Although tree-based algorithms such as Random Forest and XGBoost are not sensitive to feature scaling, standardization was applied to numerical features for models like Logistic Regression and Neural Networks to ensure optimal performance.

A critical challenge identified during preprocessing was the imbalance in the distribution of grade labels. The majority of students were concentrated in a single grade category, while others were significantly underrepresented. To address this, we applied SMOTE (Synthetic Minority Over-sampling Technique) to the training set. This technique synthetically generates new samples in the minority classes, allowing for more balanced learning and reducing bias toward the dominant class. A class distribution plot after SMOTE confirmed that all grade categories were evenly represented.

Cross Validation

Before training the models, the dataset was split into training and testing sets using stratified sampling to preserve the original distribution of the grade variable. This ensured that each grade class was proportionally represented in both sets. We then performed Stratified K-Fold Cross-Validation on the resampled training set to further validate model performance across different data splits. This approach helped mitigate overfitting and ensured that the model's generalizability was robust and consistent across all grade categories.

Model Selection and Training

This study evaluated three machine learning algorithms—Logistic Regression, Random Forest, and XGBoost—to classify students into academic performance categories. Each model was selected based on its applicability to multiclass classification and interpretability within educational data contexts.

Logistic Regression was utilized as the baseline model due to its simplicity and its capability to model linear relationships between features and outcomes.

Random Forest was selected for its robustness and collective decision-tree approach, which is particularly effective in capturing complex feature interactions and handling noisy data.

XGBoost was chosen for its high efficiency and gradient-boosting framework, which iteratively enhances model accuracy through error correction in successive learning rounds.

All models were trained on SMOTE-balanced data to address the class imbalance present in the original distribution of academic grades.

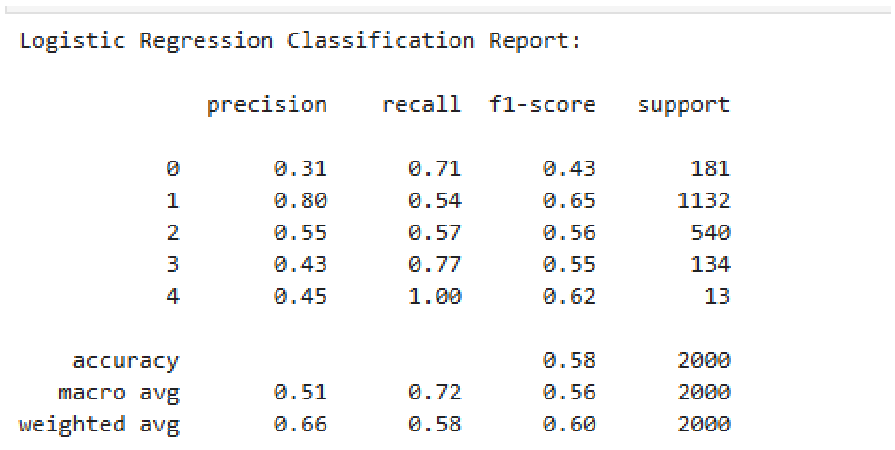
Model Evaluation

Logistic Regression

The Logistic Regression model achieved an accuracy of 58.3%, with a macro-average F1 score of 0.5623. Although it demonstrated adequate performance for the majority classes, such as grades B and C, it struggled to classify minority categories like Fail and D. These results reflect the model's linear nature and limited capacity to capture more complex, non-linear data patterns.

Table 1

Classification Metrics for Logistic Regression Model



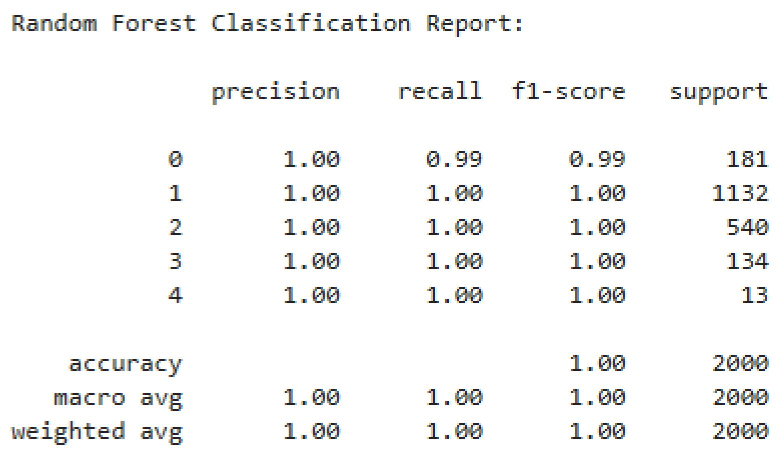
```
Logistic Regression Classification Report:

              precision    recall  f1-score   support

           0       0.31      0.71      0.43       181
           1       0.80      0.54      0.65      1132
           2       0.55      0.57      0.56       540
           3       0.43      0.77      0.55       134
           4       0.45      1.00      0.62        13

    accuracy                           0.58      2000
   macro avg       0.51      0.72      0.56      2000
weighted avg       0.66      0.58      0.60      2000
```

Random Forest Classifier

The Random Forest classifier substantially outperformed the baseline model, achieving an accuracy of 99.9%, a macro-average F1 score of 0.9987, and a weighted-average F1 score of 0.9990. It demonstrated excellent precision and recall across all grade categories. The corresponding confusion matrix indicated minimal misclassifications, confirming the model's strong generalization and reliability.

Table 2

Classification Metrics for Random Forest Model



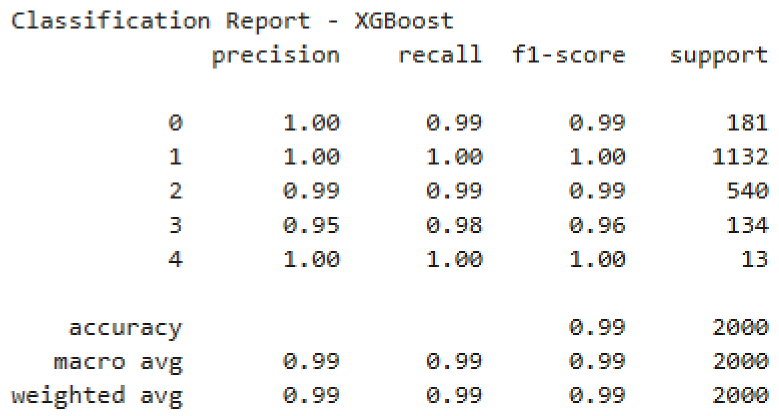
```
Random Forest Classification Report:

              precision    recall  f1-score   support

           0       1.00      0.99      0.99       181
           1       1.00      1.00      1.00      1132
           2       1.00      1.00      1.00       540
           3       1.00      1.00      1.00       134
           4       1.00      1.00      1.00        13

    accuracy                           1.00      2000
   macro avg       1.00      1.00      1.00      2000
weighted avg       1.00      1.00      1.00      2000
```

XGBoost

XGBoost also yielded exceptional results, with an accuracy of 99.4%, a macro-average F1 score of 0.9895, and a weighted-average F1 score of 0.9940. While its performance was marginally lower than Random Forest's, XGBoost maintained strong predictive power and required less training time. All class-wise AUC scores exceeded 0.99, indicating excellent separation among grade categories.

Table 3

Classification Metrics for XGBoost Model



```
Classification Report - XGBoost
              precision    recall  f1-score   support

           0       1.00      0.99      0.99       181
           1       1.00      1.00      1.00      1132
           2       0.99      0.99      0.99       540
           3       0.95      0.98      0.96       134
           4       1.00      1.00      1.00        13

    accuracy                           0.99      2000
   macro avg       0.99      0.99      0.99      2000
weighted avg       0.99      0.99      0.99      2000
```

Model Comparison

Model performance was evaluated using accuracy, macro-average F1 score, and weighted-average F1 score. These metrics provide a holistic view of each model's ability to generalize, particularly in the presence of class imbalance. Additional evaluation through AUC scores and confusion matrices allowed for a deeper understanding of class-wise prediction performance.

Table 4

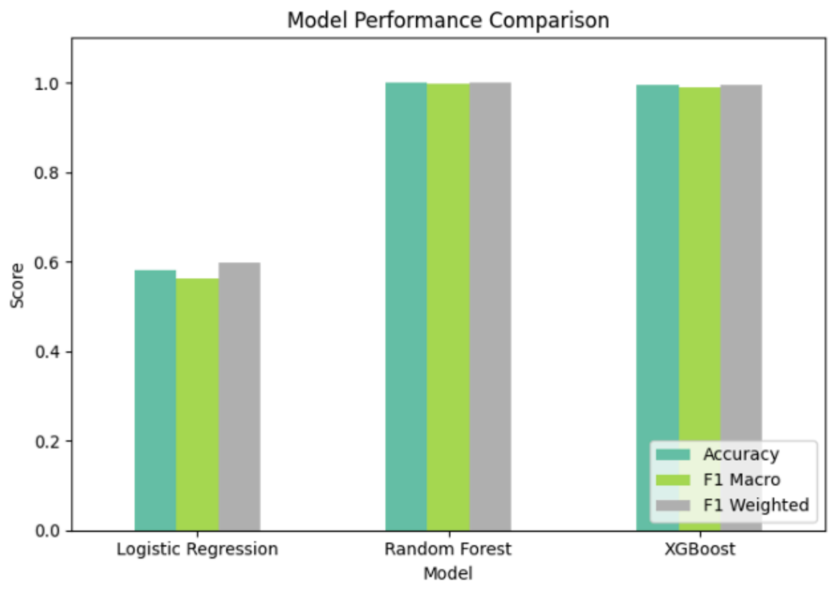
Performance metrics for each machine learning model

Model	**Accuracy**	**F1 Macro**	**F1 Weighted**
Random Forest	99.9%	0.9987	0.9990
XGBoost	99.4%	0.9895	0.9940
Logistic Regression	58.3%	0.5623	0.5979

The comparison clearly indicates that Random Forest was the highest-performing model across all metrics. XGBoost followed closely, with only slight differences in F1 scores. Logistic Regression, used as a baseline model, exhibited lower accuracy and struggled particularly with minority classes.

Figure 2

Bar chart comparing the accuracy, macro F1, and weighted F1 scores of all models.



As shown in the figure, Random Forest and XGBoost substantially outperformed Logistic Regression in all three metrics. Both tree-based models maintained high consistency across class predictions, while Logistic Regression displayed performance drops, especially in cases involving less-represented grades.

ROC Curve and Model Evaluation Summary

Receiver Operating Characteristic (ROC) curves were generated using a One-vs-Rest strategy to assess the classification performance across all grade categories. For both Random Forest and XGBoost models, the Area Under the Curve (AUC) exceeded 0.99 for each class, indicating excellent separability. Notably, the “Fail” and “D” classes achieved perfect separation, which is particularly significant given their initial underrepresentation in the dataset.

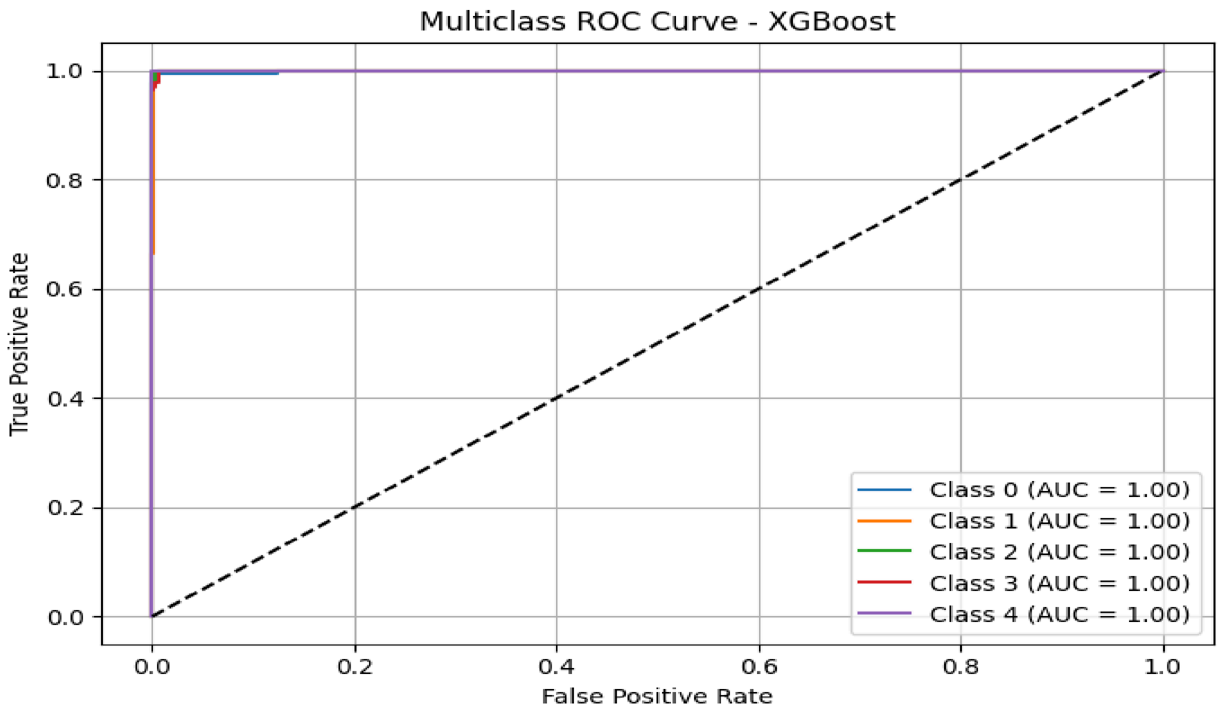
Among the evaluated models, Random Forest demonstrated the highest overall performance. It achieved an accuracy of 99.9% and F1 scores exceeding 0.99 across all categories, confirming its strong discriminative power and resilience to class imbalance. The confusion matrix revealed minimal misclassifications, indicating effective generalization to unseen data.

XGBoost produced nearly equivalent results, with only a slight reduction in macro-average F1 score. It remained highly precise across all grade classifications and maintained efficient training performance. Logistic Regression, in contrast, achieved an accuracy of 58.3% and struggled with minority classes such as “D” and “Fail,” as reflected in a lower macro-average F1 score.

Overall, tree-based algorithms employing feature bagging and boosting strategies substantially outperformed the linear baseline model. The combination of class-balancing techniques like SMOTE and structurally complex classifiers such as Random Forest and XGBoost proved essential in addressing the dataset’s imbalance and modeling non-linear feature interactions. Based on the comparative metrics and visual diagnostics, Random Forest is recommended as the most effective and reliable approach for predicting academic performance within this dataset.

