Final Team Project: Predicting Student Academic Performance Using Machine Learning

Course: ADS 504, Machine Learning and Deep Learning for Data Science
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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')
```

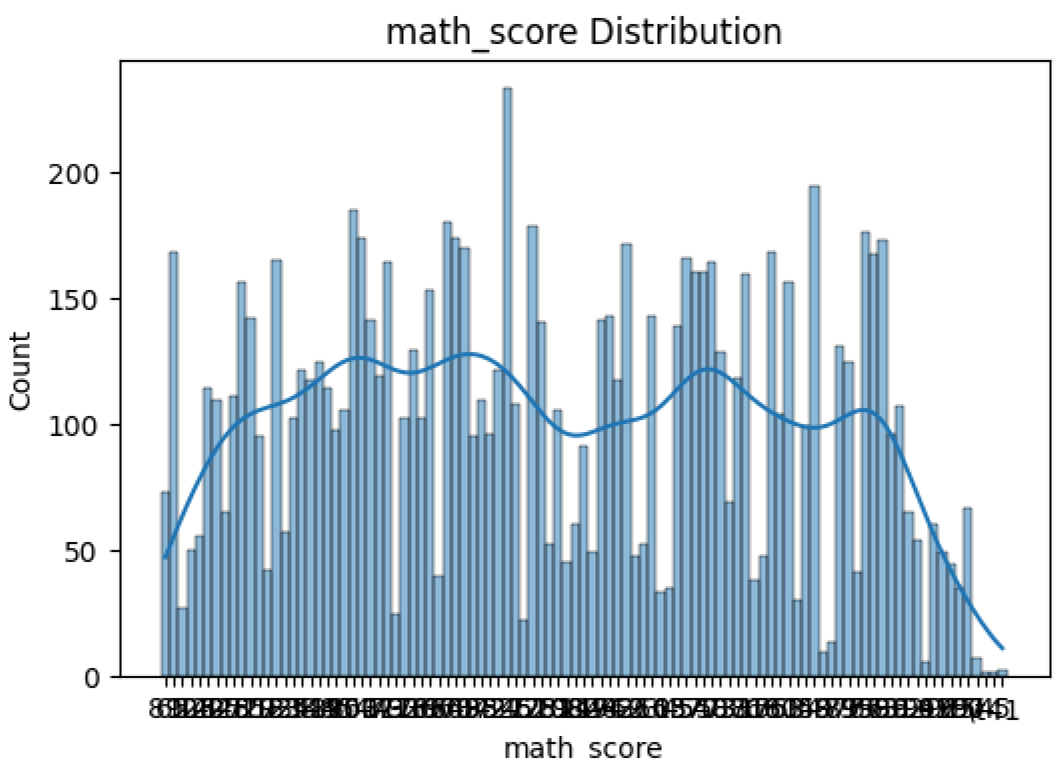
Out[7]:

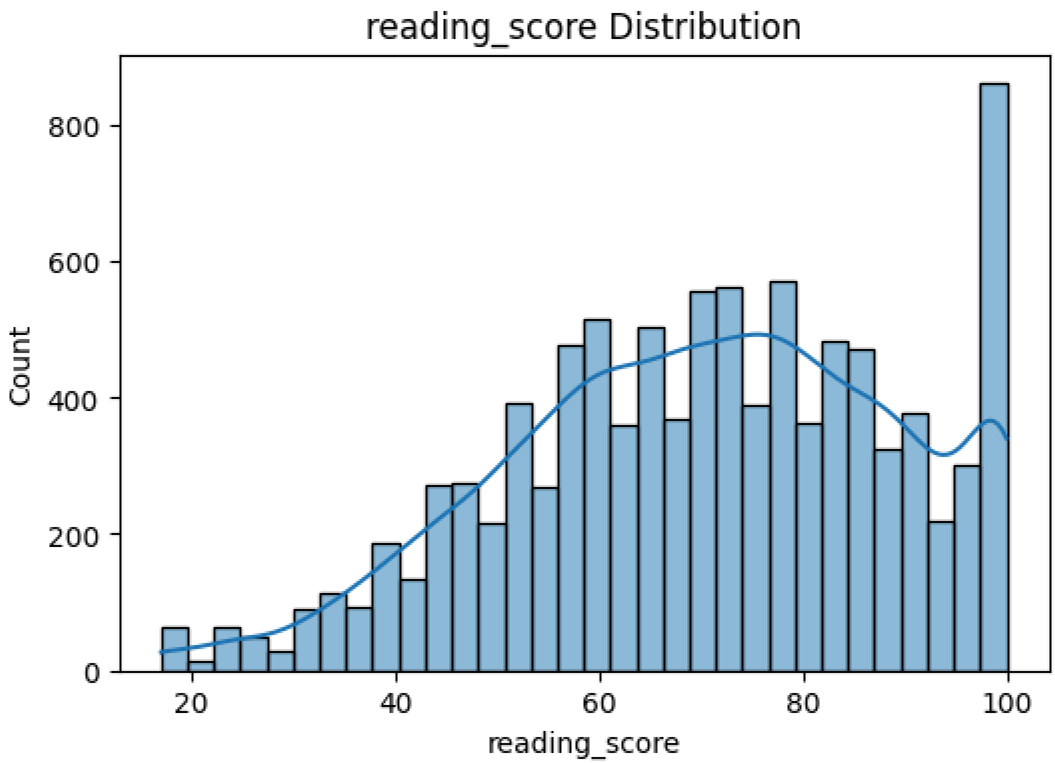
	roll_no	gender	race_ethnicity	parental_level_of_education	lunch	test_prepa
count	9999	9982	9977	9978	9976.000000	
unique	9999	5	11	6	NaN	
top	std-10000	female	group C	some college	NaN	
freq	1	4983	2921	2272	NaN	
mean	NaN	NaN	NaN	NaN	0.644246	
std	NaN	NaN	NaN	NaN	0.478765	
min	NaN	NaN	NaN	NaN	0.000000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

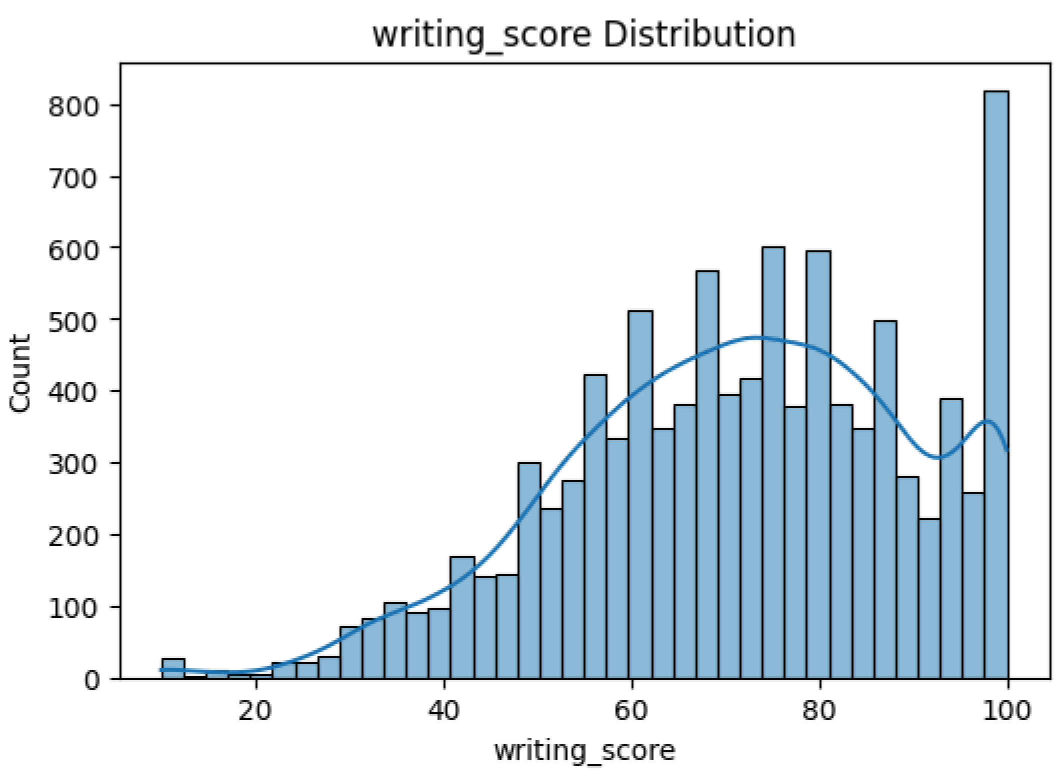
In [8]:

