Predict the price of the Uber ride from a given pickup point to the agreed drop-off location.
Perform following tasks:

1. Pre-process the dataset.
2. Identify outliers.
3. Check the correlation.
4. Implement linear regression and random forest regression models.
5. Evaluate the models and compare their respective scores like R2, RMSE, etc.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
```

In [2]:
```
df = pd.read_csv('https://raw.githubusercontent.com/sahil-gidwani/ML/main/data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 9 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   Unnamed: 0         200000 non-null  int64  
 1   key                200000 non-null  object 
 2   fare_amount        200000 non-null  float64
 3   pickup_datetime    200000 non-null  object 
 4   pickup_longitude   200000 non-null  float64
 5   pickup_latitude    200000 non-null  float64
 6   dropoff_longitude  199999 non-null  float64
 7   dropoff_latitude   199999 non-null  float64
 8   passenger_count    200000 non-null  int64  
dtypes: float64(5), int64(2), object(2)
memory usage: 13.7+ MB
```

1. Pre-process the dataset.

In [3]:
```
df.shape
```

Out[3]:
```
(200000, 9)
```

In [4]:
```
df.head()
```

Out[4]:

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitud
0	24238194	2015-05-07 19:52:06.0000003	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.73835
1	27835199	2009-07-17 20:04:56.0000002	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.72822
2	44984355	2009-08-24 21:45:00.00000061	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.74077
3	25894730	2009-06-26 08:22:21.0000001	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.79084
4	17610152	2014-08-28 17:47:00.000000188	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.74408

In [5]:
```
df.isnull()
```

Out[5]:

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	drop
0	False	False	False	False	False	False	
1	False	False	False	False	False	False	
2	False	False	False	False	False	False	
3	False	False	False	False	False	False	
4	False	False	False	False	False	False	
...	...	...	...	...	...	...	
199995	False	False	False	False	False	False	
199996	False	False	False	False	False	False	
199997	False	False	False	False	False	False	
199998	False	False	False	False	False	False	
199999	False	False	False	False	False	False	

200000 rows × 9 columns

In [6]:
```
df.drop(columns=["Unnamed: 0", "key"], inplace=True)
df.head()
```

Out[6]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_la
0	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.7
1	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.7
2	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.7
3	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	40.8
4	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	40.7

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1
passenger_count      0
dtype: int64
```

In [8]:
```
df['dropoff_latitude'].fillna(value=df['dropoff_latitude'].mean(),inplace = Tr
df['dropoff_longitude'].fillna(value=df['dropoff_longitude'].median(),inplace
```

In [9]:
```
df.dtypes
```

Out[9]:
```
fare_amount          float64
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
dtype: object
```

In [10]:
```
# From the above output, we see that the data type of 'pickup_datetime' is 'ob
# But 'pickup_datetime'is a date time stamp variable, which is wrongly interpr
```

In [11]:
```
df.pickup_datetime = pd.to_datetime(df.pickup_datetime)
df.dtypes
```

Out[11]:
```
fare_amount                       float64
pickup_datetime      datetime64[ns, UTC]
pickup_longitude                  float64
pickup_latitude                   float64
dropoff_longitude                 float64
dropoff_latitude                  float64
passenger_count                     int64
dtype: object
```

In [12]:
```
# we will extract time feature from the 'pickup_datetime'
# we will add a variable which measures the distance between pickup and drop
```

In [13]:
```
df = df.assign(hour = df.pickup_datetime.dt.hour,
               day = df.pickup_datetime.dt.day,
               month = df.pickup_datetime.dt.month,
               year = df.pickup_datetime.dt.year,
               dayofweek = df.pickup_datetime.dt.dayofweek)
```

In [14]:
```
df
```

Out[14]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	drop
0	7.5	2015-05-07 19:52:06+00:00	-73.999817	40.738354	-73.999512	
1	7.7	2009-07-17 20:04:56+00:00	-73.994355	40.728225	-73.994710	
2	12.9	2009-08-24 21:45:00+00:00	-74.005043	40.740770	-73.962565	
3	5.3	2009-06-26 08:22:21+00:00	-73.976124	40.790844	-73.965316	
4	16.0	2014-08-28 17:47:00+00:00	-73.925023	40.744085	-73.973082	
...	...	...	...	...	...	
199995	3.0	2012-10-28 10:49:00+00:00	-73.987042	40.739367	-73.986525	
199996	7.5	2014-03-14 01:09:00+00:00	-73.984722	40.736837	-74.006672	
199997	30.9	2009-06-29 00:42:00+00:00	-73.986017	40.756487	-73.858957	
199998	14.5	2015-05-20 14:56:25+00:00	-73.997124	40.725452	-73.983215	
199999	14.1	2010-05-15 04:08:00+00:00	-73.984395	40.720077	-73.985508	

200000 rows × 12 columns

In [15]:
```
df = df.drop(["pickup_datetime"], axis =1)
df
```

Out[15]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	pass
0	7.5	-73.999817	40.738354	-73.999512	40.723217	
1	7.7	-73.994355	40.728225	-73.994710	40.750325	
2	12.9	-74.005043	40.740770	-73.962565	40.772647	
3	5.3	-73.976124	40.790844	-73.965316	40.803349	
4	16.0	-73.925023	40.744085	-73.973082	40.761247	
...	...	...	...	...	...	
199995	3.0	-73.987042	40.739367	-73.986525	40.740297	
199996	7.5	-73.984722	40.736837	-74.006672	40.739620	
199997	30.9	-73.986017	40.756487	-73.858957	40.692588	
199998	14.5	-73.997124	40.725452	-73.983215	40.695415	
199999	14.1	-73.984395	40.720077	-73.985508	40.768793	

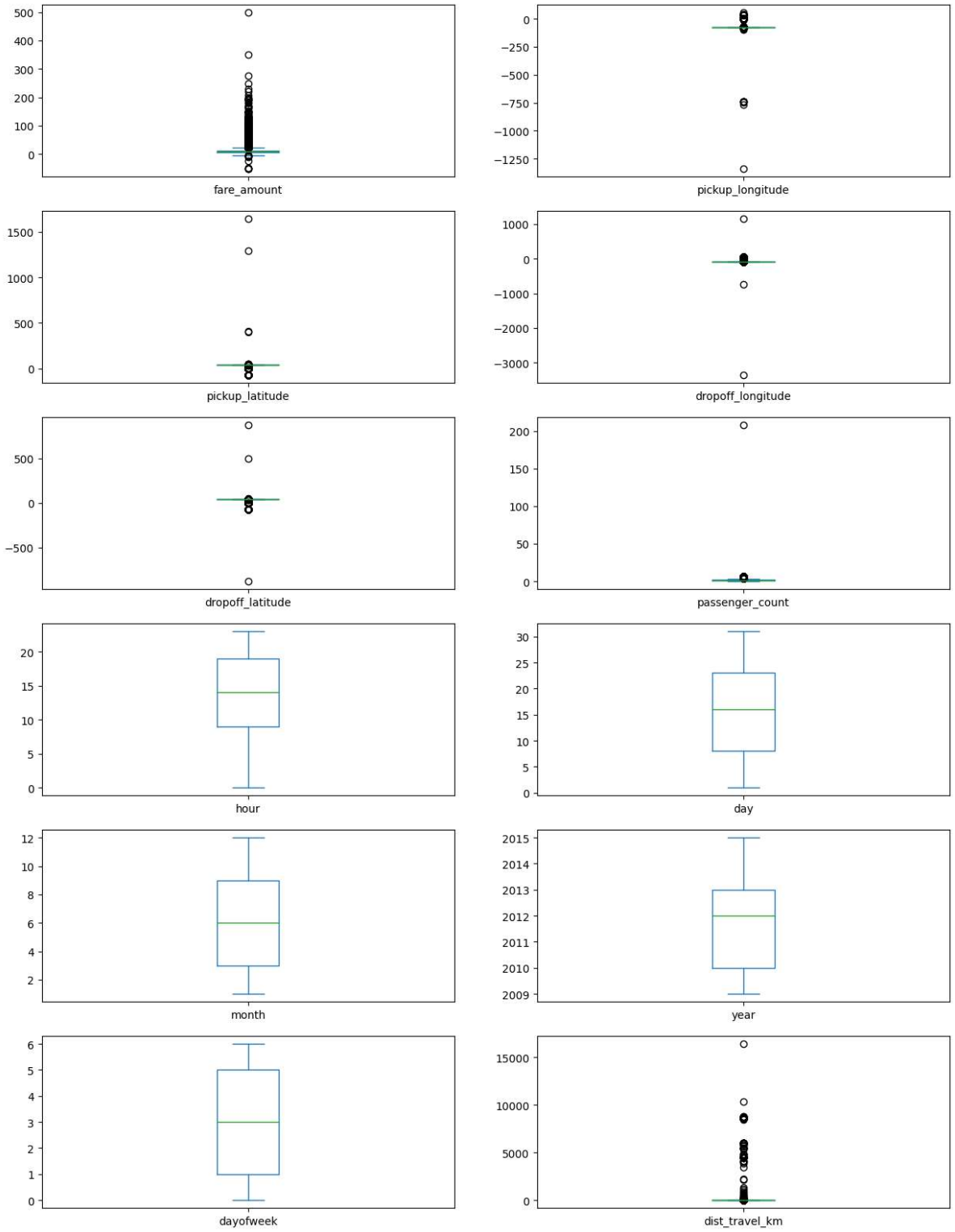
200000 rows × 11 columns

In [16]:
```
# function to calculate the travel distance from the longitudes and latitudes
from math import *

def distance_formula(longitude1, latitude1, longitude2, latitude2):
    travel_dist = []

    for pos in range (len(longitude1)):
        lon1, lan1, lon2, lan2 = map(radians, [longitude1[pos], latitude1[pos]
        dist_lon = lon2 - lon1
        dist_lan = lan2 - lan1

        a = sin(dist_lan/2)**2 + cos(lan1) * cos(lan2) * sin(dist_lon/2)**2

        #radius of earth = 6371
        c = 2 * asin(sqrt(a)) * 6371
        travel_dist.append(c)

    return  travel_dist
```

In [17]:
```
df['dist_travel_km'] = distance_formula(df.pickup_longitude.to_numpy(), df.pic
```

