Model_Building_Part_2

April 18, 2025

Import all Modules

[105]:
```
# Import Modules
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

#Import os
import os

# Import Sklearn modules
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪accuracy_score

# Import Pytorch modules
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader, random_split
```

Displaying Data

[106]:
```
# Load the dataset
current_path = os.getcwd()
parent_folder = os.path.dirname(current_path)
data_file_path = os.path.join(parent_folder, "Data", "Student_performance_data.
 ↪csv")
df = pd.read_csv(str(data_file_path))

# Load train and test indices
train_index_path = os.path.join(parent_folder, "Data", "train_index.csv")
test_index_path = os.path.join(parent_folder, "Data", "test_index.csv")
train_index = pd.read_csv(train_index_path, header=None).iloc[:, 0].tolist()
test_index = pd.read_csv(test_index_path, header=None).iloc[:, 0].tolist()
```

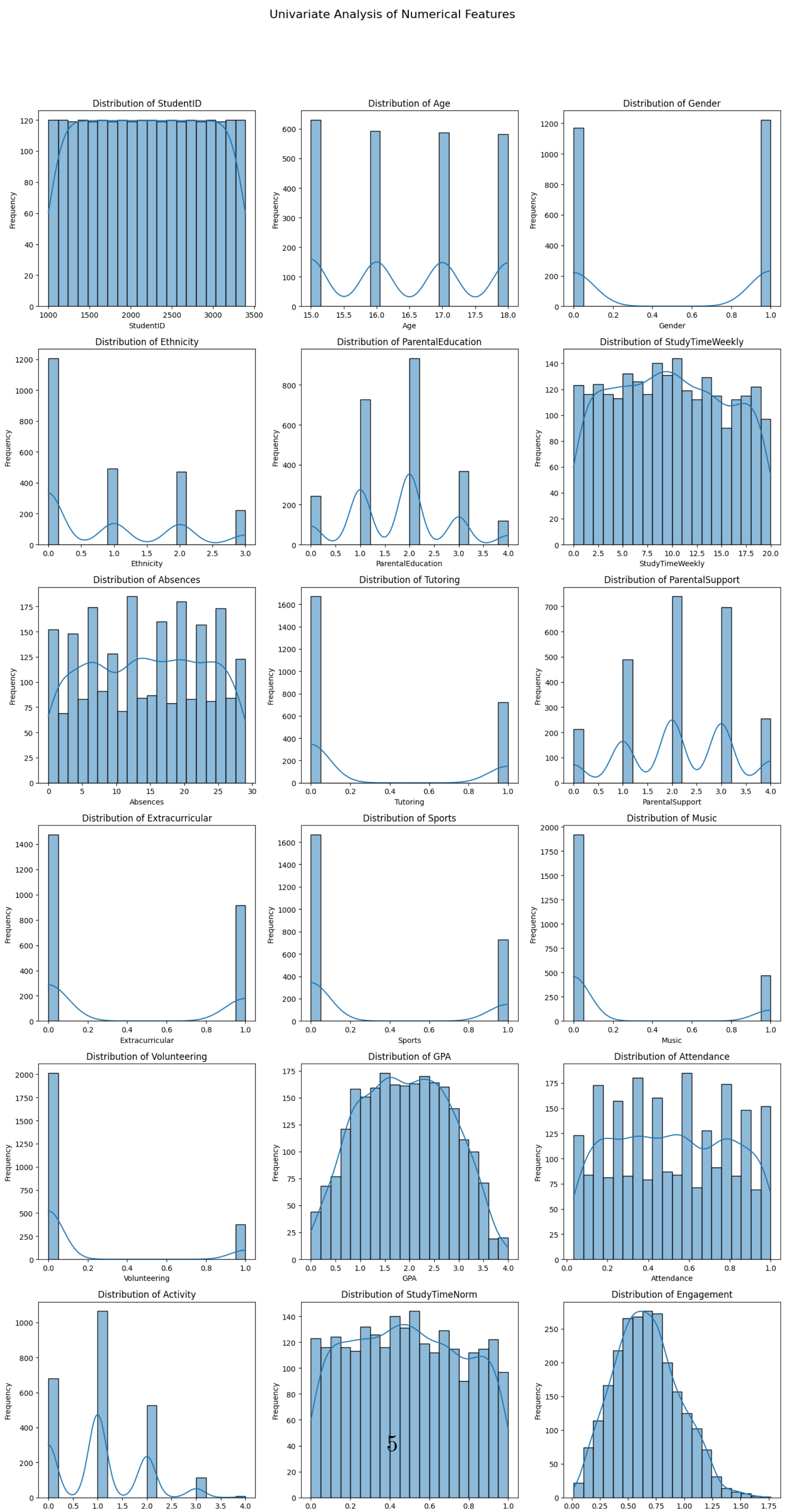
```
# Feature engineering (same as before)
df['Attendance'] = 1 - (df['Absences'] / 30)
df['Activity'] = df[['Extracurricular', 'Music', 'Sports', 'Volunteering']].
↪sum(axis=1)
df['StudyTimeNorm'] = df['StudyTimeWeekly'] / 20
df['Engagement'] = (df['Attendance'] * 0.4 + df['Activity'] * 0.3 +␣
↪df['StudyTimeNorm'] * 0.3)

# Separate features and labels
X = df.drop('GradeClass', axis=1)
y = df['GradeClass']
```

