

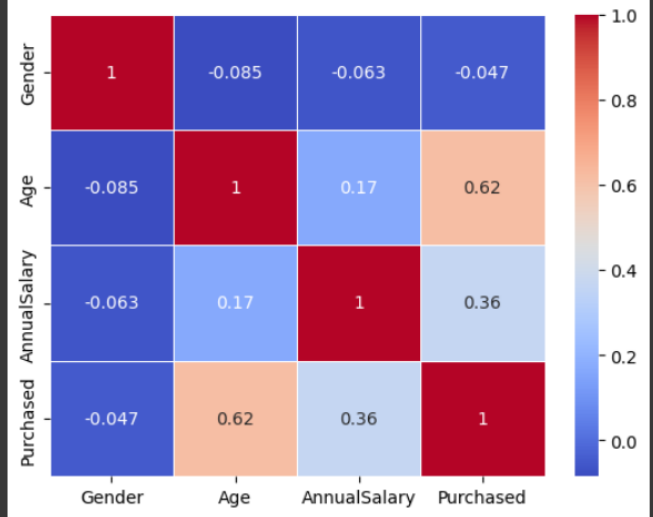
Project Development Phase Model Performance Test

| | |
|---------------|-------------------------|
| Date | 8 November 2023 |
| Team ID | Team-593136 |
| Project Name | Car Purchase prediction |
| Maximum Marks | 10 Marks |

Model Performance Testing:

Project team shall fill the following information in model performance testing template.

| S.No. | Parameter | Values | Screenshot | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|--------------|-----------|---|--|---------|---|---|-----------|--|--|---|-----|---|---|---|----|--|-----------|--------|----------|---------|---|------|------|------|-----|---|------|------|------|----|----------|--|--|------|-----|-----------|------|------|------|-----|--------------|------|------|------|-----|
| 1. | Metrics | Classification Model: Confusion Matrix - , Accuray Score- & Classification Report - | <p>Accuracy Score</p> <pre># accuracy scores print("Train Set Accuracy:", train_accuracy) print("Test Set Accuracy:", test_accuracy)</pre> <p>Train Set Accuracy: 0.9975 Test Set Accuracy: 0.94</p> <p>Confusion matrix</p> <pre>] from sklearn.metrics import confusion_matrix pd.crosstab(y_test,y_pred)</pre> <table><thead><tr><th>col_0</th><th>0</th><th>1</th></tr></thead><tbody><tr><td>Purchased</td><td></td><td></td></tr><tr><td>0</td><td>115</td><td>6</td></tr><tr><td>1</td><td>6</td><td>73</td></tr></tbody></table> <p>Classification Report</p> <pre># Display a classification report print(classification_report(y_test, y_pred))</pre> <table><thead><tr><th></th><th>precision</th><th>recall</th><th>f1-score</th><th>support</th></tr></thead><tbody><tr><td>0</td><td>0.95</td><td>0.95</td><td>0.95</td><td>121</td></tr><tr><td>1</td><td>0.92</td><td>0.92</td><td>0.92</td><td>79</td></tr><tr><td>accuracy</td><td></td><td></td><td>0.94</td><td>200</td></tr><tr><td>macro avg</td><td>0.94</td><td>0.94</td><td>0.94</td><td>200</td></tr><tr><td>weighted avg</td><td>0.94</td><td>0.94</td><td>0.94</td><td>200</td></tr></tbody></table> | col_0 | 0 | 1 | Purchased | | | 0 | 115 | 6 | 1 | 6 | 73 | | precision | recall | f1-score | support | 0 | 0.95 | 0.95 | 0.95 | 121 | 1 | 0.92 | 0.92 | 0.92 | 79 | accuracy | | | 0.94 | 200 | macro avg | 0.94 | 0.94 | 0.94 | 200 | weighted avg | 0.94 | 0.94 | 0.94 | 200 |
| col_0 | 0 | 1 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Purchased | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 0 | 115 | 6 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 1 | 6 | 73 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | precision | recall | f1-score | support | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 0 | 0.95 | 0.95 | 0.95 | 121 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 1 | 0.92 | 0.92 | 0.92 | 79 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| accuracy | | | 0.94 | 200 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| macro avg | 0.94 | 0.94 | 0.94 | 200 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| weighted avg | 0.94 | 0.94 | 0.94 | 200 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| 2. | Tune the Model | <p>Feature Engineering:</p> <p>We have created a new feature “Age_Salary_Interact” as they have a positive interaction with the “Purchased” feature, that is, a positive correlation</p> | <pre>sns.heatmap(df.drop(columns=['User ID','Age_Less_Than_Avg','Salary_Grade']))</pre>  <p>Correlation of all variables with each other (We can see Age and AnnualSalary have a positive correlation with purchased)</p> <pre>from sklearn.model_selection import train_test_split # since age and annual salary show relatively high correlation to purchased df['Age_Salary_Interact'] = df['Age'] * df['AnnualSalary'] # Define the features and target variable X = df[['Gender', 'Age', 'AnnualSalary', 'Age_Salary_Interact']] y = df['Purchased']</pre> <p>We can see that Age_Salary_Interact is the product of age and AnnualSalary feature of the same observation</p> <pre>X.head()</pre> <table><tr><th></th><th>Gender</th><th>Age</th><th>AnnualSalary</th><th>Age_Salary_Interact</th></tr><tr><td>0</td><td>1</td><td>35</td><td>20000</td><td>700000</td></tr><tr><td>1</td><td>1</td><td>40</td><td>43500</td><td>1740000</td></tr><tr><td>2</td><td>1</td><td>49</td><td>74000</td><td>3626000</td></tr><tr><td>3</td><td>1</td><td>40</td><td>107500</td><td>4300000</td></tr><tr><td>4</td><td>1</td><td>25</td><td>79000</td><td>1975000</td></tr></table> | | Gender | Age | AnnualSalary | Age_Salary_Interact | 0 | 1 | 35 | 20000 | 700000 | 1 | 1 | 40 | 43500 | 1740000 | 2 | 1 | 49 | 74000 | 3626000 | 3 | 1 | 40 | 107500 | 4300000 | 4 | 1 | 25 | 79000 | 1975000 |
|----|----------------|--|--|---------------------|--------|-----|--------------|---------------------|---|---|----|-------|--------|---|---|----|-------|---------|---|---|----|-------|---------|---|---|----|--------|---------|---|---|----|-------|---------|
| | Gender | Age | AnnualSalary | Age_Salary_Interact | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 0 | 1 | 35 | 20000 | 700000 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 1 | 1 | 40 | 43500 | 1740000 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2 | 1 | 49 | 74000 | 3626000 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 3 | 1 | 40 | 107500 | 4300000 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 4 | 1 | 25 | 79000 | 1975000 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |