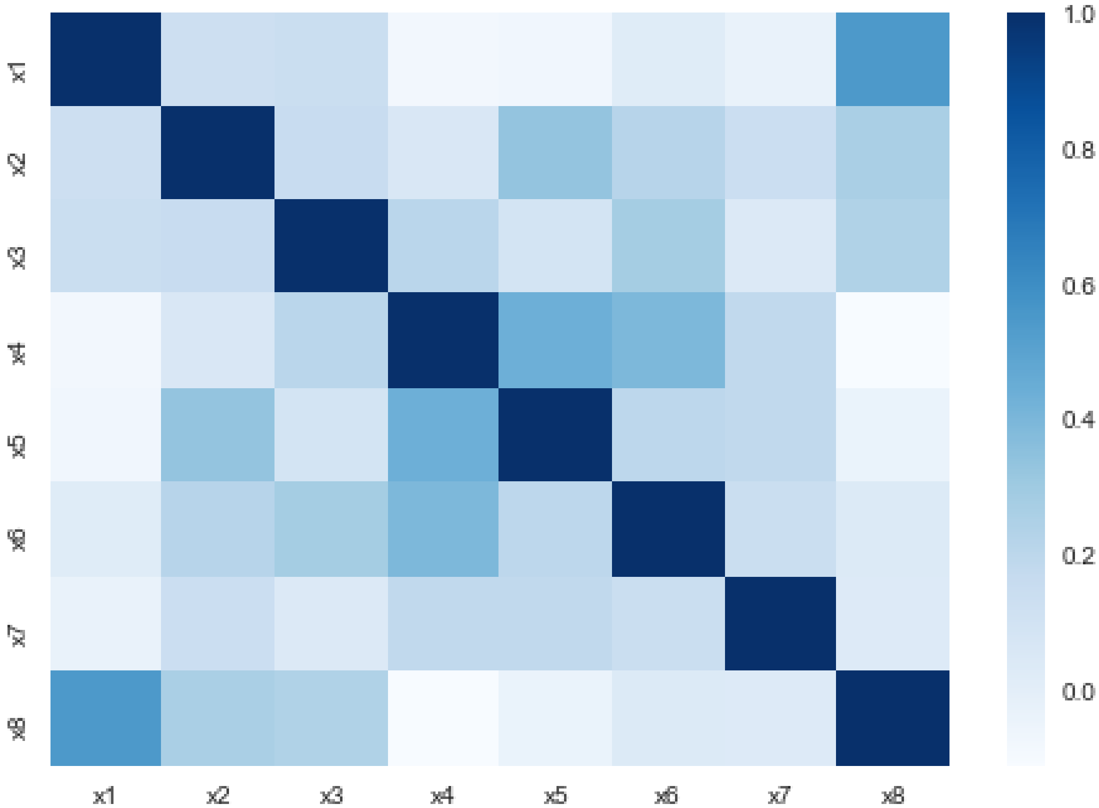
Machine Learning: Assignment 1

```
import numpy as np
import pandas as pd
import time
import gc
import random
from sklearn.model_selection import cross_val_score, GridSearchCV, cross_validate, train_tes
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, f1_scor
from sklearn.datasets import make_classification
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.preprocessing import StandardScaler, normalize
from sklearn.decomposition import PCA
from sklearn.impute import SimpleImputer
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import validation_curve
from sklearn.neural_network import MLPClassifier
import seaborn as sns
import matplotlib.pyplot as plt
from yellowbrick.model_selection import LearningCurve, ValidationCurve
from sklearn.preprocessing import OneHotEncoder

#Random State
rs = 614
```

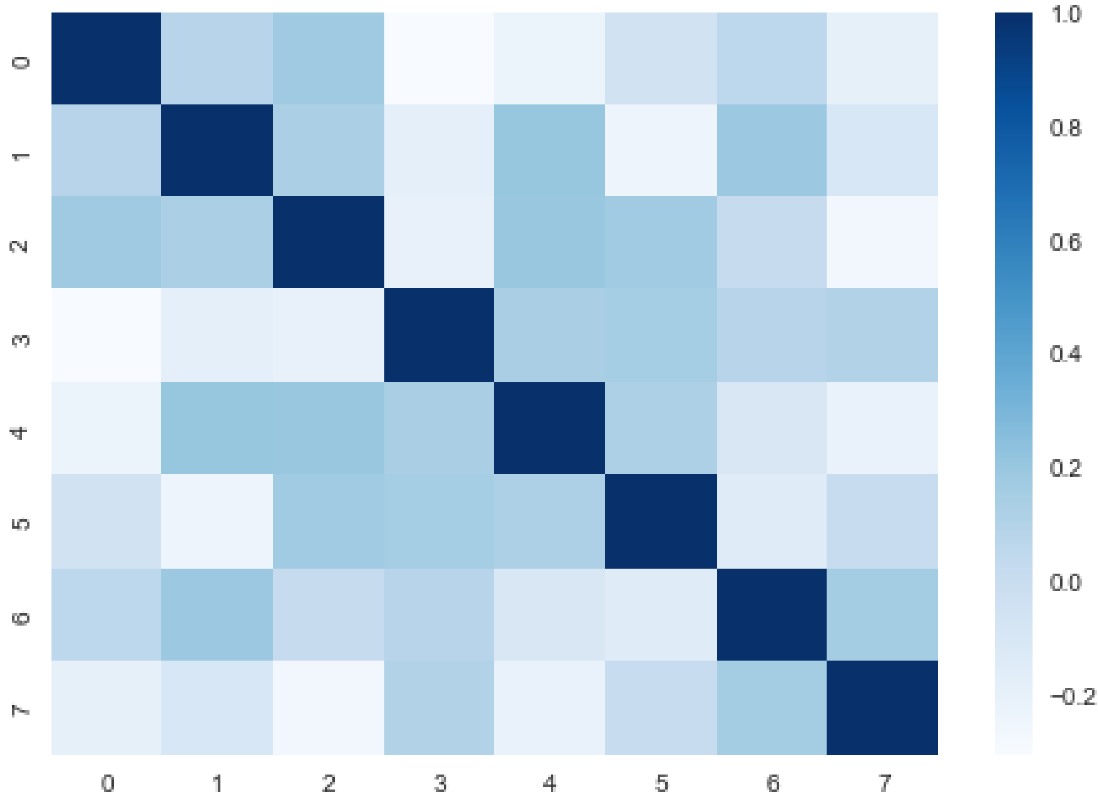
1. Data Import, leansing Setup and helper functions

```
class Data():
    def dataAllocation(self,path):
        df = pd.read_csv(path)
        x_data = df.iloc[:, :-1]
        y_data = df.iloc[:, -1 ]
        return x_data,y_data
        # X, y = make_classification(n_samples=500, n_features=5, n_informative=5, n_redunda
        # return X, y

    def syntheticData(self):
        return make_classification(n_samples=2000, n_features=8, n_informative=8, n_redundan

    def trainSets(self,x_data,y_data):
        x_train, x_test, y_train, y_test = train_test_split(x_data, y_data, test_size = 0.3,
```

```
        return x_train, x_test, y_train, y_test

data = 'data/pima-indians-diabetes.csv'
dataset = Data()
x1_data,y1_data = dataset.dataAllocation(data)
x1_train, x1_test, y1_train, y1_test = dataset.trainSets(x1_data,y1_data)
scaler = StandardScaler()
scaled_x1_train = scaler.fit_transform(x1_train)
scaled_x1_test = scaler.transform(x1_test)

x2_data,y2_data = dataset.syntheticData()
x2_train, x2_test, y2_train, y2_test = dataset.trainSets(x2_data,y2_data)
scaler = StandardScaler()
scaled_x2_train = scaler.fit_transform(x2_train)
scaled_x2_test = scaler.transform(x2_test)

x_data = [x1_data, x2_data]
y_data = [y1_data, y2_data]
x_test = [x1_test, x2_test]
y_test = [y1_test, y2_test]
x_train = [x1_train, x2_train]
y_train = [y1_train, y2_train]
scaled_x_train = [scaled_x1_train, scaled_x2_train]
scaled_x_test = [scaled_x1_test, scaled_x2_test]


sizes = np.linspace(0.3, 1.0, 10)
print("Heatmap for Features")
data_corr = sns.heatmap(pd.DataFrame(x_data[0]).corr(), cmap='Blues')
Heatmap for Features
```




```
data_corr = sns.heatmap(pd.DataFrame(x_data[1]).corr(), cmap='Blues')
```




```
def fakeTunedData(i):
    fakeData = [{'max_depth': 9, 'min_samples_leaf': 1}, {'C': 0.01, 'kernel': 'linear'}, {'
    return 72+i, fakeData[i]

def learningCurvePlot(tuned, data_n):
    v1 = LearningCurve(tuned, scoring='f1_weighted', train_sizes=sizes, n_jobs=4)
    v1.fit(x_data[data_n],y_data[data_n])
    v1.show()
```

