Experiment_7_Assessment

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1 Data Mining and machine Learning

2 Experiment 7

2.1 19 February

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5 Decision Tree: Bagging, Boosting, RandomForestClassifier

5.1 Q1. Today we will try to see how bagging, boosting etc can be implemented.

[5]:
```
## Loading the necessary libraries
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
```

[6]:
```
## Loading the dataset

df = pd.read_csv(r"D:\study material\VIT_Data_Science\Winter_Sem\Data Mining␣
↪and Machine Learning Lab\Class_notes\ML_exp7\liver_patient.csv")
df
```

[6]:
```
     Age  Gender  Total_Bilirubin  Direct_Bilirubin  Alkaline_Phosphotase  \
0     65  Female              0.7               0.1                   187
1     62    Male             10.9               5.5                   699
2     62    Male              7.3               4.1                   490
3     58    Male              1.0               0.4                   182
4     72    Male              3.9               2.0                   195
..   …     …               …               …                   …
578   60    Male              0.5               0.1                   500
579   40    Male              0.6               0.1                    98
580   52    Male              0.8               0.2                   245
581   31    Male              1.3               0.5                   184
```

```
582   38     Male             1.0             0.3                 216

     Alamine_Aminotransferase  Aspartate_Aminotransferase  Total_Protiens  \
0                          16                          18             6.8
1                          64                         100             7.5
2                          60                          68             7.0
3                          14                          20             6.8
4                          27                          59             7.3
..                        …                         …            …
578                        20                          34             5.9
579                        35                          31             6.0
580                        48                          49             6.4
581                        29                          32             6.8
582                        21                          24             7.3

     Albumin  Albumin_and_Globulin_Ratio  liver_disease
0        3.3                        0.90              1
1        3.2                        0.74              1
2        3.3                        0.89              1
3        3.4                        1.00              1
4        2.4                        0.40              1
..       …                        …            …
578      1.6                        0.37              0
579      3.2                        1.10              1
580      3.2                        1.00              1
581      3.4                        1.00              1
582      4.4                        1.50              0

[583 rows x 11 columns]
```

5.1.1 Dropping the unnecessary Age and Gender column

[8]:
```
df.drop(['Age','Gender'],axis=1,inplace = True)
```

5.1.2 Perform Min-Max scaling

[10]:
```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
X = scaler.fit_transform(df)
```

[11]:
```
x = X[:,:-1]
y = X[:,-1]
```

5.2 Do the train test split of the data with test size 20%.

[13]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.
↪2,random_state=0)
```

5.2.1 Fit the LogisticRegression model to the this training data.

[15]:
```
model_lr = LogisticRegression()
model_lr.fit(x_train,y_train)
y_pred_lr = model_lr.predict(x_test)
print(f"The accuracy of the logistic regression model is:
↪{round(accuracy_score(y_test,y_pred_lr)*100,3)} %")
```

```
The accuracy of the logistic regression model is:66.667 %
```

5.3 Next for the same data fit a Decision Tree with the same training data and check for the testing accuracy.

[17]:
```
from sklearn.tree import DecisionTreeClassifier

model_dc = DecisionTreeClassifier()
model_dc.fit(x_train,y_train)
y_pred_dc = model_dc.predict(x_test)
print(f"Accuracy score of decision tree:
↪{round(accuracy_score(y_test,y_pred_dc)*100,2)}%")
```

```
Accuracy score of decision tree:63.25%
```

5.3.1 - The accuracy of the logistic regression model is:66.667 %

5.3.2 - Accuracy score of decision tree:60.68%

6 Bagging: Bagging Classfier and Bagging regressor.

[20]:
```
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier
BC = BaggingClassifier(n_estimators = 100,random_state = 0)
#n_estimator is number of trees we are fitting for bagging
BC.fit(x_train,y_train)
print(BC.predict(x_test))
print(accuracy_score(BC.predict(x_test),y_test)*100)
```

