



Model Optimization and Tuning Phase Template

Date	24 April 2024
Team ID	Team-738169
Project Title	Rainfall 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
Random Forest	# Create the random grid random_grid={'n_estimators':n_estimators,	<pre>from sklearn.metrics import accuracy_score y_pred = best_random_grid.predict(X_test) print(confusion_matrix(y_test,y_pred)) print('Accuracy_score {}'.format(accuracy_score(y_test,y_pred))) print('classification_report {}'.format(classification_report(y_test,y_pred))) [[1686 172] [221 321]] Accuracy_score 0.83625</pre>





```
# Create the random grid
                                  random_grid = {'n_estimators': n_estimators,
                                                    'learning_rate': learning_rate,
                                                    'max_depth': max_depth,
                                                    'subsample': subsample,
                                                    'min_child_weight': min_child_weight}
                                  print(random_grid)
                                  {'n_estimators': [100, 200, 300, 400, 500, 600, 700, 800,
                                                                                                              from sklearn.metrics import accuracy_score
y_predict = xg_random.predict(X_test)
print((confusion_matrix(y_test,y_predict))
print('Accuracy_score()'.'format(accuracy_score(y_test,y_predict)))
print('Classification_report()'.'format(classification_report(y_test,y_predict)))
                                  h': [5, 10, 15, 20, 25, 30], 'subsample': [0.7, 0.6, 0.8],
XGBoost
                                                                                                              [[1716 154]
[ 218 312]]
Accuracy score 0.845
                                    xg_random.best_params_
                                    {'subsample': 0.6,
                                      'n_estimators': 400,
                                      'min_child_weight': 5,
                                       'max_depth': 25,
                                       'learning_rate': '0.05'}
```

Performance Metrics Comparison Report (2 Marks):

Model	<pre>Optimized Metric y_pred2 = logreg.predict(X_test) print(confusion_matrix(y_test,y_pred2)) print(accuracy_score(y_test,y_pred2)) print(classification_report(y_test,y_pred2))</pre>					
	[[17456 5261] [1508 4867]] 0.7673243503368624					
Logistic Regression	р	recision	recall	f1-score	support	
	0	0.92	0.77	0.84	22717	
	1	0.48	0.76	0.59	6375	
	accuracy			0.77	29092	
	macro avg	0.70	0.77	0.71	29092	
	weighted avg	0.82	0.77	0.78	29092	





	<pre>y_pred = model_dt.predict(X_test) print(confusion_matrix(y_test,y_pred)) print(accuracy_score(y_test,y_pred)) print(classification_report(y_test,y_pred))</pre>					
Decision Tree	[[1616 240] [236 308]] 0.8016666666666	6666 precision	recall	f1-score	support	
	0	0.87	0.87	0.87	1856	
	1	0.56	0.57	0.56	544	
	accuracy			0.80	2400	
	macro avg weighted avg	0.72 0.80	0.72 0.80	0.72 0.80	2400 2400	
	weighted avg	0.00	0.00	0.80	2400	
	y_pred1 = rf.pre print(confusion_ print(accuracy_s print(classifica	_matrix(y_t core(y_tes	est,y_pred: t,y_pred1))		
Random Forest	[[1683 175] [225 317]] 0.83333333333333	334 recision	recall f	1-score s	support	
	0	0.88	0.91	0.89	1858	
	1	0.64	0.58	0.61	542	
	accuracy			0.83	2400	
	macro avg weighted avg	0.76 0.83	0.75 0.83	0.75 0.83	2400 2400	
	v pped4 = kpp	nnodict(Y	tost)			
	<pre>y_pred4 = knn.predict(X_test) print(confusion_matrix(y_test,y_pred4)) print(accuracy_score(y_test,y_pred4)) print(classification_report(y_test,y_pred4))</pre>					
WNINI	[[17410 5307] [1811 4564] 0.755327925202]] 28 0 49				
KNN		precision	recall	f1-score	support	
	0 1	0.91 0.46	0.77 0.72	0.83 0.56	22717 6375	
		0.40	0.72			
	accuracy macro avg	0.68	0.74	0.76 0.70	29092 29092	
	weighted avg	0.81	0.76	0.77	29092	





	<pre>y_pred5 = svc.predict(X_test) print(confusion_matrix(y_test,y_pred5)) print(accuracy_score(y_test,y_pred5)) print(classification_report(y_test,y_pred5))</pre>	
SVM	[[1436 463] [137 364]] 0.75 precision recall f1-score	support
	0 0.91 0.76 0.83 1 0.44 0.73 0.55	1899 501
	accuracy 0.75 macro avg 0.68 0.74 0.69 weighted avg 0.81 0.75 0.77	2400 2400 2400
	<pre>y_pred = xgb.predict(X_test)</pre>	
	<pre>y_pred = xgb.predict(X_test) print(confusion_matrix(y_test,y_pred)) print(accuracy_score(y_test,y_pred)) print(classification_report(y_test,y_pred))</pre>	
VOD	<pre>print(confusion_matrix(y_test,y_pred)) print(accuracy_score(y_test,y_pred))</pre>	
XGBoost	<pre>print(confusion_matrix(y_test,y_pred)) print(accuracy_score(y_test,y_pred)) print(classification_report(y_test,y_pred)) [[1709 161] [218 312]]</pre>	support
XGBoost	<pre>print(confusion_matrix(y_test,y_pred)) print(accuracy_score(y_test,y_pred)) print(classification_report(y_test,y_pred)) [[1709 161] [218 312]] 0.842083333333333</pre>	1870
XGBoost	<pre>print(confusion_matrix(y_test,y_pred)) print(accuracy_score(y_test,y_pred)) print(classification_report(y_test,y_pred)) [[1709 161] [218 312]] 0.842083333333333</pre>	
XGBoost	<pre>print(confusion_matrix(y_test,y_pred)) print(accuracy_score(y_test,y_pred)) print(classification_report(y_test,y_pred)) [[1709 161] [218 312]] 0.842083333333333</pre>	1870 530 2400

Final Model Selection Justification (2 Marks):

Final Model	Reasoning
	Thorough experimentation and hyperparameter tuning, the XGBoost model consistently outperformed other models in terms of accuracy metrics. XGBoost's inherent capability to handle missing values and its regularization techniques contribute to its superior performance and
XGBoost	generalization ability, justifying its selection as the final model.