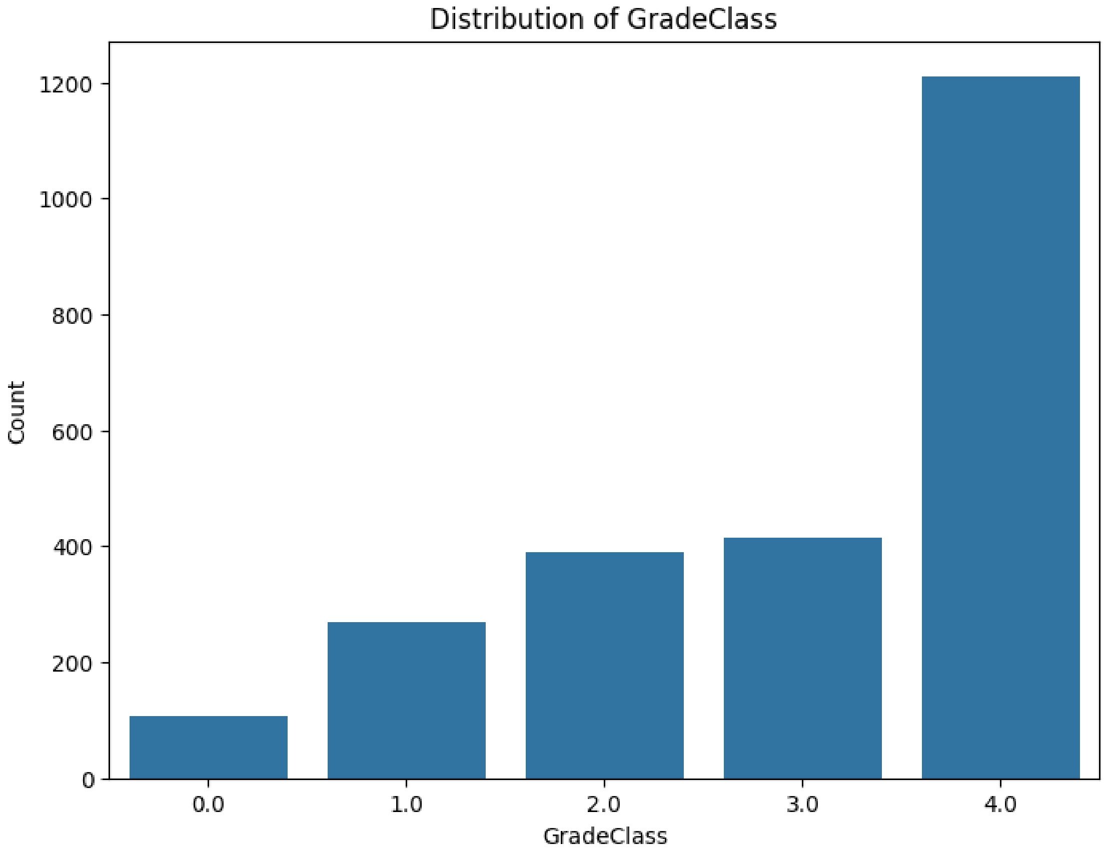
Exploratory Data Analysis (EDA)

[107]:
```
#  Exploratory Data Analysis (EDA)

def univariate_analysis(X, y):
    """
    Performs univariate analysis on numerical features and the target variable.

    Args:
        X (pd.DataFrame): The feature DataFrame.
        y (pd.Series): The target Series.
    """

    #  Univariate Analysis of Numerical Features
    numerical_features = X.select_dtypes(include=np.number).columns
    num_cols = 3  # Number of columns in the plot grid
    num_rows = (len(numerical_features) + num_cols - 1) // num_cols  #␣
↪Calculate number of rows

    plt.figure(figsize=(15, 5 * num_rows))  # Adjust figure height dynamically
    for i, feature in enumerate(numerical_features):
        plt.subplot(num_rows, num_cols, i + 1)
        sns.histplot(X[feature], bins=20, kde=True)  # Use histplot for better␣
↪visuals
        plt.title(f'Distribution of {feature}')
        plt.xlabel(feature)
        plt.ylabel('Frequency')
    plt.suptitle('Univariate Analysis of Numerical Features', y=0.99,␣
↪fontsize=16)  # Move suptitle to the end
    plt.tight_layout(rect=[0, 0.03, 1, 0.95])  # Adjust layout to prevent␣
↪overlap
    plt.show()

    #  Univariate Analysis of Target Variable
```

