

Model Optimization and Tuning Phase Report

Date	25 June 2025
Team ID	SWTID1750155746
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	<pre>dt_classifier = DecisionTreeClassifier() 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] } # Perform GridSearchCV grid_search = GridSearchCV(dt_classifier, param_grid, cv=5, scoring='accuracy') grid_search.fit(x_train, y_train) # Get the best parameters and best model best_params = grid_search.best_params_ best_dt_model = grid_search.best_estimator_</pre>	<pre># Make predictions with the best model y_pred = best_dt_model.predict(x_test) # Calculate accuracy 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': 50, 'min_samples_leaf': 1, 'min_samples_split': 2, 'splitter': 'best'} Accuracy on Test Set: 0.9279115411807</pre>
Random Forest	<pre>rf_classifier = RandomForestClassifier(random_state=42, n_jobs=-1) param_dist = { 'n_estimators': randint(50, 200), 'criterion': ['gini', 'entropy'], 'max_depth': [None, 10, 20, 30], 'min_samples_split': randint(2, 11), 'min_samples_leaf': randint(1, 5), } # Perform GridSearchCV grid_search = GridSearchCV(rf_classifier, param_dist, cv=5, scoring='accuracy') grid_search.fit(x_train, y_train) # Get the best parameters and best model best_params = grid_search.best_params_ best_rf_model = grid_search.best_estimator_</pre>	<pre># Make predictions with the best model y_pred = best_rf_model.predict(x_test) # Calculate accuracy 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': 10, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 100} Accuracy on Test Set: 0.945524051772326</pre>

KNN	<pre>knn_classifier = KNeighborsClassifier() param_dist = { 'n_neighbors': [3, 5, 7, 9], 'weights': ['uniform', 'distance'], 'p': [1, 2] } random_search = RandomizedSearchCV(knn_classifier, param_distributions=param_dist, n_iter=10, cv=3, scoring='accuracy', n_jobs=-1, verbose=1, random_state=42)</pre>	<pre># Make predictions with the best model y_pred = best_knn_model.predict(x_test) # Calculate accuracy accuracy = accuracy_score(y_test, y_pred) print(f'Optimal Hyperparameters: {best_params}') print(f'Accuracy on Test Set: {accuracy}') Optimal Hyperparameters: {'weights': 'distance', 'p': 1, 'n_neighbors': 3} Accuracy on Test Set: 0.9075255950006648</pre>
XG Boost	<pre>xgb_classifier = XGBClassifier(random_state=42, n_jobs=-1, verbosity=0) param_dist = { 'n_estimators': randint(50, 150), 'max_depth': randint(3, 10), 'learning_rate': uniform(0.01, 0.3), 'subsample': uniform(0.7, 0.3), 'colsample_bytree': uniform(0.7, 0.3), 'gamma': uniform(0, 5) }</pre>	<pre># Make predictions with the best model y_pred = best_xgb_model.predict(x_test) # Calculate accuracy accuracy = accuracy_score(y_test, y_pred) print(f'Optimal Hyperparameters: {best_params}') print(f'Accuracy on Test Set: {accuracy}') Optimal Hyperparameters: {'colsample_bytree': np.float64(0.8199582715145766), 'gamma': np.float64(2.233281160487714)}, Accuracy on Test Set: 0.9075255950006648</pre>

Performance Metrics Comparison Report (2 Marks):

Model	Optimized Metric																														
Decision Tree	<pre>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>0.94</td><td>0.92</td><td>0.93</td><td>15065</td></tr><tr><td>1</td><td>0.92</td><td>0.94</td><td>0.93</td><td>15019</td></tr><tr><td>accuracy</td><td></td><td></td><td>0.93</td><td>30084</td></tr><tr><td>macro avg</td><td>0.93</td><td>0.93</td><td>0.93</td><td>30084</td></tr><tr><td>weighted avg</td><td>0.93</td><td>0.93</td><td>0.93</td><td>30084</td></tr></tbody></table> <pre>print(confusion_matrix(y_test, y_pred))</pre> <pre>[[13818 1247] [921 14098]]</pre>		precision	recall	f1-score	support	0	0.94	0.92	0.93	15065	1	0.92	0.94	0.93	15019	accuracy			0.93	30084	macro avg	0.93	0.93	0.93	30084	weighted avg	0.93	0.93	0.93	30084
	precision	recall	f1-score	support																											
0	0.94	0.92	0.93	15065																											
1	0.92	0.94	0.93	15019																											
accuracy			0.93	30084																											
macro avg	0.93	0.93	0.93	30084																											
weighted avg	0.93	0.93	0.93	30084																											

Random Forest

```
print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
0	0.95	0.94	0.95	15065
1	0.94	0.95	0.95	15019
accuracy			0.95	30084
macro avg	0.95	0.95	0.95	30084
weighted avg	0.95	0.95	0.95	30084

```
print(confusion_matrix(y_test, y_pred))
```

```
[[14187  878]
 [ 760 14259]]
```

KNN

```
print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
0	0.95	0.86	0.90	15065
1	0.87	0.95	0.91	15019
accuracy			0.91	30084
macro avg	0.91	0.91	0.91	30084
weighted avg	0.91	0.91	0.91	30084

```
print(confusion_matrix(y_test, y_pred))
```

```
[[12975 2090]
 [ 692 14327]]
```

XG Boost

```
print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
0	0.95	0.86	0.90	15065
1	0.87	0.95	0.91	15019
accuracy			0.91	30084
macro avg	0.91	0.91	0.91	30084
weighted avg	0.91	0.91	0.91	30084

```
print(confusion_matrix(y_test, y_pred))
```

```
[[12975 2090]
 [ 692 14327]]
```

Final Model Selection Justification (2 Marks):

Final Model	Reasoning
Random Forest	The Random Forest model was selected for its superior performance, exhibiting the highest accuracy during hyperparameter tuning. Its ability to handle complex feature interactions, reduce overfitting, and deliver reliable predictions aligns with the project objectives, justifying its selection as the final model.