Model Optimization and Tuning Phase Template

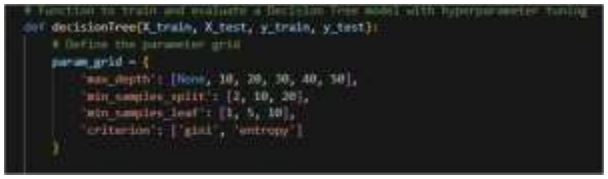
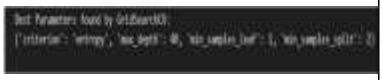
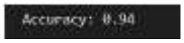
Date	15 March 2024
Team ID	xxxxxx
Project Title	Human Resource Management: Predicting Employee Promotions Using Machine Learning
Maximum Marks	10 Marks

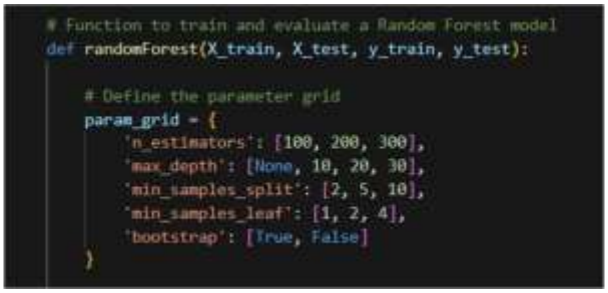
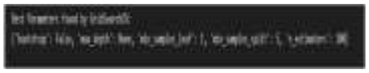
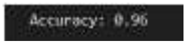
Model Optimization and Tuning Phase

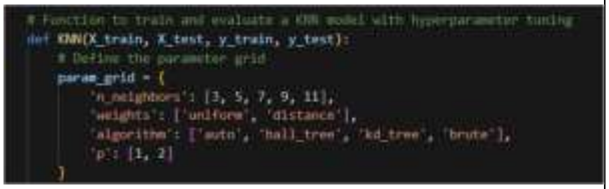
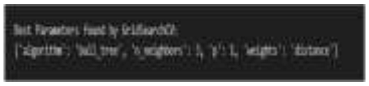
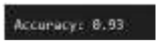
The Model Optimization and Tuning Phase involves refining machine learning models for peak performance. It includes optimized model code, fine-tuning hyperparameters, comparing performance metrics, and justifying the final model selection for enhanced predictive accuracy and efficiency.

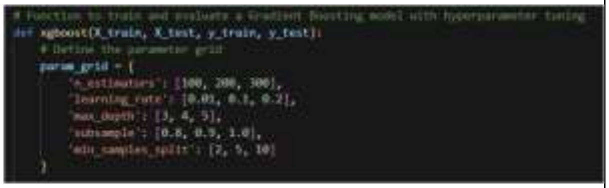
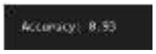
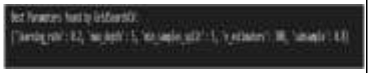
Hyperparameter Tuning Documentation (6 Marks):

Model	Tuned Hyperparameters	Optimal Values

Decision Tree	
	`# Function to train and evaluate a Decision Tree model with hyperparameter tuning`
	`def decisionTree(X_train, X_test, y_train, y_test):`
	`    # Define the parameter grid`
	`    param_grid = {`
	`        'max_depth': [None, 10, 20, 30, 40, 50],`
	`        'min_samples_split': [2, 10, 20],`
	`        'min_samples_leaf': [1, 5, 10],`
	`        'criterion': ['gini', 'entropy']`
	`    }`
		
		`Best Parameters found by GridSearchCV:`
		`{'criterion': 'entropy', 'max_depth': 40, 'min_samples_leaf': 1, 'min_samples_split': 2`
		
		`Accuracy: 0.94`

Random Forest	
	# Function to train and evaluate a Random Forest model
	def randomForest(X_train, X_test, y_train, y_test):
	# Define the parameter grid
	param_grid = {
	'n_estimators': [100, 200, 300],
	'max_depth': [None, 10, 20, 30],
	'min_samples_split': [2, 5, 10],
	'min_samples_leaf': [1, 2, 4],
	'bootstrap': [True, False]
	}
		
		Best Parameters found by GridSearchCV:
		{'bootstrap': False, 'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': [illegible], 'n_estimators': [illegible]}
		