```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()
```

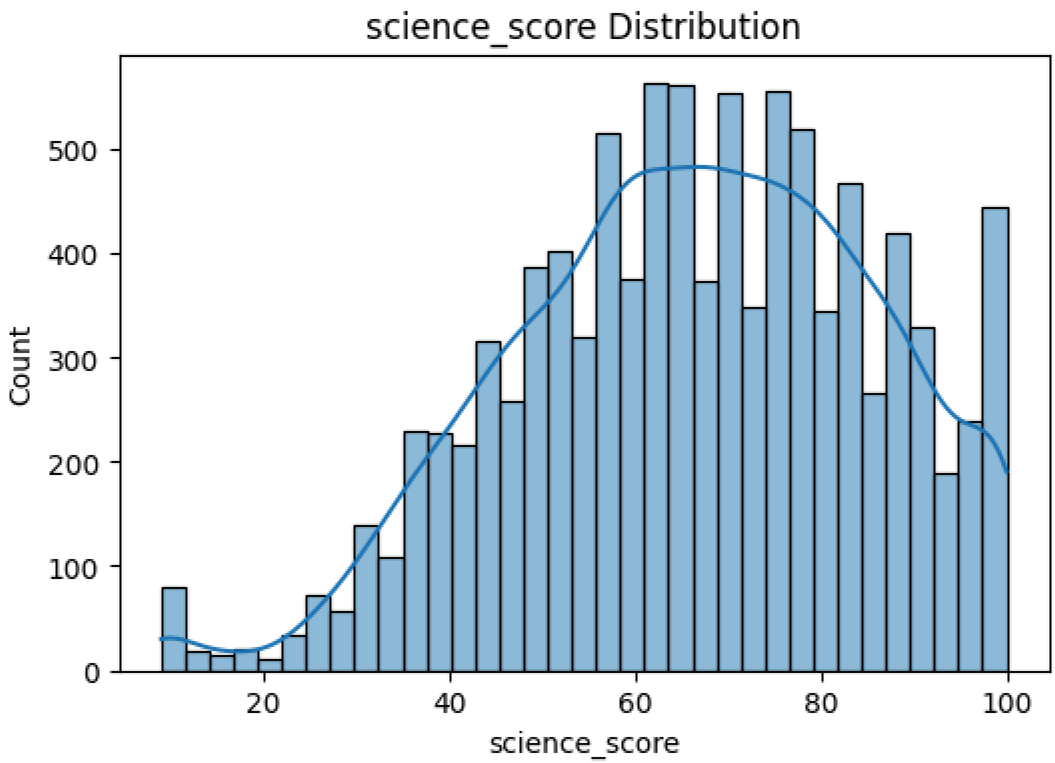


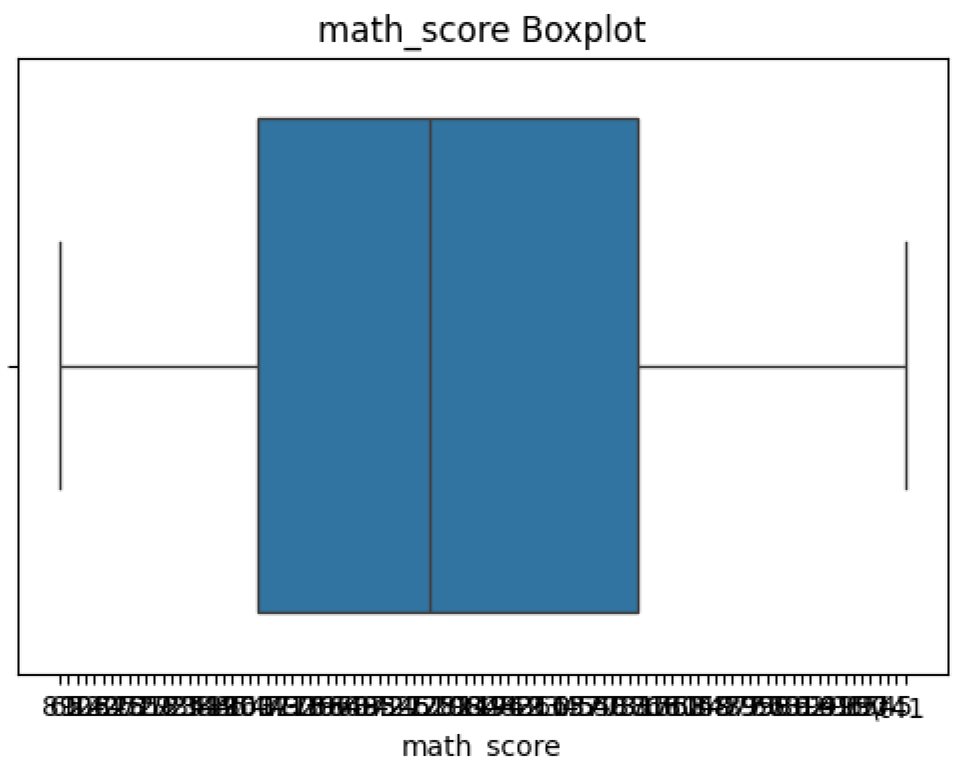


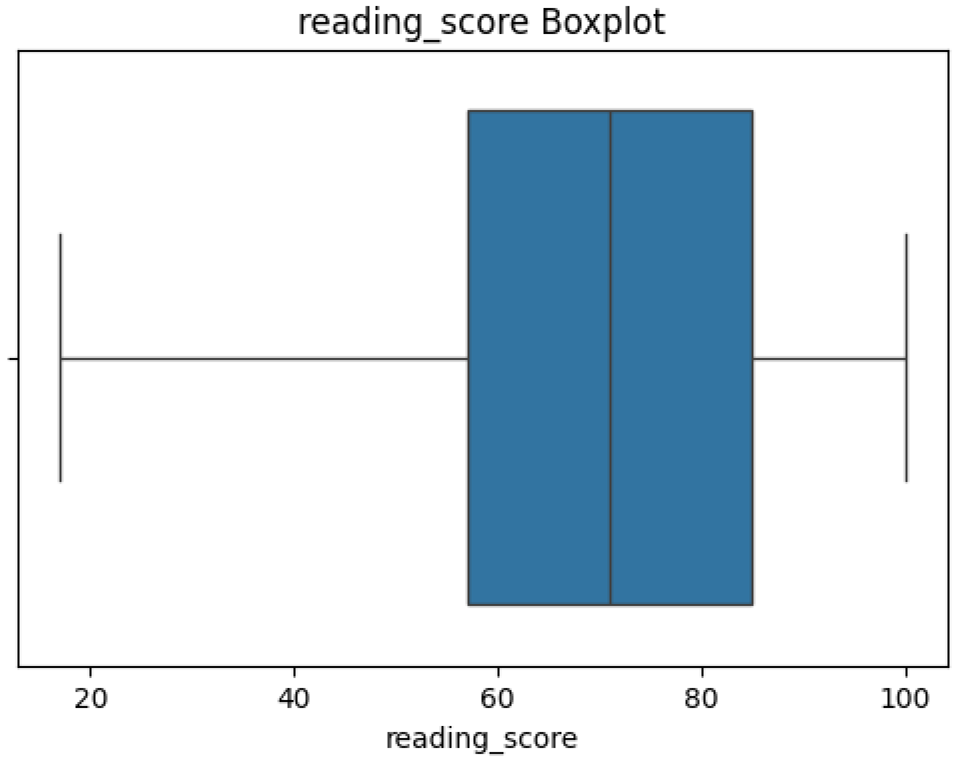
reading_score Distribution
Count
0
200
400
600
800
20
40
60
80
100
reading_score

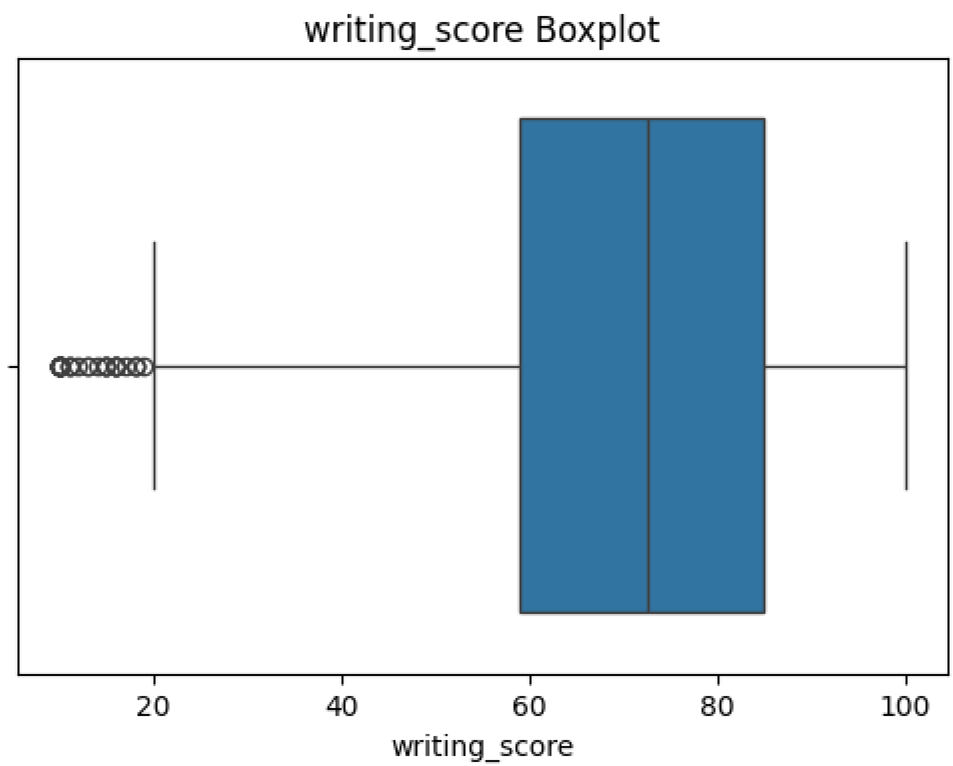


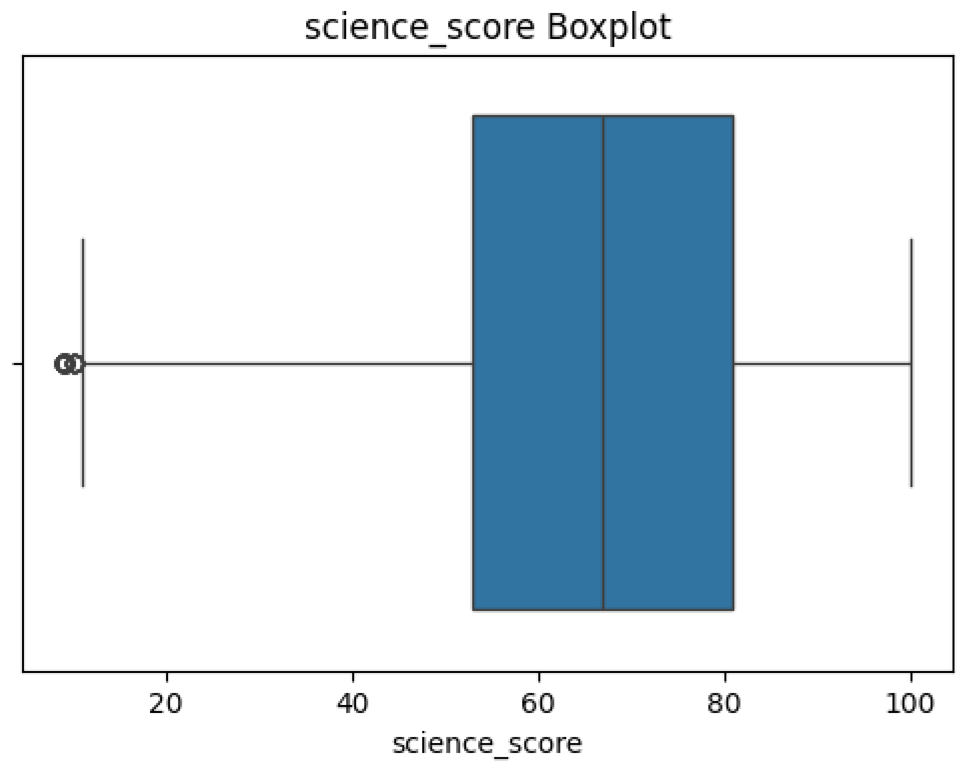
writing_score Distribution
