AIDI1009-25W: Neural Networks

Assignment #1: Dataset Exploration and Regression

Due Date: 18th Feb 2025

Student 1 Name: Puja Shreshta (200573293)
Student 2 Name: Tirth Doshi (200609650)
Student 3 Name: Kelvin Krisna de Rodrigues Silva (2005885799)

1. Goals

- Understand the fundamentals of Regression Analysis.
- Explore and clean real-world datasets.
- Apply Scikit-Learn for regression modeling.
- Evaluate models using MSE & RMSE.
- Perform feature selection and hyperparameter tuning.

2. Introduction

Problem Statement

This assignment focuses on building a regression model to predict an engineering graduate's **annual salary** based on academic performance, test scores, and other factors.

Assumptions & Constraints

- Using `pandas`, `numpy`, `seaborn`, and `scikit-learn` for implementation.
- Missing values are handled via **imputation or column removal**.
- Data is scaled using **MinMaxScaler**.
- Performance evaluation metrics: **MSE & RMSE**.

3. Dataset Overview

About the Dataset

The dataset contains **33 independent variables** and **1 target variable (Salary)**. It provides information about students' academic backgrounds, domain knowledge, and soft skills.

Key Features:

- **Salary**: Target variable (Annual salary in INR).
- **10percentage, 12percentage, CollegeGPA**: Academic performance.
- **Domain Knowledge Scores**: Scores in AMCAT modules (Quant, Logical, etc.).
- **Personality Traits**: Conscientiousness, Agreeableness, etc.

Data Challenges:

- Some fields have **missing values**.
- Not all features **strongly correlate** with Salary.
- Some categories are **imbalanced**.

Python Code For The Problem

2. Perform Data Exploration

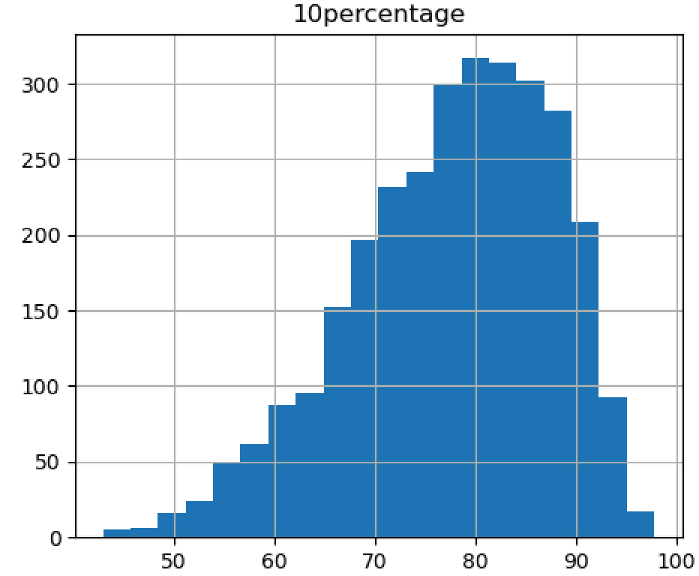
- (a) Display the **first few records** in the dataset.
- (b) Display the **number of rows and columns** of the dataset.
- (c) Display the **dataset statistics** (min, max, mean, etc.).
- (d) Display the **Null values** of each feature.
- (e) Plot **graphs** of the data to assist in data exploration.

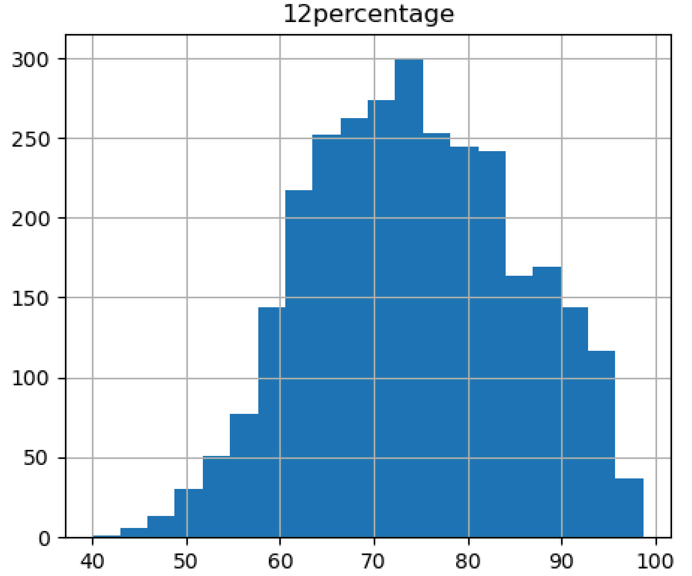
In [13]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Lasso

file_path = "Engineering_graduate_salary.csv"
df = pd.read_csv(file_path)