```
[1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
 1. 0. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 0. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 0. 1.
 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1.
 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 0. 1. 0. 1. 0. 1. 1. 1.]
67.52136752136752
```

6.1 For pasting

[22]:
```
PBC = BaggingClassifier(n_estimators = 100,random_state = 0, bootstrap=False)
#bootstrap = False is samples are drawn with replacement
PBC.fit(x_train,y_train)
print(PBC.predict(x_test))
print(accuracy_score(PBC.predict(x_test),y_test)*100)
```

```
[0. 1. 1. 1. 1. 1. 1. 0. 1. 0. 0. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0.
 1. 0. 1. 1. 1. 0. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 0. 1. 1. 1. 1.
 1. 1. 1. 0. 1. 0. 1. 0. 1. 0. 1. 0. 1. 1. 1. 0. 1. 1. 1. 1. 0. 1. 0. 1.
 1. 1. 1. 1. 1. 1. 0. 0. 1. 1. 1. 1. 0. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1.
 1. 0. 1. 1. 0. 1. 1. 0. 1. 1. 1. 1. 0. 0. 0. 0. 0. 0. 1. 0. 1.]
62.39316239316239
```

6.2 Implementation of Random Forest classifier

[24]:
```
RFC = RandomForestClassifier(n_estimators=100,
 ↪max_features='sqrt',random_state=0)
RFC.fit(x_train,y_train)
print(RFC.predict(x_test))
print(accuracy_score(RFC.predict(x_test),y_test)*100)
```

```
[1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 0. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 0. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 0. 1.
 1. 0. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 0. 1.]
68.37606837606837
```

6.3 Checking the crucial features

[26]:
```
print(RFC.feature_importances_)
```

```
[0.11831252 0.07608059 0.17098602 0.16769726 0.1466726  0.11859783
 0.1066352  0.09501798]
```

6.4 - Features with large score were crucial in modelling

6.5 Q2. Form a synthetic dataset using the make classification class which we have used in the previous labs with two features and 3 classes. Fit the decisiontreeclassfier,baggingclassifier and randomforestclassifier and print the decsion boundaries for the different classifiers. Visualizing in the previous case is not possible so we can see how the nonlinear boundaries are getting created in these models except for a linear boundary that we have seen by other classifiers in the previous labs.

[29]:
```
from sklearn.datasets import make_classification
# generating a fake data first
x, y = make_classification(
 n_samples=200, # total nummer of samples in the dataset
 n_features=2,
 n_classes= 3,
 n_redundant=0,
 n_clusters_per_class=1, # number of cluster per class
 random_state=0)
```

[30]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.
 ↪2,random_state=0)
```

6.5.1 Fitting decision tree classifier

[32]:
```
model_dtc = DecisionTreeClassifier()
model_dtc.fit(x_train,y_train)
y_pred_dc = model_dtc.predict(x_test)
print(f"Accuracy score of decision tree:
 ↪{round(accuracy_score(y_test,y_pred_dc)*100,2)}%")
```

```
Accuracy score of decision tree:80.0%
```

6.5.2 Bagging classifier

[34]:
```
BC = BaggingClassifier(n_estimators = 100,random_state = 0)
#n_estimator is number of trees we are fitting for bagging
BC.fit(x_train,y_train)

print(accuracy_score(BC.predict(x_test),y_test)*100)
```

```
85.0
```

