```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
import seaborn as sns
```

```
df=pd.read_csv("bmd_logistic_regression.csv")
```

```
df
```

```
        id        age sex     fracture  weight_kg  height_cm       
medication  \
0      469  57.052768   F  no fracture       64.0      155.5       
Anticonvulsant
1     8724  75.741225   F  no fracture       78.0      162.0   No 
medication
2     6736  70.778900   M  no fracture       73.0      170.5   No 
medication
3    24180  78.247175   F  no fracture       60.0      148.0   No 
medication
4    17072  54.191877   M  no fracture       55.0      161.0   No 
medication
..     ...        ...  ..          ...        ...        ...   
...
164  21892  77.982543   M     fracture       74.0      164.0   No 
medication
165  24140  50.285303   F     fracture       59.0      161.0   No 
medication
166   6969  46.359721   M     fracture       67.0      169.0   No 
medication
167   5505  54.788368   M     fracture       70.0      166.0   No 
medication
168     71  69.994822   F     fracture       68.5      165.0   No 
medication

     waiting_time     bmd
0              18  0.8793
1              56  0.7946
2              10  0.9067
3              14  0.7112
4              20  0.7909
..            ...     ...
164            49  0.7941
165             6  0.7971
166            10  0.8037
167            14  0.8072
168            25  0.8664

[169 rows x 9 columns]
```

```
print("*********This Dataset contains physical and medical details
patients, using i will be making a prediction model to predict weather
a person is prone to get a bone fracture or not*********")
print("\n\
n*********************************************Features****************
************************************")
print("\n\n\t\t(1)id=id of individual.\n\t\t(2)age=age of person.\n\t\
t(3)sex=gender of a person.\n\t\t(4)fracture= fracture status of
person\n\t\t(5)weight in kg and height in cm given.\n\t\
t(6)Medication= medication any person is taking.\n\t\t(7)bmd= Bone
mineral density of individual.")
```

```
*********This Dataset contains physical and medical details patients,
using i will be making a prediction model to predict weather a person
is prone to get a bone fracture or not*********


*********************************************Features*****************
***********************************


		(1)id=id of individual.
		(2)age=age of person.
		(3)sex=gender of a person.
		(4)fracture= fracture status of person
		(5)weight in kg and height in cm given.
		(6)Medication= medication any person is taking.
		(7)bmd= Bone mineral density of individual.
```

What's the meaning of BMD?

Bone mineral density: BMD, a measure of bone density, reflecting the strength of bones as represented by calcium content. The BMD test detects osteopenia (mild bone loss, usually without symptoms) and osteoporosis (more severe bone loss, which may cause symptoms).

```
print("************************************************Analysis*******
*****************************************************")
print("\n\n\t***So we have total of 9 columns out of which 6 are
numercial and 3 are categorical columns.***\n\n\t***Data set has 169
rows and 9 columns***\n\n")
df.info()
```

```
************************************************Analysis**************
**********************************************
```

So we have total of 9 columns out of which 6 are numercial and 3 are categorical columns.

Data set has 169 rows and 9 columns

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 169 entries, 0 to 168
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   id            169 non-null    int64
 1   age           169 non-null    float64
 2   sex           169 non-null    object
 3   fracture      169 non-null    object
 4   weight_kg     169 non-null    float64
 5   height_cm     169 non-null    float64
 6   medication    169 non-null    object
 7   waiting_time  169 non-null    int64
 8   bmd           169 non-null    float64
dtypes: float64(4), int64(2), object(3)
memory usage: 12.0+ KB
```

PREPROCESSING.

```
df.isnull().sum()/len(df)*100
```

```
id              0.0
age             0.0
sex             0.0
fracture        0.0
weight_kg       0.0
height_cm       0.0
medication      0.0
waiting_time    0.0
bmd             0.0
dtype: float64
```

```
print("\n\t~~So there are no null values in this data set\n\n\
t~~Droping id,waiting time columns as i donot require id column in my
analysis.")
```

~~So there are no null values in this data set

~~Droping id,waiting time columns as i donot require id column in my analysis.

```
df.drop("id",axis=1,inplace=True)
```

```
df.drop("waiting_time",axis=1,inplace=True)
```

UNIVARIATE ANALYSIS.

```
df.describe()
```

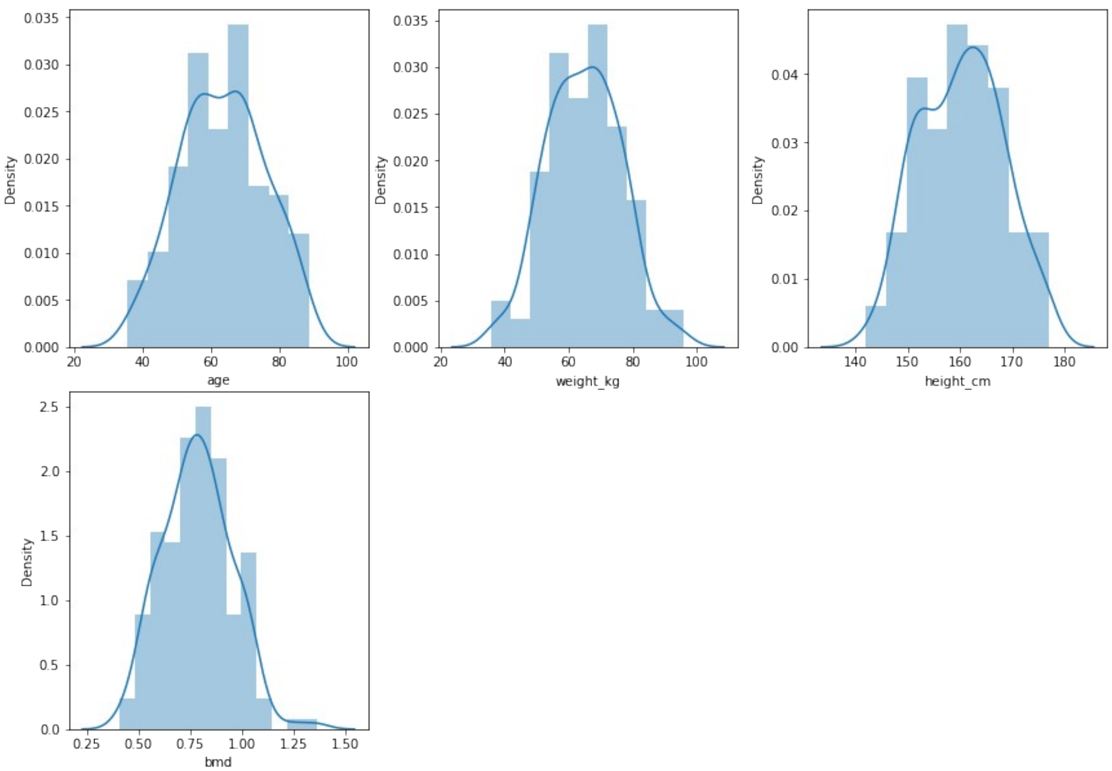
	age	weight_kg	height_cm	bmd
count	169.000000	169.000000	169.000000	169.000000
mean	63.631531	64.665680	160.254438	0.783104
std	12.356936	11.537171	7.928272	0.166529
min	35.814058	36.000000	142.000000	0.407600
25%	54.424211	56.000000	154.000000	0.670800
50%	63.487837	64.500000	160.500000	0.786100
75%	72.080558	73.000000	166.000000	0.888800
max	88.753795	96.000000	177.000000	1.362400