print("First Few Records:\n", df.head())

print("\nDataset Shape:", df.shape)

print("\nDataset Statistics:\n", df.describe())

print("\nNull Values Per Column:\n", df.isnull().sum())

plt.figure(figsize=(18, 10))
df.hist(column=['10percentage', '12percentage', 'Salary'], bins=20, figsize=(12, 10))
plt.show()
```

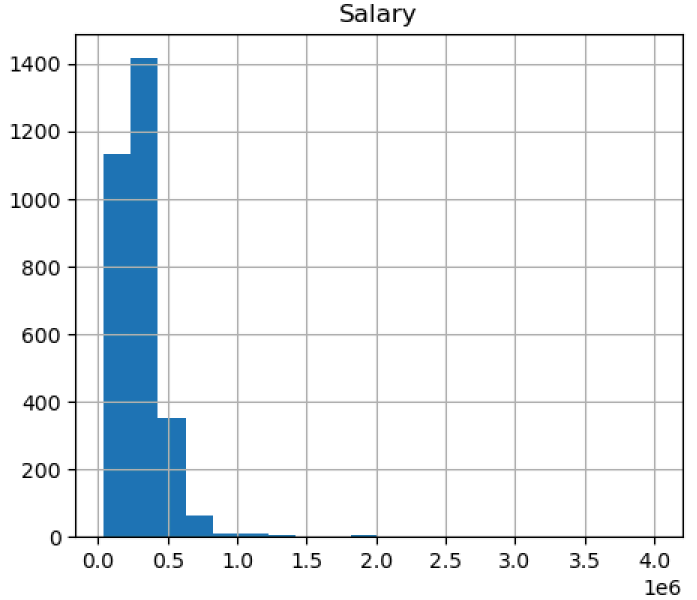
```
First Few Records:
       ID Gender         DOB  10percentage                      10board  \
0  604399      f  1990-10-22         87.80                         cbse
1  988334      m  1990-05-15         57.00                         cbse
2  301647      m  1989-08-21         77.33  maharashtra state board,pune
3  582313      m  1991-05-04         84.30                         cbse
4  339001      f  1990-10-30         82.00                         cbse

   12graduation  12percentage                   12board  CollegeID  \
0          2009         84.00                      cbse       6920
1          2010         64.50                      cbse       6624
2          2007         85.17  amravati divisional board       9084
3          2009         86.00                      cbse       8195
4          2008         75.00                      cbse       4889

   CollegeTier  ... MechanicalEngg ElectricalEngg  TelecomEngg  CivilEngg  \
0            1  ...             -1             -1           -1         -1
1            2  ...             -1             -1           -1         -1
2            2  ...             -1             -1          260         -1
3            1  ...             -1             -1           -1         -1
4            2  ...             -1             -1           -1         -1

   conscientiousness agreeableness  extraversion  nueroticism  \
0            -0.1590        0.3789        1.2396      0.14590
1             1.1336        0.0459        1.2396      0.52620
2             0.5100       -0.1232        1.5428     -0.29020
3            -0.4463        0.2124        0.3174      0.27270
4            -1.4992       -0.7473       -1.0697      0.06223

   openess_to_experience  Salary
0                 0.2889  445000
1                -0.2859  110000
2                -0.2875  255000
3                 0.4805  420000
4                 0.1864  200000

[5 rows x 34 columns]

Dataset Shape: (2998, 34)

Dataset Statistics:
                 ID  10percentage  12graduation  12percentage     CollegeID  \
count  2.998000e+03   2998.000000   2998.000000   2998.000000   2998.000000
mean   6.648926e+05     77.666264   2008.080720     74.341061   5210.210807
std    3.648951e+05     10.002785      1.631814     11.120299   4776.609877
min    1.124400e+04     43.000000   1998.000000     40.000000      2.000000
25%    3.334648e+05     71.140000   2007.000000     66.000000    526.250000
50%    6.396945e+05     78.965000   2008.000000     74.000000   4027.500000
75%    9.951770e+05     85.600000   2009.000000     82.600000   8822.250000
max    1.297877e+06     97.760000   2012.000000     98.700000  18409.000000

       CollegeTier   collegeGPA  CollegeCityID  CollegeCityTier  \
count  2998.000000  2998.000000    2998.000000      2998.000000
mean      1.924616    71.509857    5210.210807         0.296197
```

```
std       0.264053     8.122462    4776.609877         0.456655
min       1.000000     6.630000       2.000000         0.000000
25%       2.000000    66.530000     526.250000         0.000000
50%       2.000000    71.800000    4027.500000         0.000000
75%       2.000000    76.300000    8822.250000         1.000000
max       2.000000    99.930000   18409.000000         1.000000