2. Identify outliers.

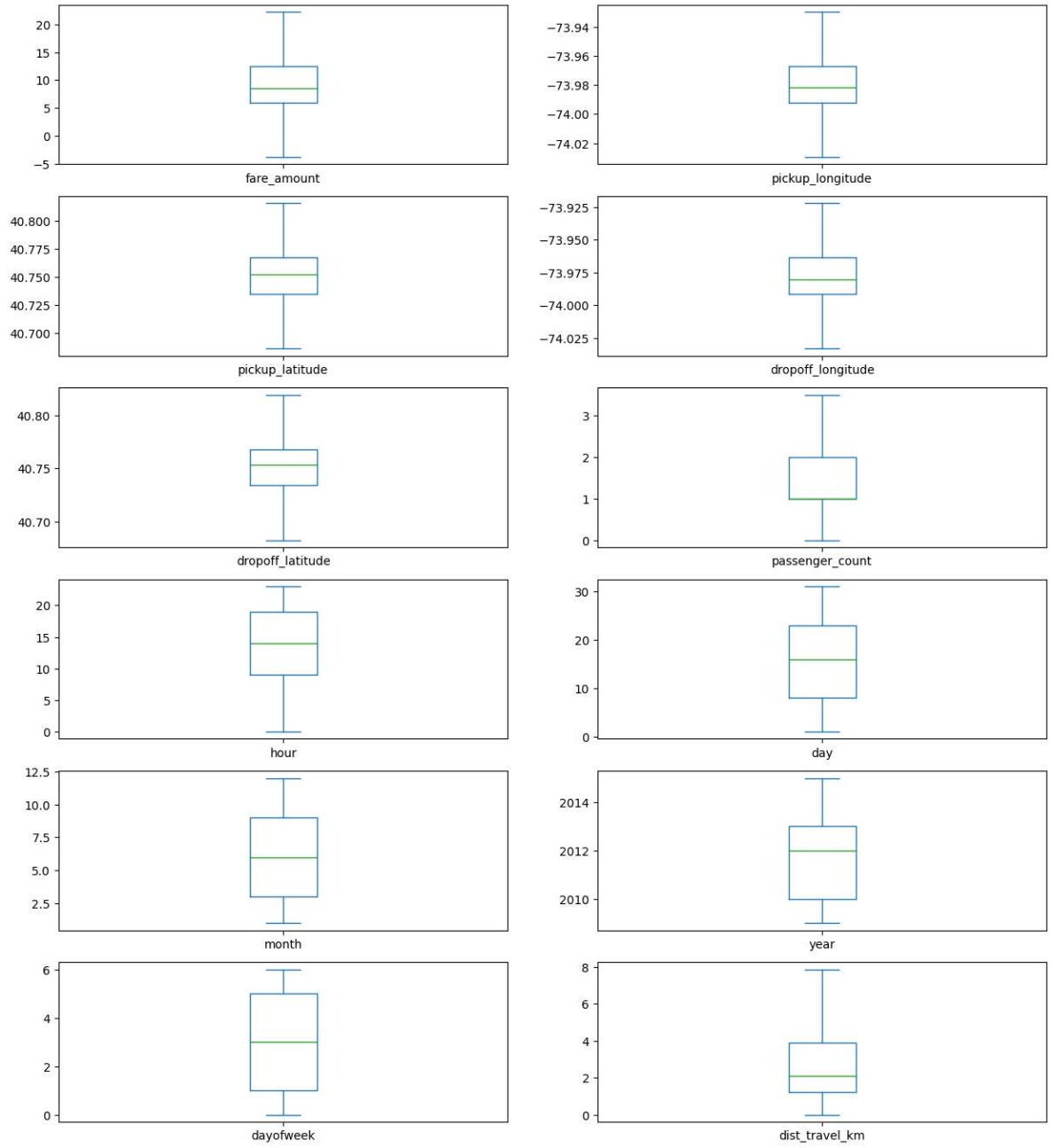
In [18]:
```
df.plot(kind = "box",subplots = True,layout = (6,2),figsize=(15,20)) #Boxplot
plt.show()
```



In [19]:
```
#Using the InterQuartile Range to fill the values
def remove_outlier(df1 , col):
    Q1 = df1[col].quantile(0.25)
    Q3 = df1[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_whisker = Q1-1.5*IQR
    upper_whisker = Q3+1.5*IQR
    df[col] = np.clip(df1[col] , lower_whisker , upper_whisker)
    return df1

def treat_outliers_all(df1 , col_list):
    for c in col_list:
        df1 = remove_outlier(df , c)
    return df1
```

In [20]:
```
df = treat_outliers_all(df , df.iloc[: , 0::])
```

In [21]:
```
#Boxplot shows that dataset is free from outliers
df.plot(kind = "box",subplots = True,layout = (7,2),figsize=(15,20))
plt.show()
```



3. Check the correlation.

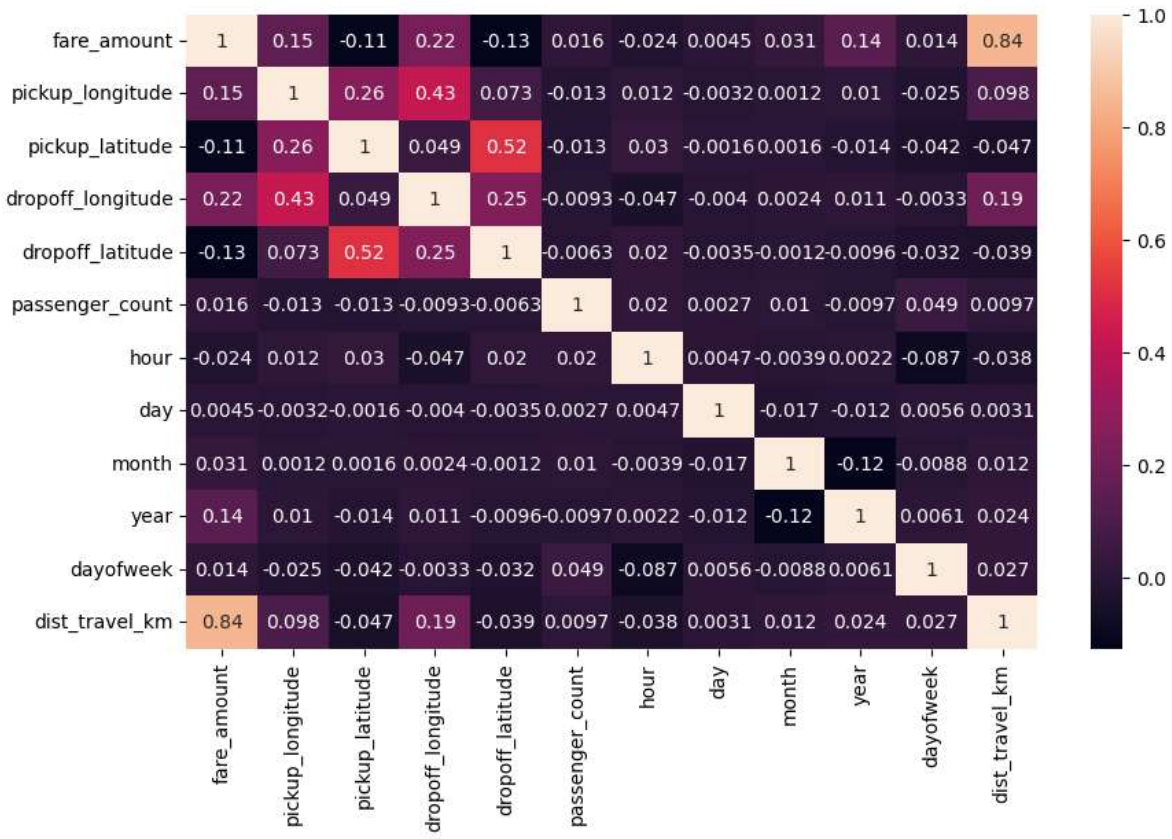
In [22]:
```
#Function to find the correlation
corr = df.corr()
corr
```

Out[22]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latit
fare_amount	1.000000	0.154069	-0.110842	0.218675	-0.125
pickup_longitude	0.154069	1.000000	0.259497	0.425619	0.073
pickup_latitude	-0.110842	0.259497	1.000000	0.048889	0.515
dropoff_longitude	0.218675	0.425619	0.048889	1.000000	0.245
dropoff_latitude	-0.125898	0.073290	0.515714	0.245667	1.000
passenger_count	0.015778	-0.013213	-0.012889	-0.009303	-0.006
hour	-0.023623	0.011579	0.029681	-0.046558	0.019
day	0.004534	-0.003204	-0.001553	-0.004007	-0.003
month	0.030817	0.001169	0.001562	0.002391	-0.001
year	0.141277	0.010198	-0.014243	0.011346	-0.009
dayofweek	0.013652	-0.024652	-0.042310	-0.003336	-0.031
dist_travel_km	0.844374	0.098094	-0.046812	0.186531	-0.038

In [23]:
```
fig,axis = plt.subplots(figsize = (10,6))
sns.heatmap(df.corr(),annot = True) #Correlation Heatmap (Light values means h
```

Out[23]: <Axes: >



4. Implement linear regression and random forest regression models.

In [24]:
```
# Dividing the dataset into feature and target values
df_x = df[['pickup_longitude','pickup_latitude','dropoff_longitude','dropoff_l
df_y = df['fare_amount']
```

In [25]:
```
# Dividing the dataset into training and testing dataset
x_train, x_test, y_train, y_test = train_test_split(df_x, df_y, test_size=0.2,
```

In [26]:
```
df
```

Out[26]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	pass
0	7.50	-73.999817	40.738354	-73.999512	40.723217	
1	7.70	-73.994355	40.728225	-73.994710	40.750325	
2	12.90	-74.005043	40.740770	-73.962565	40.772647	
3	5.30	-73.976124	40.790844	-73.965316	40.803349	
4	16.00	-73.929786	40.744085	-73.973082	40.761247	
...	...	...	...	...	...	
199995	3.00	-73.987042	40.739367	-73.986525	40.740297	
199996	7.50	-73.984722	40.736837	-74.006672	40.739620	
199997	22.25	-73.986017	40.756487	-73.922036	40.692588	
199998	14.50	-73.997124	40.725452	-73.983215	40.695415	
199999	14.10	-73.984395	40.720077	-73.985508	40.768793	

200000 rows × 12 columns

In [27]:
```
from sklearn.linear_model import LinearRegression

# initialize the linear regression model
reg = LinearRegression()

# Train the model with our training data
reg.fit(x_train, y_train)
```

Out[27]:
```
LinearRegression()
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [28]:
```
y_pred_lin = reg.predict(x_test)
print(y_pred_lin)
```

```
[ 6.27615184  5.09986098  9.43641238 ... 11.07663949 12.15392248
 11.41496075]
```

In [29]:
```
from sklearn.ensemble import RandomForestRegressor

#Here n_estimators means number of trees you want to build before making the p
rf = RandomForestRegressor(n_estimators=100)
rf.fit(x_train,y_train)
```

Out[29]:
```
RandomForestRegressor()
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [30]:
```
y_pred_rf = rf.predict(x_test)
print(y_pred_rf)
```

```
[ 5.105   6.561   9.5875 ... 11.415  11.6615 13.659 ]
```

5. Evaluate the models and compare their respective scores like R2, RMSE, etc

In [31]:
```
cols = ['Model', 'RMSE', 'R-Squared']

# create a empty dataframe of the colums
# columns: specifies the columns to be selected
result_tabulation = pd.DataFrame(columns = cols)
```

In [32]:
```
from sklearn import metrics
from sklearn.metrics import r2_score

reg_RMSE = np.sqrt(metrics.mean_squared_error(y_test, y_pred_lin))
reg_squared = r2_score(y_test, y_pred_lin)

full_metrics = pd.Series({'Model': "Linear Regression", 'RMSE' : reg_RMSE, 'R-

# append our result table using append()
# ignore_index=True: does not use the index labels
# python can only append a Series if ignore_index=True or if the Series has a
result_tabulation = result_tabulation.append(full_metrics, ignore_index = True

# print the result table
result_tabulation
```

```
<ipython-input-32-3a51173ca998>:12: FutureWarning: The frame.append method is
deprecated and will be removed from pandas in a future version. Use pandas.co
ncat instead.
  result_tabulation = result_tabulation.append(full_metrics, ignore_index = T
rue)
```

Out[32]:

	Model	RMSE	R-Squared
0	Linear Regression	2.703957	0.753906

In [33]:
```
rf_RMSE = np.sqrt(metrics.mean_squared_error(y_test, y_pred_rf))
rf_squared = r2_score(y_test, y_pred_rf)


full_metrics = pd.Series({'Model': "Random Forest ", 'RMSE':rf_RMSE, 'R-Square
# append our result table using append()
# ignore_index=True: does not use the index labels
# python can only append a Series if ignore_index=True or if the Series has a
result_tabulation = result_tabulation.append(full_metrics, ignore_index = True

# print the result table
result_tabulation
```

```
<ipython-input-33-37c52c9744f2>:9: FutureWarning: The frame.append method is
deprecated and will be removed from pandas in a future version. Use pandas.co
ncat instead.
  result_tabulation = result_tabulation.append(full_metrics, ignore_index = T
rue)
```

Out[33]:

	Model	RMSE	R-Squared
0	Linear Regression	2.703957	0.753906
1	Random Forest	2.363103	0.812040

Classify the email using the binary classification method. Email Spam detection has two states: a) Normal State – Not Spam, b) Abnormal State – Spam. Use K-Nearest Neighbors and Support Vector Machine for classification. Analyze their performance. Dataset link: The emails.csv dataset on the Kaggle https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv (https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv)