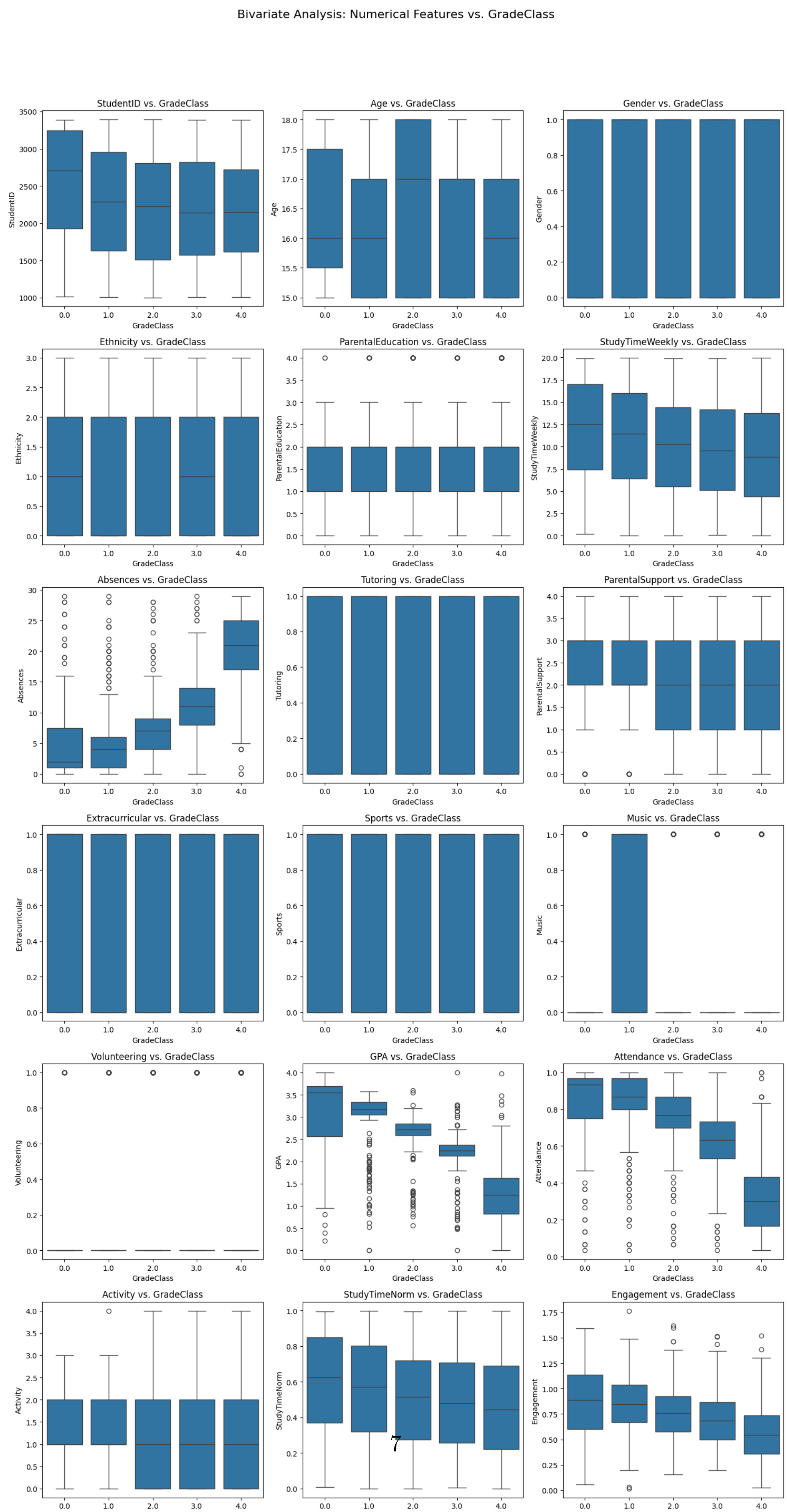
```
    plt.figure(figsize=(8, 6))
    sns.countplot(x=y)
    plt.title('Distribution of GradeClass')
    plt.xlabel('GradeClass')
    plt.ylabel('Count')
    plt.show()


def bivariate_analysis(X, y):
    """
    Performs bivariate analysis between numerical features and the target␣
 ↪variable.

    Args:
        X (pd.DataFrame): The feature DataFrame.
        y (pd.Series): The target Series.
    """

    #  Bivariate Analysis: Numerical Features vs. GradeClass (Boxplots)
    numerical_features = X.select_dtypes(include=np.number).columns
    num_cols = 3
    num_rows = (len(numerical_features) + num_cols - 1) // num_cols

    plt.figure(figsize=(15, 5 * num_rows))
    for i, feature in enumerate(numerical_features):
        plt.subplot(num_rows, num_cols, i + 1)
        sns.boxplot(x=y, y=X[feature])
        plt.title(f'{feature} vs. GradeClass')
        plt.xlabel('GradeClass')
        plt.ylabel(feature)
    plt.suptitle('Bivariate Analysis: Numerical Features vs. GradeClass', y=0.
 ↪99, fontsize=16)
    plt.tight_layout(rect=[0, 0.03, 1, 0.95])
    plt.show()

    #  Bivariate Analysis: Correlation Heatmap (Lower Triangle)
    corr_matrix = X.corr()
    mask = np.triu(np.ones_like(corr_matrix, dtype=bool))  # Create a mask for␣
 ↪the upper triangle
    plt.figure(figsize=(15, 13))
    sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f",␣
 ↪annot_kws={"size": 10}, mask=mask) # Apply the mask
    plt.title('Correlation Heatmap (Lower Triangle)')
    plt.show()


#  Main EDA Execution
```

