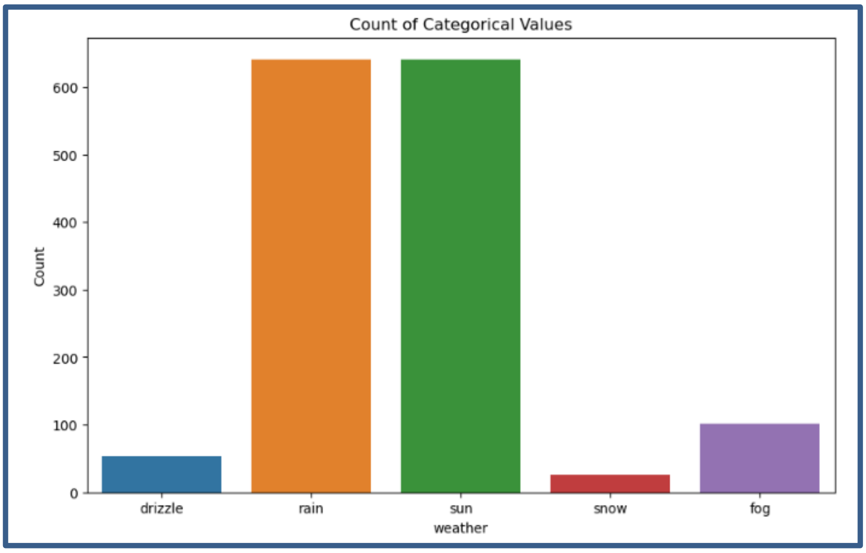
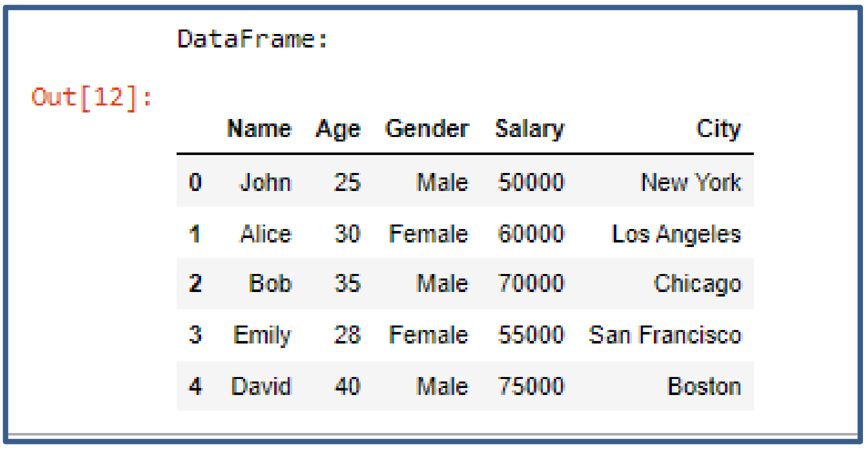
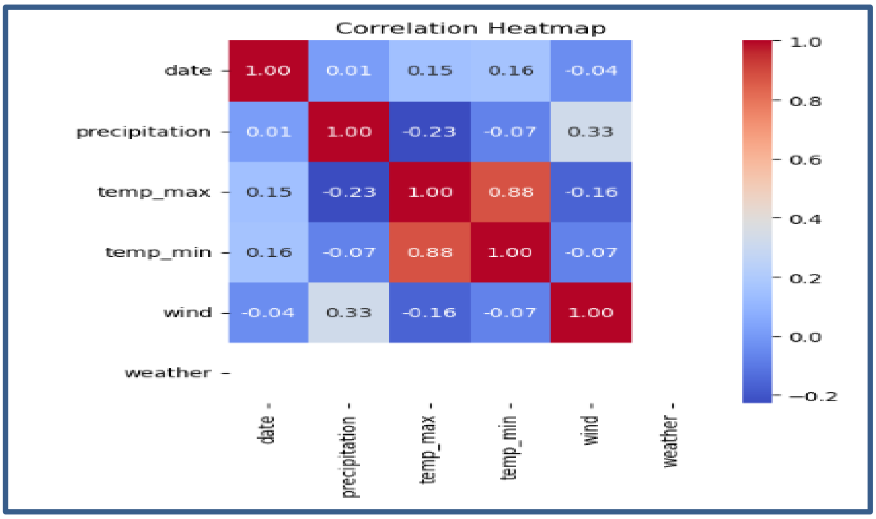


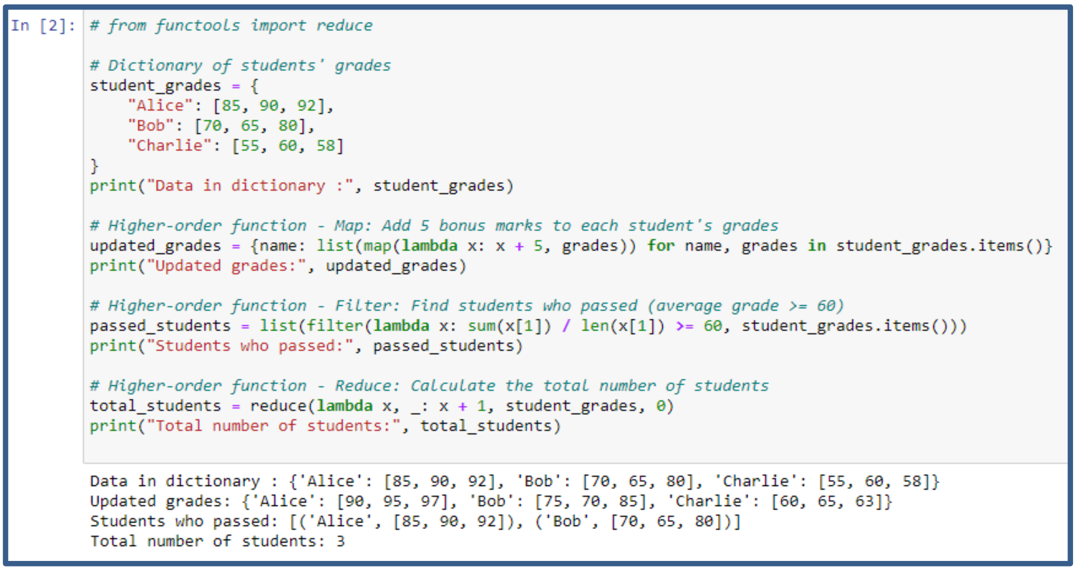


```
DataFrame:
```

Out[12]:

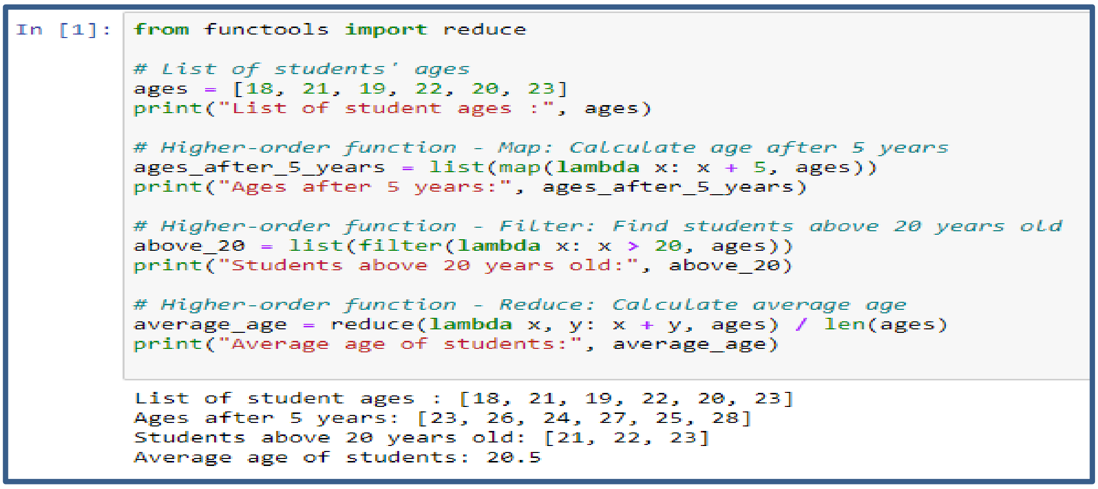
|   | Name | Age | Gender | Salary | City |
|---|---|---|---|---|---|
| 0 | John | 25 | Male | 50000 | New York |
| 1 | Alice | 30 | Female | 60000 | Los Angeles |
| 2 | Bob | 35 | Male | 70000 | Chicago |
| 3 | Emily | 28 | Female | 55000 | San Francisco |
| 4 | David | 40 | Male | 75000 | Boston |





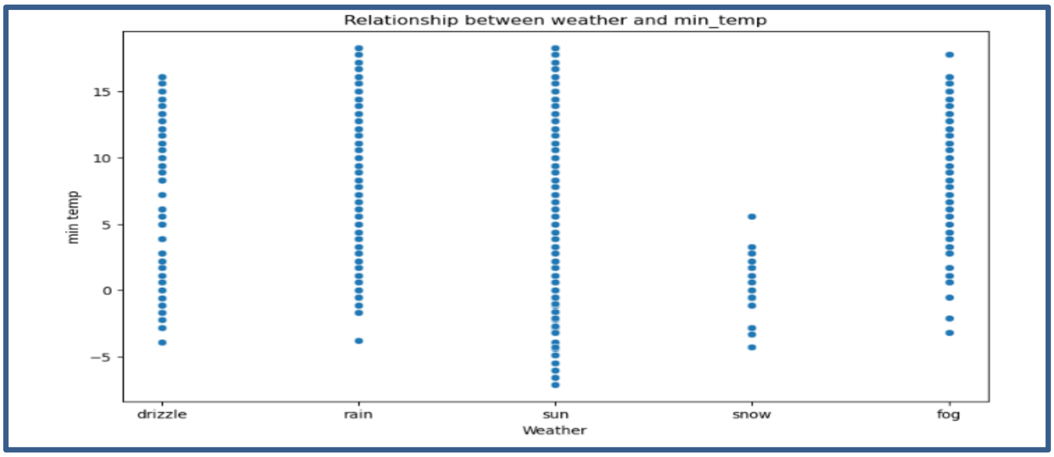
```
In [2]: # from functools import reduce

        # Dictionary of students' grades
        student_grades = {
            "Alice": [85, 90, 92],
            "Bob": [70, 65, 80],
            "Charlie": [55, 60, 58]
        }
        print("Data in dictionary :", student_grades)

