In [ ]:

```
# Table
import pandas as pd
import numpy as np
import datetime

# Graphic
import seaborn as sns
import missingno as msno

# Classification Algorithm
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_

# Classification
from sklearn.neural_network import MLPClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier , GradientBoostingClassif
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
```

In [ ]:

```
#Step-1 Load data
# Add column name to make data easier to interpret
columns = ['Age','Workclass','Final_Weight','Education','Education Num','Mari
            'Hours/Week','Country','Above 50K']

train=pd.read_csv('adult.data', names=columns, delimiter =' *, *', engine='py
test=pd.read_csv('adult.test', names=columns, delimiter =' *, *', engine='pyt
test = test.iloc[1:] # ignore first row ('1x3 Cross validator')

#Check column correctly set
print("=================TRAIN================")
print(train.head(2))
print(train.shape)
print("=================TEST==================")
print(test.head(2))
print(test.shape)
```

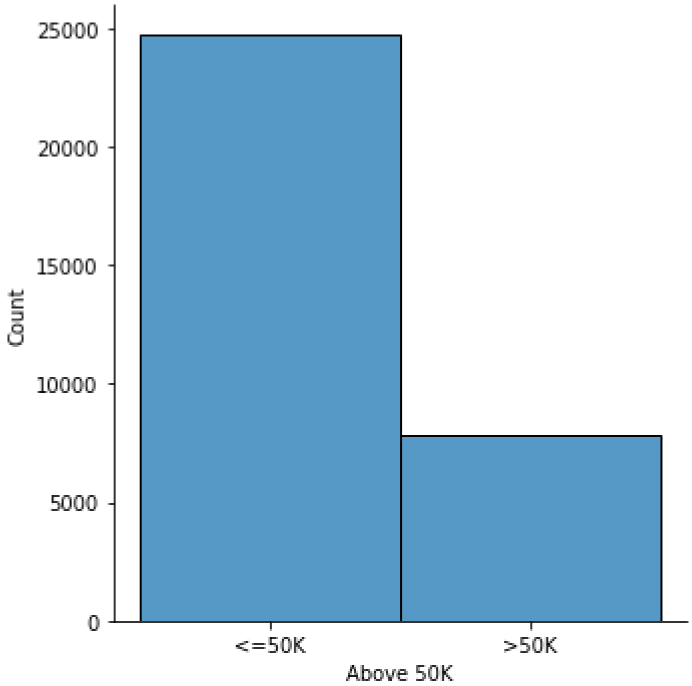
```
=================TRAIN================
   Age         Workclass  Final_Weight  Education  Education Num  \
0   39         State-gov         77516  Bachelors             13
1   50  Self-emp-not-inc         83311  Bachelors             13

       Marital Status       Occupation   Relationship   Race   Sex  \
0       Never-married     Adm-clerical  Not-in-family  White  Male
1  Married-civ-spouse  Exec-managerial        Husband  White  Male

   Capital Gain  Capital Loss  Hours/Week        Country Above 50K
0          2174             0          40  United-States     <=50K
1             0             0          13  United-States     <=50K
(32561, 15)
=================TEST==================
  Age Workclass Final_Weight Education  Education Num      Marital Status  \
1  25   Private      226802.0      11th            7.0       Never-married
2  38   Private       89814.0   HS-grad            9.0  Married-civ-spouse

           Occupation Relationship   Race   Sex  Capital Gain  Capital Loss  \
1  Machine-op-inspct     Own-child  Black  Male           0.0           0.0
2    Farming-fishing       Husband  White  Male           0.0           0.0
```

```
   Hours/Week        Country Above 50K
1        40.0  United-States    <=50K.
2        50.0  United-States    <=50K.
(16281, 15)
```

In [ ]:

```
sns.displot(train['Above 50K'])
```

Out[ ]: <seaborn.axisgrid.FacetGrid at 0x11a3a5790>



In [ ]:

```
#Step-2 Analyse (missing values: null)
print("=================TRAIN================")
print(train.isnull().sum())
print("=================TRAIN================")
print(test.isnull().sum())
```

```
=================TRAIN================
Age               0
Workclass         0
Final_Weight      0
Education         0
Education Num     0
Marital Status    0
Occupation        0
Relationship      0
Race              0
Sex               0
Capital Gain      0
Capital Loss      0
Hours/Week        0
Country           0
Above 50K         0
dtype: int64
=================TRAIN================
Age               0
Workclass         0
Final_Weight      0
Education         0
Education Num     0
Marital Status    0
Occupation        0
Relationship      0
```

```
Race              0
Sex               0
Capital Gain      0
Capital Loss      0
Hours/Week        0
Country           0
Above 50K         0
dtype: int64
```