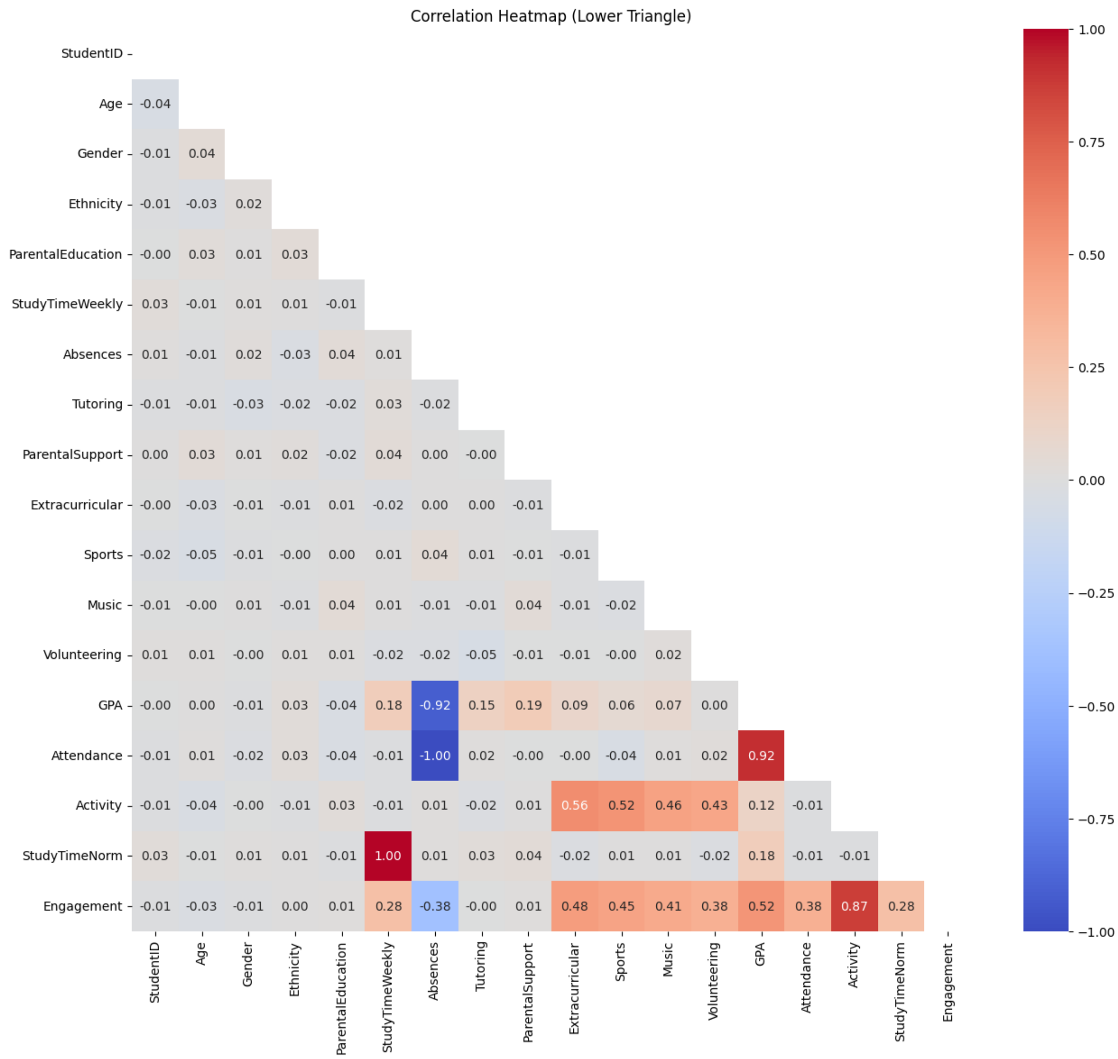
```
univariate_analysis(X, y)
bivariate_analysis(X, y)
```


Univariate Analysis of Numerical Features
Distribution of StudentID
Distribution of Age
Distribution of Gender
Distribution of Ethnicity
Distribution of ParentalEducation
Distribution of StudyTimeWeekly
Distribution of Absences
Distribution of Tutoring
Distribution of ParentalSupport
Distribution of Extracurricular
Distribution of Sports
Distribution of Music
Distribution of Volunteering
Distribution of GPA
Distribution of Attendance
Distribution of Activity
Distribution of StudyTimeNorm
Distribution of Engagement
Frequency
StudentID
Age
Gender
Ethnicity
ParentalEducation
StudyTimeWeekly
Absences
Tutoring
ParentalSupport
Extracurricular
Sports
Music
Volunteering
GPA
Attendance
Activity
StudyTimeNorm
Engagement



Distribution of GradeClass
Count
GradeClass
0
200
400
600
800
1000
1200
0.0
1.0
2.0
3.0
4.0