```
num_col=df.select_dtypes(include=["int","float"])
num_col.columns
```

```
Index(['age', 'weight_kg', 'height_cm', 'bmd'], dtype='object')
```

```
print("\n***********************************ALL COLUMNS ARE NORMALLY DISTRIBUTED**********************************************")
plt.figure(figsize=(12,12))
count=1
for i in num_col:
    plt.subplot(3,3,count)
    sns.distplot(df[i])
    count+=1
plt.tight_layout(pad=0.5,w_pad=0.5,h_pad=0.2)
```

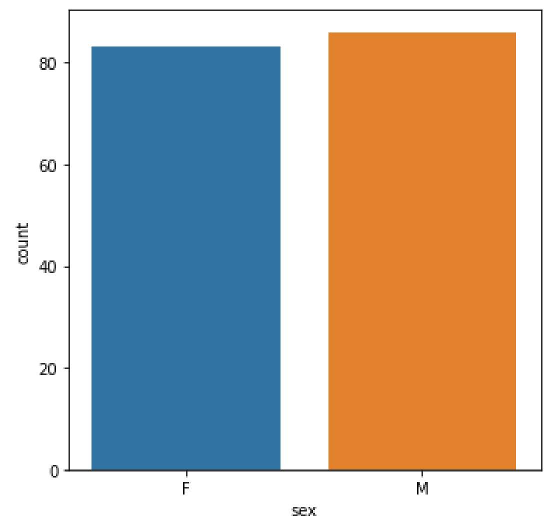
```
***********************************ALL COLUMNS ARE NORMALLY DISTRIBUTED**********************************************
```

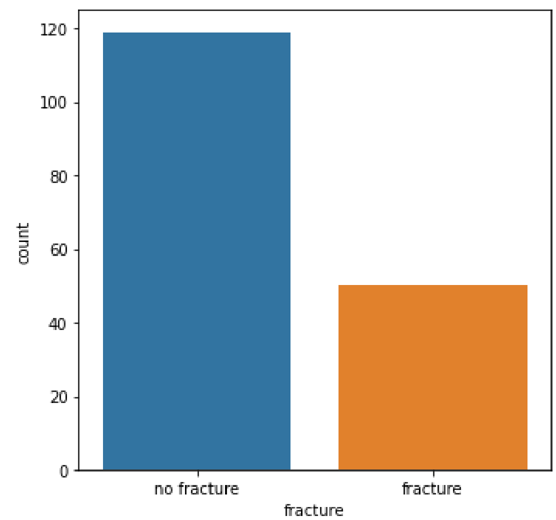


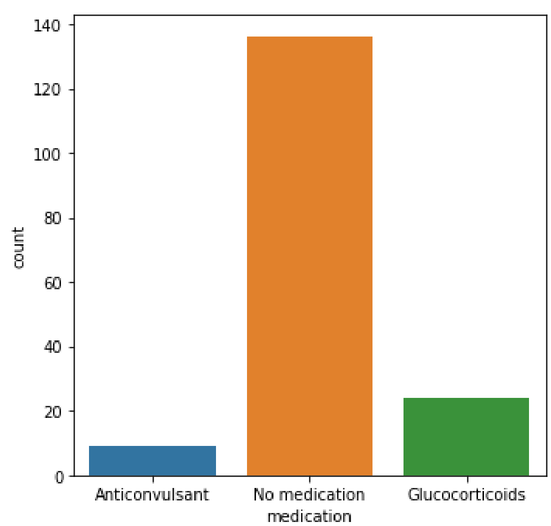

```
cat_col=df.select_dtypes(include="O")
cat_col.columns
```

```
Index(['sex', 'fracture', 'medication'], dtype='object')
```

```
plt.figure(figsize=(12,12))
count=1
for i in cat_col:
    plt.subplot(2,2,count)
    sns.countplot(df[i])
    count+=1
plt.show()
```








```
print("\n\t\t(1)Male and female count is almost equal\n\n\t\t(2)My target variable Fracture is imbalanced(On the side of no fracture\n\n\t\t(3)Highest number of people are not on any medications.")
```

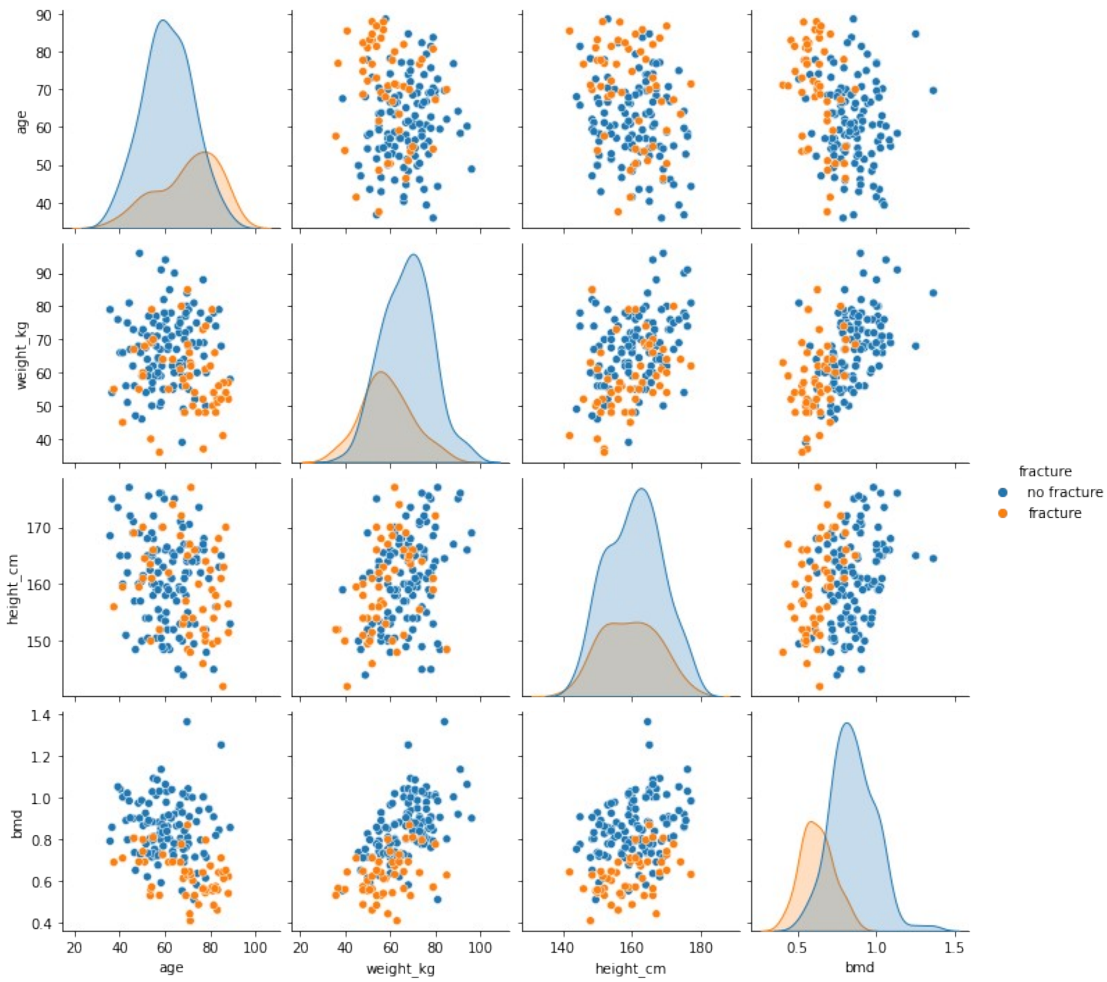
```
		(1)Male and female count is almost equal