2. Decision Tree Classifier

```
class DTClassifier():

    def trainTest(self, data_n):
        df = []
        for i in range(16):
            for j in range(20):
                dt_clf = DecisionTreeClassifier(max_depth=i+1, min_samples_leaf=j+1)
```

```
                dt_clf.fit(x_train[data_n], y_train[data_n])

                y1_predict_train = dt_clf.predict(x_train[data_n])
                y1_predict_test = dt_clf.predict(x_test[data_n])
                df.append([i+1, j+1, "Train", accuracy_score(y_train[data_n], y1_predict_tra
                df.append([i+1, j+1, "Test", accuracy_score(y_test[data_n], y1_predict_test)

        return pd.DataFrame(df, columns=["Depth", "Leaf Size", "Sample Type", "F1 Score" ])

    def hyperParameterTuning(self, data_n):
        param_grid = {'max_depth': range(1, 21), 'min_samples_leaf': range(1, 20)}
        tuned = GridSearchCV(estimator = DecisionTreeClassifier(random_state = rs), param_gr
        tuned.fit(x_train[data_n], y_train[data_n])
        return tuned.best_score_, tuned.best_params_

    def dataExplorePlot(self, df):
        g = sns.FacetGrid(df, hue="Sample Type", col="Depth", height=2, col_wrap=4)
        g.map(sns.lineplot, "Leaf Size", "F1 Score" )

    def showLearningCurve(self, best_params, data_n):
        tuned = DecisionTreeClassifier(max_depth=best_params['max_depth'], min_samples_leaf=
        learningCurvePlot(tuned, data_n)
```

3. Support Vector Machine

```
class SupportVectorMachine():
    def trainTest(self, data_n):
        cs = [x/10000 for x in [1, 10, 100, 1000, 10000, 100000, 1000000]]
        df = []
        for c in cs:
            for k in ["linear", "sigmoid"]:
                model = SVC(kernel = k, C=c)
                model.fit(scaled_x_train[data_n],y_train[data_n])
                y1_predict_train = model.predict(scaled_x_train[data_n])
                y1_predict_test = model.predict(scaled_x_test[data_n])
                df.append([k, c, accuracy_score(y_test[data_n], y1_predict_test)])
        return pd.DataFrame(df, columns=["Kernel", "C", "Accuracy"])

    def hyperParameterTuning(self, data_n):
        param_grid = {'C': [x/10000 for x in [1, 10, 100, 1000, 10000, 100000, 1000000]],
            'kernel': ["linear", "sigmoid"]}
        svm_tune = SVC(gamma = "auto")
        svm_cv = GridSearchCV(estimator = svm_tune, param_grid = param_grid, n_jobs=5, retur
        svm_cv.fit(scaled_x_train[data_n], y_train[data_n])
        best_score = svm_cv.best_score_
```

```
        return best_score, svm_cv.best_params_

    def dataExplorePlot(self, df):
        g = sns.FacetGrid(df, col="Kernel",  height=4)
        g.map(sns.pointplot, "C", "Accuracy")

    def showLearningCurve(self, best_params, data_n):
        tuned = SVC(kernel=best_params['kernel'], C=best_params['C'])
        learningCurvePlot(tuned, data_n)
```

4. KNN

```
class KNN():
    def trainTest(self, data_n):
        df = []
        for i in range(20):
            model = KNeighborsClassifier(n_neighbors= i+1)
            model.fit(x_train[data_n], y_train[data_n])
            y1_predict_test = model.predict(x_test[data_n])
            df.append([i+1, accuracy_score(y_test[data_n], y1_predict_test)])
        return pd.DataFrame(df, columns= ["Neighbors", "Accuracy"])

    def hyperParameterTuning(self, data_n):
        tuned = GridSearchCV(KNeighborsClassifier(), {"n_neighbors" : range(1, 21)})
        tuned.fit(x_train[data_n], y_train[data_n])
        return tuned.best_score_, tuned.best_params_

    def dataExplorePlot(self, df):
        sns.lineplot(data=df, x="Neighbors", y="Accuracy")

    def showLearningCurve(self, best_params, data_n):
        tuned = KNeighborsClassifier(n_neighbors=best_params['n_neighbors'])
        learningCurvePlot(tuned, data_n)
```

5. Neural Network

```
class NN():

    def trainTest(self, data_n):
        df = []
        for i in [0.01, 0.02, 0.04, 0.08, 0.1]:
            model = MLPClassifier(max_iter=300, learning_rate_init=i)
            model.fit(scaled_x_train[data_n],y_train[data_n])
```

```
            y1_predict_train = model.predict(scaled_x_train[data_n])
            y1_predict_test = model.predict(scaled_x_test[data_n])
            df.append([i, accuracy_score(y_test[data_n], y1_predict_test)])
        return pd.DataFrame(df, columns=["Learning Rate", "Accuracy"])

    def hyperParameterTuning(self, data_n):
        param_grid = {
            'hidden_layer_sizes': [x**2 for x in range(2, 11)],
            'learning_rate_init': [0.01, 0.02, 0.04, 0.08, 0.1]
        }
        tuned = GridSearchCV(MLPClassifier(max_iter=200), param_grid = param_grid, cv=10)
        tuned.fit(scaled_x_train[data_n], y_train[data_n])
        return tuned.best_score_, tuned.best_params_

    def dataExplorePlot(self, df):
        sns.lineplot(data=df, x="Learning Rate", y="Accuracy")

    def showLearningCurve(self, best_params, data_n):
        tuned = MLPClassifier(max_iter=50, learning_rate_init=best_params['learning_rate_ini
        learningCurvePlot(tuned, data_n)
```

6. Boost

```
class Boost():
    def trainTest(self, data_n):
        df = []
        for i in range(50, 251, 10):
            model = GradientBoostingClassifier(n_estimators=i, max_depth=3, min_samples_leaf
            model.fit(scaled_x_train[data_n],y_train[data_n])
            y1_predict_train = model.predict(scaled_x_train[data_n])
            y1_predict_test = model.predict(scaled_x_test[data_n])
            df.append([i, accuracy_score(y_test[data_n], y1_predict_test)])
        return pd.DataFrame(df, columns=["Estimators", "Accuracy"])

    def hyperParameterTuning(self, data_n):
        param_grid = {'n_estimators': range(50, 151, 40), 'max_depth': range(2, 4)}
        tuned = GridSearchCV(GradientBoostingClassifier(), param_grid, cv=10)
        tuned.fit(scaled_x_train[data_n], y_train[data_n])
        return tuned.best_score_, tuned.best_params_

    def dataExplorePlot(self, df):
        sns.lineplot(data=df, x="Estimators", y="Accuracy")

    def showLearningCurve(self, best_params, data_n):
```

```
        tuned = GradientBoostingClassifier(n_estimators=best_params['n_estimators'], max_dep
        learningCurvePlot(tuned, data_n)

classifiers = [DTClassifier(), SupportVectorMachine(), KNN(), NN(), Boost()]
# classifiers = [KNN()]

classifiers_name = ["Decision Tree", "Support Vector Machine", "K-Nearest Neighbors", "Neura

i = 0

for classifier in classifiers:
    name = classifiers_name[i]
    print(str(i+1)+".", name, end="\n\n")
    df1 = classifier.trainTest(0)
    df2 = classifier.trainTest(1)

    #best_score, best_params = fakeTunedData(i)
    best_score1, best_params1 = classifier.hyperParameterTuning(0)
    best_score2, best_params2 = classifier.hyperParameterTuning(1)
    print(str(i+1)+".1","Hyperparameters Exploration", end="\n\n")
    print("For this project,", name, "will be hypertuned by adjusting:", [x for x in best_pa
    print("The following charts show how the accuracy is affected when the hyperparamter(s)

    classifier.dataExplorePlot(df1)
    plt.figure()
    classifier.dataExplorePlot(df2)
    plt.figure()


    print("\n\n")
    print(str(i+1)+".2","Hypertuning", end="\n\n")
    print("GridSearchCV was performed for", name, "classifier." , end="\n\n")
    print("Dataset 1 Results:")
    for key in best_params1:
        print("The optimal value of", key, "was", best_params1[key], end = ". ")
    print("Likewise the accuracy of", name, "classifier", "was", best_score1, "when the opti
    classifier.showLearningCurve(best_params1, 0)

    print("Dataset 2 Results:")
    for key in best_params2:
        print("The optimal value of", key, "was", best_params2[key], end = ". ")
    print("Likewise the accuracy of", name, "classifier", "was", best_score2, "when the opti
    classifier.showLearningCurve(best_params2, 1)
    print()
    print()
```