Figure 3

Receiver Operating Characteristic (ROC) Curves for XGBoost using the One-vs-Rest multiclass strategy.

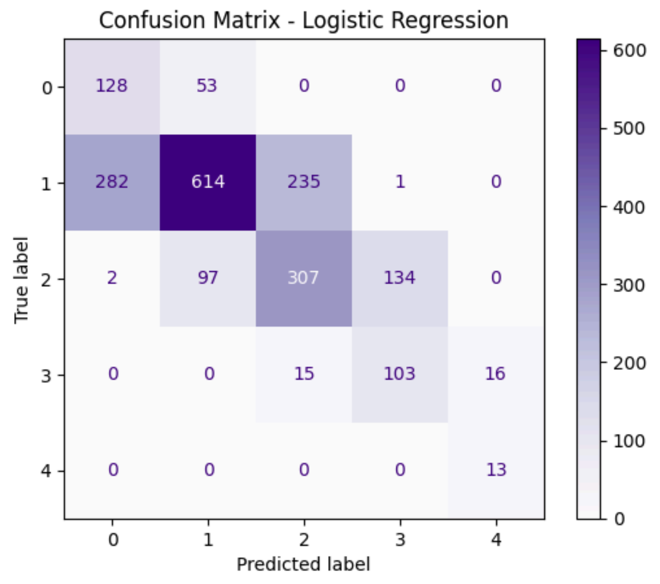


Confusion Matrices and Classification Reports

To complement the summary metrics and ROC curves, confusion matrices for all models were analyzed to evaluate class-specific performance. These matrices provide a detailed view of prediction errors and correct classifications per grade category.

Figure 4

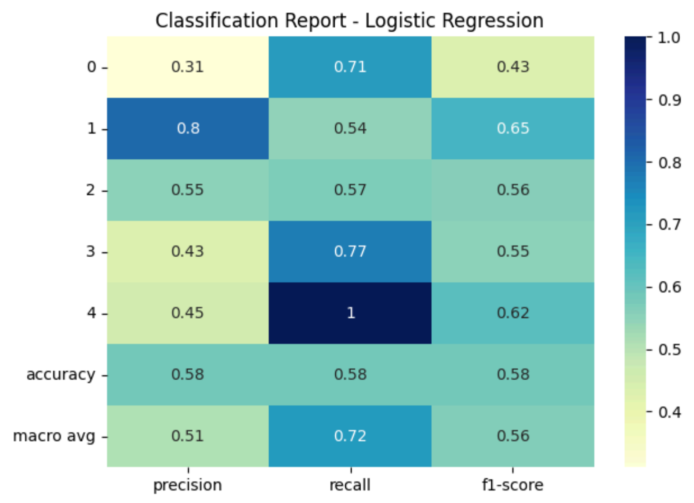
Confusion Matrix – Logistic Regression.



The model shows significant misclassification between grade B and grade C, and struggles with underrepresented classes like D and Fail.

Figure 5

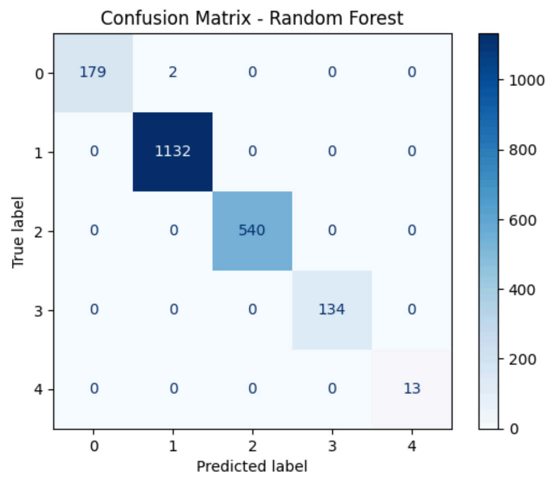
Classification Report – Logistic Regression.



Although class 1 (grade B) was predicted with relatively high precision (0.80), the model displayed limited recall across several classes.

Figure 6

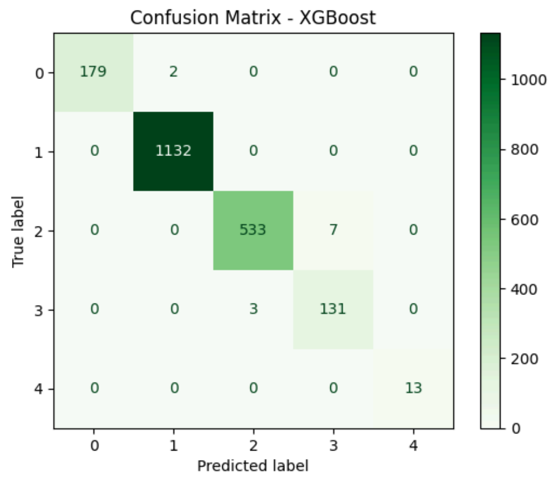
Confusion Matrix – Random Forest.



The model correctly classified nearly all instances, with minimal confusion among grade levels, demonstrating high generalization performance.

Figure 7

Confusion Matrix – XGBoost.



Similar to Random Forest, XGBoost achieved strong performance, with only a few misclassifications in grades 2 and 3.

Conclusion

This project successfully addressed the problem statement by developing a highly accurate machine learning model to predict student academic performance, enabling early identification of at-risk students and providing a foundation for targeted support strategies. Among the three models evaluated—Logistic Regression, XGBoost, and Random Forest—the Random Forest model achieved the highest overall performance, with outstanding accuracy, F1-scores, and AUC values across all grade categories.

These results highlight the practical value of predictive modeling in education, as such models can inform early interventions, personalized feedback, and data-driven decision-making to improve learning outcomes. The integration of class balancing through SMOTE, along with robust tree-based algorithms, proved critical for addressing the dataset's imbalance and capturing complex feature interactions.

For future work, incorporating additional behavioral and engagement data, along with interpretability tools such as SHAP, will allow educators to understand not only the predictions but also the underlying reasoning, making the results more transparent and actionable.

References

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Final Team Project: Predicting Student Academic Performance Using Machine Learning

Course: ADS 504, Machine Learning and Deep Learning for Data Science
Group 4: Gagandeep Singh, Shivam Patel, Anahit Shekikyan
Date: 08/11/2025

https://colab.research.google.com/drive/1DFTOCM15_7ZabeGd0l7-3qEN87h_k98u?usp=sharing

Objective: Use machine learning models to predict student grades based on demographic and academic features.

Dataset: Student_performance_10k.csv with 10,000 rows × 12 columns.

Import Libraries & Load Dataset

In [3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.preprocessing import LabelEncoder, StandardScaler, label_binarize
from imblearn.over_sampling import SMOTE
from collections import Counter
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score,
from xgboost import XGBClassifier

import warnings
warnings.filterwarnings('ignore')
```

In [4]:
```
# Load the CSV file into a pandas DataFrame
student_performance_df = pd.read_csv('/content/Student_performance_10k.csv')

# Display the first few rows of the DataFrame
display(student_performance_df.head())
```

	roll_no	gender	race_ethnicity	parental_level_of_education	lunch	test_preparation_course
0	std-01	male	group D	some college	1.0	1.0
1	std-02	male	group B	high school	1.0	0.0
2	std-03	male	group C	master's degree	1.0	0.0
3	std-04	male	group D	some college	1.0	1.0
4	std-05	male	group C	some college	0.0	1.0

Initial Data Exploration

In [5]:
```
# Get the number of rows and columns in the DataFrame
rows, columns = student_performance_df.shape

