# APPLIED MACHINE LEARNING PROJECT

## Predictive Analysis of Depression in Students

Prepared by:

| Name | Batch | SAP ID | Specialization |
|---|---|---|---|
| Rashi Raj | 5 | 500122395 | AIML CSE |

School Of Computer Science
UNIVERSITY OF PETROLEUM & ENERGY STUDIES,
Dehradun-248007, Uttarakhand

## Predictive Modeling for Student Depression: A Data-Driven Approach

# Objective

The goal of this project is to identify the **most influential factors** contributing to **depression among students** using a combination of **feature selection techniques** and exploratory data analysis. The insights gained lay the foundation for building predictive models that could assist educational institutions and mental health professionals in **early detection and intervention**.

# Dataset Overview

- **Dataset:** Student Depression Dataset
- **Source:** Kaggle
- **Total Records:** 27,901
- **Features:** 18 variables, including demographic, academic, psychological, and lifestyle aspects
- **Target Variable:** Depression (Binary: 0 = No Depression, 1 = Depression)

## 📌 Key Features:

- **Demographic:** Age, Gender, City, Degree
- **Academic:** CGPA, Academic Pressure, Study/Work Hours
- **Lifestyle:** Sleep Duration, Dietary Habits
- **Psychological:** Study Satisfaction, Financial Stress, Suicidal Thoughts, Family Mental Health History

# Data Preprocessing & Cleaning

- **Missing Values:** Dataset was complete with no missing values.
- **Encoding:** Categorical features (e.g., Sleep Duration, Financial Stress) encoded appropriately.
- **Outlier Detection:** Analyzed via standard deviation and boxplots.
- **Standardization:** Applied to numerical variables where necessary.

# Feature Selection Techniques

A multi-method approach was adopted to ensure **robust feature relevance**:

## 1. Filter Methods:

- **Correlation Matrix** and **Mutual Information Scores** identified statistically significant variables.

## 2. Wrapper Methods:

- **Recursive Feature Elimination (RFE)** was used with logistic regression to iteratively rank features.

## 3. Embedded Methods:

- **Lasso Regression** highlighted variables with the strongest coefficients.
- **Decision Tree Classifier** ranked features by Gini-based importance.

# Key Predictive Features Identified

After consolidating results from all three selection methods, the most impactful predictors of depression are:

| Rank | Feature | Insight |
|---|---|---|
| 1 | **Academic Pressure** | High academic burden strongly correlates with depression. |
| 2 | **Study Satisfaction** | Lower satisfaction levels are indicative of psychological |
| 3 | **Sleep Duration** | Students sleeping less than 6 hours show higher depression |
| 4 | **Financial Stress** | Economic strain is a consistent stressor impacting mental health. |
| 5 | **Suicidal Thoughts** | The presence of suicidal ideation is a critical indicator. |
| 6 | **Family History of Mental Illness** | A known predictor of hereditary mental health risks. |
| 7 | **Work/Study Hours** | Extended study/work hours are linked to fatigue and mental burnout. |

# Evaluation and Visualization Highlights

- **Heatmaps** demonstrated strong correlations between academic pressure, financial stress, and depression.
- **Bar plots** from decision tree feature importances ranked Suicidal Thoughts, Academic Pressure, and Sleep Duration highest.
- **Boxplots** revealed that depressed students typically had:
  - Lower CGPA
  - Higher academic/work pressure
  - Shorter sleep durations

# Insights and Implications

This analysis uncovers several important conclusions:

1. **Multifactorial Nature of Depression:**
   Depression in students isn't triggered by a single cause—it results from a **combination of academic, psychological, and lifestyle stressors**.
2. **Psychological Indicators Matter:**
   Variables like **suicidal thoughts** and **family history of mental illness** are critical red flags for intervention.
3. **Academic Environment Plays a Major Role:**
   High academic pressure, long working hours, and low satisfaction with studies contribute significantly to mental fatigue and depression.
4. **Lifestyle Factors Are Often Overlooked:**
   Poor sleep hygiene and unhealthy dietary habits, while less strongly correlated, still contribute to the overall risk.

### CODE SNIPPETS :

```python
import pandas as pd
from sklearn.preprocessing import LabelEncoder

# Step 2: Load the dataset
df = pd.read_csv('student_depression_dataset.csv')  # change path if needed

# Step 3: Drop unnecessary ID column
df.drop(columns=['id'], inplace=True)

# Step 4: Convert Yes/No columns to binary
df['Suicidal_Thoughts'] = df['Have you ever had suicidal thoughts ?'].map({'Yes': 1, 'No': 0})
df['Family_History'] = df['Family History of Mental Illness'].map({'Yes': 1, 'No': 0})
df.drop(columns=['Have you ever had suicidal thoughts ?', 'Family History of Mental Illness'], inplace=True)

# Step 5: Map ordinal values to numbers
sleep_map = {
    "'Less than 5 hours'": 1,
    "'5-6 hours'": 2,
    "'7-8 hours'": 3,
    "'More than 8 hours'": 4,
    "'Irregular'": 0
}
df['Sleep_Duration'] = df['Sleep Duration'].map(sleep_map)
diet_map = {
    'Healthy': 2,
    'Moderate': 1,
    'Unhealthy': 0,
    'Irregular': 0
}
df['Dietary_Habits'] = df['Dietary Habits'].map(diet_map)

# Convert Financial Stress to numeric
df['Financial_Stress'] = pd.to_numeric(df['Financial Stress'], errors='coerce')
df.drop(columns=['Sleep Duration', 'Financial Stress'], inplace=True)

# Step 6: Label Encode remaining categorical columns
label_cols = ['Gender', 'City', 'Profession', 'Degree']
le = LabelEncoder()
for col in label_cols:
    df[col] = le.fit_transform(df[col])
```