Count
0
100
200
300
400
500
600
700
800
20
40
60
80
100
writing_score

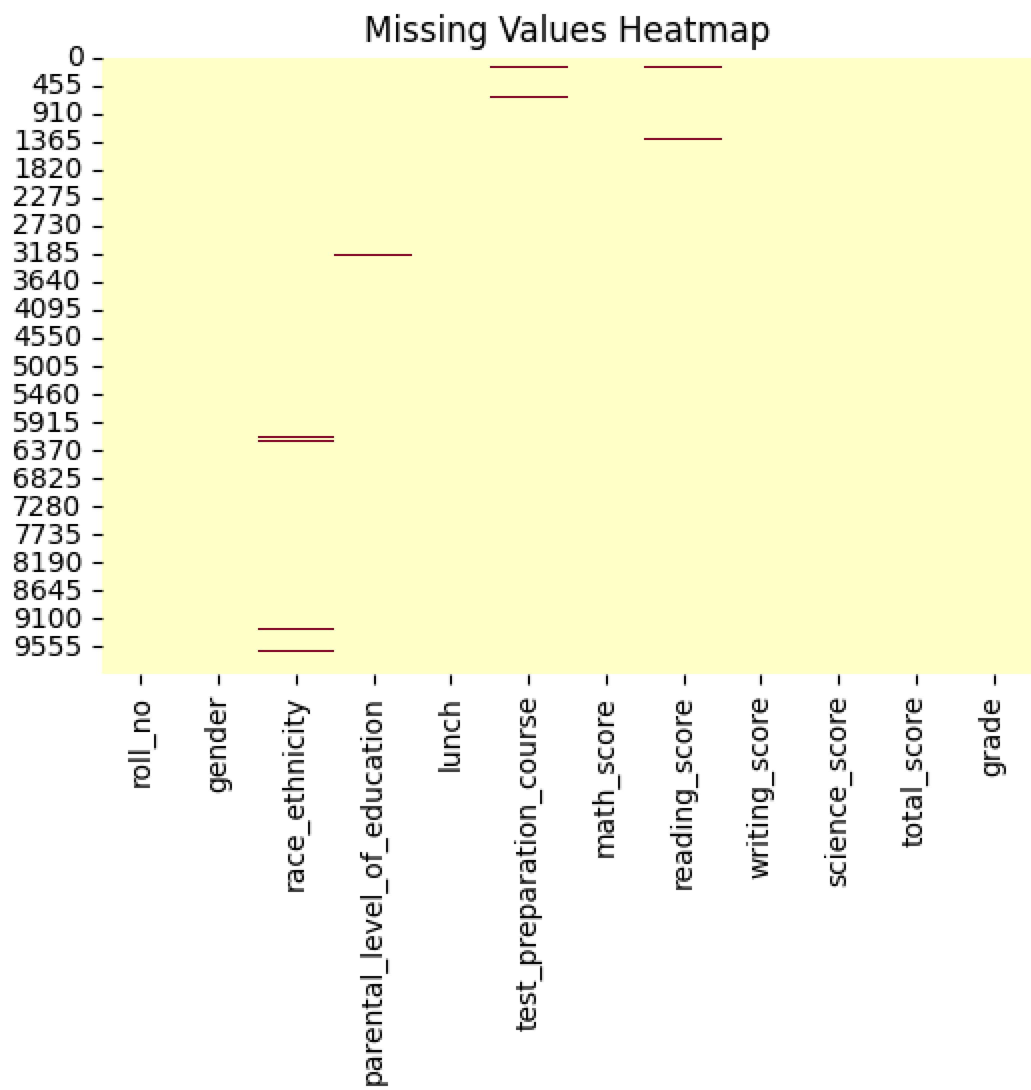

science_score Distribution
Count
0
100
200
300
400
500
20
40
60
80
100
science_score


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]:
```
# 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
```

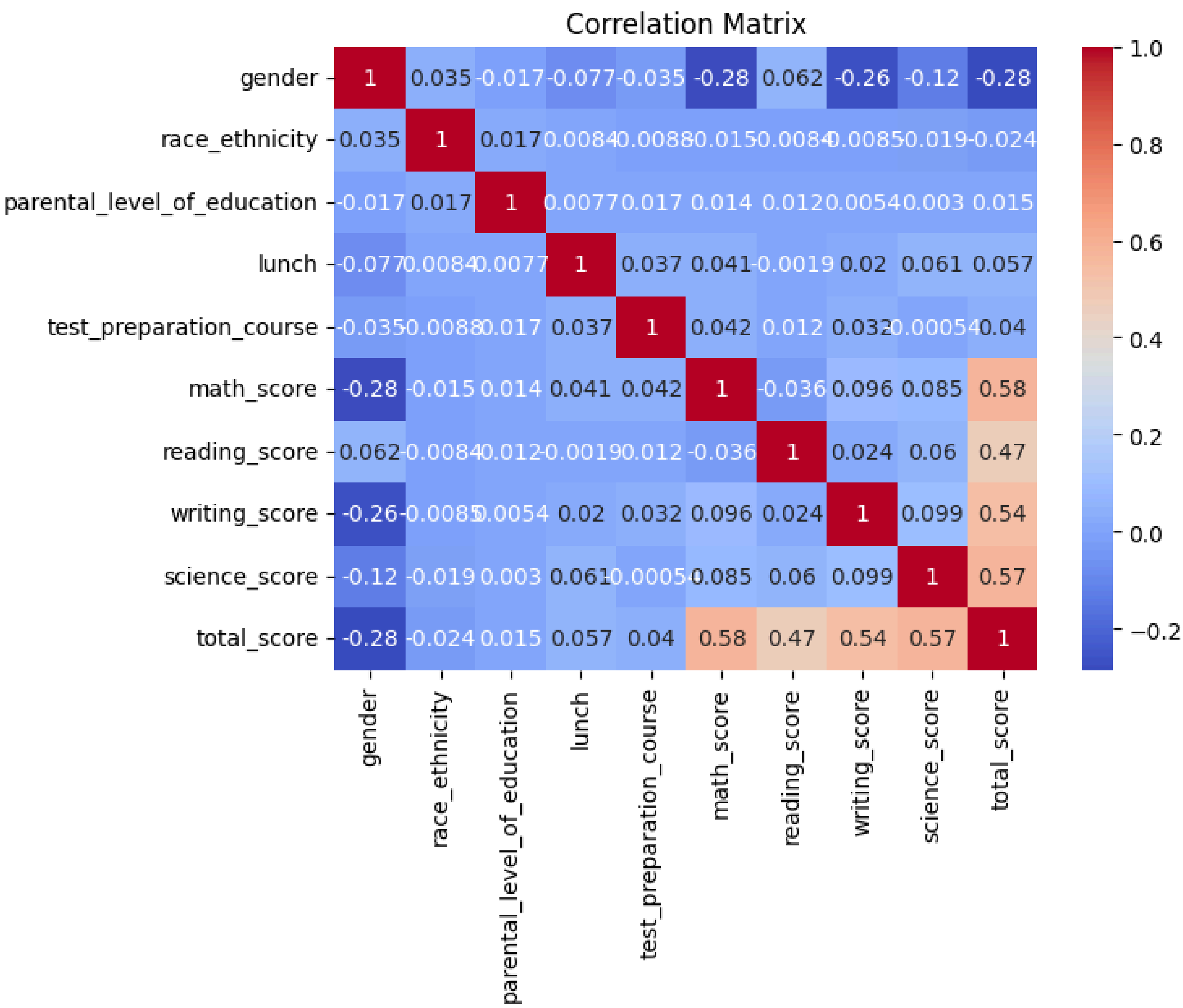