Bivariate Analysis: Numerical Features vs. GradeClass
StudentID vs. GradeClass
Age vs. GradeClass
Gender vs. GradeClass
Ethnicity vs. GradeClass
ParentalEducation vs. GradeClass
StudyTimeWeekly vs. GradeClass
Absences vs. GradeClass
Tutoring vs. GradeClass
ParentalSupport vs. GradeClass
Extracurricular vs. GradeClass
Sports vs. GradeClass
Music vs. GradeClass
Volunteering vs. GradeClass
GPA vs. GradeClass
Attendance vs. GradeClass
Activity vs. GradeClass
StudyTimeNorm vs. GradeClass
Engagement vs. GradeClass
GradeClass
0.0
1.0
2.0
3.0
4.0



Create Train and Test Sets

[108]:
```python
# Create train and test sets using the loaded indices
X_train = X.iloc[train_index]
X_test = X.iloc[test_index]
y_train = y.iloc[train_index]
y_test = y.iloc[test_index]

print("X_train head:")
print(X_train.head())

print("\nData shapes:")
```

```
print("X_train:", X_train.shape)
print("X_test:", X_test.shape)
print("y_train:", y_train.shape)
print("y_test:", y_test.shape)
```

```
X_train head:
      StudentID  Age  Gender  Ethnicity  ParentalEducation  StudyTimeWeekly  \
1764       2765   15       1          1                  1         9.247229
1479       2480   18       0          0                  4         8.978234
1529       2530   18       0          0                  1        10.088421
2196       3197   17       1          1                  1         1.001291
2146       3147   15       0          0                  1        12.324485

      Absences  Tutoring  ParentalSupport  Extracurricular  Sports  Music  \
1764        21         1                2                0       1      0
1479         3         0                2                0       1      0
1529        13         0                1                0       0      0
2196         0         0                2                0       0      0
2146         0         0                1                1       0      0

      Volunteering       GPA  Attendance  Activity  StudyTimeNorm  Engagement
1764             0  1.455085    0.300000         1       0.462361    0.558708
1479             0  2.747908    0.900000         1       0.448912    0.794674
1529             0  1.820844    0.566667         0       0.504421    0.377993
2196             0  2.995458    1.000000         0       0.050065    0.415019
2146             0  3.333970    1.000000         1       0.616224    0.884867

Data shapes:
X_train: (1902, 18)
X_test: (476, 18)
y_train: (1902,)
y_test: (476,)
```

Processing and Tensors

[109]:
```
# Scale numerical features -  FIT only on training data, TRANSFORM both
numerical_cols = X_train.select_dtypes(include=np.number).columns
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train[numerical_cols])
X_test_scaled = scaler.transform(X_test[numerical_cols])  # Apply same scaling␣
 ↪to test

# Encode the target variable - ONLY FIT on the training data
label_encoder = LabelEncoder()
y_train_encoded = label_encoder.fit_transform(y_train.values.ravel())
y_test_encoded = label_encoder.transform(y_test.values.ravel())

# Convert to PyTorch tensors
```

```
X_train_tensor = torch.tensor(X_train_scaled, dtype=torch.float32)
y_train_tensor = torch.tensor(y_train_encoded, dtype=torch.long)
X_test_tensor = torch.tensor(X_test_scaled, dtype=torch.float32)
y_test_tensor = torch.tensor(y_test_encoded, dtype=torch.long)
```

Create TensorDatasets and DataLoaders

[110]:
```
# Create TensorDatasets
train_dataset = TensorDataset(X_train_tensor, y_train_tensor)
test_dataset = TensorDataset(X_test_tensor, y_test_tensor)

# Create DataLoaders
batch_size = 128   # Experiment with this
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=batch_size)

# Validation loader (create if needed, or load a separate validation set)
# For simplicity, I'll resplit train_dataset
train_dataset, val_dataset = torch.utils.data.
 ↪random_split(train_dataset,[int(len(train_dataset)*0.85),len(train_dataset)␣
 ↪- int(len(train_dataset)*0.85)])
val_loader = DataLoader(val_dataset, batch_size=batch_size)
```

Define the Neural Network Model

[111]:
```
class Net(nn.Module):
    def __init__(self, input_size, num_classes):
        super(Net, self).__init__()
        self.fc1 = nn.Linear(input_size, 256)
        self.bn1 = nn.BatchNorm1d(256)
        self.relu1 = nn.ReLU()
        self.dropout1 = nn.Dropout(0.5)
        self.fc2 = nn.Linear(256, 256)
        self.bn2 = nn.BatchNorm1d(256)
        self.relu2 = nn.ReLU()
        self.dropout2 = nn.Dropout(0.5)
        self.fc3 = nn.Linear(256, 128)
        self.bn3 = nn.BatchNorm1d(128)
        self.relu3 = nn.ReLU()
        self.dropout3 = nn.Dropout(0.3)
        self.fc4 = nn.Linear(128, 64)
        self.relu4 = nn.ReLU()
        self.fc5 = nn.Linear(64, num_classes)

    def forward(self, x):
        x = self.fc1(x)
        x = self.bn1(x)
        x = self.relu1(x)
```

```
        x = self.dropout1(x)
        x = self.fc2(x)
        x = self.bn2(x)
        x = self.relu2(x)
        x = self.dropout2(x)
        x = self.fc3(x)
        x = self.bn3(x)
        x = self.relu3(x)
        x = self.dropout3(x)
        x = self.fc4(x)
        x = self.relu4(x)
        x = self.fc5(x)
        return x

input_size = X_train_tensor.shape[1]
num_classes = len(label_encoder.classes_)
model = Net(input_size, num_classes)
```

