Model Optimization and Tuning Phase Report

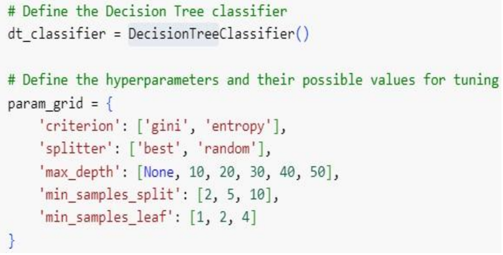
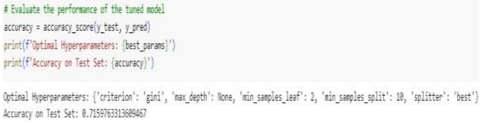
Date	10s July 2024
Team ID	739722
Project Title	Credit card approval prediction using ML
Maximum Marks	10 Marks

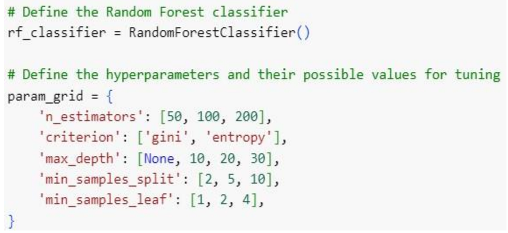
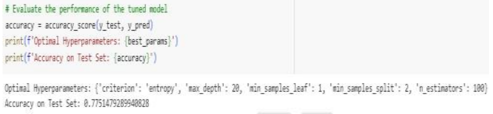
Model Optimization and Tuning Phase

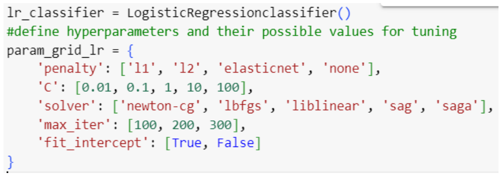
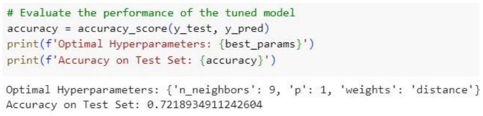
The Model Optimization and Tuning Phase involves refining machine learning models for peak performance. It includes optimized model code, fine-tuning hyperparameters, comparing performance metrics, and justifying the final model selection for enhanced predictive accuracy and efficiency.

Hyperparameter Tuning Documentation (6 Marks):

Model	Tuned Hyperparameters	Optimal Values

Decision Tree	
	# Define the Decision Tree classifier
	dt_classifier = DecisionTreeClassifier()
	
	# Define the hyperparameters and their possible values for tuning
	param_grid = {
	    'criterion': ['gini', 'entropy'],
	    'splitter': ['best', 'random'],
	    'max_depth': [None, 10, 20, 30, 40, 50],
	    'min_samples_split': [2, 5, 10],
	    'min_samples_leaf': [1, 2, 4]
	}
		
		# Evaluate the performance of the tuned model
		accuracy = accuracy_score(y_test, y_pred)
		print(f'Optimal Hyperparameters: {best_params}')
		print(f'Accuracy on Test Set: {accuracy}')
		
		Optimal Hyperparameters: {'criterion': 'gini', 'max_depth': None, 'min_samples_leaf': 2, 'min_samples_split': 10, 'splitter': 'best'}
		Accuracy on Test Set: 0.7159763313609467

Random Forest	
	# Define the Random Forest classifier
	rf_classifier = RandomForestClassifier()
	
	# Define the hyperparameters and their possible values for tuning
	param_grid = {
	    'n_estimators': [50, 100, 200],
	    'criterion': ['gini', 'entropy'],
	    'max_depth': [None, 10, 20, 30],
	    'min_samples_split': [2, 5, 10],
	    'min_samples_leaf': [1, 2, 4],
	}
		
		# Evaluate the performance of the tuned model
		accuracy = accuracy_score(y_test, y_pred)
		print(f'Optimal Hyperparameters: {best_params}')
		print(f'Accuracy on Test Set: {accuracy}')
		
		Optimal Hyperparameters: {'criterion': 'entropy', 'max_depth': 20, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 100}
		Accuracy on Test Set: 0.7751479289940828

<table>
<tr>
<td>Logistic Regression</td>
<td>
<pre>
lr_classifier = LogisticRegressionclassifier()
#define hyperparameters and their possible values for tuning
param_grid_lr = {
    'penalty': ['l1', 'l2', 'elasticnet', 'none'],
    'C': [0.01, 0.1, 1, 10, 100],
    'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'],
    'max_iter': [100, 200, 300],
    'fit_intercept': [True, False]
}
</pre></td>
<td>
<pre>
# Evaluate the performance of the tuned model
accuracy = accuracy_score(y_test, y_pred)
print(f'Optimal Hyperparameters: {best_params}')
print(f'Accuracy on Test Set: {accuracy}')

Optimal Hyperparameters: {'n_neighbors': 9, 'p': 1, 'weights': 'distance'}
Accuracy on Test Set: 0.7218934911242604
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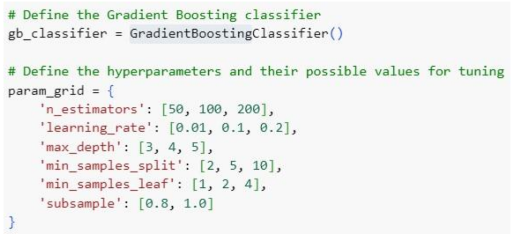
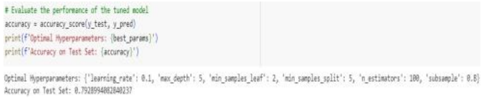
<tr>
<td>Gradient Boosting</td>
<td>
<pre>
# Define the Gradient Boosting classifier
gb_classifier = GradientBoostingClassifier()