        # Higher-order function - Map: Add 5 bonus marks to each student's grades
        updated_grades = {name: list(map(lambda x: x + 5, grades)) for name, grades in student_grades.items()}
        print("Updated grades:", updated_grades)

        # Higher-order function - Filter: Find students who passed (average grade >= 60)
        passed_students = list(filter(lambda x: sum(x[1]) / len(x[1]) >= 60, student_grades.items()))
        print("Students who passed:", passed_students)

        # Higher-order function - Reduce: Calculate the total number of students
        total_students = reduce(lambda x, _: x + 1, student_grades, 0)
        print("Total number of students:", total_students)
```

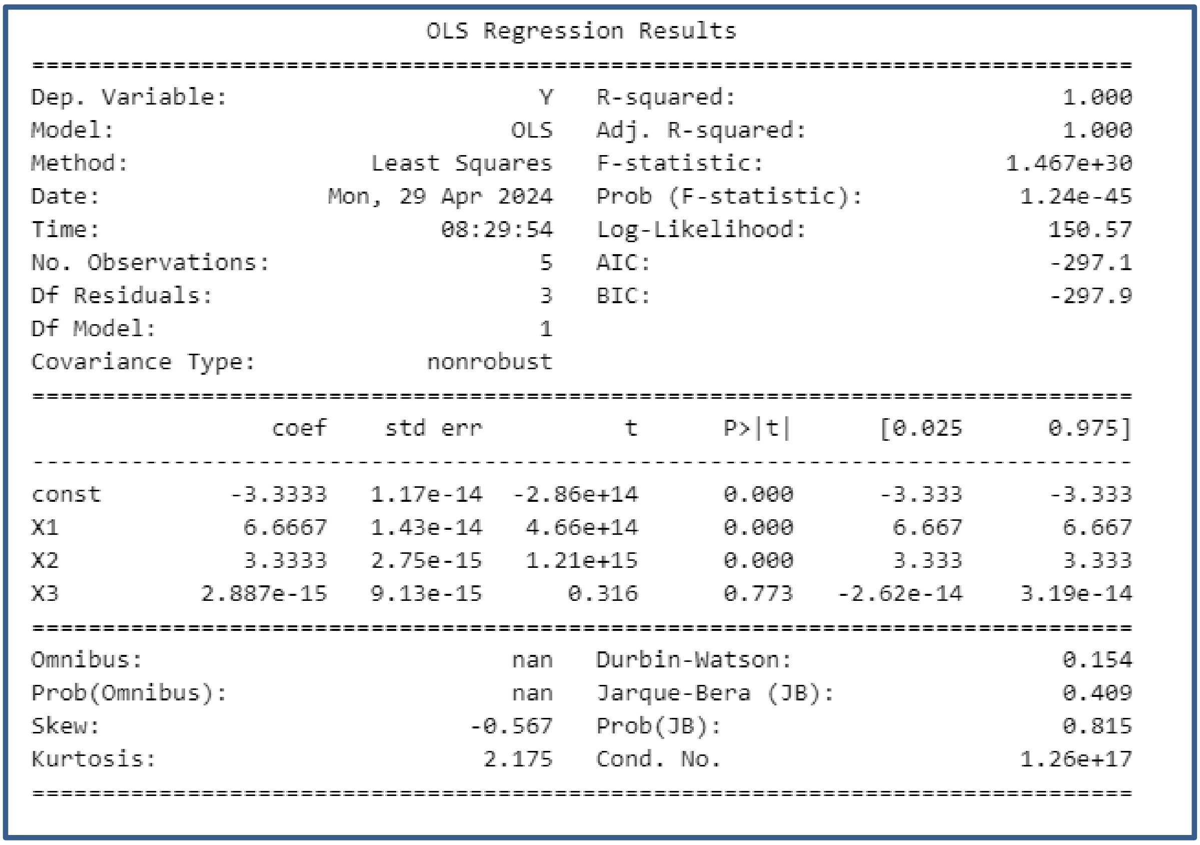
```
        Data in dictionary : {'Alice': [85, 90, 92], 'Bob': [70, 65, 80], 'Charlie': [55, 60, 58]}