In [15]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
```

In [16]:
```
df = pd.read_csv('emails.csv')
df
```

Out[16]:

	Email No.	the	to	ect	and	for	of	a	you	hou	...	connevey	jay	valued	lay	infrastru
0	Email 1	0	0	1	0	0	0	2	0	0	...	0	0	0	0	
1	Email 2	8	13	24	6	6	2	102	1	27	...	0	0	0	0	
2	Email 3	0	0	1	0	0	0	8	0	0	...	0	0	0	0	
3	Email 4	0	5	22	0	5	1	51	2	10	...	0	0	0	0	
4	Email 5	7	6	17	1	5	2	57	0	9	...	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
5167	Email 5168	2	2	2	3	0	0	32	0	0	...	0	0	0	0	
5168	Email 5169	35	27	11	2	6	5	151	4	3	...	0	0	0	0	
5169	Email 5170	0	0	1	1	0	0	11	0	0	...	0	0	0	0	
5170	Email 5171	2	7	1	0	2	1	28	2	0	...	0	0	0	0	
5171	Email 5172	22	24	5	1	6	5	148	8	2	...	0	0	0	0	

5172 rows × 3002 columns

In [17]:
```
df.shape
```

Out[17]:
```
(5172, 3002)
```

In [18]:
```
df.isnull().any()
```

Out[18]:
```
Email No.     False
the           False
to            False
ect           False
and           False
              ...
military      False
allowing      False
ff            False
dry           False
Prediction    False
Length: 3002, dtype: bool
```

In [19]:
```
df.drop(columns='Email No.', inplace=True)
df
```

Out[19]:

	the	to	ect	and	for	of	a	you	hou	in	...	connevey	jay	valued	lay	infrastructu
0	0	0	1	0	0	0	2	0	0	0	...	0	0	0	0	
1	8	13	24	6	6	2	102	1	27	18	...	0	0	0	0	
2	0	0	1	0	0	0	8	0	0	4	...	0	0	0	0	
3	0	5	22	0	5	1	51	2	10	1	...	0	0	0	0	
4	7	6	17	1	5	2	57	0	9	3	...	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
5167	2	2	2	3	0	0	32	0	0	5	...	0	0	0	0	
5168	35	27	11	2	6	5	151	4	3	23	...	0	0	0	0	
5169	0	0	1	1	0	0	11	0	0	1	...	0	0	0	0	
5170	2	7	1	0	2	1	28	2	0	8	...	0	0	0	0	
5171	22	24	5	1	6	5	148	8	2	23	...	0	0	0	0	

5172 rows × 3001 columns

In [20]:
```
df.columns
```

Out[20]:
```
Index(['the', 'to', 'ect', 'and', 'for', 'of', 'a', 'you', 'hou', 'in',
       ...
       'connevey', 'jay', 'valued', 'lay', 'infrastructure', 'military',
       'allowing', 'ff', 'dry', 'Prediction'],
      dtype='object', length=3001)
```

In [21]:
```
df.Prediction.unique()
```

Out[21]:
```
array([0, 1])
```

In [22]:
```
df['Prediction'] = df['Prediction'].replace({0:'Not spam', 1:'Spam'})
```

In [23]:
```
df
```

Out[23]:

	the	to	ect	and	for	of	a	you	hou	in	...	connevey	jay	valued	lay	infrastructu
0	0	0	1	0	0	0	2	0	0	0	...	0	0	0	0	
1	8	13	24	6	6	2	102	1	27	18	...	0	0	0	0	
2	0	0	1	0	0	0	8	0	0	4	...	0	0	0	0	
3	0	5	22	0	5	1	51	2	10	1	...	0	0	0	0	
4	7	6	17	1	5	2	57	0	9	3	...	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
5167	2	2	2	3	0	0	32	0	0	5	...	0	0	0	0	
5168	35	27	11	2	6	5	151	4	3	23	...	0	0	0	0	
5169	0	0	1	1	0	0	11	0	0	1	...	0	0	0	0	
5170	2	7	1	0	2	1	28	2	0	8	...	0	0	0	0	
5171	22	24	5	1	6	5	148	8	2	23	...	0	0	0	0	

5172 rows × 3001 columns

KNN

In [24]:
```
X = df.drop(columns='Prediction',axis = 1)
Y = df['Prediction']
```

In [25]:
```
X.columns
```

Out[25]:
```
Index(['the', 'to', 'ect', 'and', 'for', 'of', 'a', 'you', 'hou', 'in',
       ...
       'enhancements', 'connevey', 'jay', 'valued', 'lay', 'infrastructure',
       'military', 'allowing', 'ff', 'dry'],
      dtype='object', length=3000)
```

In [26]:
```
Y.head()
```

Out[26]:
```
0    Not spam
1    Not spam
2    Not spam
3    Not spam
4    Not spam
Name: Prediction, dtype: object
```

In [27]:
```
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, rando
```

In [28]:
```
KN = KNeighborsClassifier
knn = KN(n_neighbors=7)
knn.fit(x_train, y_train)
y_pred = knn.predict(x_test)
```

In [29]:
```
print("Prediction: \n")
print(y_pred)
```

```
Prediction:

['Not spam' 'Spam' 'Not spam' ... 'Not spam' 'Not spam' 'Not spam']
```

In [30]:
```
# Accuracy

M = metrics.accuracy_score(y_test,y_pred)
print("KNN accuracy: ", M)
```

```
KNN accuracy:  0.8714975845410629
```

In [31]:
```
C = metrics.confusion_matrix(y_test,y_pred)
print("Confusion matrix: ", C)
```

```
Confusion matrix:  [[635  84]
 [ 49 267]]
```

SVM Classifier

In [32]:
```
model = SVC(C = 1)   # cost C = 1

model.fit(x_train, y_train)

y_pred = model.predict(x_test)      # predict
```

In [33]:
```
kc = metrics.confusion_matrix(y_test, y_pred)
print("SVM accuracy: ", kc)
```

```
SVM accuracy:  [[700  19]
 [189 127]]
```

In [33]:

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
import io
```

Read the Dataset ¶

In [2]:
```
df=pd.read_csv("https://raw.githubusercontent.com/sahil-gidwani/ML/main/datase
df.head()
```

Out[2]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance
0	1	15634602	Hargrave	619	France	Female	42	2	0.00
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86
2	3	15619304	Onio	502	France	Female	42	8	159660.80
3	4	15701354	Boni	699	France	Female	39	1	0.00
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82

2. Drop the Columns which are unique for all users

In [3]:
```
df=df.drop(['RowNumber','CustomerId','Surname'],axis=1)
df.head()
```

Out[3]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActi
0	619	France	Female	42	2	0.00	1	1	
1	608	Spain	Female	41	1	83807.86	1	0	
2	502	France	Female	42	8	159660.80	3	1	
3	699	France	Female	39	1	0.00	2	0	
4	850	Spain	Female	43	2	125510.82	1	1	

In [4]:
```
df.isna().any()
df.isna().sum()
```

Out[4]:
```
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

BiVariate Analysis

In [5]:
```
print(df.shape)
df.info()
```