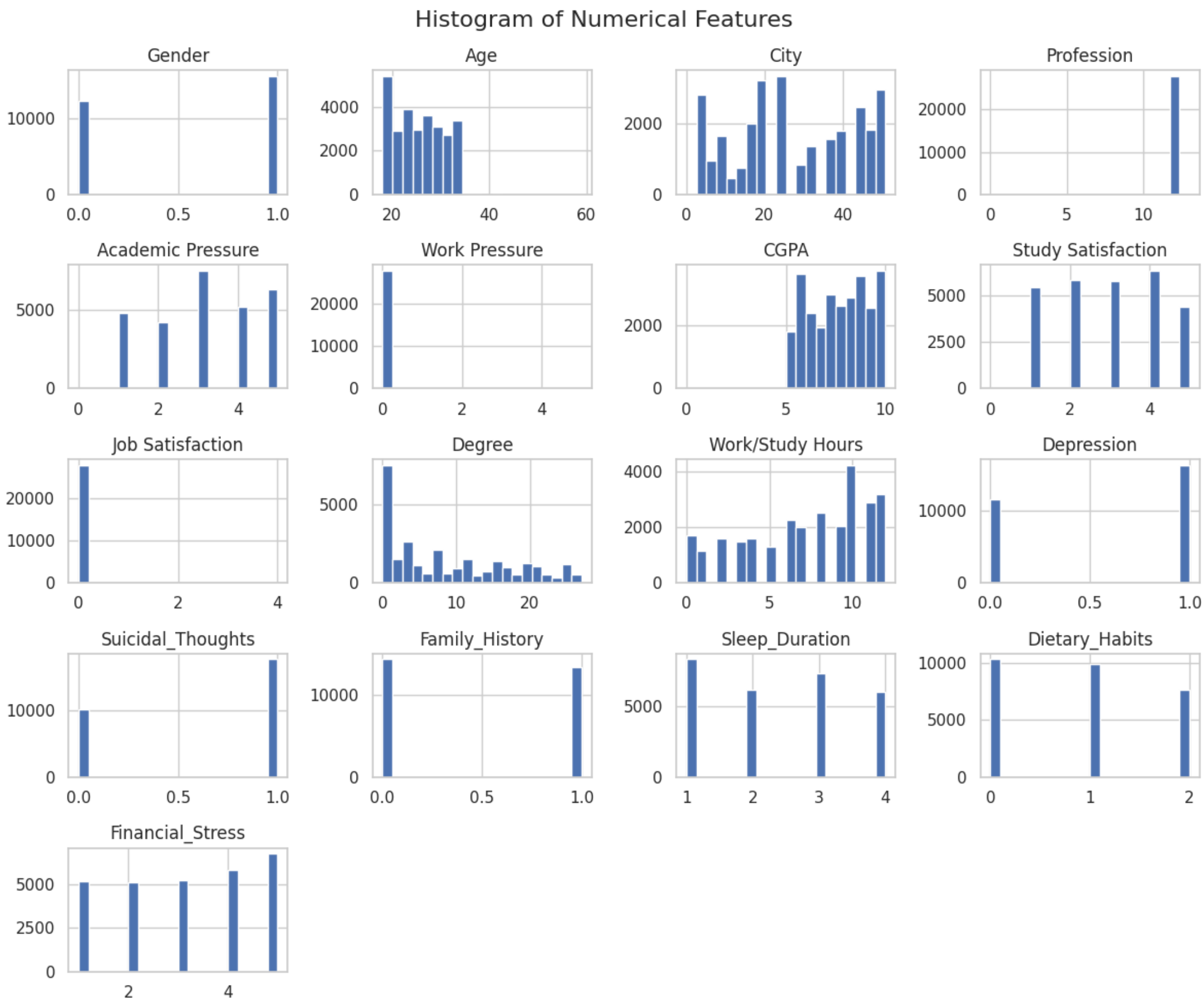
```
# Step 7: Handle missing values (if any)
for col in df.columns:
    if df[col].isnull().sum() > 0:
        if df[col].dtype in ['float64', 'int64']:
            df[col].fillna(df[col].median(), inplace=True)
        else:
            df[col].fillna(df[col].mode()[0], inplace=True)

# Step 8: Final check
print(df.info())
print(df.head())
```

```
Data columns (total 18 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Gender              27901 non-null  int64  
 1   Age                 27901 non-null  float64
 2   City                27901 non-null  int64  
 3   Profession          27901 non-null  int64  
 4   Academic Pressure   27901 non-null  float64
 5   Work Pressure       27901 non-null  float64
 6   CGPA                27901 non-null  float64
 7   Study Satisfaction  27901 non-null  float64
 8   Job Satisfaction    27901 non-null  float64
 9   Dietary Habits      27901 non-null  object 
 10  Degree              27901 non-null  int64  
 11  Work/Study Hours    27901 non-null  float64
 12  Depression          27901 non-null  int64  
 13  Suicidal_Thoughts   27901 non-null  int64  
 14  Family_History      27901 non-null  int64  
 15  Sleep_Duration      27901 non-null  float64
 16  Dietary_Habits      27901 non-null  float64
 17  Financial_Stress    27901 non-null  float64
dtypes: float64(10), int64(7), object(1)
memory usage: 3.8+ MB
None
   Gender   Age  City  Profession  Academic Pressure  Work Pressure  CGPA  \
0       1  33.0    51          12                5.0            0.0  8.97   
1       0  24.0     5          12                2.0            0.0  5.90   
2       1  31.0    44          12                3.0            0.0  7.03   
3       0  28.0    49          12                3.0            0.0  5.59   
4       0  25.0    18          12                4.0            0.0  8.13   

   Study Satisfaction  Job Satisfaction Dietary Habits  Degree  \
0                 2.0               0.0        Healthy       4   
1                 5.0               0.0       Moderate      11   
2                 5.0               0.0        Healthy       6   
3                 2.0               0.0       Moderate       8   
4                 3.0               0.0       Moderate      17   

   Work/Study Hours  Depression  Suicidal_Thoughts  Family_History  \
0               3.0           1                  1               0   
1               3.0           0                  0               1   
2               9.0           0                  0               1   
3               4.0           1                  1               1   
4               1.0           0                  1               0   

   Sleep_Duration  Dietary_Habits  Financial_Stress  
0             2.0             2.0               1.0  
1             2.0             1.0               2.0  
2             1.0             2.0               1.0  
3             3.0             1.0               5.0  
4             2.0             1.0               1.0  
<ipython-input-3-0a0977cc9d71>:47: FutureWarning: A value is trying
The behavior will change in pandas 3.0. This inplace method will nev
```

