Assignment 02

S14490

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1. Screenshots with an explanation of the tools you used for the above training process

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import imblearn

#importing ML model from sklearn-library

from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier

#Importing metrix functions from SK-Learn

from sklearn.metrics import roc_auc_score, r2_score, mean_absolute_error, mean_squared_error
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.preprocessing import LabelEncoder
```

Pandas – Import excel file and create a data frame

Numpy – Transform vector and perform dot product between vectors

sklearn

sklearn.neighbors - provides functionality for unsupervised and supervised neighbors-based learning methods

sklearn.linear_model - class of the sklearn module if contain different functions for performing machine learning with linear models

sklearn.svm - Support vector machines (SVMs) are a set of supervised learning methods used for classification, regression and outliers detection

sklearn.ensemble - includes two averaging algorithms based on randomized decision trees

sklearn.metrics - implements several loss, score, and utility functions to measure classification performance

sklearn.model_selection - method for setting a blueprint to analyze data and then using it to measure new data

2. Brief explanation of the pre-processing steps you followed.

- Import necessary libraries
- Import data set
- Checking the missing values in the train data set – no missing values
- Checking the missing values in the test data set – one missing value
- Remove null value from both data sets
- Visualize respond variable
- Fitting the model
- Dropping the converted group data points
- Dropping the unwanted columns
- Checking data types of the data frame
- Convert to numerical once
- Again check the null values and remove them
- Train the data set by dividing in to 2 parts
- Appling cross validation – reduce overfitting and bais
- Appling random forest , logistic regression, gradient boosting - test best performing model
- Get confusion matrix and test Accuracy, precision, sensitivity, specificity and error rate

Using data we can take the conclusion that the best performing classifier is Random Forest classifier

3. Generated Confusion matrix for the Test dataset.

- Confusion matrix for Random Forest

```
[[ 84   0]
 [  4 205]]
```

4. List of below measures calculated for the Test dataset.

- Out of this classifiers best performing model is Random Forest classifier

```
Accuracy:  0.9863481228668942

Precision:  1.0

Sensitivity:  0.9808612440191388

Specificity:  1.0

Error Rate:  0.013651877133105802
```

```
!pip install imbalanced-learn
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/p
Requirement already satisfied: imbalanced-learn in /usr/local/lib/python3.7/dist-pack
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.7/dist-package
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: scipy>=0.19.1 in /usr/local/lib/python3.7/dist-package
Requirement already satisfied: scikit-learn>=0.24 in /usr/local/lib/python3.7/dist-pa
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-
```

```
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import numpy as np
import matplotlib.pyplot as plt
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from sklearn.tree import DecisionTreeClassifier

#Importing metrix functions from SK-Learn

from sklearn.metrics import roc_auc_score, r2_score, mean_absolute_error, mean_squared_err
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.preprocessing import LabelEncoder
```

```
!pip install openpyxl
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/p
Requirement already satisfied: openpyxl in /usr/local/lib/python3.7/dist-packages (3
Requirement already satisfied: et-xmlfile in /usr/local/lib/python3.7/dist-packages (
```

```
from google.colab import drive
drive.mount('/gdrive')
%cd /gdrive
```

```
Drive already mounted at /gdrive; to attempt to forcibly remount, call drive.mount("",
/gdrive
```

```
data_train = pd.read_excel("/gdrive/My Drive/Colab Notebooks/4th Year/Data Analytics/Assig
data_test = pd.read_excel("/gdrive/My Drive/Colab Notebooks/4th Year/Data Analytics/Assign
```

```
data_train.head() #first 5 data
```

	ID	Age	Gender	TB	DB	ALK	SGPT	SGOT	TP	ALB	AG_Ratio	Class
0	1	65	Female	0.7	0.1	187	16	18	6.8	3.3	0.9	Yes
1	2	62	Male	10.9	5.5	699	64	100	7.5	3.2	0.74	Yes
2	3	62	Male	7.3	4.1	490	60	68	7	3.3	0.89	Yes
3	4	58	Male	1	0.4	182	14	20	6.8	3.4	1	Yes
4	5	72	Male	3.9	2	195	27	59	7.3	2.4	0.4	Yes