       GraduationYear  ...  MechanicalEngg  ElectricalEngg  TelecomEngg  \
count     2998.000000  ...     2998.000000     2998.000000  2998.000000
mean      2011.939960  ...       24.138759       16.267845    31.068379
std         36.780582  ...       99.785138       86.054739   103.552963
min          0.000000  ...       -1.000000       -1.000000    -1.000000
25%       2012.000000  ...       -1.000000       -1.000000    -1.000000
50%       2013.000000  ...       -1.000000       -1.000000    -1.000000
75%       2014.000000  ...       -1.000000       -1.000000    -1.000000
max       2017.000000  ...      623.000000      660.000000   548.000000

         CivilEngg  conscientiousness  agreeableness  extraversion  \
count  2998.000000        2998.000000    2998.000000   2998.000000
mean      1.946965          -0.038714       0.126217     -0.008662
std      32.241501           1.024974       0.955831      0.962695
min      -1.000000          -3.893300      -5.781600     -4.600900
25%      -1.000000          -0.649100      -0.435300     -0.604800
50%      -1.000000           0.046400       0.212400      0.091400
75%      -1.000000           0.702700       0.812800      0.672000
max     500.000000           1.995300       1.904800      2.161700

       nueroticism  openess_to_experience        Salary
count  2998.000000            2998.000000  2.998000e+03
mean     -0.145965              -0.141111  3.051748e+05
std       1.012901               1.007134  2.123312e+05
min      -2.643000              -7.375700  3.500000e+04
25%      -0.868200              -0.669200  1.800000e+05
50%      -0.172700              -0.094300  3.000000e+05
75%       0.526200               0.502400  3.700000e+05
max       3.352500               1.630200  4.000000e+06

[8 rows x 27 columns]

Null Values Per Column:
 ID                       0
Gender                   0
DOB                      0
10percentage             0
10board                  0
12graduation             0
12percentage             0
12board                  0
CollegeID                0
CollegeTier              0
Degree                   0
Specialization           0
collegeGPA               0
CollegeCityID            0
```

```
CollegeCityTier          0
CollegeState             0
GraduationYear           0
English                  0
Logical                  0
Quant                    0
Domain                   0
ComputerProgramming      0
ElectronicsAndSemicon    0
ComputerScience          0
MechanicalEngg           0
ElectricalEngg           0
TelecomEngg              0
CivilEngg                0
conscientiousness        0
agreeableness            0
extraversion             0
nueroticism              0
openess_to_experience    0
Salary                   0
dtype: int64
<Figure size 1800x1000 with 0 Axes>
```







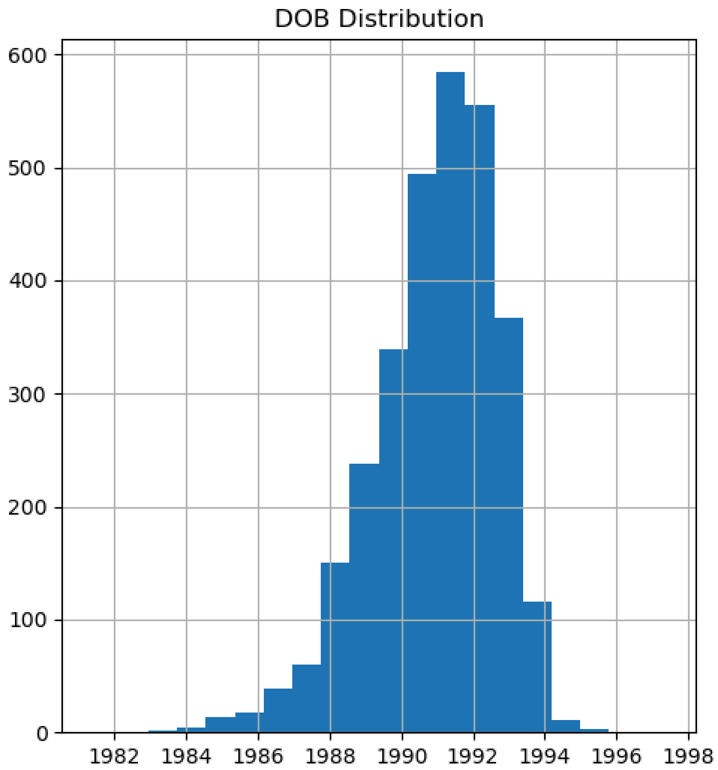
3. Perform Initial Data Cleaning

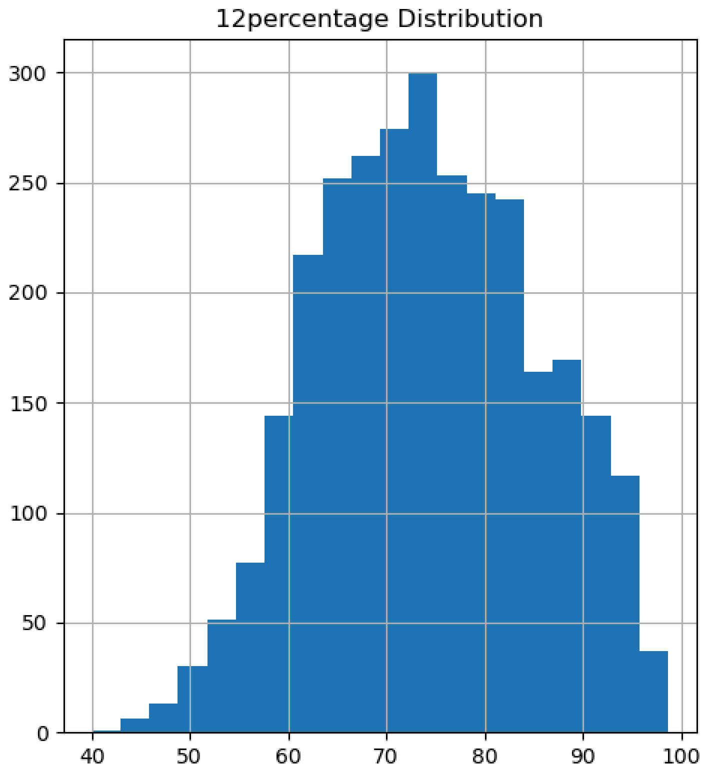
- (a) **Delete columns** that mainly contain Null values.
- (b) **Remove duplicate columns** (obvious redundant information).
- (c) **Fill missing values** in numeric columns if necessary.
- (d) Display the **number of rows and columns** after cleaning.
- (e) Display the **features left** after cleaning.
- (f) Plot the **distribution (histogram)** of the following features:
  - **DOB**
  - **12percentage**

In [14]:
```
df = df.dropna(thresh=len(df) * 0.5, axis=1)