In [ ]:

```
#Step-2 Analyse (missing values: ?)
print("=================TRAIN=================")
print(train.isin(["?"]).sum())
print("=================TRAIN=================")
print(test.isin(["?"]).sum())
```

```
=================TRAIN=================
Age                  0
Workclass         1836
Final_Weight         0
Education            0
Education Num        0
Marital Status       0
Occupation        1843
Relationship         0
Race                 0
Sex                  0
Capital Gain         0
Capital Loss         0
Hours/Week           0
Country            583
Above 50K            0
dtype: int64
=================TRAIN=================
Age                 0
Workclass         963
Final_Weight        0
Education           0
Education Num       0
Marital Status      0
Occupation        966
Relationship        0
Race                0
Sex                 0
Capital Gain        0
Capital Loss        0
Hours/Week          0
Country           274
Above 50K           0
dtype: int64
```

In [ ]:

```
#Step-2 Analyse (data features)
print("=================TRAIN=================")
print(train.describe())
print("=================TEST==================")
print(test.describe())
```

```
=================TRAIN=================
                Age  Final_Weight  Education Num  Capital Gain  Capital Loss  \
count  32561.000000  3.256100e+04   32561.000000  32561.000000  32561.000000
mean      38.581647  1.897784e+05      10.080679   1077.648844     87.303830
std       13.640433  1.055500e+05       2.572720   7385.292085    402.960219
min       17.000000  1.228500e+04       1.000000      0.000000      0.000000
25%       28.000000  1.178270e+05       9.000000      0.000000      0.000000
```

```
50%       37.000000  1.783560e+05      10.000000      0.000000      0.000000
75%       48.000000  2.370510e+05      12.000000      0.000000      0.000000
max       90.000000  1.484705e+06      16.000000  99999.000000   4356.000000

         Hours/Week
count  32561.000000
mean      40.437456
std       12.347429
min        1.000000
25%       40.000000
50%       40.000000
75%       45.000000
max       99.000000
=================TEST===================
       Final_Weight  Education Num  Capital Gain  Capital Loss    Hours/Week
count  1.628100e+04   16281.000000  16281.000000  16281.000000  16281.000000
mean   1.894357e+05      10.072907   1081.905104     87.899269     40.392236
std    1.057149e+05       2.567545   7583.935968    403.105286     12.479332
min    1.349200e+04       1.000000      0.000000      0.000000      1.000000
25%    1.167360e+05       9.000000      0.000000      0.000000     40.000000
50%    1.778310e+05      10.000000      0.000000      0.000000     40.000000
75%    2.383840e+05      12.000000      0.000000      0.000000     45.000000
max    1.490400e+06      16.000000  99999.000000   3770.000000     99.000000
```

In [ ]:

```
#Step-3 Preprocess (remove instance with missing values)
train = train.replace('?', np.nan)
train.dropna(how='any',inplace=True)

test = test.replace('?', np.nan)
test.dropna(how='any',inplace=True)

print("=================TRAIN=================")
print(train.isin(["?"]).sum()) # check if successful
print("=================TEST===================")
print(test.isin(["?"]).sum()) # check if successful
```

```
=================TRAIN=================
Age                 0
Workclass           0
Final_Weight        0
Education           0
Education Num       0
Marital Status      0
Occupation          0
Relationship        0
Race                0
Sex                 0
Capital Gain        0
Capital Loss        0
Hours/Week          0
Country             0
Above 50K           0
dtype: int64
=================TEST===================
Age                 0
Workclass           0
Final_Weight        0
Education           0
Education Num       0
Marital Status      0
Occupation          0
Relationship        0
Race                0
Sex                 0
```

```
Capital Gain      0
Capital Loss      0
Hours/Week        0
Country           0
Above 50K         0
dtype: int64
```

