Digital Assignment

Autism Prediction Using Different Algorithms

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Importing Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.linear_model import LogisticRegression
    from sklearn.tree import DecisionTreeClassifier, plot_tree
    from sklearn.ensemble import BaggingClassifier, RandomForestClassifier, GradientBoostingClassifier, AdaBoostClassifier

from sklearn.preprocessing import LabelEncoder, MinMaxScaler
    from sklearn.model_selection import train_test_split, GridSearchCV
    from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

In [2]:

data = pd.read_csv('autism_train.csv')
data.head()
```

Out[2]:		ID	A1_Score	A2_Score	A3_Score	A4_Score	A5_Score	A6_Score	A7_Score	A8_Score	A9_Score	•••	gender	ethnicity	jaundice	aus
	0	1	1	0	1	0	1	0	1	0	1		f	?	no	
	1	2	0	0	0	0	0	0	0	0	0		m	?	no	
	2	3	1	1	1	1	1	1	1	1	1		m	White- European	no	
	3	4	0	0	0	0	0	0	0	0	0		f	?	no	
	4	5	0	0	0	0	0	0	0	0	0		m	?	no	

5 rows × 22 columns

In [3]: data.info()

> <class 'pandas.core.frame.DataFrame'> RangeIndex: 800 entries, 0 to 799 Data columns (total 22 columns): Non-Null Count Dtype Column ID 800 non-null int64 1 A1 Score 800 non-null int64 A2 Score 800 non-null int64 A3 Score 800 non-null int64 800 non-null A4 Score int64 A5 Score 800 non-null int64 A6 Score 800 non-null int64 800 non-null int64 A7 Score 800 non-null A8 Score int64 A9 Score 800 non-null int64 800 non-null int64 A10 Score 11 age 800 non-null float64 gender 800 non-null object 12 ethnicity 800 non-null object 14 jaundice 800 non-null object 15 austim 800 non-null object 16 contry of res 800 non-null object 800 non-null used app before object 18 result 800 non-null float64 age desc 800 non-null object 20 relation 800 non-null object 21 Class/ASD 800 non-null int64 dtypes: float64(2), int64(12), object(8)

memory usage: 137.6+ KB

Data Preprocessing

```
data['age'] = data['age'].astype('int64')
data['age'].info()
```

Binary Type Columns

```
In [6]: for col in ['gender', 'jaundice', 'austim', 'used_app_before']:
    print(f"{col} --- has {len(data[col].unique())} unique values.")
    for i in data[col].unique():
        print(f"\n{i}")

    print("-"*40)
```

```
gender --- has 2 unique values.
       f
       jaundice --- has 2 unique values.
       no
       yes
       austim --- has 2 unique values.
       no
       yes
       used app before --- has 2 unique values.
       no
       yes
In [7]: encoder = LabelEncoder()
        for col in ['gender', 'jaundice', 'austim', 'used app before']:
            data[col] = encoder.fit_transform(data[col])
            print(f"{col} ---- label encoding --- Done")
       gender ---- label encoding --- Done
       jaundice ---- label encoding --- Done
       austim ---- label encoding --- Done
       used app before ---- label encoding --- Done
In [8]: data[['gender', 'jaundice', 'austim', 'used_app_before']].head()
```

Out[8]:		gender	jaundice	austim	used_app_before
	0	0	0	0	0
	1	1	0	0	0
	2	1	0	1	0
	3	0	0	0	0
	4	1	0	0	0

Countries

```
In [9]: data["contry_of_res"].unique()
Out[9]: array(['Austria', 'India', 'United States', 'South Africa', 'Jordan',
                 'United Kingdom', 'Brazil', 'New Zealand', 'Canada', 'Kazakhstan',
                 'United Arab Emirates', 'Australia', 'Ukraine', 'Iraq', 'France',
                 'Malaysia', 'Viet Nam', 'Egypt', 'Netherlands', 'Afghanistan',
                 'Oman', 'Italy', 'AmericanSamoa', 'Bahamas', 'Saudi Arabia',
                 'Ireland', 'Aruba', 'Sri Lanka', 'Russia', 'Bolivia', 'Azerbaijan',
                 'Armenia', 'Serbia', 'Ethiopia', 'Sweden', 'Iceland', 'Hong Kong',
                 'Angola', 'China', 'Germany', 'Spain', 'Tonga', 'Pakistan', 'Iran',
                 'Argentina', 'Japan', 'Mexico', 'Nicaragua', 'Sierra Leone',
                 'Czech Republic', 'Niger', 'Romania', 'Cyprus', 'Belgium',
                 'Burundi', 'Bangladesh'], dtype=object)
In [10]: # replace redundant countries
         mapping = {
             "Viet Nam": "Vietnam",
             "AmericanSamoa": "United States",
             "Hong Kong": "China"
         data["contry of res"] = data["contry of res"].replace(mapping)
In [11]:
         data["contry of res"] = encoder.fit transform(data["contry of res"])
         print(f"{"contry of res"} ---- label encoding --- Done")
```

