



Model Optimization and Tuning Phase Report

Date	03 October 2024
Team ID	LTVIP2024TMID24947
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	# Hyperparameter tuning for Decision Tree param_prid_tt = { "max_depth" [None, 5, 10], # Limit max_depth "min_samples_split": [2, 5] # Limit minimum samples to split } dt_grid = GridSearchCV(estimator=DecisionTreeClassifier(), param_gridsparam_grid_dt, cv=3, scoring='accuracy', n_jobs=-1) dt_grid.fil(_train_scaled, y_train) print('Best Decision Tree Parameters:", dt_grid.best_params_) print('Best Decision Tree Accuracy:", dt_grid.best_score_)	- Best Random Forest Parameters: ('max_depth': None, 'min_ramples_split': 5, 'm_estimators': 100) Best Random Forest Accuracy: 0.9799041642814564 Best CMD Parameters: ('m.estimators': 100) Best Win Accuracy: 0.9880971566666 Best Win Accuracy: 0.9880971566666 Best Win Accuracy: 0.9880971566666 Best Min Accuracy: 0.9880971566666 Best Min Accuracy: 0.9880971567666 Best Min Accuracy: 0.9880971676 Best Min Accuracy: 0.98809716571676 Best Min Accuracy: 0.98809716571147140 Best Min Accuracy: 0.988097167147140 Bes
Random Forest	# Hyperparameter tuning for Random Forest param_grid_rf = { "n_estimators': [50, 100], # Reduced number of estimators "max_dopth': [100a, 10], # Limit max_dopth "min_emaples_split': [2, 5] # Limit minimum samples to split } rf_grid = GridSearchCV(estimator=Random=GreatClassifier(), param_grid=param_grid_rf, cv=3, scoring='accuracy', n_jobs=-1) rf_grid_fit(x_train_scaled_y_train) orint("Best Random Forest Parameters:", rf_grid_best_params_print("Best_Random Forest Accuracy:", rf_grid_best_score_)	- Best Random Forest Parameters: { max_depth': None, 'min_samples_split': 5, 'n_estimators': 100} Best Kandom Forest Accuracy: 0.9793041642814564 Best KNIR Jarameters: ('m_neighbors': 7, 'weights': 'distance') Best KNIR Jarameters: ('max_depth': None, 'min_samples_split': 2) Best KNIR Jarameters: ('max_depth': None, 'min_samples_split': 2) Best Decision Tree Accuracy: 0.981259835307022 Best Decision Tree Accuracy: 0.981259835307022 Best KXGBoost Accuracy: 0.9830165311147140 0.1, 'max_depth': 5, 'n_estimators': 100} Best XXGBoost Accuracy: 0.9830165311147140