		Accuracy: 0.96

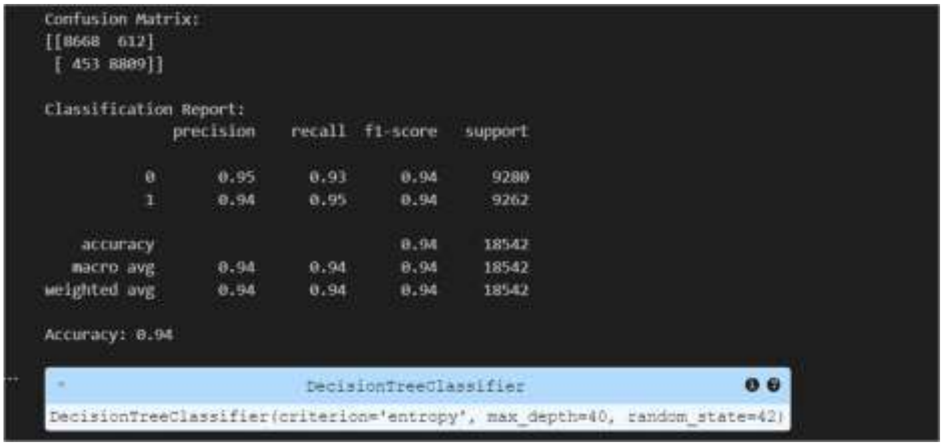
KNN	
	# Function to train and evaluate a KNN model with hyperparameter tuning
	def KNN(X_train, X_test, y_train, y_test):
	# Define the parameter grid
	param_grid = {
	'n_neighbors': [3, 5, 7, 9, 11],
	'weights': ['uniform', 'distance'],
	'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute'],
	'p': [1, 2]
	}
		
		Best Parameters found by GridSearchCV:
		{'algorithm': 'ball_tree', 'n_neighbors': [illegible], 'p': 1, 'weights': 'distance'}
		
		Accuracy: 0.93

Gradient Boost	
	# Function to train and evaluate a Gradient Boosting model with hyperparameter tuning
	def xgboost(X_train, X_test, y_train, y_test):
	# Define the parameter grid
	param_grid = {
	'n_estimators': [100, 200, 300],
	'learning_rate': [0.01, 0.1, 0.2],
	'max_depth': [3, 4, 5],
	'subsample': [0.8, 0.9, 1.0],
	'min_samples_split': [2, 5, 10]
	}
		
		Accuracy: 0.93
		
		Best Parameters found by GridSearchCV:
		{'learning_rate': 0.2, 'max_depth': [illegible], 'min_samples_split': [illegible], 'n_estimators': [illegible], 'subsample': [illegible]}

Performance Metrics Comparison Report (2 Marks):

Model	Optimized Metric

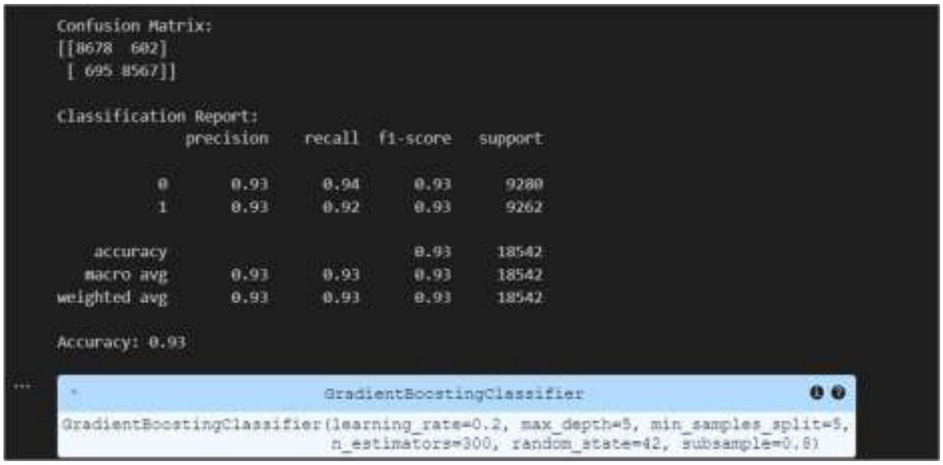
Decision Tree



```
Confusion Matrix:
[[8668  612]
 [ 453 8809]]

Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.93      0.94      9280
           1       0.94      0.95      0.94      9262

    accuracy                           0.94     18542
   macro avg       0.94      0.94      0.94     18542
weighted avg       0.94      0.94      0.94     18542

Accuracy: 0.94
```