df = df.loc[:, ~df.columns.duplicated()]

num_cols = df.select_dtypes(include=['number']).columns
imputer = SimpleImputer(strategy="mean")
df[num_cols] = imputer.fit_transform(df[num_cols])

print("\nDataset Shape After Cleaning:", df.shape)

print("\nRemaining Features:\n", df.columns)
```

```
Dataset Shape After Cleaning: (2998, 34)

Remaining Features:
 Index(['ID', 'Gender', 'DOB', '10percentage', '10board', '12graduation',
       '12percentage', '12board', 'CollegeID', 'CollegeTier', 'Degree',
       'Specialization', 'collegeGPA', 'CollegeCityID', 'CollegeCityTier',
       'CollegeState', 'GraduationYear', 'English', 'Logical', 'Quant',
       'Domain', 'ComputerProgramming', 'ElectronicsAndSemicon',
       'ComputerScience', 'MechanicalEngg', 'ElectricalEngg', 'TelecomEngg',
       'CivilEngg', 'conscientiousness', 'agreeableness', 'extraversion',
       'nueroticism', 'openess_to_experience', 'Salary'],
      dtype='object')
```

In [15]:
```
plt.figure(figsize=(12, 6))

plt.subplot(1, 2, 1)
df['DOB'] = pd.to_datetime(df['DOB'], errors='coerce')
df['DOB'].hist(bins=20)
plt.title("DOB Distribution")

plt.subplot(1, 2, 2)
df['12percentage'].hist(bins=20)
plt.title("12percentage Distribution")