        Updated grades: {'Alice': [90, 95, 97], 'Bob': [75, 70, 85], 'Charlie': [60, 65, 63]}
        Students who passed: [('Alice', [85, 90, 92]), ('Bob', [70, 65, 80])]
        Total number of students: 3
```



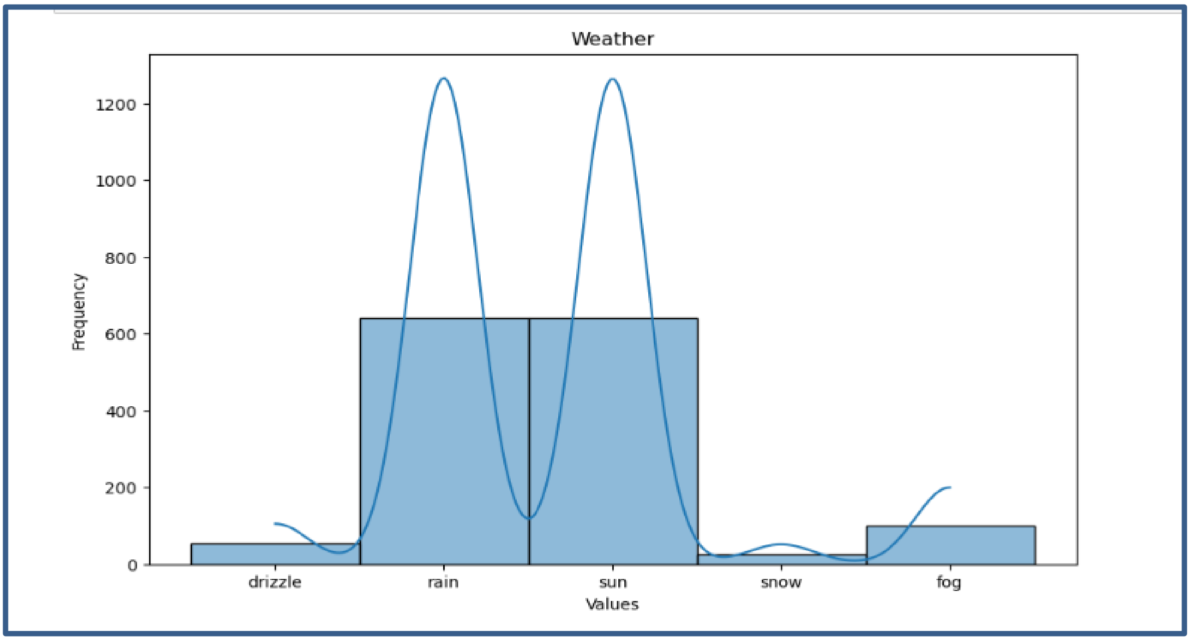
```
In [1]: from functools import reduce

        # List of students' ages
        ages = [18, 21, 19, 22, 20, 23]
        print("List of student ages :", ages)

        # Higher-order function - Map: Calculate age after 5 years
        ages_after_5_years = list(map(lambda x: x + 5, ages))
        print("Ages after 5 years:", ages_after_5_years)

        # Higher-order function - Filter: Find students above 20 years old
        above_20 = list(filter(lambda x: x > 20, ages))
        print("Students above 20 years old:", above_20)

        # Higher-order function - Reduce: Calculate average age
        average_age = reduce(lambda x, y: x + y, ages) / len(ages)
