IT-641 Deep Learning

#Lab 1

1. Introduction

Machine Learning Pipeline

During this Lab Session we shall revise classification and regression tasks using standard machine learning algorithms. Moreover we shall also try and define a machine learning pipeline that shall help us develop more complex deep learning algorithms in the future:

Figure 1(Machine Learning Flowchart)

2. Datasets

1. User dataset This dataset contains information of users from the company's database. It contains information about UserID, Gender, Age, EstimatedSalary,Purchased.
2. Pima Indians Diabetes Database This dataset is originally from the National Institute of Diabetes and Digestive and Kidney Diseases. The objective of the dataset is to diagnostically predict whether or not a patient has diabetes, based on certain diagnostic measurements included in the dataset. The datasets consist of several medical predictor variables and one target variable, Outcome. Predictor variables include the number of pregnancies the patient has had, their BMI, insulin level, age, and so on.
3. 50_Startups This dataset has data collected from New York, California and Florida about 50 business Startups. The variables used in the dataset are Profit, R&D spending, Administration Spending, and Marketing Spending.

3. Tasks

For each of the above given datasets

1. Load Data and check if the data has missing value
2. Identify which features need to be encoded and encode them
3. Identify which features to normalize and normalize them
4. Identify whether the given task is of classification of regression
5. Split the data into train set (75%) validation set (10%) and test set (15%)
6. Fit the data into 2 models of your choice

REFERENCE CODE - https://colab.research.google.com/drive/1lEqUTriS66KBbn1V648NooaqIsTB3MvE?usp=sharing

DATASET 1

User dataset

This dataset contains information of users from the company's database. It contains information about UserID, Gender, Age, EstimatedSalary,Purchased.

1.Loading Required Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
sb.set_style("whitegrid")
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler,LabelEncoder,LabelBinarizer
from sklearn.linear_model import LogisticRegression,SGDClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import precision_score,recall_score,f1_score,confusion_matrix
import warnings
warnings.filterwarnings(action = "ignore")
```

2.Loading Data

```
data = pd.read_csv("https://raw.githubusercontent.com/Jatansahu/DEEP_LEARNING_ASSIGNMENTS/main/LAB_01/
```

```
# Previewing data
data.head(8)
```

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0
5	15728773	Male	27	58000	0
6	15598044	Female	27	84000	0
7	15694829	Female	32	150000	1

Looking at the above dataset our target variable is the column "Purchased"

3.Looking for Null values

```
print(data.isnull().sum())
```

```
User ID            0
Gender             0
Age                0
EstimatedSalary    0
Purchased          0
dtype: int64
```

There is no null values in our dataset so we will go forward

4.Preprocessing

```
data.head()
```

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0

1.Removing Unnecessary columns

Feature 'User ID' are meaningless when we fit them to our model. Thus we drop these feature.

```
data.drop(["User ID"],1,inplace = True)
```

2.Converting Categorical Variables into their corresponding form

```
print(data.dtypes)
```

```
Gender             object
Age                 int64
EstimatedSalary     int64
Purchased           int64
dtype: object
```

```
#encoding the Gender column
lb = LabelBinarizer()
data['Gender'] = lb.fit_transform(data['Gender'])
```

3.Scaling Features

In the same way as encoding features we can also scale features manually. Scikit learn as inbuilt scalers that do the same task. Here we shall use standard scaler for our task

```
data.describe()
```

	Gender	Age	EstimatedSalary	Purchased
count	400.000000	400.000000	400.000000	400.000000
mean	0.490000	37.655000	69742.500000	0.357500
std	0.500526	10.482877	34096.960282	0.479864
min	0.000000	18.000000	15000.000000	0.000000
25%	0.000000	29.750000	43000.000000	0.000000
50%	0.000000	37.000000	70000.000000	0.000000
75%	1.000000	46.000000	88000.000000	1.000000
max	1.000000	60.000000	150000.000000	1.000000

```
# sc = StandardScaler()
sc = MinMaxScaler()

# Fit and transform the data using the scaler
# X_scaled = scaler.fit_transform(X)
data["EstimatedSalary"] = sc.fit_transform(data["EstimatedSalary"].values.reshape(-1,1))
```

```
# sc = StandardScaler()
sc = MinMaxScaler()
data["Age"] = sc.fit_transform(data["Age"].values.reshape(-1,1))
```

5.Basic EDA

1.Gathering some info about data

```
1 data.describe().T
```

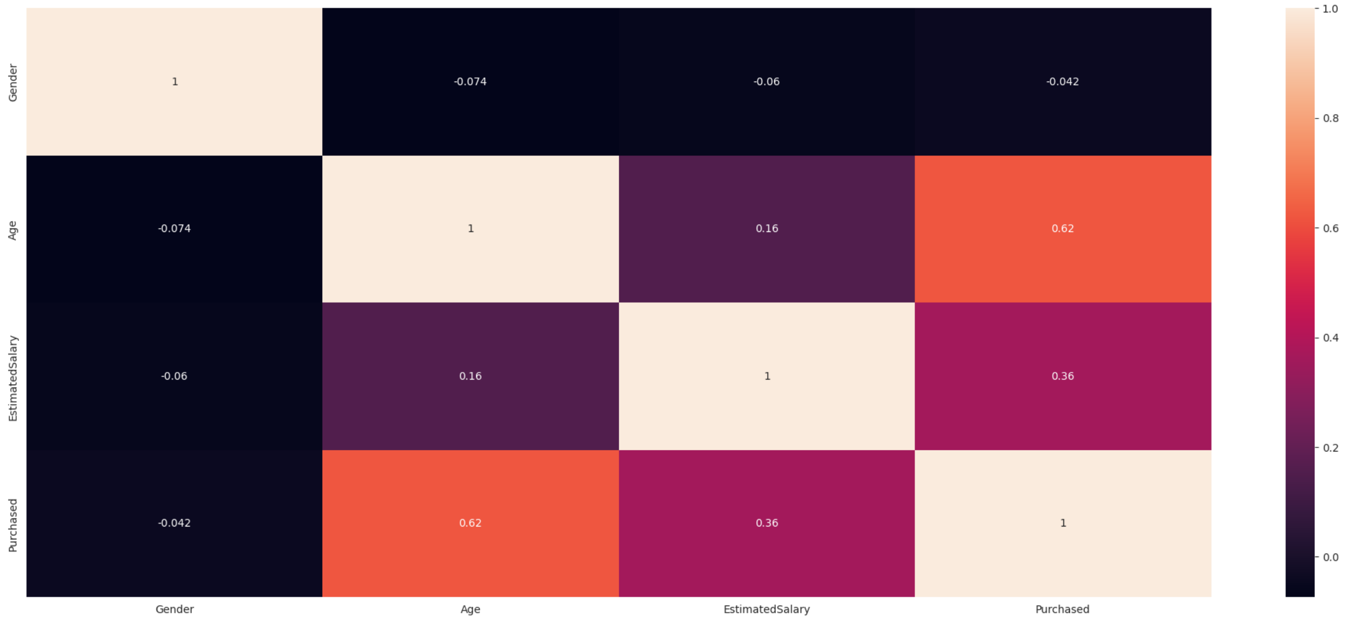
	count	mean	std	min	25%	50%	75%	max
Gender	400.0	0.490000	0.500526	0.0	0.000000	0.000000	1.000000	1.0
Age	400.0	0.467976	0.249592	0.0	0.279762	0.452381	0.666667	1.0
EstimatedSalary	400.0	0.405500	0.252570	0.0	0.207407	0.407407	0.540741	1.0
Purchased	400.0	0.357500	0.479864	0.0	0.000000	0.000000	1.000000	1.0

```
1 data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 4 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Gender           400 non-null    int64  
 1   Age              400 non-null    float64
 2   EstimatedSalary  400 non-null    float64
 3   Purchased        400 non-null    int64  
dtypes: float64(2), int64(2)
memory usage: 12.6 KB
```

2.Correlation plot

```
1 plt.figure(figsize = (25,10))
2 sb.heatmap(data.corr(),annot = True);
```



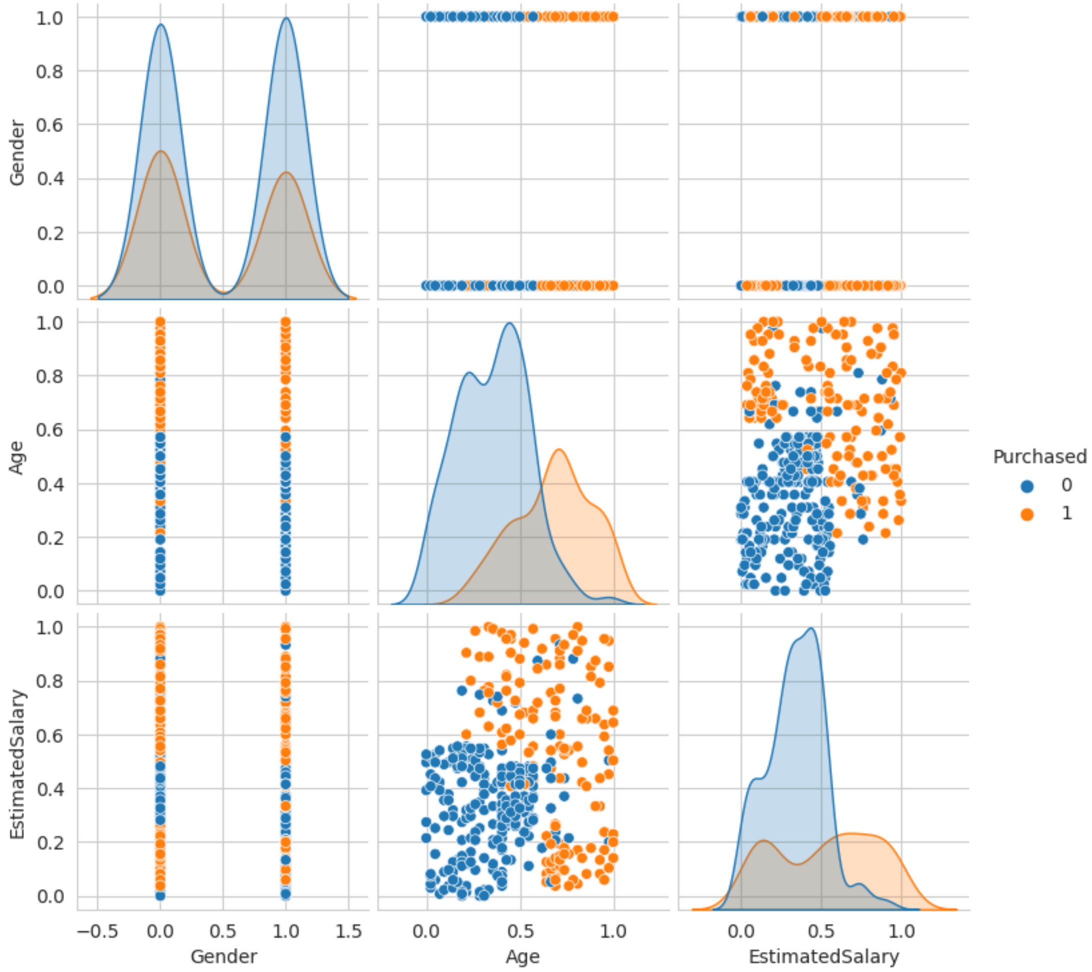
OBSERVATION:

We clearly see that attribute **Age** and **Purchased** attribute have a correlation of 0.62 suggests a moderately strong positive correlation. It implies that as age increases, the purchases tend to increase as well, but not necessarily in a perfectly linear fashion

3.Pairplot

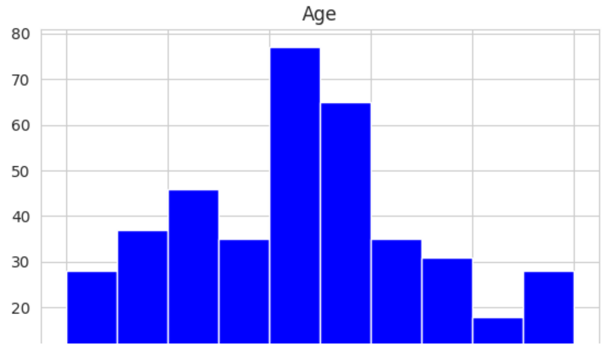
```
plt.figure(figsize = (25,25))
sb.pairplot(data,hue = "Purchased");
```

```
<Figure size 2500x2500 with 0 Axes>
```



4.You can plot using pandas too.

