```
In [68]:
           # William Barker
           # DSC680
           # Project 1
           import pandas as pd
           import numpy as np
           import matplotlib.pyplot as plt
           import seaborn as sns
           # downloading my dataset
           df = pd.read csv('salary prediction data.csv', encoding = "ISO-8859-1")
                                                                            Salary
Out[68]:
                Education Experience Location Job_Title Age Gender
            0 High School
                                        Urban
                                                         63
                                                                      84620.053665
                                                Manager
                                                                Male
            1
                     PhD
                                  11 Suburban
                                                Director
                                                         59
                                                                Male
                                                                     142591.255894
                                                                      97800.255404
            2
                  Bachelor
                                  28 Suburban
                                                Manager
                                                              Female
                                                          61
               High School
                                  29
                                                                      96834.671282
            3
                                         Rural
                                                Director
                                                         45
                                                                Male
                                  25
            4
                     PhD
                                        Urban
                                                 Analyst
                                                         26
                                                              Female
                                                                      132157.786175
                                  ...
          995 High School
                                  8 Suburban
                                                 Analyst
                                                         25
                                                              Female
                                                                      64683.389864
          996 High School
                                                                      74468.205020
                                  24
                                        Urban
                                                Engineer
                                                         30
                                                              Female
          997
                   Master
                                  18
                                                                      98207.026024
                                         Rural
                                                 Analyst
                                                         44
                                                                Male
          998
                                     Suburban
                                                             Female 108544.922720
                  Bachelor
                                  27
                                                Director
                                                          31
          999 High School
                                                                      71077.000066
                                  25
                                        Urban
                                                Director
                                                          41 Female
         1000 rows × 7 columns
In [69]:
           # checking the unique values
           education values = df['Education'].unique()
           education values
          array(['High School', 'PhD', 'Bachelor', 'Master'], dtype=object)
Out[69]:
In [70]:
           # checking the unique values
           location values = df['Location'].unique()
          location values
          array(['Urban', 'Suburban', 'Rural'], dtype=object)
Out[70]:
In [71]:
           # checking the unique values
           job values = df['Job Title'].unique()
           job values
          array(['Manager', 'Director', 'Analyst', 'Engineer'], dtype=object)
Out[71]:
In [72]:
           # mapping the unique values to numbers
           df['Education'] = df['Education'].map({'High School': 1, 'Bachelor': 2, 'Master': 3, 'PhD
```

df

Out[72]:		Education	Experience	Location	Job_Title	Age	Gender	Salary
	0	1	8	Urban	Manager	63	Male	84620.053665
	1	4	11	Suburban	Director	59	Male	142591.255894
	2	2	28	Suburban	Manager	61	Female	97800.255404
	3	1	29	Rural	Director	45	Male	96834.671282
	4	4	25	Urban	Analyst	26	Female	132157.786175
	•••							
	995	1	8	Suburban	Analyst	25	Female	64683.389864
	996	1	24	Urban	Engineer	30	Female	74468.205020
	997	3	18	Rural	Analyst	44	Male	98207.026024
	998	2	27	Suburban	Director	31	Female	108544.922720
	999	1	25	Urban	Director	41	Female	71077.000066

1000 rows × 7 columns

Out

```
In [73]:
# mapping the unique values to numbers
df['Location'] = df['Location'].map({'Urban': 1, 'Suburban': 2, 'Rural': 3})
df
```

[73]:		Education	Experience	Location	Job_Title	Age	Gender	Salary
	0	1	8	1	Manager	63	Male	84620.053665
	1	4	11	2	Director	59	Male	142591.255894
	2	2	28	2	Manager	61	Female	97800.255404
	3	1	29	3	Director	45	Male	96834.671282
	4	4	25	1	Analyst	26	Female	132157.786175
	•••						•••	
99	95	1	8	2	Analyst	25	Female	64683.389864
99	96	1	24	1	Engineer	30	Female	74468.205020
99	97	3	18	3	Analyst	44	Male	98207.026024
99	8	2	27	2	Director	31	Female	108544.922720
99	9	1	25	1	Director	41	Female	71077.000066

1000 rows × 7 columns

```
In [74]: # mapping the unique values to numbers
    df['Job_Title'] = df['Job_Title'].map({'Analyst': 1, 'Engineer': 2, 'Manager': 3, 'Directo
    df
```

Out[74]:		Education	Experience	Location	Job_Title	Age	Gender	Salary
	0	1	8	1	3	63	Male	84620.053665
	1	4	11	2	4	59	Male	142591.255894
	2	2	28	2	3	61	Female	97800.255404