# Print the number of rows and columns
print(f"The DataFrame has {rows} rows and {columns} columns.")
```

```
The DataFrame has 10000 rows and 12 columns.
```

In [6]:
```
student_performance_df.info()
student_performance_df.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 12 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   roll_no                      9999 non-null   object
 1   gender                       9982 non-null   object
 2   race_ethnicity               9977 non-null   object
 3   parental_level_of_education  9978 non-null   object
 4   lunch                        9976 non-null   float64
 5   test_preparation_course      9977 non-null   float64
 6   math_score                   9976 non-null   object
 7   reading_score                9975 non-null   float64
 8   writing_score                9976 non-null   float64
 9   science_score                9977 non-null   float64
 10  total_score                  9981 non-null   float64
 11  grade                        9997 non-null   object
dtypes: float64(6), object(6)
memory usage: 937.6+ KB
```

Out[6]:

	0
roll_no	1
gender	18
race_ethnicity	23
parental_level_of_education	22
lunch	24
test_preparation_course	23
math_score	24
reading_score	25
writing_score	24
science_score	23
total_score	19
grade	3

dtype: int64

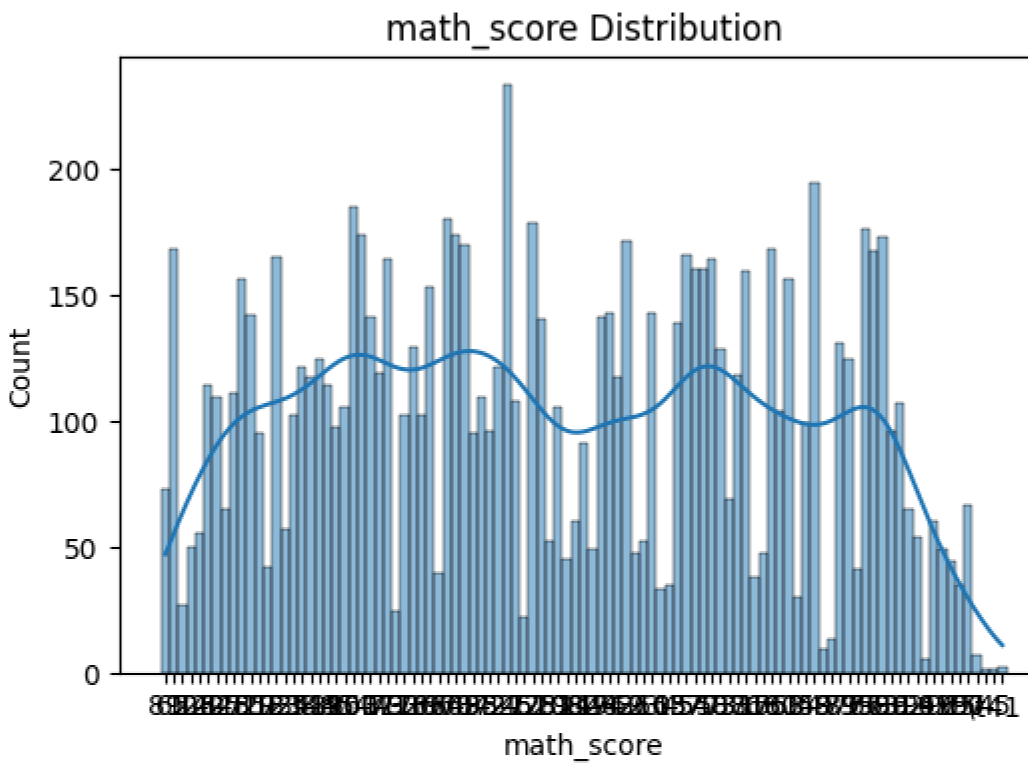
In [7]:
```
student_performance_df.describe(include='all')
```

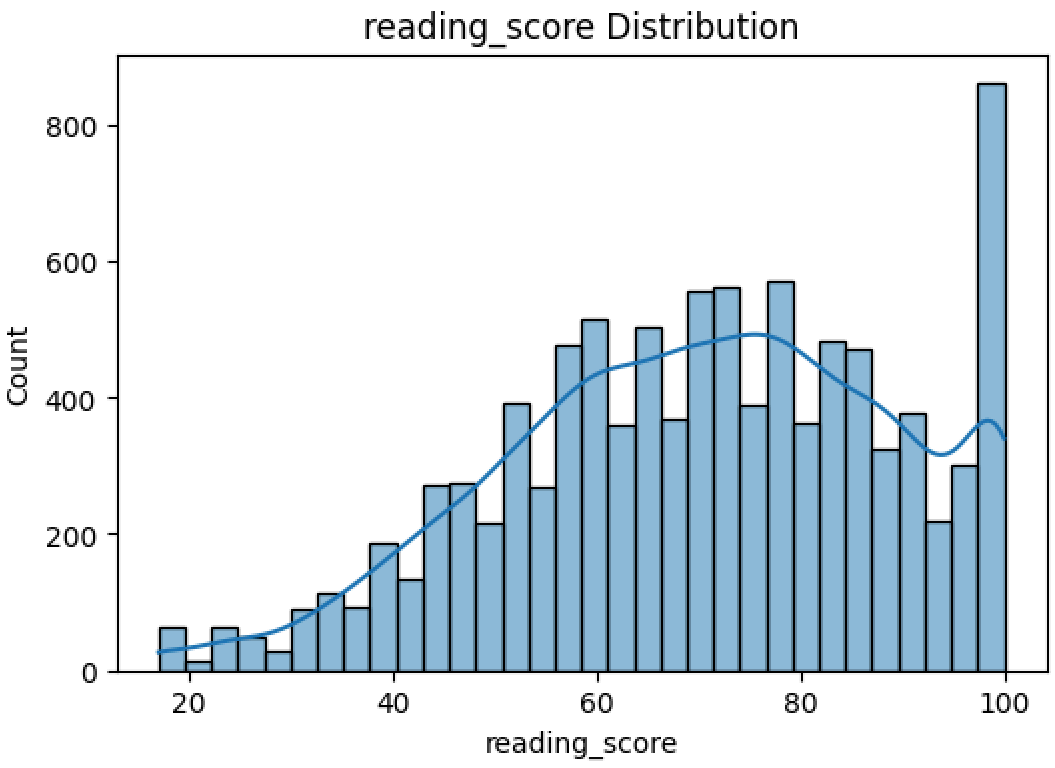
Out[7]:

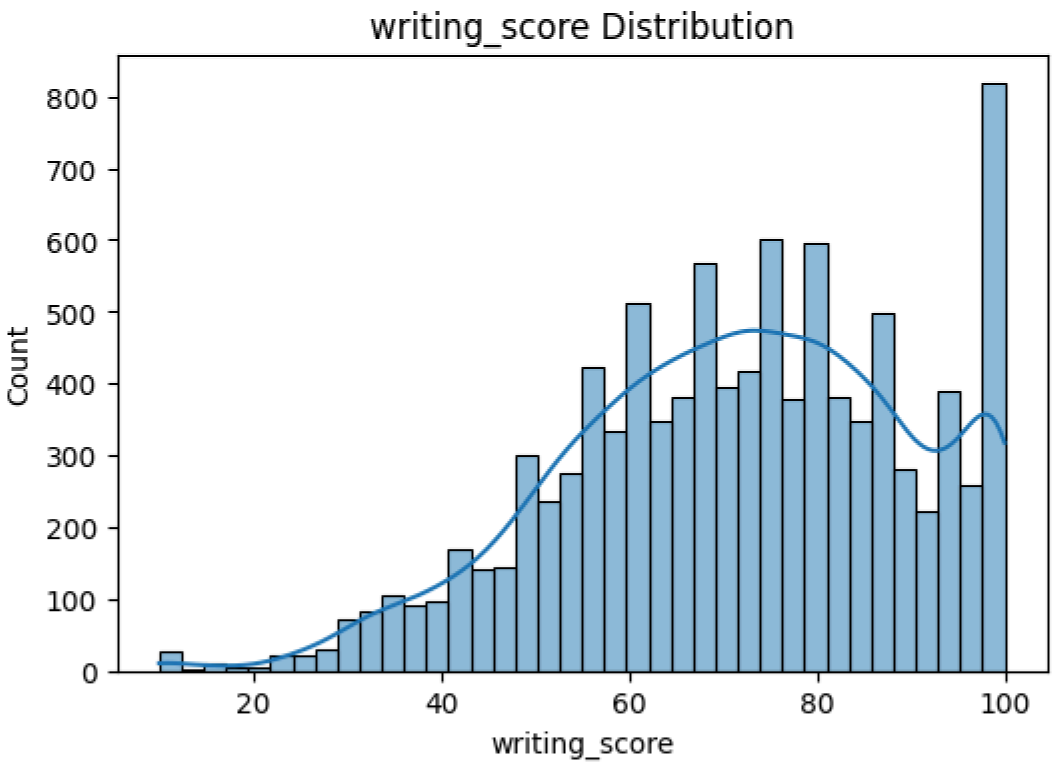
	roll_no	gender	race_ethnicity	parental_level_of_education	lunch	test_prepa
count	9999	9982	9977	9978	9976.000000	
unique	9999	5	11	6	NaN	
top	std-10000	female	group C	some college	NaN	
freq	1	4983	2921	2272	NaN	
mean	NaN	NaN	NaN	NaN	0.644246	
std	NaN	NaN	NaN	NaN	0.478765	
min	NaN	NaN	NaN	NaN	0.000000	
25%	NaN	NaN	NaN	NaN	0.000000	
50%	NaN	NaN	NaN	NaN	1.000000	
75%	NaN	NaN	NaN	NaN	1.000000	
max	NaN	NaN	NaN	NaN	1.000000	

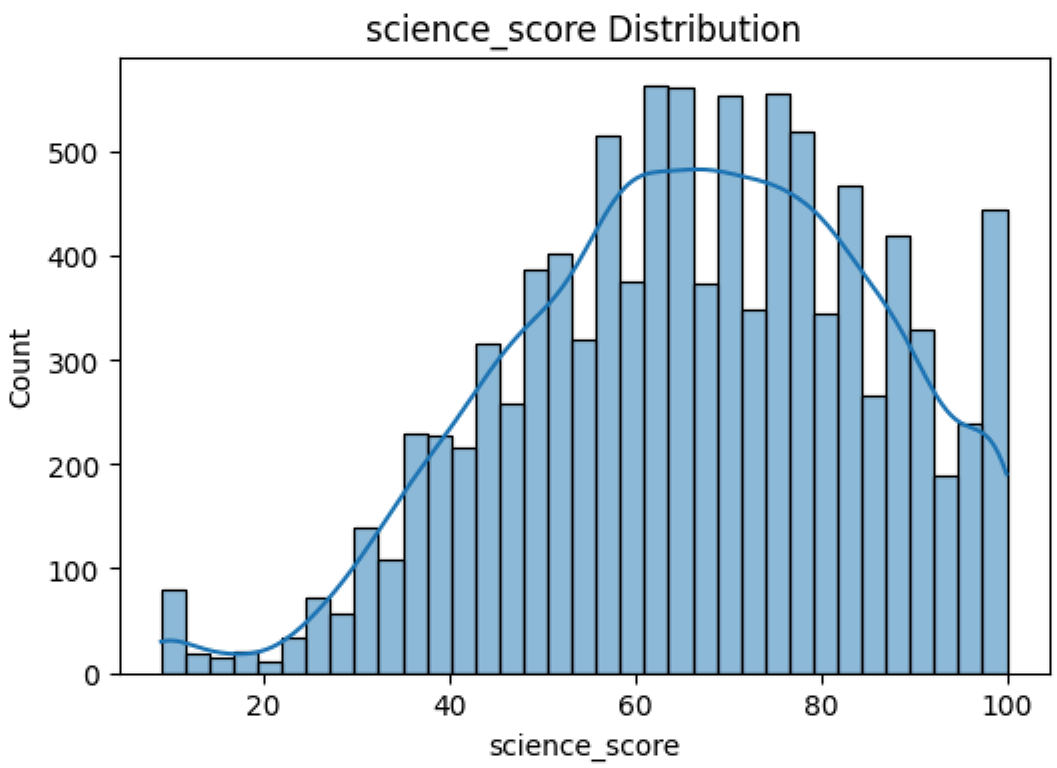
Early Visualizations to Do Before Cleaning

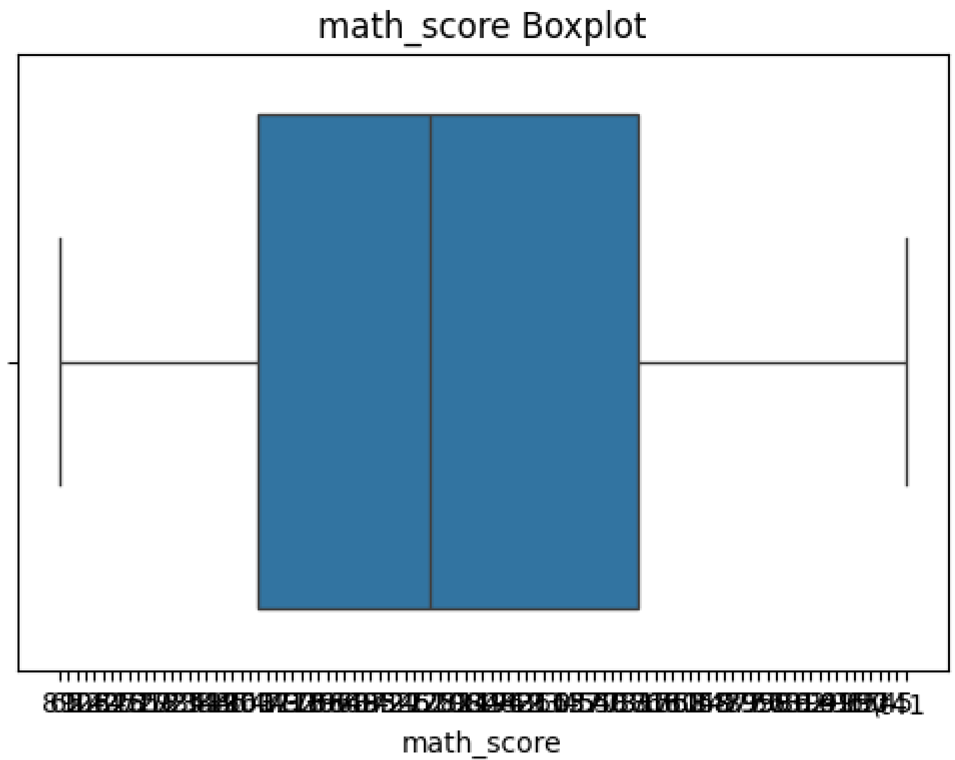
In [8]:
```python
# Histogram of scores (will show if some columns are strings or missing)
score_columns = ['math_score', 'reading_score', 'writing_score', 'science_score']
for col in score_columns:
    plt.figure(figsize=(6, 4))
    sns.histplot(student_performance_df[col], kde=True)
    plt.title(f'{col} Distribution')
    plt.show()

# Boxplot to spot outliers
for col in score_columns:
    plt.figure(figsize=(6, 4))
    sns.boxplot(x=student_performance_df[col])
    plt.title(f'{col} Boxplot')
    plt.show()