# Visualisation

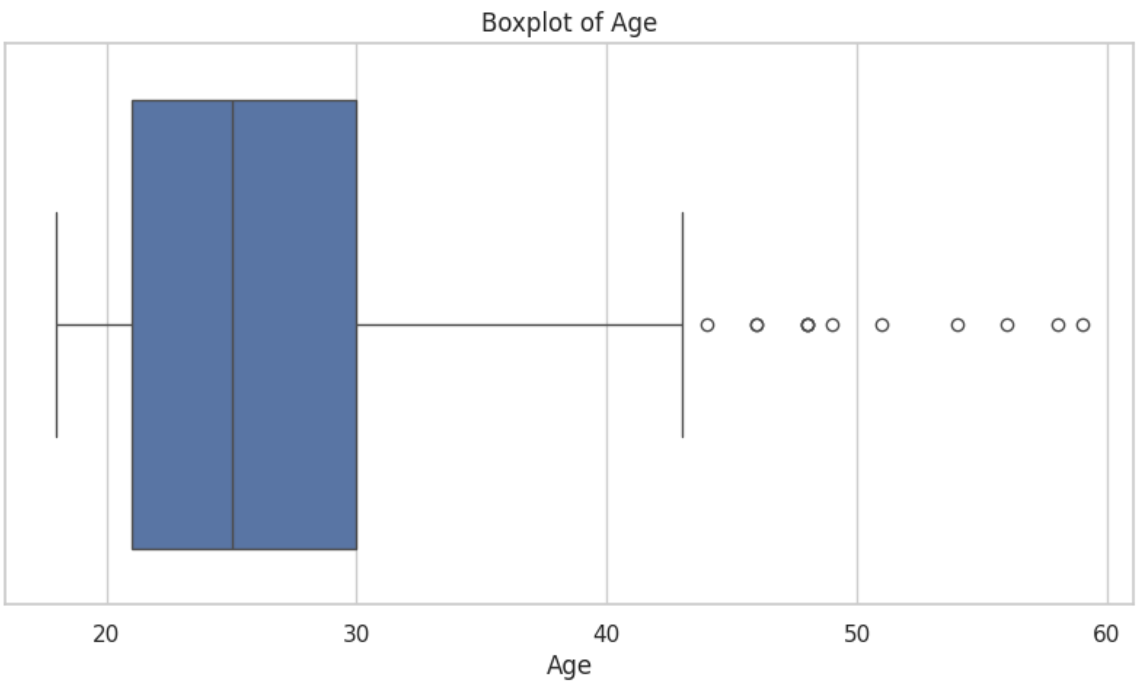
## I) Histogram

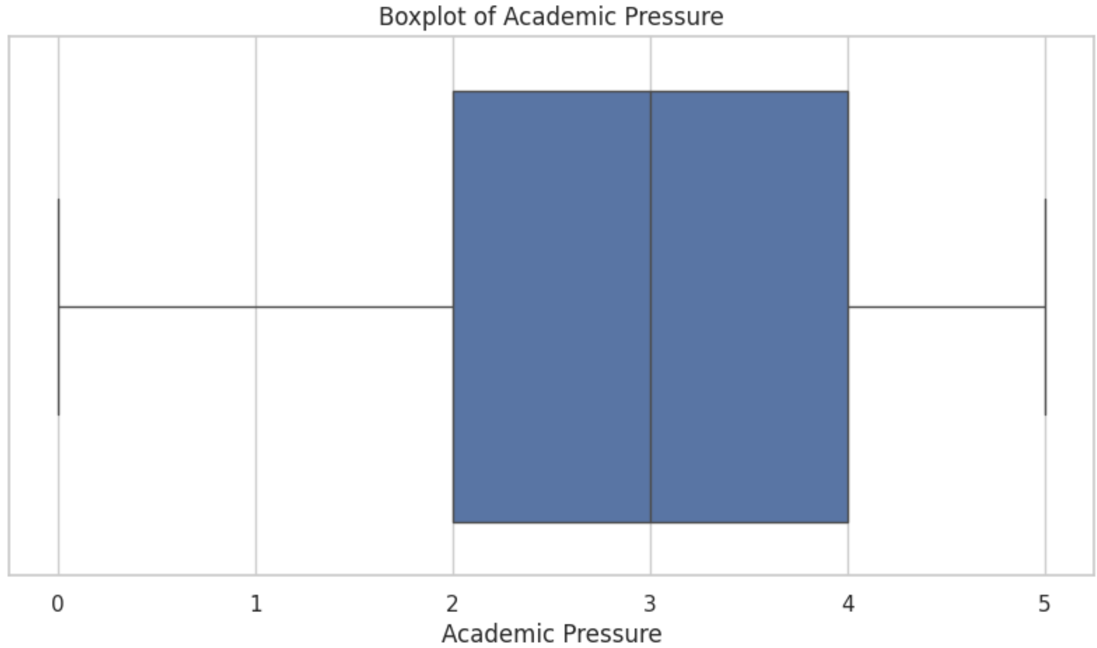
```
df.hist(figsize=(12, 10), bins=20)
plt.suptitle('Histogram of Numerical Features', fontsize=16)
plt.tight_layout()
plt.show()
```

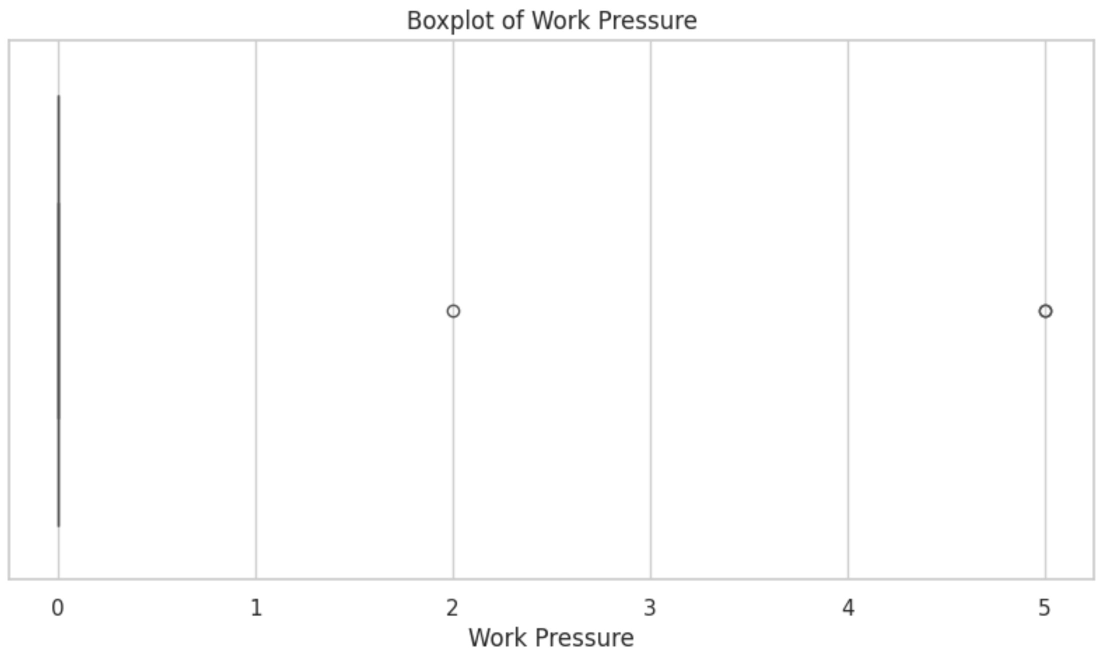


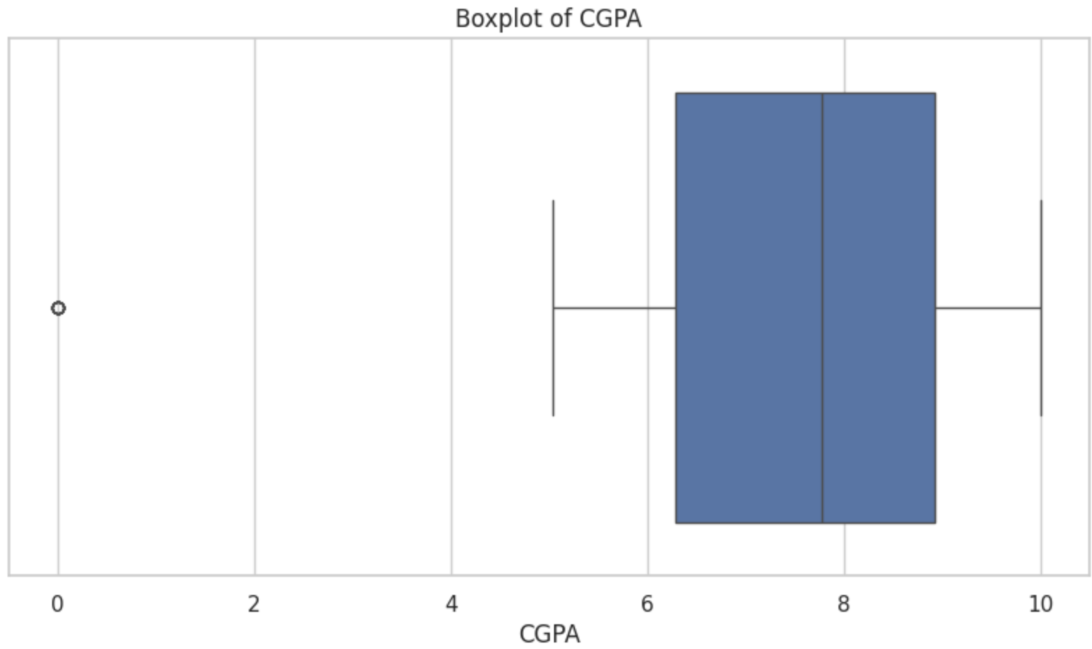
### ii) Box Plot (Outlier Detection)