```
(10000, 11)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   CreditScore      10000 non-null  int64  
 1   Geography        10000 non-null  object 
 2   Gender           10000 non-null  object 
 3   Age              10000 non-null  int64  
 4   Tenure           10000 non-null  int64  
 5   Balance          10000 non-null  float64
 6   NumOfProducts    10000 non-null  int64  
 7   HasCrCard        10000 non-null  int64  
 8   IsActiveMember   10000 non-null  int64  
 9   EstimatedSalary  10000 non-null  float64
 10  Exited           10000 non-null  int64  
dtypes: float64(2), int64(7), object(2)
memory usage: 859.5+ KB
```

In [6]:
```
df.describe()
```

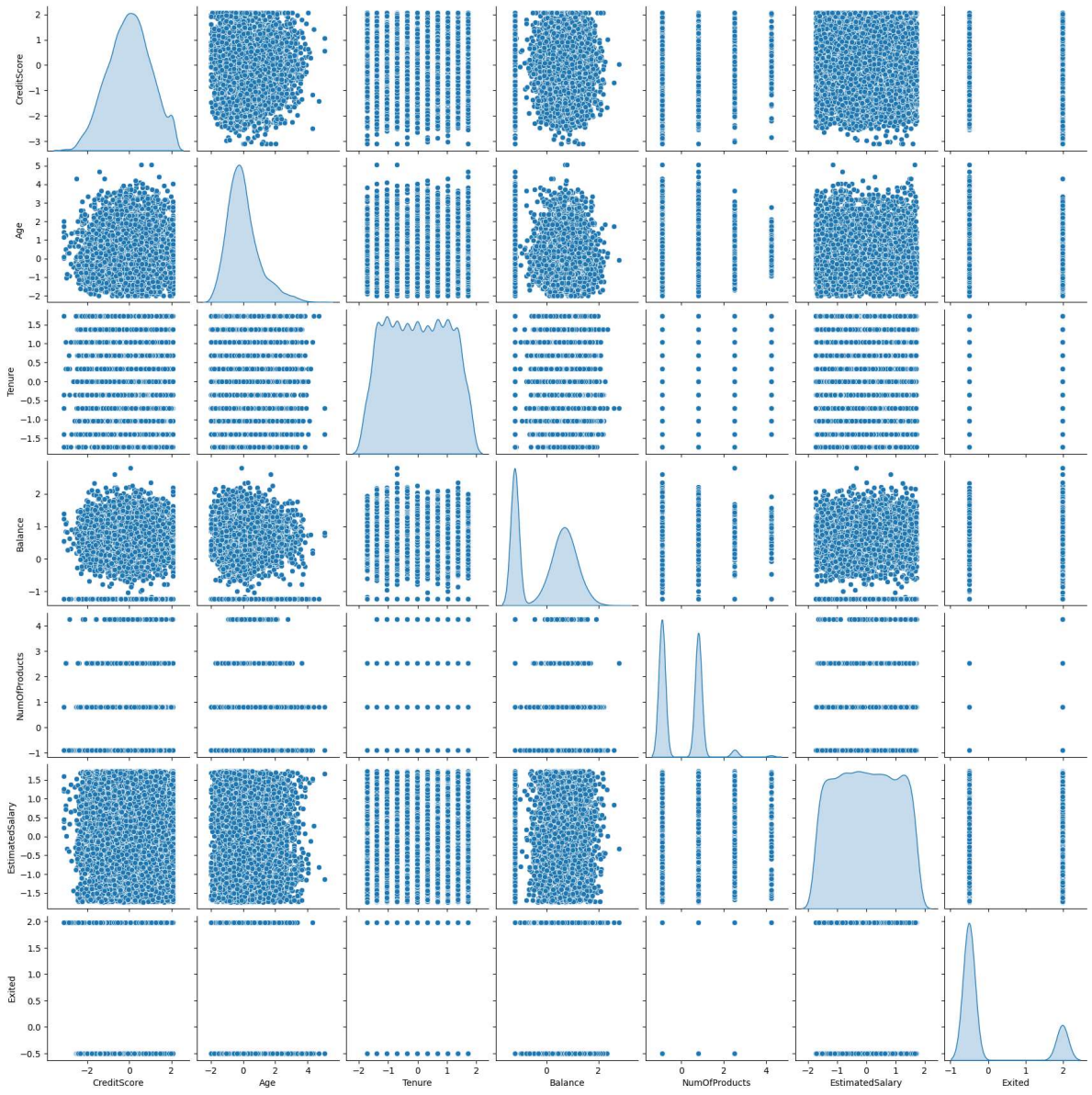
Out[6]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000
mean	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550
std	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584
min	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000
25%	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000
50%	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000
75%	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000
max	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000

Before performing Bivariate analysis, Lets bring all the features to the same range

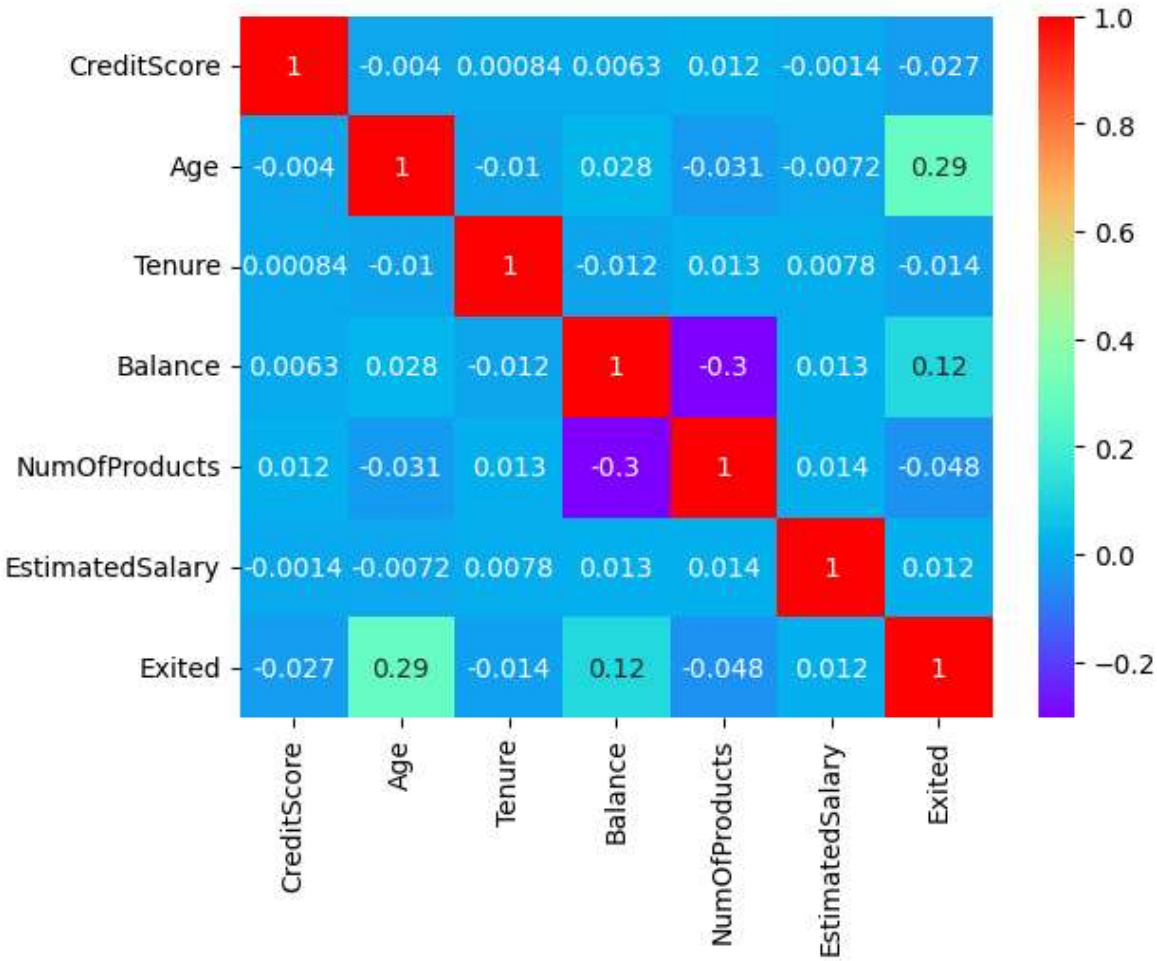
In [7]:
```
## Scale the data
scaler=StandardScaler()
## Extract only the Numerical Columns to perform Bivariate Analysis
subset=df.drop(['Geography','Gender','HasCrCard','IsActiveMember'],axis=1)
scaled=scaler.fit_transform(subset)
scaled_df=pd.DataFrame(scaled,columns=subset.columns)
sns.pairplot(scaled_df,diag_kind='kde')
```

Out[7]: <seaborn.axisgrid.PairGrid at 0x7828c8f03f40>



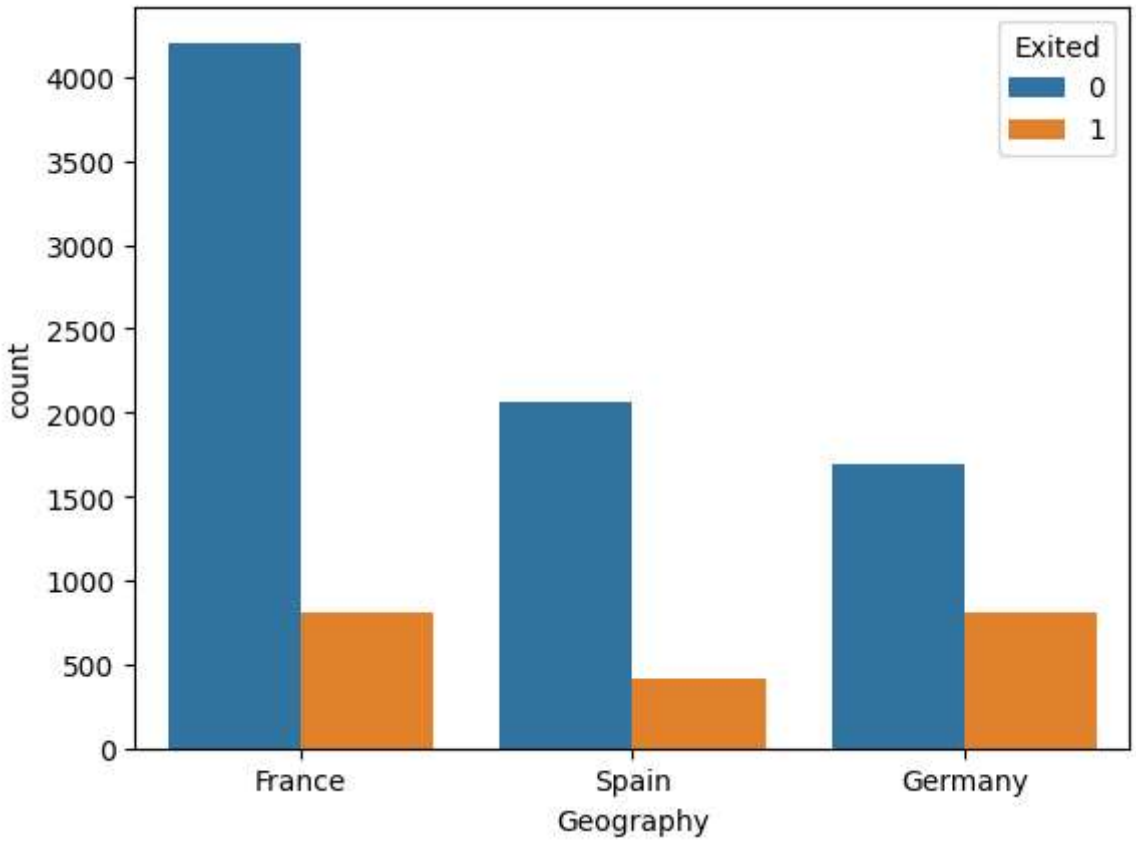
In [8]:
```
sns.heatmap(scaled_df.corr(),annot=True,cmap='rainbow')
```

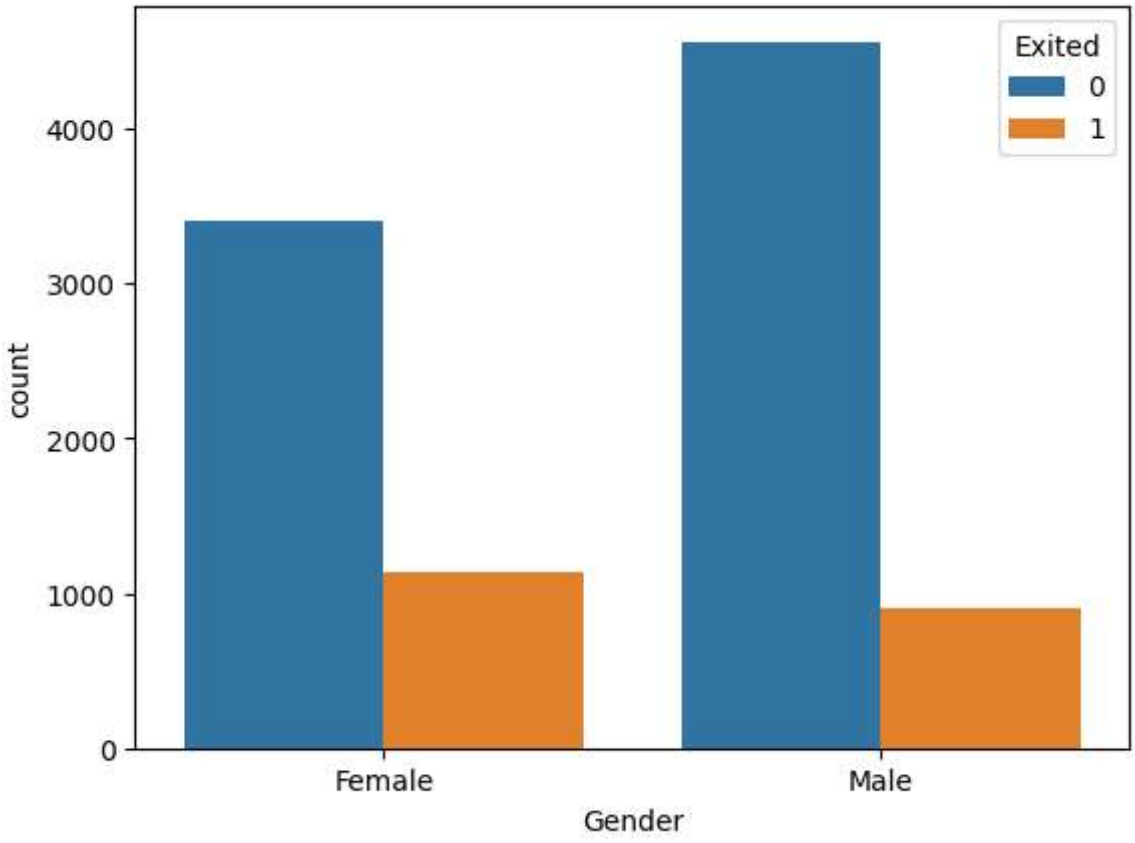
Out[8]: <Axes: >

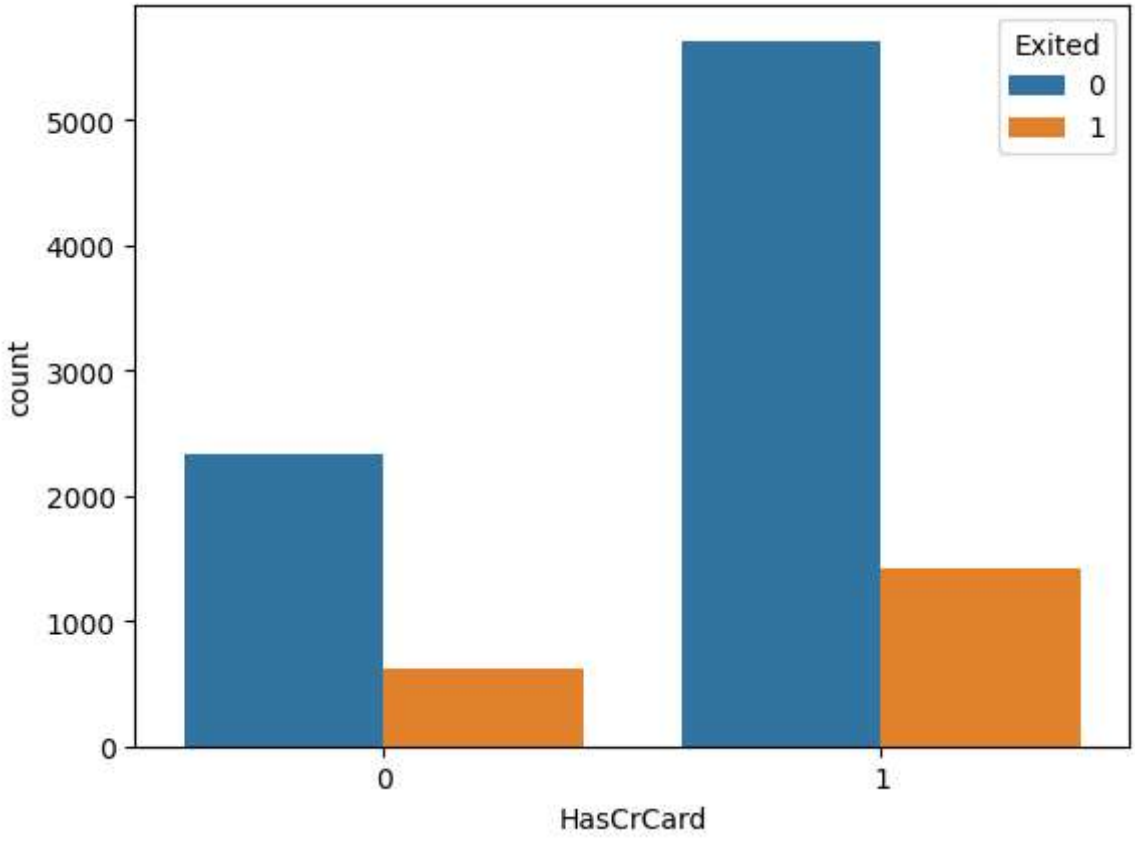


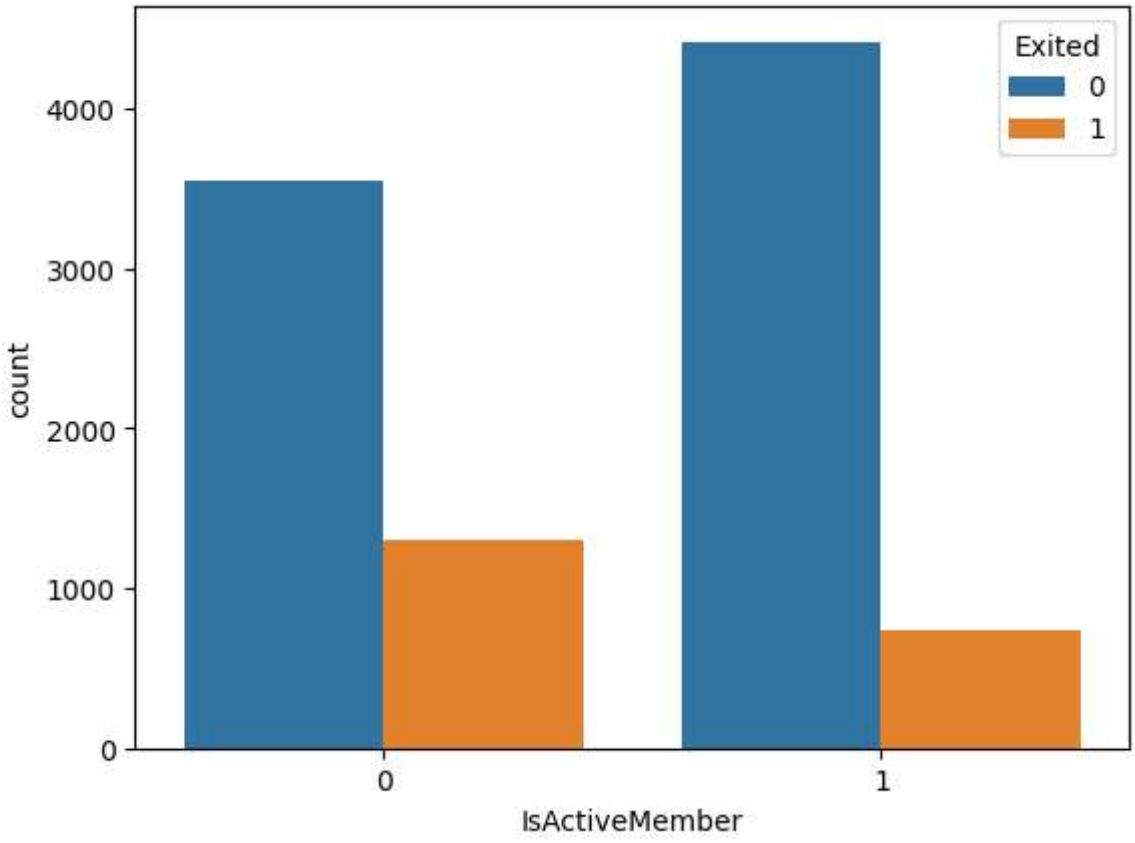
From the above plots, We can see that there is no significant Linear relationship between the features

In [9]:
```
## Categorical Features vs Target Variable
sns.countplot(x='Geography',data=df,hue='Exited')
plt.show()
sns.countplot(x='Gender',data=df,hue='Exited')
plt.show()
sns.countplot(x='HasCrCard',data=df,hue='Exited')
plt.show()
sns.countplot(x='IsActiveMember',data=df,hue='Exited')
plt.show()
```



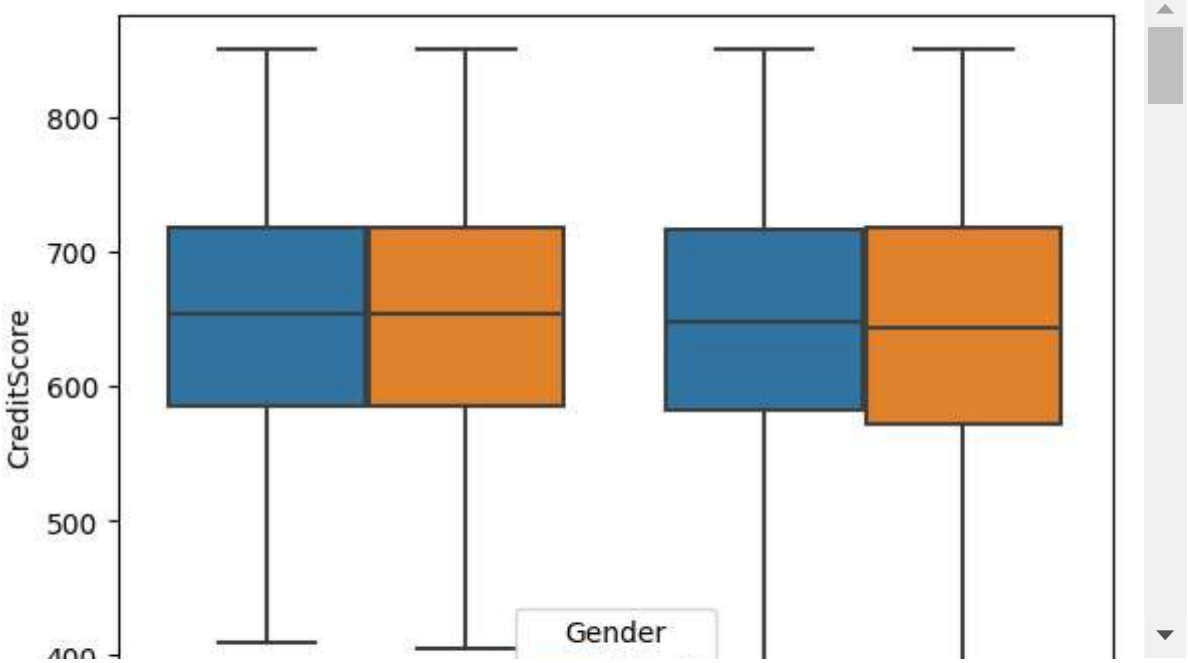

Exited
0
1
4000
3000
2000
1000
0
count
Female
Male
Gender


Exited
0
1
5000
4000
3000
2000
1000
0
count
0
1
HasCrCard



Analysing the Numerical Features relationship with the Target variable. Here 'Exited' is the Target Feature.

In [10]:
```
subset = subset.drop('Exited', axis=1)
for i in subset.columns:
  sns.boxplot(x=df['Exited'], y=df[i], hue=df['Gender'])
  plt.show()
```



Insights from Bivariate Plots

1. The Avg Credit Score seem to be almost the same for Active and Churned customers
2. Young People seem to stick to the bank compared to older people
3. The Average Bank Balance is high for Churned Customers
4. The churning rate is high with German Customers
5. The Churning rate is high among the Non-Active Members

4. Distinguish the Target and Feature Set and divide the dataset into Training and Test sets

In [11]:
```
X=df.drop('Exited',axis=1)
y=df.pop('Exited')
```

In [12]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.10,random_state
X_train,X_val,y_train,y_val=train_test_split(X_train,y_train,test_size=0.10,ra
print("X_train size is {}".format(X_train.shape[0]))
print("X_val size is {}".format(X_val.shape[0]))
print("X_test size is {}".format(X_test.shape[0]))
```

```
X_train size is 8100
X_val size is 900
X_test size is 1000
```