```
data["contry of res"]
        contry of res ---- label encoding --- Done
Out[11]: 0
                  6
          1
                 23
          2
                 52
                 52
                 44
          795
                 34
          796
                 16
          797
                 34
          798
                 14
          799
                 50
          Name: contry of res, Length: 800, dtype: int64
```

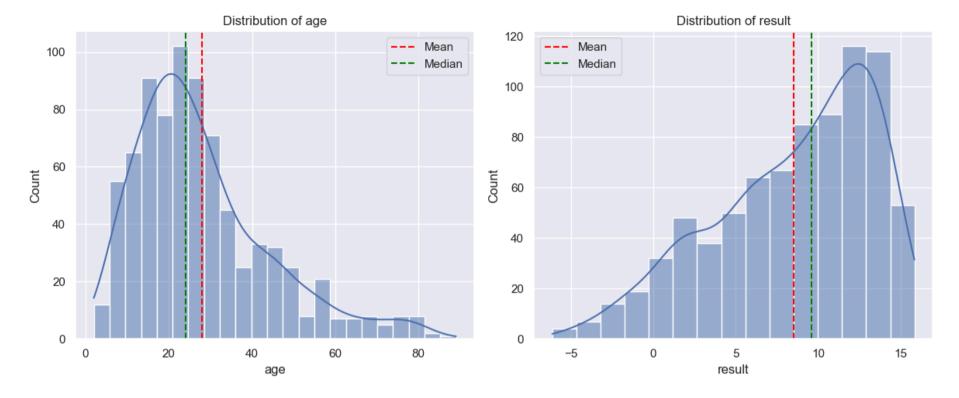
Dropping columns

```
In [15]:
         data.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 800 entries, 0 to 799
        Data columns (total 19 columns):
                              Non-Null Count Dtype
             Column
             -----
             A1 Score
                              800 non-null
                                              int64
             A2 Score
                              800 non-null
                                              int64
             A3 Score
                              800 non-null
                                              int64
             A4 Score
                              800 non-null
                                              int64
             A5 Score
                              800 non-null
                                              int64
             A6 Score
                              800 non-null
                                              int64
             A7 Score
                              800 non-null
                                              int64
                              800 non-null
                                              int64
             A8 Score
             A9 Score
                              800 non-null
                                              int64
             A10 Score
                              800 non-null
                                              int64
             age
                              800 non-null
                                              int64
         10
             gender
                              800 non-null
         11
                                              int64
         12 jaundice
                              800 non-null
                                              int64
         13 austim
                              800 non-null
                                              int64
             contry of res
                              800 non-null
                                              int64
             used app before
                              800 non-null
                                              int64
         16 result
                              800 non-null
                                              float64
         17 relation
                              800 non-null
                                              int64
         18 Class/ASD
                              800 non-null
                                              int64
        dtypes: float64(1), int64(18)
        memory usage: 118.9 KB
```

Data Visualizations