	Education	Experience	Location	Job_Title	Age	Gender	Salary
3	1	29	3	4	45	Male	96834.671282
4	4	25	1	1	26	Female	132157.786175
			•••				•••
995	1	8	2	1	25	Female	64683.389864
996	1	24	1	2	30	Female	74468.205020
997	3	18	3	1	44	Male	98207.026024
998	2	27	2	4	31	Female	108544.922720
999	1	25	1	4	41	Female	71077.000066

1000 rows × 7 columns

```
In [75]: # mapping the unique values to numbers
    df['Gender'] = df['Gender'].map({'Male': 1, 'Female': 2})
    df
```

Out[75]:		Education	Experience	Location	Job_Title	Age	Gender	Salary
	0	1	8	1	3	63	1	84620.053665
	1	4	11	2	4	59	1	142591.255894
	2	2	28	2	3	61	2	97800.255404
	3	1	29	3	4	45	1	96834.671282
	4	4	25	1	1	26	2	132157.786175
	•••						•••	
	995	1	8	2	1	25	2	64683.389864
	996	1	24	1	2	30	2	74468.205020
	997	3	18	3	1	44	1	98207.026024
	998	2	27	2	4	31	2	108544.922720
	999	1	25	1	4	41	2	71077.000066

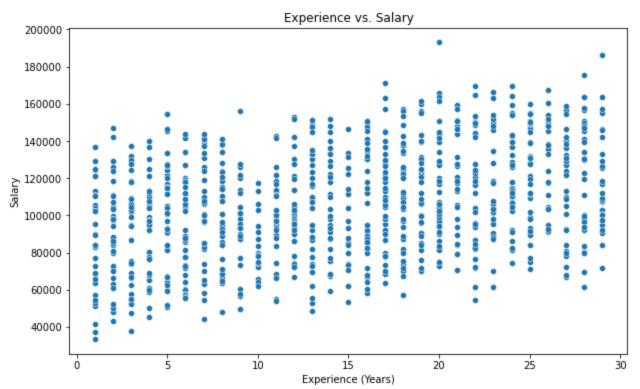
1000 rows × 7 columns

plt.figure(figsize=(10, 6))

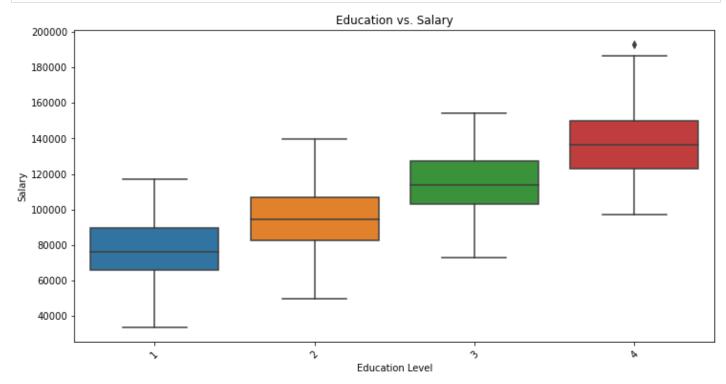
sns.scatterplot(data=df, x='Experience', y='Salary')

```
In [76]:
          # checking for Nan values
          missing_values = df.isnull().sum()
          missing values
         Education
                       0
Out[76]:
         Experience
                       0
         Location
                       0
         Job Title
                       0
         Age
         Gender
         Salary
         dtype: int64
In [77]:
          # Scatter plot for Experience vs. Salary
```