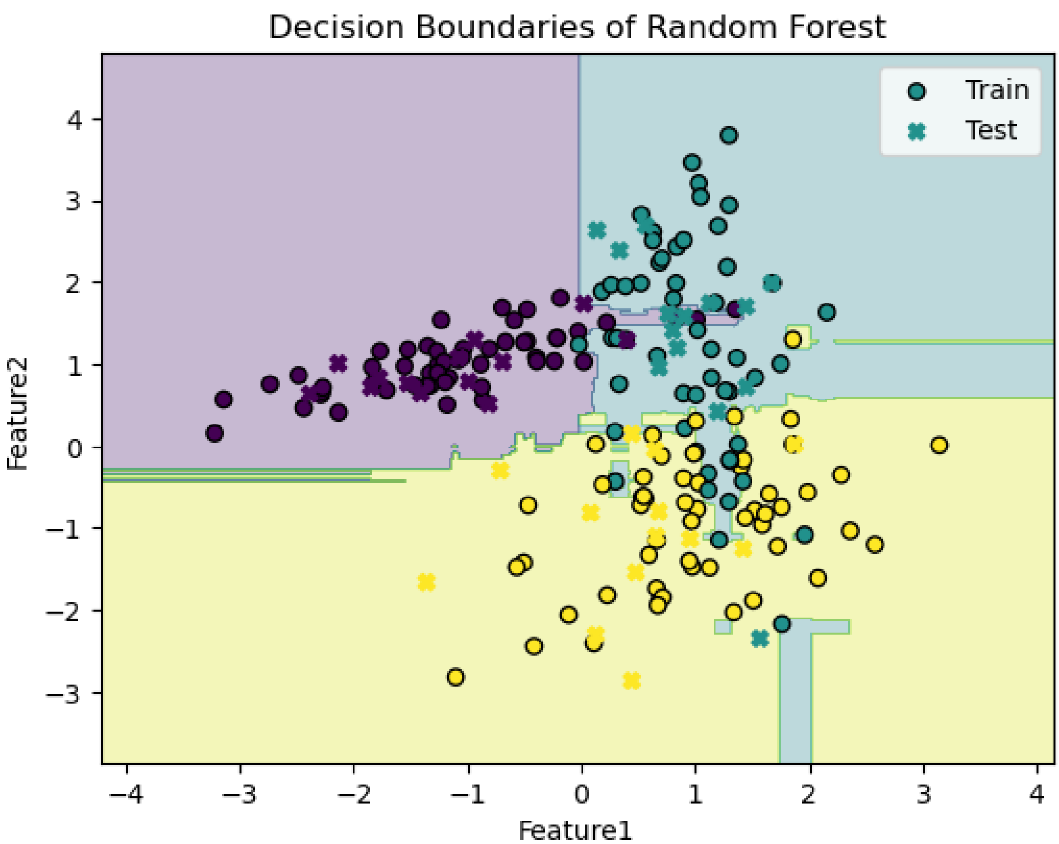
6.5.3 Random forest classifier

[36]:
```
RFC = RandomForestClassifier(n_estimators=100,␣
 ↪max_features='sqrt',random_state=42)
RFC.fit(x_train,y_train)
print(accuracy_score(RFC.predict(x_test),y_test)*100)
```