```
data.hist(figsize = (15,10),color = 'blue');
```



6.Splitting the dataset

We split the given data as follows: 80% Train, 15%test and 5%validation. Note that we will face class imbalance problem but we do not aim to solve it here currently

```
data
```

	Gender	Age	EstimatedSalary	Purchased
0	1	0.023810	0.029630	0
1	1	0.404762	0.037037	0
2	0	0.190476	0.207407	0
3	0	0.214286	0.311111	0
4	1	0.023810	0.451852	0
...	...	...	...	...
395	0	0.666667	0.192593	1
396	1	0.785714	0.059259	1
397	0	0.761905	0.037037	1
398	1	0.428571	0.133333	0
399	0	0.738095	0.155556	1

400 rows × 4 columns

```
x = data.iloc[:,:3]
y = data['Purchased']
```

```
x_train,x_part,y_train,y_part = train_test_split(x,y,test_size = 0.2,random_state = 42)
x_test,x_valid,y_test,y_valid = train_test_split(x_part,y_part,test_size = 0.25,random_state = 42)
```

```
print(x_train.shape,x_test.shape,x_valid.shape)
print(y_train.shape,y_test.shape,y_valid.shape)
```

```
(320, 3) (60, 3) (20, 3)
(320,) (60,) (20,)
```

7.Model Selection

Before we fit our data into our model we need to define some metrics with the help of which we can select the best fitting model

As our current task is classification we shall create a function that evaluates our model based on precision score,recall score and F1-score

```
def evaluate(model,model_name,x_train = x_train,y_train = y_train,x_test = x_test,y_test = y_test,x_va
  print(f"Model performance for{model_name}")
  y_train_pred = model.predict(x_train)
  y_test_pred = model.predict(x_test)
  y_valid_pred = model.predict(x_valid)

  #confusion matrix
  plt.figure(figsize = (10,10))
```

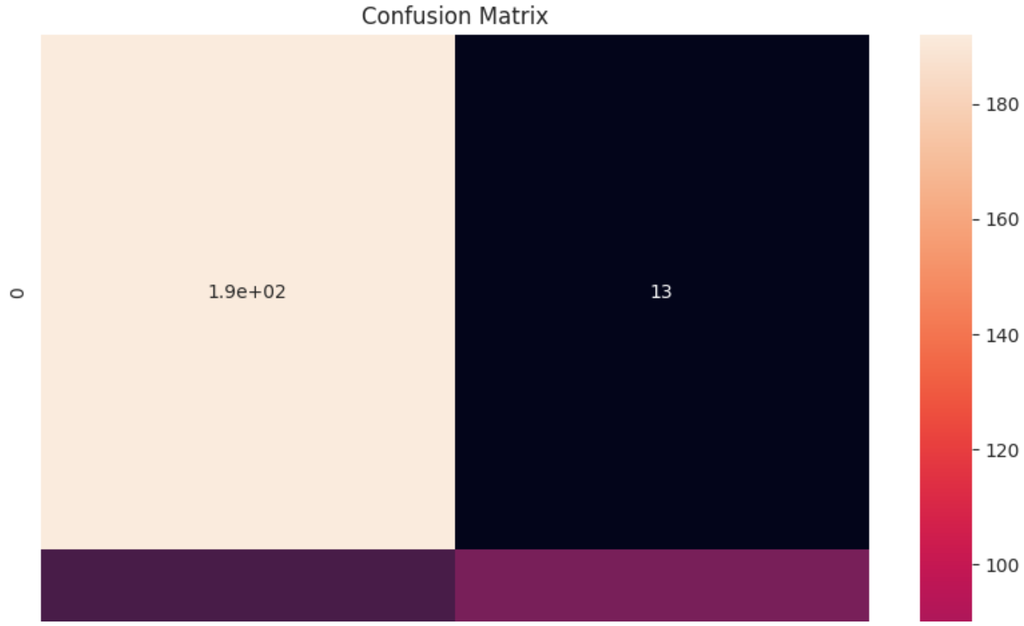
```
  sb.heatmap(confusion_matrix(y_train,y_train_pred),annot = True)
  plt.title('Confusion Matrix')
  plt.show()

  #precision score
  precision_score_train = precision_score(y_train,y_train_pred)
  precision_score_test = precision_score(y_test,y_test_pred)
  precision_score_valid = precision_score(y_valid,y_valid_pred)

  #recallscore
  recall_score_train = recall_score(y_train,y_train_pred)
  recall_score_test = recall_score(y_test,y_test_pred)
  recall_score_valid = recall_score(y_valid,y_valid_pred)

  #f1 score
  f1_score_train = f1_score(y_train,y_train_pred)
  f1_score_test = f1_score(y_test,y_test_pred)
  f1_score_valid = f1_score(y_valid,y_valid_pred)

  print("Precision Score Train:",precision_score_train)
  print("Precision Score Test:",precision_score_test)
  print("Precision Score Validation",precision_score_valid)

  print("recall Score Train:",recall_score_train)
  print("recal Score Test:",recall_score_test)
  print("recall Score Validation",recall_score_valid)

  print("f1 Score Train:",f1_score_train)
  print("f1 Score Test:",f1_score_test)
  print("f1 Score Validation",f1_score_valid)



  return precision_score_train,precision_score_test,precision_score_valid,recall_score_train,recall_sc

```

```
clf1 = LogisticRegression()
clf1.fit(x_train,y_train)
```

```
▾ LogisticRegression
LogisticRegression()
```

```
LR = evaluate(clf1,clf1)
```

```
Model performance forLogisticRegression()
```



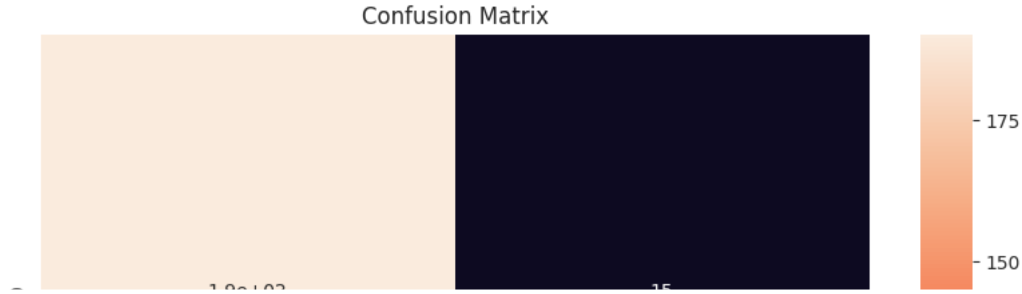
2.KNN

```
1 clf2 = KNeighborsClassifier(n_neighbors = 3)
2 clf2.fit(x_train,y_train)
```

```
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```

```
1 KNN = evaluate(clf2,clf2)
```

```
Model performance forKNeighborsClassifier(n_neighbors=3)
```



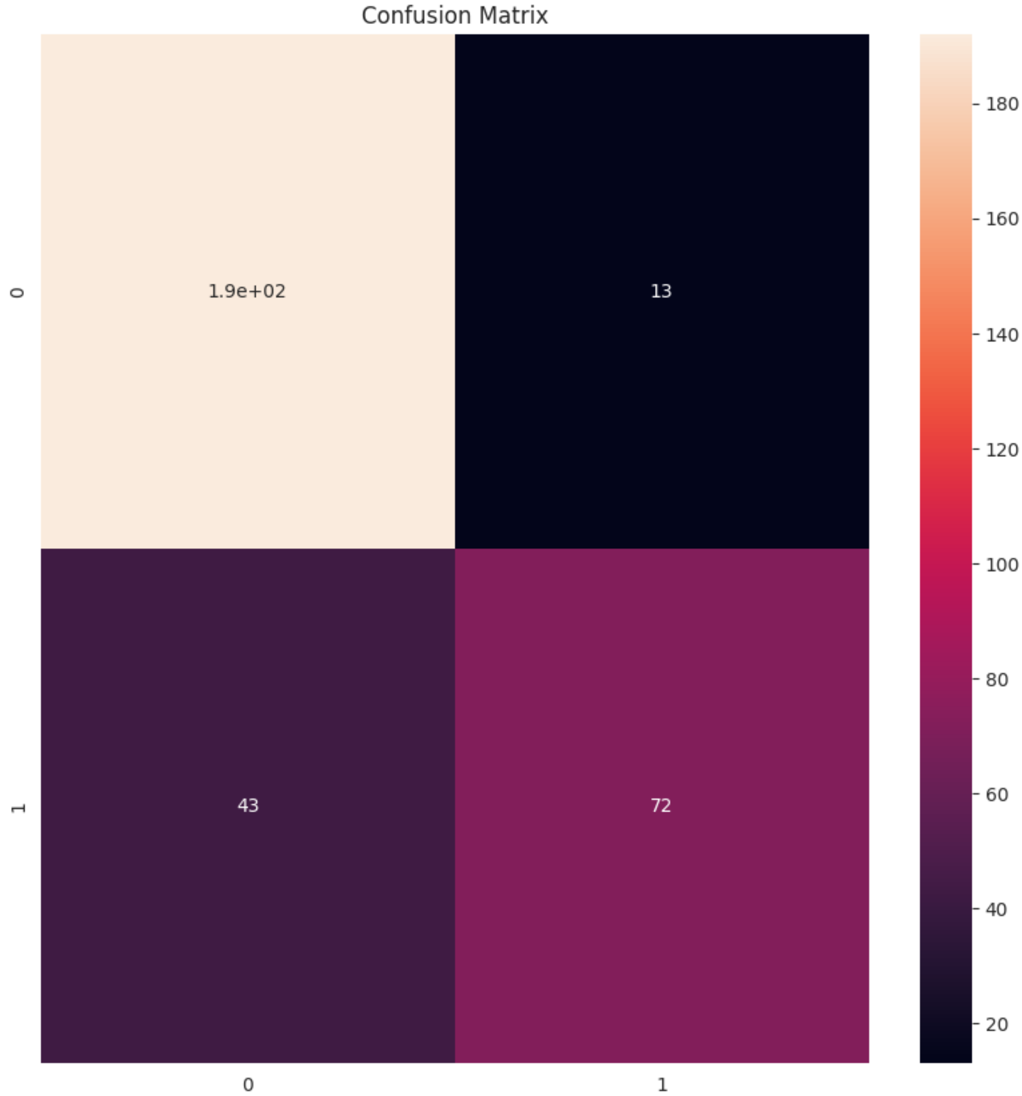
3.SVM

```
1 clf3 = SVC(kernel = "linear")
2 clf3.fit(x_train,y_train)
```

```
SVC
SVC(kernel='linear')
```

```
1 svc = evaluate(clf3,clf3)
```

```
Model performance forSVC(kernel='linear')
```




```
Precision Score Train: 0.8470588235294118
Precision Score Test: 0.9375
Precision Score Validation 1.0
recall Score Train: 0.6260869565217392
recal Score Test: 0.7142857142857143
recall Score Validation 0.5714285714285714
f1 Score Train: 0.72
f1 Score Test: 0.8108108108108109
f1 Score Validation 0.7272727272727273
```