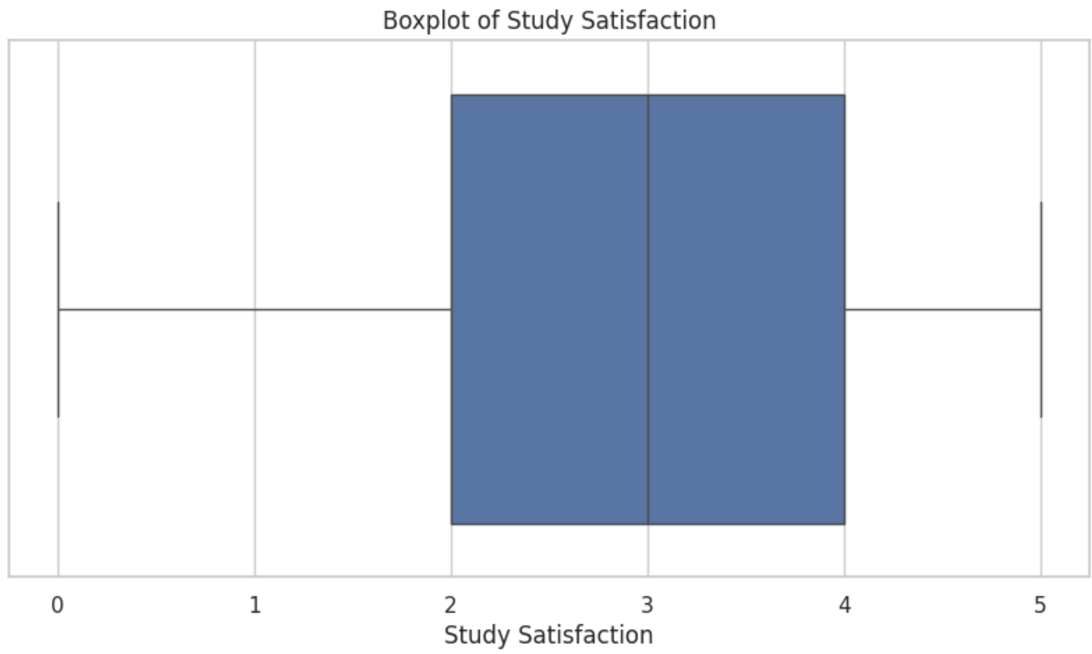
```
[ ]  import matplotlib.pyplot as plt
     import seaborn as sns

     sns.set(style="whitegrid")

     numeric_columns = [
         'Age',
         'Academic Pressure',
         'Work Pressure',
         'CGPA',
         'Study Satisfaction',
         'Job Satisfaction',
         'Work/Study Hours',
         'Financial_Stress'
     ]


     for col in numeric_columns:
         plt.figure(figsize=(10, 5))
         sns.boxplot(x=df[col])
         plt.title(f'Boxplot of {col}')
         plt.xlabel(col)
         plt.show()
```