Define Loss Function

[112]:
```
# Loss and Optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-5)

# DataLoaders
batch_size = 64
train_dataset = TensorDataset(X_train_tensor, y_train_tensor)
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
val_dataset = TensorDataset(X_val_tensor, y_val_tensor)
val_loader = DataLoader(val_dataset, batch_size=batch_size)
test_dataset = TensorDataset(X_test_tensor, y_test_tensor)
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)
```

Train the Model

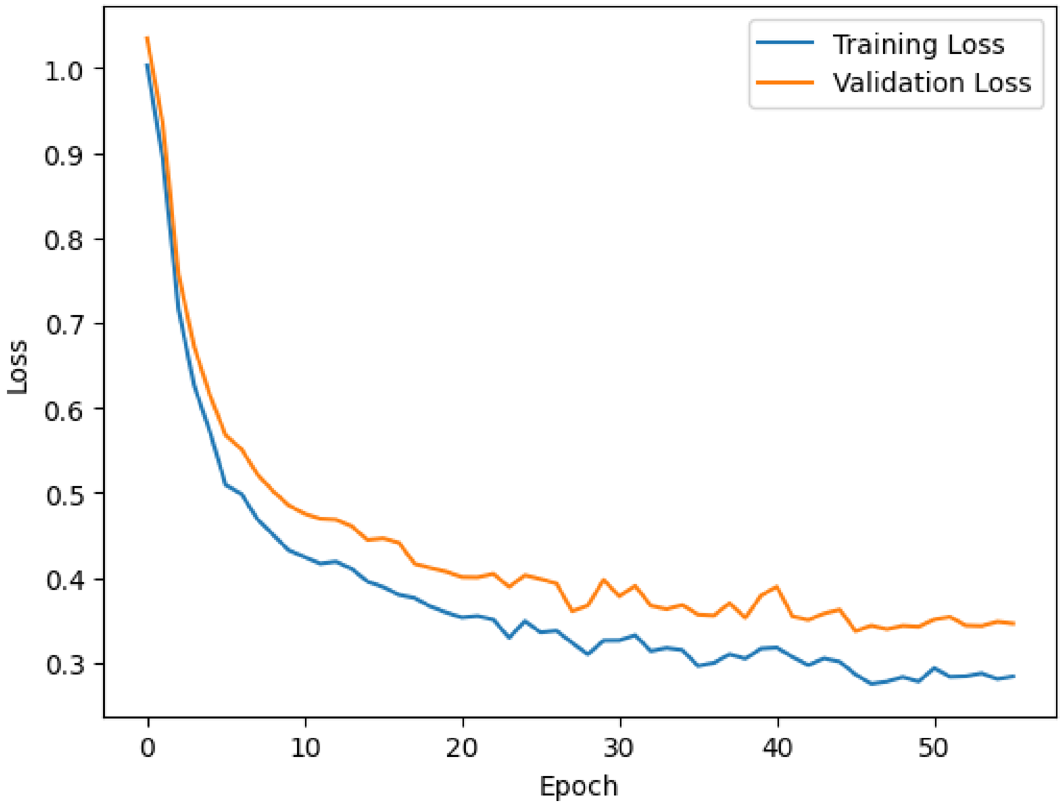
[113]:
```
num_epochs = 300
patience = 10
best_val_loss = float('inf')
no_improve_count = 0
train_losses = []
val_losses = []

for epoch in range(num_epochs):
    model.train()
    for inputs, labels in train_loader:
        optimizer.zero_grad()
        outputs = model(inputs)
        loss = criterion(outputs, labels)
```

```
        loss.backward()
        optimizer.step()

    model.eval()
    with torch.no_grad():
        train_loss = sum(criterion(model(inputs), labels).item() for inputs,␣
↪labels in train_loader) / len(train_loader)
        val_loss = sum(criterion(model(inputs), labels).item() for inputs,␣
↪labels in val_loader) / len(val_loader)

    train_losses.append(train_loss)
    val_losses.append(val_loss)

    print(f'Epoch [{epoch+1}/{num_epochs}], Train Loss: {train_loss:.4f}, Val␣
↪Loss: {val_loss:.4f}')

    if val_loss < best_val_loss:
        best_val_loss = val_loss
        no_improve_count = 0
        torch.save(model.state_dict(), 'Neural_Network_Best_Model.pth')
    else:
        no_improve_count += 1
        if no_improve_count >= patience:
            print('Early stopping!')
            model.load_state_dict(torch.load('Neural_Network_Best_Model.pth'))
            break

# Plotting Loss Curves
plt.plot(train_losses, label='Training Loss')
plt.plot(val_losses, label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()

# Evaluation and Confusion Matrix (AFTER the training loop)
model.eval()
with torch.no_grad():
    y_pred = []
    y_true = []
    for inputs, labels in test_loader:
        outputs = model(inputs)
        _, predicted = torch.max(outputs, 1)
        y_pred.extend(predicted.cpu().numpy())
        y_true.extend(labels.cpu().numpy())

    y_pred = np.array(y_pred, dtype=np.int64)
```