```
In [16]: sns.set_theme(style="darkgrid")
In [17]: data.columns
```

```
Out[17]: Index(['A1 Score', 'A2 Score', 'A3 Score', 'A4 Score', 'A5 Score', 'A6 Score',
                  'A7 Score', 'A8 Score', 'A9 Score', 'A10 Score', 'age', 'gender',
                  'jaundice', 'austim', 'contry of res', 'used app before', 'result',
                  'relation', 'Class/ASD'],
                dtvpe='object')
In [18]: data.describe()
Out[18]:
                   A1 Score
                              A2 Score
                                          A3 Score A4 Score
                                                                 A5 Score
                                                                            A6 Score
                                                                                        A7 Score
                                                                                                    A8 Score
                                                                                                               A9 Score A10 Score
                                                                                                                                            age
          count 800.00000
                                        800.000000
                                                    800.0000
                                                                           800.00000
                             800.000000
                                                               800.000000
                                                                                       00000000
                                                                                                  800.00000
                                                                                                              800.000000
                                                                                                                          800.000000
                                                                                                                                      800.00000
                   0.560000
                               0.530000
                                           0.450000
                                                       0.41500
                                                                 0.395000
                                                                             0.303750
                                                                                         0.397500
                                                                                                    0.508750
                                                                                                                0.495000
                                                                                                                            0.617500
                                                                                                                                      27.963750
          mean
                   0.496697
                               0.499411
                                           0.497805
                                                       0.49303
                                                                 0.489157
                                                                             0.460164
                                                                                         0.489687
                                                                                                    0.500236
                                                                                                                0.500288
                                                                                                                            0.486302
                                                                                                                                       16.329827
            std
                   0.000000
                               0.000000
                                           0.000000
                                                       0.00000
                                                                 0.000000
                                                                             0.000000
                                                                                         0.000000
                                                                                                    0.000000
                                                                                                                0.000000
                                                                                                                            0.000000
                                                                                                                                        2.000000
            min
           25%
                   0.000000
                               0.000000
                                           0.000000
                                                       0.00000
                                                                 0.000000
                                                                             0.000000
                                                                                                    0.000000
                                                                                                                0.000000
                                                                                                                            0.000000
                                                                                                                                      17.000000
                                                                                         0.000000
           50%
                   1.000000
                               1.000000
                                           0.000000
                                                       0.00000
                                                                 0.000000
                                                                             0.000000
                                                                                         0.000000
                                                                                                    1.000000
                                                                                                                0.000000
                                                                                                                            1.000000
                                                                                                                                      24.000000
           75%
                   1.000000
                               1.000000
                                           1.000000
                                                       1.00000
                                                                 1.000000
                                                                             1.000000
                                                                                         1.000000
                                                                                                    1.000000
                                                                                                                1.000000
                                                                                                                                       35.250000
                                                                                                                            1.000000
                   1.000000
                               1.000000
                                           1.000000
                                                       1.00000
                                                                 1.000000
                                                                             1.000000
                                                                                         1.000000
                                                                                                    1.000000
                                                                                                                1.000000
                                                                                                                            1.000000
                                                                                                                                       89.000000
           max
         fig, ax = plt.subplots(1, 2, figsize=(12, 5))
In [19]:
          for i, col in enumerate(['age', 'result']):
              sns.histplot(data[col], kde=True, ax=ax[i])
              ax[i].axvline(data[col].mean(), color="red", linestyle="--", label="Mean")
              ax[i].axvline(data[col].median(), color="green", linestyle="--", label="Median")
              ax[i].set title(f"Distribution of {col}")
              ax[i].legend() # Put Legend in each subplot
          plt.tight layout()
          plt.show()
```

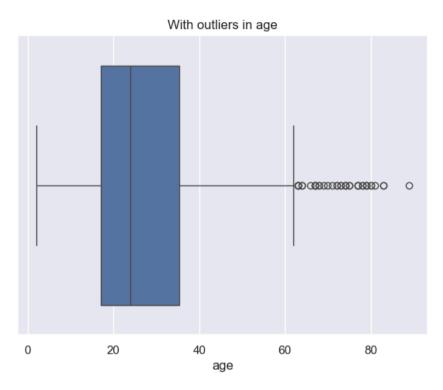


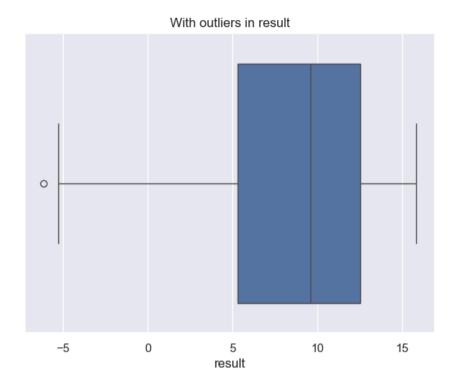
Outliers Detection