		(2)My target variable Fracture is imbalanced(On the side of no fracture

		(3)Highest number of people are not on any medications.
```

Bivariate analysis.

```
sns.pairplot(df,hue="fracture")
plt.show()
```




```
print("***********************************************ANALYSIS*****************************************************************")
print("\n\t\t(1)Aged people have high chance of getting fracture.\n\t\t(2)people with low body weight are getting more fractures.\n\t\t(3)Height has no impact on getting fracture.\n\t\t(4)People with less bone density have high chance of getting fracture.")
```

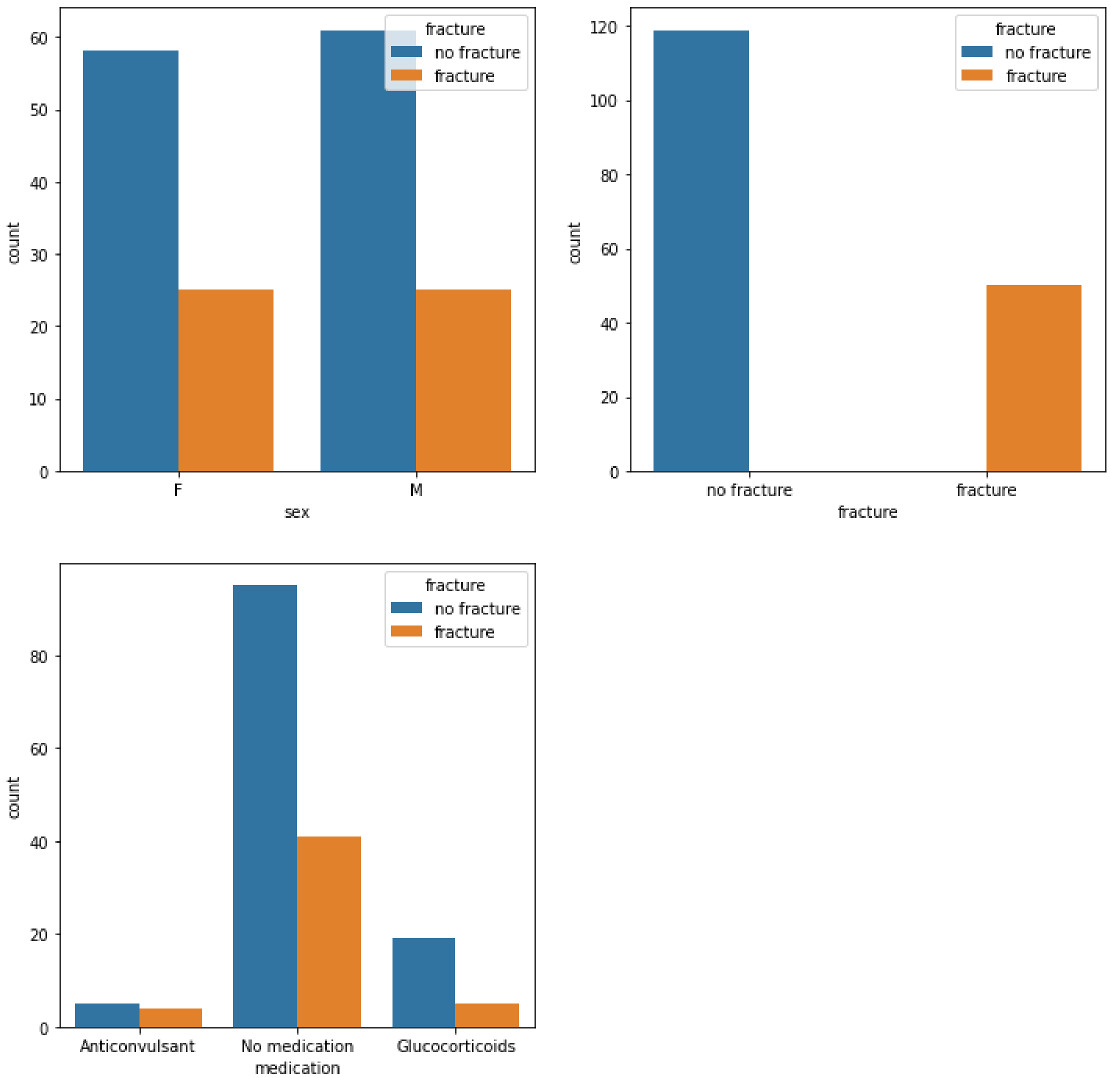
```
***********************************************ANALYSIS***************
**********************************************


		(1)Aged people have high chance of getting fracture.
		(2)people with low body weight are getting more fractures.
		(3)Height has no impact on getting fracture.
		(4)People with less bone density have high chance of getting fracture.
```

```
print("\n\t\t(1)Gender has no impact on Fracture.")
plt.figure(figsize=(12,12))
count=1
for i in cat_col:
    plt.subplot(2,2,count)
```

```
    sns.countplot(x=i,hue="fracture",data=df)
    count+=1
plt.show()
```

(1)Gender has no impact on Fracture.



Encoding Categorical Features.