In [10]:
```
# Check for duplicate rows
duplicates = student_performance_df.duplicated()
print(f"Number of duplicate rows is {duplicates.sum()}.")
```

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

Exploratory Data Analysis (EDA)

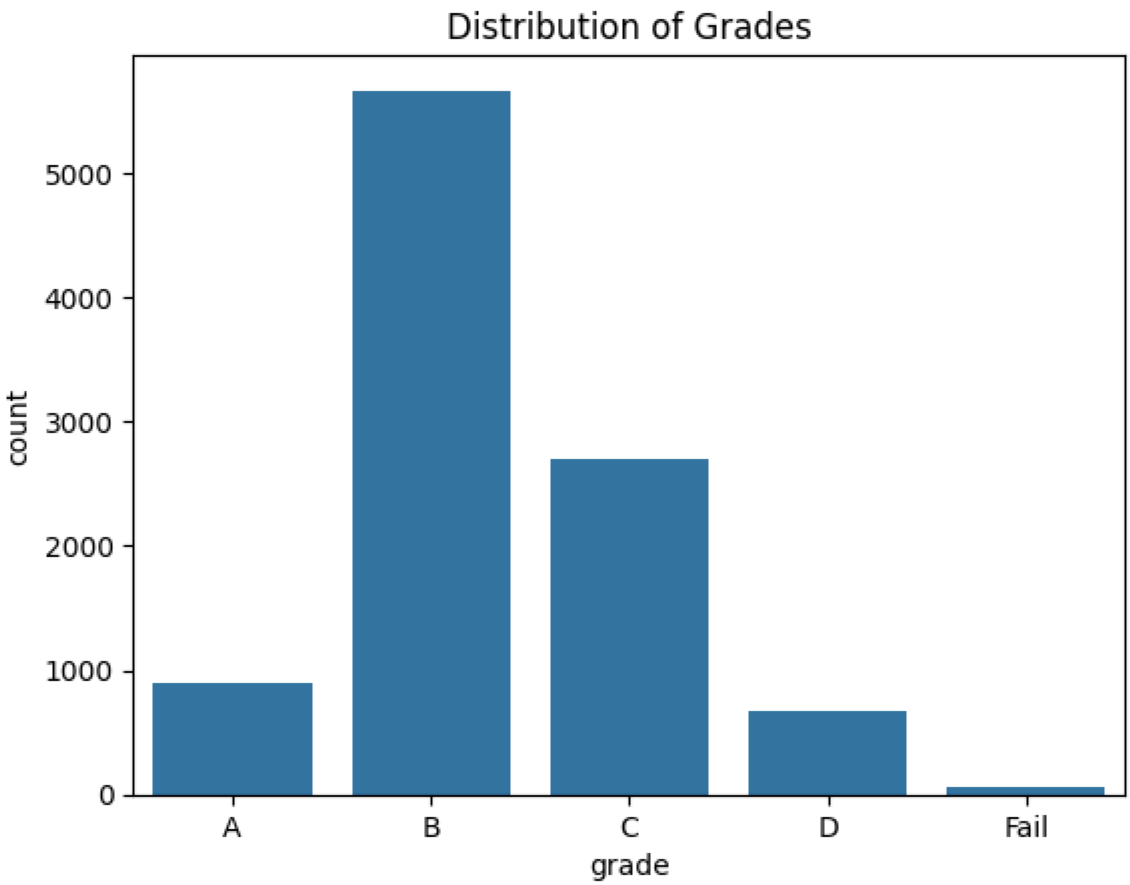
In [11]:
```
# Correlation heatmap (only for numeric columns)
plt.figure(figsize=(7, 5))
```