KNN	# Hyperparameter tuning for ENN parms grid_Non = { 'n_neighbors': [3, 5, 7], # Reduced number of reighbors 'wights': ['uniform', 'distance'] # Explore different weighting schemes } kmn_grid = GridSearch(V(estimator=NkighborsClassifier(), param_grid=param_grid_knn, cv=3, scoring='accuracy', n_jobs=-1) kmn_grid = GridSearch(V(estimator=NkighborsClassifier(), param_grid=param_grid_knn, cv=3, scoring='accuracy', n_jobs=-1) kmn_grid = GridSearch(V(estimator=NkighborsClassifier(), param_grid=param_grid_knn, cv=3, scoring='accuracy', n_jobs=-1) print("Best KON Parameters", knn_grid_best_params_) print("Best KON Parameters", knn_grid_best_params_) print("Best KON Accuracy", knn_grid_best_params_)	Eest Random Forest Parameters: ('max_depth': None, 'min_samples_split': 5, 'm_estimators': 100) Eest Random Forest Accuracy: 0.9798041642814994 Eest XUN Parameters: ('m_estimators': 1, 'meistimator') Eest XUN Accuracy: 0.18009713656467 Eest Diction Three Parameters: ('max_depth': None, 'min_samples_split': 2) Eest XGEoost Parameters: ('lear-depth': None, 'min_samples_split': 2) Eest XGEoost Accuracy: 0.9830165311147140 Eest XGEoost Accuracy: 0.9830165311147140
XG Boost	# Hyperparameter tuning for NGBoost param grid ymp : "mestimators' [59, 100], # Reduced number of estimators 'mestimators' [59, 100], # Reduced number of estimators 'mestimators' [50, 100], # Reduced number of estimators 'mestimators' [50, 100], # Reduced number of estimators 'mestimators' [50, 100], # Reduced number of estimators 'learning rate': [61, 0.01] # Explore different learning rates } ght grid = GridSearchCV(estimatorsygh.NGEClassifier(), param gridvparam_grid ymp, cv=3, scorings'accuracy', n_jobs=-1) sph grid = GridSearchCV(estimatorsygh.NGEClassifier(), param gridvparam_grid ymp, cv=3, scorings'accuracy', n_jobs=-1) sph grid = GridSearchCV(estimatorsygh.NGEClassifier(), param gridvparam_grid ymp, cv=3, scorings'accuracy', n_jobs=-1) sph grid = GridSearchCV(estimatorsygh.NGEClassifier(), param gridvparam_grid ymp, cv=3, scorings'accuracy', n_jobs=-1) sph grid = GridSearchCV(estimatorsygh.NGEClassifier(), param gridvparam_grid ymp, cv=3, scorings'accuracy', n_jobs=-1) sph grid = GridSearchCV(estimatorsygh.NGEClassifier(), param gridvparam_grid ymp, cv=3, scorings'accuracy', n_jobs=-1) sph grid = GridSearchCV(estimatorsygh.NGEClassifier(), param gridvparam_grid ymp, cv=3, scorings'accuracy', n_jobs=-1) sph grid = GridSearchCV(estimatorsygh.NGEClassifier(), param gridvparam_grid ymp, cv=3, scorings'accuracy', n_jobs=-1) sph grid = GridSearchCV(estimatorsygh.NGEClassifier(), param gridvparam_grid ymp, cv=3, scorings'accuracy', n_jobs=-1) sph grid = GridSearchCV(estimatorsygh.NGEClassifier(), param gridvparam_grid ymp, cv=3, scorings'accuracy', n_jobs=-1) sph grid = GridSearchCV(estimatorsygh.NGEClassifier(), param gridvparam_grid ymp, cv=3, scorings'accuracy', n_jobs=-1) sph grid = GridSearchCV(estimatorsygh.NGEClassifier(), param gridvparam_grid ymp, cv=3, scorings'accuracy', n_jobs=-1) sph grid = GridSearchCV(estimatorsygh.NGEClassifier(), param gridvparam_grid ymp, cv=3, scorings'accuracy', n_jobs=-1) sph grid = GridSearchCV(estimatorsygh.NGEClassifier(), param gridvparam_grid ym	Best Random Forest Parameters: ('max_depth': None, 'min_samples_split': 5, 'n_estimators': 100) Best Kandom Forest Accuracy: 0.979041642814594 Best ZUNP Parameters: ('n_estimators': 1

Performance Metrics Comparison Report (2 Marks):

Model	Optimized Metric					
Decision Tree	0 1 accuracy macro avg	Tree Confus Tree Classic precision 0.97 0.99 0.98	ion Matri fication recall 0.98 0.99	x: Report: f1-score 0.98 0.99 0.98 0.98	support 316 538 854 854	
	weighted avg	0.98	0.98	0.98	854	





	<u> </u>					
	Best Random For	rest Confus	ion Matri	x:		
	[[308 8]					
	[14 524]]					
	Best Random For	rest Classi	fication	Report:		
		precision		•	support	
Random Forest						
	0	0.96	0.97	0.97	316	
	1	0.98	0.97	0.98	538	
	accuracy			0.97	854	
	macro avg	0.97	0.97	0.97	854	
	weighted avg	0.97	0.97	0.97	854	
	Best KNN Conf	usion Matri	x:			
	[[288 28]					
	[43 495]]					
	Best KNN Clas	sification	Report:			
		precision	recall	f1-score	support	
KNN						
	0			0.89		
	1	0.95	0.92	0.93	538	
	accuracy		0.00		854	
	_	0.91				
	weighted avg	0.92	0.92	0.92	854	
	Best XGBoost Co	onfusion Mat	rix:			
	[[311 5]					
	[10 528]]					
	Best XGBoost C					
	ı	precision	recall f	1-score s	upport	
XG Boost	0	0.97	0.98	0.98	316	
	1	0.99	0.98	0.99	538	
				0.00	054	
	accuracy	0 00	0.98	0.98 0.98	854 854	
	macro avg weighted avg	0.98 0.98	0.98	0.98	854 854	
	wergineed avg	0.50	0.50	0.50	054	





Final Model Selection Justification (2 Marks):

Final Model	Reasoning
Random forest	After evaluating the models based on several metrics such as accuracy, precision, recall, and F1-score, all models demonstrated good performance. However, Random Forest (RF) was selected as the final model due to its combination of accuracy, robustness, and interpretability. While XGBoost showed competitive performance, RF was easier to interpret and required less computational overhead for deployment, making it more suitable for this application. Final Choice: Random Forest was chosen as the model for predicting loan eligibility because of its high performance and the ability to generalize well to new, unseen data.