87.5

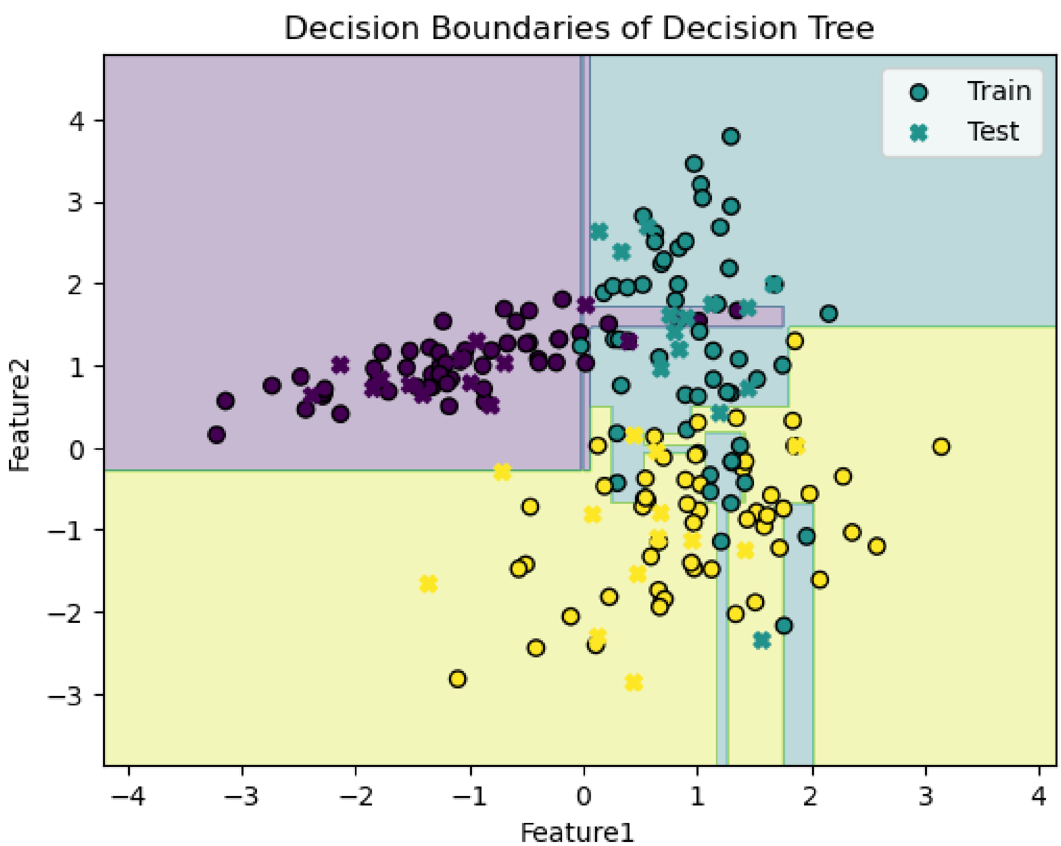
6.6 Decision boundary for random forest

[38]:
```
import matplotlib.pyplot as plt
x_min,x_max = x[:,0].min()-1, x[:,0].max()+1
y_min,y_max = x[:,1].min()-1,x[:,1].max()+1
xx,yy = np.meshgrid(np.linspace(x_min,x_max,500),np.linspace(y_min,y_max,500))
z = RFC.predict(np.c_[xx.ravel(),yy.ravel()])
z = z.reshape(xx.shape)
plt.contourf(xx,yy,z,alpha = 0.3)
plt.scatter(x_train[:,0],x_train[:,1],c = y_train,edgecolors='k',label =␣
↪'Train')
plt.scatter(x_test[:,0],x_test[:,1],c = y_test,marker='X',label = 'Test')
plt.xlabel("Feature1")
plt.ylabel("Feature2")
plt.title("Decision Boundaries of Random Forest")
plt.legend()
plt.show()
```



