# PROJECT DVELOPMENT PHASE SPRINT-2

# **BUILDING MODELS**

#### SPLIT THE DATAS

x=df.drop(['Serial No.','Chance of Admit '],axis=1)
y=df['Chance of Admit ']
print(x.shape,y.shape)

# TRAIN AND TEST THE DATA

from sklearn.model\_selection import train\_test\_split

x\_train,x\_test,y\_train,y\_test=train\_test\_split(x,y,test\_size=0.2)

print(x\_train.shape)

print(y\_train.shape)

print(y\_test.shape)

## SCALING:

from sklearn.preprocessing import MinMaxScaler

mms=MinMaxScaler()

x\_train[x\_train.columns]=mms.fit\_transform(x\_train[x\_train.columns].values)

x\_test[x\_test.columns]=mms.transform(x\_test[x\_test.columns].values)

#### **BUILDING MODELS**

# MODEL 1: RANDOM FOREST REGRESSOR

from sklearn.ensemble import RandomForestRegressor model=RandomForestRegressor()

```
model.fit(x_train,y_train)
y_pred=model.predict(x_test)
print(y_pred)
print(y_test)
EVALUATION
from sklearn.metrics import mean_squared_error,
r2_score,mean_absolute_error,roc_auc_score,recall_score
print('model score:',model.score(x_test,y_test))
print('Mean Absolute Error:', mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(mean_squared_error(y_test, y_pred)))
print('roc score:',roc_auc_score(y_test>0.5, y_pred>0.5))
print('recall score:',recall_score(y_test>0.5, y_pred>0.5))
MODEL 2: LINEAR REGRESSION
x1=df.drop(['Serial No.','Chance of Admit '],axis=1)
y1=df['Chance of Admit']
x1_train,x1_test,y1_train,y1_test=train_test_split(x1,y1,test_size=0.2)
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
x1_train=sc.fit_transform(x1_train)
x1_test=sc.fit_transform(x1_test)
from sklearn.linear_model import LinearRegression
model1=LinearRegression()
model1.fit(x1_train,y1_train)
```

```
y1_pred=model1.predict(x1_test)
```

#### **EVALUATION**

```
print('model score:',model1.score(x1_test,y1_test))

print('Mean Absolute Error:', mean_absolute_error(y1_test, y1_pred))

print('Mean Squared Error:', mean_squared_error(y1_test, y1_pred))

print('Root Mean Squared Error:', np.sqrt(mean_squared_error(y1_test, y1_pred)))

print('roc score:',roc_auc_score(y1_test>0.5, y1_pred>0.5))

print('recall score:',recall_score(y1_test>0.5, y1_pred>0.5))
```

## **MODEL 3: LOGISTIC REGRESSION**

```
x2=df.iloc[:,1:8].values
y2=df.iloc[:,-1:].values
x2_train,x2_test,y2_train,y2_test=train_test_split(x1,y1,test_size=0.2)
y2_train=y2_train>0.5
y2_test=y2_test>0.5
from sklearn.linear_model import LogisticRegression
model2=LogisticRegression()
model2.fit(x2_train,y2_train)
```

#### **EVALUATION**

```
from sklearn.metrics import accuracy_score,roc_auc_score,recall_score
y2_pred=model2.predict(x2_test)
print('model score:',model2.score(x2_test,y2_test))
```

```
print('roc score:',roc_auc_score(y2_test, y2_pred))
print('recall score:',recall_score(y2_test, y2_pred))
print(type(y2_test),type(y2_pred))
```

## XGBREGRESSOR

```
import xgboost as xgb

xg_reg=xgb.XGBRegressor(objective='reg:logistic',colsample_bytree=0.3,learn
ing_rate=0.5,max_depth=5,n_estimators=100)

x3=df.iloc[:,1:8].values

y3=df.iloc[:,-1:].values

x3_train,x3_test,y3_train,y3_test=train_test_split(x3,y3,test_size=0.2)

xg_reg.fit(x3_test,y3_test)

xg_reg.score(x3_test,y3_test)

y3_pred=xg_reg.predict(x3_test)

np.sqrt(mean_squared_error(y3_test,y3_pred))
```