```
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()
```



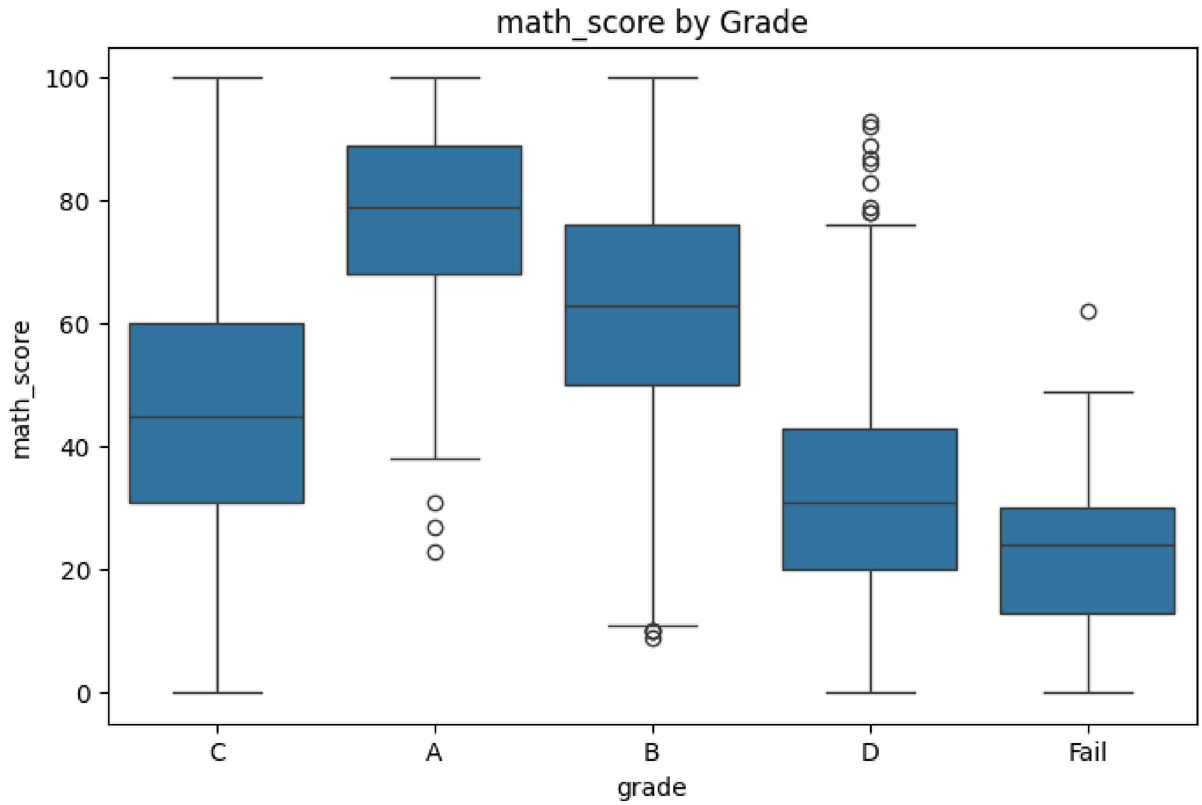
The heatmap shows strong positive correlations between the core academic scores, especially between writing and reading `(r = 0.96)`, and writing and science `(r = 0.99)`. This suggests some redundancy and potential multicollinearity. Gender shows a moderate negative correlation with math `(r = -0.28)`,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

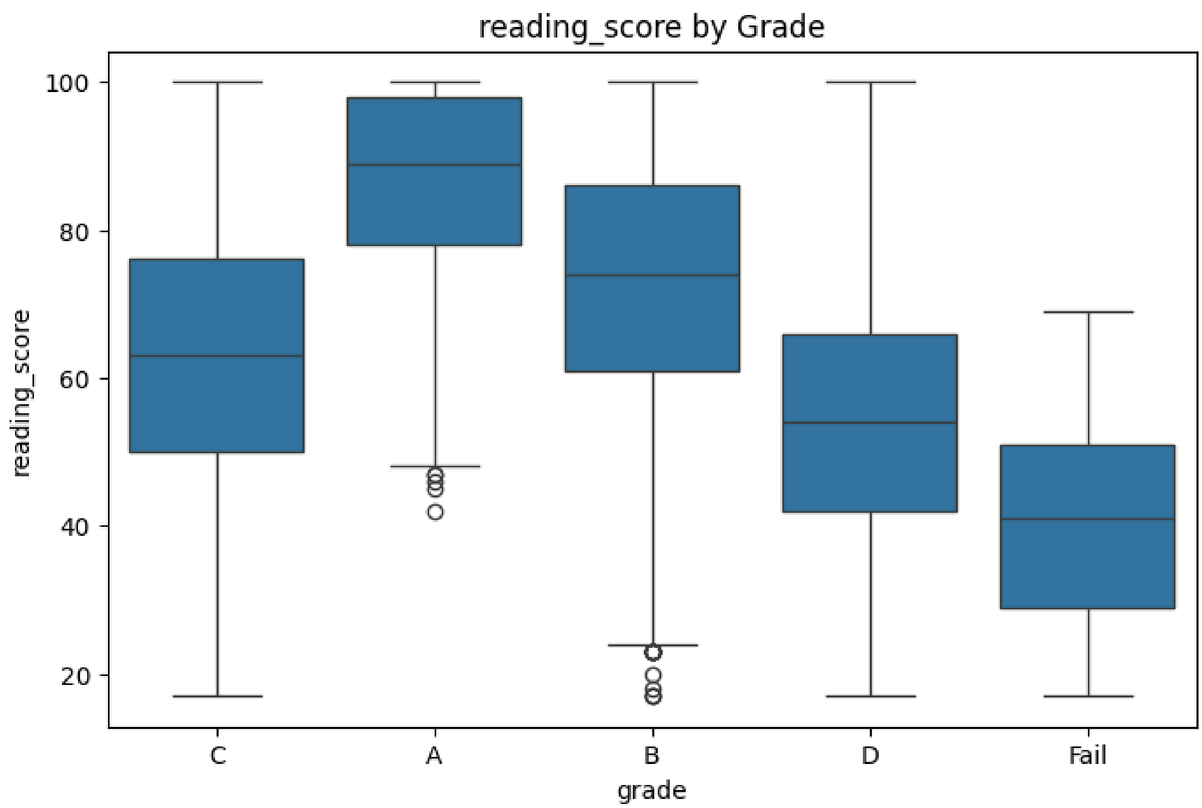
In [12]:
```
# Grade distribution
sns.countplot(data=student_performance_df, x='grade', order=sorted(student_performa
plt.title('Distribution of Grades')
plt.show()
```

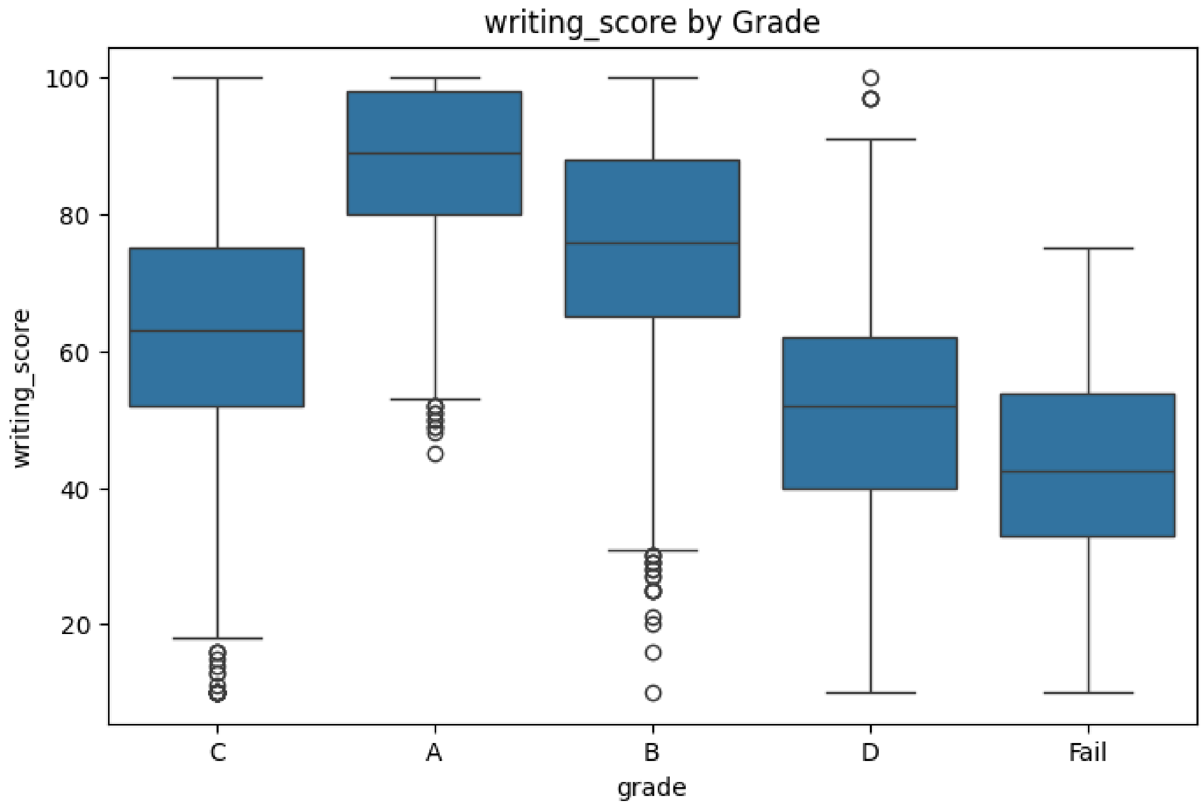


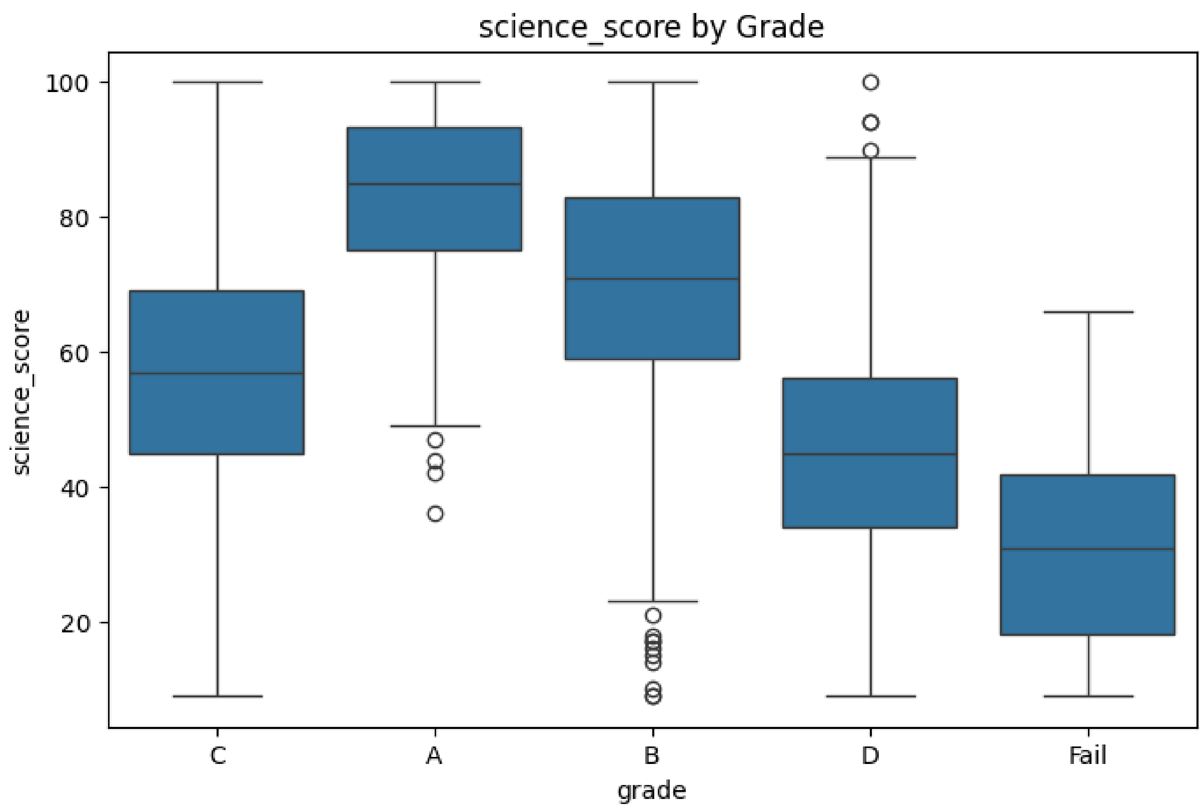
Grade distribution is imbalanced, with the majority of students earning a B, followed by C, and a small number failing. This imbalance will need to be addressed during model evaluation, possibly using weighted metrics or resampling techniques.

In [13]:
```
# 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
grade
100
80
60
40
20
0
C
A
B
D
Fail


