Laboratory 4: Applying Ensemble Techniques to the Data

1. Import all the modules required to manipulate the data and evaluate the model:

```
import pandas as pd
import numpy as np

%matplotlib inline
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score, confusion_matrix
from sklearn.model_selection import KFold
```

2. Import your dataset that you used from previous laboratory

```
df = pd.read_csv('/content/DE_BODA Laboratory_Activity_3_Cleaned_dataset.csv')
```

3. Import and Read the dataset

```
df.head()
```

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mean
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809

5 rows × 31 columns

4. Split the dataset into training and validation sets.

```
X = df.drop(columns='diagnosis')
y = df['diagnosis']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=11)
```

Ensemble Modelling

Bagging

Use the Bagging Classifier!

```
# Import Bagging Classifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingClassifier
```

```
# Specify Hyperparameters
dt_params = {
    'criterion': 'entropy',
    'random_state': 11
}
```

```
dt = DecisionTreeClassifier(**dt_params)
# dt = DecisionTreeClassifier(criterion='entropy', random_state=11)

bc_params = {
    'estimator': dt,
    'n_estimators': 20,
    'max_samples': 0.5,
    'random_state': 11,
    'n_jobs': -1,
}

bc = BaggingClassifier(**bc_params)
```

Fit the bagging classifier model to the training data and calculate the prediction accuracy.

```
dt.fit(X_train, y_train)
dt_preds_train = dt.predict(X_train)
dt_preds_val = dt.predict(X_test)
```

```
print('Decision Tree:\n> Accuracy on training data = {:.4f}\n> Accuracy on validation data = {:.4f}'.format(
    accuracy_score(y_true=y_train, y_pred=dt_preds_train),
    accuracy_score(y_true=y_test, y_pred=dt_preds_val)
))
```

```
Decision Tree:
> Accuracy on training data = 1.0000
> Accuracy on validation data = 0.9510
```

Fit the bagging classifier model to the test data and calculate the prediction accuracy.

```
bc.fit(X_train, y_train)
bc_preds_train = bc.predict(X_train)
bc_preds_val = bc.predict(X_test)

print('Bagging Classifier:\n> Accuracy on training data = {:.4f}\n> Accuracy on validation data = {:.4f}'.format(
    accuracy_score(y_true=y_train, y_pred=bc_preds_train),
    accuracy_score(y_true=y_test, y_pred=bc_preds_val)
))
```

```
Bagging Classifier:
> Accuracy on training data = 0.9883
> Accuracy on validation data = 0.9650
```

```
from sklearn.ensemble import RandomForestClassifier
```

```
rf_params = {
    'n_estimators': 100,
    'criterion': 'entropy',
    'max_features': 0.5,
    'min_samples_leaf': 5,
    'random_state': 11,
    'n_jobs': -1
}
rf = RandomForestClassifier(**rf_params)

bc_params = {
    'estimator': rf,
    'n_estimators': 100,
    'max_samples': 0.5,
    'random_state': 11,
    'n_jobs': -1
}
bc = BaggingClassifier(**bc_params)
```

```
rf.fit(X_train, y_train)
rf_preds_train = rf.predict(X_train)
rf_preds_val = rf.predict(X_test)

print('Random Forest:\n> Accuracy on training data = {:.4f}\n> Accuracy on validation data = {:.4f}'.format(
```

```
    accuracy_score(y_true=y_train, y_pred=rf_preds_train),
    accuracy_score(y_true=y_test, y_pred=rf_preds_val)
))
```

```
Random Forest:
> Accuracy on training data = 0.9812
> Accuracy on validation data = 0.9790
```

```
bc.fit(X_train, y_train)
bc_preds_train = bc.predict(X_train)
bc_preds_val = bc.predict(X_test)

print('Bagging Classifier:\n> Accuracy on training data = {:.4f}\n> Accuracy on validation data = {:.4f}'.format(
    accuracy_score(y_true=y_train, y_pred=bc_preds_train),
    accuracy_score(y_true=y_test, y_pred=bc_preds_val)
))
```

```
Bagging Classifier:
> Accuracy on training data = 0.9671
> Accuracy on validation data = 0.9860
```

Boosting

Import the ensemble classifier for boosting:

```
from sklearn.ensemble import AdaBoostClassifier
```

Specify the hyperparameters and initialize the model.

```
dt_params = {
    'max_depth': 1,
    'random_state': 11
}
dt = DecisionTreeClassifier(**dt_params)

ab_params = {
    'n_estimators': 80,
    'estimator': dt,
    'random_state': 11
}
ab1 = AdaBoostClassifier(**ab_params)
```

```
rf_params = {
    'n_estimators': 100,
    'criterion': 'entropy',
    'max_features': 0.5,
    'min_samples_leaf': 10,
    'random_state': 11,
    'n_jobs': -1
}
rf = RandomForestClassifier(**rf_params)

ab_params = {
    'n_estimators': 80,
    'estimator': rf,
    'random_state': 11
}
ab2 = AdaBoostClassifier(**ab_params)
```