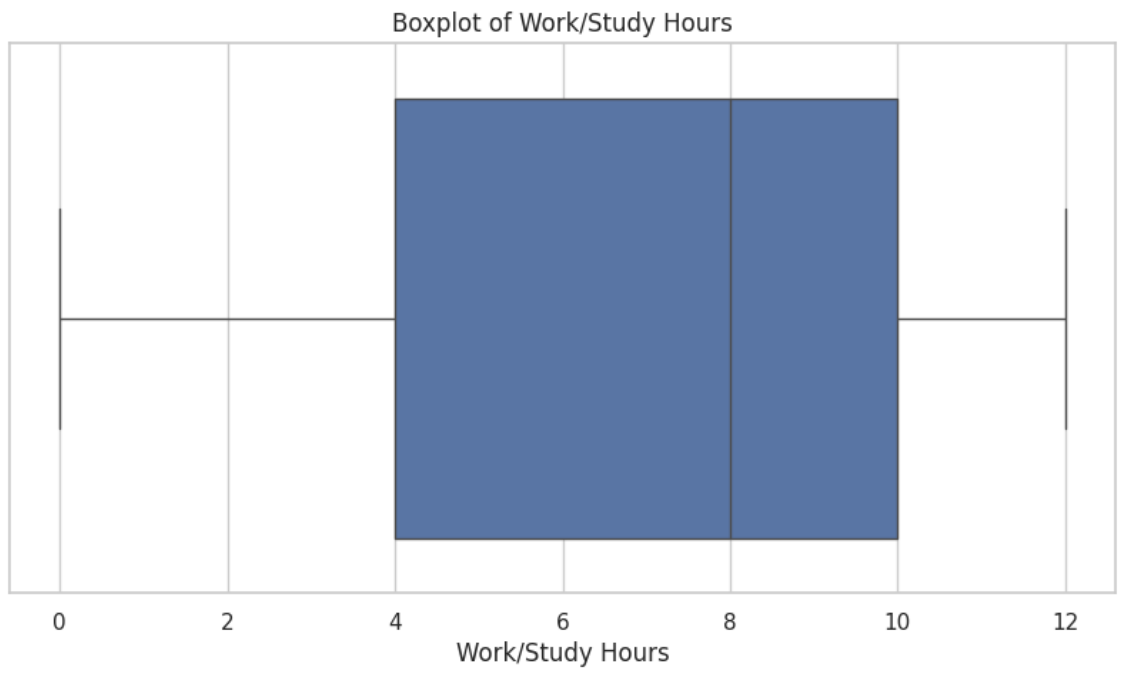


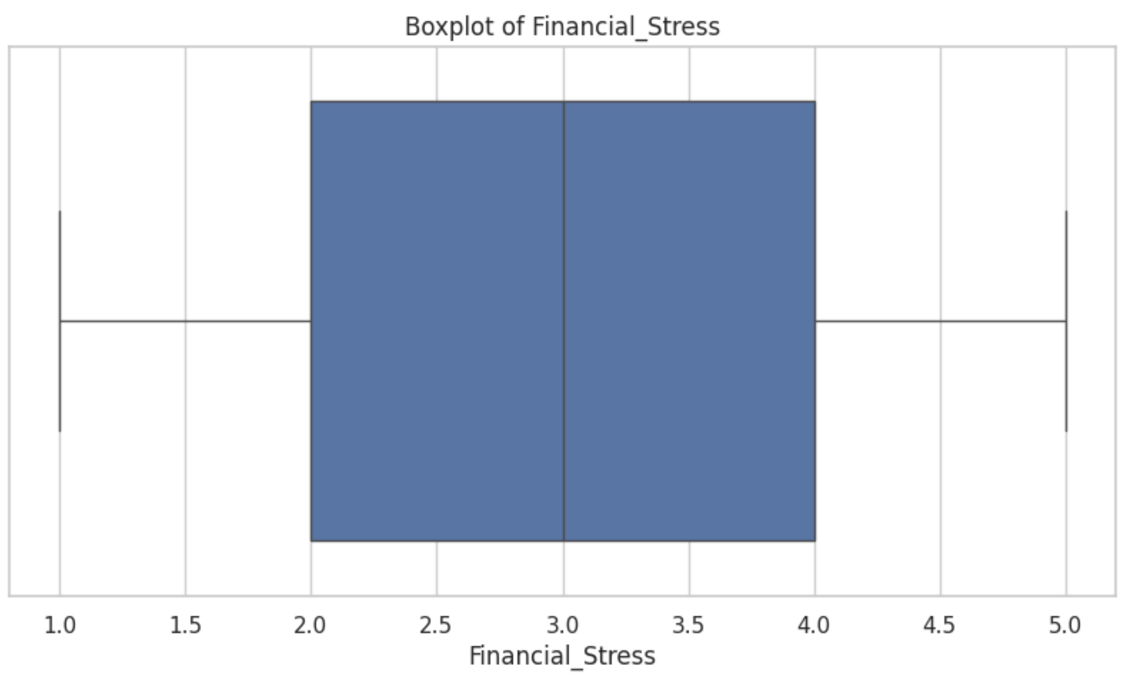

Boxplot of Academic Pressure
0
1
2
3
4
5
Academic Pressure


Boxplot of Work Pressure
0
1
2
3
4
5
Work Pressure


Boxplot of CGPA
0
2
4
6
8
10
CGPA

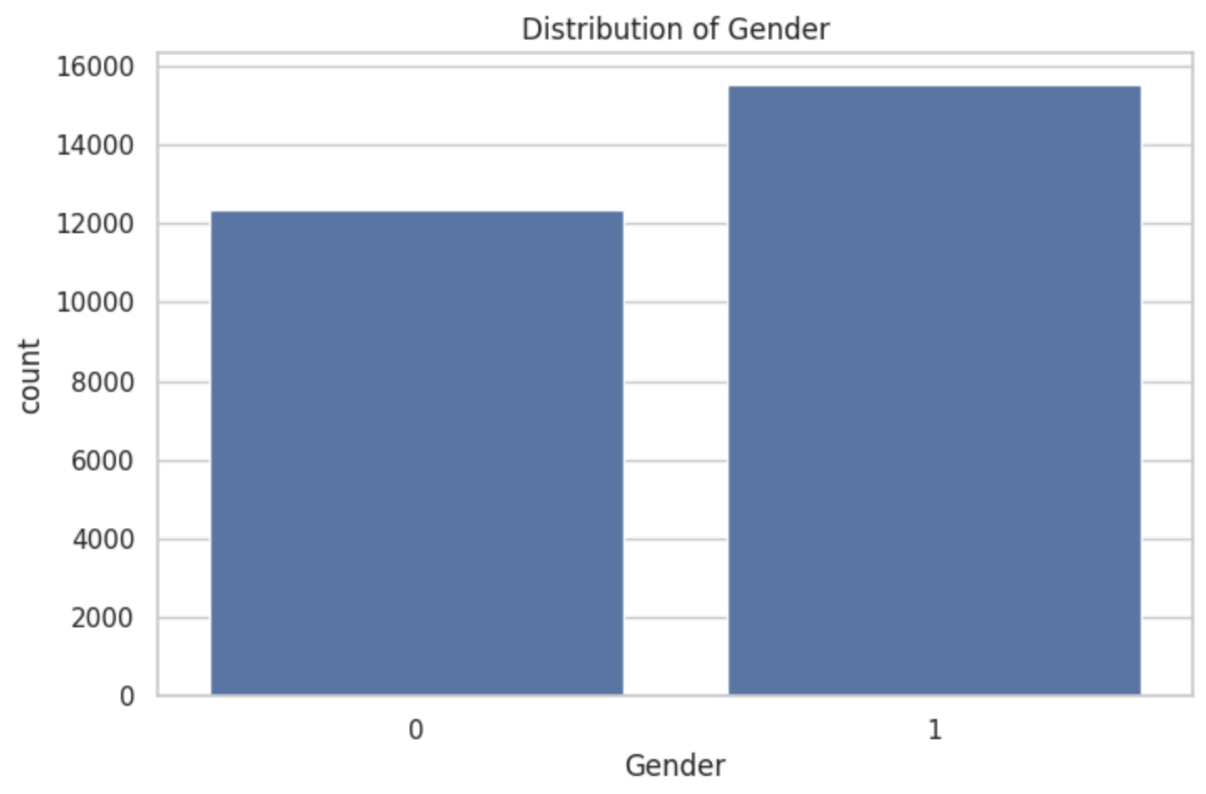

Boxplot of Study Satisfaction
0
1
2
3
4
5
Study Satisfaction


Boxplot of Work/Study Hours
0
2
4
6
8
10
12
Work/Study Hours


Boxplot of Financial_Stress
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Financial_Stress

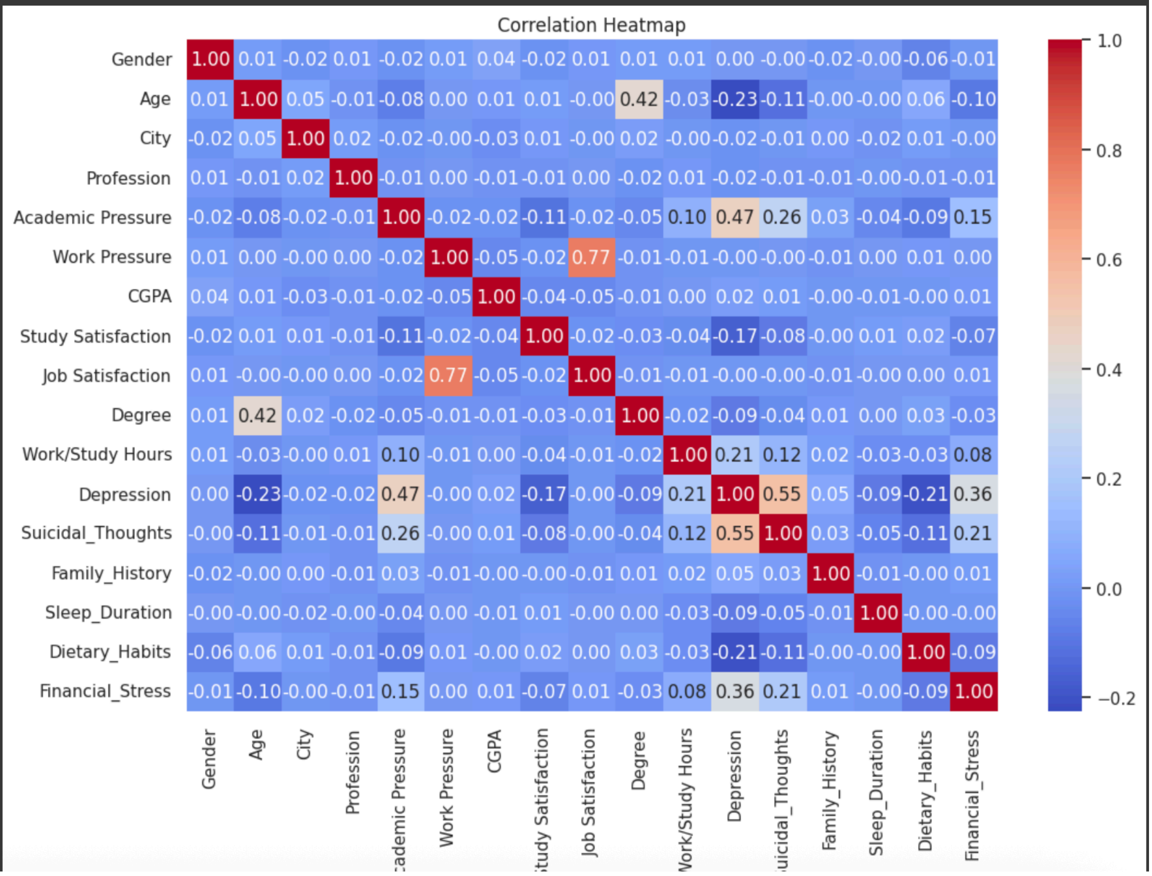
### iii) Bar Charts for Categorical Data

```
[ ] plt.figure(figsize=(8, 5))
    sns.countplot(x='Gender', data=df)
    plt.title('Distribution of Gender')
    plt.show()
```



## iv) Correlation Heatmap

```python
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(numeric_only=True), annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')
plt.show()
```




## V) Remove Outliers Using Z-Score

```python
from scipy.stats import zscore

# Select numerical columns
num_cols = ['Age', 'CGPA', 'Work/Study Hours', 'Academic Pressure', 'Work Pressure']

# Compute Z-scores
z_scores = df[num_cols].apply(zscore)

# Filter rows where all Z-scores are within [-3, 3]
df_no_outliers = df[(z_scores.abs() <= 3).all(axis=1)]

# Display shape before and after
print("Original shape:", df.shape)
print("Shape after removing outliers:", df_no_outliers.shape)

# Optionally, save the cleaned dataset
df_no_outliers.to_csv("cleaned_student_depression_dataset.csv", index=False)
```

```
Original shape: (27901, 18)
Shape after removing outliers: (27873, 18)
```