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





`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

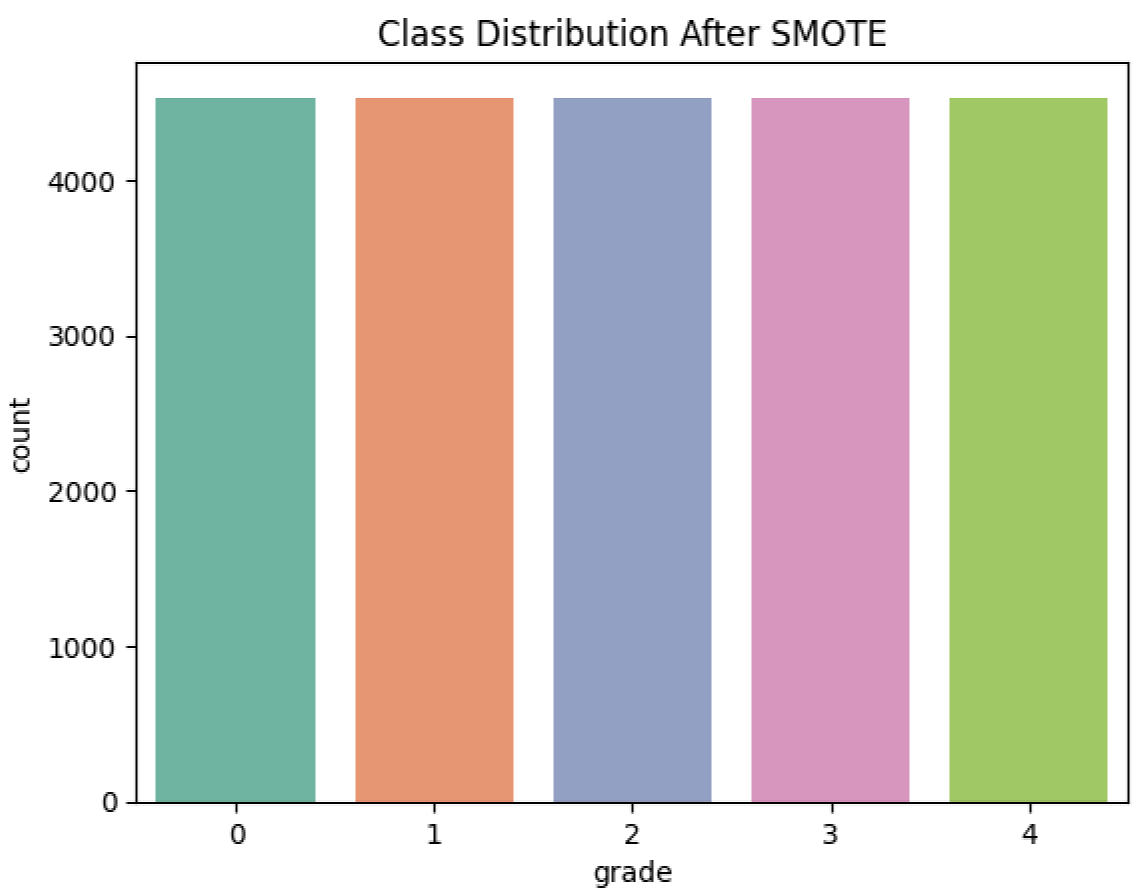
In [16]:
```
# Stratified train-test split (before balancing)
X = student_performance_df.drop(columns='grade')
y = student_performance_df['grade']
```

```python
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]:

```python
# 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]:

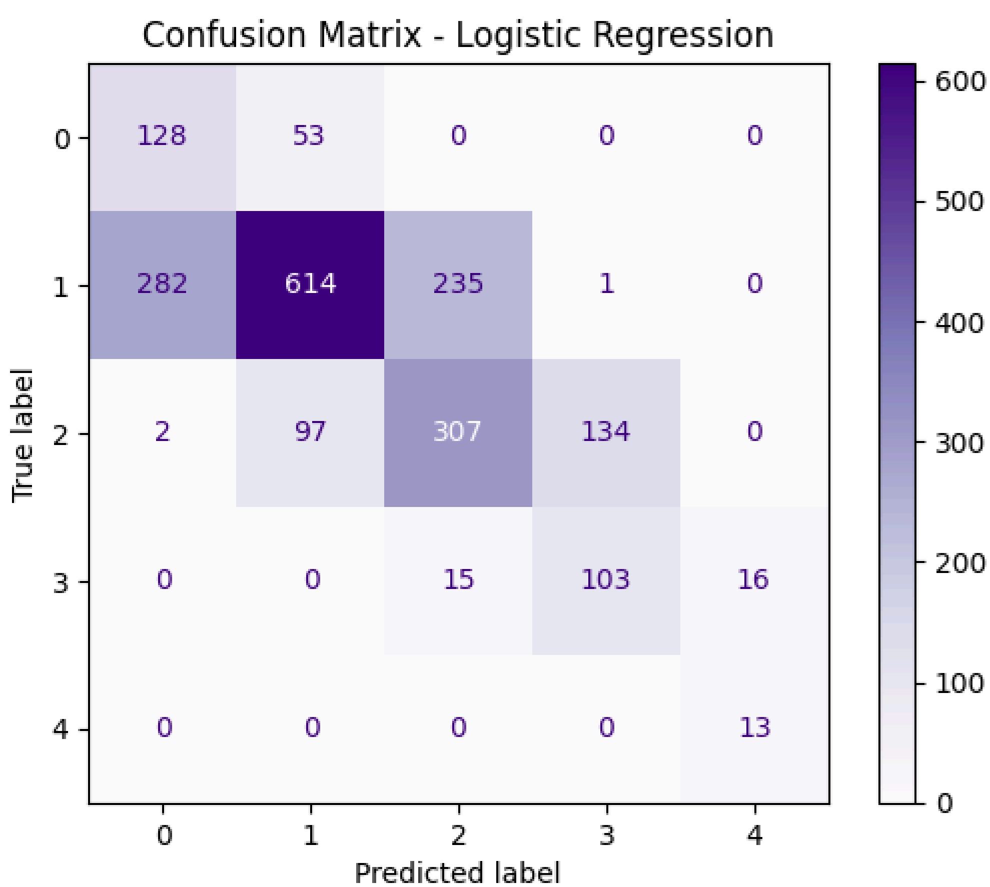
```python
lr_model = LogisticRegression(max_iter=1000)
lr_model.fit(X_train_resampled, y_train_resampled)
y_pred_lr = lr_model.predict(X_test)
```

```
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]:

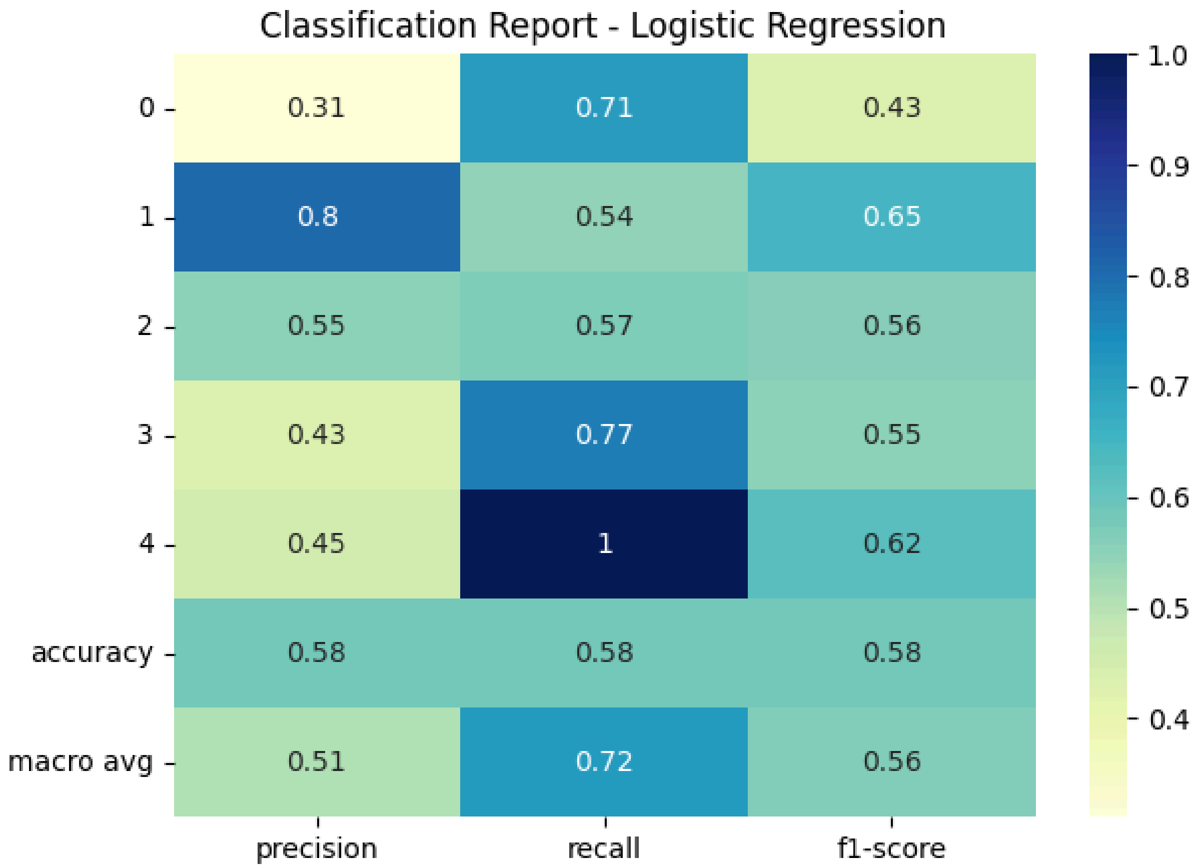
```
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_lr, cmap='Purples')
plt.title("Confusion Matrix - Logistic Regression")
plt.show()
```



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()
```