```
In [20]: fig, axs = plt.subplots(1,2, figsize=(15, 5))
    sns.boxplot(x=data.age, ax=axs[0])
    axs[0].set_title("With outliers in age")

sns.boxplot(x=data.result, ax=axs[1])
    axs[1].set_title("With outliers in result")

plt.show()
```





```
In [21]: Q1 = data.age.quantile(0.25)
Q3 = data.age.quantile(0.75)

IQR = Q3 - Q1

lb = Q1 - 1.5*IQR
    ub = Q3 + 1.5*IQR

age_outliers = data[(data.age < lb) | (data.age > ub)]
len(age_outliers)
```

Out[21]: 39

```
In [22]: def replace_outliers(df, col):
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
```

```
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

median = df[col].median()

# replace outliers with median
df[col] = df[col].apply(lambda x: median if x < lower_bound or x > upper_bound else x)

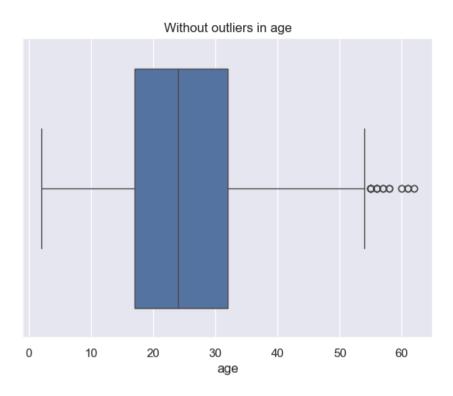
return df

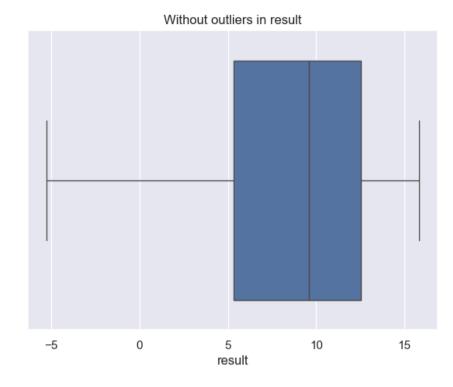
for i in ['age', 'result']:
    data = replace_outliers(data, i)

fig, axs = plt.subplots(1,2, figsize=(15, 5))
sns.boxplot(x=data.age, ax=axs[0])
axs[0].set_title("Without outliers in age")

sns.boxplot(x=data.result, ax=axs[1])
axs[1].set_title("Without outliers in result")

plt.show()
```





Normalize Data

```
In [23]: scaler = MinMaxScaler()
    scaled_data = scaler.fit_transform(data)
    data = pd.DataFrame(scaled_data, columns=data.columns)
    data.head()
```

Out[23]:		A1_Score	A2_Score	A3_Score	A4_Score	A5_Score	A6_Score	A7_Score	A8_Score	A9_Score	A10_Score	age	gender	jaundice
	0	1.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0	1.0	1.0	0.600000	0.0	0.0
	1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.750000	1.0	0.0
	2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.083333	1.0	0.0
	3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.350000	0.0	0.0
	4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.683333	1.0	0.0
	4 (•

Split the Dataset

```
In [24]: X = data.drop(['Class/ASD'], axis=1)
y = data['Class/ASD']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

In [25]: print(f"X_train shape: {X_train.shape}")
print(f"X_test shape: {X_test.shape}")
print(f"y_train shape: {y_train.shape}")
print(f"y_test shape: {y_test.shape}")

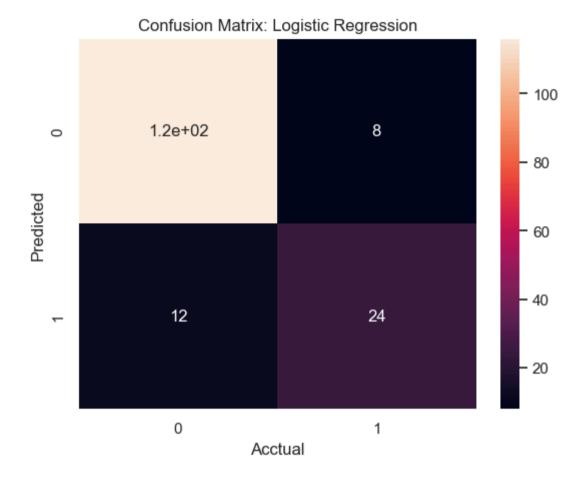
X_train shape: (640, 18)
X_test shape: (160, 18)
y_train shape: (640,)
y_test shape: (160,)
```

Logistic Regression