# Heatmap of missing values
plt.figure(figsize=(6, 4))
sns.heatmap(student_performance_df.isnull(), cbar=False, cmap='YlOrRd')
plt.title('Missing Values Heatmap')
plt.show()
```

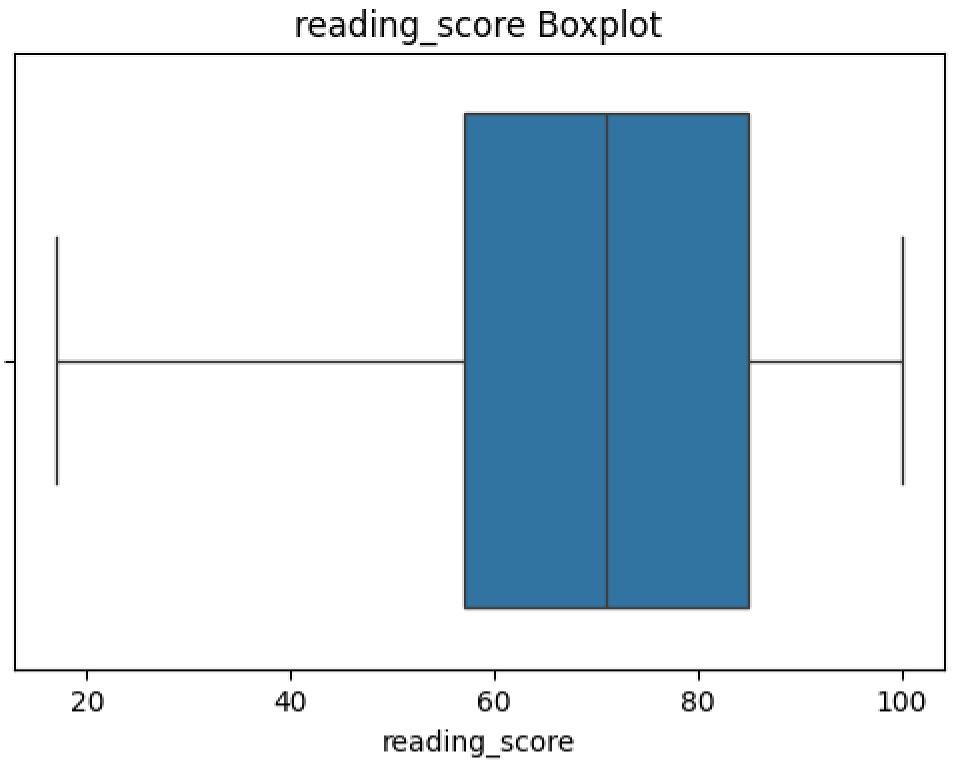


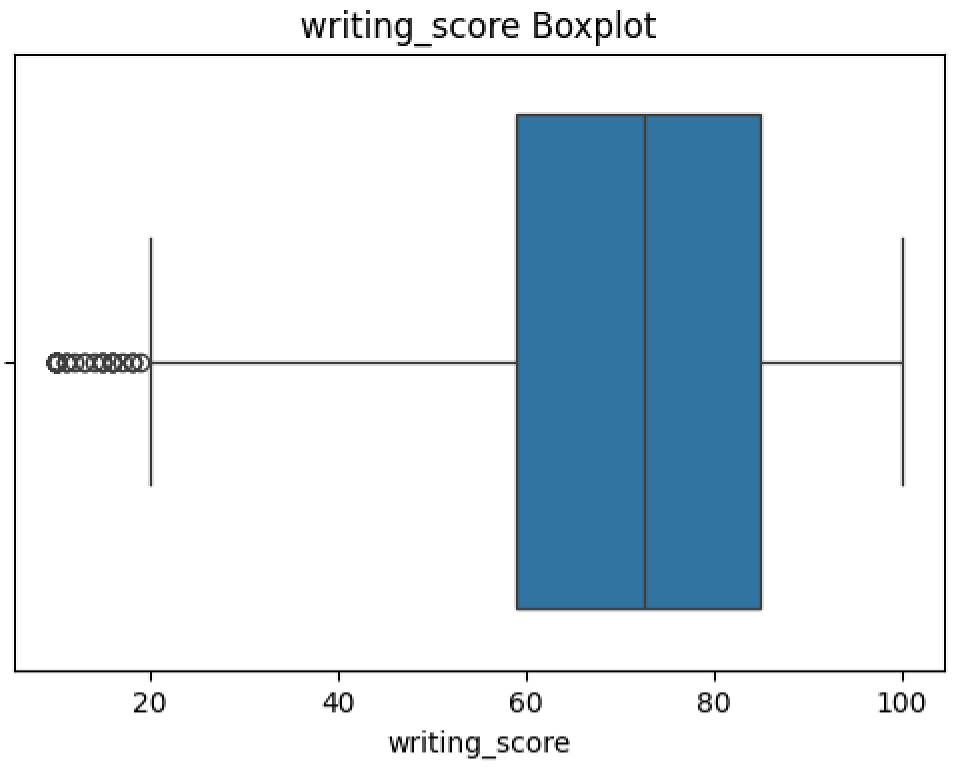

reading_score Distribution
Count
0
200
400
600
800
20
40
60
80
100
reading_score

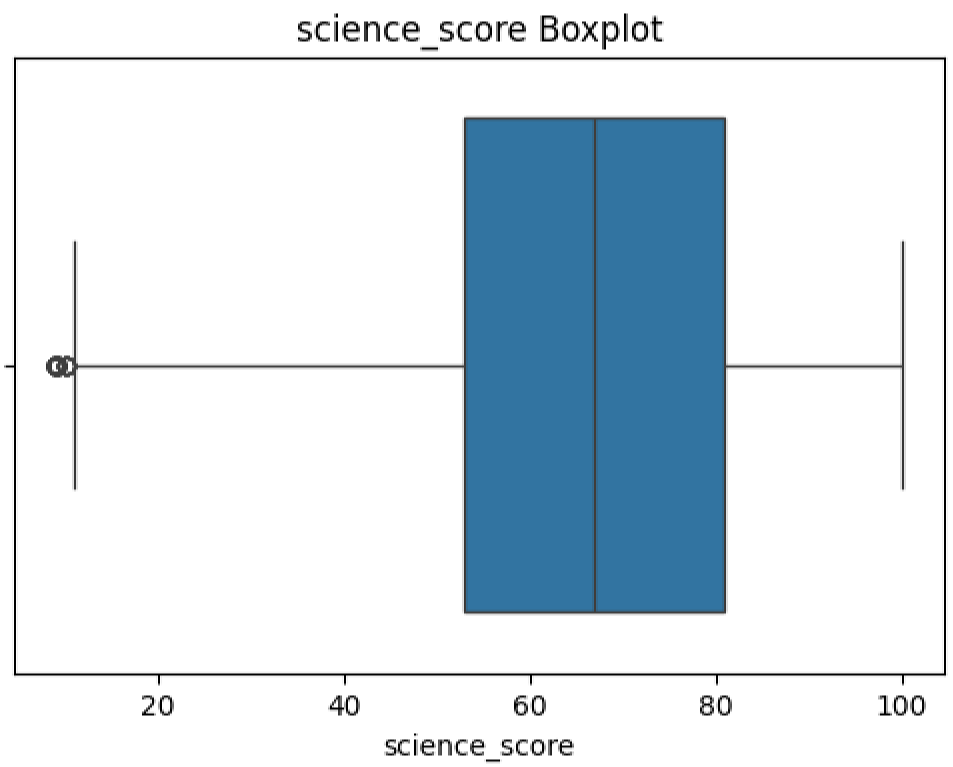

writing_score Distribution
Count
0
100
200
300
400
500
600
700
800
20
40
60
80
100
writing_score

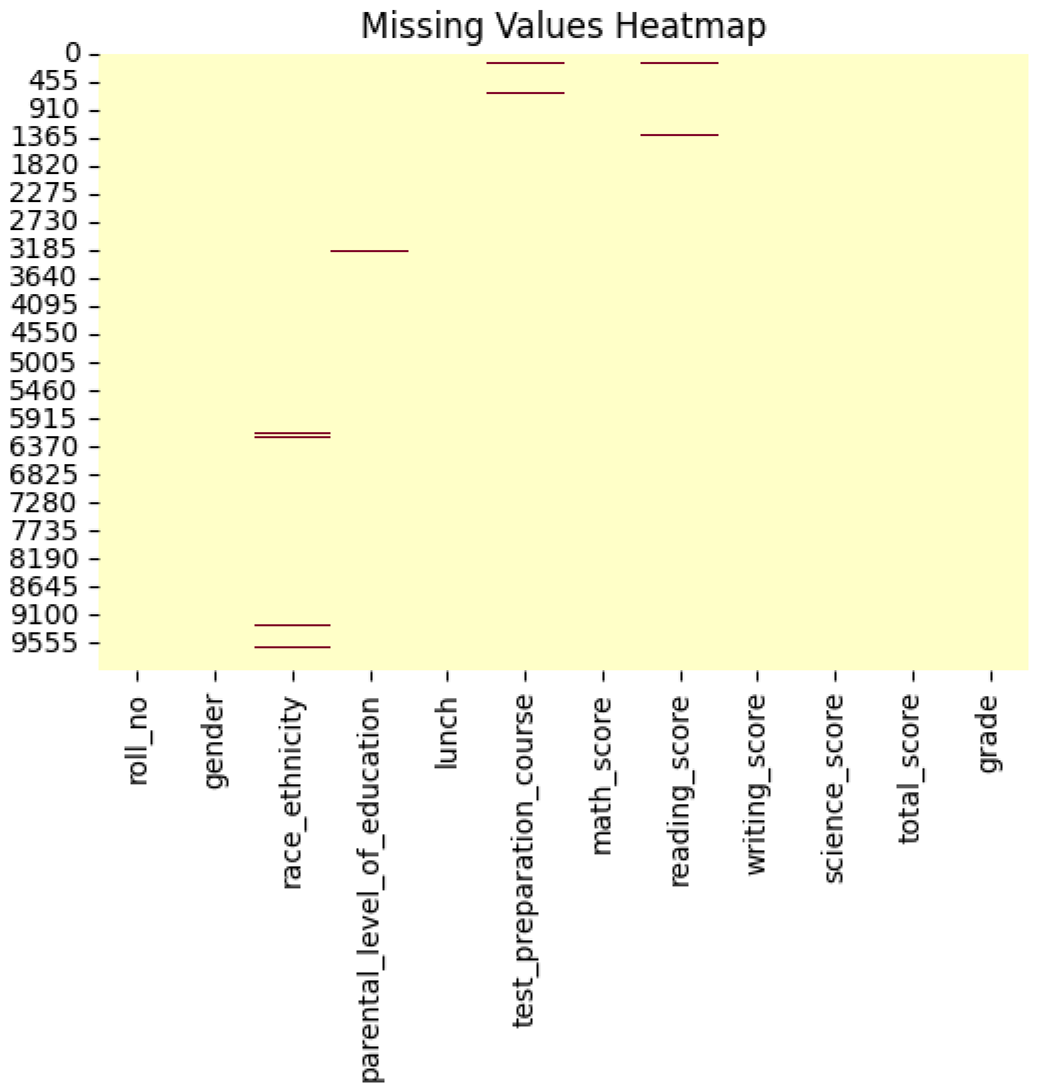

science_score Distribution
Count
0
100
200
300
400
500
20
40
60
80
100
science_score


math_score Boxplot
math_score


reading_score Boxplot
20
40
60
80
100
reading_score


writing_score Boxplot
20
40
60
80
100
writing_score


science_score Boxplot
20
40
60
80
100
science_score


Missing Values Heatmap
0
455
910
1365
1820
2275
2730
3185
3640
4095
4550
5005
5460
5915
6370
6825
7280
7735
8190
8645
9100
9555
roll_no
gender
race_ethnicity
parental_level_of_education
lunch
test_preparation_course
math_score
reading_score
writing_score
science_score
total_score
grade

Histogram & KDE (Score Distributions)

`math_score` Distribution

The math score histogram appears irregular and possibly corrupted, the x-axis shows overlapping text, which suggests `math_score` may still contain non-numeric or string-like values. We'll ensure proper conversion before modeling. The spread looks roughly uniform, indicating no major skew.

`reading_score` and `writing_score` Distributions

Both distributions are slightly right-skewed, with a peak around the 60–80 range and a sharp increase near 100, suggesting many students score well. Imputation with median might be safer than mean due to this skew.

`science_score` Distribution

This feature is nearly normally distributed, with most students scoring between 50 and 80. The tail isn't severe, so mean or median imputation would both work fine here.

Boxplots (Outlier Detection)

Boxplot: `math_score`

Due to data-type issues (non-numeric values), the boxplot x-axis looks jumbled. This confirms that math_score needs to be cleaned and converted to numeric properly before being used.

Boxplots: `reading_score` , `writing_score` , `science_score`

These plots show:

- Mild outliers in writing_score and science_score (low-end)
- Overall good spread
- Most students score between 60 and 90 in reading and writing

Outliers may be valid (e.g., struggling students), so we will retain them but may consider their influence during modeling (e.g., with robust algorithms).

Missing Values Heatmap

This plot clearly shows sporadic missing values across multiple features such as `gender` , `race_ethnicity` , `parental_level_of_education` , and all 4 subject scores. The missingness is small (under 0.5–1% of rows per column), so imputation rather than deletion is appropriate.

Data Cleaning & Preprocessing

In [9]:
```python
# Drop 'roll_no' as it's an identifier (safe drop)
student_performance_df.drop('roll_no', axis=1, inplace=True, errors='ignore')

# Convert 'math_score' to numeric before anything else (critical)
student_performance_df['math_score'] = pd.to_numeric(student_performance_df['math_s

# Impute categorical columns (object dtype) with mode
for col in student_performance_df.select_dtypes(include='object').columns:
    student_performance_df[col].fillna(student_performance_df[col].mode()[0], inpla

# Impute numerical columns (mean or median, depending on skew, if strongly skewed,
for col in student_performance_df.select_dtypes(include=['float64', 'int64']).colum
    skew = student_performance_df[col].skew()
    if abs(skew) > 1:
        student_performance_df[col].fillna(student_performance_df[col].median(), in
    else:
        student_performance_df[col].fillna(student_performance_df[col].mean(), inpl

# Just in case math_score has NaNs after conversion
student_performance_df['math_score'].fillna(student_performance_df['math_score'].me

# Label encode all remaining categorical variables except the target 'grade'
categorical_cols = student_performance_df.select_dtypes(include='object').drop(colu
le = LabelEncoder()
for col in categorical_cols:
    student_performance_df[col] = le.fit_transform(student_performance_df[col])

# Final check for missing values
print("Missing values after preprocessing:")
print(student_performance_df.isnull().sum())
```

```
Missing values after preprocessing:
gender                         0
race_ethnicity                 0
parental_level_of_education    0
lunch                          0
test_preparation_course        0
math_score                     0
reading_score                  0
writing_score                  0
science_score                  0
total_score                    0
grade                          0
dtype: int64
```

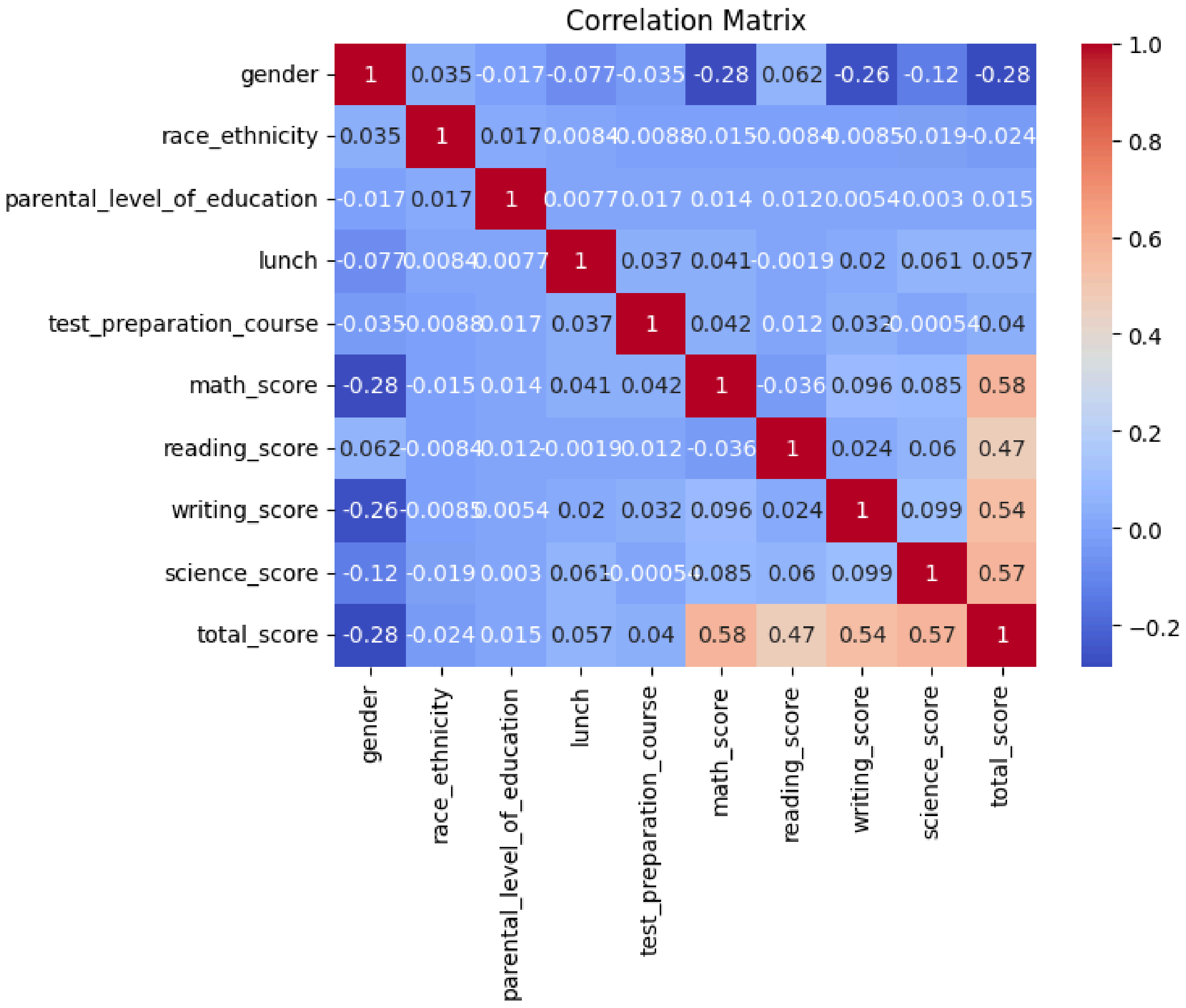
In [10]:
```python
# Check for duplicate rows
duplicates = student_performance_df.duplicated()
print(f"Number of duplicate rows is {duplicates.sum()}.")
```