i = i + 1

1. Decision Tree

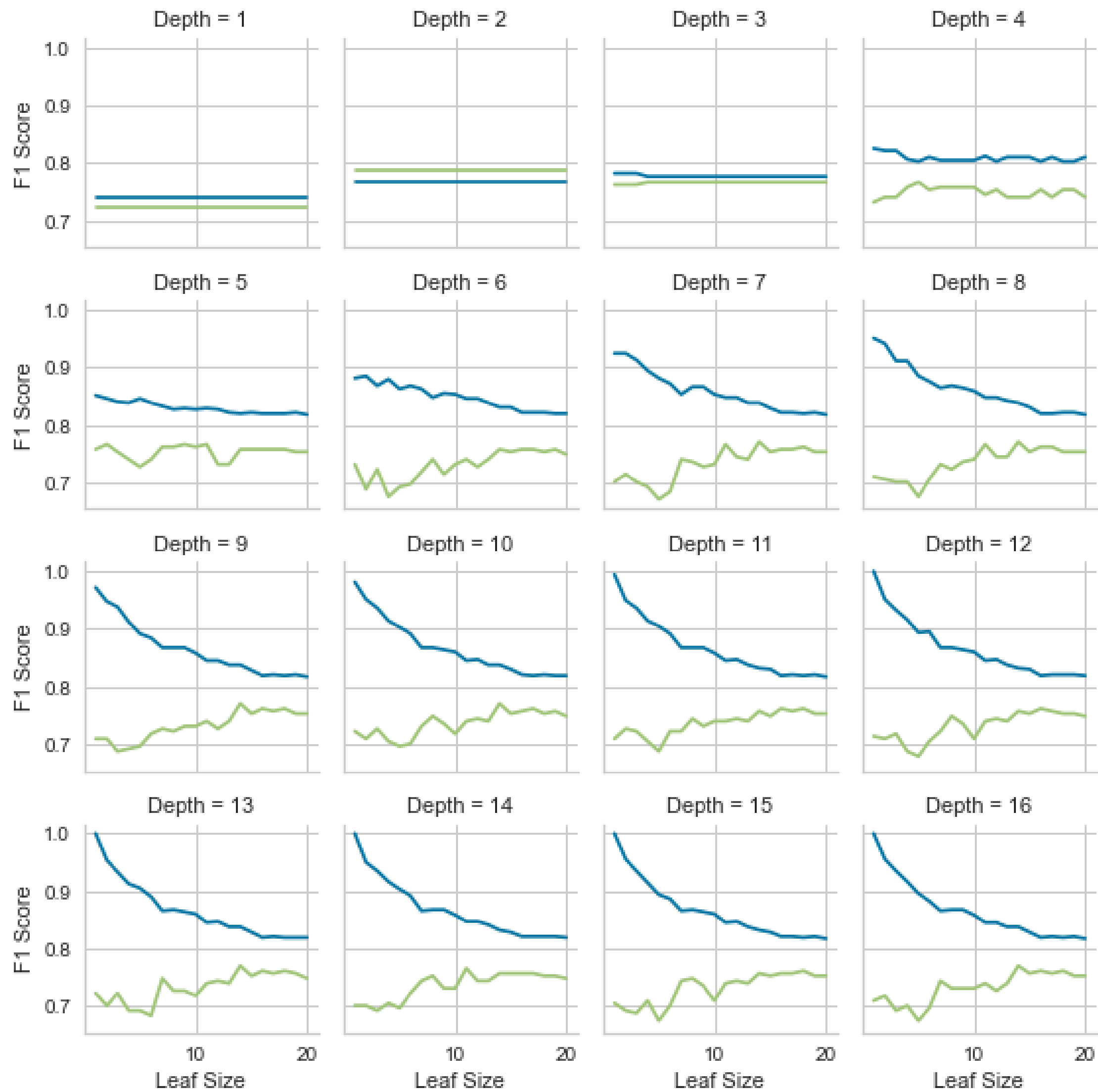
1.1 Hyperparameters Exploration

For this project, Decision Tree will be hypertuned by adjusting: ['max_depth', 'min_samples_

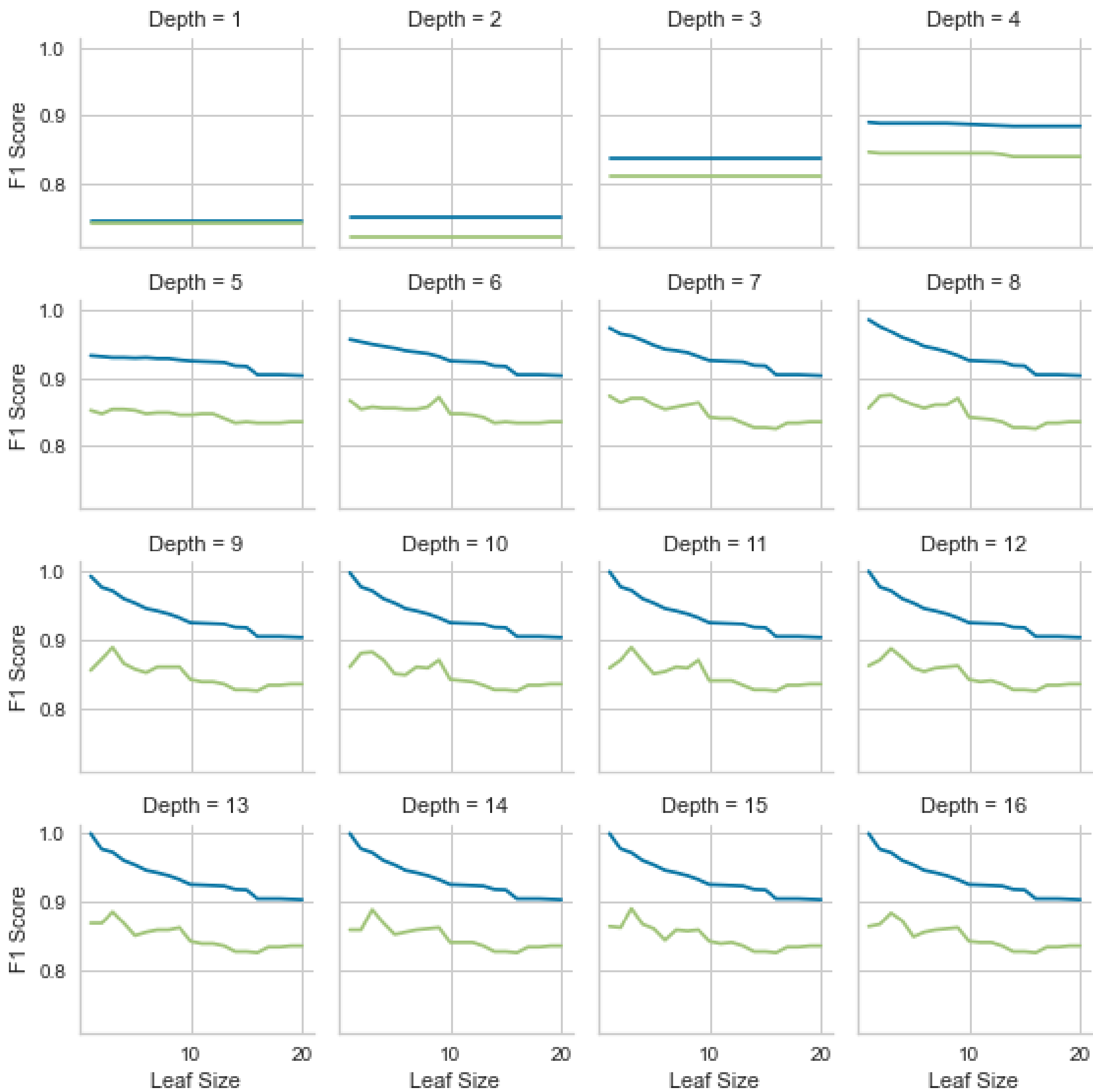
1.2 Hypertuning

GridSearchCV was performed for Decision Tree classifier.

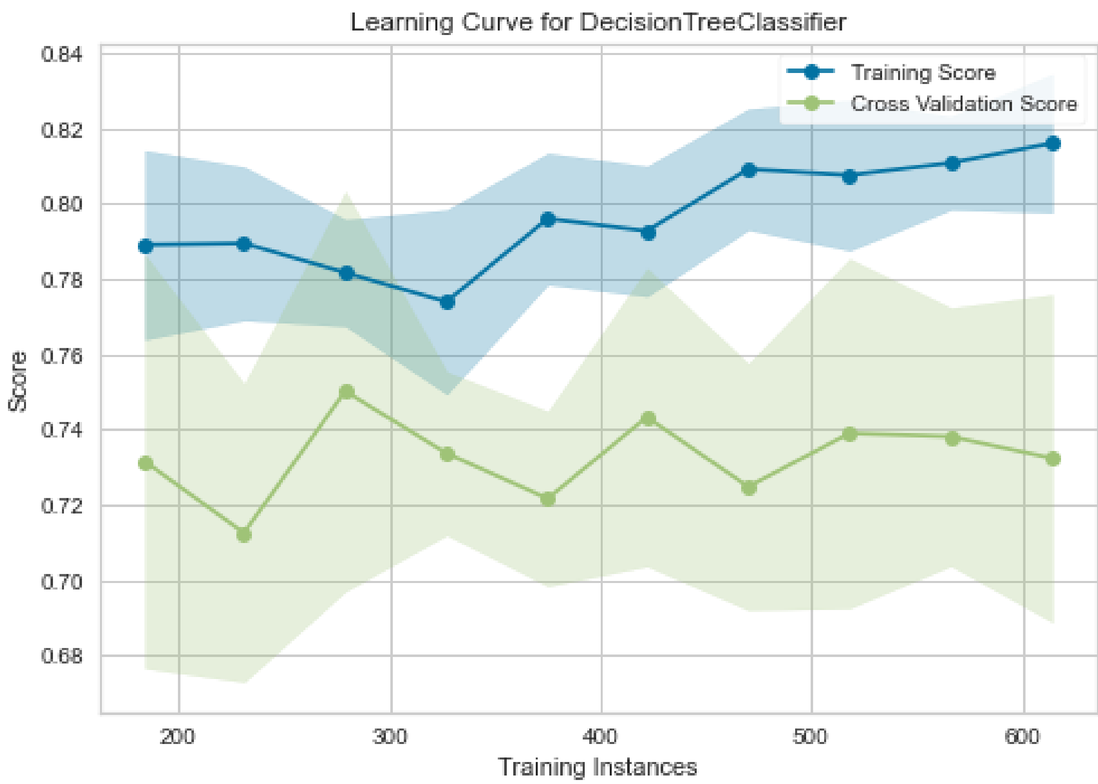
Dataset 1 Results:
The optimal value of max_depth was 6. The optimal value of min_samples_leaf was 17. Likewise