# Define the hyperparameters and their possible values for tuning
param_grid = {
    'n_estimators': [50, 100, 200],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 4, 5],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'subsample': [0.8, 1.0]
}
</pre></td>
<td>
<pre>
# Evaluate the performance of the tuned model
accuracy = accuracy_score(y_test, y_pred)
print(f'Optimal Hyperparameters: {best_params}')
print(f'Accuracy on Test Set: {accuracy}')

Optimal Hyperparameters: {'learning_rate': 0.1, 'max_depth': 5, 'min_samples_leaf': 2, 'min_samples_split': 5, 'n_estimators': 100, 'subsample': 0.8}
Accuracy on Test Set: 0.7928994082840237
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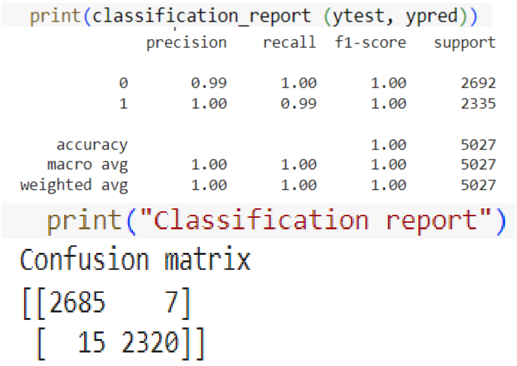
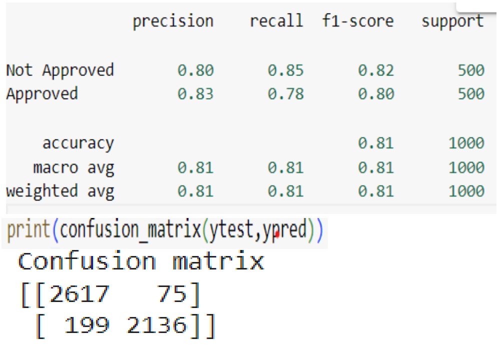
Performance Metrics Comparison Report (2 Marks):

<table>
<tr>
<th>Model</th>
<th>Optimized Metric</th>
</tr>
<tr>
<td>Decision Tree</td>
<td>
<pre>
print(classification_report (ytest, ypred))
              precision   recall f1-score   support

           0   0.99   1.00   1.00   2692
           1   1.00   0.99   1.00   2335

    accuracy   1.00   5027
   macro avg   1.00   1.00   1.00   5027
weighted avg   1.00   1.00   1.00   5027
print("Classification report")
Confusion matrix
[[2685   7]
 [15 2320]]
</pre></td>
</tr>
</table>

<table>
<tr>
<td>Random Forest</td>
<td>



```
              precision    recall  f1-score   support

Not Approved       0.80      0.85      0.82       500
Approved           0.83      0.78      0.80       500

    accuracy                           0.81      1000
   macro avg       0.81      0.81      0.81      1000
weighted avg       0.81      0.81      0.81      1000
print(confusion_matrix(ytest,ypred))
 Confusion matrix
 [[2617   75]
  [ 199 2136]]
```

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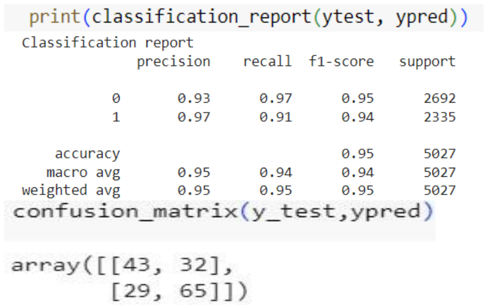
<tr>
<td>Logistic Regression</td>
<td>



```
print(classification_report(ytest, ypred))
Classification report
              precision    recall  f1-score   support

           0       0.93      0.97      0.95      2692
           1       0.97      0.91      0.94      2335

    accuracy                           0.95      5027
   macro avg       0.95      0.94      0.94      5027
weighted avg       0.95      0.95      0.95      5027
confusion_matrix(y_test,ypred)

array([[43, 32],
       [29, 65]])
```

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<tr>
<td>Gradient Boosting</td>
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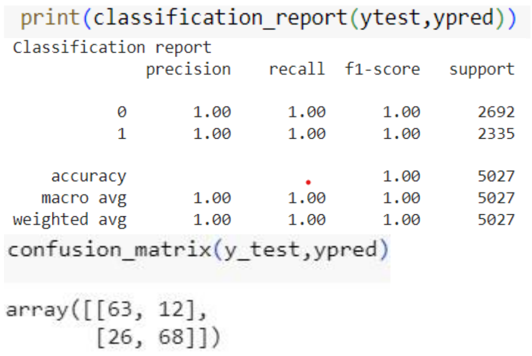

```
print(classification_report(ytest,ypred))
Classification report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2692
           1       1.00      1.00      1.00      2335

    accuracy                           1.00      5027
   macro avg       1.00      1.00      1.00      5027
weighted avg       1.00      1.00      1.00      5027
confusion_matrix(y_test,ypred)

array([[63, 12],
       [26, 68]])
```

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</tr>
</table>

Final Model Selection Justification (2 Marks):

Final Model	Reasoning
Gradient Boosting	The Gradient Boosting model was selected for its superior performance, exhibiting high accuracy during hyperparameter tuning. Its ability to handle complex relationships, minimize overfitting, and optimize predictive accuracy aligns with project objectives, justifying its selection as the final model.