```
Number of duplicate rows is 0.
```

Exploratory Data Analysis (EDA)

In [11]:
```python
# Correlation heatmap (only for numeric columns)
plt.figure(figsize=(7, 5))
```

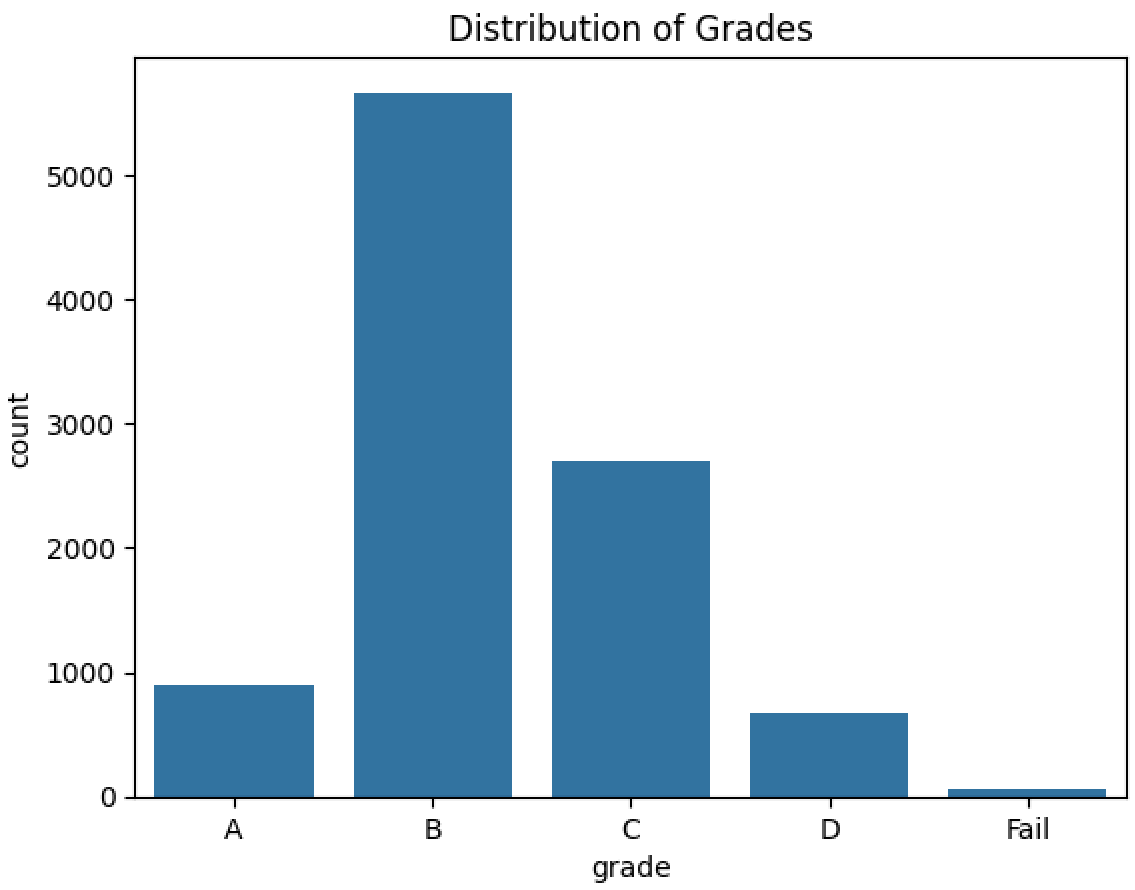
```
numeric_df = student_performance_df.select_dtypes(include=['int64', 'float64'])
sns.heatmap(numeric_df.corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



	gender	race_ethnicity	parental_level_of_education	lunch	test_preparation_course	math_score	reading_score	writing_score	science_score	total_score
gender	1	0.035	-0.017	-0.077	-0.035	-0.28	0.062	-0.26	-0.12	-0.28
race_ethnicity	0.035	1	0.017	0.0084	-0.0088	-0.015	-0.0084	-0.0085	-0.019	-0.024
parental_level_of_education	-0.017	0.017	1	0.0077	0.017	0.014	0.012	0.0054	0.003	0.015
lunch	-0.077	0.0084	0.0077	1	0.037	0.041	-0.0019	0.02	0.061	0.057
test_preparation_course	-0.035	-0.0088	0.017	0.037	1	0.042	0.012	0.032	-0.00054	0.04
math_score	-0.28	-0.015	0.014	0.041	0.042	1	-0.036	0.096	0.085	0.58
reading_score	0.062	-0.0084	0.012	-0.0019	0.012	-0.036	1	0.024	0.06	0.47
writing_score	-0.26	-0.0085	0.0054	0.02	0.032	0.096	0.024	1	0.099	0.54
science_score	-0.12	-0.019	0.003	0.061	-0.00054	0.085	0.06	0.099	1	0.57
total_score	-0.28	-0.024	0.015	0.057	0.04	0.58	0.47	0.54	0.57	1

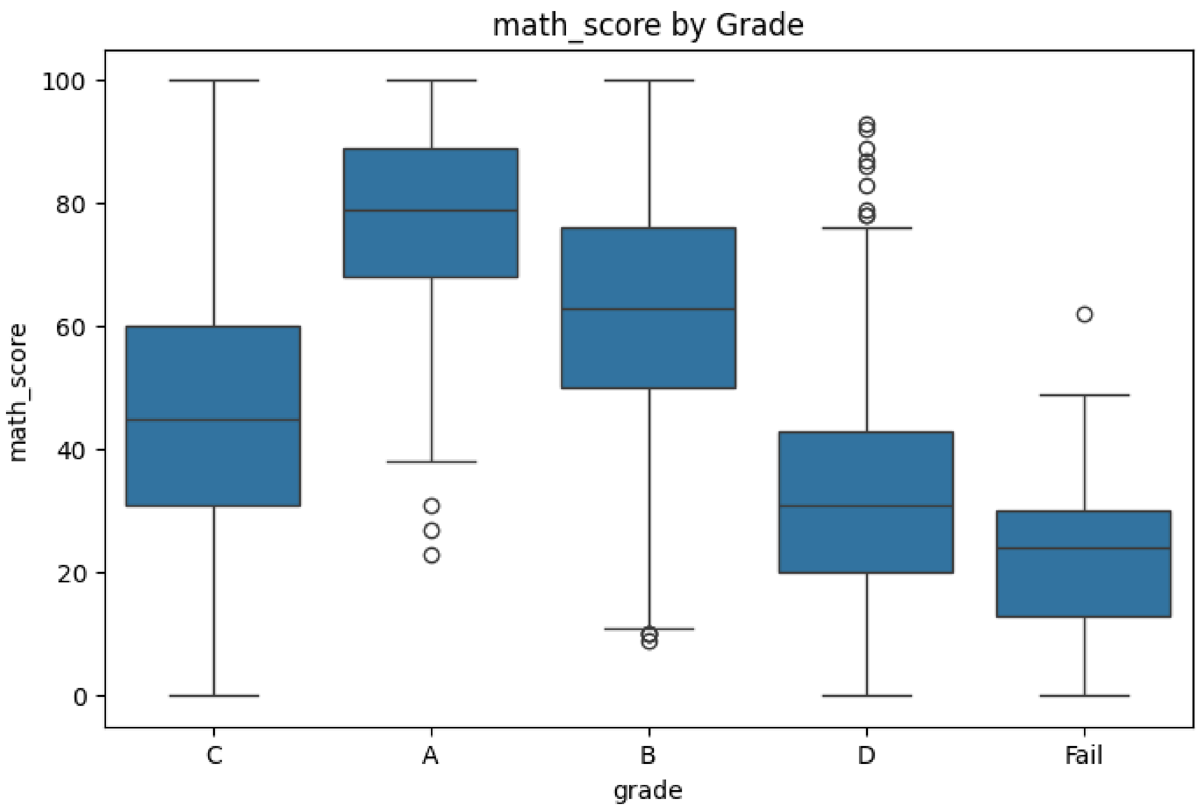
The heatmap shows strong positive correlations between the core academic scores, especially between writing and reading `(r = 0.96)`, and writing and science `(r = 0.99)`. This suggests some redundancy and potential multicollinearity. Gender shows a moderate negative correlation with math `(r = -0.28)`, indicating possible performance differences between groups. Total score is strongly correlated with individual scores as expected.

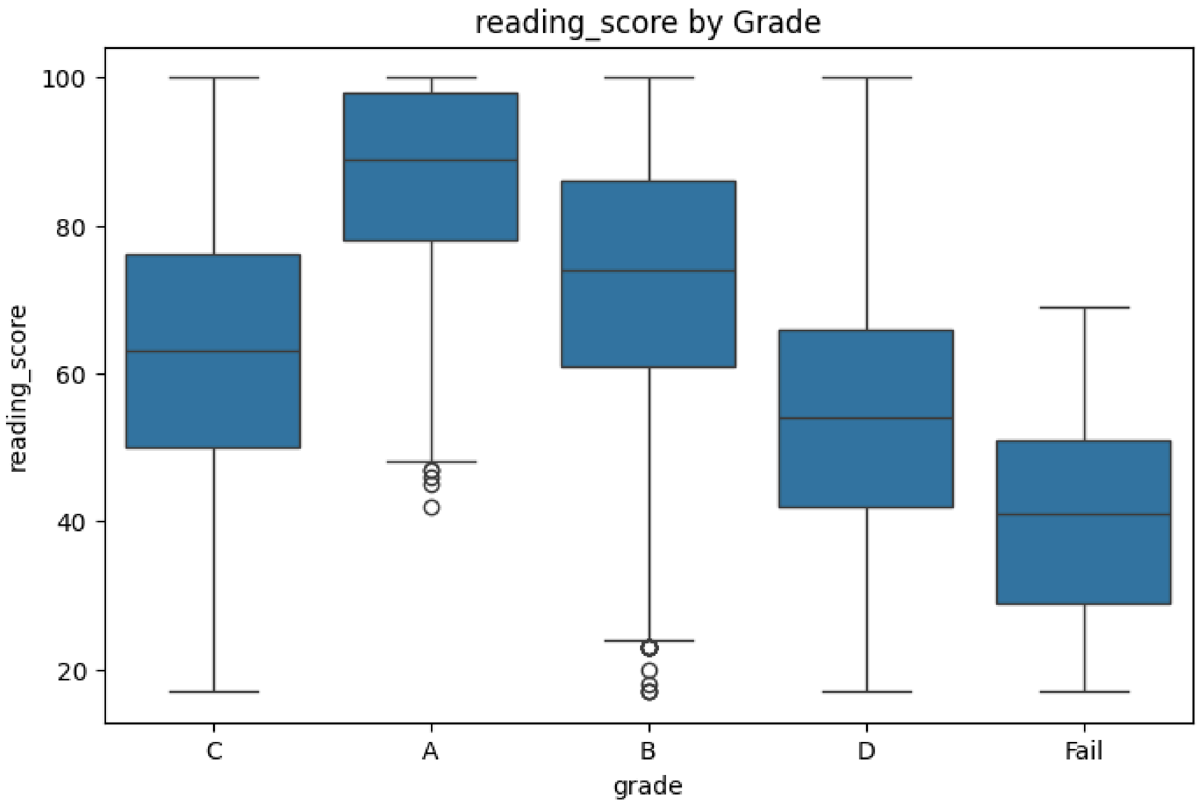
In [12]:
```
# Grade distribution
sns.countplot(data=student_performance_df, x='grade', order=sorted(student_performa
plt.title('Distribution of Grades')
plt.show()
```

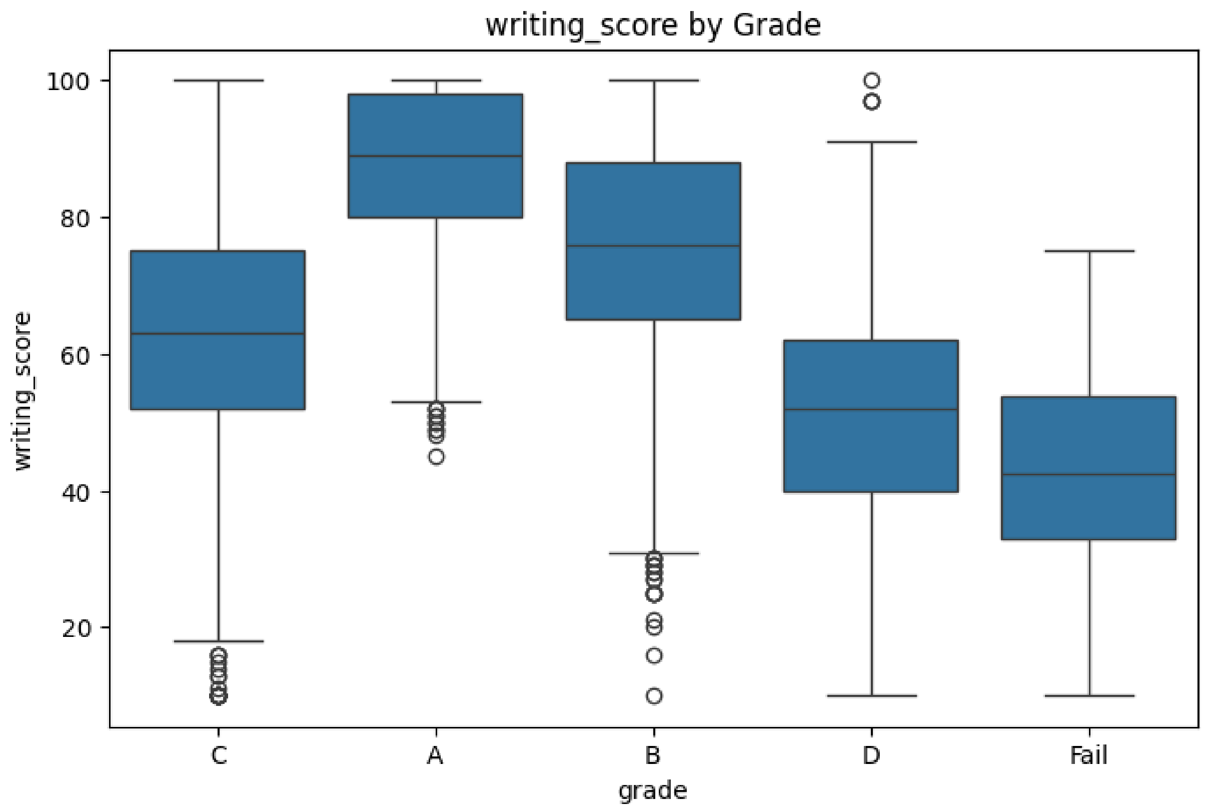


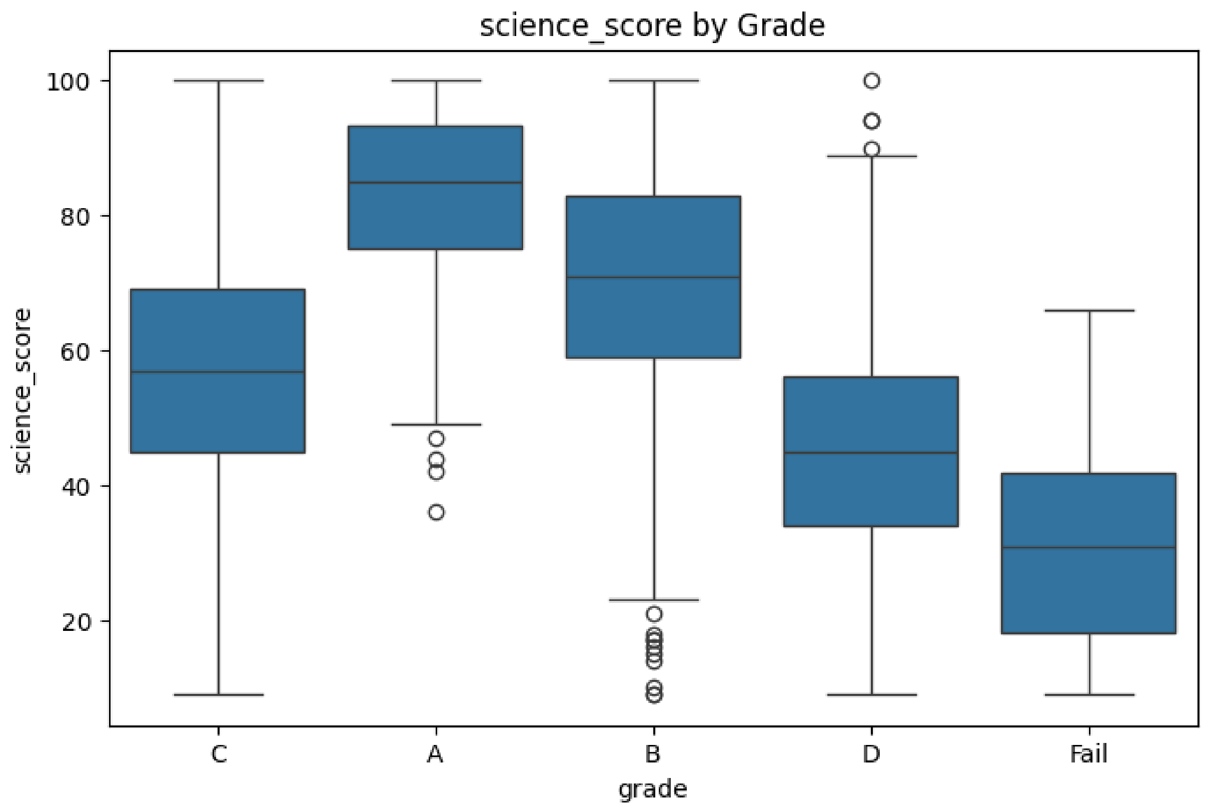
Grade distribution is imbalanced, with the majority of students earning a B, followed by C, and a small number failing. This imbalance will need to be addressed during model evaluation, possibly using weighted metrics or resampling techniques.