```
In [26]: LR = LogisticRegression()
    LR.fit(X_train, y_train)
    LR_predict = LR.predict(X_test)
    print(f"Logistic Regression accuracy: {accuracy_score(y_test,LR_predict)}")
```

Logistic Regression accuracy: 0.875

```
In [27]: print(classification report(y test, LR predict))
                     precision
                                  recall f1-score support
                 0.0
                          0.91
                                    0.94
                                              0.92
                                                         124
                 1.0
                          0.75
                                    0.67
                                              0.71
                                                          36
           accuracy
                                              0.88
                                                         160
           macro avg
                          0.83
                                    0.80
                                              0.81
                                                         160
                          0.87
        weighted avg
                                    0.88
                                              0.87
                                                         160
In [28]: LR cfm = confusion matrix(y test, LR predict)
         sns.heatmap(LR_cfm, annot=True)
         plt.xlabel('Acctual')
         plt.ylabel('Predicted')
         plt.title("Confusion Matrix: Logistic Regression")
         plt.show()
```



Decision Tree Classifier

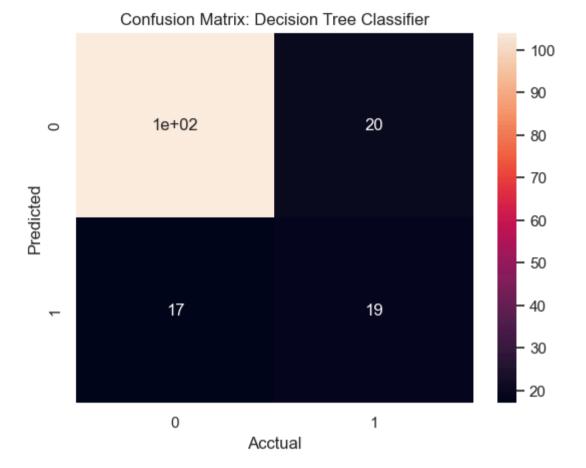
```
In [29]: DT = DecisionTreeClassifier()
DT.fit(X_train, y_train)
DT_predict = DT.predict(X_test)
print(f"Decison Tree Classifier accuracy: {accuracy_score(y_test,DT_predict)}")

Decison Tree Classifier accuracy: 0.76875

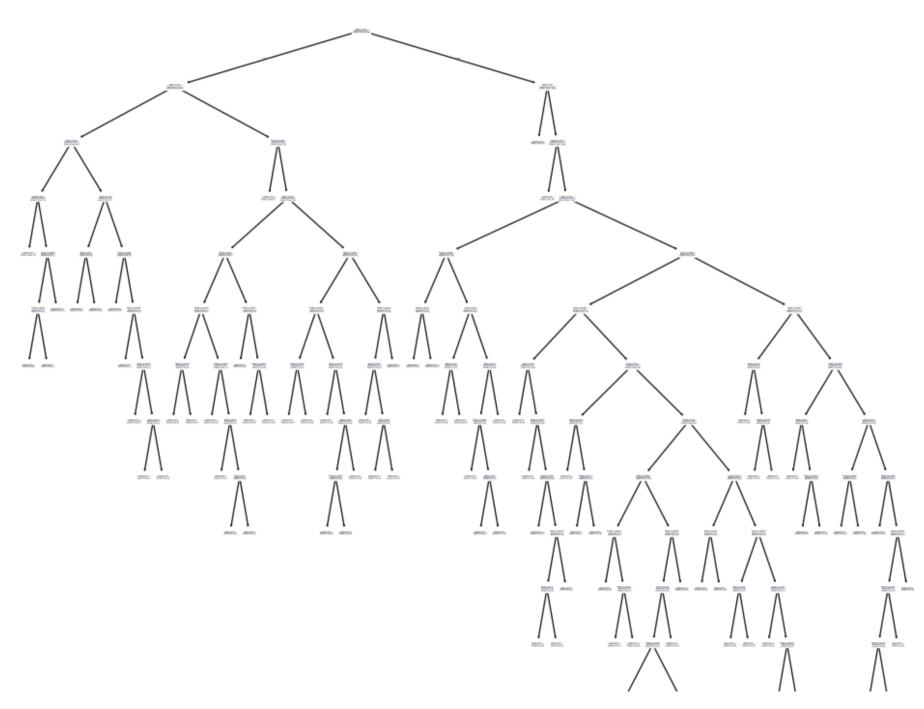
In [30]: print(classification_report(y_test, DT_predict))
```

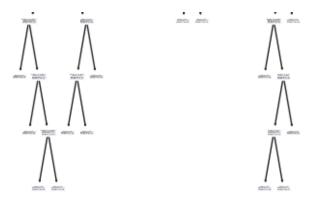
```
recall f1-score support
             precision
        0.0
                  0.86
                           0.84
                                     0.85
                                                124
                  0.49
                           0.53
                                     0.51
        1.0
                                                36
                                     0.77
                                                160
   accuracy
                                     0.68
                                                160
  macro avg
                  0.67
                           0.68
weighted avg
                  0.78
                           0.77
                                     0.77
                                                160
```