In [13]:
```
## Standardising the train, Val and Test data
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
num_cols=['CreditScore','Age','Tenure','Balance','NumOfProducts','EstimatedSal
num_subset=scaler.fit_transform(X_train[num_cols])
X_train_num_df=pd.DataFrame(num_subset,columns=num_cols)
X_train_num_df['Geography']=list(X_train['Geography'])
X_train_num_df['Gender']=list(X_train['Gender'])
X_train_num_df['HasCrCard']=list(X_train['HasCrCard'])
X_train_num_df['IsActiveMember']=list(X_train['IsActiveMember'])
X_train_num_df.head()
## Standardise the Validation data
num_subset=scaler.fit_transform(X_val[num_cols])
X_val_num_df=pd.DataFrame(num_subset,columns=num_cols)
X_val_num_df['Geography']=list(X_val['Geography'])
X_val_num_df['Gender']=list(X_val['Gender'])
X_val_num_df['HasCrCard']=list(X_val['HasCrCard'])
X_val_num_df['IsActiveMember']=list(X_val['IsActiveMember'])
## Standardise the Test data
num_subset=scaler.fit_transform(X_test[num_cols])
X_test_num_df=pd.DataFrame(num_subset,columns=num_cols)
X_test_num_df['Geography']=list(X_test['Geography'])
X_test_num_df['Gender']=list(X_test['Gender'])
X_test_num_df['HasCrCard']=list(X_test['HasCrCard'])
X_test_num_df['IsActiveMember']=list(X_test['IsActiveMember'])
```

In [14]:
```
## Convert the categorical features to numerical
X_train_num_df=pd.get_dummies(X_train_num_df,columns=['Geography','Gender'])
X_test_num_df=pd.get_dummies(X_test_num_df,columns=['Geography','Gender'])
X_val_num_df=pd.get_dummies(X_val_num_df,columns=['Geography','Gender'])
X_train_num_df.head()
```

Out[14]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	EstimatedSalary	HasCrCard	IsA
0	-1.178587	-1.041960	-1.732257	0.198686	0.820905	1.560315	1	
1	-0.380169	-1.326982	1.730718	-0.022020	-0.907991	-0.713592	1	
2	-0.349062	1.808258	-0.693364	0.681178	0.820905	-1.126515	1	
3	0.625629	2.378302	-0.347067	-1.229191	0.820905	-1.682740	1	
4	-0.203895	-1.136967	1.730718	0.924256	-0.907991	1.332535	1	

Initialise and build the Model

In [15]:
```
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense

model=Sequential()
model.add(Dense(7,activation='relu'))
model.add(Dense(10,activation='relu'))
model.add(Dense(1,activation='sigmoid'))
```

In [16]:
```
import tensorflow as tf
optimizer=tf.keras.optimizers.Adam(0.01)
model.compile(loss='binary_crossentropy',optimizer=optimizer,metrics=['accurac
```