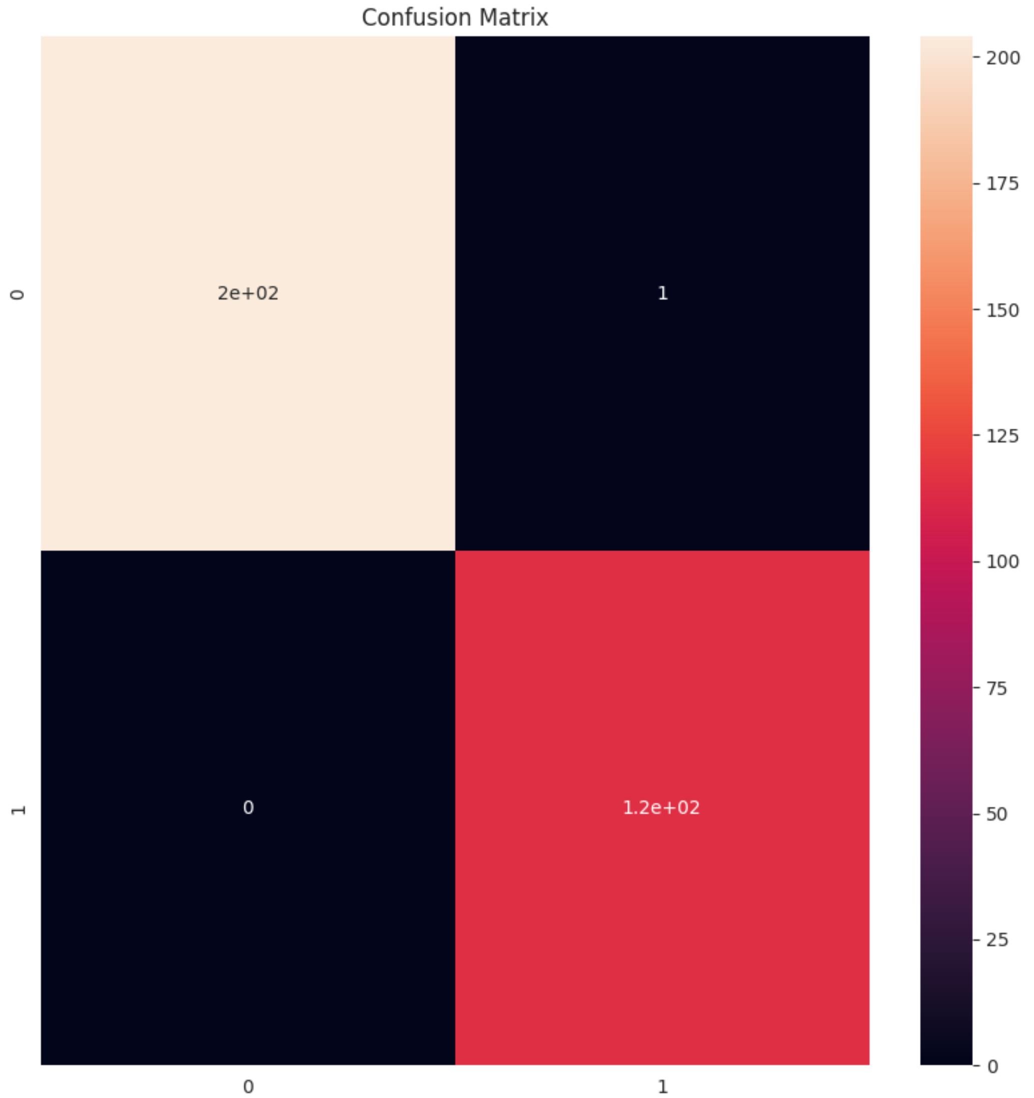
4 Random Forest

```
clf4 = RandomForestClassifier(n_estimators=100, random_state=42)
clf4.fit(x_train,y_train)
```

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

```
rf = evaluate(clf4,clf4)
```

```
Model performance forRandomForestClassifier(random_state=42)
```




```
Precision Score Train: 0.9913793103448276
Precision Score Test: 0.8181818181818182
Precision Score Validation 0.8571428571428571
recall Score Train: 1.0
recal Score Test: 0.8571428571428571
recall Score Validation 0.8571428571428571
f1 Score Train: 0.9956709956709957
f1 Score Test: 0.8372093023255814
f1 Score Validation 0.8571428571428571
```

```
model_performance = [["Logistic Regression",LR[0],LR[1],LR[3],LR[4],LR[5],LR[6],LR[7],LR[8]],
                     ["Knearest Neighbors",KNN[0],KNN[1],KNN[3],KNN[4],KNN[5],KNN[6],KNN[7],KNN[8]],
                     ["Support Vector Machine",svc[0],svc[1],svc[3],svc[4],svc[5],svc[6],svc[7],svc[8]
                     ["Random Forest",rf[0],rf[1],rf[3],rf[4],rf[5],rf[6],rf[7],rf[8]]
                     ]
```

```
model_performance = pd.DataFrame(model_performance,columns = ["Precision Score Train","Precision Score
```

```
model_performance
```

	Precision Score Train	Precision Score Test	Precision Score Validation	Recall Score Train	Recall Score Test	Recall Score Validation	F1 Score Train	F1 Score Test	F1 Score Validation
0	Logistic Regression	0.839506	0.937500	0.591304	0.714286	0.571429	0.693878	0.810811	0.727273
1	Knearest Neighbors	0.876033	0.900000	0.921739	0.857143	0.857143	0.898305	0.878049	0.857143
2	Support Vector Machine	0.847059	0.937500	0.626087	0.714286	0.571429	0.720000	0.810811	0.727273
3	Random Forest	0.991379	0.818182	1.000000	0.857143	0.857143	0.995671	0.837209	0.857143

DATASET - 2

Pima Indians Diabetes Database

This dataset is originally from the National Institute of Diabetes and Digestive and Kidney Diseases. The objective of the dataset is to diagnostically predict whether or not a patient has diabetes, based on certain diagnostic measurements included in the dataset. The datasets consist of several medical predictor variables and one target variable, Outcome. Predictor variables include the number of pregnancies the patient has had, their BMI, insulin level, age, and so on.

1.Loading Required Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
sb.set_style("whitegrid")
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler,LabelEncoder,LabelBinarizer
from sklearn.linear_model import LogisticRegression,SGDClassifier
from sklearn.linear_model import LogisticRegression,SGDClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import precision_score,recall_score,f1_score,confusion_matrix
import warnings
warnings.filterwarnings(action = "ignore")
```

2.Loading Data

```
data = pd.read_csv("https://raw.githubusercontent.com/Jatansahu/DEEP_LEARNING_ASSIGNMENTS/main/LAB_01/
```

```
# Previewing data
data.head()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

Looking at the above dataset our target variable is the column "Outcome"

3.Looking for Null values

```
1 print(data.isnull().sum())
```

```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

There is no missing or null values in the dataset

4.Preprocessing

```
1 data.head()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

1.Removing Unnecessary columns

```
1 data.columns
```

```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

Based on general domain knowledge, some features may be considered more directly related to diabetes risk than others. In many cases, "Pregnancies" might not be directly related to diabetes risk but could have an indirect impact through other factors. It's important to conduct a thorough analysis, such as feature importance from a machine learning model, to determine the relative importance of each feature in predicting diabetes for a given dataset.

2.Converting Categorical Variables into their corresponding form

```
1 print(data.dtypes)
```

```
Pregnancies                   int64
Glucose                       int64
BloodPressure                 int64
SkinThickness                 int64
Insulin                       int64
BMI                         float64
DiabetesPedigreeFunction    float64
Age                           int64
Outcome                       int64
dtype: object
```

There is no categorical varirables in the dataset.

3.Scaling Features

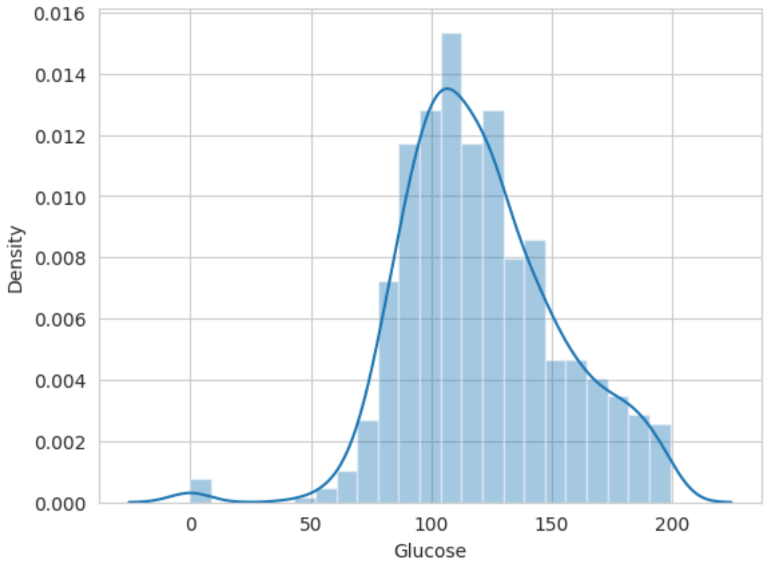
StandardScaler: This scaler assumes that the data follows a Gaussian (normal) distribution

MinMaxScaler:This scaler is more appropriate when your data doesn't follow a normal distribution or when you have features with significantly different scales.