        print("Average age of students:", average_age)
```

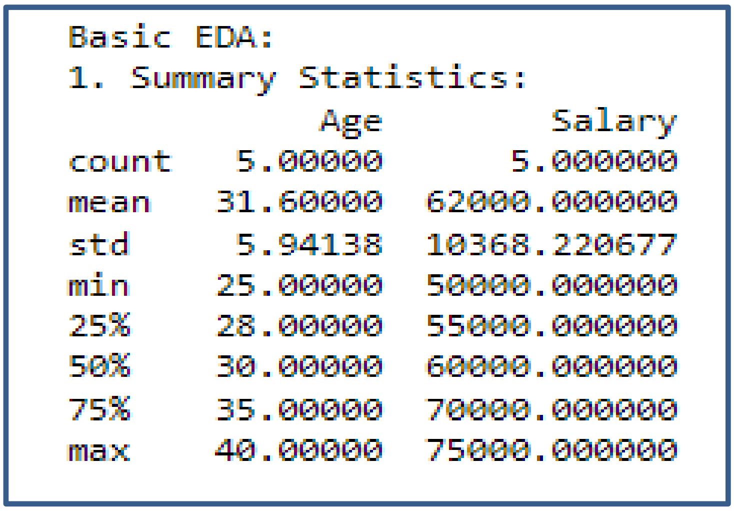
```
        List of student ages : [18, 21, 19, 22, 20, 23]
        Ages after 5 years: [23, 26, 24, 27, 25, 28]
        Students above 20 years old: [21, 22, 23]
        Average age of students: 20.5
```



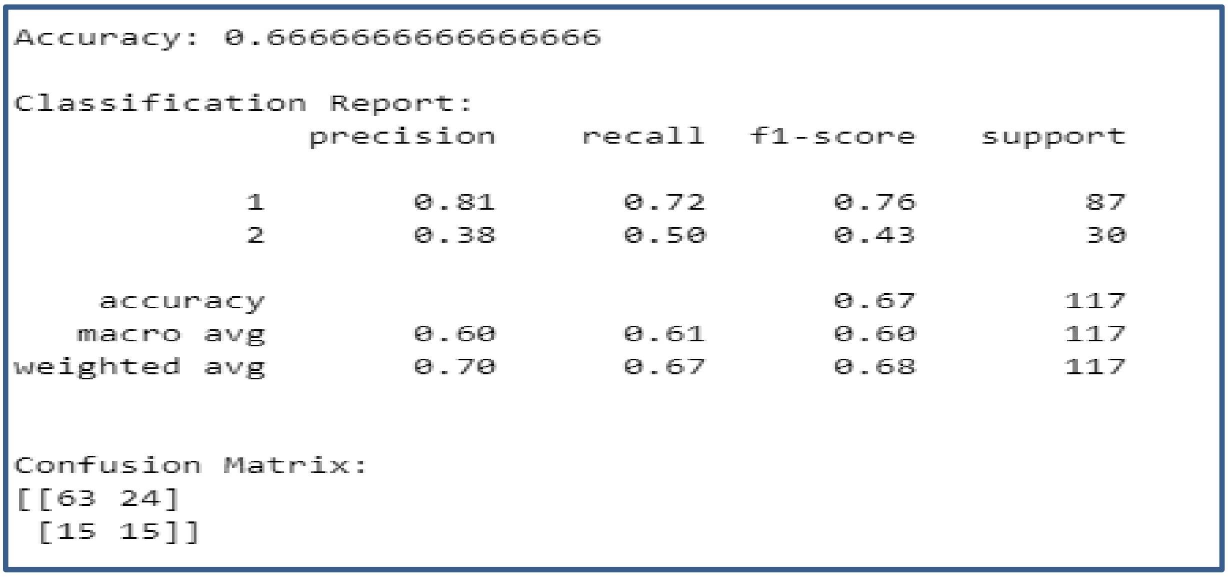


```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      Y   R-squared:                       1.000
Model:                            OLS   Adj. R-squared:                  1.000
Method:                 Least Squares   F-statistic:                 1.467e+30
Date:                Mon, 29 Apr 2024   Prob (F-statistic):           1.24e-45
Time:                        08:29:54   Log-Likelihood:                 150.57
No. Observations:                   5   AIC:                            -297.1