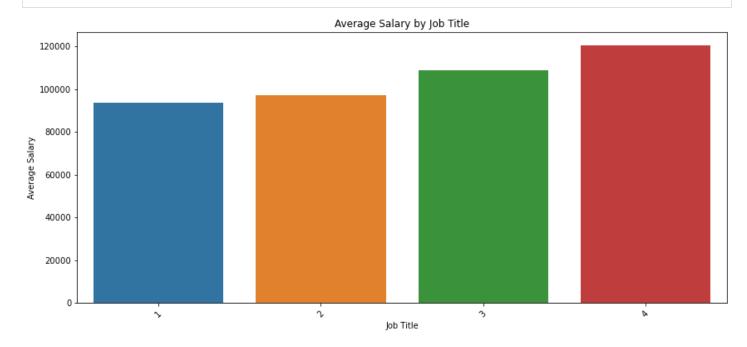
```
plt.title('Experience vs. Salary')
plt.xlabel('Experience (Years)')
plt.ylabel('Salary')
plt.show()
```



```
In [78]:
# Box plot for Education vs. Salary
plt.figure(figsize=(12, 6))
sns.boxplot(data=df, x='Education', y='Salary')
plt.title('Education vs. Salary')
plt.xlabel('Education Level')
plt.ylabel('Salary')
plt.xticks(rotation=45)
plt.show()
```



```
# Bar plot for Job Title vs. Average Salary
plt.figure(figsize=(14, 6))
average_salary_by_job_title = df.groupby('Job_Title')['Salary'].mean().reset_index()
sns.barplot(data=average_salary_by_job_title, x='Job_Title', y='Salary')
plt.title('Average Salary by Job Title')
plt.xlabel('Job Title')
plt.ylabel('Average Salary')
plt.xticks(rotation=45)
plt.show()
```



```
In [80]:
    from sklearn.model_selection import train_test_split
    from sklearn.linear_model import LinearRegression
    from sklearn.preprocessing import OneHotEncoder
    from sklearn.compose import ColumnTransformer
    from sklearn.pipeline import Pipeline
    from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

# Selecting features and target variable
    features = ['Education', 'Experience', 'Location', 'Job_Title', 'Age', 'Gender']
    target = 'Salary'

X = df[features]
y = df[target]
```

```
In [81]: # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
In [82]: from sklearn.linear_model import LinearRegression

# Initialize the linear regression model
lr_model = LinearRegression()

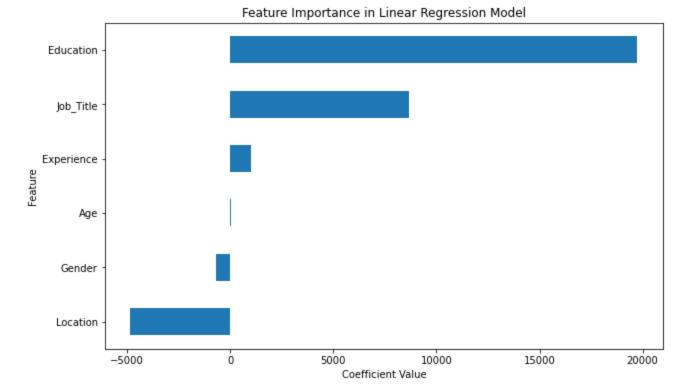
# Train the linear regression model
lr_model.fit(X_train, y_train)

# Predict on the test set using linear regression
lr_y_pred = lr_model.predict(X_test)

# Calculate evaluation metrics for linear regression
lr_mse = mean_squared_error(y_test, lr_y_pred)
lr_mae = mean_absolute_error(y_test, lr_y_pred)
```

```
lr r2 = r2 score(y test, lr y pred)
          print("Linear Regression Metrics:")
          print(f"Mean Squared Error: {lr mse}")
          print(f"Mean Absolute Error: {lr mae}")
          print(f"R-squared: {lr r2}")
         Linear Regression Metrics:
         Mean Squared Error: 104532131.71307541
         Mean Absolute Error: 8247.815038380479
         R-squared: 0.8719795075733404
In [83]:
          from sklearn.ensemble import RandomForestRegressor
          # Initialize the random forest model
          rf model = RandomForestRegressor(random state=42)
          # Train the random forest model
          rf model.fit(X train, y train)
          # Predict on the test set using random forest
          rf y pred = rf model.predict(X test)
          # Calculate evaluation metrics for random forest
          rf mse = mean squared error(y test, rf y pred)
          rf mae = mean absolute error(y test, rf y pred)
          rf r2 = r2 score(y test, rf y pred)
          print("Random Forest Metrics:")
          print(f"Mean Squared Error: {rf mse}")
          print(f"Mean Absolute Error: {rf mae}")
          print(f"R-squared: {rf r2}")
         Random Forest Metrics:
         Mean Squared Error: 127929799.23398338
         Mean Absolute Error: 9208.641830556251
         R-squared: 0.8433243862381729
In [84]:
          # finding the average of the salary column
          average salary = df['Salary'].mean()
          print(f"The average salary is: {average salary}")
         The average salary is: 105558.40423878135
In [85]:
          # Extract the coefficients
          coefficients = lr model.coef
          feature importance = pd.Series(coefficients, index=features)
          # Plot the feature importance
          plt.figure(figsize=(10, 6))
          feature importance.sort values().plot(kind='barh')
          plt.title('Feature Importance in Linear Regression Model')
          plt.xlabel('Coefficient Value')
          plt.ylabel('Feature')
```

plt.show()



In []:	
In []:	
In []:	