### VI) Encode Categorical Variables using OneHot Encoder.

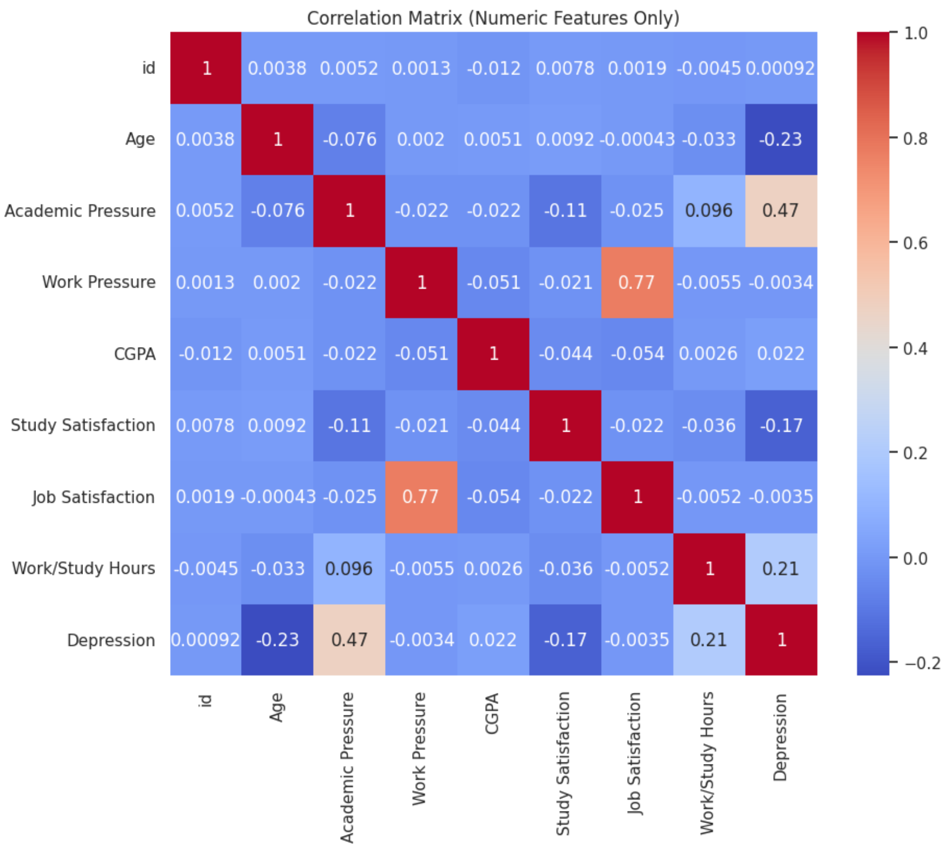
```
[ ] import pandas as pd


    cat_cols = df.select_dtypes(include='object').columns

    # One-Hot Encoding
    df_encoded = pd.get_dummies(df, columns=cat_cols, drop_first=True)

    print("Original shape:", df.shape)
    print("Encoded shape:", df_encoded.shape)
```

```
Original shape: (27901, 18)
Encoded shape: (27901, 20)
```

# Feature Selection

## i. Correlation Matrix - for numerical features

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

df = pd.read_csv('student_depression_dataset.csv')

#only numeric columns
numeric_df = df.select_dtypes(include=['number'])

plt.figure(figsize=(10, 8))
sns.heatmap(numeric_df.corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Matrix (Numeric Features Only)')
plt.show()
```



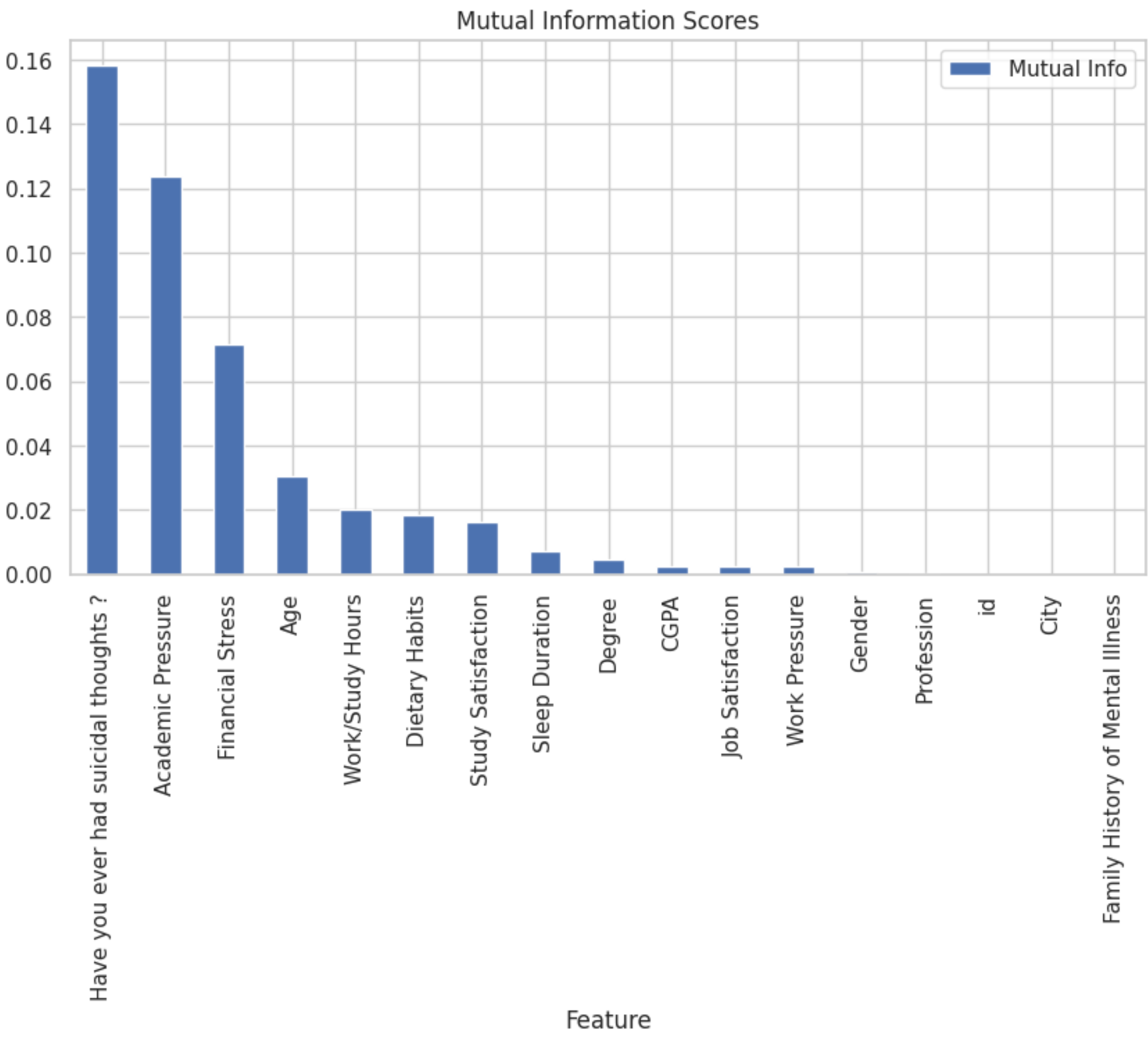
## II) Chi-Square Test

```
[ ] from sklearn.feature_selection import chi2
    from sklearn.preprocessing import LabelEncoder
    import pandas as pd


    # Encode categorical features
    df_encoded = df.copy()
    for col in df_encoded.select_dtypes(include='object').columns:
        df_encoded[col] = LabelEncoder().fit_transform(df_encoded[col])