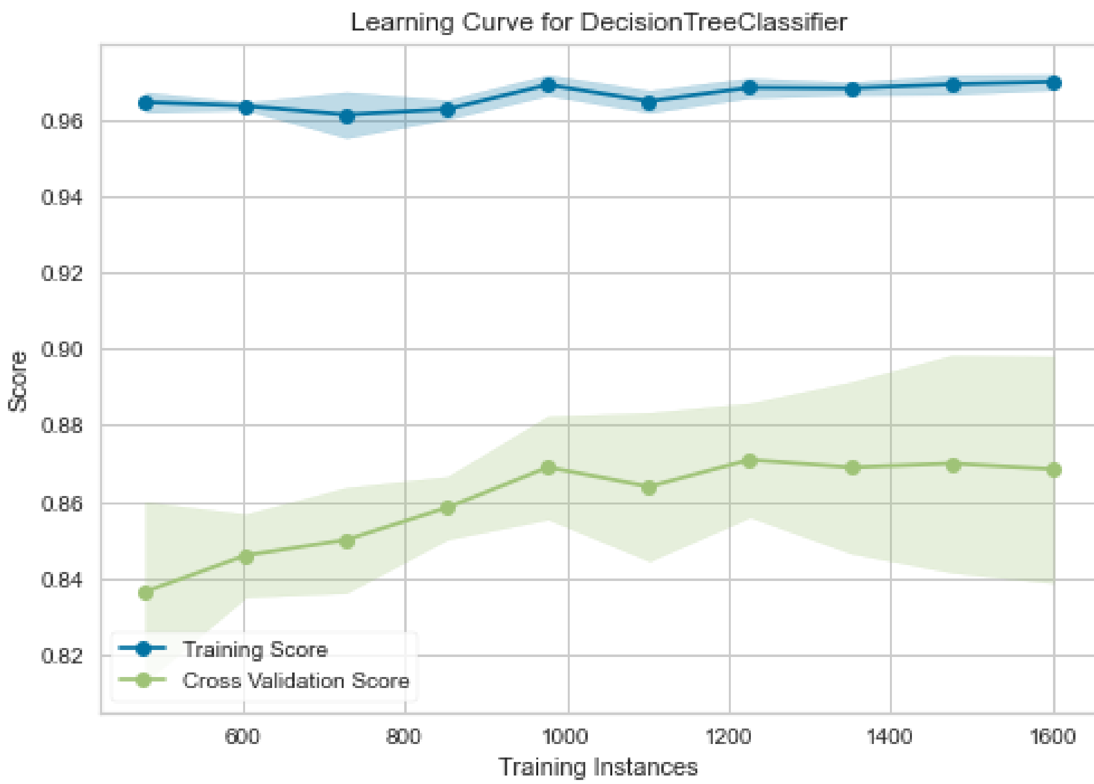

```
<Figure size 576x396 with 0 Axes>
```



Depth = 1
Depth = 2
Depth = 3
Depth = 4
Depth = 5
Depth = 6
Depth = 7
Depth = 8
Depth = 9
Depth = 10
Depth = 11
Depth = 12
Depth = 13
Depth = 14
Depth = 15
Depth = 16
F1 Score
1.0
0.9
0.8
10
20
Leaf Size




```
Dataset 2 Results:
The optimal value of max_depth was 10. The optimal value of min_samples_leaf was 3. Likewise
```



2. Support Vector Machine

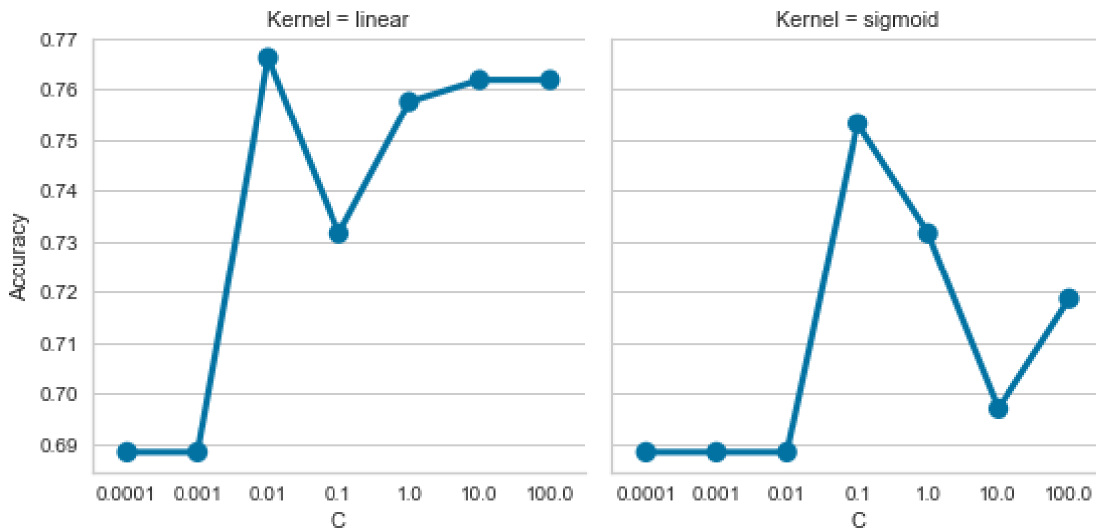
2.1 Hyperparameters Exploration

For this project, Support Vector Machine will be hypertuned by adjusting: ['C', 'kernel']. T

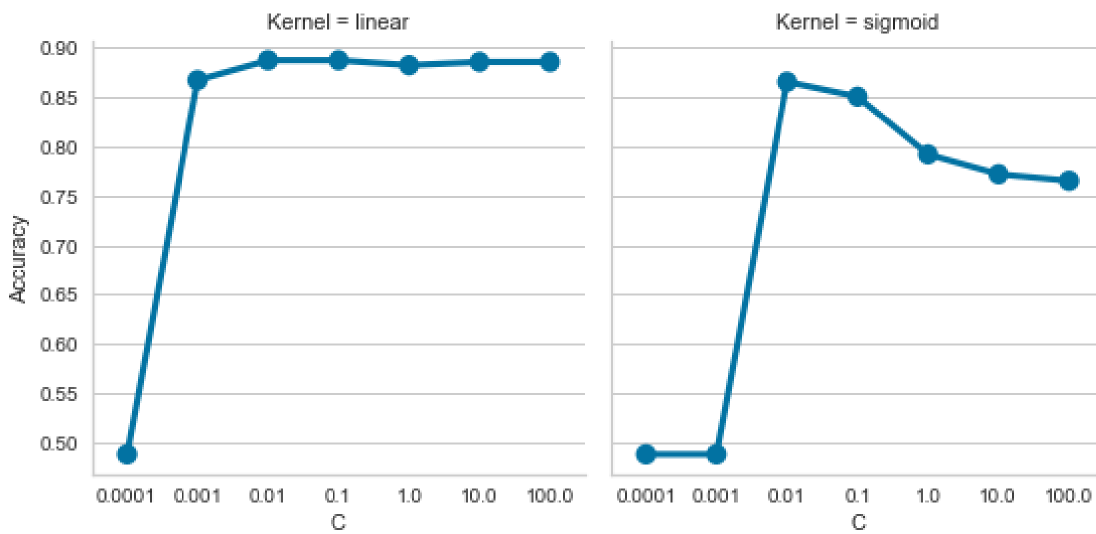
2.2 Hypertuning

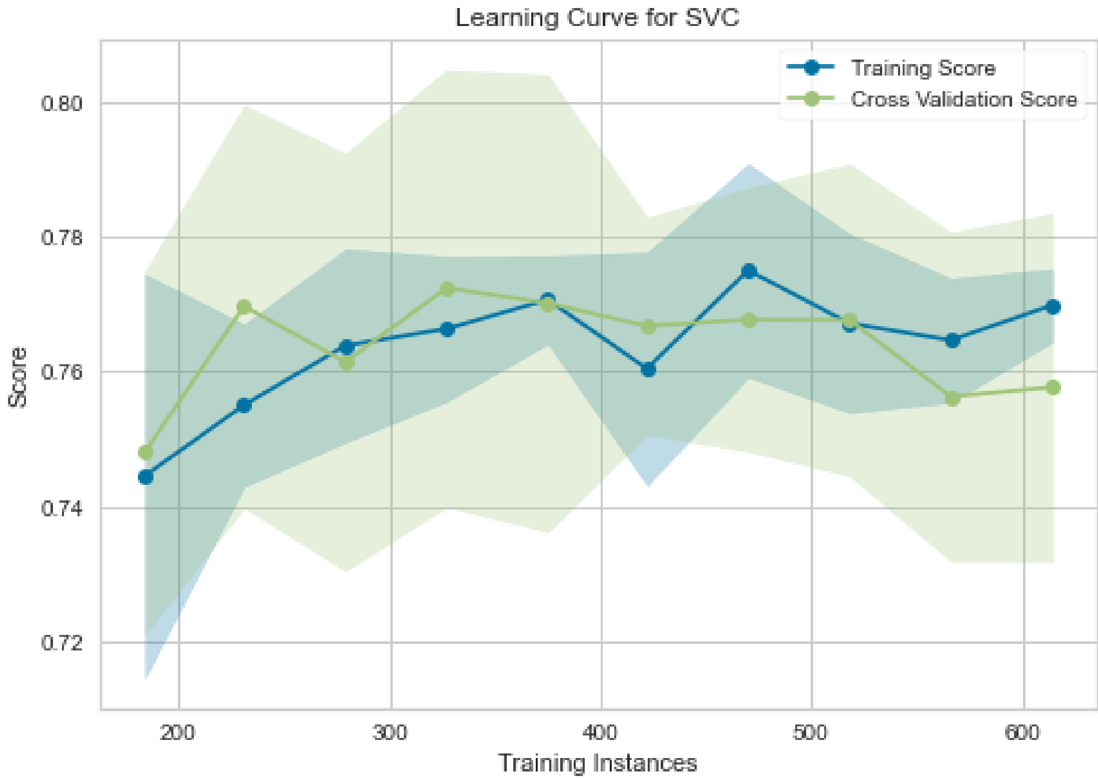
GridSearchCV was performed for Support Vector Machine classifier.