## SAVING THE MODEL:

import joblib

joblib.dump(model, 'model.pkl')

## SPLIT THE DATA INTO DEPENDENT AND INDEPENDENT VARIABLES

```
In [18]: x=df.drop(['Serial No.','Chance of Admit '],axis=1)
y=df['Chance of Admit ']
print(x.shape,y.shape)

(488, 7) (488,)
```

#### TRAIN AND TEST THE DATA

#### BUILDING MODEL(RANDOM FOREST REGRESSOR)

```
In [21]:

| from sklearn.ensemble import NandomForestRegressor | modul-HandomForestRegressor() | modul-fit(x train,y train) | y pred-modul.predict(x test) | print(y pred) | print(y pred) | print(y pred) | print(y test) |
| [8,7122 8.871 8.4652 8.735 8.7675 8.5536 8.7658 8.7311 8.9252 8.8572 8.667 8.6446 8.6406 8.7404 8.7868 8.4745 8.624 8.6988 8.6927 8.6968 8.8995 8.5204 8.5888 8.7383 8.7711 8.7774 8.6875 8.4735 8.6785 8.6115 8.5809 8.68 8.5307 8.8431 8.6541 8.717 8.657 8.9688 8.723 8.5406 8.7322 8.7328 8.9598 8.9507 8.6918 8.855 8.6528 8.927 8.9368 8.812 8.5818 8.7888 8.6626 8.671 8.6695 8.9528 8.0528 8.9278 8.9387 8.6815 8.585 8.726 8.9388 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7338 8.7
```

#### **EVALUATION**

```
In [22]: From silearn.metrics laport main squared error, r2 score, main_absolute error, rec_auc_score, recall_score print( maid) score; _modal.score(x_text, y_text))
    print( maid) score; _modal.score(x_text, y_text))
    print( main squared error); _mo.sqr(main, squared error(y_text, y_pred))
    print( main squared error); _mo.sqr(main, squared error(y_text, y_pred)))
    print( main squared error); _mo.sqr(main, squared error(y_text, y_pred)))
    print( mo.score; _mo.sqr(y_text, do.s, y_pred), do.s))

modal score; _modal_score(y_text, do.s, y_pred), do.s))

modal_score; _modal_score(y_text, do.s, y_pred), do.s))

modal_score; _modal_score(y_text, do.s, y_pred), do.s)

modal_score; _modal_score(y_text, do.s, y_pred), do.s, do.
```

```
In [27]:

from island.linear model import logisticHegression
model2.stagisticHegression()
model2.stagisticHegression()
model2.stagisticHegression()

(intervisith unaconda3\lib\site-packages\wklearn\linear_model\legistic.py:814: Convergencekarning: lbfgs failed to converge
(status-1):
SiGP: TOTAL MO. of TIBRITHON REACHED LIRIT.

Increase the number of iterations (sax iter) or scale the data as shown in:
https://schit-learn.mod/stable/models/proprocessing.html

Place also refer to the documentation for alternative solver options:
https://schit-learn.mody/stable/models/schinor_model.html#logistic-regression

n.itre_i = _check_optimize_result

Out[27]: ungisticHegression()

In [28]: from sklearn.matrics import accuracy_score.por_auc_score.por_alsocreprocessing.ntml
print("model score": model.score("statis.score(%) test, y2_pend))

print("recall score": necall score(%) test, y2_pend))

model score: 0.95
por_score(0.95
por_score(0.95)
```

#### SAVING THE MODEL

#Though the accuracy of Logistic regression model is more we prefer Random forest regressor if we also want the percentage of chance or else we can use Logistic regression model.