```
data_train.Class.unique()
```

```
array(['Yes', 'No'], dtype=object)
```

```
len(data_test)
len(data_train)
```

```
583
```

```
#Check Missing values in train dataset

data_train.isnull().sum()
```

```
ID          0
Age         0
Gender      0
TB          0
DB          0
ALK         0
SGPT        0
SGOT        0
TP          0
ALB         0
AG_Ratio    0
Class       0
dtype: int64
```

No any missing value

```
#Check Missing values in test dataset

data_test.isnull().sum()
```

```
ID          0
Age         0
Gender      0
TB          0
DB          0
ALK         0
SGPT        0
SGOT        0
```

```
TP          0
ALB         0
AG_Ratio    0
Class       0
dtype: int64
```

There is 1 null value AG_Ratio, So we can remove it because it is small proportion of data set.

```
data_test.dropna(inplace = True)
data_test.isnull().sum()
len(data_test)
```

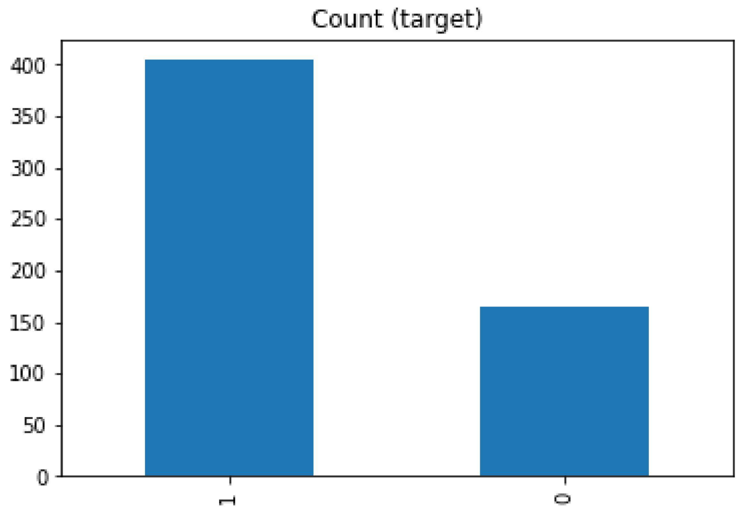
```
293
```

```
target_count =data_train.Class.value_counts()
```

```
print('Class 0:', target_count[0])
print('Class 1:', target_count[1])

target_count.plot(kind='bar', title='Count (target)');
```

```
Class 0: 164
Class 1: 404
```



416 observations belong to 'yes' and 167 obervations belong to 'No'. There for this is unbalance

Fitting model

```
# Dropping the converted Group data points

# Dropping the unwanted columns

le=LabelEncoder()
```

```
data_train[['Gender','Class']]=data_train[['Gender','Class']].apply(le.fit_transform)

data_test[['Gender','Class']]=data_test[['Gender','Class']].apply(le.fit_transform)
```

```
data_train.head()
```

	ID	Age	Gender	TB	DB	ALK	SGPT	SGOT	TP	ALB	AG_Ratio	Class
0	1	65	0	0.7	0.1	187.0	16.0	18.0	6.8	3.3	0.90	1
1	2	62	1	10.9	5.5	699.0	64.0	100.0	7.5	3.2	0.74	1
2	3	62	1	7.3	4.1	490.0	60.0	68.0	7.0	3.3	0.89	1
3	4	58	1	1.0	0.4	182.0	14.0	20.0	6.8	3.4	1.00	1
4	5	72	1	3.9	2.0	195.0	27.0	59.0	7.3	2.4	0.40	1

```
data_test.head()
```

	ID	Age	Gender	TB	DB	ALK	SGPT	SGOT	TP	ALB	AG_Ratio	Class
0	1	65	0	0.7	0.1	187.0	16.0	18.0	6.8	3.3	0.90	1
1	2	62	1	10.9	5.5	699.0	64.0	100.0	7.5	3.2	0.74	1
2	3	62	1	7.3	4.1	490.0	60.0	68.0	7.0	3.3	0.89	1
3	4	58	1	1.0	0.4	182.0	14.0	20.0	6.8	3.4	1.00	1
4	5	72	1	3.9	2.0	195.0	27.0	59.0	7.3	2.4	0.40	1