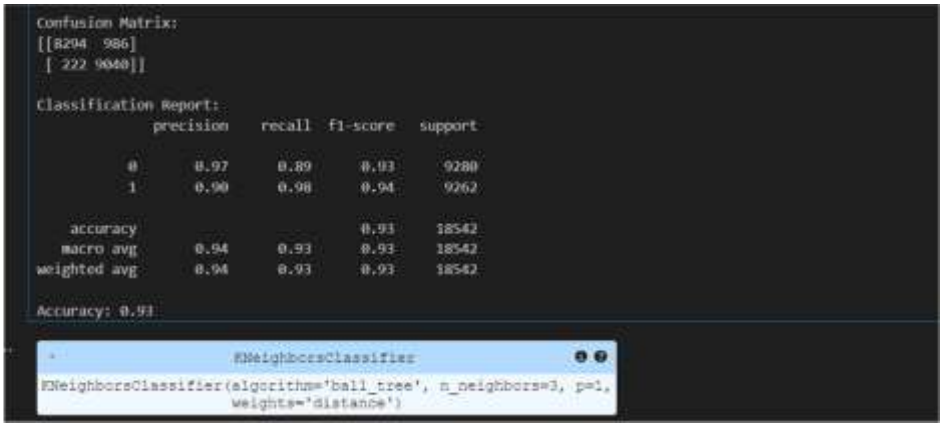
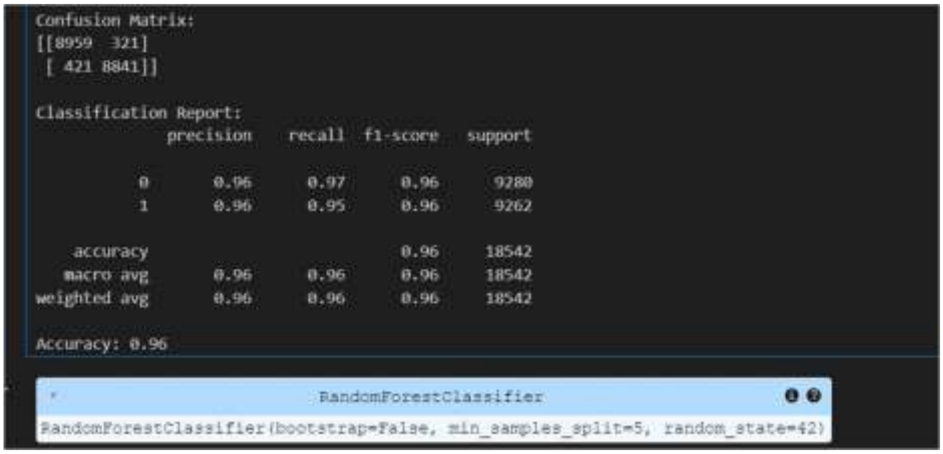
```
DecisionTreeClassifier(criterion='entropy', max_depth=40, random_state=42)
```

Gradient Boost



```
Confusion Matrix:
[[8678  602]
 [ 695 8567]]

Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.94      0.93      9280
           1       0.93      0.92      0.93      9262

    accuracy                           0.93     18542
   macro avg       0.93      0.93      0.93     18542
weighted avg       0.93      0.93      0.93     18542

Accuracy: 0.93
```

```
GradientBoostingClassifier(learning_rate=0.2, max_depth=5, min_samples_split=5,
                           n_estimators=300, random_state=42, subsample=0.8)
```

KNN	
Random Forest	

```
Confusion Matrix:
[[8294  986]
 [ 222 9040]]

Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.89      0.93      9280
           1       0.90      0.98      0.94      9262

    accuracy                           0.93     18542
   macro avg       0.94      0.93      0.93     18542
weighted avg       0.94      0.93      0.93     18542

Accuracy: 0.93
```

KNeighborsClassifier

```
KNeighborsClassifier(algorithm='ball_tree', n_neighbors=3, p=1,
                     weights='distance')
```

```
Confusion Matrix:
[[8959  321]
 [ 421 8841]]

Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.97      0.96      9280
           1       0.96      0.95      0.96      9262

    accuracy                           0.96     18542
   macro avg       0.96      0.96      0.96     18542
weighted avg       0.96      0.96      0.96     18542

Accuracy: 0.96
```

RandomForestClassifier

```
RandomForestClassifier(bootstrap=False, min_samples_split=5, random_state=42)
```

Final Model Selection Justification (2 Marks):

Final Model	Reasoning

Random Forest	I chose the Random Forest model as the final model for predicting employee promotions due to its superior accuracy (96%) compared to other models like Decision Tree, KNN, and Gradient Boosting. Random Forest is robust, handles overfitting well, and provides insights into feature importance. It captures complex, non-linear relationships within the data and is scalable for large datasets. Additionally, hyperparameter tuning further optimized its performance, making it a reliable and efficient choice for this task