plt.show()
```

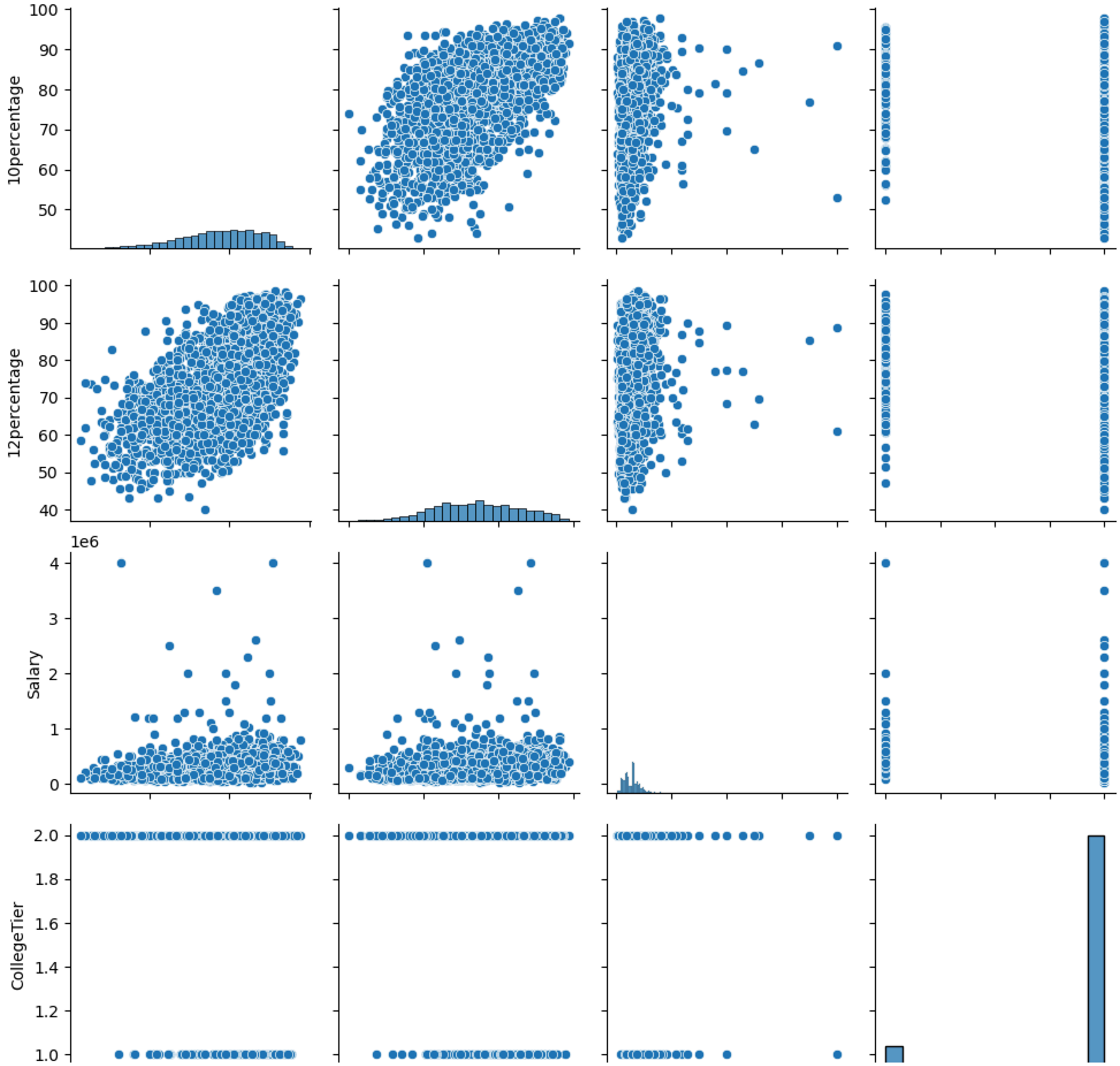


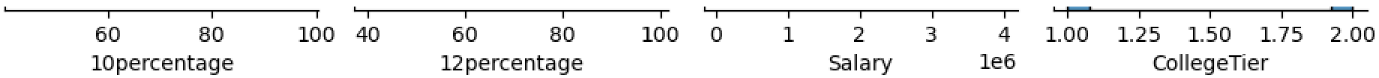


4. Analyze the Pairwise Relationship Between Features

- Use pairwise plots to visualize relationships between dataset features.

In [16]:
```
selected_features = ['10percentage', '12percentage', 'Salary', 'CollegeTier']
sns.pairplot(df[selected_features])
plt.show()
```

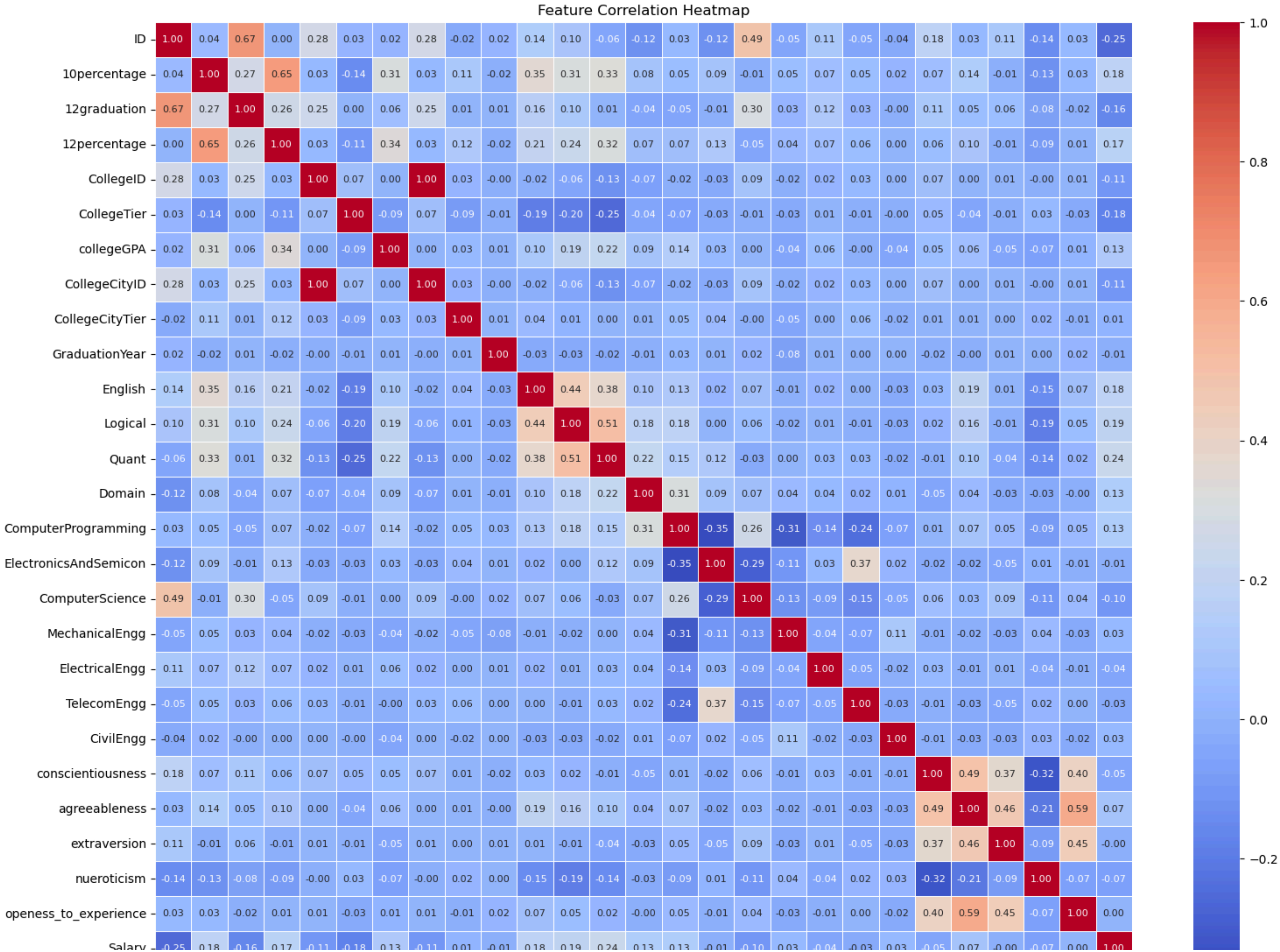

10percentage
12percentage
Salary
CollegeTier
1e6
100
90
80
70
60
50
40
4
3
2
1
0
2.0
1.8
1.6
1.4
1.2
1.0

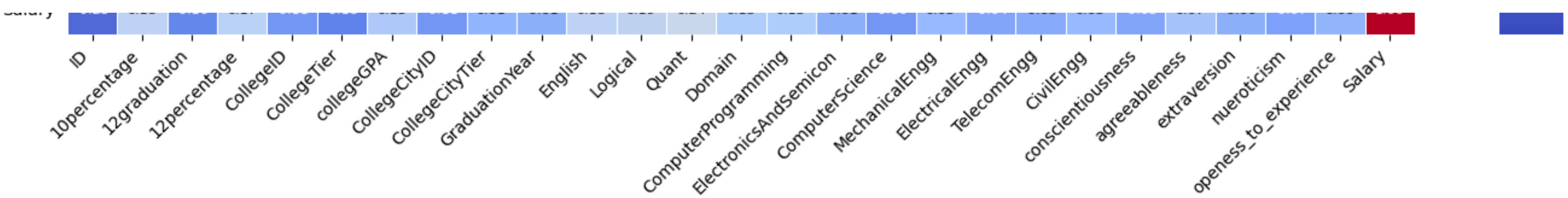


5. Plot the Correlation Heatmap

- Generate a **heatmap** from the pairwise correlation matrix.

In [17]:
```
numeric_df = df.select_dtypes(include=['number'])
corr_matrix = numeric_df.corr()
plt.figure(figsize=(18, 14))
sns.heatmap(numeric_df.corr(), annot=True, cmap="coolwarm", fmt=".2f", linewidths=0.6, annot_kws={"size": 8})
plt.xticks(rotation=45, ha='right', fontsize=10)
plt.yticks(fontsize=10)
plt.title("Feature Correlation Heatmap")
plt.show()
```


Feature Correlation Heatmap
ID
10percentage
12graduation
12percentage
CollegeID
CollegeTier
collegeGPA
CollegeCityID
CollegeCityTier
GraduationYear
English
Logical
Quant
Domain
ComputerProgramming
ElectronicsAndSemicon
ComputerScience
MechanicalEngg
ElectricalEngg
TelecomEngg
CivilEngg
conscientiousness
agreeableness
extraversion
nueroticism
openess_to_experience
Salary
1.0
0.8
0.6
0.4
0.2
0.0
−0.2



6. Perform Necessary Data Preprocessing (Transformation)

- (a) **Scale** values in numeric columns to a **(0,1) range** if needed.
- (b) **Encode categorical data** into **one-hot vectors**.
- (c) **Split the dataset** into **training, validation, and testing** sets.

In [18]:
```
scaler = MinMaxScaler()