```
sc = StandardScaler()
data["Pregnancies"] = sc.fit_transform(data["Pregnancies"].values.reshape(-1,1))
```

```
sb.distplot(data["Glucose"]);
print("Mean",np.round(np.mean(data["Glucose"]),0))
```

```
Mean 121.0
```




```
sc = StandardScaler()
data["Glucose"] = sc.fit_transform(data["Glucose"].values.reshape(-1,1))
```

```
sc = StandardScaler()
data["BloodPressure"] = sc.fit_transform(data["BloodPressure"].values.reshape(-1,1))
```

```
sc = StandardScaler()
data["Insulin"] = sc.fit_transform(data["Insulin"].values.reshape(-1,1))
```

```
sc = StandardScaler()
data["BMI"] = sc.fit_transform(data["BMI"].values.reshape(-1,1))
```

```
sc = StandardScaler()
data["DiabetesPedigreeFunction"] = sc.fit_transform(data["DiabetesPedigreeFunction"].values.reshape(-1
```

```
sc = StandardScaler()
data["Age"] = sc.fit_transform(data["Age"].values.reshape(-1,1))
```

```
sc = StandardScaler()
data["SkinThickness"] = sc.fit_transform(data["SkinThickness"].values.reshape(-1,1))
```

5.Basic EDA

1.Gathering some info about data

```
data.describe().T
```

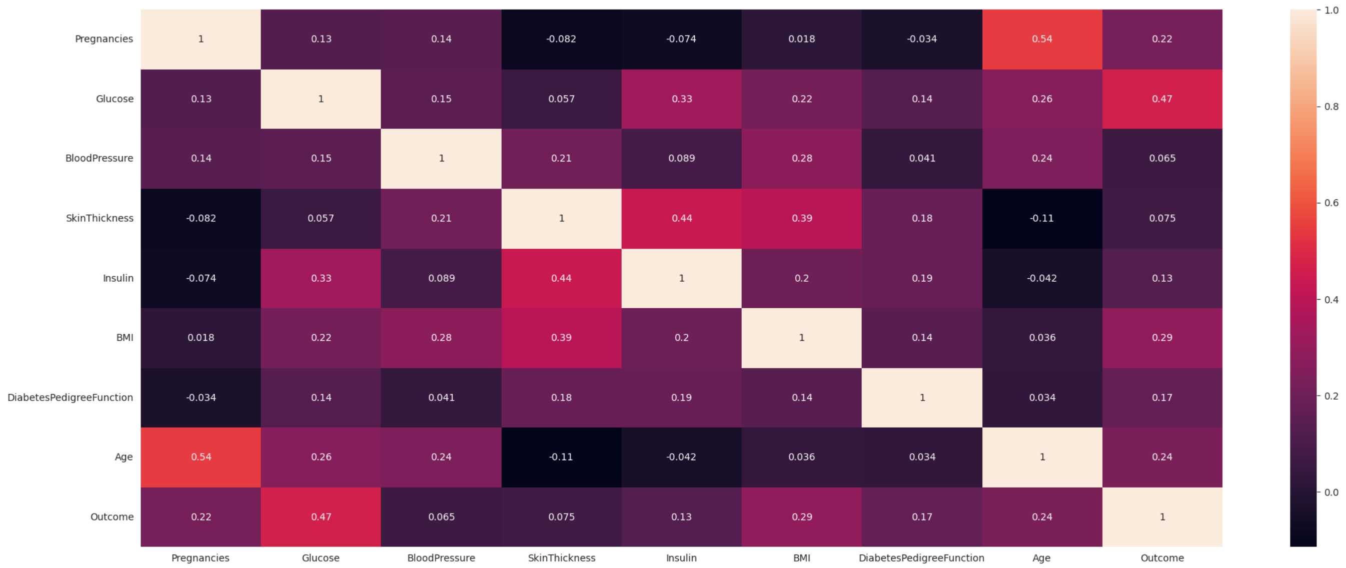
	count	mean	std	min	25%	50%	75%	max
Pregnancies	768.0	-6.476301e-17	1.000652	-1.141852	-0.844885	-0.250952	0.639947	3.906578
Glucose	768.0	-9.251859e-18	1.000652	-3.783654	-0.685236	-0.121888	0.605771	2.444478
BloodPressure	768.0	1.503427e-17	1.000652	-3.572597	-0.367337	0.149641	0.563223	2.734528
SkinThickness	768.0	1.006140e-16	1.000652	-1.288212	-1.288212	0.154533	0.719086	4.921866

```
1 data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               768 non-null    float64
 1   Glucose                   768 non-null    float64
 2   BloodPressure             768 non-null    float64
 3   SkinThickness             768 non-null    float64
 4   Insulin                   768 non-null    float64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    float64
 8   Outcome                   768 non-null    int64  
dtypes: float64(8), int64(1)
memory usage: 54.1 KB
```

2.Correlation plot

```
1 plt.figure(figsize = (25,10))
2 sb.heatmap(data.corr(),annot = True);
```



In general, a common approach is to set a correlation threshold (often a positive value) and keep features with correlations above that threshold. Common threshold values can range from 0.1 to 0.3

In this case I have decided the threshold value of 0.1

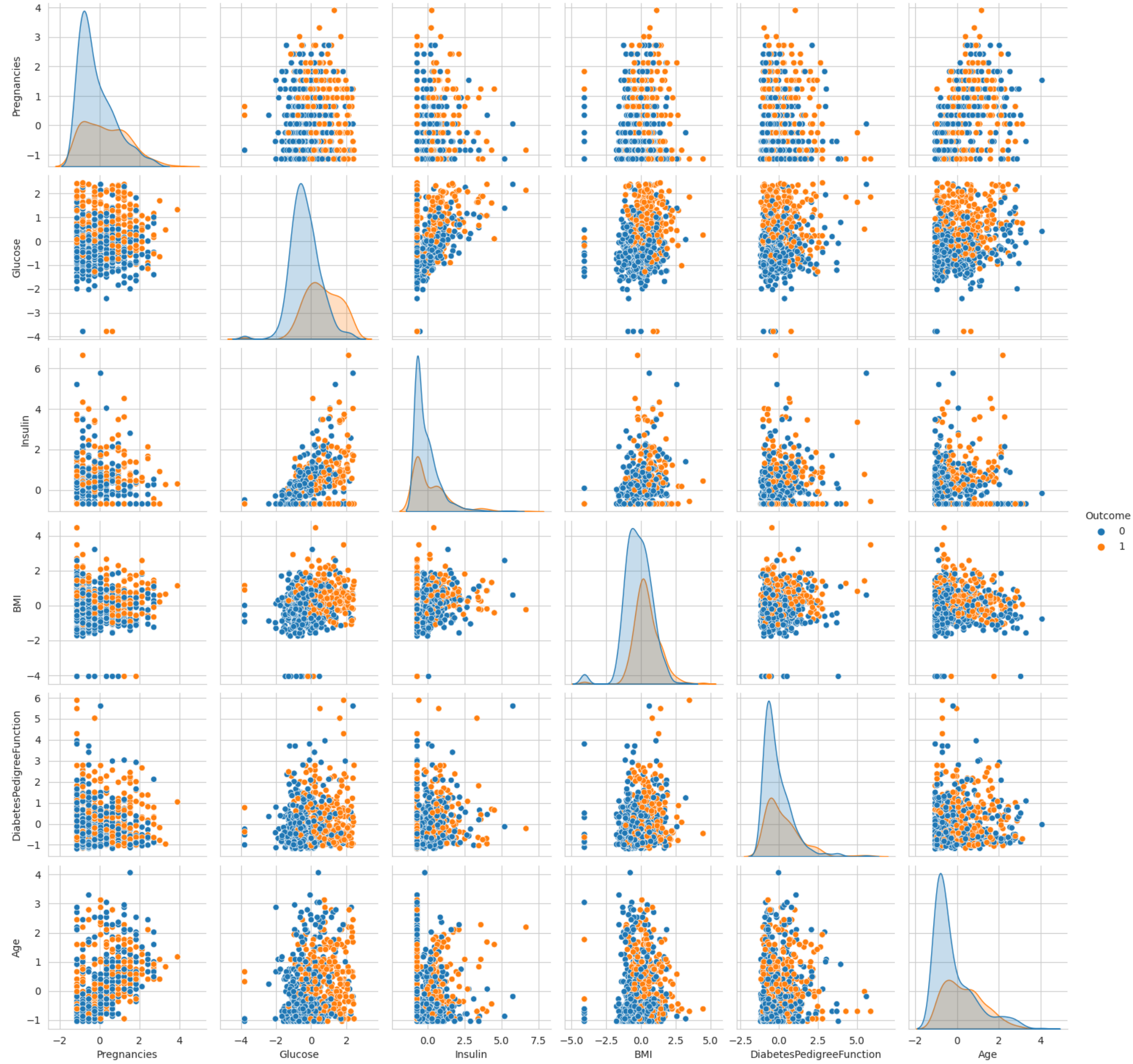
From above correlation chart we are rejecting BloodPressure and Skinthickness feature.

```
1 data.drop(["BloodPressure","SkinThickness"],1,inplace = True)
```

3.Pairplot

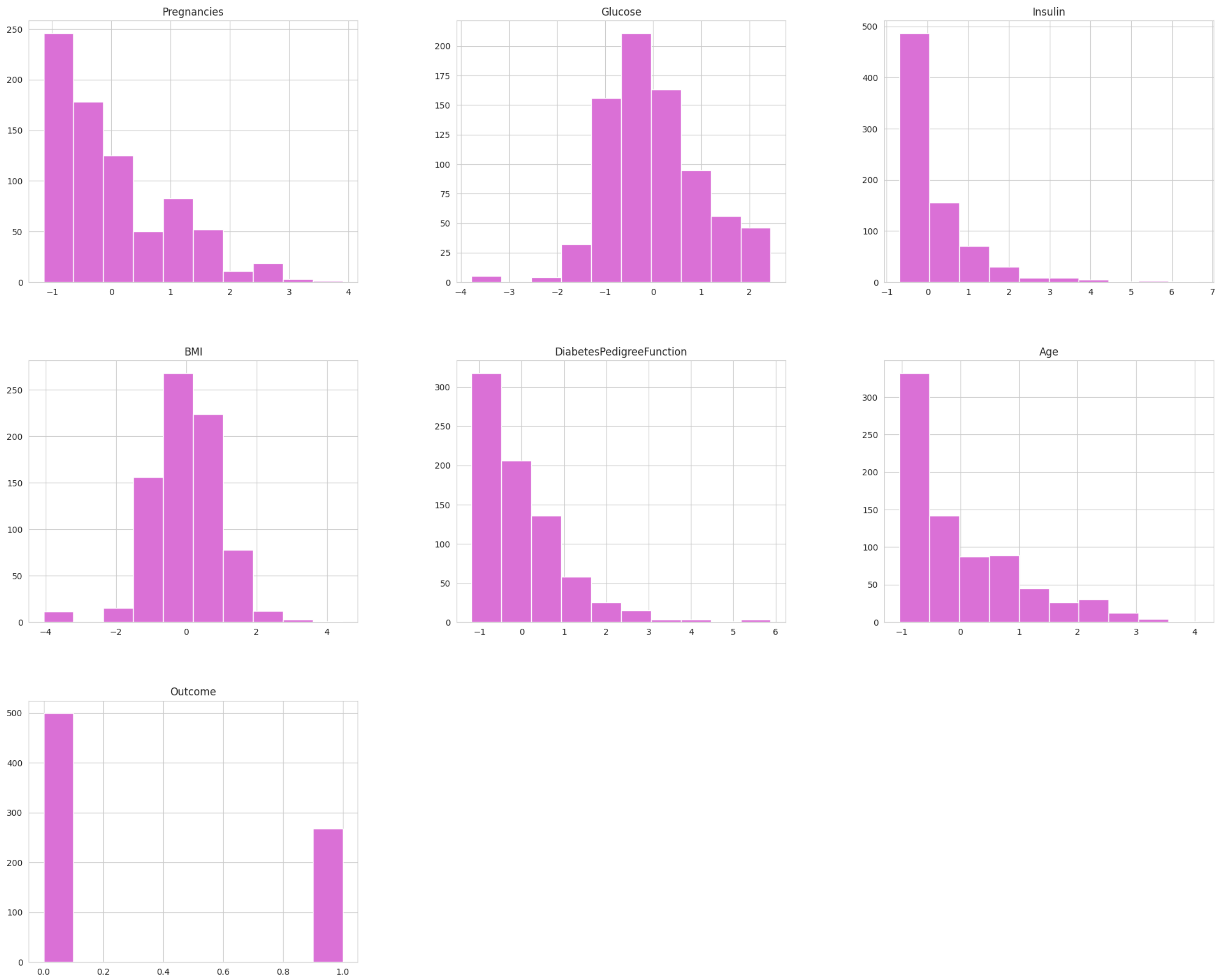
```
plt.figure(figsize = (25,25))
sb.pairplot(data,hue = "Outcome");
```

```
<Figure size 2500x2500 with 0 Axes>
```



4.You can plot using pandas too..

