

Model Optimization and Tuning Phase Report

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Team ID	SWTID1720530286
Project Title	Ecommerce Shipping Prediction 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
Logistic Regression	<pre>lg = LogisticRegressionCV(n_jobs=-1, random_state=1234) lg_param_grid = { 'cs': [6, 8, 10, 15, 20], 'max_iter': [60, 80, 100] }</pre>	<pre>lg_cv.fit(x_train_normalized, y_train) print("Best Score:", lg_cv.best_score_) print("Best Parameters:", lg_cv.best_params_)</pre> <p>Fitting 5 folds for each of 15 candidates, totalling 75 fits Best Score: 0.6412089126053026 Best Parameters: {'cs': 20, 'max_iter': 60}</p>
Random Forest	<pre>rf = RandomForestClassifier(random_state=1234) rf_param_grid = { 'n_estimators': [200, 300, 500], 'criterion': ['entropy', 'gini'], 'max_depth': [7, 8, 60, 80, 100], 'max_features': ['auto', 'sqrt', 'log2'] }</pre>	<pre>rf_cv = GridSearchCV(rf, param_grid=rf_param_grid, cv=5, scoring='accuracy', n_jobs=-1, verbose=1) rf_cv.fit(x_train_normalized, y_train) print("Best Score:", rf_cv.best_score_) print("Best Parameters:", rf_cv.best_params_)</pre> <p>Best Score: 0.6801309307075096 Best Parameters: {'criterion': 'entropy', 'max_depth': 8, 'max_features': 'sqrt', 'n_estimators': 200}</p>

KNN	<pre>knn = KNeighborsClassifier() # Define the parameter grid for KNN knn_param_grid = { 'n_neighbors': [3, 5, 7, 9, 11], 'weights': ['uniform', 'distance'], 'metric': ['euclidean', 'manhattan', 'minkowski'] }</pre>	<pre># Initialize GridSearchCV knn_cv = GridSearchCV(knn, knn_param_grid, cv=7, scoring='accuracy', n_jobs=-1, verbose=3) # Fit the model knn_cv.fit(x_train_normalized, y_train) # Output the best score and parameters print("Best Score: " + str(knn_cv.best_score_)) print("Best Parameters: " + str(knn_cv.best_params_)) Fitting 7 folds for each of 30 candidates, totalling 210 fits Best Score: 0.6537106489373793 Best Parameters: {'metric': 'euclidean', 'n_neighbors': 9, 'weights': 'distance'}</pre>
Gradient Boosting	<pre>xgb = XGBClassifier(learning_rate=0.5, n_estimators=100, objective='binary:logistic', nthread=3) # Define the parameter grid for XGBoost params = { 'min_child_weight': [10, 20], 'gamma': [1.5, 2.0, 2.5], 'colsample_bytree': [0.6, 0.8, 0.9], 'max_depth': [4, 5, 6] }</pre>	<pre># Initializing GridSearchCV for XGBoost fitmodel = GridSearchCV(xgb, param_grid=params, cv=5, refit=True, scoring='accuracy', n_jobs=-1, verbose=3) # Fit the model using the normalized training data fitmodel.fit(x_train_normalized, y_train) # Print the best estimator, parameters, and score print("Best Estimator:", fitmodel.best_estimator_) print("Best Parameters:", fitmodel.best_params_) print("Best Score:", fitmodel.best_score_) Fitting 5 folds for each of 54 candidates, totalling 270 fits Best Estimator: XGBClassifier(base_score=None, booster=None, callbacks=None, colsample_bytree=None, colsample_bynode=None, colsample_bylevel=None, device=None, early_stopping_rounds=None, enable_categorical=False, eval_metric=None, feature_types=None, gamma=2.0, grow_policy=None, importance_type=None, interaction_constraints=None, learning_rate=0.5, max_bin=None, max_cat_threshold=None, max_cat_to_onehot=None, max_delta_step=None, max_depth=4, max_leaves=None, min_child_weight=20, missing=nan, monotone_constraints=None, multi_strategy=None, n_estimators=100, n_jobs=None, nthread=3, num_parallel_tree=None, ...) Best Parameters: {'colsample_bytree': 0.9, 'gamma': 2.0, 'max_depth': 4, 'min_child_weight': 20} Best Score: 0.676326812751811</pre>

Performance Metrics Comparison Report (2 Marks):

Model	Optimized Metric
KNN	<pre># Initialize GridSearchCV knn_cv = GridSearchCV(knn, knn_param_grid, cv=7, scoring='accuracy', n_jobs=-1, verbose=3) # Fit the model knn_cv.fit(x_train_normalized, y_train) # Output the best score and parameters print("Best Score: " + str(knn_cv.best_score_)) print("Best Parameters: " + str(knn_cv.best_params_)) Fitting 7 folds for each of 30 candidates, totalling 210 fits Best Score: 0.6537106489373793 Best Parameters: {'metric': 'euclidean', 'n_neighbors': 9, 'weights': 'distance'}</pre>

Final Model Selection Justification (2 Marks):

Final Model	Reasoning
KNN	The KNN model was selected for its balanced performance across various metrics. Its ability to classify based on the nearest neighbors makes it adaptable to data patterns and effective for capturing local variations in loan approval criteria. The high F1 score and recall values indicate its robustness in correctly identifying loan approvals, which aligns with project objectives, justifying its selection as the final model.