```
In [31]: DT_cfm = confusion_matrix(y_test, DT_predict)
    sns.heatmap(DT_cfm, annot=True)
    plt.xlabel('Acctual')
    plt.ylabel('Predicted')
    plt.title("Confusion Matrix: Decision Tree Classifier")
    plt.show()
```



```
In [32]: plt.figure(figsize=(12, 12))
    plot_tree(DT)
    plt.show()
```





Bagging Classifier

```
In [33]: bc_param_grid = {
    'n_estimators':[ 10, 50, 80 ,100, 150, 200, 250, 300]
    }

bc_base_model = BaggingClassifier(random_state=0)
bc_gs = GridSearchCV(estimator = bc_base_model, param_grid = bc_param_grid,cv=5, n_jobs = -1)
bc_gs.fit(X_train, y_train)
print(f'Best parameters for "Bagging Classifier": {bc_gs.best_params_}')
print(f'Best Accuracy: {bc_gs.best_score_}')

Best parameters for "Bagging Classifier": {'n_estimators': 10}
Best Accuracy: 0.8609375
```

Training with Optimized parameters

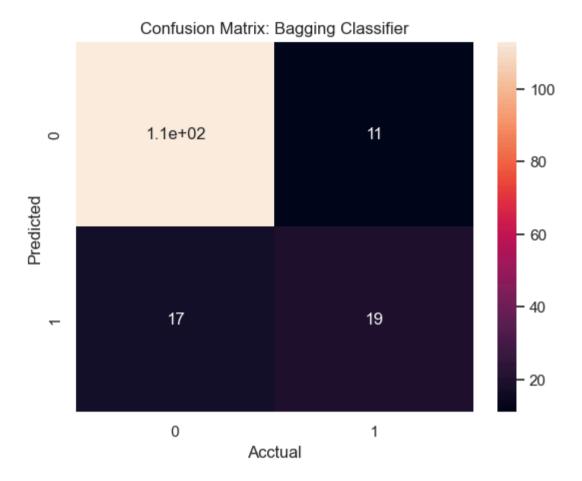
```
In [34]: BC = BaggingClassifier(n_estimators = 10, random_state=0)
    BC.fit(X_train, y_train)
    BC_predict = BC.predict(X_test)
    print(f"Bagging Classifier accuracy: {accuracy_score(y_test,BC_predict)}")

Bagging Classifier accuracy: 0.825

In [35]: print(classification_report(y_test, BC_predict))
```

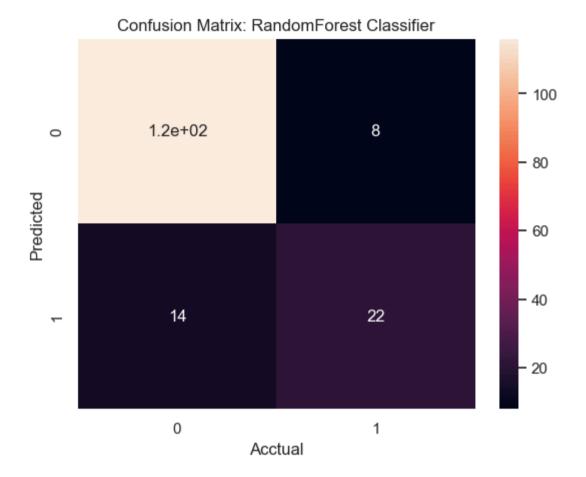
	precision	recall	f1-score	support
0.0	0.87 0.63	0.91 0.53	0.89 0.58	124 36
accuracy			0.82	160
macro avg	0.75	0.72	0.73	160
weighted avg	0.82	0.82	0.82	160