In [ ]:

```
#Step-3 Preprocess (remove full stop in Above/Below 50K )
print("=================TRAIN================")
train = train.replace("<=50K.", "<=50K")
train = train.replace(">50K.", ">50K")
train = train.replace("<=50K", "1")
train = train.replace(">50K", "0")
print(train.head(2))

print("=================TEST==================")
test = test.replace("<=50K.", "<=50K")
test = test.replace(">50K.", ">50K")
test = test.replace("<=50K", "1")
test = test.replace(">50K", "0")
print(test.head(2))
```

```
=================TRAIN================
   Age          Workclass  Final_Weight  Education  Education Num  \
0   39          State-gov         77516  Bachelors             13
1   50   Self-emp-not-inc         83311  Bachelors             13

       Marital Status        Occupation   Relationship   Race   Sex  \
0       Never-married      Adm-clerical  Not-in-family  White  Male
1  Married-civ-spouse   Exec-managerial        Husband  White  Male

   Capital Gain  Capital Loss  Hours/Week        Country Above 50K
0          2174             0          40  United-States         1
1             0             0          13  United-States         1
=================TEST==================
  Age Workclass  Final_Weight Education  Education Num      Marital Status  \
1  25   Private      226802.0      11th            7.0       Never-married
2  38   Private       89814.0   HS-grad            9.0  Married-civ-spouse

          Occupation Relationship   Race   Sex  Capital Gain  Capital Loss  \
1  Machine-op-inspct    Own-child  Black  Male           0.0           0.0
2    Farming-fishing      Husband  White  Male           0.0           0.0

   Hours/Week        Country Above 50K
1        40.0  United-States         1
2        50.0  United-States         1
```

In [ ]:

```
#Step-3 Preprocess (remove unnessary columns)
# Education has numerical column
train = train.drop('Education', axis =1)
test = test.drop('Education', axis =1)

#final weight is an irrelevant feature
train = train.drop('Final_Weight', axis =1)
test = test.drop('Final_Weight', axis =1)

print("=================TRAIN================")
print(train.head(1))

print("=================TEST==================")
print(test.head(1))
```

```
=================TRAIN================
   Age  Workclass  Education Num Marital Status    Occupation   Relationship
```

```
\
0   39   State-gov              13   Never-married   Adm-clerical   Not-in-family

    Race    Sex   Capital Gain   Capital Loss   Hours/Week         Country  \
0  White   Male           2174              0           40   United-States

  Above 50K
0         1
=================TEST==================
  Age Workclass  Education Num Marital Status         Occupation Relationship
\
1  25    Private            7.0   Never-married   Machine-op-inspct    Own-child

    Race    Sex   Capital Gain   Capital Loss   Hours/Week         Country  \
1  Black   Male            0.0            0.0         40.0   United-States

  Above 50K
1         1
```

In [ ]:

```
#Step-3 Convert categorical features to numerical (TRAIN)
categorical_vars = ['Workclass', 'Marital Status', 'Occupation', 'Relationshi

#for each variable in the categorical variable list
for var in categorical_vars:
    categorical_list = 'var' + '_' + var
    categorical_list = pd.get_dummies(train[var], prefix = var)
    train = train.join(categorical_list)

data_vars = train.columns.values.tolist()
to_keep = [i for i in data_vars if i not in categorical_vars]

train = train[to_keep]
train['Above 50K'] = LabelEncoder().fit_transform(train['Above 50K'])

train.columns.values
print(train.head(1))
```

```
   Age  Education Num  Capital Gain  Capital Loss  Hours/Week  Above 50K  \
0   39             13          2174             0          40          1

   Workclass_Federal-gov  Workclass_Local-gov  Workclass_Private  \
0                      0                    0                  0

   Workclass_Self-emp-inc  ...  Country_Portugal  Country_Puerto-Rico  \
0                       0  ...                 0                    0

   Country_Scotland  Country_South  Country_Taiwan  Country_Thailand  \
0                 0              0               0                 0

   Country_Trinadad&Tobago  Country_United-States  Country_Vietnam  \
0                        0                      1                0

   Country_Yugoslavia
0                   0

[1 rows x 88 columns]
```