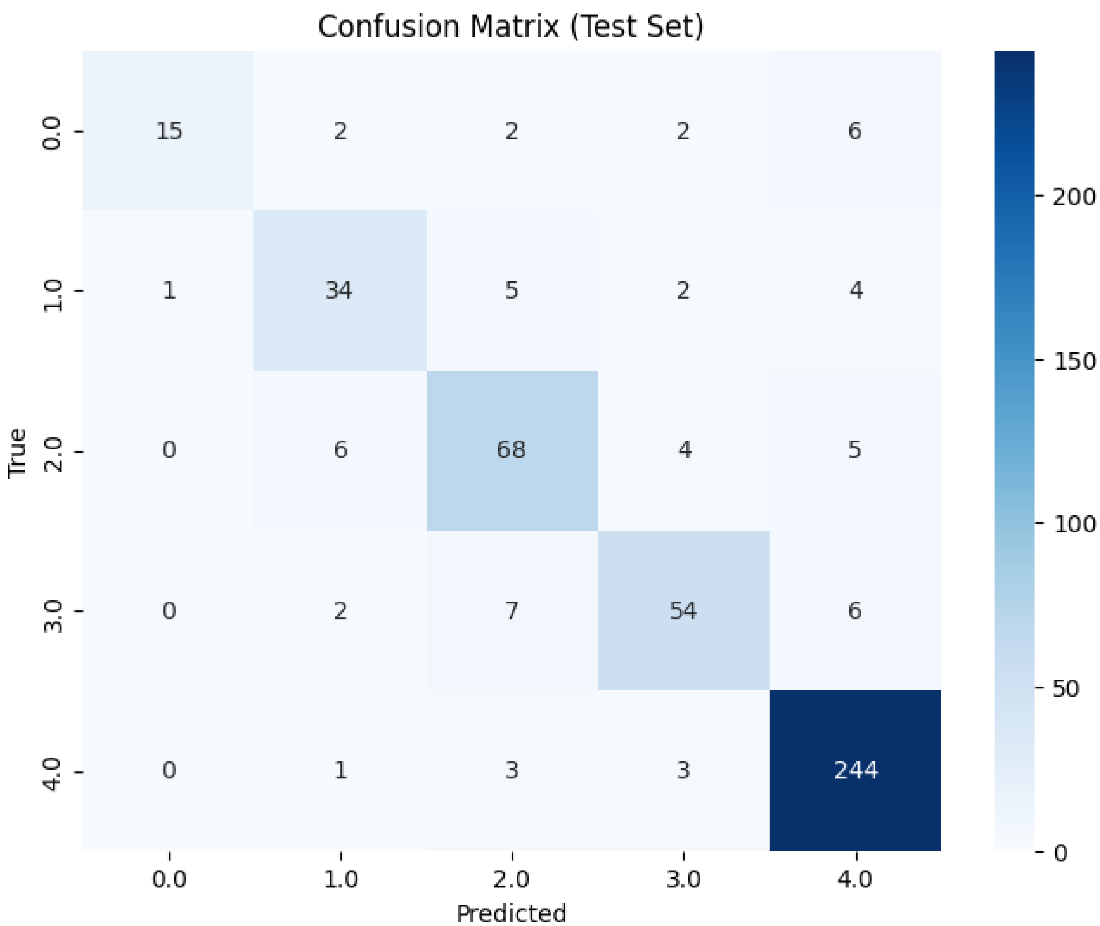
```
    y_true = np.array(y_true, dtype=np.int64)

    target_names = [str(cls) for cls in label_encoder.classes_]
    print("Classification Report:\n", classification_report(y_true, y_pred,␣
↪target_names=target_names))

    # Confusion Matrix
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',␣
↪xticklabels=target_names, yticklabels=target_names)
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.title('Confusion Matrix (Test Set)')
    plt.show()

    print("Model Evaluation Complete")
```

```
Epoch [1/300], Train Loss: 1.0032, Val Loss: 1.0350
Epoch [2/300], Train Loss: 0.8934, Val Loss: 0.9348
Epoch [3/300], Train Loss: 0.7166, Val Loss: 0.7576
Epoch [4/300], Train Loss: 0.6257, Val Loss: 0.6715
Epoch [5/300], Train Loss: 0.5716, Val Loss: 0.6147
Epoch [6/300], Train Loss: 0.5089, Val Loss: 0.5674
Epoch [7/300], Train Loss: 0.4984, Val Loss: 0.5512
Epoch [8/300], Train Loss: 0.4691, Val Loss: 0.5218
Epoch [9/300], Train Loss: 0.4505, Val Loss: 0.5018
Epoch [10/300], Train Loss: 0.4322, Val Loss: 0.4851
Epoch [11/300], Train Loss: 0.4243, Val Loss: 0.4753
Epoch [12/300], Train Loss: 0.4163, Val Loss: 0.4692
Epoch [13/300], Train Loss: 0.4187, Val Loss: 0.4682
Epoch [14/300], Train Loss: 0.4102, Val Loss: 0.4605
Epoch [15/300], Train Loss: 0.3954, Val Loss: 0.4443
Epoch [16/300], Train Loss: 0.3889, Val Loss: 0.4462
Epoch [17/300], Train Loss: 0.3797, Val Loss: 0.4410
Epoch [18/300], Train Loss: 0.3759, Val Loss: 0.4161
Epoch [19/300], Train Loss: 0.3659, Val Loss: 0.4113
Epoch [20/300], Train Loss: 0.3589, Val Loss: 0.4068
Epoch [21/300], Train Loss: 0.3529, Val Loss: 0.4006
Epoch [22/300], Train Loss: 0.3546, Val Loss: 0.4003
Epoch [23/300], Train Loss: 0.3505, Val Loss: 0.4043
Epoch [24/300], Train Loss: 0.3291, Val Loss: 0.3890
Epoch [25/300], Train Loss: 0.3487, Val Loss: 0.4028
Epoch [26/300], Train Loss: 0.3355, Val Loss: 0.3982
Epoch [27/300], Train Loss: 0.3374, Val Loss: 0.3932
Epoch [28/300], Train Loss: 0.3232, Val Loss: 0.3603
Epoch [29/300], Train Loss: 0.3096, Val Loss: 0.3670
```

```
Epoch [30/300], Train Loss: 0.3258, Val Loss: 0.3974
Epoch [31/300], Train Loss: 0.3259, Val Loss: 0.3779
Epoch [32/300], Train Loss: 0.3320, Val Loss: 0.3903
Epoch [33/300], Train Loss: 0.3135, Val Loss: 0.3669
Epoch [34/300], Train Loss: 0.3171, Val Loss: 0.3628
Epoch [35/300], Train Loss: 0.3146, Val Loss: 0.3677
Epoch [36/300], Train Loss: 0.2958, Val Loss: 0.3564
Epoch [37/300], Train Loss: 0.2995, Val Loss: 0.3553
Epoch [38/300], Train Loss: 0.3098, Val Loss: 0.3699
Epoch [39/300], Train Loss: 0.3045, Val Loss: 0.3526
Epoch [40/300], Train Loss: 0.3164, Val Loss: 0.3789
Epoch [41/300], Train Loss: 0.3175, Val Loss: 0.3892
Epoch [42/300], Train Loss: 0.3065, Val Loss: 0.3543
Epoch [43/300], Train Loss: 0.2967, Val Loss: 0.3502
Epoch [44/300], Train Loss: 0.3049, Val Loss: 0.3576
Epoch [45/300], Train Loss: 0.3008, Val Loss: 0.3622
Epoch [46/300], Train Loss: 0.2858, Val Loss: 0.3369
Epoch [47/300], Train Loss: 0.2748, Val Loss: 0.3434
Epoch [48/300], Train Loss: 0.2775, Val Loss: 0.3391
Epoch [49/300], Train Loss: 0.2828, Val Loss: 0.3432
Epoch [50/300], Train Loss: 0.2776, Val Loss: 0.3421
Epoch [51/300], Train Loss: 0.2933, Val Loss: 0.3506
Epoch [52/300], Train Loss: 0.2831, Val Loss: 0.3537
Epoch [53/300], Train Loss: 0.2837, Val Loss: 0.3436
Epoch [54/300], Train Loss: 0.2871, Val Loss: 0.3430
Epoch [55/300], Train Loss: 0.2805, Val Loss: 0.3480
Epoch [56/300], Train Loss: 0.2835, Val Loss: 0.3459
Early stopping!
```