In [13]:
```python
# Boxplot of scores by grade
score_cols = ['math_score', 'reading_score', 'writing_score', 'science_score']
for col in score_cols:
    plt.figure(figsize=(8, 5))
    sns.boxplot(x='grade', y=col, data=student_performance_df)
    plt.title(f'{col} by Grade')
    plt.show()
```


math_score by Grade
math_score
100
80
60
40
20
0
C
A
B
D
Fail
grade


reading_score by Grade
reading_score
100
80
60
40
20
C
A
B
D
Fail
grade





`math_score` by Grade Higher grades (A, B) are associated with higher median math scores, while failing students cluster below 40. This feature is a strong predictor of performance.

`reading_score` by Grade Reading scores increase consistently with grades. A students have scores tightly clustered near the top, while failing students have a wide spread with many scoring below 50.

`writing_score` by Grade Similar to reading, more separation between grades and high predictive value. Some outliers are present in low-grade categories.

`science_score` by Grade Again, clear separation across grades. Students with A and B grades have much higher science scores than D or Fail.

In [14]:
```
# Create and apply a fresh encoder for 'grade'
grade_encoder = LabelEncoder()
student_performance_df['grade'] = grade_encoder.fit_transform(student_performance_d

# Print the class-to-number mapping
for index, label in enumerate(grade_encoder.classes_):
    print(f"{label} → {index}")
```

```
A → 0
B → 1
C → 2
D → 3
Fail → 4
```

Feature Engineering

In [15]:
```
# Separate features and target
X = student_performance_df.drop(columns='grade')
y = student_performance_df['grade']

# Check balance of target classes
y.value_counts().sort_index()
```

Out[15]:

grade	count
0	904
1	5662
2	2701
3	671
4	62

dtype: int64

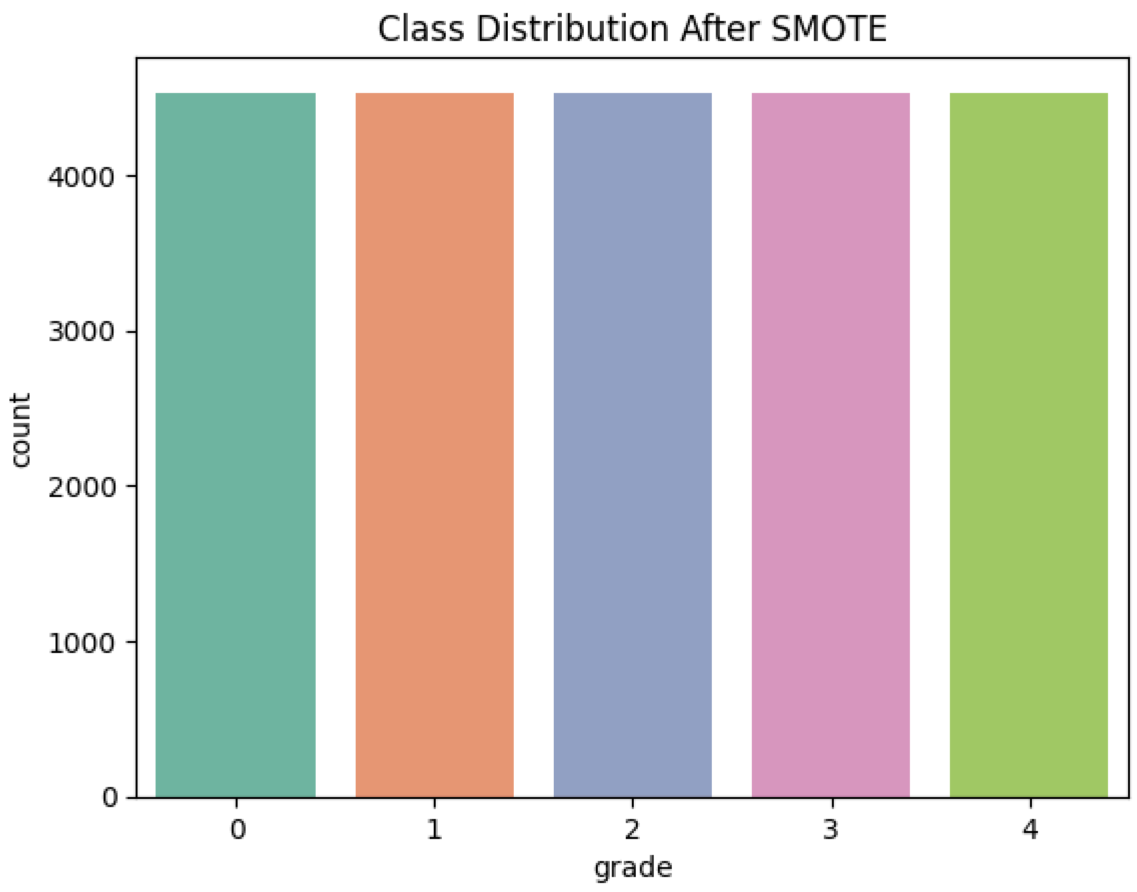
Train-Test Split

In [16]:
```
# Stratified train-test split (before balancing)
X = student_performance_df.drop(columns='grade')
y = student_performance_df['grade']
```

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)

print("Before SMOTE:", Counter(y_train))

# SMOTE to the training data
sm = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = sm.fit_resample(X_train, y_train)

print("After SMOTE:", Counter(y_train_resampled))
```

```
Before SMOTE: Counter({1: 4530, 2: 2161, 0: 723, 3: 537, 4: 49})
After SMOTE: Counter({3: 4530, 2: 4530, 0: 4530, 1: 4530, 4: 4530})
```

In [17]:
```
# Visualization After SMOTE
sns.countplot(x=y_train_resampled, palette='Set2')
plt.title("Class Distribution After SMOTE")
plt.show()
```



Model Training & Evaluation

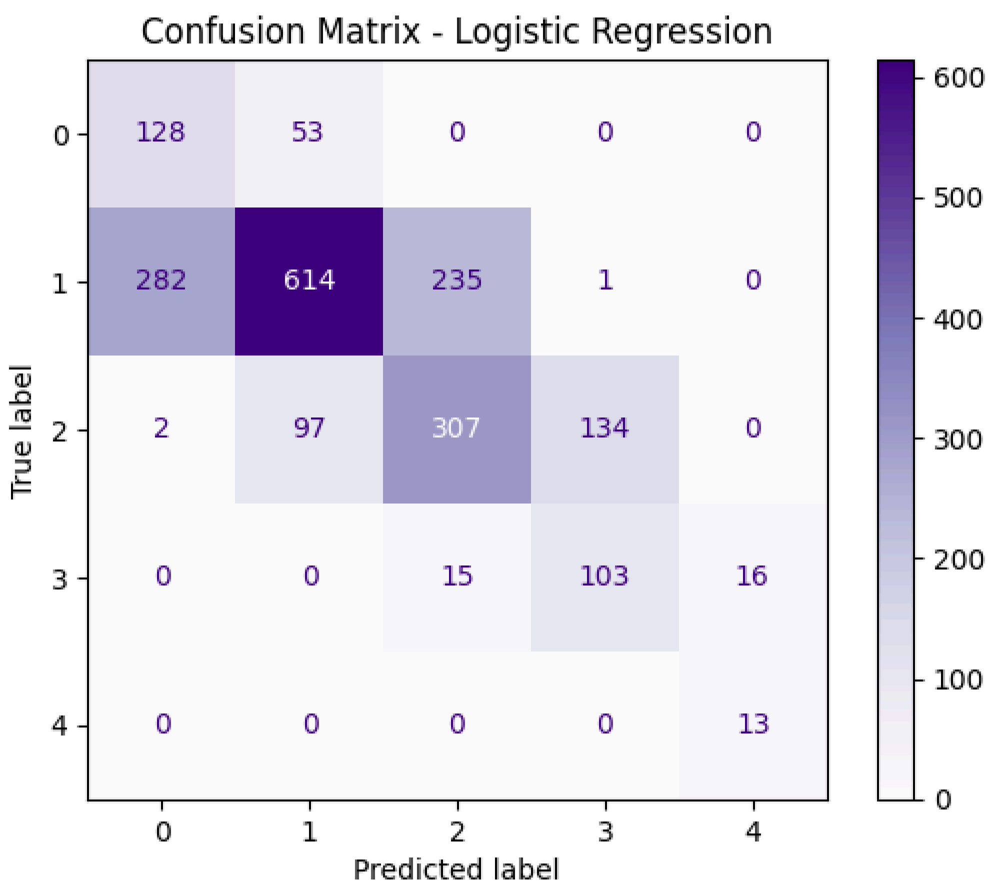
Logistic Regression

In [18]:
```
lr_model = LogisticRegression(max_iter=1000)
lr_model.fit(X_train_resampled, y_train_resampled)
y_pred_lr = lr_model.predict(X_test)
```

```
print("Logistic Regression Classification Report:\n")
print(classification_report(y_test, y_pred_lr))
```

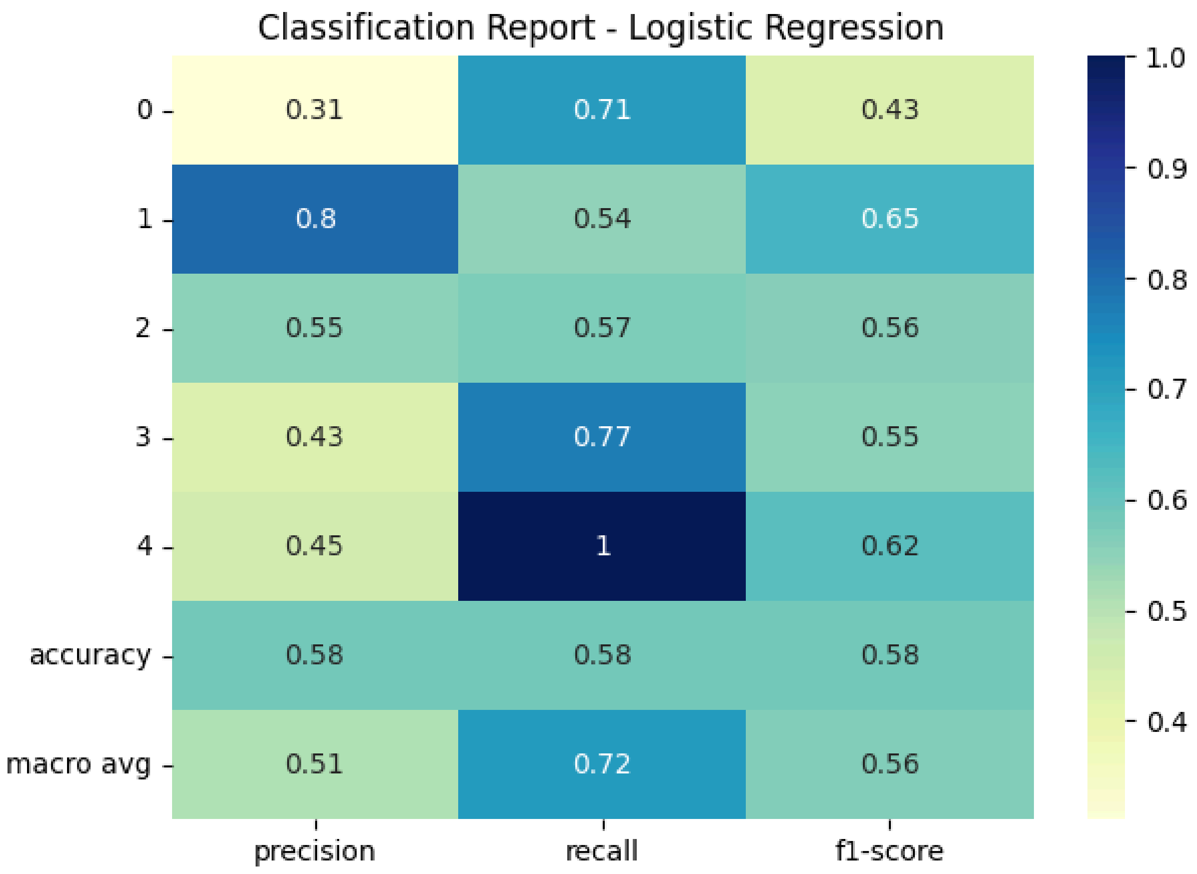
```
Logistic Regression Classification Report:

              precision    recall  f1-score   support

           0       0.31      0.71      0.43       181
           1       0.80      0.54      0.65      1132
           2       0.55      0.57      0.56       540
           3       0.43      0.77      0.55       134
           4       0.45      1.00      0.62        13

    accuracy                           0.58      2000
   macro avg       0.51      0.72      0.56      2000
weighted avg       0.66      0.58      0.60      2000
```

In [19]:
```
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_lr, cmap='Purples')
plt.title("Confusion Matrix - Logistic Regression")
plt.show()
```



In [20]:
```
# Get classification report as dict
report = classification_report(y_test, y_pred_lr, output_dict=True)
df_report = pd.DataFrame(report).transpose()