    # Define X (features) and y (target)
    X = df_encoded.drop('Depression', axis=1)
    y = df_encoded['Depression']

    # Apply chi-square test
    chi_scores = chi2(X, y)

    # Display results
    chi2_results = pd.DataFrame({'Feature': X.columns, 'Chi2 Score': chi_scores[0], 'p-value': chi_scores[1]})
    chi2_results.sort_values(by='Chi2 Score', ascending=False, inplace=True)
    print(chi2_results)
```

```
                                Feature   Chi2 Score        p-value
5                     Academic Pressure  3821.833425   0.000000e+00
15                     Financial Stress  3557.476357   0.000000e+00
13  Have you ever had suicidal thoughts ?  3057.294614   0.000000e+00
14                     Work/Study Hours  2331.007175   0.000000e+00
12                               Degree  1629.322633   0.000000e+00
2                                   Age  1333.049964  7.431387e-292
11                      Dietary Habits  1248.711851  1.581353e-273
0                                    id   557.480304  2.969886e-123
8                   Study Satisfaction   495.417900  9.439564e-110
3                                  City   146.570269   9.742568e-34
16        Family History of Mental Illness    41.103170   1.444020e-10
10                       Sleep Duration    10.478948   1.207425e-03
7                                  CGPA     3.888342   4.862242e-02
6                         Work Pressure     1.409416   2.351533e-01
9                      Job Satisfaction     0.978809   3.224929e-01
1                                Gender     0.039780   8.419114e-01
4                            Profession     0.033266   8.552766e-01
```

### iii) Mutual Information

```
from sklearn.feature_selection import mutual_info_classif

mutual_info = mutual_info_classif(X, y)
mi_df = pd.DataFrame({'Feature': X.columns, 'Mutual Info': mutual_info})
mi_df.sort_values(by='Mutual Info', ascending=False).plot(x='Feature', y='Mutual Info', kind='bar', figsize=(10,5))
plt.title('Mutual Information Scores')
plt.show()
```



## iv) Feature Selection Method

### A. Filter Method - Mutual information

```python
from sklearn.feature_selection import mutual_info_classif

mi_scores = mutual_info_classif(X, y)
mi_df = pd.DataFrame({'Feature': X.columns, 'MI Score': mi_scores})
mi_df = mi_df.sort_values(by='MI Score', ascending=False)
mi_df.head()
```

| | Feature | MI Score |
|---|---|---|
| 13 | Have you ever had suicidal thoughts ? | 0.157499 |
| 5 | Academic Pressure | 0.124283 |
| 15 | Financial Stress | 0.066204 |
| 2 | Age | 0.034810 |
| 11 | Dietary Habits | 0.025127 |

### B. Wrapper method - RFE

```python
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply RFE on scaled data
model = LogisticRegression(max_iter=1000)
rfe = RFE(model, n_features_to_select=5)
rfe.fit(X_scaled, y)

# Get top features
rfe_features = X.columns[rfe.support_]
print("Top RFE Features:", list(rfe_features))
```

```
Top RFE Features: ['Age', 'Academic Pressure', 'Have you ever had suicidal thoughts ?', 'Work/Study Hours', 'Financial Stress']
```

### C. Embedded Method - Decision Tree

```
[ ] from sklearn.tree import DecisionTreeClassifier

    tree = DecisionTreeClassifier()
    tree.fit(X, y)
    tree_importance = tree.feature_importances_
    tree_df = pd.DataFrame({'Feature': X.columns, 'Importance': tree_importance})
    tree_df = tree_df.sort_values(by='Importance', ascending=False)
    tree_df.head()
```

| | Feature | Importance |
|---|---|---|
| 13 | Have you ever had suicidal thoughts ? | 0.298418 |
| 5 | Academic Pressure | 0.132755 |
| 0 | id | 0.093564 |
| 7 | CGPA | 0.077204 |
| 15 | Financial Stress | 0.069449 |

## Compare and count frequently Selected features

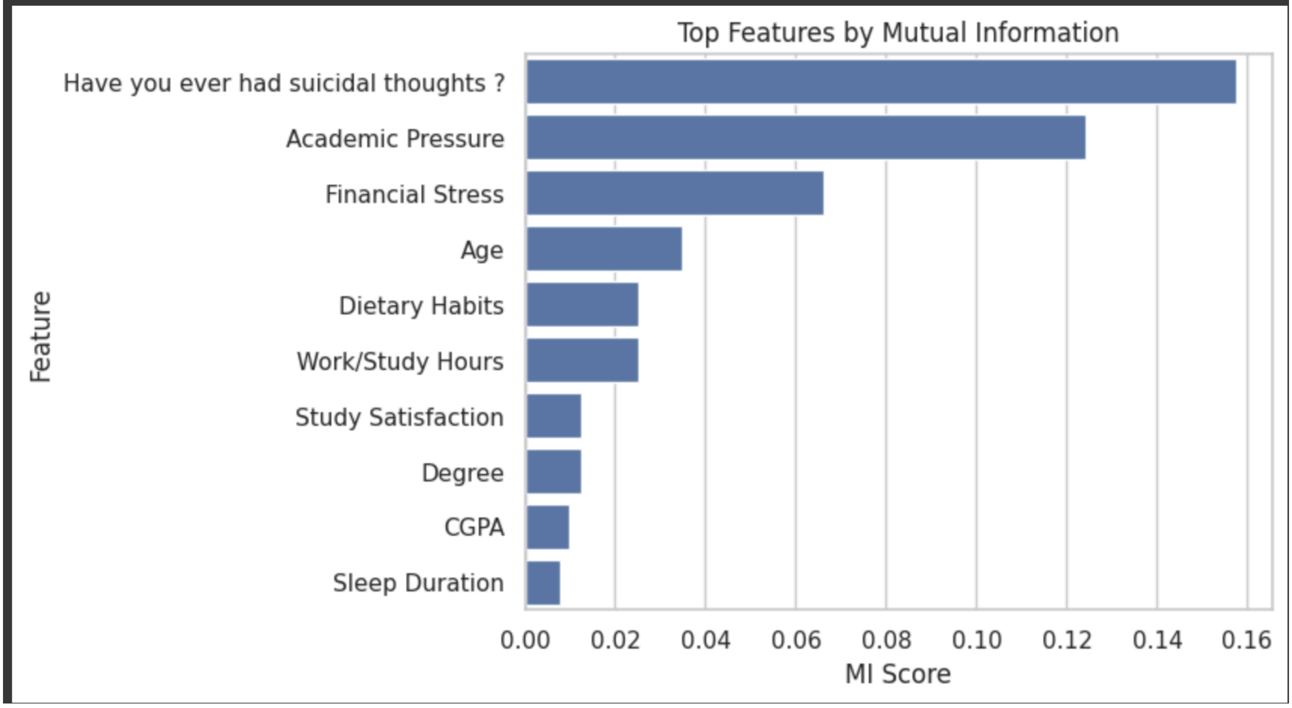
```
# Combine selected top features from each method
top_mi = list(mi_df['Feature'].head(5))
top_rfe = list(rfe_features)
top_tree = list(tree_df['Feature'].head(5))

# Count feature frequency
from collections import Counter
all_selected = top_mi + top_rfe + top_tree
feature_counts = Counter(all_selected)

# Display features sorted by frequency
final_features = pd.DataFrame.from_dict(feature_counts, orient='index', columns=['Count'])
final_features = final_features.sort_values(by='Count', ascending=False)
print(final_features)
```