```
for i in cat_col:
    print(i)
    print(df[i].unique())
```

```
sex
['F' 'M']
fracture
```

```
['no fracture' 'fracture']
medication
['Anticonvulsant' 'No medication' 'Glucocorticoids']
```

```python
def gender(i):
    if 'F' in i:
        return(0)
    else:
        return(1)

df["sex"]=df['sex'].map(gender)
df["sex"]=df["sex"].astype("int")

def fracture(i):
    if "no fracture" in i:
        return(0)
    else:
        return(1)

df["fracture"]=df["fracture"].map(fracture)
df["fracture"]=df["fracture"].astype("int")

df=pd.get_dummies(df,drop_first=True)

df.rename(columns = {'medication_No 
medication':'medication_No_medication'}, inplace = True)

df["age"]=df["age"].astype("int")

df["FRACTURE"]=df["fracture"]
df.drop("fracture",axis=1,inplace=True)

df
```

```
     age  sex  weight_kg  height_cm     bmd  
medication_Glucocorticoids  \
0     57    0       64.0      155.5  0.8793                           
0  
1     75    0       78.0      162.0  0.7946                           
0  
2     70    1       73.0      170.5  0.9067                           
0  
3     78    0       60.0      148.0  0.7112                           
0  
4     54    1       55.0      161.0  0.7909                           
0  
..   ...  ...        ...        ...     ...                          ..
.  
164   77    1       74.0      164.0  0.7941                           
0  
165   50    0       59.0      161.0  0.7971                           
0  
```

```
166   46    1       67.0      169.0  0.8037
0
167   54    1       70.0      166.0  0.8072
0
168   69    0       68.5      165.0  0.8664
0

     medication_No_medication  FRACTURE
0                           0         0
1                           1         0
2                           1         0
3                           1         0
4                           1         0
..                        ...       ...
164                         1         1
165                         1         1
166                         1         1
167                         1         1
168                         1         1

[169 rows x 8 columns]
```

```
#Creating a copy of dataframe so that for logistic regression scalled data can be used and for all other algorithms non scalled data can be used

df1=df.copy()
```

FEATURE ENGINERRING.

Using Standard scalar for scaling my features so that there wont be weightage problem while building model.

```
from sklearn.preprocessing import StandardScaler

sc=StandardScaler()

for i in num_col.columns:
    df1[i]=sc.fit_transform(df1[[i]])

df1
```

```
          age  sex  weight_kg  height_cm       bmd  \
0   -0.498079    0  -0.057870  -0.601464  0.579369
1    0.965840    0   1.159205   0.220824  0.069237
2    0.559196    1   0.724535   1.296122  0.744394
3    1.209827    0  -0.405606  -1.550257 -0.433065
```

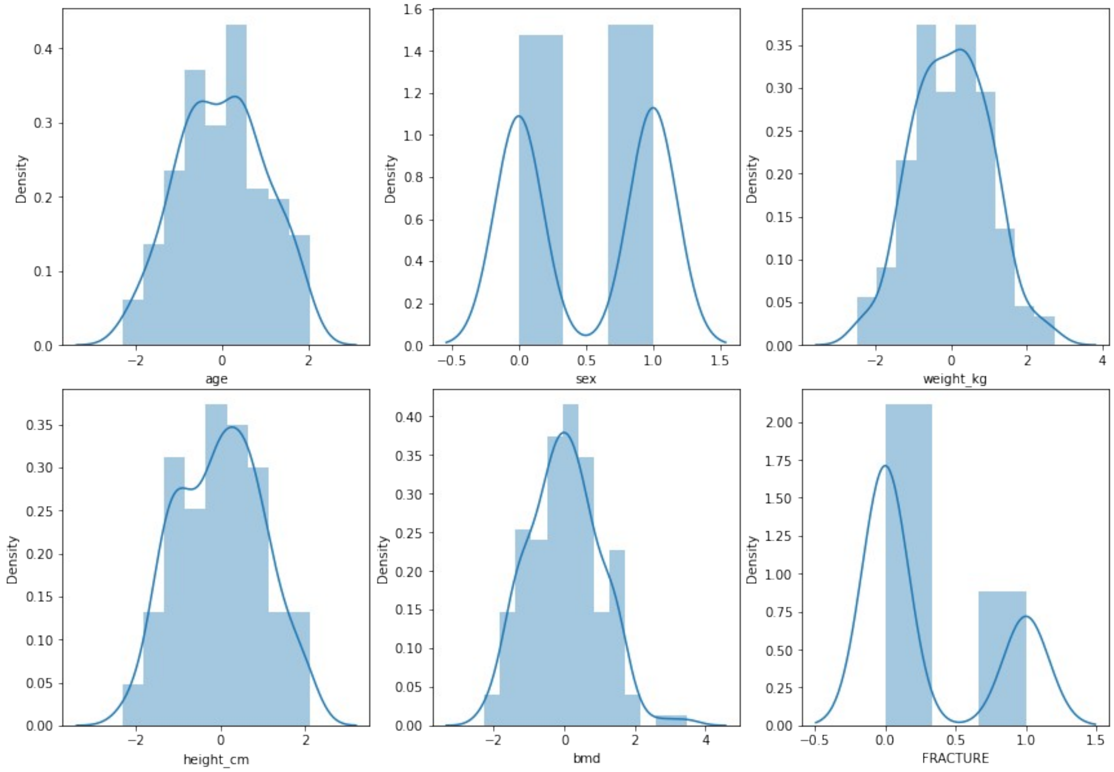
```
4   -0.742066    1  -0.840276   0.094318  0.046953
..        ...  ...        ...        ...       ...
164  1.128498    1   0.811469   0.473835  0.066226
165 -1.067381    0  -0.492540   0.094318  0.084294
166 -1.392696    1   0.202932   1.106364  0.124045
167 -0.742066    1   0.463733   0.726846  0.145125
168  0.477867    0   0.333333   0.600341  0.501675

     medication_Glucocorticoids  medication_No_medication  FRACTURE
0                             0                         0         0
1                             0                         1         0
2                             0                         1         0
3                             0                         1         0
4                             0                         1         0
..                          ...                       ...       ...
164                           0                         1         1
165                           0                         1         1
166                           0                         1         1
167                           0                         1         1
168                           0                         1         1

[169 rows x 8 columns]
```

```
num_columns=df1.select_dtypes(include=["int","float"])
```

```
plt.figure(figsize=(12,12))
count=1
for i in num_columns:
    plt.subplot(3,3,count)
    sns.distplot(df1[i])
    count+=1
plt.tight_layout(pad=0.5,w_pad=0.5,h_pad=0.2)
```



spliting data.

```
X=df1.iloc[:,:-1]
y=df1.iloc[:,-1]
```

```
X.shape
```

```
(169, 7)
```

```
y.shape
```

```
(169,)
```

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.20,rand
om_state=25)
```

Oversampling data to avoid problem of imbalanced ratio of fracture and non fracture.

```
from imblearn.over_sampling import RandomOverSampler
os = RandomOverSampler(sampling_strategy=1.0)
```

```
X_train_res, y_train_res=os.fit_resample(X_train,y_train)
```

LOGISTIC REGRESSION.