In [17]:
```
model.fit(X_train_num_df,y_train,epochs=100,batch_size=10,verbose=1)
```

```
Epoch 1/100
810/810 [==============================] - 2s 2ms/step - loss: 0.3977 - ac
curacy: 0.8241
Epoch 2/100
810/810 [==============================] - 2s 2ms/step - loss: 0.3599 - ac
curacy: 0.8552
Epoch 3/100
810/810 [==============================] - 2s 2ms/step - loss: 0.3529 - ac
curacy: 0.8559
Epoch 4/100
810/810 [==============================] - 2s 3ms/step - loss: 0.3527 - ac
curacy: 0.8559
Epoch 5/100
810/810 [==============================] - 2s 3ms/step - loss: 0.3455 - ac
curacy: 0.8610
Epoch 6/100
810/810 [==============================] - 2s 3ms/step - loss: 0.3469 - ac
curacy: 0.8577
Epoch 7/100
```

Predict the Results using 0.5 threshold

In [18]:
```
y_pred_val=model.predict(X_val_num_df)
y_pred_val[y_pred_val>0.5]=1
y_pred_val[y_pred_val <0.5]=0
```

```
29/29 [==============================] - 0s 3ms/step
```

In [19]:
```
y_pred_val=y_pred_val.tolist()
X_compare_val=X_val.copy()
X_compare_val['y_actual']=y_val
X_compare_val['y_pred']=y_pred_val
X_compare_val.head(10)
```

Out[19]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	Is/
340	642	Germany	Female	40	6	129502.49	2	0	
8622	706	Germany	Male	36	9	58571.18	2	1	
8401	535	Spain	Male	58	1	0.00	2	1	
4338	714	Spain	Male	25	2	0.00	1	1	
8915	606	France	Male	36	1	155655.46	1	1	
2624	605	Spain	Female	29	3	116805.82	1	0	
2234	720	France	Female	38	10	0.00	2	1	
349	582	France	Male	39	5	0.00	2	1	
3719	850	France	Female	62	1	124678.35	1	1	
2171	526	Germany	Male	58	9	190298.89	2	1	

Confusion Matrix of the Validation set

In [20]:
```
from sklearn.metrics import confusion_matrix
cm_val=confusion_matrix(y_val,y_pred_val)
cm_val
```

Out[20]:
```
array([[689,  27],
       [101,  83]])
```

In [26]:
```
# Extract TP, TN, FP, FN from the confusion matrix
TP = cm_val[1, 1]  # True Positives
TN = cm_val[0, 0]  # True Negatives
FP = cm_val[0, 1]  # False Positives
FN = cm_val[1, 0]  # False Negatives

# Calculate accuracy
accuracy = (TP + TN) / (TP + TN + FP + FN)

print("Accuracy:", accuracy)
```

```
Accuracy: 0.8577777777777778
```

In [22]:
```
loss1,accuracy1=model.evaluate(X_train_num_df,y_train,verbose=False)
loss2,accuracy2=model.evaluate(X_val_num_df,y_val,verbose=False)
print("Train Loss {}".format(loss1))
print("Train Accuracy {}".format(accuracy1))
print("Val Loss {}".format(loss2))
print("Val Accuracy {}".format(accuracy2))
```

```
Train Loss 0.32568806409835815
Train Accuracy 0.8662962913513184
Val Loss 0.35947299003601074
Val Accuracy 0.8577777743339539
```

Since our Training Accuracy and Validation Accuracy are pretty close, we can conclude that our model generalises well. So, lets apply the model on the Test set and make predictions and evaluate the model against the Test.

In [23]:
```
from sklearn import metrics
y_pred_test=model.predict(X_test_num_df)
y_pred_test[y_pred_test>0.5]=1
y_pred_test[y_pred_test <0.5]=0
cm_test=metrics.confusion_matrix(y_test,y_pred_test)
cm_test
print("Test Confusion Matrix")
```

```
32/32 [==============================] - 0s 2ms/step
Test Confusion Matrix
```

In [24]:
```
cm_test
```

Out[24]:
```
array([[755,  39],
       [119,  87]])
```

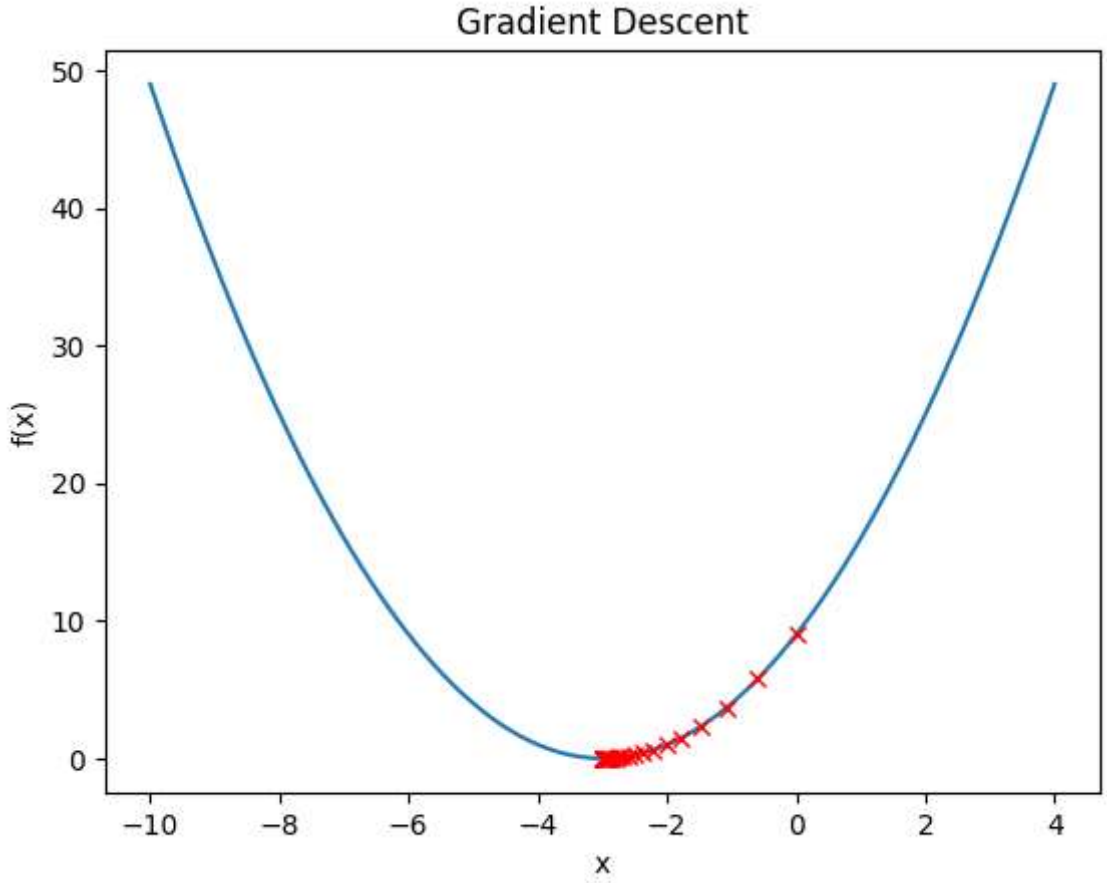
In [25]:
```
loss3,accuracy3=model.evaluate(X_test_num_df,y_test,verbose=False)
print("Test Accuracy is {}".format(accuracy3))
print("Test loss is {}".format(loss3))
```

```
Test Accuracy is 0.8420000076293945
Test loss is 0.3749040365219116
```

In [25]:
```
```

In [2]:
```
import numpy as np
import matplotlib.pyplot as plt

def f(x):
   return (x + 3) ** 2

def df(x):
   return 2 * (x + 3)

def gradient_descent(initial_x, learning_rate, num_iterations):
   x = initial_x
   x_history = [x]

   for i in range(num_iterations):
       gradient = df(x)
       x = x - learning_rate * gradient
       x_history.append(x)

   return x, x_history

initial_x = 0
learning_rate = 0.1
num_iterations = 50

x, x_history = gradient_descent(initial_x, learning_rate, num_iterations)

print("Local minimum: {:.2f}".format(x))

# Create a range of x values to plot
x_vals = np.linspace(-10, 4, 100)

# Plot the function f(x)
plt.plot(x_vals, f(x_vals))

# Plot the values of x at each iteration
plt.plot(x_history, f(np.array(x_history)), 'rx')

# Label the axes and add a title
plt.xlabel('x')
plt.ylabel('f(x)')
plt.title('Gradient Descent')

# Show the plot
plt.show()
```

```
Local minimum: -3.00
```



In [ ]:

Diabetes classification using KNN

In [1]:
```
import pandas as pd
import numpy as np
```

In [2]:
```
data = pd.read_csv("https://raw.githubusercontent.com/sahil-gidwani/ML/main/da
data.head()
```

Out[2]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Pedigree	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

In [3]:
```
data.isnull().any()
```

Out[3]:
```
Pregnancies      False
Glucose          False
BloodPressure    False
SkinThickness    False
Insulin          False
BMI              False
Pedigree         False
Age              False
Outcome          False
dtype: bool
```

In [4]:
```
data.describe().T
```

Out[4]:

	count	mean	std	min	25%	50%	75%	max
Pregnancies	768.0	3.845052	3.369578	0.000	1.00000	3.0000	6.00000	17.00
Glucose	768.0	120.894531	31.972618	0.000	99.00000	117.0000	140.25000	199.00
BloodPressure	768.0	69.105469	19.355807	0.000	62.00000	72.0000	80.00000	122.00
SkinThickness	768.0	20.536458	15.952218	0.000	0.00000	23.0000	32.00000	99.00
Insulin	768.0	79.799479	115.244002	0.000	0.00000	30.5000	127.25000	846.00
BMI	768.0	31.992578	7.884160	0.000	27.30000	32.0000	36.60000	67.10
Pedigree	768.0	0.471876	0.331329	0.078	0.24375	0.3725	0.62625	2.42
Age	768.0	33.240885	11.760232	21.000	24.00000	29.0000	41.00000	81.00
Outcome	768.0	0.348958	0.476951	0.000	0.00000	0.0000	1.00000	1.00

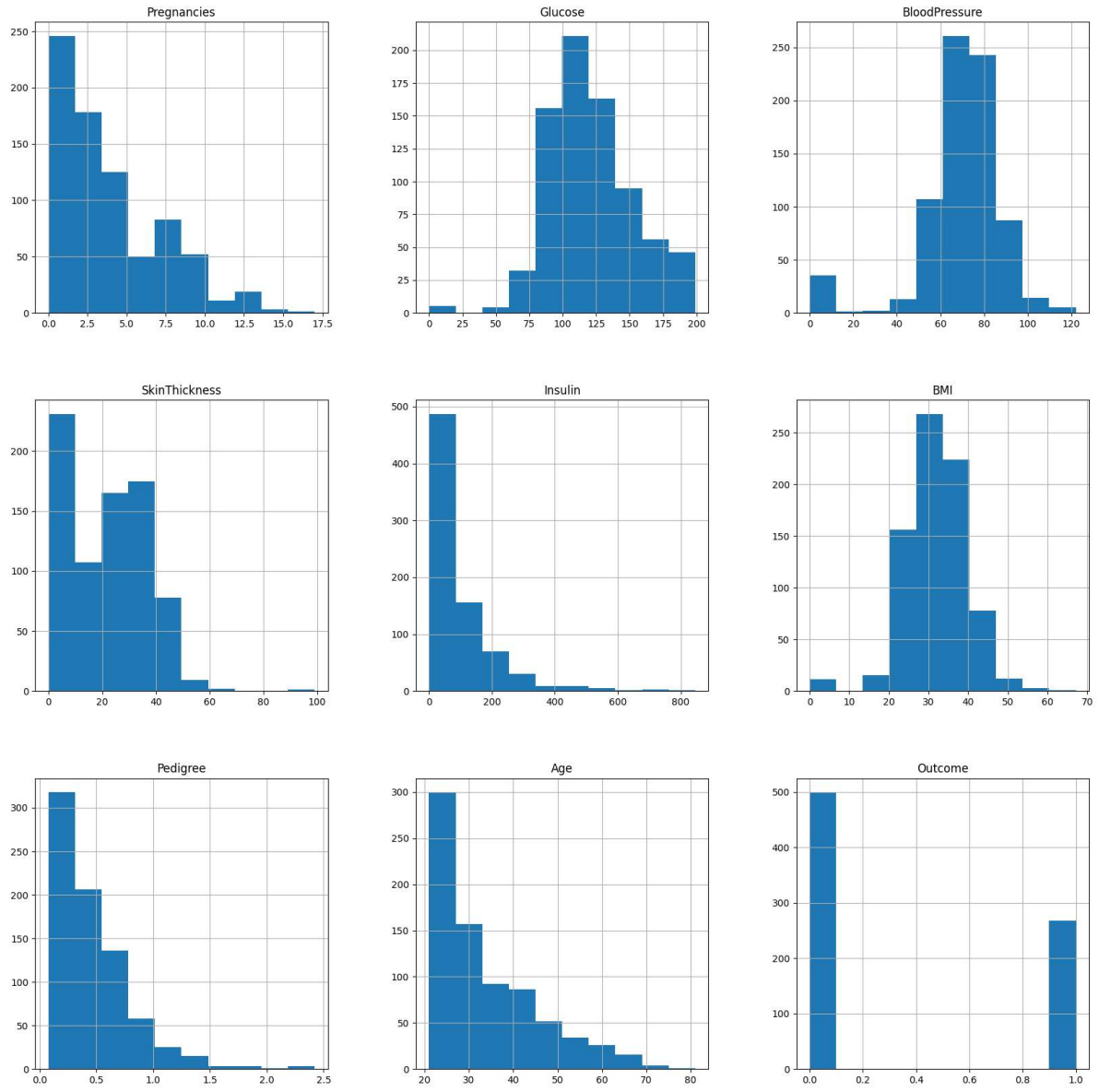
Glucose, BloodPressure, SkinThickness, Insulin, BMI
columns have values 0 which does not ake sense , hence are missing values

