

## Model Optimization and Tuning Phase Report

Date	23 September 2024
Team ID	LTVIP2024TMID24967
Project Title	SmartLender - Applicant Credibility Prediction for Loan Approval
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># 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] }</pre>	<pre>best_dt = grid_search_dt.best_estimator_ print("Best Hyperparameters for Decision Tree:", grid_search_dt.best_params_) y_pred_dt = best_dt.predict(X_test) print("Decision Tree Accuracy: {:.2f}".format(accuracy_score(y_test, y_pred_dt)))</pre> <p>Fitting 5 folds for each of 216 candidates, totalling 1080 fits Best Hyperparameters for Decision Tree: {'criterion': 'gini', 'max_depth': 10, 'max_... Decision Tree Accuracy: 0.74</p>
Random Forest	<pre># 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], }</pre>	<pre>best_rf = grid_search_rf.best_estimator_ print("Best Hyperparameters for Random Forest:", grid_search_rf.best_params_) y_pred_rf = best_rf.predict(X_test) print("Random Forest Accuracy: {:.2f}".format(accuracy_score(y_test, y_pred_rf)))</pre> <p>Fitting 5 folds for each of 216 candidates, totalling 1080 fits Best Hyperparameters for Random Forest: {'bootstrap': True, 'max_depth': 30, 'min_samp... Random Forest Accuracy: 0.80</p>

KNN	<pre>knn_classifier = KNeighborsClassifier()  # Define the hyperparameters and their possible values for tuning param_grid = {     'n_neighbors': [3, 5, 7, 9],     'weights': ['uniform', 'distance'],     'p': [1, 2] }</pre>	<pre>best_knn = grid_search_knn.best_estimator_ print("Best Hyperparameters for KNN:", grid_search_knn.best_params_) y_pred_knn = best_knn.predict(X_test) print("KNN Accuracy: {:.2f}".format(accuracy_score(y_test, y_pred_knn)))  Fitting 5 folds for each of 192 candidates, totalling 960 fits Best Hyperparameters for KNN: {'algorithm': 'auto', 'leaf_size': 10, 'n_neighbors': 5, 'p': 1, 'weights': 'distance'} KNN Accuracy: 0.79</pre>
Gradient Boosting	<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>	<pre>print("Best Hyperparameters for Gradient Boosting:", grid_search_gb.best_params_) y_pred_gb = best_gb.predict(X_test) print("Gradient Boosting Accuracy: {:.2f}".format(accuracy_score(y_test, y_pred_gb)))  Fitting 5 folds for each of 1 candidates, totalling 5 fits Best Hyperparameters for Gradient Boosting: {'learning_rate': 0.1, 'max_depth': 5, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 100, 'subsample': 1.0} Gradient Boosting Accuracy: 0.77</pre>

### Performance Metrics Comparison Report (2 Marks):

Model	Optimized Metric				
Decision Tree	<pre> **Decision Tree Classifier** Confusion matrix [[54 20]  [13 57]] Classification report               precision    recall  f1-score   support               0       0.81      0.73      0.77         74              1       0.74      0.81      0.78         70     accuracy: 0.77   macro avg: 0.77  weighted avg: 0.77 </pre>				

Random Forest	<pre> *** Random Forest Classifier *** Confusion matrix: [[54 20]  [ 5 65]] Classification report:               precision    recall  f1-score   support        0       0.92      0.73      0.81         74       1       0.76      0.93      0.84         70   accuracy          0.83         144  macro avg          0.84         144  weighted avg       0.84         144 </pre>
KNN	<pre> *** KNeighbors Classifier *** Confusion matrix: [[45 29]  [ 7 63]] Classification report:               precision    recall  f1-score   support        0       0.87      0.61      0.71         74       1       0.68      0.90      0.78         70   accuracy          0.75         144  macro avg          0.78         144  weighted avg       0.78         144 </pre>
Gradient Boosting	<pre> *** Gradient Boosting Classifier *** Confusion matrix: [[44 30]  [ 5 65]] Classification report:               precision    recall  f1-score   support        0       0.90      0.59      0.72         74       1       0.68      0.93      0.79         70   accuracy          0.76         144  macro avg          0.79         144  weighted avg       0.79         144 </pre>

**Final Model Selection Justification (2 Marks):**

Final Model	Reasoning
Random Forest	The Random Forest model was selected for its robust performance and strong generalization capabilities. Its ability to handle a large number of features, mitigate overfitting through bagging, and provide feature importance metrics made it a top contender. Random Forest demonstrated competitive accuracy during hyperparameter tuning, and its ensemble nature ensures better stability and resilience to noise in the dataset. These factors align with the project's objectives, making it an excellent choice as the final model.