Model building.

```
from sklearn.linear_model import LogisticRegression

reg=LogisticRegression()

reg.fit(X_train_res, y_train_res)

LogisticRegression()

y_pred_train=reg.predict(X_train_res)
y_pred_test=reg.predict(X_test)
```

Evaluation.

```
from sklearn.metrics import classification_report,confusion_matrix

print("Train Data")
print(classification_report(y_train_res,y_pred_train))
print("Test Data")
print(classification_report(y_test,y_pred_test))

Train Data
              precision    recall  f1-score   support

           0       0.87      0.84      0.85        93
           1       0.84      0.87      0.86        93

    accuracy                           0.85       186
   macro avg       0.86      0.85      0.85       186
weighted avg       0.86      0.85      0.85       186

Test Data
              precision    recall  f1-score   support

           0       0.93      0.96      0.94        26
           1       0.86      0.75      0.80         8

    accuracy                           0.91        34
   macro avg       0.89      0.86      0.87        34
weighted avg       0.91      0.91      0.91        34
```

```
print("Train Data")
print(confusion_matrix(y_train_res,y_pred_train))
print("Test Data")
print(confusion_matrix(y_test,y_pred_test))
```

```
Train Data
[[76 17]
 [11 82]]
Test Data
[[23  3]
 [ 2  6]]
```

```
print("*****************************************Predictions**********
**********************************************")
print("\n*********************Approximately 85% of accuracy is
obtained on both train and test data*************************")
print("\n*********************Got recall rate of approximately 85% for
both train and test data***************************")
```

```
******************************************Predictions*****************
****************************************

*********************Approximately 85% of accuracy is obtained on both
train and test data*************************

*********************Got recall rate of approximately 85% for both
train and test data***************************
```

```
#For all other Algorithms i will be using copy of my original data
frame and wont be scaling this data, as advanced algorithms donot
require scaling

df
```

```
     age  sex  weight_kg  height_cm     bmd
medication_Glucocorticoids  \
0     57    0       64.0      155.5  0.8793
0
1     75    0       78.0      162.0  0.7946
0
2     70    1       73.0      170.5  0.9067
0
3     78    0       60.0      148.0  0.7112
0
4     54    1       55.0      161.0  0.7909
0
..   ...  ...        ...        ...     ...                         ..
```

```
.
164   77    1       74.0      164.0  0.7941
0
165   50    0       59.0      161.0  0.7971
0
166   46    1       67.0      169.0  0.8037
0
167   54    1       70.0      166.0  0.8072
0
168   69    0       68.5      165.0  0.8664
0

     medication_No_medication  FRACTURE
0                           0         0
1                           1         0
2                           1         0
3                           1         0
4                           1         0
..                        ...       ...
164                         1         1
165                         1         1
166                         1         1
167                         1         1
168                         1         1

[169 rows x 8 columns]
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 169 entries, 0 to 168
Data columns (total 8 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   age                           169 non-null    int32
 1   sex                           169 non-null    int32
 2   weight_kg                     169 non-null    float64
 3   height_cm                     169 non-null    float64
 4   bmd                           169 non-null    float64
 5   medication_Glucocorticoids    169 non-null    uint8
 6   medication_No_medication      169 non-null    uint8
 7   FRACTURE                      169 non-null    int32
dtypes: float64(3), int32(3), uint8(2)
memory usage: 6.4 KB
```

Spliting Data

```
X1=df.drop("FRACTURE",axis=1)
y1=df["FRACTURE"]
```

```
from sklearn.model_selection import train_test_split
X1_train,X1_test,y1_train,y1_test=train_test_split(X1,y1,test_size=0.2
0,random_state=95)
```

Oversampling

```
from imblearn.over_sampling import RandomOverSampler
os = RandomOverSampler(sampling_strategy=1.0)

X1_train_res, y1_train_res=os.fit_resample(X1_train,y1_train)
```

KNN

model building

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report,recall_score
from sklearn.model_selection import GridSearchCV

clf=KNeighborsClassifier(n_neighbors=5)
clf.fit(X1_train_res,y1_train_res)
y_pred_train1=clf.predict(X1_train_res)
y_pred_test1=clf.predict(X1_test)
print("Train Data")
print(classification_report(y1_train_res,y_pred_train1))
print("Test Data")
print(classification_report(y1_test,y_pred_test1))
```

```
Train Data
              precision    recall  f1-score   support

           0       0.87      0.74      0.80        92
           1       0.77      0.89      0.83        92

    accuracy                           0.82       184
   macro avg       0.82      0.82      0.81       184
weighted avg       0.82      0.82      0.81       184

Test Data
              precision    recall  f1-score   support

           0       0.90      0.67      0.77        27
           1       0.36      0.71      0.48         7
```

```
    accuracy                           0.68        34
   macro avg       0.63      0.69      0.62        34
weighted avg       0.79      0.68      0.71        34
```

hyper parameter tuning.

To find optimum K value.

```
param_grid1={"n_neighbors":np.arange(1,15),"weights":
["uniform","distance"],"metric":["minkowski","manhattan","euclidean"]}

grid_clf1=GridSearchCV(clf,param_grid=param_grid1,scoring="recall",cv=
5,n_jobs=-1)
grid_clf1.fit(X1_train_res,y1_train_res)

GridSearchCV(cv=5, estimator=KNeighborsClassifier(), n_jobs=-1,
             param_grid={'metric': ['minkowski', 'manhattan',
'euclidean'],
                         'n_neighbors': array([ 1,  2,  3,  4,  5,  6,
7,  8,  9, 10, 11, 12, 13, 14]),
                         'weights': ['uniform', 'distance']},
             scoring='recall')

grid_clf1.best_params_

{'metric': 'minkowski', 'n_neighbors': 14, 'weights': 'distance'}

grid_clf1.best_score_

0.956140350877193

grid_train_pred1=grid_clf1.predict(X1_train_res)
grid_test_pred1=grid_clf1.predict(X1_test)

print("Train Data")
print(classification_report(y1_train_res,grid_train_pred1))
print("Test Data")
print(classification_report(y1_test,grid_test_pred1))

Train Data
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        92
           1       1.00      1.00      1.00        92

    accuracy                           1.00       184
   macro avg       1.00      1.00      1.00       184
weighted avg       1.00      1.00      1.00       184
```

```
Test Data
              precision    recall  f1-score   support

           0       0.86      0.67      0.75        27
           1       0.31      0.57      0.40         7

    accuracy                           0.65        34
   macro avg       0.58      0.62      0.57        34
weighted avg       0.74      0.65      0.68        34
```

Overfitting

2nd method to find k value

```
for i in range(1,30):
    clf=KNeighborsClassifier(n_neighbors=i)
    clf.fit(X1_train_res,y1_train_res)
    y_pred_train1=clf.predict(X1_train_res)
    y_pred_test1=clf.predict(X1_test)
    print("For k:",i)
    print("Train Data")
    print(recall_score(y1_train_res,y_pred_train1))
    print("Test Data")
    print(recall_score(y1_test,y_pred_test1))
```

```
For k: 1
Train Data
1.0
Test Data
0.2857142857142857
For k: 2
Train Data
0.9456521739130435
Test Data
0.2857142857142857
For k: 3
Train Data
0.9782608695652174
Test Data
0.7142857142857143
For k: 4
Train Data
0.8586956521739131
Test Data
0.5714285714285714
For k: 5
Train Data
```