Dataset 1 Results:
The optimal value of C was 1.0. The optimal value of kernel was linear. Likewise the accura

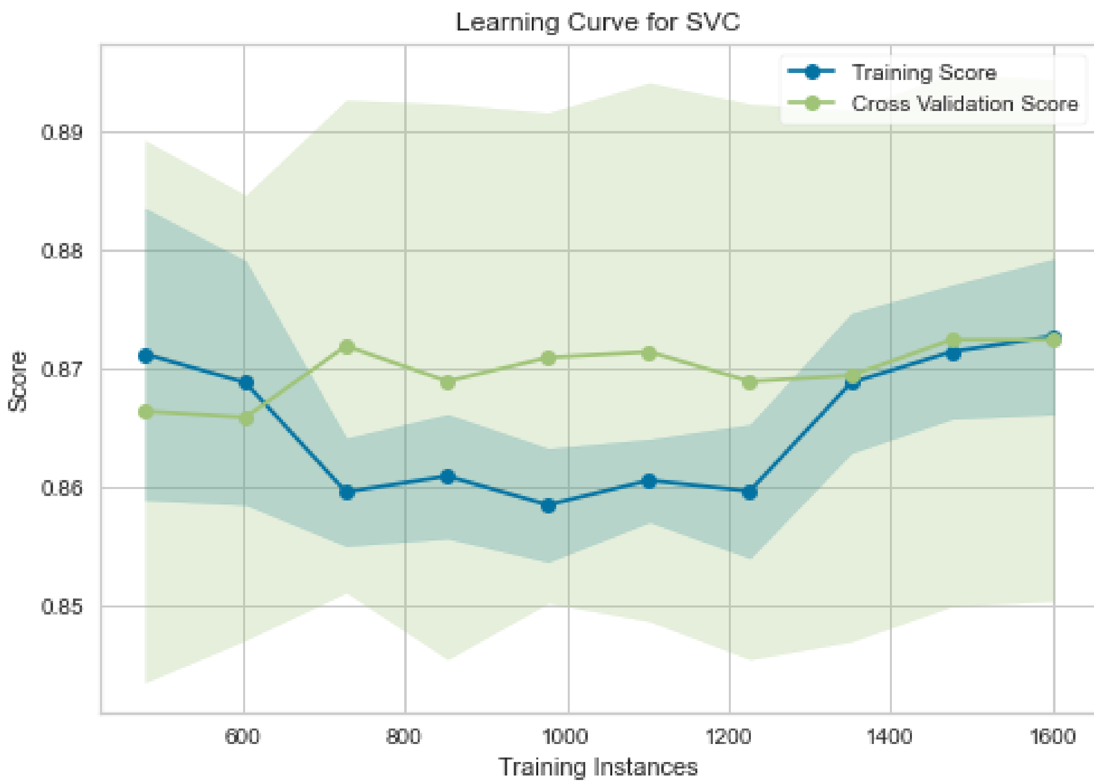


<Figure size 576x396 with 0 Axes>





Dataset 2 Results:
The optimal value of C was 100.0. The optimal value of kernel was linear. Likewise the accur



3. K-Nearest Neighbors

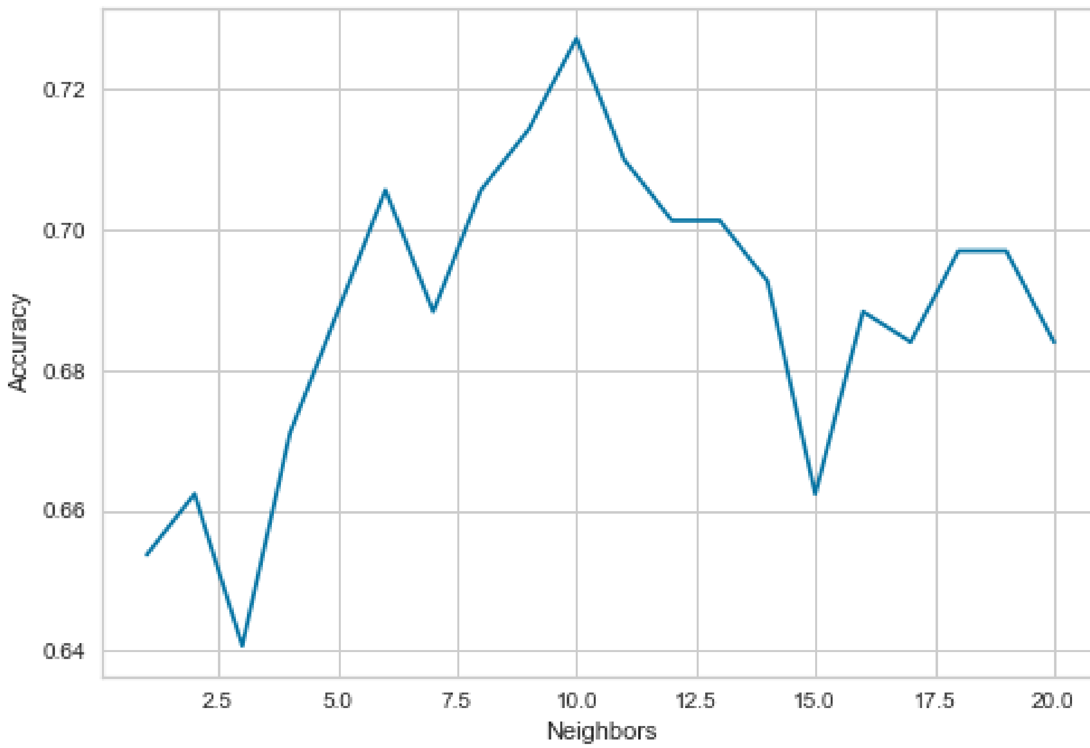
3.1 Hyperparameters Exploration

For this project, K-Nearest Neighbors will be hypertuned by adjusting: ['n_neighbors']. The