In [5]:
```
data_copy = data.copy(deep = True)
data_copy[['Glucose','BloodPressure','SkinThickness','Insulin','BMI']] = data_
data_copy.isnull().sum()
```

Out[5]:
```
Pregnancies        0
Glucose            5
BloodPressure     35
SkinThickness    227
Insulin          374
BMI               11
Pedigree           0
Age                0
Outcome            0
dtype: int64
```

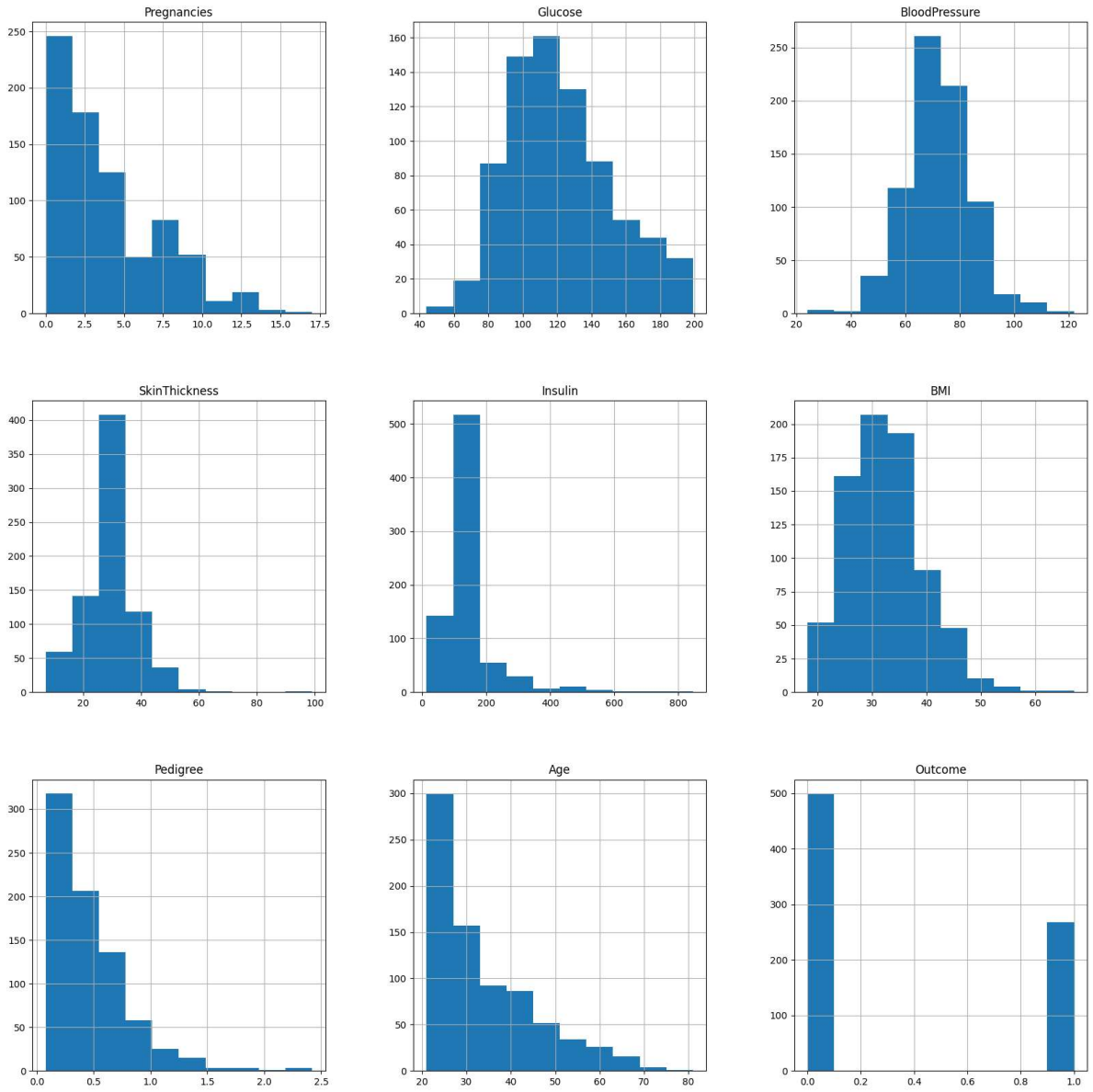
To fill these Nan values the data distribution needs to be understood

In [6]:
```
p = data.hist(figsize = (20,20))
```

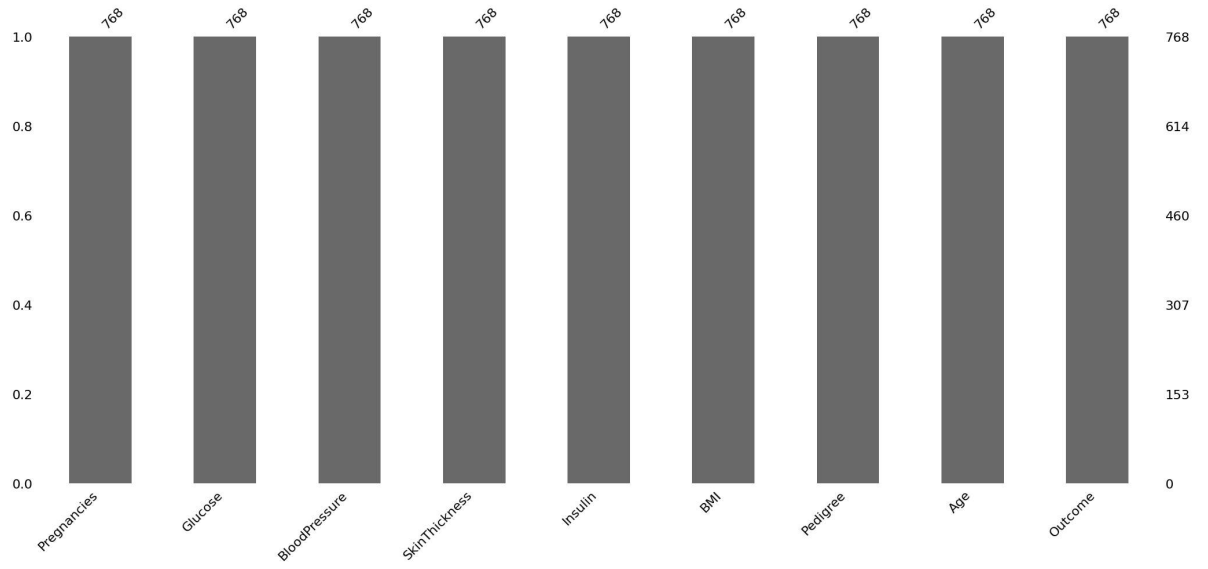


In [7]:
```
data_copy['Glucose'].fillna(data_copy['Glucose'].mean(), inplace = True)
data_copy['BloodPressure'].fillna(data_copy['BloodPressure'].mean(), inplace =
data_copy['SkinThickness'].fillna(data_copy['SkinThickness'].median(), inplace
data_copy['Insulin'].fillna(data_copy['Insulin'].median(), inplace = True)
data_copy['BMI'].fillna(data_copy['BMI'].median(), inplace = True)
```

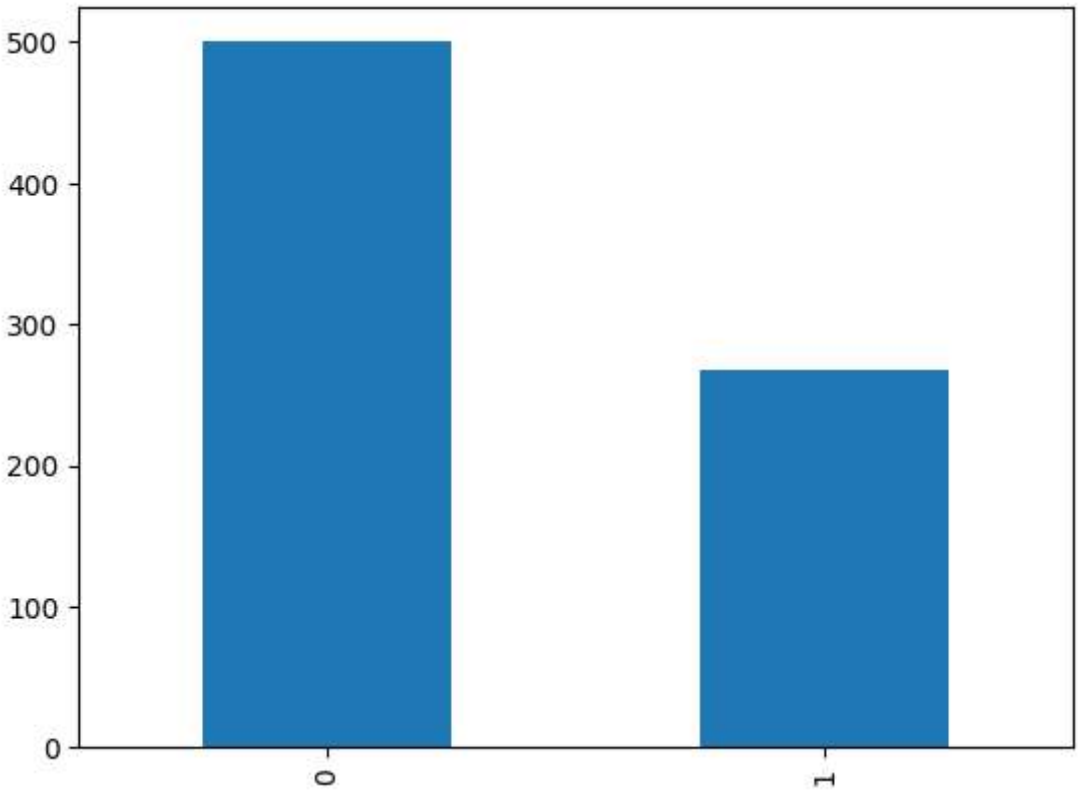
In [8]:
```
p = data_copy.hist(figsize = (20,20))
```