# Heatmap
plt.figure(figsize=(7, 5))
```

```
sns.heatmap(df_report.iloc[:-1, :-1], annot=True, cmap="YlGnBu")
plt.title("Classification Report - Logistic Regression")
plt.show()
```

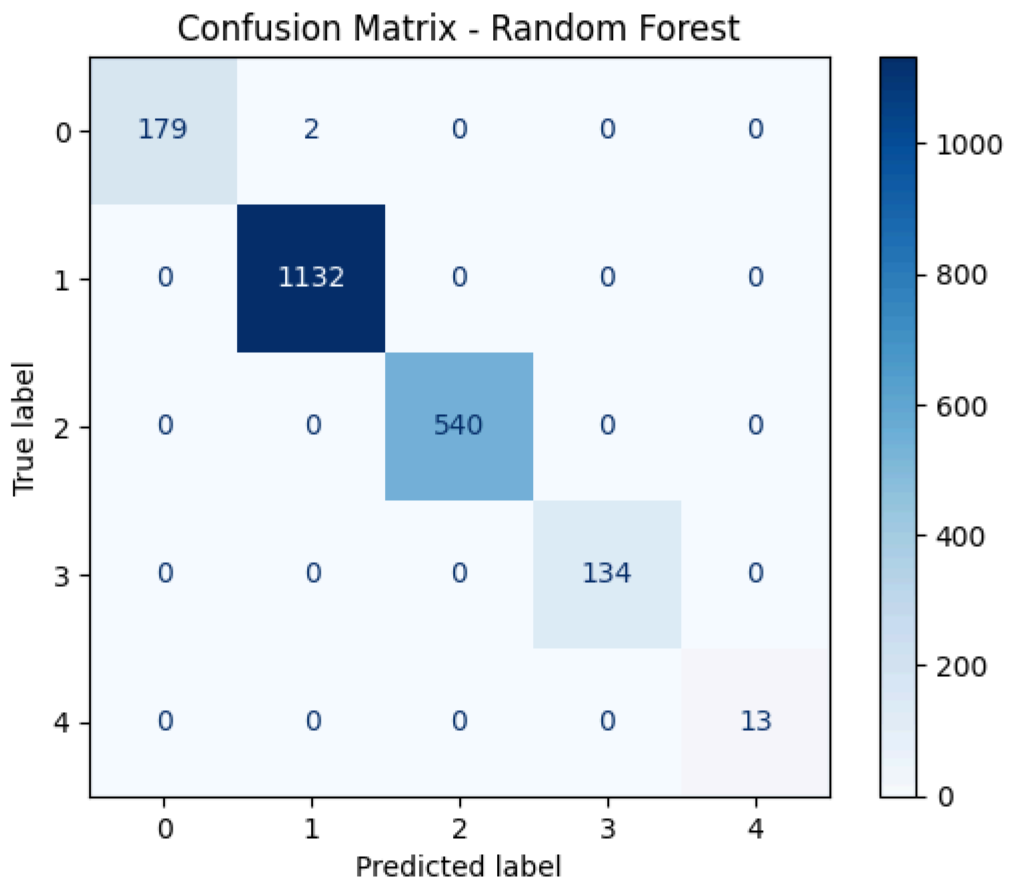


Random Forest

In [21]:
```
# Train the model
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train_resampled, y_train_resampled)

# Predict on test set
y_pred_rf = rf_model.predict(X_test)

# Evaluate
print("Random Forest Classification Report:\n")
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Classification Report:

              precision    recall  f1-score   support

           0       1.00      0.99      0.99       181
           1       1.00      1.00      1.00      1132
           2       1.00      1.00      1.00       540
           3       1.00      1.00      1.00       134
           4       1.00      1.00      1.00        13

    accuracy                           1.00      2000
   macro avg       1.00      1.00      1.00      2000
weighted avg       1.00      1.00      1.00      2000
```

In [22]:
```
# Confusion matrix
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_rf, cmap='Blues')
plt.title("Confusion Matrix - Random Forest")
plt.show()
```



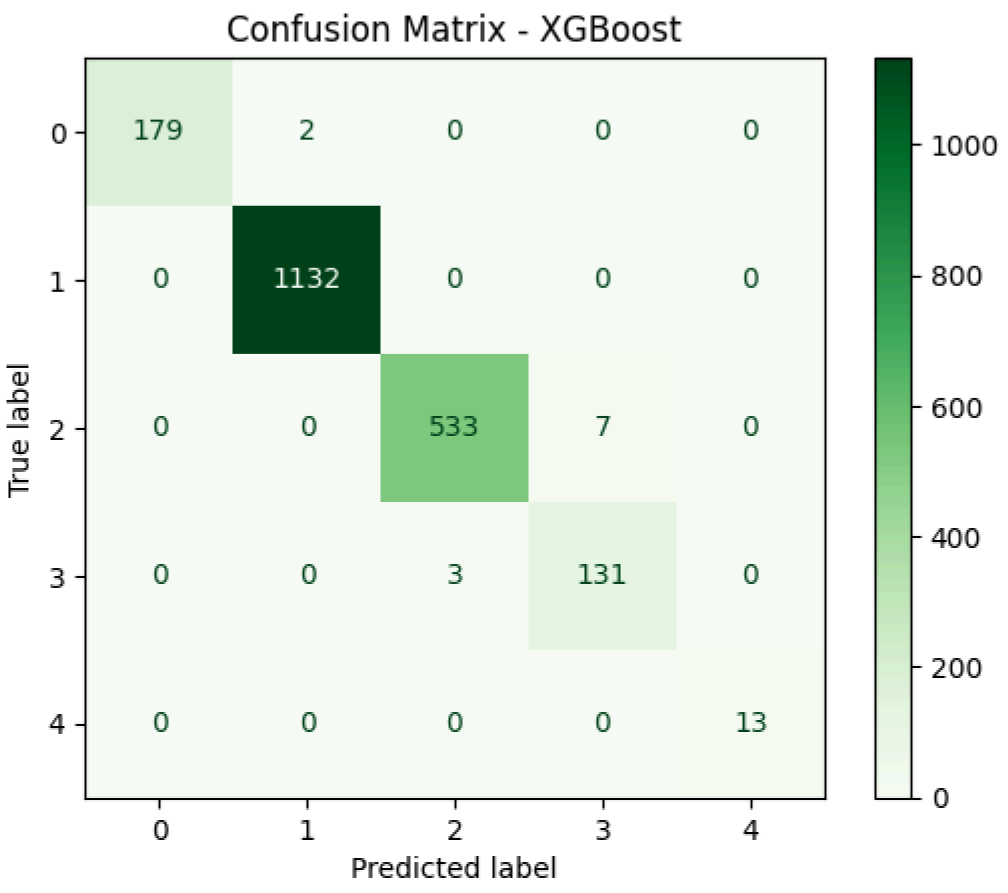
XGBoost

In [23]:
```
#  Initialize the model
xgb_model = XGBClassifier(
    use_label_encoder=False,
    eval_metric='mlogloss',
    random_state=42
)
```

```
# Train the model on balanced training set
xgb_model.fit(X_train_resampled, y_train_resampled)

# Predict on test data
y_pred_xgb = xgb_model.predict(X_test)

# Classification report
print("Classification Report - XGBoost")
print(classification_report(y_test, y_pred_xgb))
```

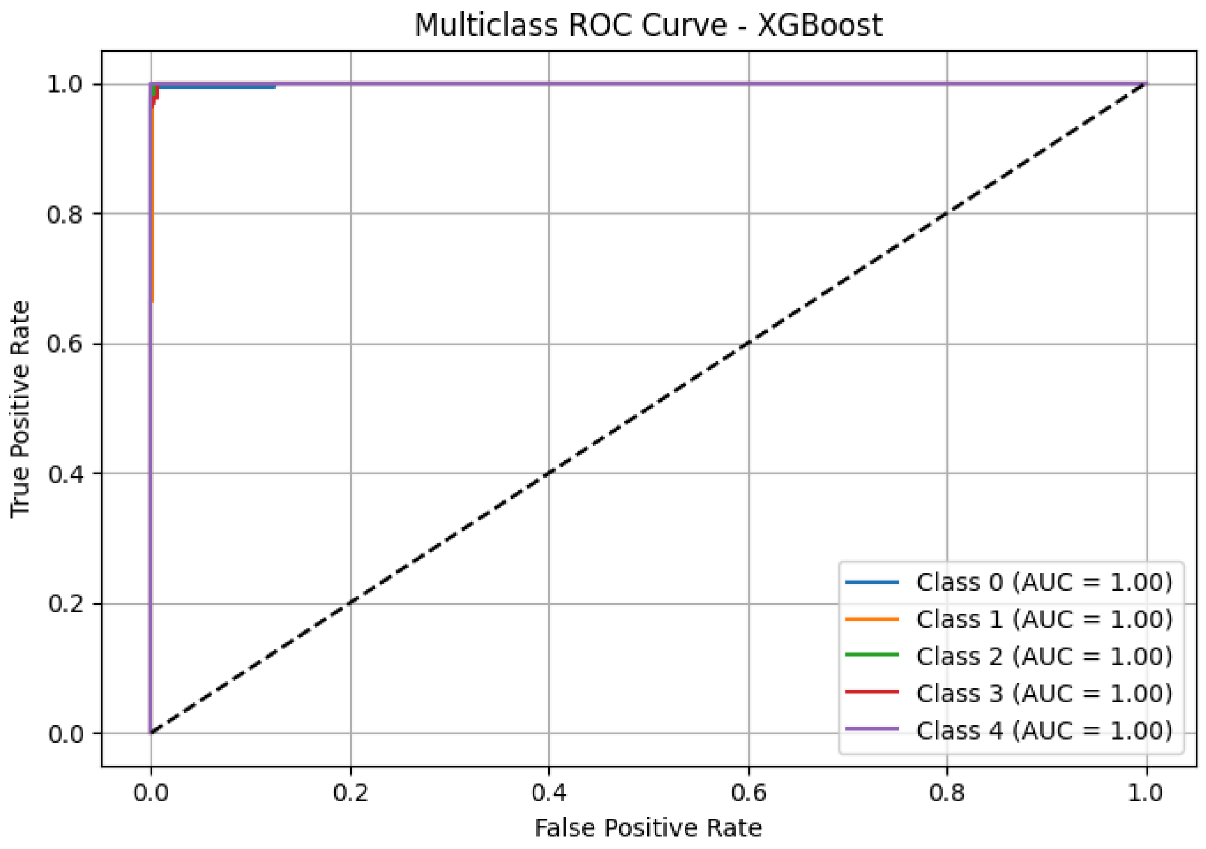
```
Classification Report - XGBoost
              precision    recall  f1-score   support

           0       1.00      0.99      0.99       181
           1       1.00      1.00      1.00      1132
           2       0.99      0.99      0.99       540
           3       0.95      0.98      0.96       134
           4       1.00      1.00      1.00        13

    accuracy                           0.99      2000
   macro avg       0.99      0.99      0.99      2000
weighted avg       0.99      0.99      0.99      2000
```

In [24]:
```
# Confusion matrix visualization
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_xgb, cmap='Greens')
plt.title("Confusion Matrix - XGBoost")
plt.show()
```



ROC Curve

In [25]:
```
# Binarize the labels for multiclass ROC
y_test_bin = label_binarize(y_test, classes=[0, 1, 2, 3, 4])
y_score = xgb_model.predict_proba(X_test)
n_classes = y_test_bin.shape[1]

# ROC curves
plt.figure(figsize=(7, 5))
for i in range(n_classes):
    fpr, tpr, _ = roc_curve(y_test_bin[:, i], y_score[:, i])
    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, label=f'Class {i} (AUC = {roc_auc:.2f})')

plt.plot([0, 1], [0, 1], 'k--')  # Diagonal line
plt.title('Multiclass ROC Curve - XGBoost')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [26]:
```
for i in range(n_classes):
    auc_score = roc_auc_score(y_test_bin[:, i], y_score[:, i])
    print(f"AUC for Class {i}: {auc_score:.4f}")
```

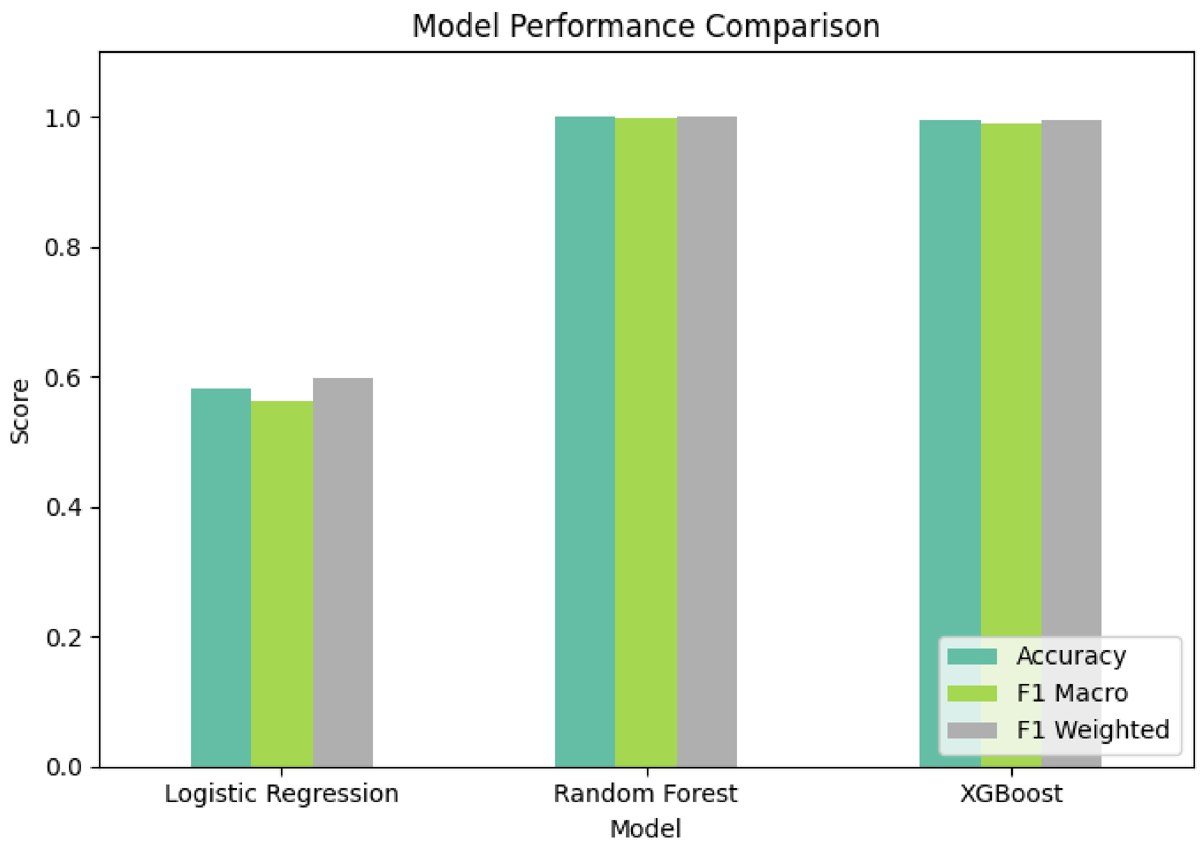
```
AUC for Class 0: 0.9993
AUC for Class 1: 0.9996
AUC for Class 2: 0.9999
AUC for Class 3: 0.9998
AUC for Class 4: 1.0000
```