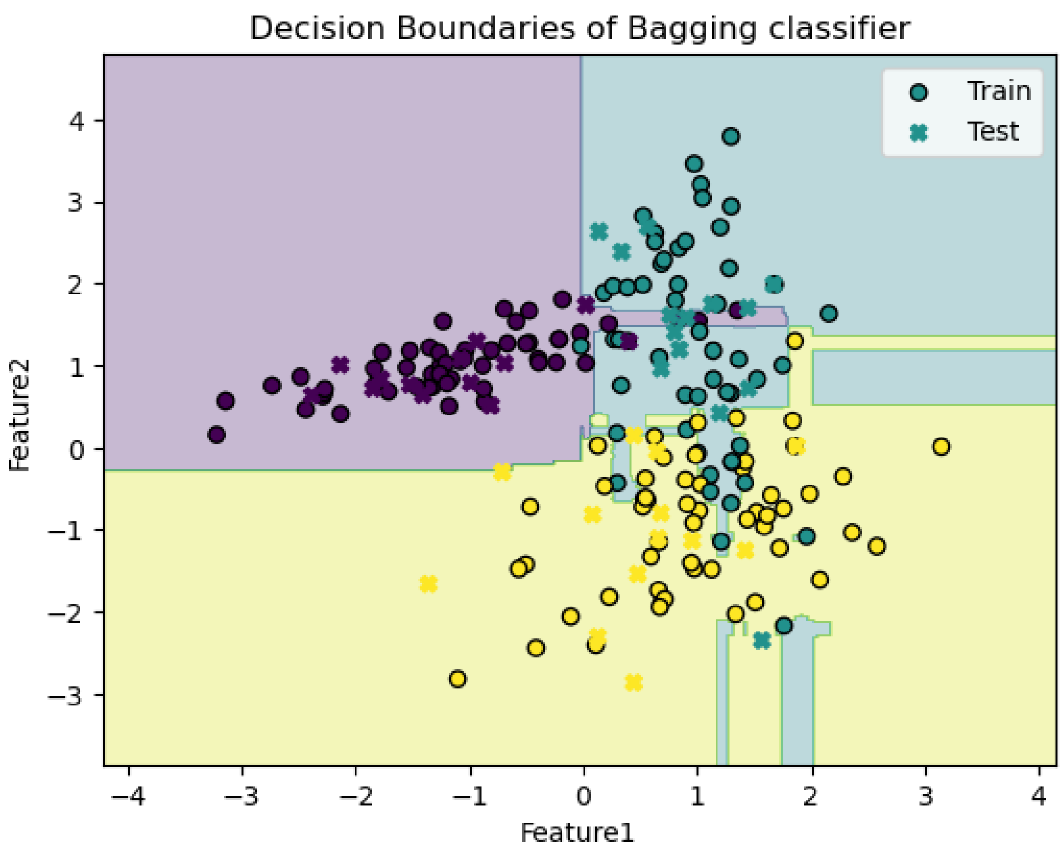
6.7 Decision boundary for Decision tree

[40]:
```
x_min,x_max = x[:,0].min()-1, x[:,0].max()+1
y_min,y_max = x[:,1].min()-1,x[:,1].max()+1
xx,yy = np.meshgrid(np.linspace(x_min,x_max,500),np.linspace(y_min,y_max,500))
z = model_dtc.predict(np.c_[xx.ravel(),yy.ravel()])
z = z.reshape(xx.shape)
plt.contourf(xx,yy,z,alpha = 0.3)
plt.scatter(x_train[:,0],x_train[:,1],c = y_train,edgecolors='k',label =
 'Train')
plt.scatter(x_test[:,0],x_test[:,1],c = y_test,marker='X',label = 'Test')
plt.xlabel("Feature1")
plt.ylabel("Feature2")
plt.title("Decision Boundaries of Decision Tree")
plt.legend()
plt.show()
```



6.8 Decision boundary for bagging classifier

[42]:
```
x_min,x_max = x[:,0].min()-1, x[:,0].max()+1
y_min,y_max = x[:,1].min()-1,x[:,1].max()+1
xx,yy = np.meshgrid(np.linspace(x_min,x_max,500),np.linspace(y_min,y_max,500))
z = BC.predict(np.c_[xx.ravel(),yy.ravel()])
z = z.reshape(xx.shape)
plt.contourf(xx,yy,z,alpha = 0.3)
plt.scatter(x_train[:,0],x_train[:,1],c = y_train,edgecolors='k',label =␣
↪'Train')
plt.scatter(x_test[:,0],x_test[:,1],c = y_test,marker='X',label = 'Test')
plt.xlabel("Feature1")
plt.ylabel("Feature2")
plt.title("Decision Boundaries of Bagging classifier")
plt.legend()
plt.show()
```



6.9 Voting Classifier

[44]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import VotingClassifier
from  sklearn.linear_model import LogisticRegression

log_clf = LogisticRegression()
rnd_clf = RandomForestClassifier(random_state=0)
sm_clf = LogisticRegression(multi_class='multinomial')
voting_clf =␣
 ↪VotingClassifier(estimators=[('lr',log_clf),('rf',rnd_clf),('sm',sm_clf)],
                              voting = 'hard')
voting_clf.fit(x_train,y_train)
print(accuracy_score(y_test,voting_clf.predict(x_test))*100)
```