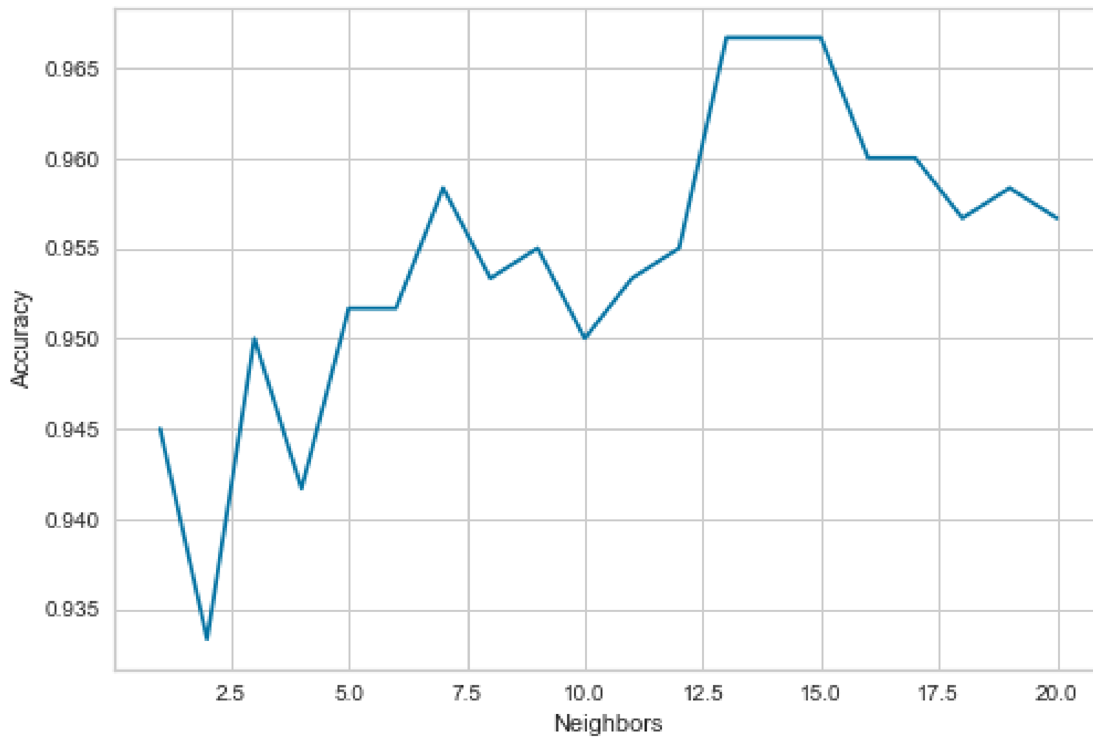
3.2 Hypertuning

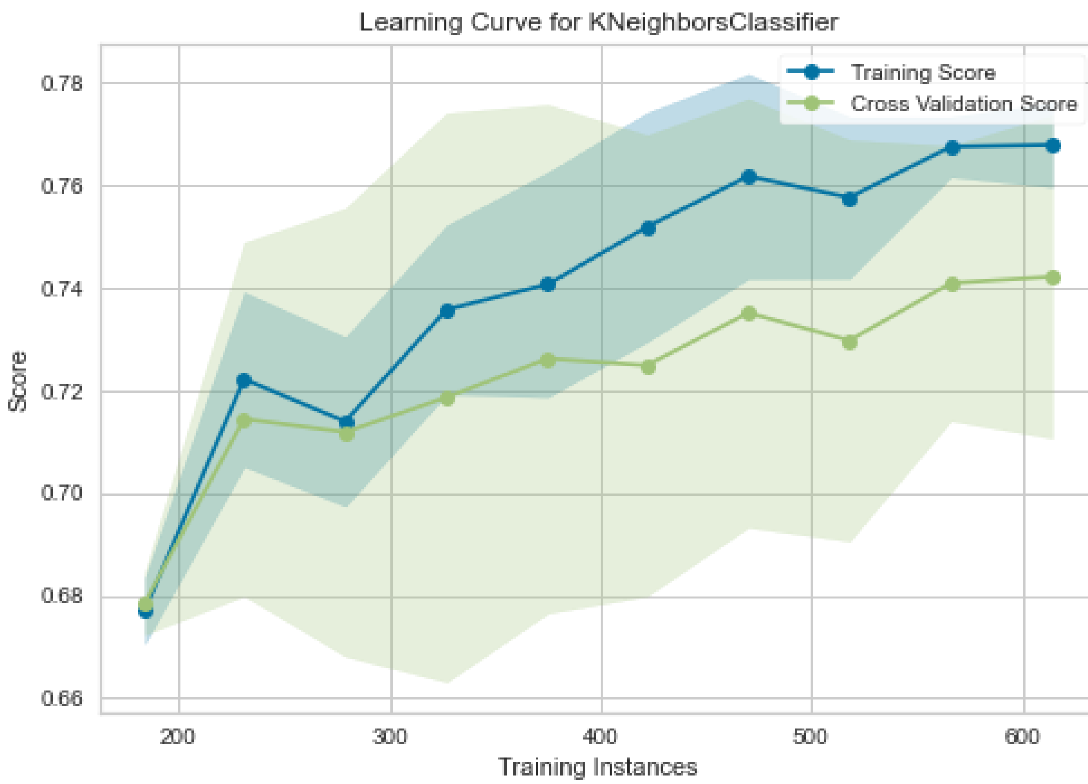
GridSearchCV was performed for K-Nearest Neighbors classifier.

Dataset 1 Results:
The optimal value of n_neighbors was 12. Likewise the accuracy of K-Nearest Neighbors classi

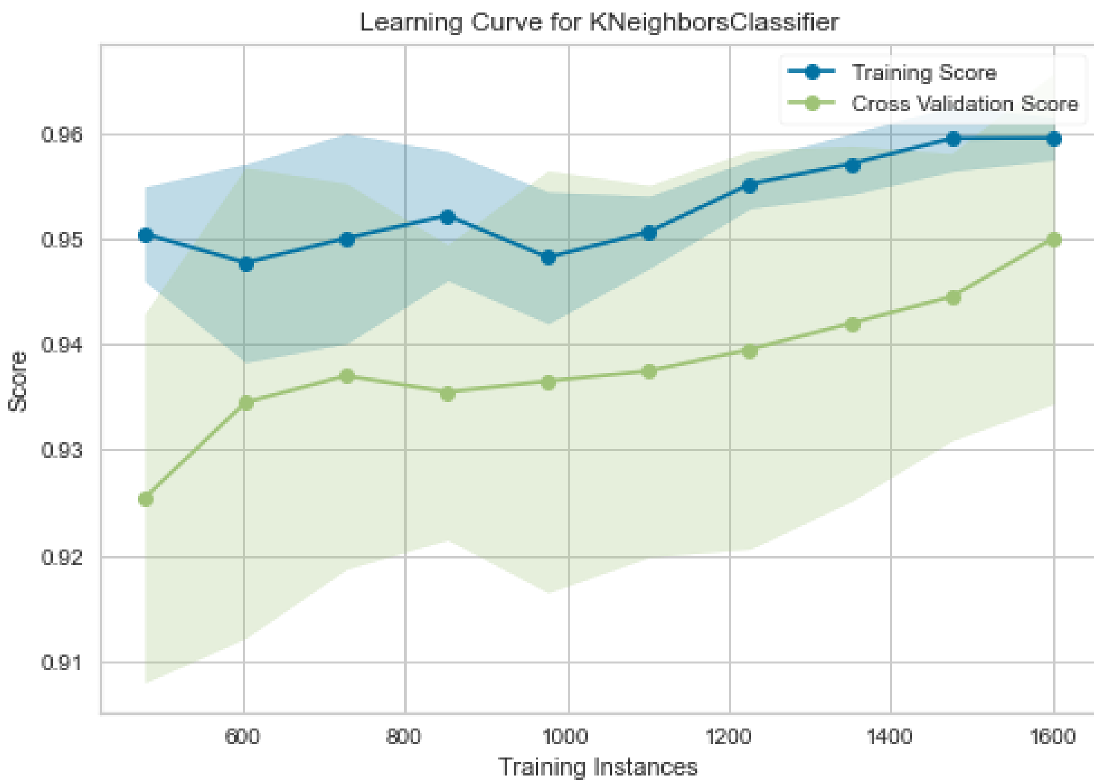


0.72
0.70
0.68
0.66
0.64
Accuracy
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Neighbors


0.965
0.960
0.955
0.950
0.945
0.940
0.935
Accuracy
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Neighbors




```
Dataset 2 Results:
The optimal value of n_neighbors was 11. Likewise the accuracy of K-Nearest Neighbors classi
```



4. Neural Network

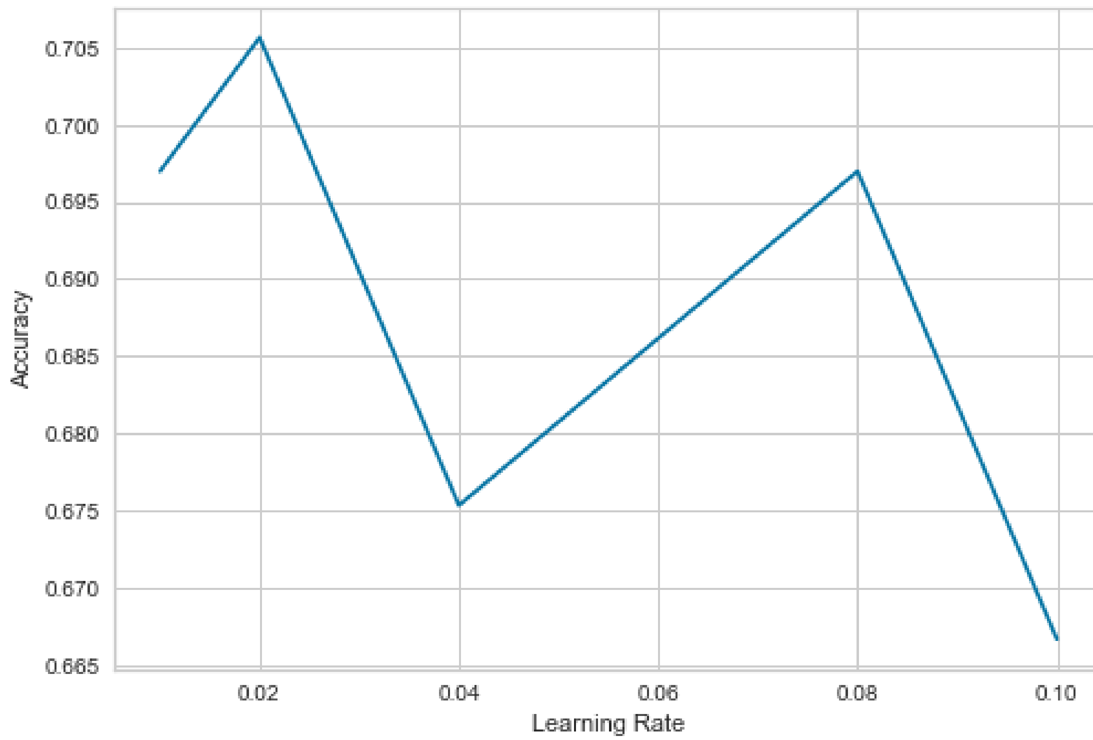
4.1 Hyperparameters Exploration

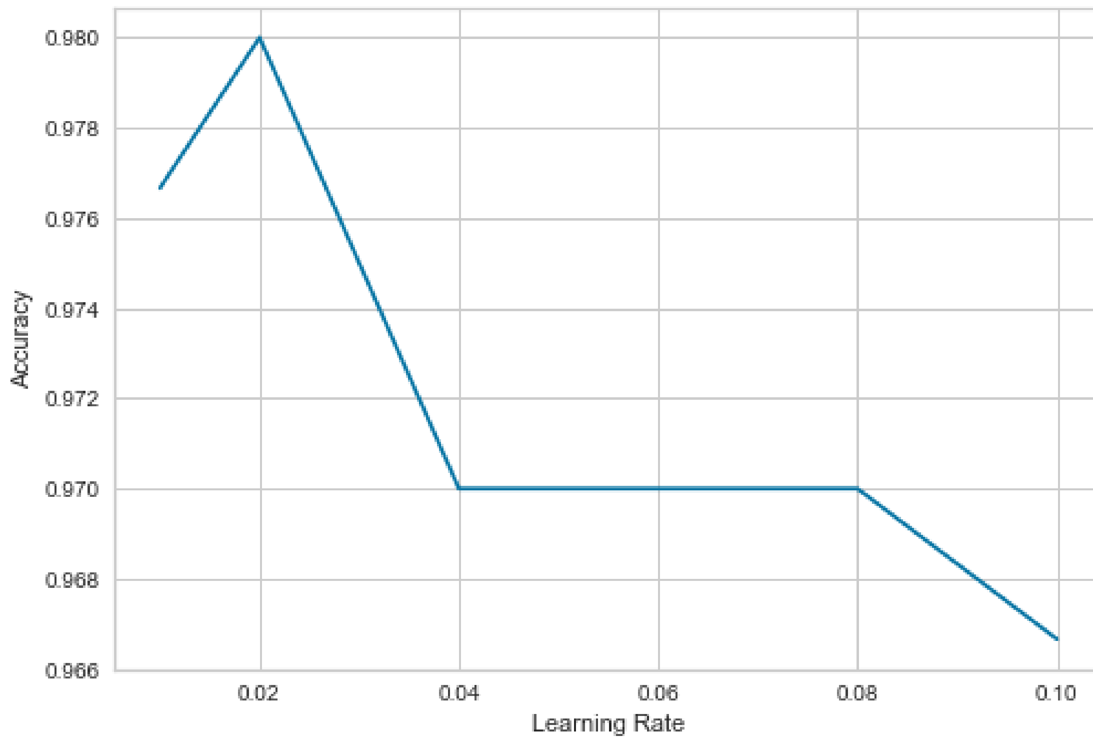
For this project, Neural Network will be hypertuned by adjusting: ['hidden_layer_sizes', 'le