Model Comparison

In [27]:
```
results = pd.DataFrame({
    'Model': ['Logistic Regression', 'Random Forest', 'XGBoost'],
    'Accuracy': [
        accuracy_score(y_test, y_pred_lr),
        accuracy_score(y_test, y_pred_rf),
        accuracy_score(y_test, y_pred_xgb)
    ],
    'F1 Macro': [
        f1_score(y_test, y_pred_lr, average='macro'),
        f1_score(y_test, y_pred_rf, average='macro'),
        f1_score(y_test, y_pred_xgb, average='macro')
    ],
    'F1 Weighted': [
        f1_score(y_test, y_pred_lr, average='weighted'),
        f1_score(y_test, y_pred_rf, average='weighted'),
        f1_score(y_test, y_pred_xgb, average='weighted')
    ]
})

display(results.sort_values(by='F1 Macro', ascending=False))
```

	Model	Accuracy	F1 Macro	F1 Weighted
1	Random Forest	0.9990	0.998712	0.998998
2	XGBoost	0.9940	0.989501	0.994025
0	Logistic Regression	0.5825	0.562380	0.597903

In [28]:
```
results.set_index('Model')[['Accuracy', 'F1 Macro', 'F1 Weighted']].plot.bar(figsiz
plt.title("Model Performance Comparison")
plt.ylabel("Score")
plt.ylim(0, 1.1)
plt.xticks(rotation=0)
plt.legend(loc='lower right')
plt.tight_layout()
plt.show()
```



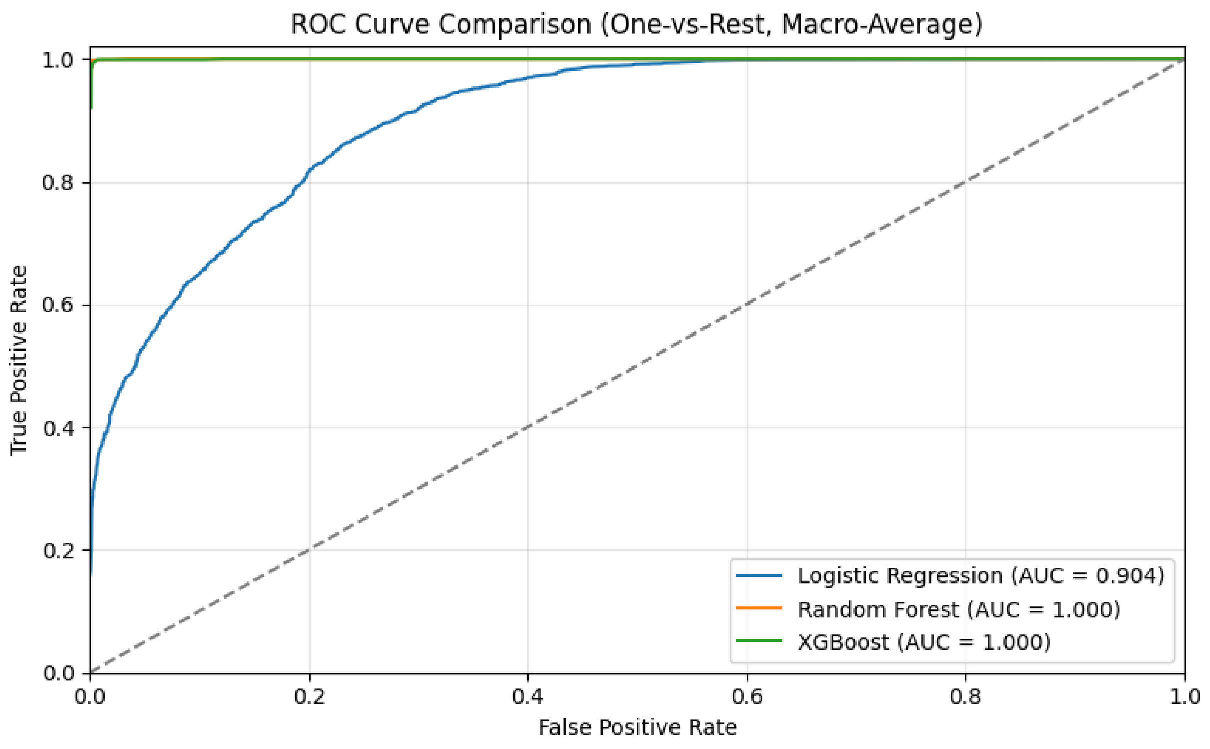
In [29]:
```
from sklearn.tree import DecisionTreeClassifier
cart_model = DecisionTreeClassifier(random_state=42)
cart_model.fit(X_train_resampled, y_train_resampled)

y_pred_cart = cart_model.predict(X_test)
```

```
print("Classification Report - Decision Tree")
print(classification_report(y_test, y_pred_cart))
```

```
Classification Report - Decision Tree
              precision    recall  f1-score   support

           0       1.00      0.99      0.99       181
           1       1.00      1.00      1.00      1132
           2       1.00      1.00      1.00       540
           3       1.00      0.99      0.99       134
           4       1.00      1.00      1.00        13

    accuracy                           1.00      2000
   macro avg       1.00      0.99      1.00      2000
weighted avg       1.00      1.00      1.00      2000
```

In [30]:
```
# Making sure that classes match the encoded labels
classes = np.sort(np.unique(y_test))
y_test_bin = label_binarize(y_test, classes=classes)
n_classes = y_test_bin.shape[1]

models = {
    "Logistic Regression": lr_model,
    "Random Forest": rf_model,
    "XGBoost": xgb_model
}

def macro_roc_for_model(model, X, y_bin):
    """Compute per-class ROC, plus micro/macro AUC; return dict with fpr/tpr and AU
    # Using predict_proba for all three models
    y_score = model.predict_proba(X)

    fpr, tpr, roc_auc = {}, {}, {}
    for i in range(n_classes):
        fpr[i], tpr[i], _ = roc_curve(y_bin[:, i], y_score[:, i])
        roc_auc[i] = auc(fpr[i], tpr[i])

    # Micro-average
    fpr["micro"], tpr["micro"], _ = roc_curve(y_bin.ravel(), y_score.ravel())
    roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

    # macro-average (uniformly average per-class TPR at all unique FPRs)
    all_fpr = np.unique(np.concatenate([fpr[i] for i in range(n_classes)]))
    mean_tpr = np.zeros_like(all_fpr)
    for i in range(n_classes):
        mean_tpr += np.interp(all_fpr, fpr[i], tpr[i])
    mean_tpr /= n_classes
    fpr["macro"] = all_fpr
    tpr["macro"] = mean_tpr
    roc_auc["macro"] = auc(fpr["macro"], tpr["macro"])

    return fpr, tpr, roc_auc

# Plot macro-average ROC curves for each model
plt.figure(figsize=(8, 5))
```

```
auc_rows = []

for name, mdl in models.items():
    fpr, tpr, roc_auc = macro_roc_for_model(mdl, X_test, y_test_bin)
    plt.plot(fpr["macro"], tpr["macro"], label=f"{name} (AUC = {roc_auc['macro']:.3
    auc_rows.append({"Model": name, "AUC macro": roc_auc["macro"], "AUC micro": roc

# Chance line
plt.plot([0, 1], [0, 1], linestyle="--", color="gray")
plt.xlim([0.0, 1.0]); plt.ylim([0.0, 1.02])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve Comparison (One-vs-Rest, Macro-Average)")
plt.legend(loc="lower right")
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

# AUC summary table
auc_table = pd.DataFrame(auc_rows).sort_values("AUC macro", ascending=False)
display(auc_table)

# (Optional) Per-class AUCs for each model
per_class_tables = {}
for name, mdl in models.items():
    fpr, tpr, roc_auc = macro_roc_for_model(mdl, X_test, y_test_bin)
    per_class = pd.DataFrame({
        "Class": classes,
        "AUC": [roc_auc[i] for i in range(n_classes)]
    })
    per_class_tables[name] = per_class
    print(f"\nPer-class AUCs – {name}")
    display(per_class)
```



	Model	AUC macro	AUC micro
1	Random Forest	0.999916	0.999916
2	XGBoost	0.999755	0.999904
0	Logistic Regression	0.904141	0.902331

```
Per-class AUCs – Logistic Regression
```

	Class	AUC
0	0	0.900543
1	1	0.828796
2	2	0.827896
3	3	0.962619
4	4	0.999458

```
Per-class AUCs – Random Forest
```

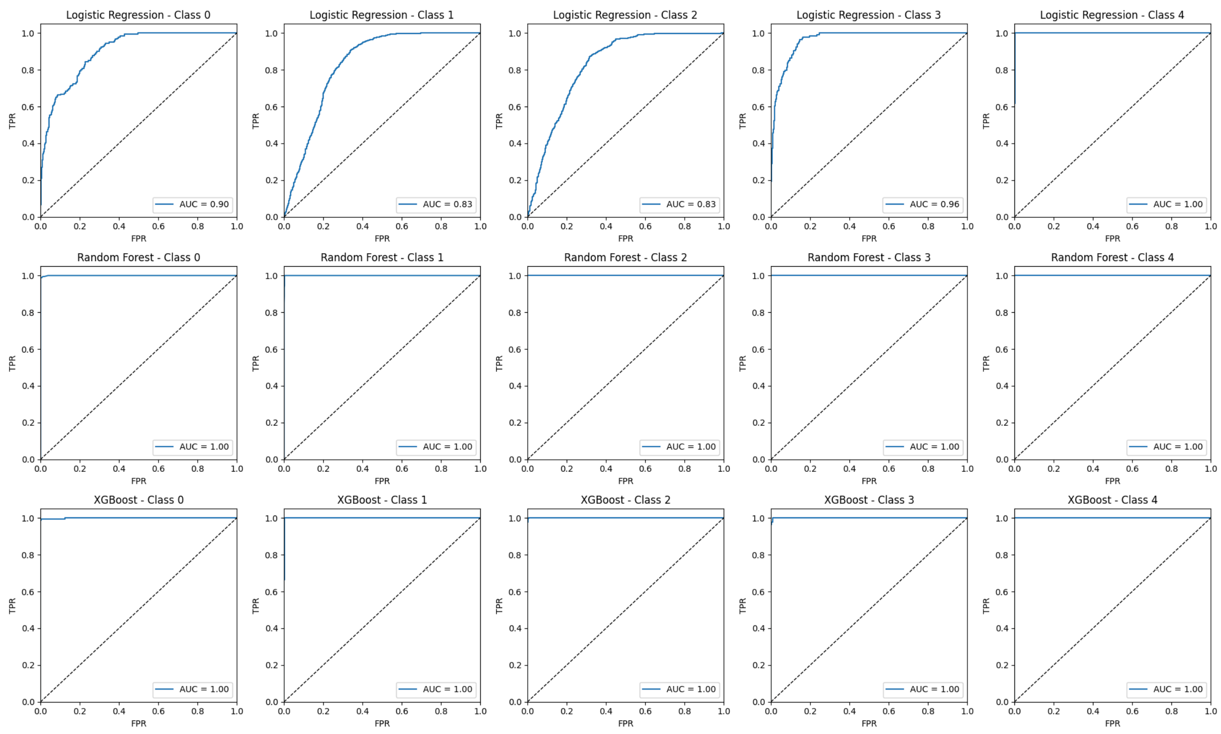
	Class	AUC
0	0	0.999792
1	1	0.999781
2	2	1.000000
3	3	1.000000
4	4	1.000000

```
Per-class AUCs – XGBoost
```

	Class	AUC
0	0	0.999311
1	1	0.999596
2	2	0.999943
3	3	0.999812
4	4	1.000000

In [31]:
```
# Binarize the output for multi-class ROC
classes = np.unique(y)
y_test_bin = label_binarize(y_test, classes=classes)
n_classes = y_test_bin.shape[1]

# Prediction probabilities
y_score_lr = lr_model.predict_proba(X_test)
y_score_rf = rf_model.predict_proba(X_test)
```

```
y_score_xgb = xgb_model.predict_proba(X_test)

models = {
    "Logistic Regression": y_score_lr,
    "Random Forest": y_score_rf,
    "XGBoost": y_score_xgb
}

# Creating subplots: rows = models, columns = classes
fig, axes = plt.subplots(len(models), n_classes, figsize=(4 * n_classes, 4 * len(mo

if len(models) == 1:
    axes = [axes]  # Ensuring iterable

for row_idx, (model_name, y_score) in enumerate(models.items()):
    for class_idx in range(n_classes):
        ax = axes[row_idx][class_idx] if len(models) > 1 else axes[class_idx]
        fpr, tpr, _ = roc_curve(y_test_bin[:, class_idx], y_score[:, class_idx])
        roc_auc = auc(fpr, tpr)

        ax.plot(fpr, tpr, label=f'AUC = {roc_auc:.2f}')
        ax.plot([0, 1], [0, 1], 'k--', lw=1)
        ax.set_xlim([0.0, 1.0])
        ax.set_ylim([0.0, 1.05])
        ax.set_title(f"{model_name} - Class {classes[class_idx]}")
        ax.set_xlabel('FPR')
        ax.set_ylabel('TPR')
        ax.legend(loc="lower right")

plt.tight_layout()
plt.show()
```


Logistic Regression - Class 0
AUC = 0.90
Logistic Regression - Class 1
AUC = 0.83
Logistic Regression - Class 2
AUC = 0.83
Logistic Regression - Class 3
AUC = 0.96
Logistic Regression - Class 4
AUC = 1.00
Random Forest - Class 0
AUC = 1.00
Random Forest - Class 1
AUC = 1.00
Random Forest - Class 2
AUC = 1.00
Random Forest - Class 3
AUC = 1.00
Random Forest - Class 4
AUC = 1.00
XGBoost - Class 0
AUC = 1.00
XGBoost - Class 1
AUC = 1.00
XGBoost - Class 2
AUC = 1.00
XGBoost - Class 3
AUC = 1.00
XGBoost - Class 4
AUC = 1.00
TPR
FPR