```
82.5
```

6.10 Change to voting criteria to soft by setting voting = 'soft' and check the output in the above case. In the case of soft voting the models output a probability that is averaged and used for prediction

[46]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import VotingClassifier
from  sklearn.linear_model import LogisticRegression

log_clf = LogisticRegression()
rnd_clf = RandomForestClassifier(random_state=0)
sm_clf = LogisticRegression(multi_class='multinomial')
voting_clf =␣
 ↪VotingClassifier(estimators=[('lr',log_clf),('rf',rnd_clf),('sm',sm_clf)],
                              voting = 'soft')
voting_clf.fit(x_train,y_train)
print(accuracy_score(y_test,voting_clf.predict(x_test))*100)
```

```
90.0
```

7 Adaboost Classifier

[48]:
```
from sklearn.ensemble import AdaBoostClassifier
base_model = DecisionTreeClassifier(max_depth=1)
ABC = AdaBoostClassifier(estimator=base_model,n_estimators=500, random_state=0)
ABC.fit(x_train, y_train)
pred_ABC = ABC.predict(x_test)
print("AdaBoost Accuracy:", accuracy_score(y_test, pred_ABC)*100)
```

```
C:\Users\TUFAN\AppData\Roaming\Python\Python312\site-
packages\sklearn\ensemble\_weight_boosting.py:519: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use the SAMME
```

```
algorithm to circumvent this warning.
  warnings.warn(
```

```
AdaBoost Accuracy: 87.5
```

7.1 Hyper parameter tuning for Randomforest

[50]:

```
from sklearn.model_selection import GridSearchCV
param_grid = {
'n_estimators': [10, 50, 100, 200, 300, 400, 500, 700],
'max_depth': [3,5,7],
'min_samples_leaf': [1, 2, 4]
}
model = RandomForestClassifier(random_state=0)
grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=5,␣
↪scoring='accuracy', n_jobs=-1)
grid_search.fit(x_train, y_train)
best_params = grid_search.best_params_
best_model = grid_search.best_estimator_
y_pred = best_model.predict(x_test)
accuracy = accuracy_score(y_test, y_pred)
print("Best Parameters:", best_params)
print("Best Cross-validation Accuracy:", grid_search.best_score_)
print("Test Accuracy:", accuracy)
```

```
Best Parameters: {'max_depth': 5, 'min_samples_leaf': 4, 'n_estimators': 50}
Best Cross-validation Accuracy: 0.875
Test Accuracy: 0.95
```

7.2 Hyper parameter tuning for Adaboost

[52]:

```
from sklearn.model_selection import GridSearchCV
param_grid = {
'n_estimators': [10, 50, 75,100,125,150, 200, 400, 500],
'estimator__max_depth':[1,2,3]
}
base_model = DecisionTreeClassifier(max_depth=1)
model = AdaBoostClassifier(estimator=base_model, random_state=0)
grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=5,␣
↪scoring='accuracy', n_jobs=-1)
grid_search.fit(x_train, y_train)
best_params = grid_search.best_params_
best_model = grid_search.best_estimator_
y_pred = best_model.predict(x_test)
accuracy = accuracy_score(y_test, y_pred)
print("Best Parameters:", best_params)
print("Best Cross-validation Accuracy:", grid_search.best_score_)
print("Test Accuracy:", accuracy*100)
```

```
C:\Users\TUFAN\AppData\Roaming\Python\Python312\site-
packages\sklearn\ensemble\_weight_boosting.py:519: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use the SAMME
algorithm to circumvent this warning.
  warnings.warn(
```

```
Best Parameters: {'estimator__max_depth': 3, 'n_estimators': 100}
Best Cross-validation Accuracy: 0.85625
Test Accuracy: 82.5
```

7.3 Now you can try to fit the multiple regression model, DecisionTreeRegressor, BaggingRegressor, RandomForestRegressor and AdaboostRegressor on the Book1.csv file and use the mean squared error to see how these ensemble models perform compared to the basic models.