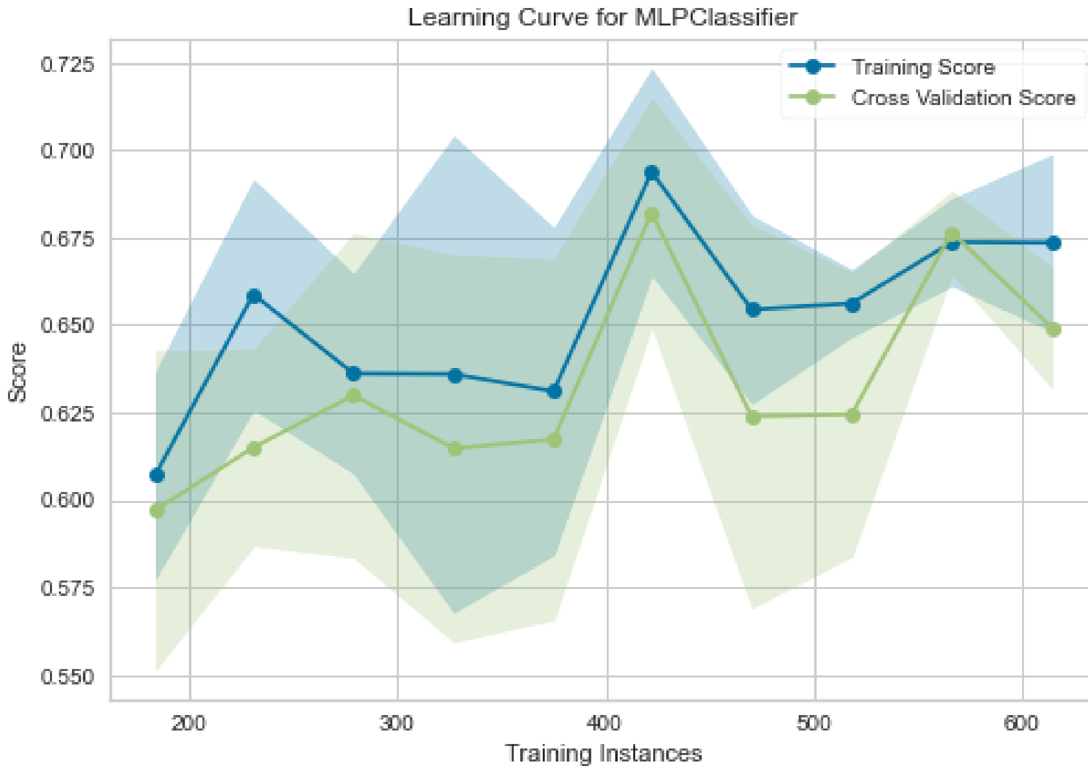
4.2 Hypertuning

GridSearchCV was performed for Neural Network classifier.

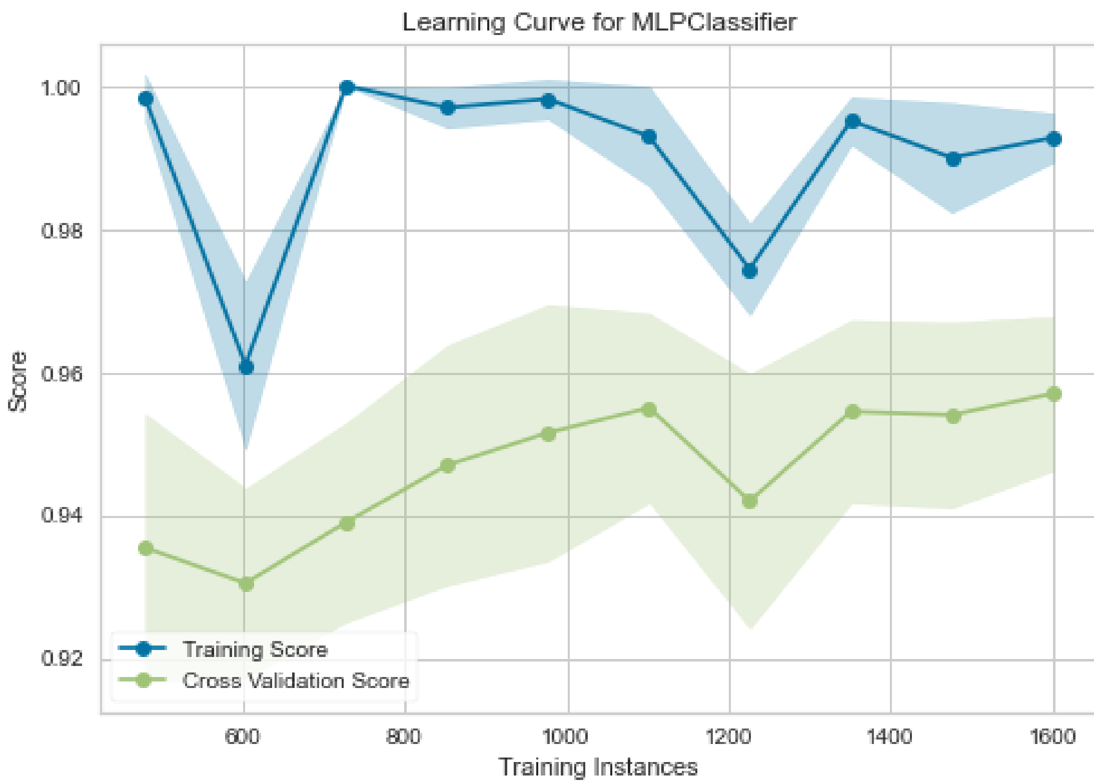
Dataset 1 Results:
The optimal value of hidden_layer_sizes was 9. The optimal value of learning_rate_init was (


0.705
0.700
0.695
0.690
0.685
0.680
0.675
0.670
0.665
Accuracy
0.02
0.04
0.06
0.08
0.10
Learning Rate


0.980
0.978
0.976
0.974
0.972
0.970
0.968
0.966
Accuracy
0.02
0.04
0.06
0.08
0.10
Learning Rate




```
Dataset 2 Results:
The optimal value of hidden_layer_sizes was 64. The optimal value of learning_rate_init was
```



5. Gradient Boosting

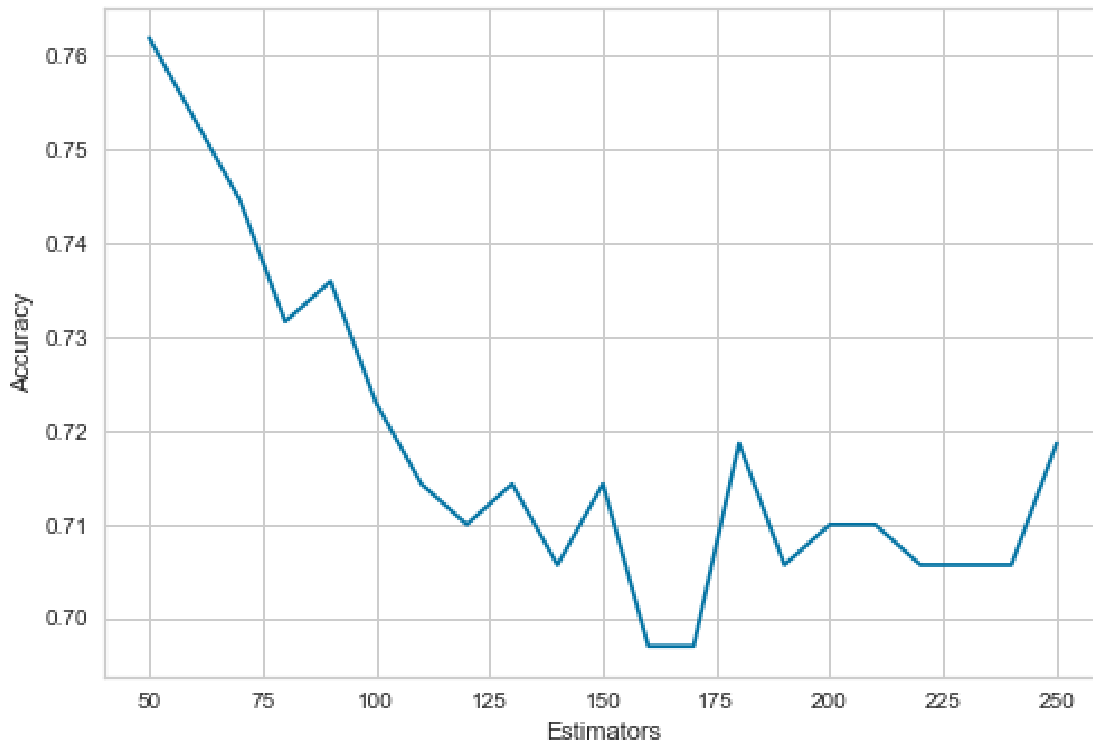
5.1 Hyperparameters Exploration

For this project, Gradient Boosting will be hypertuned by adjusting: ['max_depth', 'n_estima