```
                                       Count
Have you ever had suicidal thoughts ?      3
Academic Pressure                          3
Financial Stress                           3
Age                                        2
Dietary Habits                             1
Work/Study Hours                           1
id                                         1
CGPA                                       1
```

# Evaluation and Visualisation

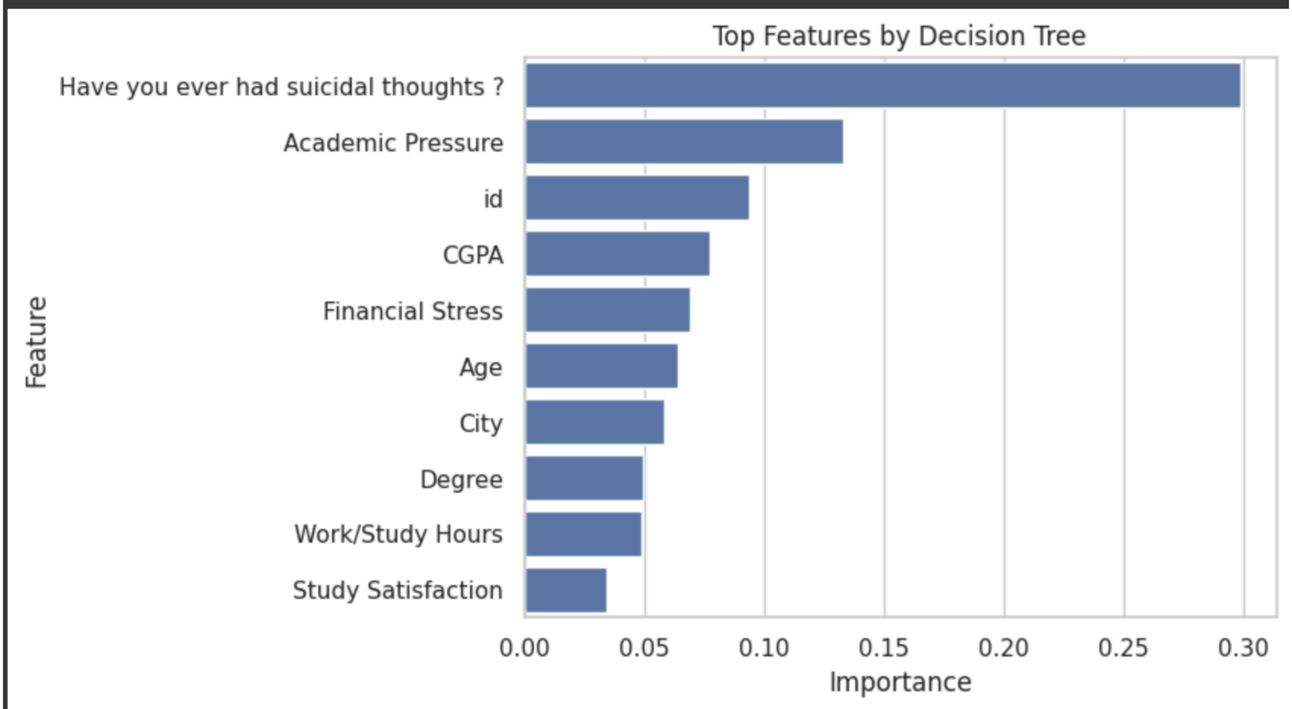
## I. Bar Chart

```
sns.barplot(x='MI Score', y='Feature', data=mi_df.head(10))
plt.title('Top Features by Mutual Information')
plt.show()
```



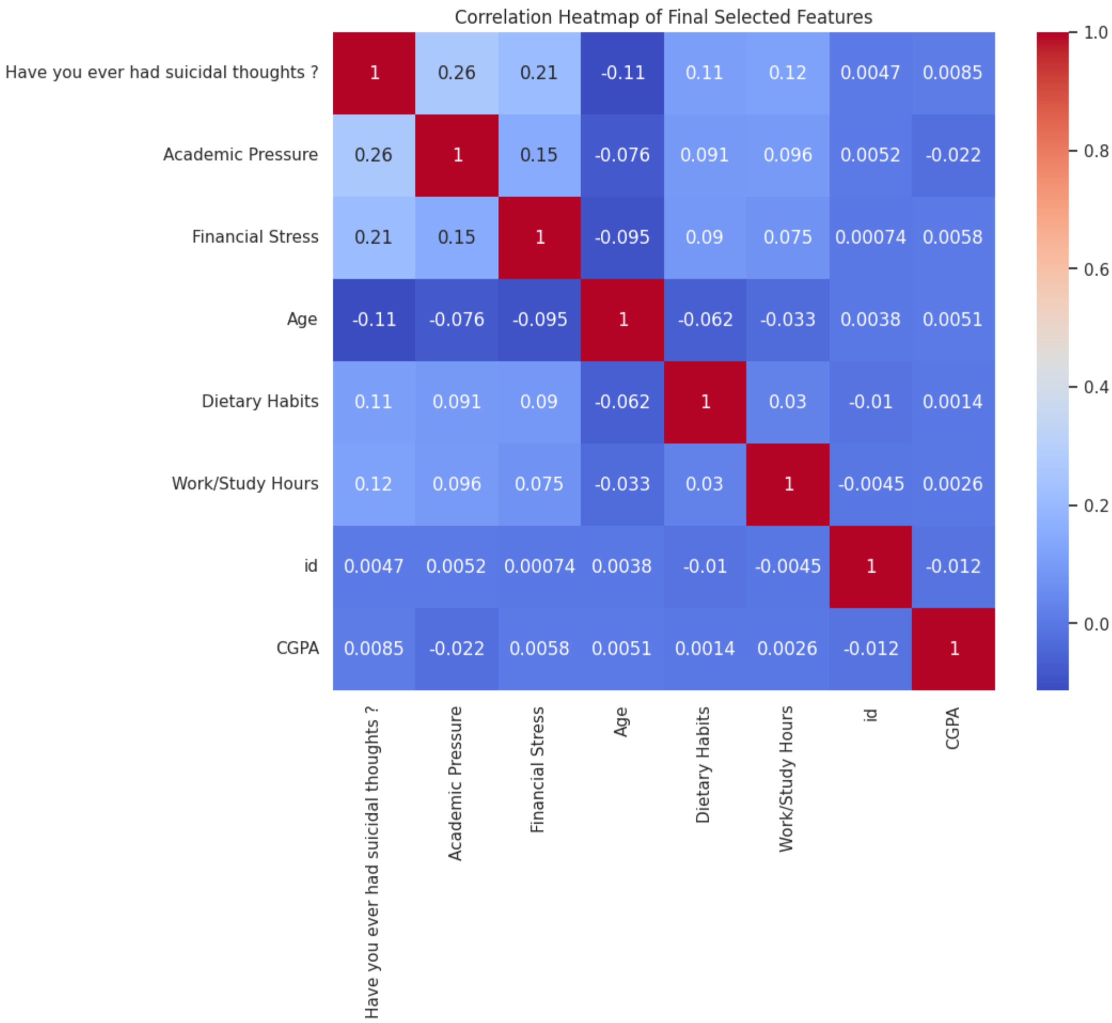

## II. Bar Chart - Decision Tree Importance

```
sns.barplot(x='Importance', y='Feature', data=tree_df.head(10))
plt.title('Top Features by Decision Tree')
plt.show()
```



### III) Correlation Heatmap - Feature Relationships

```
plt.figure(figsize=(10,8))
sns.heatmap(X[final_features['Feature']].corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap of Final Selected Features')
plt.show()
```



# Conclusion

The project successfully identified a set of **core features** that can be used to predict student depression with high confidence. These insights can drive the creation of **machine learning models** to identify at-risk students and support proactive mental health strategies in academic settings.

This work not only emphasizes but also underlines the importance of **early detection, empathy, and systemic support** in tackling student depression.