[54]:
```
## Loading the datatset
df = pd.read_csv(r"D:\study material\VIT_Data_Science\Winter_Sem\Data Mining␣
↪and Machine Learning Lab\Class_notes\ML_exp7\Book1.csv")
df.drop('furnishingstatus',axis=1,inplace = True)
```

[55]:
```
df
```

[55]:
```
        price  area  bedrooms  bathrooms  stories  parking
0    13300000  7420         4          2        3        2
1    12250000  8960         4          4        4        3
2    12250000  9960         3          2        2        2
3    12215000  7500         4          2        2        3
4    11410000  7420         4          1        2        2
..        ...   ...       ...        ...      ...      ...
244   4550000  5320         3          1        2        0
245   4550000  5360         3          1        2        2
246   4550000  3520         3          1        1        0
247   4550000  8400         4          1        4        3
248   4543000  4100         2          2        1        0

[249 rows x 6 columns]
```

[56]:
```
scaler = MinMaxScaler()
X = scaler.fit_transform(df)
x = X[:,1:]
y = X[:,0]
```

[57]:
```
## Train test splitting
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.
↪2,random_state=0)

## Fitting basic linear regression model
from sklearn.linear_model import LinearRegression
```

```
from sklearn.metrics import mean_squared_error, r2_score
model_lin = LinearRegression()
model_lin.fit(x_train,y_train)
y_pred = model_lin.predict(x_test)
print("MSE:",mean_squared_error(y_pred,y_test))
print("r2 score:",r2_score(y_test,y_pred))
```

```
MSE: 0.020077937566470735
r2 score: 0.18380110609849787
```

7.4 Using decision tree

[59]:
```
from sklearn.tree import DecisionTreeRegressor
model_dtr = DecisionTreeRegressor()
model_dtr.fit(x_train,y_train)
y_pred = model_dtr.predict(x_test)
print("MSE:",mean_squared_error(y_pred,y_test))
print("r2 score:",r2_score(y_test,y_pred))
```

```
MSE: 0.03563891581467928
r2 score: -0.4487764777737753
```

7.5 Using BaggingRegressor

[61]:
```
from sklearn.ensemble import BaggingRegressor
model_bag = BaggingRegressor()
model_bag.fit(x_train,y_train)
y_pred = model_bag.predict(x_test)
print("MSE:",mean_squared_error(y_pred,y_test))
print("r2 score:",r2_score(y_test,y_pred))
```

```
MSE: 0.020412967297335849
r2 score: 0.1701816347325068
```

7.6 Using pasting

[63]:
```
from sklearn.ensemble import BaggingRegressor
model_paste = BaggingRegressor(bootstrap=False)
model_paste.fit(x_train,y_train)
y_pred = model_paste.predict(x_test)
print("MSE:",mean_squared_error(y_pred,y_test))
print("r2 score:",r2_score(y_test,y_pred))
```

```
MSE: 0.034137753323409306
r2 score: -0.38775192474845155
```

7.7 Using randomforest regressor

[65]:
```
from sklearn.ensemble import RandomForestRegressor
model_rf = RandomForestRegressor(n_estimators=100,␣
    ↪max_features='sqrt',random_state=0)
model_rf.fit(x_train,y_train)
y_pred = model_rf.predict(x_test)
print("MSE:",mean_squared_error(y_pred,y_test))
print("r2 score:",r2_score(y_test,y_pred))
```

```
MSE: 0.020061663123497l6
r2 score: 0.1844626871154682
```

7.8 Using Adaboost regressor

[67]:
```
from sklearn.ensemble import AdaBoostRegressor
base_model = DecisionTreeRegressor(max_depth=1)
ABR = AdaBoostRegressor(estimator=base_model,n_estimators=500, random_state=0)
ABR.fit(x_train,y_train)
y_pred = ABR.predict(x_test)
print("MSE:",mean_squared_error(y_pred,y_test))
print("r2 score:",r2_score(y_test,y_pred))
```

```
MSE: 0.022650548292397O8
r2 score: 0.0792205423832919
```