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

         0.0       0.94      0.56      0.70        27
         1.0       0.76      0.74      0.75        46
         2.0       0.80      0.82      0.81        83
         3.0       0.83      0.78      0.81        69
         4.0       0.92      0.97      0.95       251

    accuracy                           0.87       476
   macro avg       0.85      0.77      0.80       476
weighted avg       0.87      0.87      0.87       476
```




```
Model Evaluation Complete
```

Evaluate the Model

[114]:
```python
# Evaluate the Model
model.eval()
with torch.no_grad():
    y_pred = []
    y_true = []
    for inputs, labels in test_loader:
        outputs = model(inputs)
        _, predicted = torch.max(outputs, 1)
        y_pred.extend(predicted.cpu().numpy())
        y_true.extend(labels.cpu().numpy())

    y_pred = np.array(y_pred)
    y_true = np.array(y_true)
```

```python
print("Classification Report:\n", classification_report(y_true, y_pred,␣
↪target_names=target_names))
print("Accuracy:\n", accuracy_score(y_true, y_pred))
```

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

         0.0       0.94      0.56      0.70        27
         1.0       0.76      0.74      0.75        46
         2.0       0.80      0.82      0.81        83
         3.0       0.83      0.78      0.81        69
         4.0       0.92      0.97      0.95       251

    accuracy                           0.87       476
   macro avg       0.85      0.77      0.80       476
weighted avg       0.87      0.87      0.87       476

Accuracy:
 0.8718487394957983
```