```
data.hist(figsize = (25,20),color = 'orchid');

```



6.Splitting the dataset

We split the given data as follows: 80% Train, 15%test and 5%validation. Note that we will face class imbalance problem but we do not aim to solve it here currently

```
1 data
```

	Pregnancies	Glucose	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	0.639947	0.848324	-0.692891	0.204013	0.468492	1.425995	1
1	-0.844885	-1.123396	-0.692891	-0.684422	-0.365061	-0.190672	0
2	1.233880	1.943724	-0.692891	-1.103255	0.604397	-0.105584	1
3	-0.844885	-0.998208	0.123302	-0.494043	-0.920763	-1.041549	0
4	-1.141852	0.504055	0.765836	1.409746	5.484909	-0.020496	1
...	...	...	...	...	...	...	...
763	1.827813	-0.622642	0.870031	0.115169	-0.908682	2.532136	0
764	-0.547919	0.034598	-0.692891	0.610154	-0.398282	-0.531023	0
765	0.342981	0.003301	0.279594	-0.735190	-0.685193	-0.275760	0
766	-0.844885	0.159787	-0.692891	-0.240205	-0.371101	1.170732	1
767	-0.844885	-0.873019	-0.692891	-0.202129	-0.473785	-0.871374	0

768 rows × 7 columns

```
x = data.iloc[:,:6]
y = data['Outcome']
```

```
x_train,x_part,y_train,y_part = train_test_split(x,y,test_size = 0.2,random_state = 42)
x_test,x_valid,y_test,y_valid = train_test_split(x_part,y_part,test_size = 0.25,random_state = 42)
```

```
print(x_train.shape,x_test.shape,x_valid.shape)
print(y_train.shape,y_test.shape,y_valid.shape)
```

```
(614, 6) (115, 6) (39, 6)
(614,) (115,) (39,)
```

7.Model Selection

Before we fit our data into our model we need to define some metrics with the help of which we can select the best fitting model

As our current task is classification we shall create a function that evaluates our model based on precision score,recall score and F1-score

```
def evaluate(model,model_name,x_train = x_train,y_train = y_train,x_test = x_test,y_test = y_test,x_va
  print(f"Model performance for{model_name}")
  y_train_pred = model.predict(x_train)
  y_test_pred = model.predict(x_test)
  y_valid_pred = model.predict(x_valid)

  #confusion matrix
  plt.figure(figsize = (10,10))
  sb.heatmap(confusion_matrix(y_train,y_train_pred),annot = True)
  plt.title('Confusion Matrix')
  plt.show()

  #precision score
  precision_score_train = precision_score(y_train,y_train_pred)
  precision_score_test = precision_score(y_test,y_test_pred)
  precision_score_valid = precision_score(y_valid,y_valid_pred)

  #recallscore
  recall_score_train = recall_score(y_train,y_train_pred)
  recall_score_test = recall_score(y_test,y_test_pred)
  recall_score_valid = recall_score(y_valid,y_valid_pred)

  #f1 score
  f1_score_train = f1_score(y_train,y_train_pred)
  f1_score_test = f1_score(y_test,y_test_pred)
  f1_score_valid = f1_score(y_valid,y_valid_pred)

  print("Precision Score Train:",precision_score_train)
  print("Precision Score Test:",precision_score_test)
  print("Precision Score Validation",precision_score_valid)

  print("recall Score Train:",recall_score_train)
  print("recal Score Test:",recall_score_test)
  print("recall Score Validation",recall_score_valid)

  print("f1 Score Train:",f1_score_train)
  print("f1 Score Test:",f1_score_test)
  print("f1 Score Validation",f1_score_valid)



  return precision_score_train,precision_score_test,precision_score_valid,recall_score_train,recall_sc

```

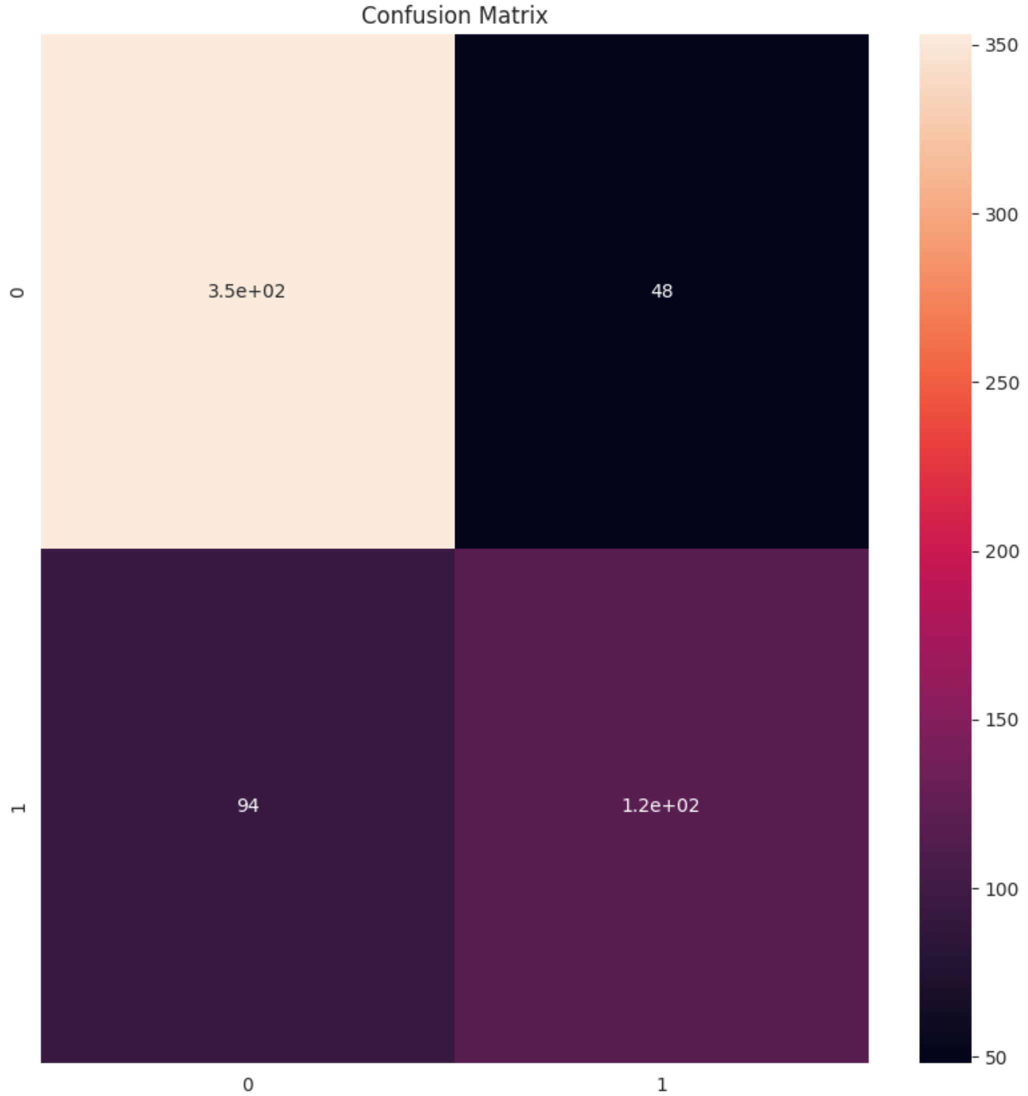
1.Logistic Regression

```
clf1 = LogisticRegression()
clf1.fit(x_train,y_train)
```

```
▾ LogisticRegression
LogisticRegression()
```

```
LR = evaluate(clf1,clf1)
```

```
Model performance forLogisticRegression()
```




```
Precision Score Train: 0.7125748502994012
Precision Score Test: 0.6410256410256411
Precision Score Validation 0.7333333333333333
recall Score Train: 0.5586854460093896
recal Score Test: 0.6578947368421053
recall Score Validation 0.6470588235294118
f1 Score Train: 0.6263157894736843
f1 Score Test: 0.6493506493506495
f1 Score Validation 0.6875
```

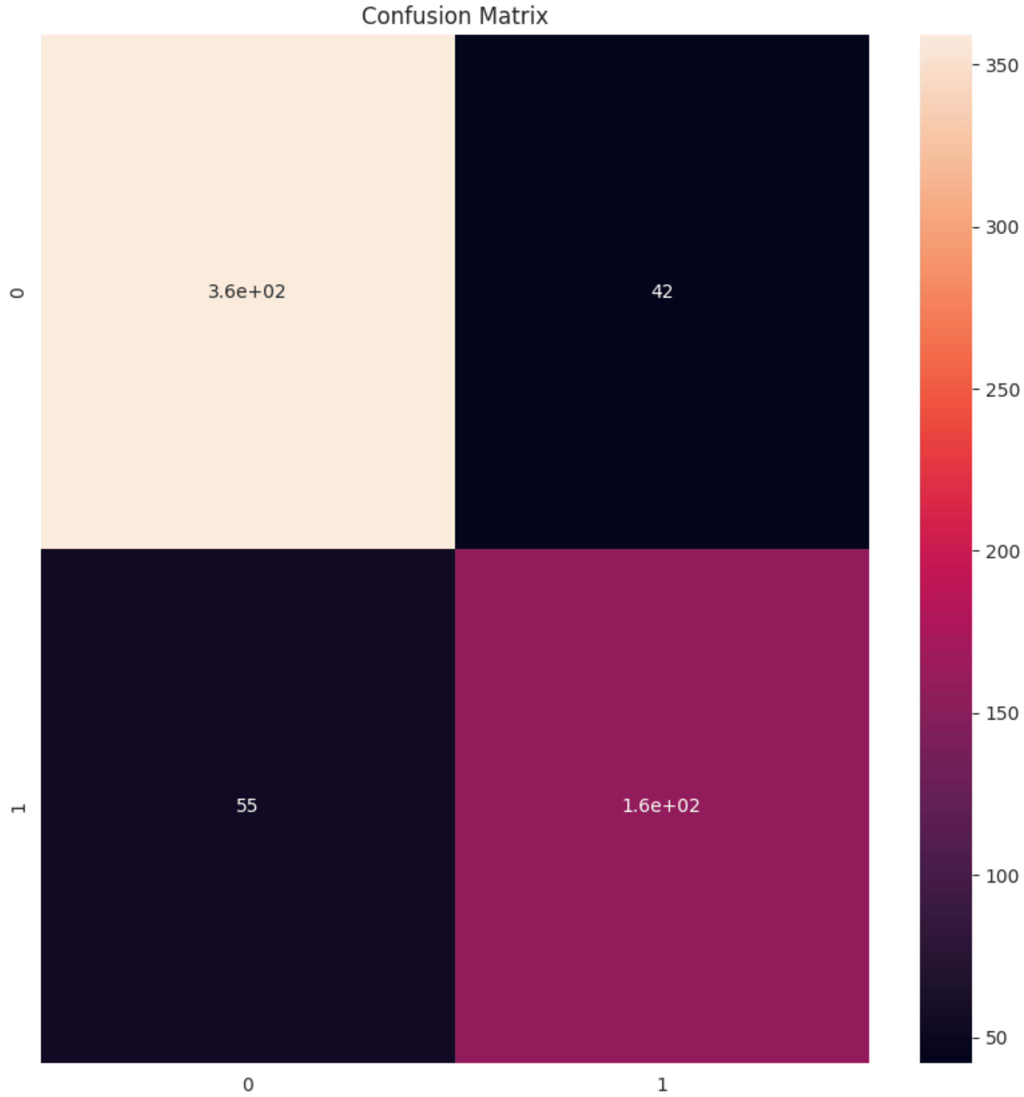
2.KNN