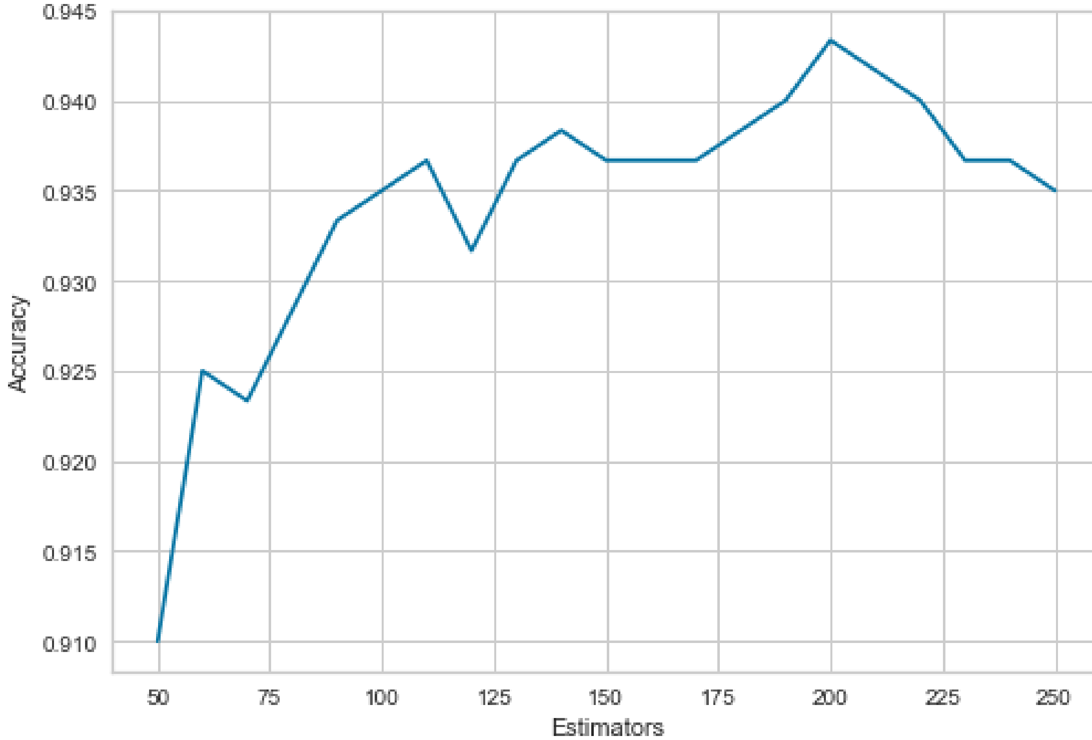
5.2 Hypertuning

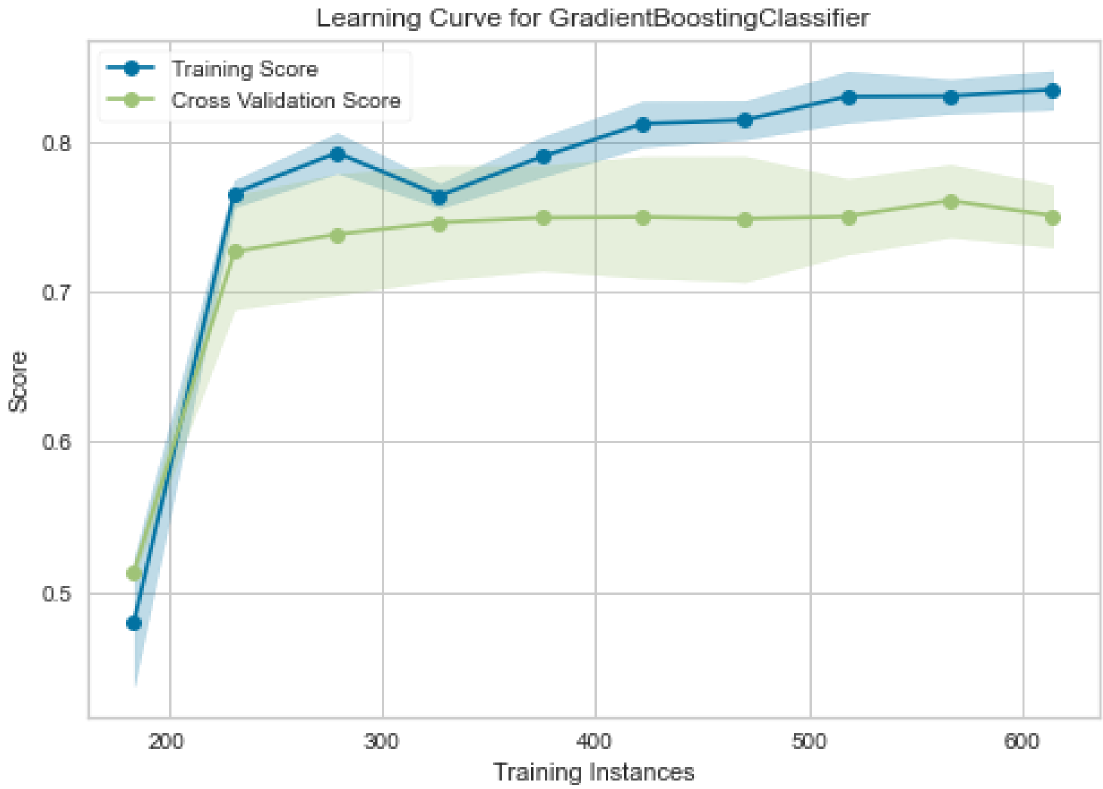
GridSearchCV was performed for Gradient Boosting classifier.

Dataset 1 Results:
The optimal value of max_depth was 3. The optimal value of n_estimators was 130. Likewise th

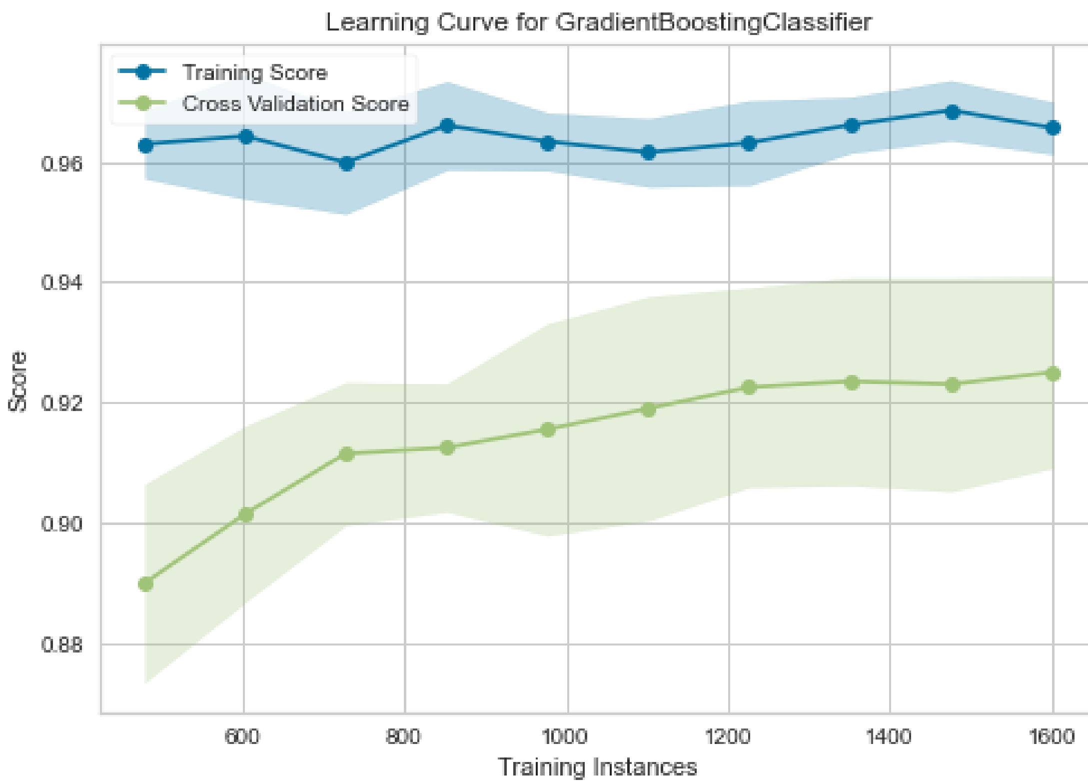


0.76
0.75
0.74
0.73
0.72
0.71
0.70
Accuracy
50
75
100
125
150
175
200
225
250
Estimators


0.945
0.940
0.935
0.930
0.925
0.920
0.915
0.910
Accuracy
50
75
100
125
150
175
200
225
250
Estimators



Dataset 2 Results:
The optimal value of max_depth was 3. The optimal value of n_estimators was 130. Likewise th



Learning Curve for GradientBoostingClassifier
Training Score
Cross Validation Score
0.96
0.94
0.92
0.90
0.88
Score
600
800
1000
1200
1400
1600
Training Instances