Fit the model to the training data.

```
ab1.fit(X_train, y_train)
abfit = ab1.fit(X_train, y_train)
ab_preds_train = ab1.predict(X_train)
ab_preds_val = ab1.predict(X_test)

print('Adaptive Boosting for Decision Tree:\n> Accuracy on training data = {:.4f}\n> Accuracy on validation data = {:.4f}\n'.format(
    accuracy_score(y_true=y_train, y_pred=ab_preds_train),
```

```
    accuracy_score(y_true=y_test, y_pred=ab_preds_val)
))

ab2.fit(X_train, y_train)
abfit = ab2.fit(X_train, y_train)
ab_preds_train = ab2.predict(X_train)
ab_preds_val = ab2.predict(X_test)

print('Adaptive Boosting for Random Forest:\n> Accuracy on training data = {:.4f}\n> Accuracy on validation data = {:.4f}'.format(
    accuracy_score(y_true=y_train, y_pred=ab_preds_train),
    accuracy_score(y_true=y_test, y_pred=ab_preds_val)
))
```

```
Adaptive Boosting for Decision Tree:
> Accuracy on training data = 1.0000
> Accuracy on validation data = 0.9790

Adaptive Boosting for Random Forest:
> Accuracy on training data = 1.0000
> Accuracy on validation data = 0.9720
```

Calculate the prediction accuracy of the model on the training and validation data for a varying number of base estimators.

```
ab_params = {
    'estimator': dt,
    'random_state': 11
}

n_estimator_values = list(range(5, 250, 5))
train_accuracies, val_accuracies = [], []

for n_estimators in n_estimator_values:
    ab = AdaBoostClassifier(n_estimators=n_estimators, **ab_params)
    ab.fit(X_train, y_train)
    ab_preds_train = ab.predict(X_train)
    ab_preds_val = ab.predict(X_test)

    train_accuracies.append(accuracy_score(y_true=y_train, y_pred=ab_preds_train))
    val_accuracies.append(accuracy_score(y_true=y_test, y_pred=ab_preds_val))
```

```
train_accuracies
```

```
[0.9389671361502347,
 0.9694835680751174,
 0.9765258215962441,
 0.9953051643192489,
 0.9976525821596244,
 0.9976525821596244,
 0.9976525821596244,
 1.0,
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```

```
val_accuracies
```

```
[0.9440559440559441,
 0.972027972027972,
 0.972027972027972,
 0.972027972027972,
 0.965034965034965,
 0.965034965034965,
 0.986013986013986,
 0.9790209790209791,
 0.986013986013986,
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 0.993006993006993,
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 0.993006993006993]
```

```
rf.fit(X_train, y_train)
ab_preds_train = rf.predict(X_train)
ab_preds_val = rf.predict(X_test)
```

```
import joblib
```

```
joblib.dump(rf, 'rf_model.pkl')
```

```
['rf_model.pkl']
```

```
from sklearn.metrics import precision_recall_curve, average_precision_score
```

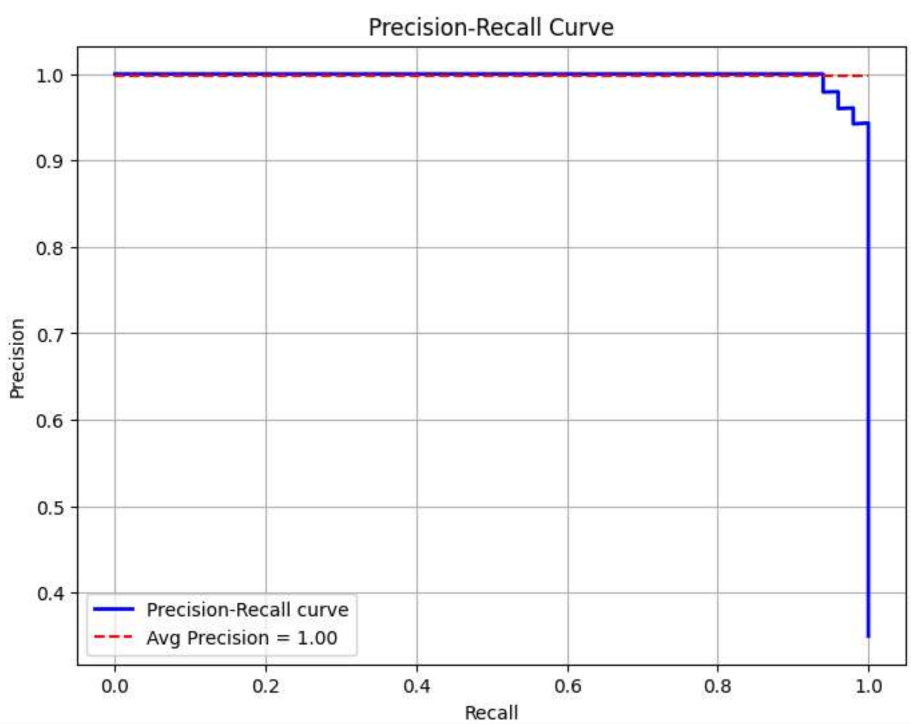
```
y_score = rf.predict_proba(X_test)[:, 1]
```