In [ ]:

```
#Step-3 Preprocess Convert categorical features to numerical (TEST)
categorical_vars = ['Workclass', 'Marital Status', 'Occupation', 'Relationshi

#for each variable in the categorical variable list
for var in categorical_vars:
    categorical_list = 'var' + '_' + var
    categorical_list = pd.get_dummies(test[var], prefix = var)
```

```
    test = test.join(categorical_list)

data_vars = test.columns.values.tolist()
to_keep = [i for i in data_vars if i not in categorical_vars]

test = test[to_keep]
test['Above 50K'] = LabelEncoder().fit_transform(test['Above 50K'])

test.columns.values
print(test.head(1))
```

```
  Age  Education Num  Capital Gain  Capital Loss  Hours/Week  Above 50K  \
1  25            7.0           0.0           0.0        40.0          1

   Workclass_Federal-gov  Workclass_Local-gov  Workclass_Private  \
1                      0                    0                  1

   Workclass_Self-emp-inc  ...  Country_Portugal  Country_Puerto-Rico  \
1                       0  ...                 0                    0

   Country_Scotland  Country_South  Country_Taiwan  Country_Thailand  \
1                 0              0               0                 0

   Country_Trinadad&Tobago  Country_United-States  Country_Vietnam  \
1                        0                      1                0

   Country_Yugoslavia
1                   0

[1 rows x 87 columns]
```

In [ ]:

```
#Step-3 Preprocess (Remove unnessary column from train)
missing_cols = set(train) - set(test) #find missing column
print(missing_cols)
train.drop(['Country_Holand-Netherlands'] , axis=1 , inplace=True)

#check if successful
print("=================TRAIN================")
print(train.shape)
print("=================TEST==================")
print(test.shape)
```

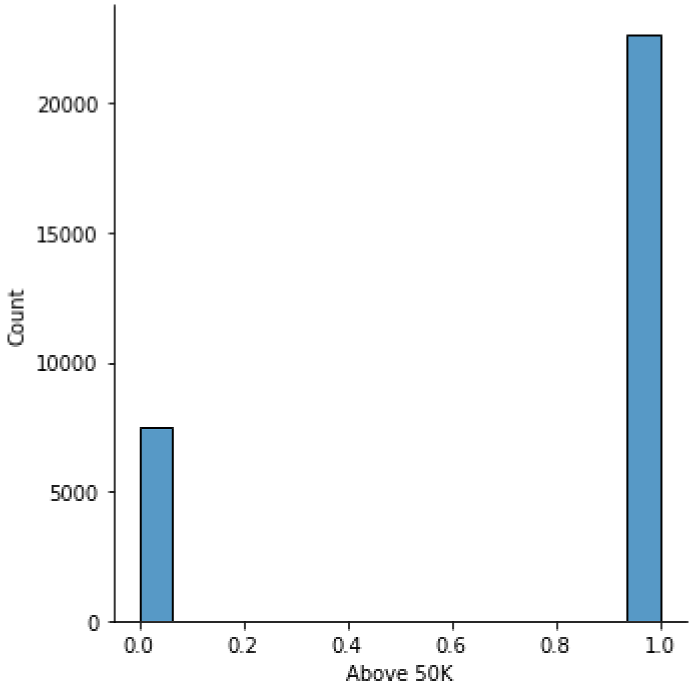
```
{'Country_Holand-Netherlands'}
=================TRAIN================
(30162, 87)
=================TEST==================
(15060, 87)
```

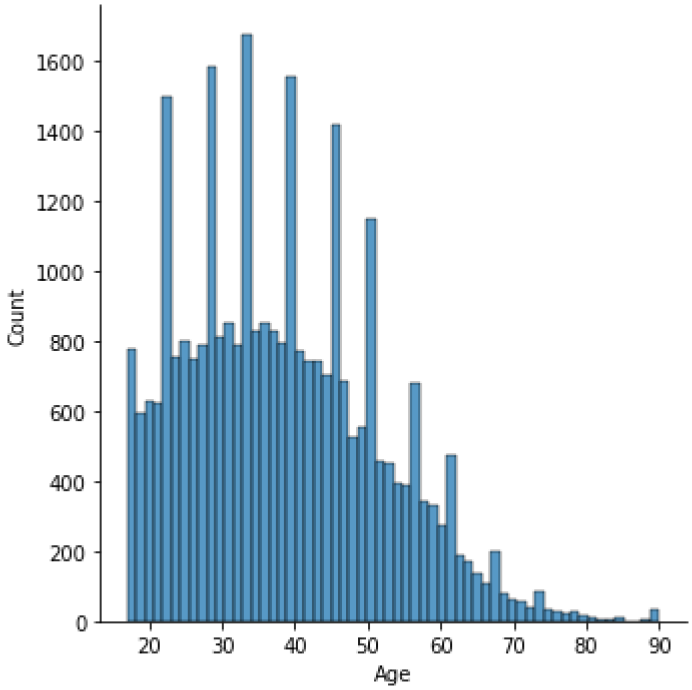
In [ ]:

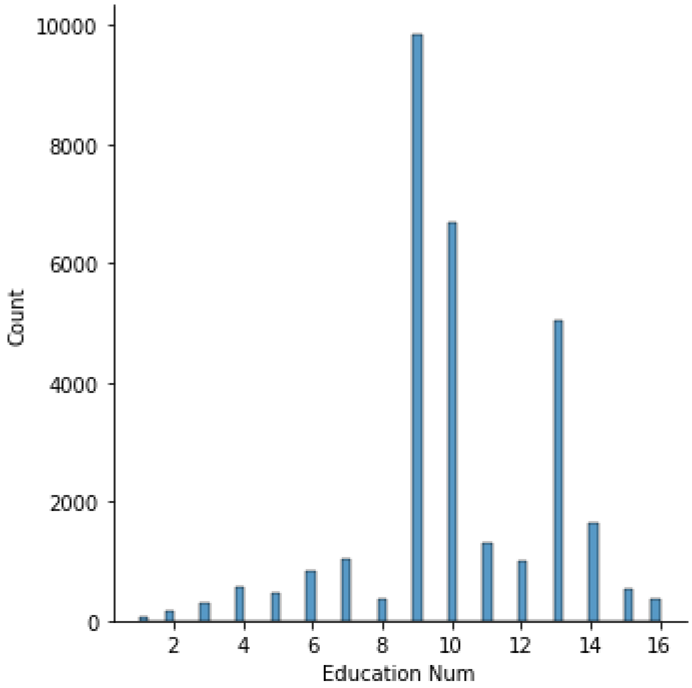
```
#Step-4 Exploratory Data Analysis
sns.displot(train['Above 50K'])
sns.displot(train['Age'])
sns.displot(train['Education Num'])
sns.displot(train['Capital Gain'])
sns.displot(train['Capital Loss'])
sns.displot(train['Hours/Week'])
```

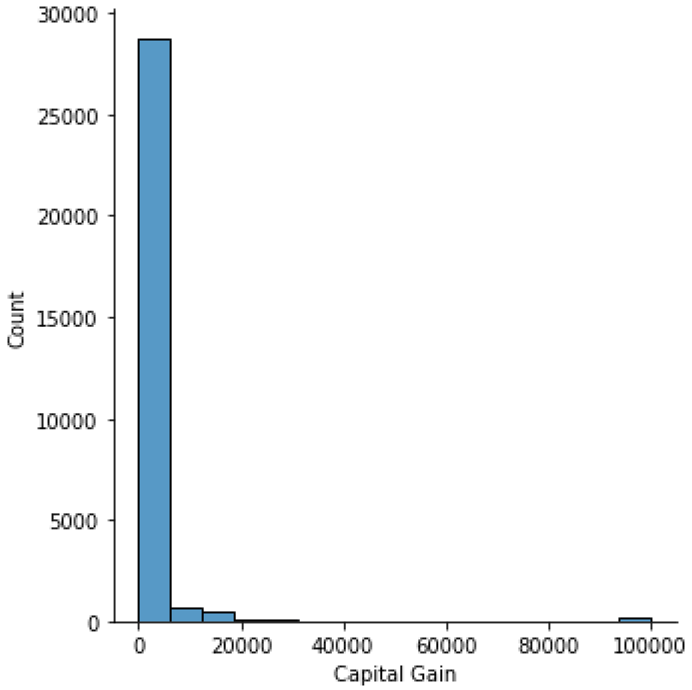
Out[ ]:

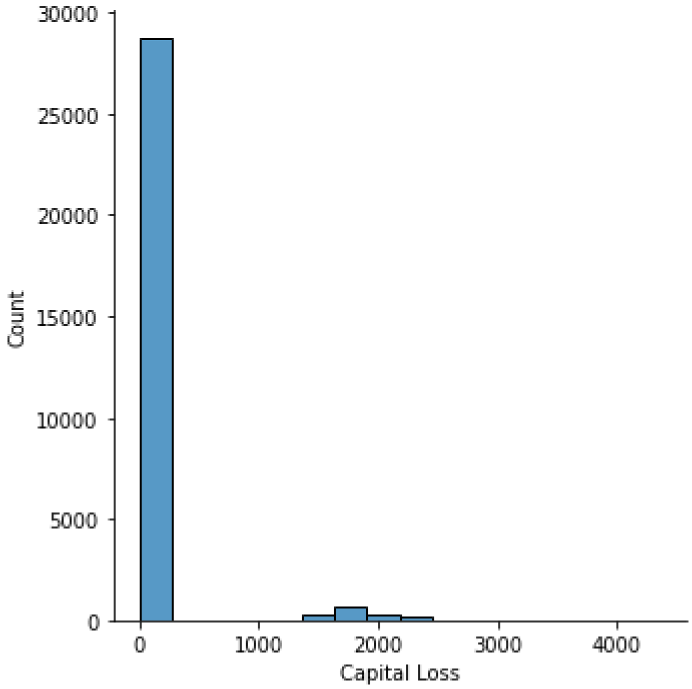
```
&lt;seaborn.axisgrid.FacetGrid at 0x11a6afdd0&gt;
```

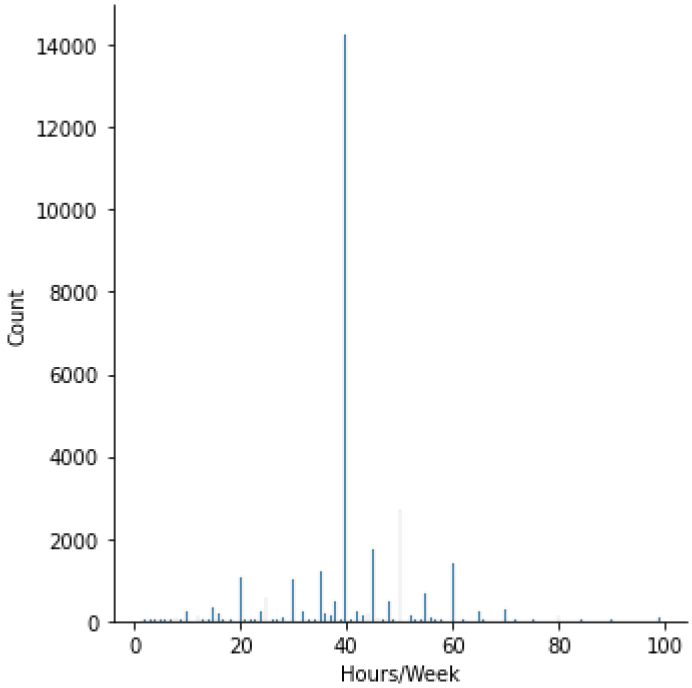

20000
15000
10000
5000
0
Count
0.0
0.2
0.4
0.6
0.8
1.0
Above 50K


1600
1400
1200
1000
800
600
400
200
0
Count
20
30
40
50
60
70
80
90
Age


Count
Education Num
0
2000
4000
6000
8000
10000
2
4
6
8
10
12
14
16


Count
Capital Gain
0
5000
10000
15000
20000
25000
30000
0
20000
40000
60000
80000
100000





In [ ]:

```
#Split data into train and test set
X_train = train.drop(['Above 50K'], axis = 1)
y_train = train['Above 50K']
X_test = test.drop(['Above 50K'], axis = 1)
y_test = test['Above 50K']
```

In [ ]:

```
#Method to print clasification result
def PrintResult(classifier, label):
    start_time = datetime.datetime.now() #start timer
    classifier.fit(X_train, y_train) #get param classifier to fit data
    y_pred = classifier.predict(X_test) #get predictions after data has been
    end_time = datetime.datetime.now() #get time at end of regression fitting
    duration = (end_time - start_time).total_seconds() #get total time it tak


#Performance Metrics :
    accuracy = accuracy_score(y_test, y_pred) # accuracy
    precision = precision_score(y_test, y_pred)  # precision
```

```
    recall = recall_score(y_test, y_pred) #recall
    F1 = f1_score(y_test, y_pred) #F1-Score
    AUC = roc_auc_score(y_test, y_pred) #AUC

# Table
    print("--------------------------")
    print("Classifier: " + label)
    print(label + ' Accuracy Score : %0.2f ' % accuracy)
    print(label + ' Precision Score : %0.2f ' % precision)
    print(label + ' Recall Score : %0.2f ' % recall)
    print(label + ' F1 Score : %0.2f ' % F1)
    print(label + ' Auc Score : %0.2f ' % AUC)
    print("Execution time: {t:.3f} seconds".format(t = duration))
    print("--------------------------")
```