```
0.8913043478260869
Test Data
0.7142857142857143
For k: 6
Train Data
0.6956521739130435
Test Data
0.7142857142857143
For k: 7
Train Data
0.7608695652173914
Test Data
0.8571428571428571
For k: 8
Train Data
0.6304347826086957
Test Data
0.7142857142857143
For k: 9
Train Data
0.6847826086956522
Test Data
0.7142857142857143
For k: 10
Train Data
0.5978260869565217
Test Data
0.5714285714285714
For k: 11
Train Data
0.6847826086956522
Test Data
0.5714285714285714
For k: 12
Train Data
0.6413043478260869
Test Data
0.5714285714285714
For k: 13
Train Data
0.717391304347826
Test Data
0.5714285714285714
For k: 14
Train Data
0.5869565217391305
Test Data
0.5714285714285714
For k: 15
Train Data
```

```
0.6630434782608695
Test Data
0.7142857142857143
For k: 16
Train Data
0.5543478260869565
Test Data
0.5714285714285714
For k: 17
Train Data
0.6413043478260869
Test Data
0.5714285714285714
For k: 18
Train Data
0.5978260869565217
Test Data
0.5714285714285714
For k: 19
Train Data
0.5978260869565217
Test Data
0.5714285714285714
For k: 20
Train Data
0.5760869565217391
Test Data
0.5714285714285714
For k: 21
Train Data
0.6195652173913043
Test Data
0.5714285714285714
For k: 22
Train Data
0.5978260869565217
Test Data
0.5714285714285714
For k: 23
Train Data
0.6413043478260869
Test Data
0.5714285714285714
For k: 24
Train Data
0.6195652173913043
Test Data
0.5714285714285714
For k: 25
Train Data
```

```
0.6304347826086957
Test Data
0.5714285714285714
For k: 26
Train Data
0.6304347826086957
Test Data
0.5714285714285714
For k: 27
Train Data
0.6304347826086957
Test Data
0.5714285714285714
For k: 28
Train Data
0.5978260869565217
Test Data
0.5714285714285714
For k: 29
Train Data
0.5978260869565217
Test Data
0.5714285714285714
```

```
clf=KNeighborsClassifier(metric="minkowski",n_neighbors=7,weights='uni
form')
clf.fit(X1_train_res,y1_train_res)
y_pred_train=clf.predict(X1_train_res)
y_pred_test=clf.predict(X1_test)
print("Train Data")
print(classification_report(y1_train_res,y_pred_train))
print("Test Data")
print(classification_report(y1_test,y_pred_test))
```

```
Train Data
              precision    recall  f1-score   support

           0       0.77      0.79      0.78        92
           1       0.79      0.76      0.77        92

    accuracy                           0.78       184
   macro avg       0.78      0.78      0.78       184
weighted avg       0.78      0.78      0.78       184

Test Data
              precision    recall  f1-score   support

           0       0.95      0.70      0.81        27
           1       0.43      0.86      0.57         7
```

```
    accuracy                           0.74        34
   macro avg       0.69      0.78      0.69        34
weighted avg       0.84      0.74      0.76        34
```

Taking K=7 as im getting best recall rate at K=7.

```
print("*********************************Recall rate = approx 
75%***********************************")
```

```
*********************************Recall rate = approx 
75%***********************************
```

```
X2=df.drop("FRACTURE",axis=1)
y2=df["FRACTURE"]
X2_train,X2_test,y2_train,y2_test=train_test_split(X2,y2,test_size=0.2
0,random_state=678)
```

DECISION TREE.

```
from sklearn.tree import DecisionTreeClassifier
```

```
dt=DecisionTreeClassifier()
```

```
dt.fit(X2_train,y2_train)
```

```
DecisionTreeClassifier()
```

```
y_train_pred2=dt.predict(X2_train)
y_test_pred2=dt.predict(X2_test)
```

```
from sklearn.metrics import classification_report
```

```
print("Train Data")
print(classification_report(y2_train,y_train_pred2))
print("Test Data")
print(classification_report(y2_test,y_test_pred2))
```

```
Train Data
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        96
```

```
           1       1.00      1.00      1.00        39

    accuracy                           1.00       135
   macro avg       1.00      1.00      1.00       135
weighted avg       1.00      1.00      1.00       135

Test Data
              precision    recall  f1-score   support

           0       0.89      0.74      0.81        23
           1       0.60      0.82      0.69        11

    accuracy                           0.76        34
   macro avg       0.75      0.78      0.75        34
weighted avg       0.80      0.76      0.77        34
```

Hyper parameter tuning.

```
param_grid={
     "criterion":["gini","entropy"],
     "max_depth":np.arange(1,50),
     "min_samples_leaf":np.arange(1,30),
     "min_samples_split":np.arange(2,20,1),
     "class_weight":["balanced"]
}
```

```
from sklearn.model_selection import GridSearchCV
grid_clf2=GridSearchCV(dt,param_grid=param_grid,cv=5,scoring=recall_sc
ore,n_jobs=-1)
grid_clf2.fit(X2_train,y2_train)
```

```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(), n_jobs=-1,
             param_grid={'class_weight': ['balanced'],
                         'criterion': ['gini', 'entropy'],
                         'max_depth': array([ 1,  2,  3,  4,  5,  6,
7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
34,
       35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49]),
                         'min_samples_leaf': array([ 1,  2,  3,  4,
5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29]),
                         'min_samples_split': array([ 2,  3,  4,  5,
6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17, 18,
```

```
       19])},
             scoring=<function recall_score at 0x000002477ECC8AF0>)
```

```
grid_clf2.best_params_
```

```
{'class_weight': 'balanced',
 'criterion': 'gini',
 'max_depth': 1,
 'min_samples_leaf': 1,
 'min_samples_split': 2}
```

```
grid_clf2.best_estimator_
```

```
DecisionTreeClassifier(class_weight='balanced', max_depth=1)
```

```
grid_train_pred2=grid_clf2.predict(X2_train)
grid_test_pred2=grid_clf2.predict(X2_test)
```

```
print("Train Data")
print(classification_report(y2_train,grid_train_pred2))
print("Test Data")
print(classification_report(y2_test,grid_test_pred2))
```

```
Train Data
              precision    recall  f1-score   support

           0       0.92      0.90      0.91        96
           1       0.76      0.82      0.79        39

    accuracy                           0.87       135
   macro avg       0.84      0.86      0.85       135
weighted avg       0.88      0.87      0.88       135

Test Data
              precision    recall  f1-score   support

           0       0.96      0.96      0.96        23
           1       0.91      0.91      0.91        11

    accuracy                           0.94        34
   macro avg       0.93      0.93      0.93        34
weighted avg       0.94      0.94      0.94        34
```

```
print("\n****************With hyper parameter tuning on DecisonTree
Recall Rate obtained is 90%********************************")
```

```
****************With hyper parameter tuning on DecisonTree Recall Rate
obtained is 90%********************************
```

RANDOM FOREST

```
from sklearn.ensemble import RandomForestClassifier

rf=RandomForestClassifier(n_estimators=200)

rf.fit(X2_train,y2_train)

