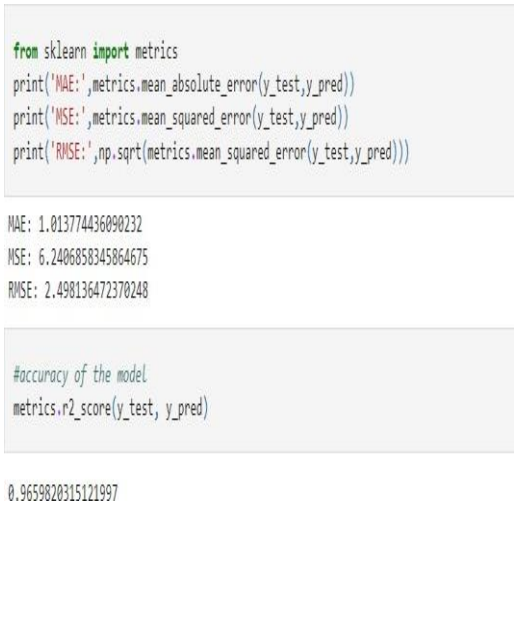
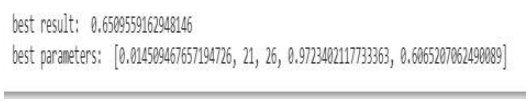
Project Development Phase
Model Performance Test

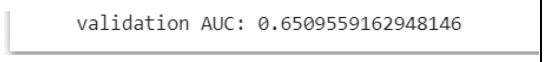
Date	11 November 2022
Team ID	PNT2022TMID16005
Project Name	Efficient Water Quality Analysis and Prediction Using Machine Learning
Maximum Marks	10 Marks

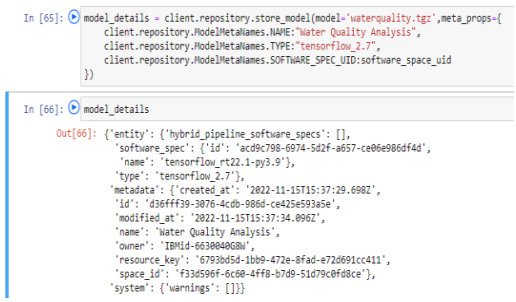
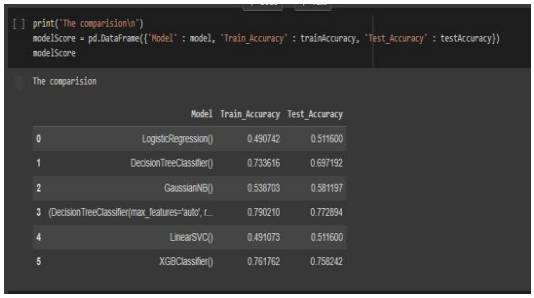
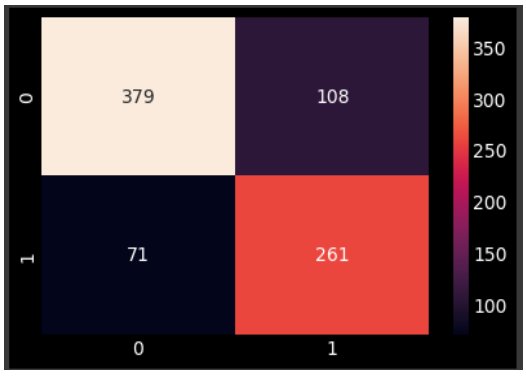
Model Performance Testing:

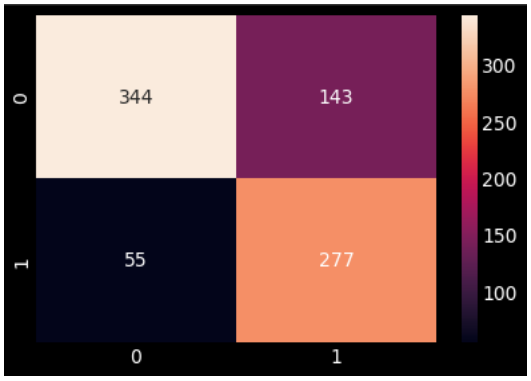
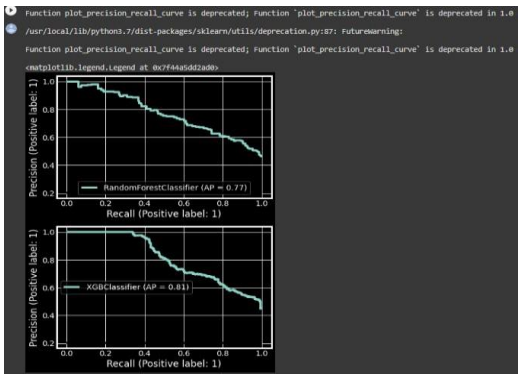
Project team shall fill the following information in model performance testing template.