```
data_train.dtypes
```

```
ID            int64
Age           int64
Gender        int64
TB          float64
DB          float64
ALK         float64
SGPT        float64
SGOT        float64
TP          float64
ALB         float64
AG_Ratio    float64
Class         int64
dtype: object
```

```
data_train["TB"] = pd.to_numeric(data_train["TB"],errors='coerce')
data_train["DB"] = pd.to_numeric(data_train["DB"],errors='coerce')
data_train["ALK"] = pd.to_numeric(data_train["ALK"],errors='coerce')
data_train["SGPT"] = pd.to_numeric(data_train["SGPT"],errors='coerce')
data_train["SGOT"] = pd.to_numeric(data_train["SGOT"],errors='coerce')
data_train["ALB"] = pd.to_numeric(data_train["ALB"],errors='coerce')
```

```
data_train["AG_Ratio"] = pd.to_numeric(data_train["AG_Ratio"],errors='coerce')
data_train["TP"] = pd.to_numeric(data_train["TP"],errors='coerce')


data_test["TB"] = pd.to_numeric(data_test["TB"],errors='coerce')
data_test["DB"] = pd.to_numeric(data_test["DB"],errors='coerce')
data_test["ALK"] = pd.to_numeric(data_test["ALK"],errors='coerce')
data_test["SGPT"] = pd.to_numeric(data_test["SGPT"],errors='coerce')
data_test["SGOT"] = pd.to_numeric(data_test["SGOT"],errors='coerce')
data_test["ALB"] = pd.to_numeric(data_test["ALB"],errors='coerce')
data_test["AG_Ratio"] = pd.to_numeric(data_test["AG_Ratio"],errors='coerce')
data_test["TP"] = pd.to_numeric(data_test["TP"],errors='coerce')
```

```
data_train.isnull().sum()
```

```
ID          0
Age         0
Gender      0
TB          0
DB          0
ALK         0
SGPT        0
SGOT        0
TP          0
ALB         0
AG_Ratio    0
Class       0
dtype: int64
```

Null values available in 'TB' ,'DB' ,'ALk', 'SGPT', 'SGOT', 'TP', 'ALB', 'AG_Ratio'

```
#Remove null values

data_train.dropna(inplace = True)
data_train.isnull().sum()
len(data_train)
```

```
568
```

```
data_test.dropna(inplace = True)
data_test.isnull().sum()
len(data_test)
```

```
293
```

```
data_train.head()
```

	ID	Age	Gender	TB	DB	ALK	SGPT	SGOT	TP	ALB	AG_Ratio	Class
0	1	65	0	0.7	0.1	187.0	16.0	18.0	6.8	3.3	0.90	1
1	2	62	1	10.9	5.5	699.0	64.0	100.0	7.5	3.2	0.74	1

```
y = data_train.Class
y_test = data_test.Class

x = data_train.drop(['Class','ID'], axis=1, inplace = False)
x_test = data_test.drop(['Class','ID'], axis=1, inplace = False)
```

Applying cross validation techiques

```
S_Models = [RandomForestClassifier(), LogisticRegression(solver='liblinear'), GradientBoos
S_Names = ["Random Forest", "Logistic Regression","Gradient Boosting"]
for model, name in zip(S_Models, S_Names):
    print(name)
    for score in ["accuracy", "precision", "recall"]:
        print(score," : ",cross_val_score(model, x, y ,scoring=score, cv=5,error_score='ra

    print('\n')
```

```
Random Forest
accuracy  :  0.695388914764788
precision  :  0.7644092970521541
recall  :  0.8467901234567901


Logistic Regression
accuracy  :  0.7095482068001863
precision  :  0.7427812712857973
recall  :  0.908611111111111


Gradient Boosting
accuracy  :  0.6936345287998759
precision  :  0.763958103014262
recall  :  0.8269753086419753
```

Accuracy of Logistic Regression model is the high

Accuracy of test data with LogisticRegression