```
In [36]: BC_cfm = confusion_matrix(y_test, BC_predict)
    sns.heatmap(BC_cfm, annot=True)
    plt.xlabel('Acctual')
    plt.ylabel('Predicted')
    plt.title("Confusion Matrix: Bagging Classifier")
    plt.show()
```



RandomForest Classifier

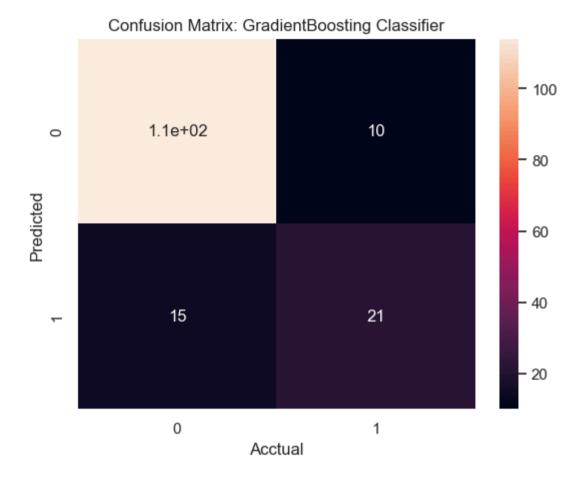
```
print(f'Best parameters for "Random Forest Classifier": {rfc gs.best params }')
         print(f'Best Accuracy: {rfc gs.best score }')
        Best parameters for "Random Forest Classifier": {'max_depth': 15, 'n estimators': 100}
        Best Accuracy: 0.8703125
In [38]: RF = RandomForestClassifier(max features='sqrt', n estimators=100, max depth=15)
         RF.fit(X train, y train)
         RF predict = RF.predict(X test)
         print(f"RandomForest Classifier accuracy: {accuracy_score(y_test,RF_predict)}")
        RandomForest Classifier accuracy: 0.8625
In [39]: print(classification report(y test, RF predict))
                      precision
                                   recall f1-score support
                 0.0
                           0.89
                                     0.94
                                               0.91
                                                          124
                           0.73
                                     0.61
                                               0.67
                 1.0
                                                           36
                                               0.86
                                                          160
            accuracy
           macro avg
                           0.81
                                     0.77
                                               0.79
                                                          160
        weighted avg
                           0.86
                                     0.86
                                               0.86
                                                          160
In [40]: RF cfm = confusion matrix(y test, RF predict)
         sns.heatmap(RF_cfm, annot=True)
         plt.xlabel('Acctual')
         plt.ylabel('Predicted')
         plt.title("Confusion Matrix: RandomForest Classifier")
         plt.show()
```



GradientBoosting Classifier