RandomForestClassifier(n_estimators=200)

y_train_predict4=rf.predict(X2_train)
y_test_predict4=rf.predict(X2_test)

print("Train Data")
print(classification_report(y2_train,y_train_predict4))
print("Test Data")
print(classification_report(y2_test,y_test_predict4))

Train Data
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        96
           1       1.00      1.00      1.00        39

    accuracy                           1.00       135
   macro avg       1.00      1.00      1.00       135
weighted avg       1.00      1.00      1.00       135

Test Data
              precision    recall  f1-score   support

           0       0.87      0.87      0.87        23
           1       0.73      0.73      0.73        11

    accuracy                           0.82        34
   macro avg       0.80      0.80      0.80        34
weighted avg       0.82      0.82      0.82        34


param_grid={

     "criterion":["gini","entropy"],
     "min_samples_split":np.arange(2,50,2),
     "n_estimators":(50,100,150,200),
     "max_samples":[0.5,0.75],
     "max_features":[2]
}

from sklearn.model_selection import GridSearchCV
grid_clf=GridSearchCV(rf,param_grid=param_grid,cv=10,scoring=recall_sc
ore,n_jobs=-1)
grid_clf.fit(X2_train,y2_train)
```

```
GridSearchCV(cv=10,
estimator=RandomForestClassifier(n_estimators=200),
             n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
'max_features': [2],
                         'max_samples': [0.5, 0.75],
                         'min_samples_split': array([ 2,  4,  6,  8,
10, 12, 14, 16, 18, 20, 22, 24, 26, 28, 30, 32, 34,
       36, 38, 40, 42, 44, 46, 48]),
                         'n_estimators': (50, 100, 150, 200)},
             scoring=<function recall_score at 0x000002477ECC8AF0>)
```

```
grid_clf.best_params_
```

```
{'criterion': 'gini',
 'max_features': 2,
 'max_samples': 0.5,
 'min_samples_split': 2,
 'n_estimators': 50}
```

```
random_train_pred=grid_clf.predict(X2_train)
random_test_pred=grid_clf.predict(X2_test)
```

```
print("Train Data")
print(classification_report(y2_train,random_train_pred))
print("Test Data")
print(classification_report(y2_test,random_test_pred))
```

```
Train Data
              precision    recall  f1-score   support

           0       0.96      0.97      0.96        96
           1       0.92      0.90      0.91        39

    accuracy                           0.95       135
   macro avg       0.94      0.93      0.94       135
weighted avg       0.95      0.95      0.95       135

Test Data
              precision    recall  f1-score   support

           0       0.88      0.91      0.89        23
           1       0.80      0.73      0.76        11

    accuracy                           0.85        34
   macro avg       0.84      0.82      0.83        34
weighted avg       0.85      0.85      0.85        34
```

GRADIENT BOOSTING CLASSIFIER

```
from sklearn.ensemble import GradientBoostingClassifier
```

```
X2=df.drop("FRACTURE",axis=1)
y2=df["FRACTURE"]
X2_train,X2_test,y2_train,y2_test=train_test_split(X2,y2,test_size=0.2
0,random_state=678)
```

```
gb_clf=GradientBoostingClassifier()
```

```
gb_clf.fit(X2_train,y2_train)
```

```
GradientBoostingClassifier()
```

```
y_pred_train11=gb_clf.predict(X2_train)
y_pred_test11=gb_clf.predict(X2_test)
```

```
from sklearn.metrics import classification_report
print("Train Data")
print(classification_report(y2_train,y_pred_train11))
print("Test Data")
print(classification_report(y2_test,y_pred_test11))
```

```
Train Data
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        96
           1       1.00      1.00      1.00        39

    accuracy                           1.00       135
   macro avg       1.00      1.00      1.00       135
weighted avg       1.00      1.00      1.00       135

Test Data
              precision    recall  f1-score   support

           0       0.86      0.83      0.84        23
           1       0.67      0.73      0.70        11

    accuracy                           0.79        34
   macro avg       0.77      0.78      0.77        34
weighted avg       0.80      0.79      0.80        34
```

```
param_grid={'n_estimators':np.arange(1,100),
            'learning_rate':(0.1,0.01,0.001)
           }
```

```
from sklearn.model_selection import GridSearchCV
grid_clf11=GridSearchCV(gb_clf,cv=10,param_grid=param_grid,n_jobs=-
1,scoring="f1")
grid_clf11.fit(X2_train,y2_train)
```

```
GridSearchCV(cv=10, estimator=GradientBoostingClassifier(), n_jobs=-1,
             param_grid={'learning_rate': (0.1, 0.01, 0.001, 1, 2),
                         'n_estimators': array([ 1,  2,  3,  4,  5,
6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
34,
       35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49])},
             scoring='f1')
```

```
grid_clf11.best_params_
```

```
{'learning_rate': 1, 'n_estimators': 22}
```

```
grid_train_pred11=grid_clf11.predict(X2_train)
grid_test_pred11=grid_clf11.predict(X2_test)
```

```
print("Train Data")
print(classification_report(y2_train,grid_train_pred11))
print("Test Data")
print(classification_report(y2_test,grid_test_pred11))
```

```
Train Data
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        96
           1       1.00      1.00      1.00        39

    accuracy                           1.00       135
   macro avg       1.00      1.00      1.00       135
weighted avg       1.00      1.00      1.00       135

Test Data
              precision    recall  f1-score   support

           0       0.89      0.74      0.81        23
           1       0.60      0.82      0.69        11

    accuracy                           0.76        34
   macro avg       0.75      0.78      0.75        34
weighted avg       0.80      0.76      0.77        34
```

```
# XGBOOST CLASSIFIER

pip install xgboost
```

```
Defaulting to user installation because normal site-packages is not
writeable
Requirement already satisfied: xgboost in c:\users\avina\appdata\
roaming\python\python310\site-packages (1.7.2)
Requirement already satisfied: numpy in c:\users\avina\appdata\
roaming\python\python310\site-packages (from xgboost) (1.23.1)
Requirement already satisfied: scipy in c:\users\avina\appdata\
roaming\python\python310\site-packages (from xgboost) (1.9.1)
Note: you may need to restart the kernel to use updated packages.