```
logreg = LogisticRegression(solver='liblinear')
logreg.fit(x, y)
```

```
logreg_predict = logreg.predict(x_test)
```

Confusion Matrix

```
print(confusion_matrix(y_test, logreg_predict))
```

```
[[ 21  63]
 [ 14 195]]
```

Classification Report

```
print(classification_report(y_test, logreg_predict))
```

```
              precision    recall  f1-score   support

           0       0.60      0.25      0.35        84
           1       0.76      0.93      0.84       209

    accuracy                           0.74       293
   macro avg       0.68      0.59      0.59       293
weighted avg       0.71      0.74      0.70       293
```

```
y_pred_rnd = logreg.predict(x_test)

tn, fp, fn, tp = confusion_matrix(y_test, y_pred_rnd).ravel()

print("Accuracy: ", (tp+tn)/(tp+tn+fp+fn), "\n")


print("Precision: ", tp/(tp+fp), "\n")


print("Sensitivity: ", tp/(tp+fn), "\n")


print("Specificity: ", tn/(tn+fp), "\n")


print("Error Rate: ", (fp+fn)/(tp+tn+fp+fn), "\n")
```

```
Accuracy:  0.7372013651877133

Precision:  0.7558139534883721

Sensitivity:  0.9330143540669856

Specificity:  0.25
```

```
Error Rate:  0.2627986348122867
```

Accuracy of test data with Randomforest

```
rf = RandomForestClassifier()
rf.fit(x, y)
rf_predict = rf.predict(x_test)
```

Confusion Matix

```
print(confusion_matrix(y_test, rf_predict))
```

```
[[ 84   0]
 [  3 206]]
```

Classification Report

```
print(classification_report(y_test, rf_predict))
```

```
              precision    recall  f1-score   support

           0       0.97      1.00      0.98        84
           1       1.00      0.99      0.99       209

    accuracy                           0.99       293
   macro avg       0.98      0.99      0.99       293
weighted avg       0.99      0.99      0.99       293
```

```
y_pred_rnd = rf.predict(x_test)

tn, fp, fn, tp = confusion_matrix(y_test, y_pred_rnd).ravel()

print("Accuracy: ", (tp+tn)/(tp+tn+fp+fn), "\n")


print("Precision: ", tp/(tp+fp), "\n")


print("Sensitivity: ", tp/(tp+fn), "\n")


print("Specificity: ", tn/(tn+fp), "\n")


print("Error Rate: ", (fp+fn)/(tp+tn+fp+fn), "\n")
```

```
Accuracy:  0.9897610921501706

Precision:  1.0

Sensitivity:  0.9856459330143541

Specificity:  1.0

Error Rate:  0.010238907849829351
```

Accuracy of test data with Gradient Boosting

```
gb = GradientBoostingClassifier()
gb.fit(x, y)
gb_predict = gb.predict(x_test)
```

Confussion Matrix

```
print(confusion_matrix(y_test, gb_predict))
```

```
[[ 65  19]
 [  6 203]]
```

Classification Report

```
print(classification_report(y_test, gb_predict))
```

```
              precision    recall  f1-score   support

           0       0.92      0.77      0.84        84
           1       0.91      0.97      0.94       209

    accuracy                           0.91       293
   macro avg       0.91      0.87      0.89       293
weighted avg       0.91      0.91      0.91       293
```

```
y_pred_rnd = gb.predict(x_test)

tn, fp, fn, tp = confusion_matrix(y_test, y_pred_rnd).ravel()

print("Accuracy: ", (tp+tn)/(tp+tn+fp+fn), "\n")


print("Precision: ", tp/(tp+fp), "\n")


print("Sensitivity: ", tp/(tp+fn), "\n")
```

```
print("Specificity: ", tn/(tn+fp), "\n")


print("Error Rate: ", (fp+fn)/(tp+tn+fp+fn), "\n")
```

```
Accuracy:  0.9146757679180887

Precision:  0.9144144144144144

Sensitivity:  0.9712918660287081

Specificity:  0.7738095238095238

Error Rate:  0.08532423208191127
```