```
In [41]:
    gbr_base_model = GradientBoostingClassifier(random_state=0)
    gbr_param_grid = {
        'n_estimators':[ 10, 50, 80 ,100, 150, 200, 250, 300],
        'max_depth': [1,2,3,4,10,15,20],
        'learning_rate': [0.01,0.02,0.1,0.05,0.5,0.07,0.9]
    }
    gbr_gs = GridSearchCV(estimator = gbr_base_model, param_grid = gbr_param_grid,cv=5, n_jobs = -1)
    gbr_gs.fit(X_train, y_train)
```

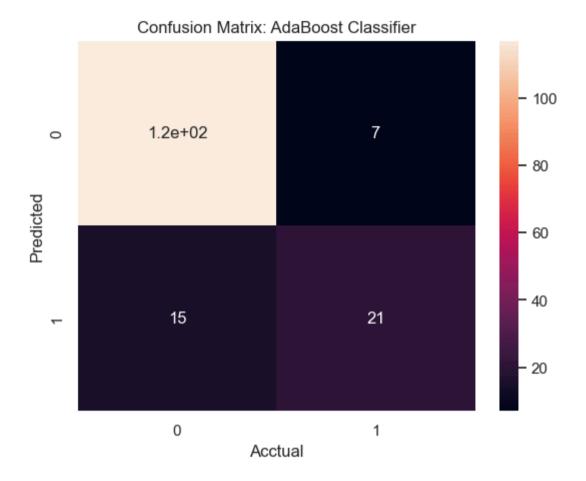
```
print(f'Best parameters for "Gradient Boosting Classifier": {gbr gs.best params }')
         print(f'Best Accuracy: {gbr gs.best score }')
        Best parameters for "Gradient Boosting Classifier": {'learning rate': 0.1, 'max depth': 1, 'n estimators': 200}
        Best Accuracy: 0.8609375
In [42]: GB = GradientBoostingClassifier(learning rate= 0.1, max depth=1, n estimators= 200, random state=0)
         GB.fit(X train, y train)
         GB predict = GB.predict(X test)
         print(f"GradientBoosting Classifier accuracy: {accuracy_score(y_test,GB_predict)}")
        GradientBoosting Classifier accuracy: 0.84375
In [43]: print(classification report(y test, GB predict))
                      precision
                                   recall f1-score support
                 0.0
                           0.88
                                     0.92
                                               0.90
                                                          124
                           0.68
                                     0.58
                 1.0
                                               0.63
                                                           36
                                               0.84
                                                          160
            accuracy
           macro avg
                           0.78
                                     0.75
                                               0.76
                                                          160
        weighted avg
                           0.84
                                               0.84
                                     0.84
                                                          160
In [44]: GB cfm = confusion matrix(y test, GB predict)
         sns.heatmap(GB_cfm, annot=True)
         plt.xlabel('Acctual')
         plt.ylabel('Predicted')
         plt.title("Confusion Matrix: GradientBoosting Classifier")
         plt.show()
```



AdaBoost Classifier

```
In [45]: ad_base_model = AdaBoostClassifier(random_state=0)
    ad_param_grid = {
        'n_estimators':[ 10, 50, 80 ,100, 150, 200, 250, 300],
        'learning_rate': [0.01,0.02,0.1,0.05,0.5,0.07,0.9]
    }
    ad_gs = GridSearchCV(estimator = ad_base_model, param_grid = ad_param_grid,cv=5, n_jobs = -1)
    ad_gs.fit(X_train, y_train)
```

```
print(f'Best parameters for "AdaBoost Classifier": {ad gs.best params }')
         print(f'Best Accuracy: {ad gs.best score }')
        Best parameters for "AdaBoost Classifier": {'learning rate': 0.1, 'n estimators': 250}
        Best Accuracy: 0.865625
In [46]: AB = AdaBoostClassifier(learning rate= 0.1, n estimators= 250, random state=0)
         AB.fit(X train, y train)
         AB predict = AB.predict(X test)
         print(f"AdaBoost Classifier accuracy: {accuracy score(y test,AB predict)}")
        AdaBoost Classifier accuracy: 0.8625
In [47]: print(classification report(y test, AB predict))
                      precision
                                   recall f1-score support
                 0.0
                           0.89
                                     0.94
                                               0.91
                                                          124
                           0.75
                                     0.58
                                               0.66
                 1.0
                                                           36
                                               0.86
                                                          160
            accuracy
           macro avg
                           0.82
                                     0.76
                                               0.79
                                                          160
        weighted avg
                           0.86
                                     0.86
                                               0.86
                                                          160
In [48]: AB cfm = confusion matrix(y test, AB predict)
         sns.heatmap(AB_cfm, annot=True)
         plt.xlabel('Acctual')
         plt.ylabel('Predicted')
         plt.title("Confusion Matrix: AdaBoost Classifier")
         plt.show()
```



Result Summery

```
In [49]:
    results = {
        'Logistic Regression': LR_predict,
        'Decision Tree': DT_predict,
        'RandomForest': RF_predict,
        'Bagging': BC_predict,
        'GradientBoosting': GB_predict,
        'AdaBoostClassifier': AB_predict
}
```

```
for classifier, result in results.items():
     print(f"\nAccuracy of {classifier} classifier: {accuracy_score(y_test, result)}\n")
     print('-'*50)
Accuracy of Logistic Regression classifier: 0.875
Accuracy of Decision Tree classifier: 0.76875
Accuracy of RandomForest classifier: 0.8625
Accuracy of Bagging classifier: 0.825
Accuracy of GradientBoosting classifier: 0.84375
Accuracy of AdaBoostClassifier classifier: 0.8625
```

Conclusion: Logistic Regression is giving better result with accuracy score of 0.875

```
In []:
```