```
clf2 = KNeighborsClassifier(n_neighbors = 3)
clf2.fit(x_train,y_train)
```

```
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```

```
KNN = evaluate(clf2,clf2)
```

```
Model performance forKNeighborsClassifier(n_neighbors=3)
```




```
Precision Score Train: 0.79
Precision Score Test: 0.4883720930232558
Precision Score Validation 0.7857142857142857
recall Score Train: 0.7417840375586855
recal Score Test: 0.5526315789473685
recall Score Validation 0.6470588235294118
f1 Score Train: 0.7651331719128329
```

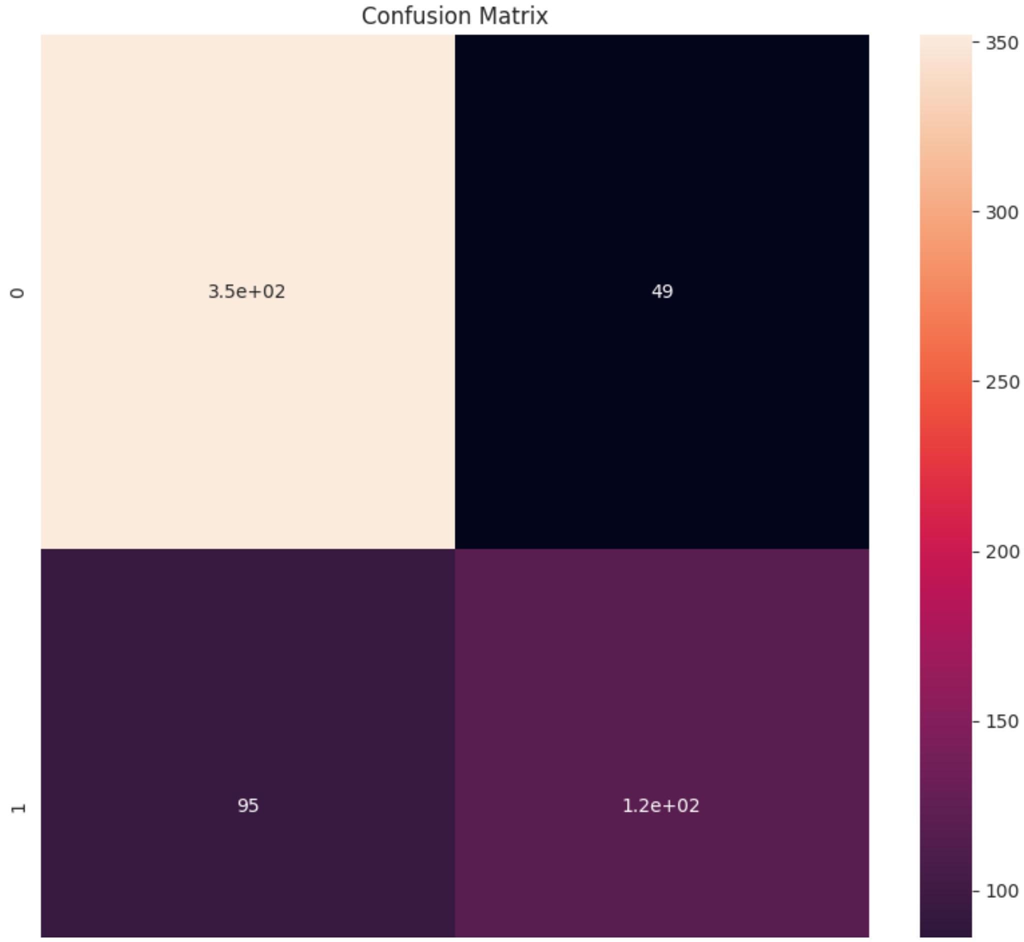
3.SVM

```
clf3 = SVC(kernel = "linear")
clf3.fit(x_train,y_train)
```

```
SVC
SVC(kernel='linear')
```

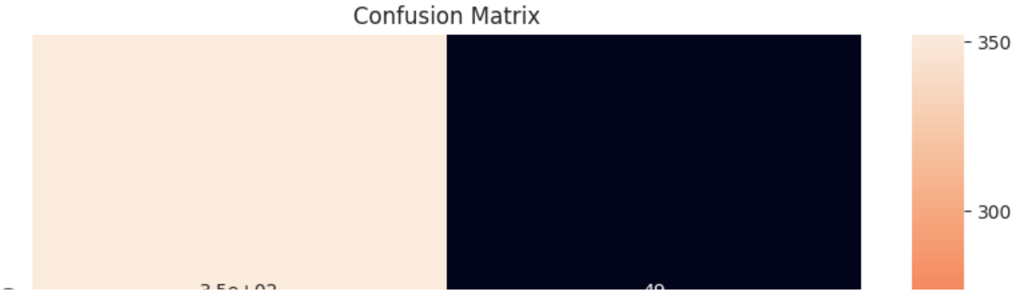
```
svc = evaluate(clf3,clf3)
```

```
Model performance forSVC(kernel='linear')
```




```
1  svc = evaluate(clf3,clf3)
```

```
Model performance forSVC(kernel='linear')
```




```
model_performance = [["Logistic Regression",LR[0],LR[1],LR[3],LR[4],LR[5],LR[6],LR[7],LR[8]],
                     ["Knearest Neighbors",KNN[0],KNN[1],KNN[3],KNN[4],KNN[5],KNN[6],KNN[7],KNN[8]],
                     ["Support Vector Machine",svc[0],svc[1],svc[3],svc[4],svc[5],svc[6],svc[7],svc[8]
```

```
model_performance = pd.DataFrame(model_performance,columns = ["Precision Score Train","Precision Score
```

```
model_performance
```

	Precision Score Train	Precision Score Test	Precision Score Validation	Recall Score Train	Recall Score Test	Recall Score Validation	F1 Score Train	F1 Score Test	F1 Score Validation
0	Logistic Regression	0.712575	0.641026	0.558685	0.657895	0.647059	0.626316	0.649351	0.687500
1	Knearest Neighbors	0.790000	0.488372	0.741784	0.552632	0.647059	0.765133	0.518519	0.709677
2	Support Vector Machine	0.706587	0.641026	0.553991	0.657895	0.647059	0.621053	0.649351	0.687500

DATASET03 - 50_Startups

50_Startups This dataset has data collected from New York, California and Florida about 50 business Startups. The variables used in the dataset are Profit, R&D spending, Administration Spending, and Marketing Spending.

1.Loading Required Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
from sklearn.preprocessing import LabelEncoder,StandardScaler
from sklearn.model_selection import train_test_split,GridSearchCV
import warnings
warnings.filterwarnings(action = 'ignore')
from sklearn.preprocessing import LabelEncoder,StandardScaler
from sklearn.linear_model import Lasso,LinearRegression,ElasticNet,Ridge
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,AdaBoostRegressor
from sklearn.model_selection import train_test_split,GridSearchCV,cross_val_score,cross_val_predict
from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
import xgboost
# import optuna
```

2. Load Dataset

```
data = pd.read_csv("https://raw.githubusercontent.com/Jatansahu/DEEP_LEARNING_ASSIGNMENTS/main/LAB_01/
```

```
# Previewing data
data.head()
```

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.80	471784.10	New York	192261.83
1	162597.70	151377.59	443898.53	California	191792.06
2	153441.51	101145.55	407934.54	Florida	191050.39
3	144372.41	118671.85	383199.62	New York	182901.99
4	142107.34	91391.77	366168.42	Florida	166187.94

Looking at the above dataset our target variable is the column "Profit"

3.Looking for Null values

```
1 print(data.isnull().sum())
```

```
R&D Spend          0
Administration     0
Marketing Spend    0
State              0
Profit             0
dtype: int64
```

Double-click (or enter) to edit

4.Preprocessing

1. Removing Unnecessary columns

```
1 data['State'].unique()
```

```
array(['New York', 'California', 'Florida'], dtype=object)
```

As of now, we don't know which column is not much related

2.Converting Categorical Variables into their corresponding form

```
1 print(data.dtypes)
```

```
R&D Spend          float64
Administration     float64
Marketing Spend    float64
State               object
Profit             float64
dtype: object
```

```
1 #encoding Embarked column
2 le = LabelEncoder()
3 data['State'] = le.fit_transform(data["State"])
```

```
1 data.head()
```

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.80	471784.10	2	192261.83
1	162597.70	151377.59	443898.53	0	191792.06
2	153441.51	101145.55	407934.54	1	191050.39
3	144372.41	118671.85	383199.62	2	182901.99
4	142107.34	91391.77	366168.42	1	166187.94

3.Scaling Features

In the same way as encoding features we can also scale features manually. Scikit learn as inbuilt scalers that do the same task. Here we shall use standard scaler for our task

```
sc = StandardScaler()
data["R&D Spend"] = sc.fit_transform(data["R&D Spend"].values.reshape(-1,1))
data["Administration"] = sc.fit_transform(data["Administration"].values.reshape(-1,1))
data["Marketing Spend"] = sc.fit_transform(data["Marketing Spend"].values.reshape(-1,1))
# data["Profit"] = sc.fit_transform(data["Profit"].values.reshape(-1,1))
```

There's an important consideration when it comes to interpretation. If we scale the target variable during preprocessing (for example, using MinMaxScaler to scale it to a specific range), we'll need to remember that any predictions made by the model will be in the scaled range. If we need to interpret the predictions in the original units (e.g., dollars for profit), we'll have to reverse the scaling transformation to get the predictions in the original scale."