In [ ]:

```
#KNN (1)
PrintResult(KNeighborsClassifier(), "KNN")
```

```
--------------------------
Classifier: KNN
KNN Accuracy Score : 0.84
KNN Precision Score : 0.89
KNN Recall Score : 0.90
KNN F1 Score : 0.90
KNN Auc Score : 0.78
Execution time: 21.939 seconds
--------------------------
```

In [ ]:

```
#NB (2)
PrintResult(GaussianNB(), "Naive Bayes")
```

```
--------------------------
Classifier: Naive Bayes
Naive Bayes Accuracy Score : 0.79
Naive Bayes Precision Score : 0.93
Naive Bayes Recall Score : 0.78
Naive Bayes F1 Score : 0.85
Naive Bayes Auc Score : 0.80
Execution time: 0.266 seconds
--------------------------
```

In [ ]:

```
#SVM (3)
PrintResult(SVC(), "SVM")
```

In [ ]:

```
#DT (4)
PrintResult(DecisionTreeClassifier(), "Decision Tree")
```

```
--------------------------
Classifier: Decision Tree
Decision Tree Accuracy Score : 0.77
Decision Tree Precision Score : 0.86
Decision Tree Recall Score : 0.83
Decision Tree F1 Score : 0.85
Decision Tree Auc Score : 0.71
Execution time: 0.555 seconds
--------------------------
```

In [ ]:

```
#RF (5)
PrintResult(RandomForestClassifier(), "Random Forest")
```

```
--------------------------
Classifier: Random Forest
Random Forest Accuracy Score : 0.81
Random Forest Precision Score : 0.86
Random Forest Recall Score : 0.89
Random Forest F1 Score : 0.87
Random Forest Auc Score : 0.72
Execution time: 5.971 seconds
--------------------------
```

In [ ]:

```
#AB (6)
PrintResult(AdaBoostClassifier(), "AdaBoost")
```

```
--------------------------
Classifier: AdaBoost
AdaBoost Accuracy Score : 0.83
AdaBoost Precision Score : 0.87
AdaBoost Recall Score : 0.92
AdaBoost F1 Score : 0.89
AdaBoost Auc Score : 0.74
Execution time: 6.170 seconds
--------------------------
```

In [ ]:

```
#GB (7)
PrintResult(GradientBoostingClassifier(), "Gradient Boosting")
```

```
--------------------------
Classifier: Gradient Boosting
Gradient Boosting Accuracy Score : 0.84
Gradient Boosting Precision Score : 0.87
Gradient Boosting Recall Score : 0.92
Gradient Boosting F1 Score : 0.89
Gradient Boosting Auc Score : 0.75
Execution time: 6.412 seconds
--------------------------
```

In [ ]:

```
#LD (8)
PrintResult(LinearDiscriminantAnalysis(), "Linear Discriminant")
```

```
--------------------------
Classifier: Linear Discriminant
Linear Discriminant Accuracy Score : 0.82
Linear Discriminant Precision Score : 0.87
Linear Discriminant Recall Score : 0.89
Linear Discriminant F1 Score : 0.88
Linear Discriminant Auc Score : 0.75
Execution time: 1.285 seconds
--------------------------
```

In [ ]:

```
#MLP (9)
PrintResult(MLPClassifier(), "MLP")
```

```
--------------------------
Classifier: MLP
MLP Accuracy Score : 0.82
MLP Precision Score : 0.88
MLP Recall Score : 0.88
MLP F1 Score : 0.88
MLP Auc Score : 0.75
Execution time: 61.623 seconds
--------------------------
```

In [ ]:

```
#LR (10)
PrintResult(LogisticRegression(solver='lbfgs', max_iter=10000), "Logistic Reg
```

```
--------------------------
Classifier: Logistic Regression
Logistic Regression Accuracy Score : 0.82
Logistic Regression Precision Score : 0.87
Logistic Regression Recall Score : 0.90
Logistic Regression F1 Score : 0.88
Logistic Regression Auc Score : 0.74
Execution time: 13.067 seconds
--------------------------
```