S.No.	Parameter	Values	Screenshot
1.	Regression Model	from sklearn.ensemble import RandomForestRegressor regressor = RandomForestRegressor(n_estimators = 10, random_state = 0) regressor.fit(x_train, y_train) y_pred = regressor.predict(x_test) from sklearn import metrics print('MAE:',metrics.mean_absolute_error(y_test,y_pred)) print('MSE:',metrics.mean_squared_error(y_test,y_pred)) print('RMSE:',np.sqrt(metrics.mean_squared_error(y_test,y_pred))) MAE: 1.013774436090232 MSE: 6.2406858345864675 RMSE: 2.498136472370248 *#accuracy of the model* metrics.r2_score(y_test, y_pred) 0.9659820315121997	

2.	Hyperparameter tuning	SPACE = [
		  skopt.space.Real(0.01, 0.5, name='learning_rate', prior='log-uniform'),
		  skopt.space.Integer(1, 30, name='max_depth'),
		  skopt.space.Integer(2, 100, name='num_leaves'),
		  skopt.space.Real(0.1, 1.0, name='feature_fraction', prior='uniform'),
		  skopt.space.Real(0.1, 1.0, name='subsample', prior='uniform')]
		@skopt.utils.use_named_args(SPACE)
		def objective(**params):
		  return -1.0 * train_evaluate(params)
		results = skopt.forest_minimize(objective, SPACE, n_calls=30, n_random_starts=10)
		best_auc = -1.0 * results.fun
		best_params = results.x
		print('best result: ', best_auc)
		print('best parameters: ', best_params)
			

3.	Validation Method	def train_evaluate(search_params):
		  path = "water_potability.csv"
		  data = pd.read_csv(path)
		  X = data.drop(['Sulfate','Potability'], axis=1)
		  y = data['Potability']
		  X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.2, random_state=1234)
		  train_data = lgb.Dataset(X_train, label=y_train)
		  valid_data = lgb.Dataset(X_valid, label=y_valid, reference=train_data)
		
		  params = {'objective': 'binary',
		  'metric': 'auc',
		  **search_params}
		  model = lgb.train(params, train_data,
		  num_boost_round=300,
		  early_stopping_rounds=30,
		  valid_sets=[valid_data],
		  valid_names=['valid'])
		
		  score = model.best_score['valid']['auc']
		  return score
		if __name__== '__main__':
		  score = train_evaluate(SEARCH_PARAMS)
		  print('validation AUC:', score)
			

4.	Model Summary	{'entity': {'hybrid_pipeline_software_specs': [], 'software_spec': {'id': 'acd9c798-6974-5d2f-a657-ce06e986df4d', 'name': 'tensorflow_rt22.1-py3.9'}, 'type': 'tensorflow_2.7'}, 'metadata': {'created_at': '2022-11-15T15:37:29.698Z', 'id': 'd36fff39-3076-4cdb-986d-ce425e593a5e', 'modified_at': '2022-11-15T15:37:34.096Z', 'name': 'Water Quality Analysis', 'owner': 'IBMid-6630040G8W', 'resource_key': '6793bd5d-1bb9-472e-8fad-e72d691cc411', 'space_id': 'f33d596f-6c60-4ff8-b7d9-51d79c0fd8ce'}, 'system': {'warnings': []}}	
5.	Accuracy	Model Train_Accuracy Test_Accuracy 0 LogisticRegression() 0.490742 0.511600 1 DecisionTreeClassifier() 0.733616 0.697192 2 GaussianNB() 0.538703 0.581197 3 (DecisionTreeClassifier(max_features='auto', r... 0.790210 0.772894 4 LinearSVC() 0.491073 0.511600 5 XGBClassifier() 0.761762 0.758242	
6.	Confusion Matrix (Random Forest Classifier)	print('Random Forest Classifier\n') Rfc = RandomForestClassifier() Rfc.fit(X_train, y_train) y_Rfc = Rfc.predict(X_test) print(metrics.classification_report(y_test, y_Rfc)) print(modelAccuracy.append(metrics.accuracy_score(y_test, y_Rfc))) sns.heatmap(confusion_matrix(y_test, y_Rfc), annot=True, fmt='d') plt.show()	

	Confusion Matrix (XGB Classifier)	print('XGB Classifier\n') xgb = XGBClassifier() xgb.fit(X_train, y_train) y_xgb = xgb.predict(X_test) print(metrics.classification_report(y_test, y_xgb)) print(modelAccuracy.append(metrics.accuracy_score(y_test, y_xgb))) sns.heatmap(confusion_matrix(y_test, y_xgb), annot=True, fmt='d') plt.show()	
7.	Precision Recall F1 Score (Random Forest Classifier)	print('Random Forest Classifier\n') Rfc = RandomForestClassifier() Rfc.fit(X_train, y_train) y_Rfc = Rfc.predict(X_test) print(metrics.classification_report(y_test, y_Rfc)) print(modelAccuracy.append(metrics.accuracy_score(y_test, y_Rfc)))	Random Forest Classifier precision recall f1-score support 0 0.84 0.78 0.81 487 1 0.71 0.79 0.74 332 accuracy 0.78 819 macro avg 0.77 0.78 0.78 819 weighted avg 0.79 0.78 0.78 819
	Precision Recall F1 Score (XGB Classifier)	print('XGB Classifier\n') xgb = XGBClassifier() xgb.fit(X_train, y_train) y_xgb = xgb.predict(X_test) print(metrics.classification_report(y_test, y_xgb)) print(modelAccuracy.append(metrics.accuracy_score(y_test, y_xgb)))	XGB Classifier precision recall f1-score support 0 0.86 0.71 0.78 487 1 0.66 0.83 0.74 332 accuracy 0.76 819 macro avg 0.76 0.77 0.76 819 weighted avg 0.78 0.76 0.76 819
8.	Precision-Recall or PR curve	from scikitplot.metrics import plot_roc_curve from sklearn.metrics import plot_precision_recall_curve plot_precision_recall_curve(Rfc,X_test,y_test) plt.plot([0,1], [0.2035,0.2035], c='k') plt.legend(loc='best') plot_precision_recall_curve(xgb,X_test,y_test) plt.plot([0,1], [0.2035,0.2035], c='k') plt.legend(loc='best')	

9.	PR vs ROC curve	plot_roc_curve(Rfc,X_test,y_test) plot_roc_curve(xgb,X_test,y_test)