```
profit_data = data[["Profit"]]  # Extracting the "Profit" column as a separate DataFrame
scaler = StandardScaler()
scaled_profit = scaler.fit_transform(profit_data.values.reshape(-1,1))
# Converting the scaled profit back to a pandas Series (if needed)
# scaled_profit_series = pd.Series(scaled_profit[:, 0], name="Scaled_Profit")
```

```
# # Get the mean and standard deviation from the scaler
# mean_profit = scaler.mean_[0]
# std_dev_profit = scaler.scale_[0]

# scaled_prediction =  2.01120333

# # Reverse the scaling to get the prediction in the original units
# original_prediction = (scaled_prediction * std_dev_profit) + mean_profit

# print("Original prediction in dollars:", original_prediction)

```

```
Original prediction in dollars: 192261.82983149818
```

```
# Droping profit column from dataset
data.drop(["Profit"],1,inplace = True)
```

```
data['scaled_profit'] = scaled_profit
```

```
data.head()
```

	R&D Spend	Administration	Marketing Spend	State	scaled_profit
0	2.016411	0.560753	2.153943	2	2.011203
1	1.955860	1.082807	1.923600	0	1.999430
2	1.754364	-0.728257	1.626528	1	1.980842
3	1.554784	-0.096365	1.422210	2	1.776627
4	1.504937	-1.079919	1.281528	1	1.357740

5.Basic EDA

1.Gathering some info about data

```
data.describe().T
```

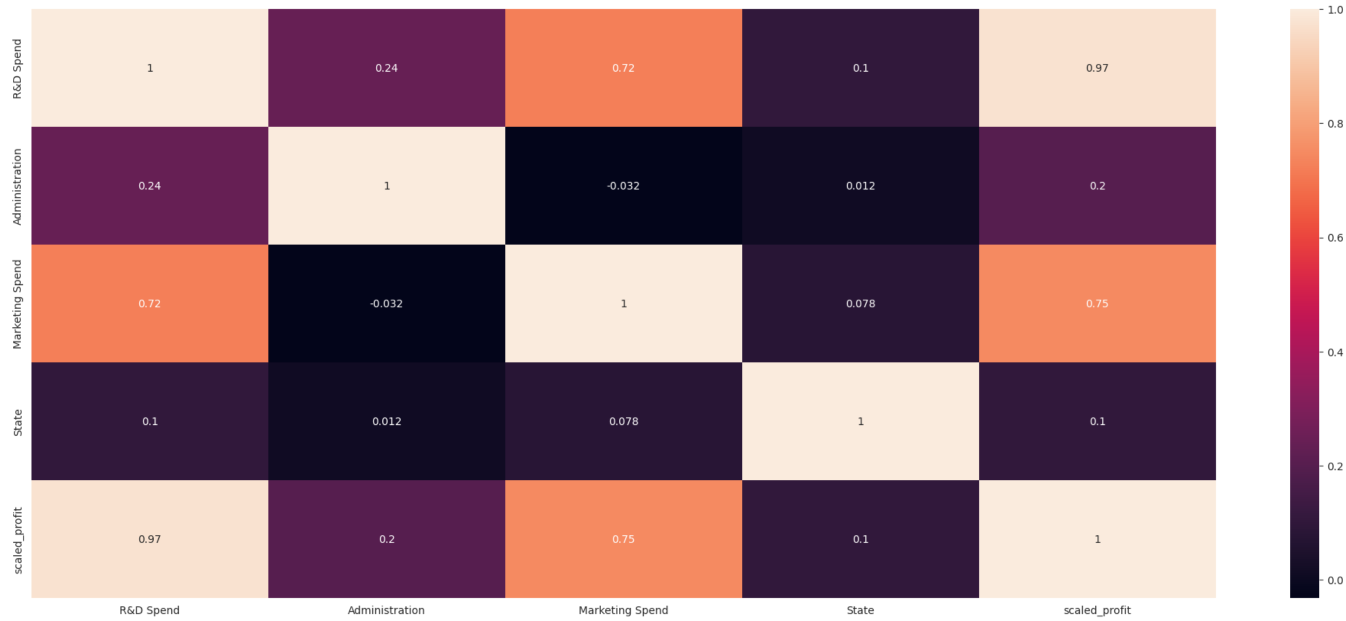
	count	mean	std	min	25%	50%	75%	max
R&D Spend	50.0	-4.884981e-17	1.010153	-1.622362	-0.743498	-0.014756	0.613570	2.016411
Administration	50.0	-2.997602e-17	1.010153	-2.525994	-0.635046	0.048859	0.847179	2.210141

```
1 data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   R&D Spend        50 non-null     float64
 1   Administration   50 non-null     float64
 2   Marketing Spend  50 non-null     float64
 3   State            50 non-null     int64  
 4   scaled_profit    50 non-null     float64
dtypes: float64(4), int64(1)
memory usage: 2.1 KB
```

2.Correlation plot

```
1 plt.figure(figsize = (25,10))
2 sb.heatmap(data.corr(),annot = True);
```

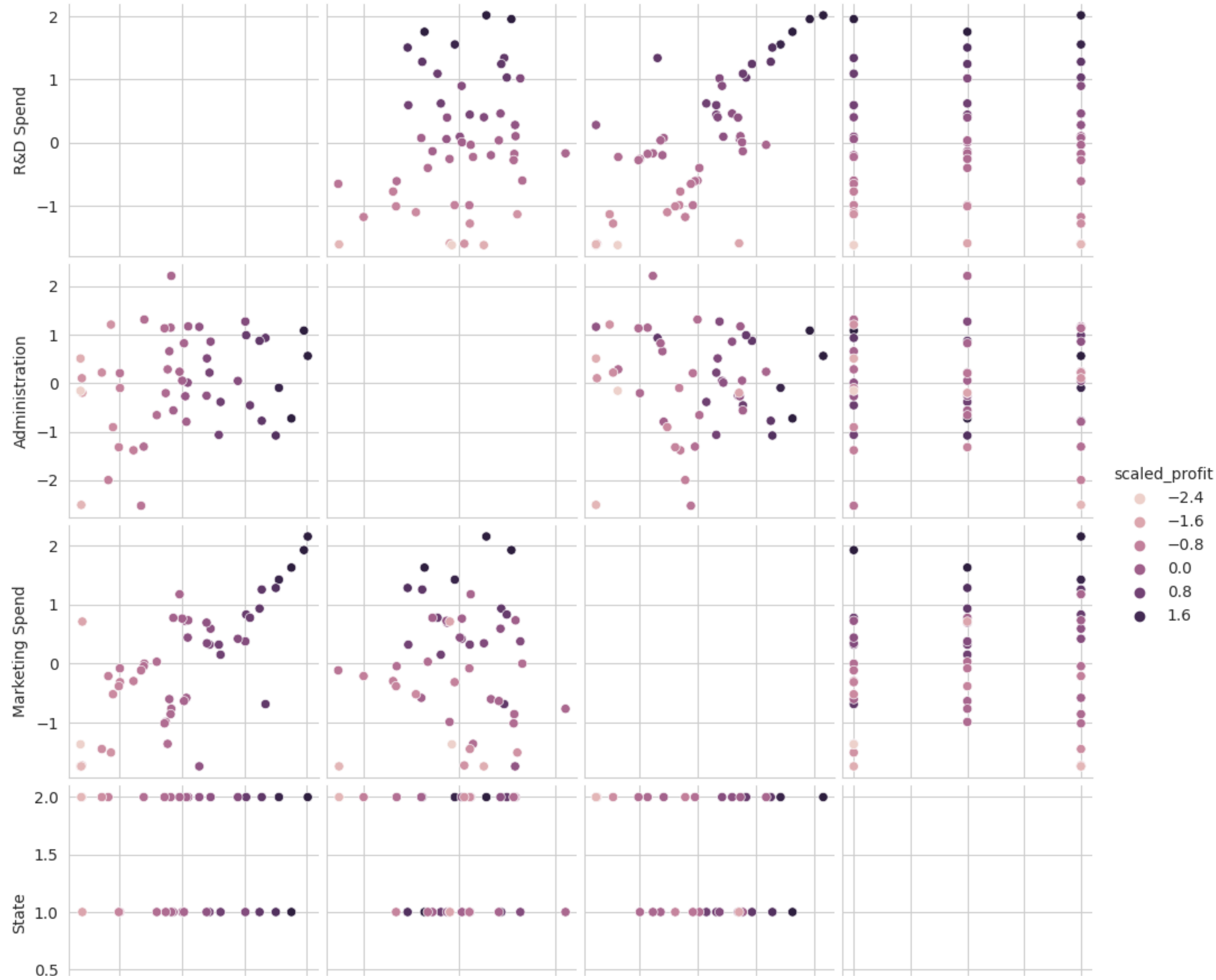


We will not take state as a feature in our data preprocessing part

3.Pairplot

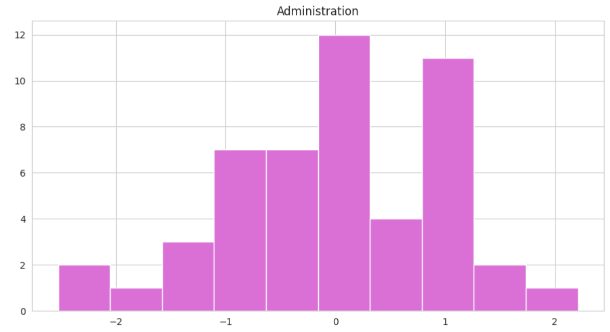
```
1 plt.figure(figsize = (25,25))
2 sb.pairplot(data,hue = "scaled_profit");
```

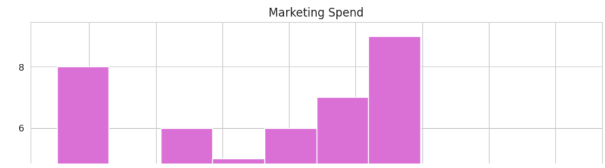
<Figure size 2500x2500 with 0 Axes>

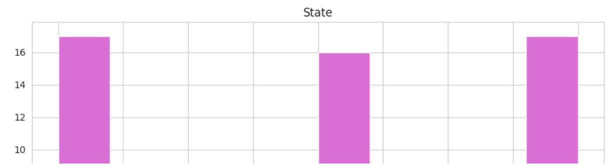


4.You can plot using pandas too..