```
precision, recall, thresholds = precision_recall_curve(y_test, y_score)

avg_precision = average_precision_score(y_test, y_score)
print(avg_precision)
```

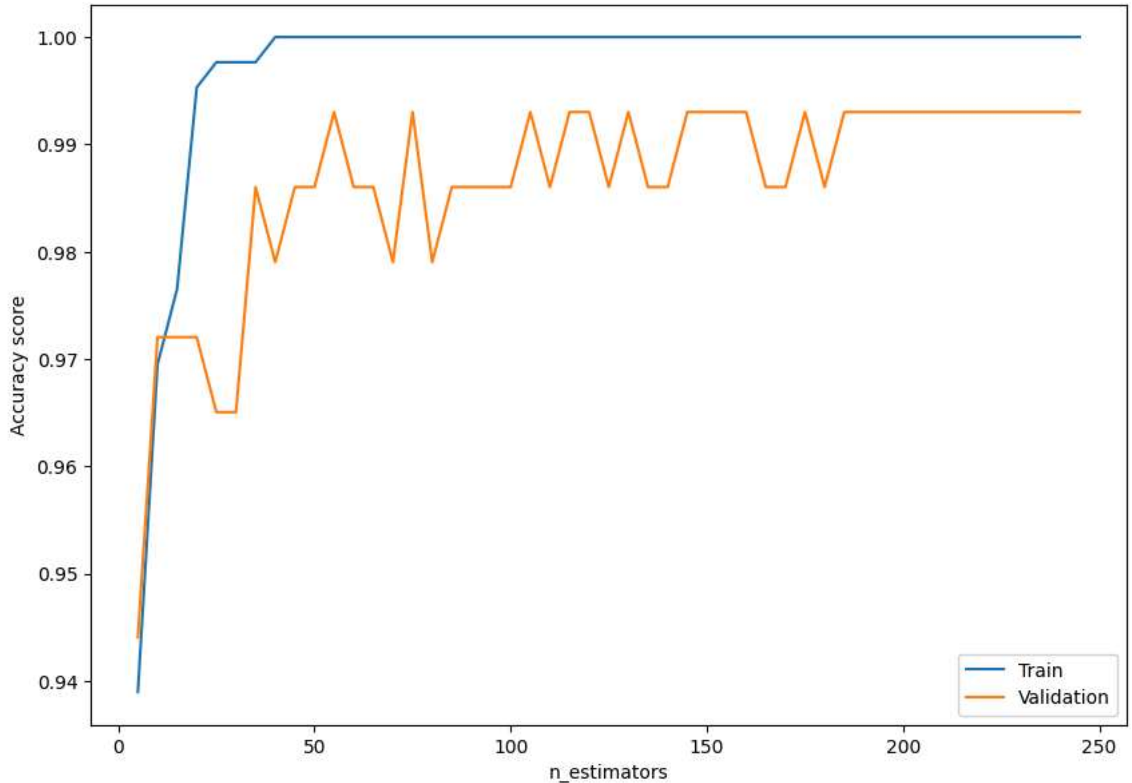
```
0.9976754475375056
```

Plot a line graph to visualize the trend of the prediction accuracies on both the training and validation datasets:

```
plt.figure(figsize=(8, 6))

# Plot Precision-Recall curve
plt.plot(recall, precision, color='b', lw=2, label='Precision-Recall curve')

# Correct way: use hlines to plot a horizontal dashed line at avg_precision
plt.hlines(avg_precision, xmin=0, xmax=1, colors='r', linestyles='--', label=f'Avg Precision = {avg_precision:.2f}')

plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend(loc='best')
plt.grid()
plt.show()
```




```
plt.figure(figsize=(10,7))
plt.plot(n_estimator_values, train_accuracies, label='Train')
plt.plot(n_estimator_values, val_accuracies, label='Validation')

plt.ylabel('Accuracy score')
plt.xlabel('n_estimators')

plt.legend()
plt.show()
```


1.00
0.99
0.98
0.97
0.96
0.95
0.94
Accuracy score
0
50
100
150
200
250
n_estimators
Train
Validation