Df Residuals:                       3   BIC:                            -297.9
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -3.3333   1.17e-14  -2.86e+14      0.000      -3.333      -3.333
X1             6.6667   1.43e-14   4.66e+14      0.000       6.667       6.667
X2             3.3333   2.75e-15   1.21e+15      0.000       3.333       3.333
X3          2.887e-15   9.13e-15      0.316      0.773   -2.62e-14    3.19e-14
==============================================================================
Omnibus:                          nan   Durbin-Watson:                   0.154
Prob(Omnibus):                    nan   Jarque-Bera (JB):                0.409
Skew:                          -0.567   Prob(JB):                        0.815
Kurtosis:                       2.175   Cond. No.                     1.26e+17
==============================================================================
```

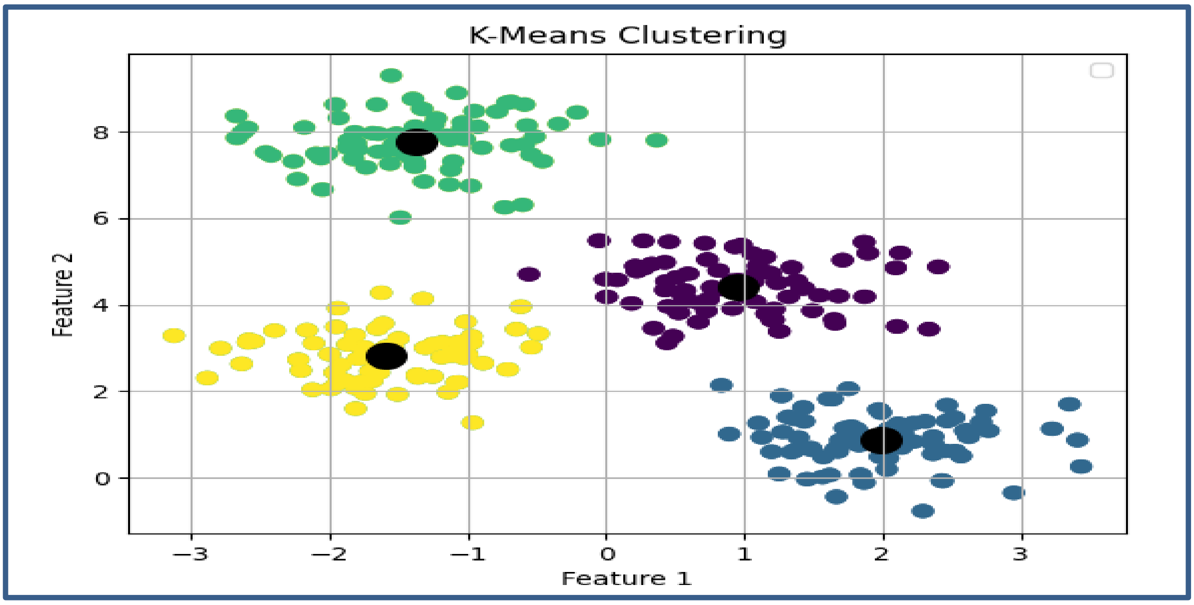




```
Basic EDA:
1. Summary Statistics:
             Age        Salary
count   5.00000      5.000000
mean   31.60000  62000.000000
std     5.94138  10368.220677
min    25.00000  50000.000000
25%    28.00000  55000.000000
50%    30.00000  60000.000000
75%    35.00000  70000.000000
max    40.00000  75000.000000
```



```
Accuracy: 0.6666666666666666

Classification Report:
              precision    recall  f1-score   support

           1       0.81      0.72      0.76        87
           2       0.38      0.50      0.43        30

    accuracy                           0.67       117
   macro avg       0.60      0.61      0.60       117
weighted avg       0.70      0.67      0.68       117


Confusion Matrix:
[[63 24]
 [15 15]]
```


K-Means Clustering
Feature 2
Feature 1