WARNING: You are using pip version 22.0.4; however, version 22.3.1 is
available.
You should consider upgrading via the 'C:\Program Files\Python310\
python.exe -m pip install --upgrade pip' command.
```

```
import xgboost as xgb

my_model = xgb.XGBClassifier()
my_model.fit(X2_train, y2_train)
```

```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1,
colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, feature_types=None, gamma=0, gpu_id=-
1,
              grow_policy='depthwise', importance_type=None,
              interaction_constraints='', learning_rate=0.300000012,
              max_bin=256, max_cat_threshold=64, max_cat_to_onehot=4,
              max_delta_step=0, max_depth=6, max_leaves=0,
min_child_weight=1,
              missing=nan, monotone_constraints='()',
n_estimators=100,
              n_jobs=0, num_parallel_tree=1, predictor='auto',
random_state=0, ...)
```

```
y_pred_train3=my_model.predict(X2_train)
y_pred_test3=my_model.predict(X2_test)

print("Train Data")
print(classification_report(y2_train,y_pred_train3))
print("Test Data")
print(classification_report(y2_test,y_pred_test3))
```

```
Train Data
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        96
```

```
           1       1.00      1.00      1.00        39

    accuracy                           1.00       135
   macro avg       1.00      1.00      1.00       135
weighted avg       1.00      1.00      1.00       135

Test Data
              precision    recall  f1-score   support

           0       0.86      0.83      0.84        23
           1       0.67      0.73      0.70        11

    accuracy                           0.79        34
   macro avg       0.77      0.78      0.77        34
weighted avg       0.80      0.79      0.80        34
```

```
param_grid2={'n_estimators':np.arange(1,200),
              "learning_rate":(0.1,0.01),
               "gamma":np.arange(1,50)}

grid_clf22=GridSearchCV(my_model,cv=10,param_grid=param_grid2,n_jobs=-
1,scoring="f1")
grid_clf22.fit(X2_train,y2_train)
```

```
GridSearchCV(cv=10,
             estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                     callbacks=None,
colsample_bylevel=1,
                                     colsample_bynode=1,
colsample_bytree=1,
                                     early_stopping_rounds=None,
                                     enable_categorical=False,
eval_metric=None,
                                     feature_types=None, gamma=0,
gpu_id=-1,
                                     grow_policy='depthwise',
                                     importance_type=None,
                                     interaction_constraints='',
                                     learning_rate=0.30000001...
       105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116,
117,
       118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129,
130,
       131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142,
143,
       144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 155,
156,
       157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168,
169,
```

```
       170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 180, 181,
182,
       183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194,
195,
       196, 197, 198, 199])},
             scoring='f1')
```

```
grid_clf22.best_params_
```

```
{'gamma': 1, 'learning_rate': 0.1, 'n_estimators': 12}
```

```
grid_train_pred2=grid_clf22.predict(X2_train)
grid_test_pred2=grid_clf22.predict(X2_test)
```

```
print("Train Data")
print(classification_report(y2_train,grid_train_pred2))
print("Test Data")
print(classification_report(y2_test,grid_test_pred2))
```

```
Train Data
              precision    recall  f1-score   support

           0       0.94      0.95      0.94        96
           1       0.87      0.85      0.86        39

    accuracy                           0.92       135
   macro avg       0.90      0.90      0.90       135
weighted avg       0.92      0.92      0.92       135

Test Data
              precision    recall  f1-score   support

           0       0.95      0.91      0.93        23
           1       0.83      0.91      0.87        11

    accuracy                           0.91        34
   macro avg       0.89      0.91      0.90        34
weighted avg       0.92      0.91      0.91        34
```

SVM

```
from sklearn.svm import SVC
```

```
svc=SVC()
```

```
svc.fit(X_train_res,y_train_res)
```

```
SVC()
```

```
y_train_predict5=svc.predict(X_train_res)
y_test_predict5=svc.predict(X_test)
```

```
print("Train Data")
print(classification_report(y_train_res,y_train_predict5))
print("Test Data")
print(classification_report(y_test,y_test_predict5))
```

```
Train Data
              precision    recall  f1-score   support

           0       0.90      0.78      0.84        93
           1       0.81      0.91      0.86        93

    accuracy                           0.85       186
   macro avg       0.86      0.85      0.85       186
weighted avg       0.86      0.85      0.85       186

Test Data
              precision    recall  f1-score   support

           0       0.92      0.92      0.92        26
           1       0.75      0.75      0.75         8

    accuracy                           0.88        34
   macro avg       0.84      0.84      0.84        34
weighted avg       0.88      0.88      0.88        34
```

```
param_grid={"C":[0.1,1,0.001],
           "gamma":[0.1,0.01],
           "kernel":["rbf","linear","poly","sigmoid"]}
```

```
grid_clf4=GridSearchCV(svc,param_grid=param_grid,scoring="f1",cv=5,n_j
obs=1)
```

```
grid_clf4.fit(X_train_res,y_train_res)
```

```
GridSearchCV(cv=5, estimator=SVC(), n_jobs=1,
             param_grid={'C': [0.1, 1, 0.001], 'gamma': [0.1, 0.01],
                         'kernel': ['rbf', 'linear', 'poly',
'sigmoid']},
             scoring='f1')
```

```
grid_clf4.best_params_
```

```
{'C': 1, 'gamma': 0.1, 'kernel': 'linear'}
```

```
y_pred_train_svm=grid_clf4.predict(X_train_res)
y_pred_test_svm=grid_clf4.predict(X_test)
```

```
print("Train Data")
print(classification_report(y_train_res,y_pred_train_svm))
print("Test Data")
print(classification_report(y_test,y_pred_test_svm))
```

```
Train Data
              precision    recall  f1-score   support

           0       0.91      0.83      0.87        93
           1       0.84      0.91      0.88        93

    accuracy                           0.87       186
   macro avg       0.87      0.87      0.87       186
weighted avg       0.87      0.87      0.87       186

Test Data
              precision    recall  f1-score   support

           0       0.92      0.92      0.92        26
           1       0.75      0.75      0.75         8

    accuracy                           0.88        34
   macro avg       0.84      0.84      0.84        34
weighted avg       0.88      0.88      0.88        34
```

```
d={"Algorithm":["Logistic Regression","KNN","DecisionTree 
classifier","RandomForest Classifier","Gradient Boosting 
classifier","XG BOOST CLASSIFIER","SVC"],"F1":
[0.91,0.62,0.77,0.82,0.80,0.80,0.84],"Regularized_F1":
["-",0.69,0.94,0.85,0.77,0.91,0.84]}

Model=pd.DataFrame(d)

Model
```

	Algorithm	F1	Regularized_F1
0	Logistic Regression	0.91	-
1	KNN	0.62	0.69
2	DecisionTree classifier	0.77	0.94
3	RandomForest Classifier	0.82	0.85
4	Gradient Boosting classifier	0.80	0.77
5	XG BOOST CLASSIFIER	0.80	0.91
6	SVC	0.84	0.84

```
print("\t(1) I have used oversampled Data for Logistic Regression,KNN 
and SVC algorithm as they are affected by imbalanced data\n\n\t(2)For
```

```
all other algorithms imbalanced dataset is used at is because they can handle imalanced dataset.\n\n\t(3)Best performance after Regularization is given by Decision Tree followed by XG BOOST")
```

(1) I have used oversampled Data for Logistic Regression,KNN and SVC algorithm as they are affected by imbalanced data

(2)For all other algorithms imbalanced dataset is used at is because they can handle imalanced dataset.

(3)Best performance after Regularization is given by Decision Tree followed by XG BOOST

```
import pickle
```

```
pickle.dump(grid_clf2,open('bmd1.pkl','wb'))
```