```
data.hist(figsize = (25,20),color = 'orchid');
```







6.Splitting the dataset

We split the given data as follows: 80% Train, 15%test and 5%validation. Note that we will face class imbalance problem but we do not aim to solve it here currently

```
data.head()
```

	R&D Spend	Administration	Marketing Spend	State	scaled_profit
0	2.016411	0.560753	2.153943	2	2.011203
1	1.955860	1.082807	1.923600	0	1.999430
2	1.754364	-0.728257	1.626528	1	1.980842
3	1.554784	-0.096365	1.422210	2	1.776627
4	1.504937	-1.079919	1.281528	1	1.357740

```
x = data.iloc[:,:3]
y = data['scaled_profit']
```

```
x.head()
```

	R&D Spend	Administration	Marketing Spend
0	2.016411	0.560753	2.153943
1	1.955860	1.082807	1.923600
2	1.754364	-0.728257	1.626528
3	1.554784	-0.096365	1.422210
4	1.504937	-1.079919	1.281528

```
x_train,x_part,y_train,y_part = train_test_split(x,y,test_size = 0.20,random_state = 42)
x_test,x_valid,y_test,y_valid = train_test_split(x_part,y_part,test_size = 0.25,random_state = 42)
```

```
print(x_train.shape,x_test.shape,x_valid.shape)
print(y_train.shape,y_test.shape,y_valid.shape)
```

```
(40, 3) (7, 3) (3, 3)
(40,) (7,) (3,)
```

7.Model Selection

```
def model_performance(model,model_name,x_train = x_train,y_train = y_train,x_test = x_test,y_test = y_

    y_train_pred = model.predict(x_train)
```

```
    y_test_pred = model.predict(x_test)
    y_val_pred = model.predict(x_valid)

    Training_Score = np.round(model.score(x_train,y_train),3)
    Testing_Score = np.round(model.score(x_test,y_test),3)
    Validation_score = np.round(model.score(x_valid,y_valid))

    mse_training = np.round(mean_squared_error(y_train,y_train_pred),3)
    mse_testing = np.round(mean_squared_error(y_test,y_test_pred),3)
    mse_validation = np.round(mean_squared_error(y_valid,y_val_pred),3)

    mae_training = np.round(mean_absolute_error(y_train,y_train_pred),3)
    mae_testing = np.round(mean_absolute_error(y_test,y_test_pred),3)
    mae_valid = np.round(mean_absolute_error(y_valid,y_val_pred),3)

    r2_training = np.round(r2_score(y_train,y_train_pred),3)
    r2_testing = np.round(r2_score(y_test,y_test_pred),3)
    r2_valid = np.round(r2_score(y_valid,y_val_pred),3)

    print("Model Performance for:",model_name)
    print("")

    print("Training Score:",Training_Score)
    print("Testing Score:",Testing_Score)
    print("Validation Score",Validation_score)
    print("")

    print("Training Data Mean Squared Error:",mse_training)
    print("Testing Data Mean Squared Error:",mse_testing)
    print("Validation Data Mean Squared Error:",mse_validation)

    print("")

    print("Training Data Mean Absolute Error:",mae_training)
    print("Testing Data Mean Absolute Error:",mae_testing)
    print("Validation Data Mean Absolute Error:",mae_valid)
    print("")

    print("Training Data r2_score:",r2_training)
    print("Testing Data r2_score:",r2_testing)
    print("Validation Data r2_score:",r2_valid)
    print("")

    print("Residual Analysis:")
    plt.figure(figsize = (20,5))
    plt.scatter(y_train,(y_train-y_train_pred),color = "red",label = 'Training Predictions')
    plt.scatter(y_test,(y_test-y_test_pred),color = "green",label = 'Testing Predictions')
    plt.scatter(y_valid,(y_valid-y_val_pred),color = 'blue',label = "Validation Predictions")
    plt.legend()
    plt.show()

    return Training_Score,Testing_Score,Validation_score,mse_training,mse_testing,mse_validation,mae_t
```

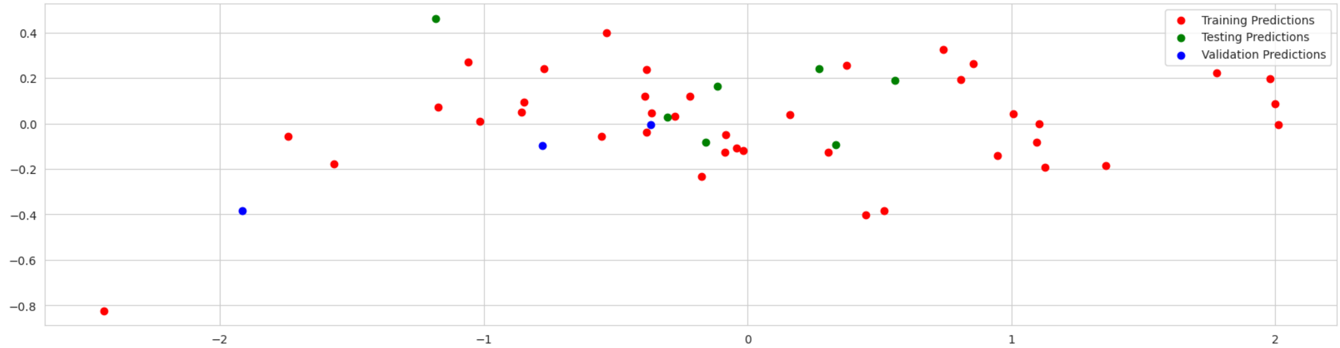
1. Linear Regression

```
model1 = LinearRegression()
model1.fit(x_train,y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
lr_perf = model_performance(model1,model_name = model1)
```

```
Model Performance for: LinearRegression()

Training Score: 0.954
Testing Score: 0.822
Validation Score 1.0

Training Data Mean Squared Error: 0.05
Testing Data Mean Squared Error: 0.05
Validation Data Mean Squared Error: 0.052

Training Data Mean Absolute Error: 0.165
Testing Data Mean Absolute Error: 0.18
Validation Data Mean Absolute Error: 0.163

Training Data r2_score: 0.954
Testing Data r2_score: 0.822
Validation Data r2_score: 0.878

Residual Analysis:
```



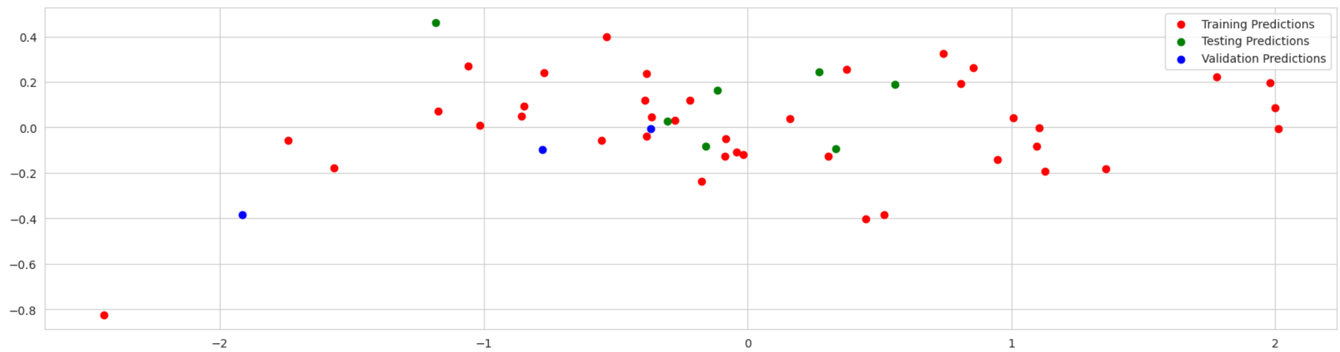
2. Ridge

```
1 model2 = Ridge(alpha = 0.01)
2 model2.fit(x_train,y_train)
```

```
▾ Ridge
Ridge(alpha=0.01)
```

```
1 ridge_perf = model_performance(model2,model2)
```

```
Model Performance for: Ridge(alpha=0.01)

Training Score: 0.954
Testing Score: 0.821
Validation Score 1.0

Training Data Mean Squared Error: 0.05
Testing Data Mean Squared Error: 0.05
Validation Data Mean Squared Error: 0.052

Training Data Mean Absolute Error: 0.165
Testing Data Mean Absolute Error: 0.18
Validation Data Mean Absolute Error: 0.163

Training Data r2_score: 0.954
Testing Data r2_score: 0.821
Validation Data r2_score: 0.878

Residual Analysis:
```



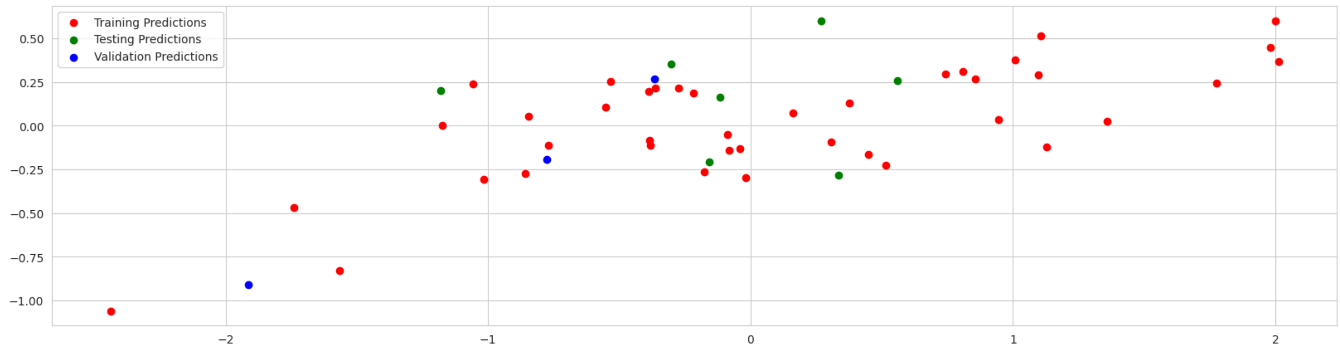
3. KNeighborsRegressor

```
model3 = KNeighborsRegressor(n_neighbors = 6)
model3.fit(x_train,y_train)
```

```
KNeighborsRegressor
KNeighborsRegressor(n_neighbors=6)
```

```
knn_perf = model_performance(model3,model3)
```

```
Model Performance for: KNeighborsRegressor(n_neighbors=6)

Training Score: 0.899
Testing Score: 0.625
Validation Score 0.0

Training Data Mean Squared Error: 0.109
Testing Data Mean Squared Error: 0.106
Validation Data Mean Squared Error: 0.312

Training Data Mean Absolute Error: 0.254
Testing Data Mean Absolute Error: 0.294
Validation Data Mean Absolute Error: 0.457

Training Data r2_score: 0.899
Testing Data r2_score: 0.625
Validation Data r2_score: 0.272

Residual Analysis:
```



Linear Regression is giving best result

```
prediction = model1.predict(x_test)
```

```
prediction
```

```
array([ 0.36817016, -0.27904443, -0.32879361,  0.02740562,  0.42895473,
       -1.64183341, -0.07508783])
```

```
# Get the mean and standard deviation from the scaler
mean_profit = scaler.mean_[0]
std_dev_profit = scaler.scale_[0]

scaled_prediction =  prediction

# Reverse the scaling to get the prediction in the original units
original_prediction = (scaled_prediction * std_dev_profit) + mean_profit

print("Original prediction in dollars:", original_prediction)
```

```
Original prediction in dollars: [126703.02716461 100878.4641454   98893.41815974 113106.15292226
 129128.39734381  46501.70815036 109016.5536578 ]
```