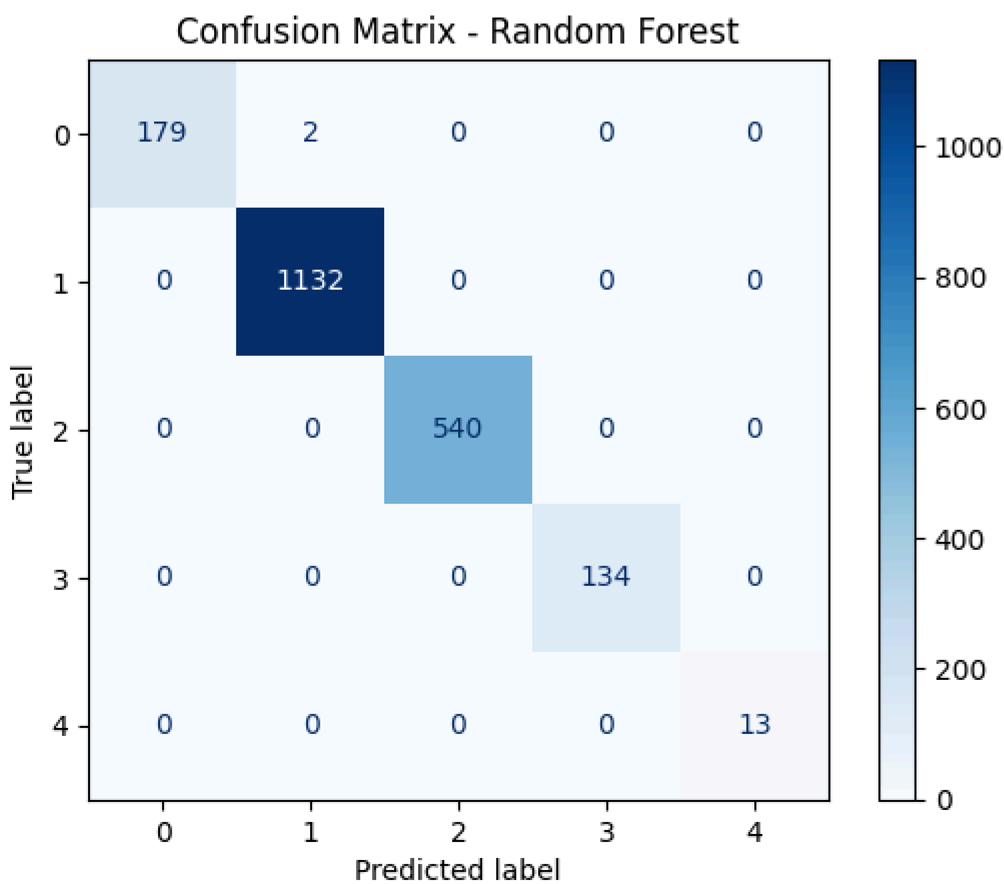
Random Forest

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]:

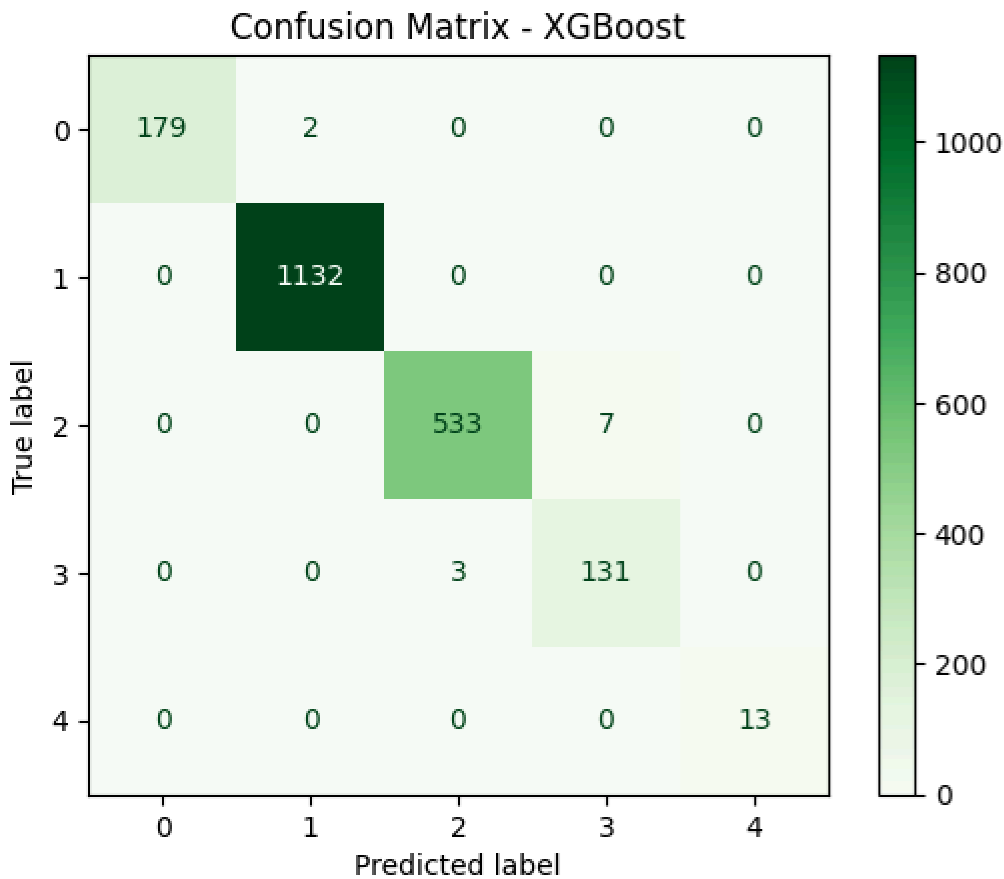
```
#  Initialize the model
xgb_model = XGBClassifier(
    use_label_encoder=False,
    eval_metric='mlogloss',
    random_state=42
)
```

```python
# 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
```