df[num_cols] = scaler.fit_transform(df[num_cols])
df['Salary'] = scaler.fit_transform(df[['Salary']])

cat_cols = df.select_dtypes(include=['object']).columns
df = pd.get_dummies(df, columns=cat_cols, drop_first=True)

corr_matrix = df.corr()

top_features = corr_matrix["Salary"].abs().sort_values(ascending=False).index[1:10]
X = df[top_features]
y = df['Salary']

X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3, random_state=42)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, random_state=42)

print("\nDataset Shapes After Fixing:")
print("Training Set:", X_train.shape, y_train.shape)
print("Validation Set:", X_val.shape, y_val.shape)
print("Testing Set:", X_test.shape, y_test.shape)
```

```
Dataset Shapes After Fixing:
Training Set: (2098, 9) (2098,)
Validation Set: (450, 9) (450,)
Testing Set: (450, 9) (450,)
```

7. Train a Simple Linear Regression Model

- Use **Scikit-Learn's** `LinearRegression` model to perform regression.

8. Evaluate Model Performance

- Use only the features after cleaning to compute:
  - (a) **Mean Squared Error (MSE)**

- (b) **Root Mean Squared Error (RMSE)**

In [19]:
```
model = LinearRegression()
model.fit(X_train, y_train)

y_val_pred = model.predict(X_val)
y_test_pred = model.predict(X_test)

y_val_pred = scaler.inverse_transform(y_val_pred.reshape(-1, 1))
y_test_pred = scaler.inverse_transform(y_test_pred.reshape(-1, 1))
y_val = scaler.inverse_transform(y_val.values.reshape(-1, 1))
y_test = scaler.inverse_transform(y_test.values.reshape(-1, 1))

mse_val = mean_squared_error(y_val, y_val_pred)
rmse_val = np.sqrt(mse_val)

mse_test = mean_squared_error(y_test, y_test_pred)
rmse_test = np.sqrt(mse_test)

print("\nModel Performance Metrics After Fixing:")
print("Validation Set - MSE:", mse_val, "RMSE:", rmse_val)
print("Test Set - MSE:", mse_test, "RMSE:", rmse_test)
```

```
Model Performance Metrics After Fixing:
Validation Set - MSE: 0.001036280594967549 RMSE: 0.0321913124144939
Test Set - MSE: 0.0036753269500475853 RMSE: 0.06062447484347873
```

10. Perform Hyperparameter Tuning

- Tune model parameters using **GridSearchCV** and compare different models.

In [20]:
```
param_grid_lasso = {'alpha': [0.01, 0.1, 1, 10, 50, 100]}

lasso_model = Lasso()
grid_search_lasso = GridSearchCV(lasso_model, param_grid_lasso, cv=5, scoring='neg_mean_squared_error')
grid_search_lasso.fit(X_train, y_train)

best_lasso = grid_search_lasso.best_estimator_

y_val_pred_lasso = best_lasso.predict(X_val)
y_test_pred_lasso = best_lasso.predict(X_test)

y_val_pred_lasso = scaler.inverse_transform(y_val_pred_lasso.reshape(-1, 1))
y_test_pred_lasso = scaler.inverse_transform(y_test_pred_lasso.reshape(-1, 1))
y_val = scaler.inverse_transform(y_val.reshape(-1, 1))
y_test = scaler.inverse_transform(y_test.reshape(-1, 1))

mse_val_lasso = mean_squared_error(y_val, y_val_pred_lasso)
rmse_val_lasso = np.sqrt(mse_val_lasso)

mse_test_lasso = mean_squared_error(y_test, y_test_pred_lasso)
rmse_test_lasso = np.sqrt(mse_test_lasso)
```

```
print("\nBest Hyperparameter for Lasso Regression:", grid_search_lasso.best_params_)
print("Validation Set - MSE:", mse_val_lasso, "RMSE:", rmse_val_lasso)
print("Test Set - MSE:", mse_test_lasso, "RMSE:", rmse_test_lasso)
```

```
Best Hyperparameter for Lasso Regression: {'alpha': 0.01}
Validation Set - MSE: 0.0015594708097316746 RMSE: 0.03949013560032017
Test Set - MSE: 0.004226605591259178 RMSE: 0.0650123495288332
```

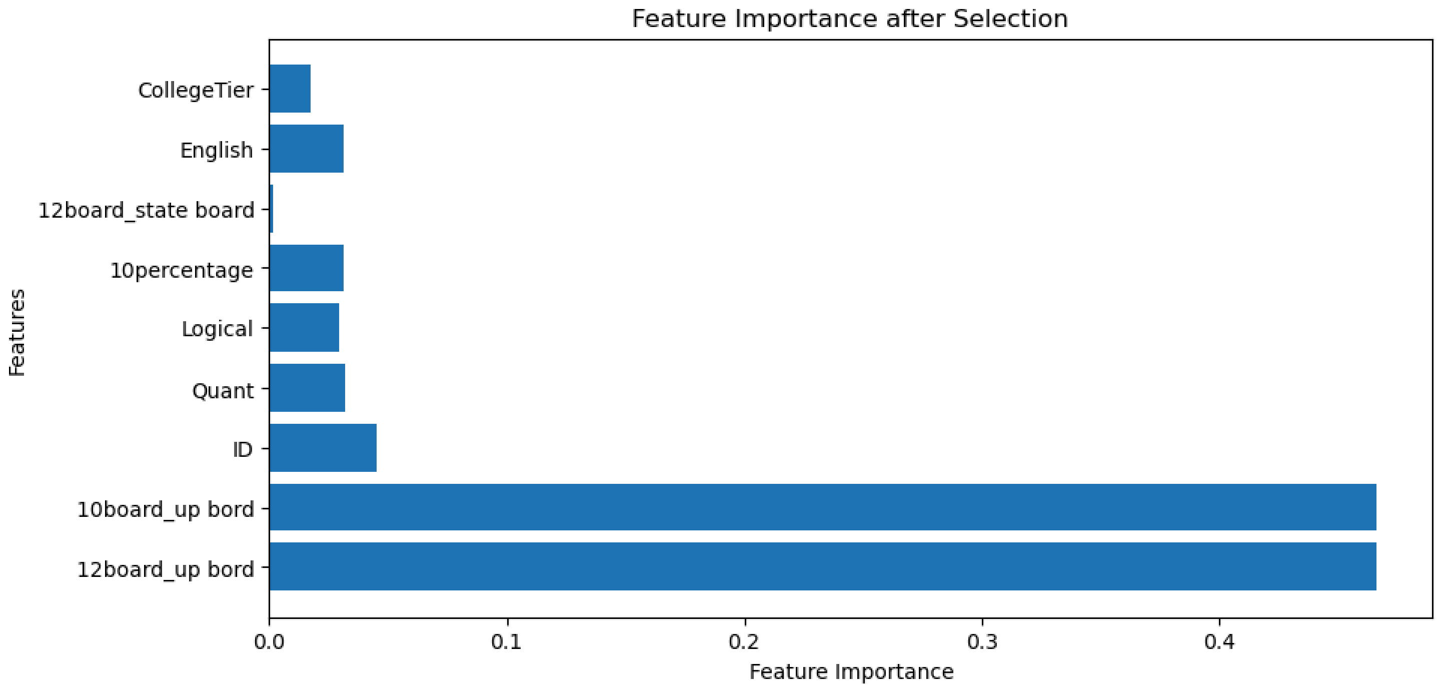
9. Perform Feature Selection and Repeat Step 8

- **Select key features** and recompute **MSE & RMSE** for performance comparison.

In [21]:
```
model_after_selection = LinearRegression()
model_after_selection.fit(X_train, y_train)

y_test_pred_after_selection = model_after_selection.predict(X_test)
y_test_pred_after_selection = scaler.inverse_transform(y_test_pred_after_selection.reshape(-1, 1))
y_test = scaler.inverse_transform(y_test.reshape(-1, 1))  # ✅ Fix: Remove `.values`


mse_test_after_selection = mean_squared_error(y_test, y_test_pred_after_selection)
rmse_test_after_selection = np.sqrt(mse_test_after_selection)

print("\nAfter Feature Selection - Linear Regression Model:")
print("Test Set - MSE:", mse_test_after_selection, "RMSE:", rmse_test_after_selection)
```

```
After Feature Selection - Linear Regression Model:
Test Set - MSE: 0.0036753269500475853 RMSE: 0.06062447484347873
```

In [22]:
```
feature_importance = abs(model_after_selection.coef_)
plt.figure(figsize=(10, 5))
plt.barh(X_train.columns, feature_importance)
plt.xlabel("Feature Importance")
plt.ylabel("Features")
plt.title("Feature Importance after Selection")
plt.show()
```


Feature Importance after Selection
CollegeTier
English
12board_state board
10percentage
Logical
Quant
ID
10board_up bord
12board_up bord
Features
0.0
0.1
0.2
0.3
0.4
Feature Importance