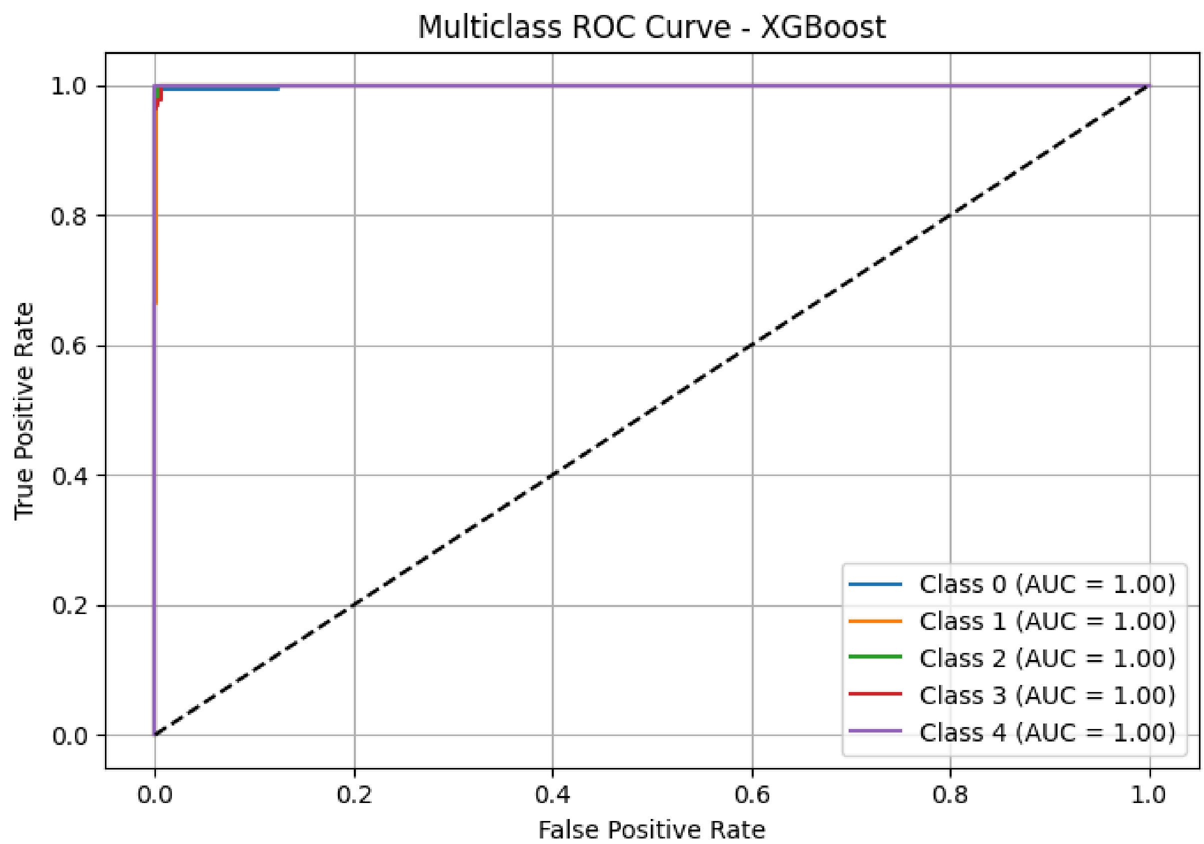
In [24]:

```python
# 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
```

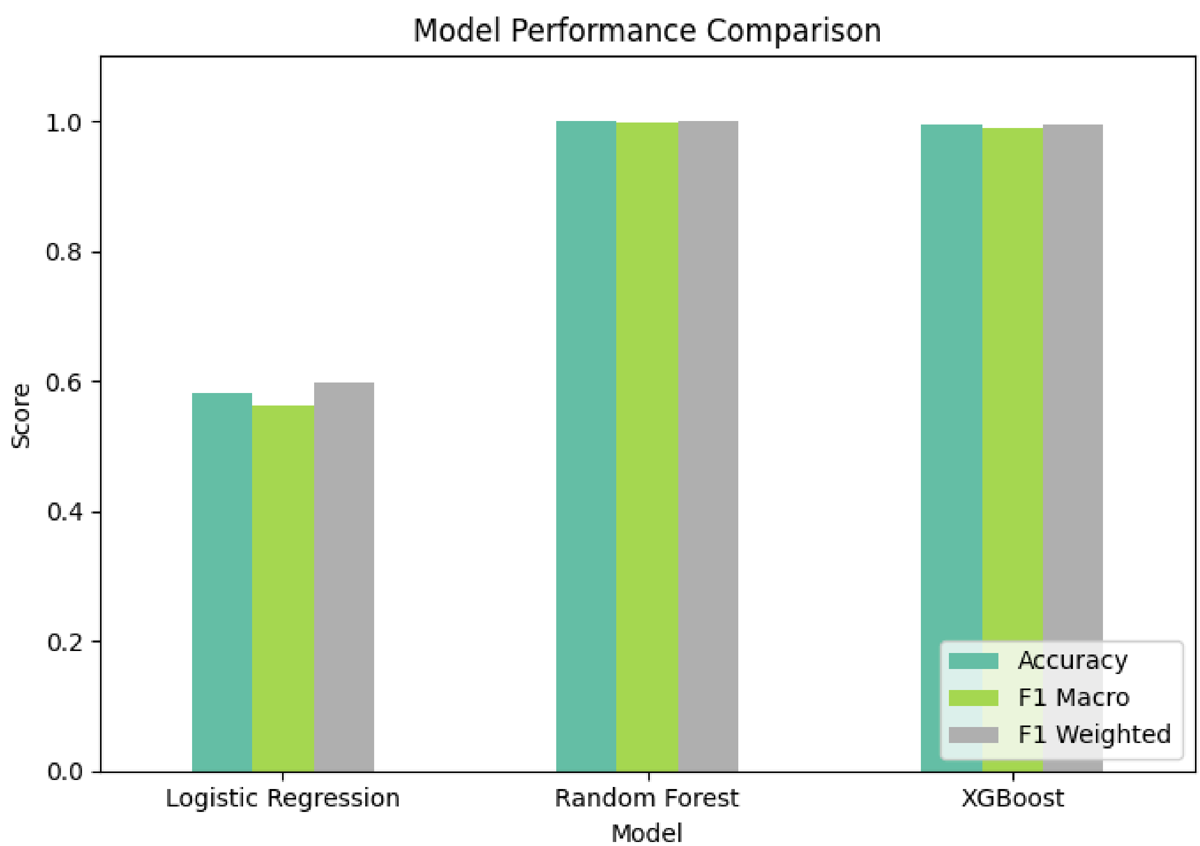
Model Comparison

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)
```

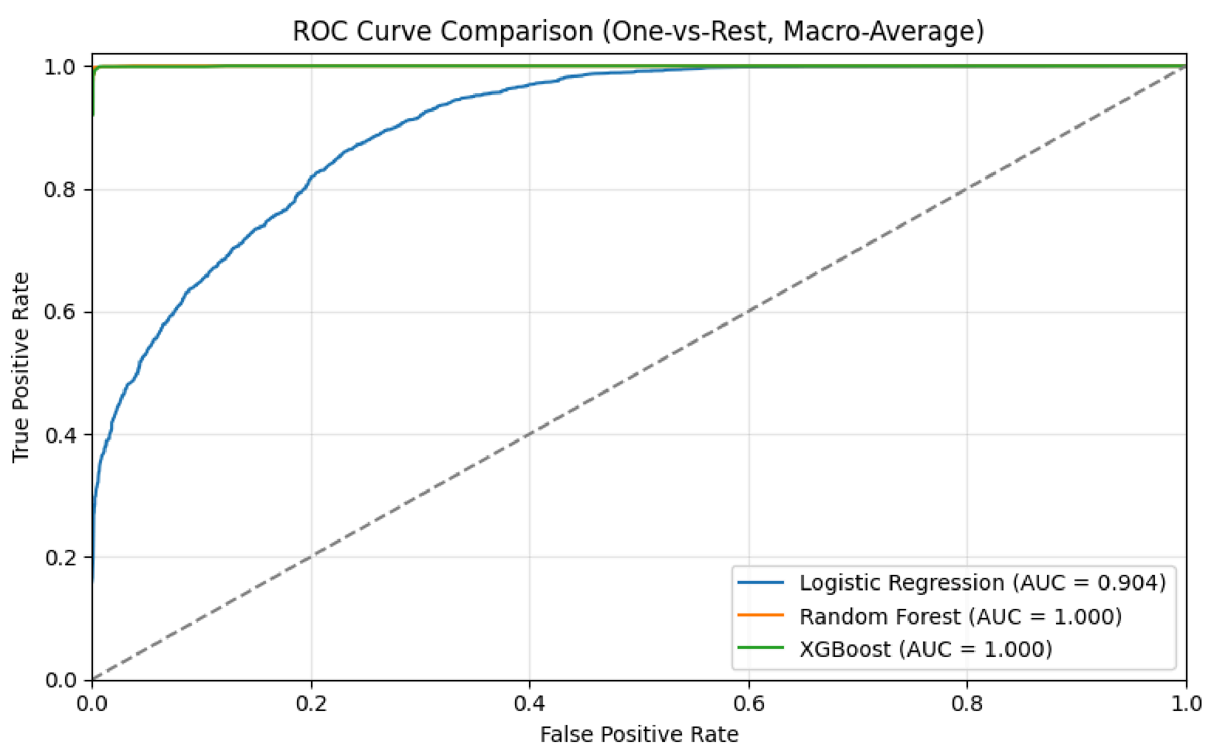
```
print("Classification Report - Decision Tree")
print(classification_report(y_test, y_pred_cart))
```

```
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)
```

```python
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()
```