In [9]:
```
import missingno as msno
p = msno.bar(data)
```



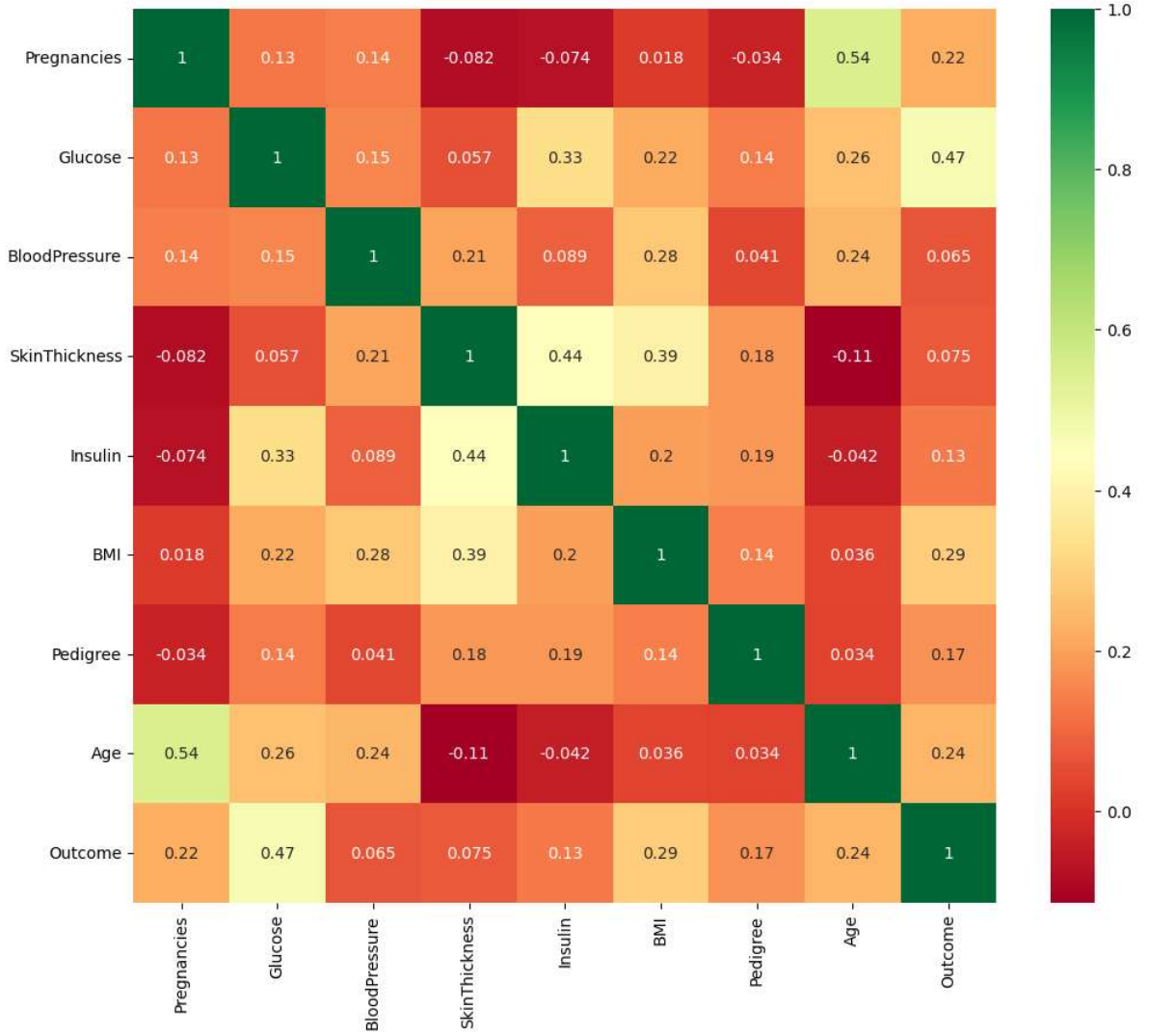
In [10]:
```
p=data.Outcome.value_counts().plot(kind="bar")
```



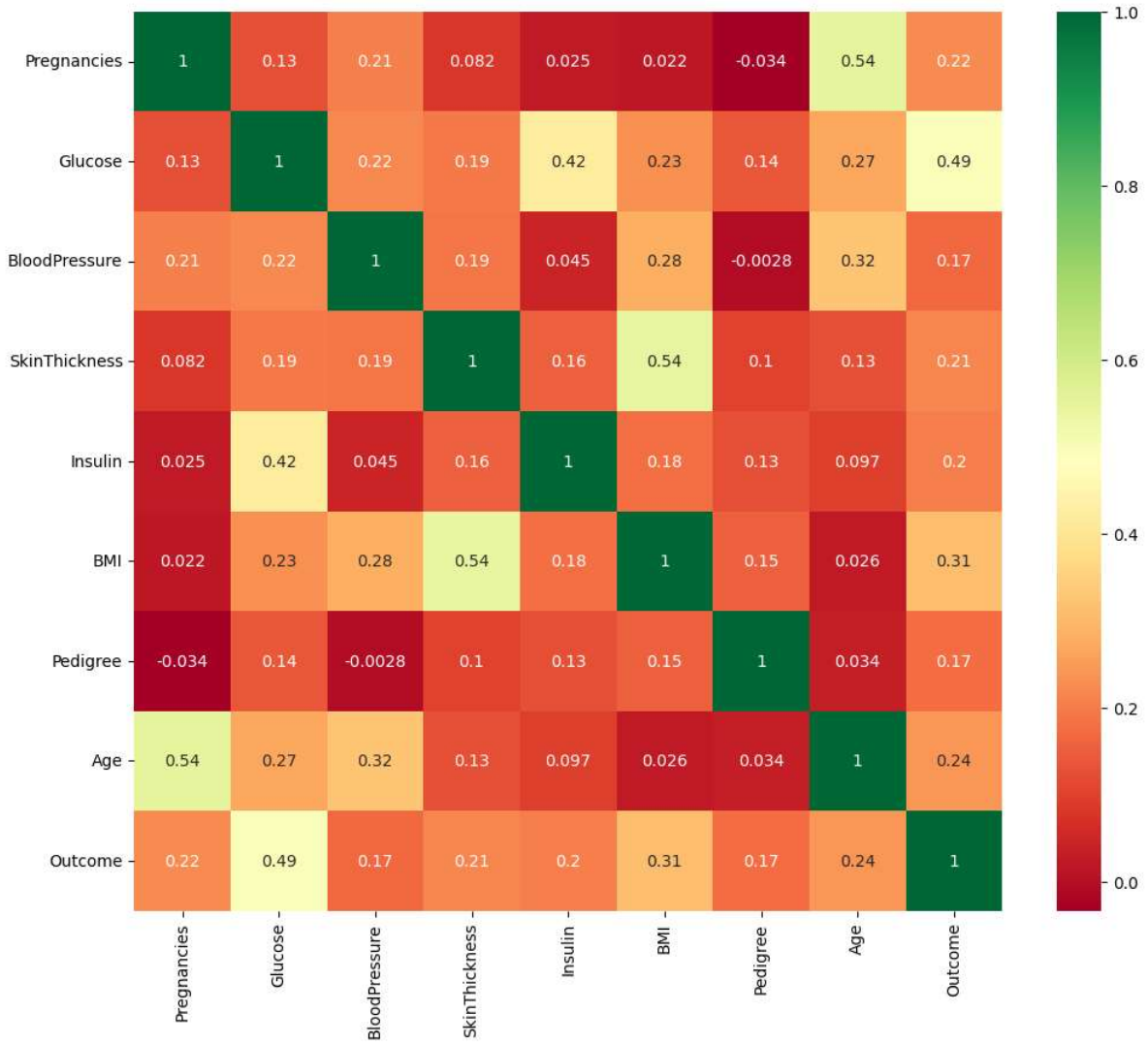
The above graph shows that the data is biased towards datapoints having outcome value as 0 where it means that diabetes was not present actually. The number of non-diabetics is almost twice the number of diabetic patients

In [11]:
```
import seaborn as sns
p=sns.pairplot(data_copy, hue = 'Outcome')
```

In [12]:
```
import matplotlib.pyplot as plt
plt.figure(figsize=(12,10))  # on this line I just set the size of figure to 1
p=sns.heatmap(data.corr(), annot=True,cmap ='RdYlGn')  # seaborn has very simp
```



In [13]:
```
plt.figure(figsize=(12,10))  # on this line I just set the size of figure to 1
p=sns.heatmap(data_copy.corr(), annot=True,cmap ='RdYlGn')  # seaborn has very
```



In [14]:
```
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
X = pd.DataFrame(sc_X.fit_transform(data_copy.drop(["Outcome"], axis =1),),col
       'BMI', 'DiabetesPedigreeFunction', 'Age'])
```

In [15]:
```
X.head()
```

Out[15]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigree
0	0.639947	0.865108	-0.033518	0.670643	-0.181541	0.166619	
1	-0.844885	-1.206162	-0.529859	-0.012301	-0.181541	-0.852200	-
2	1.233880	2.015813	-0.695306	-0.012301	-0.181541	-1.332500	
3	-0.844885	-1.074652	-0.529859	-0.695245	-0.540642	-0.633881	-
4	-1.141852	0.503458	-2.680669	0.670643	0.316566	1.549303	

In [16]:
```
y =data_copy.Outcome
```

In [17]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 1/3, ran
```

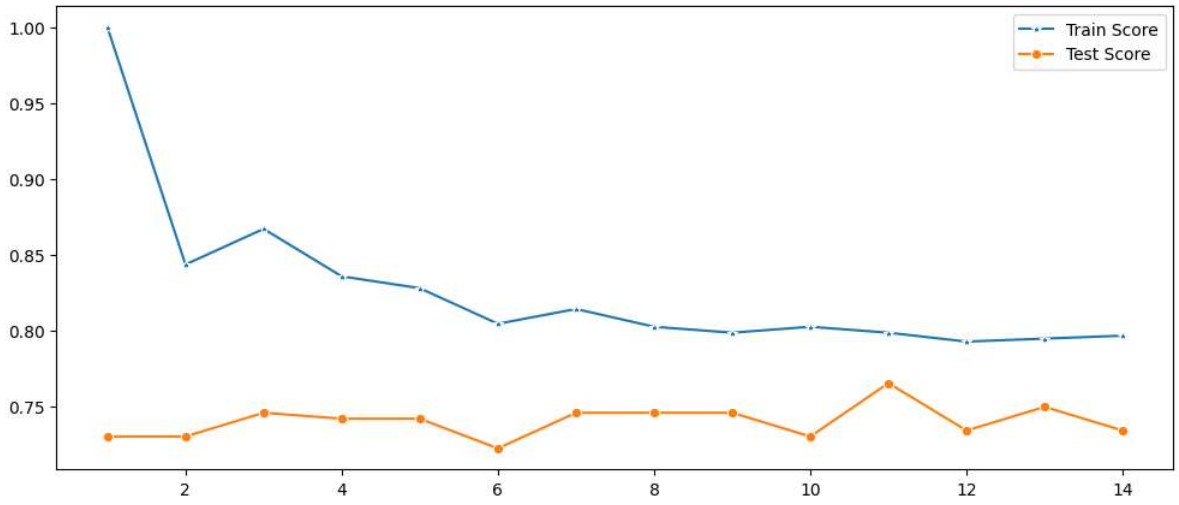
In [18]:
```
from sklearn.neighbors import KNeighborsClassifier

train_scores = []
test_scores = []

for i in range(1,15):
    knn = KNeighborsClassifier(i)
    knn.fit(X_train, y_train)
    train_scores.append(knn.score(X_train, y_train))
    test_scores.append(knn.score(X_test, y_test))
```

In [19]:
```
max_test_score =max(test_scores)
```

In [20]:
```
test_score_index = [i for i, v in enumerate(test_scores) if v== max_test_score

print('Max test score {} % and k = {}'.format(max_test_score*100,list(map(lamb
```

```
Max test score 76.5625 % and k = [11]
```

In [23]:
```
plt.figure(figsize=(12,5))
p = sns.lineplot(x=range(1, 15), y=train_scores, marker='*', label='Train Scor
p = sns.lineplot(x=range(1, 15), y=test_scores, marker='o', label='Test Score'
```

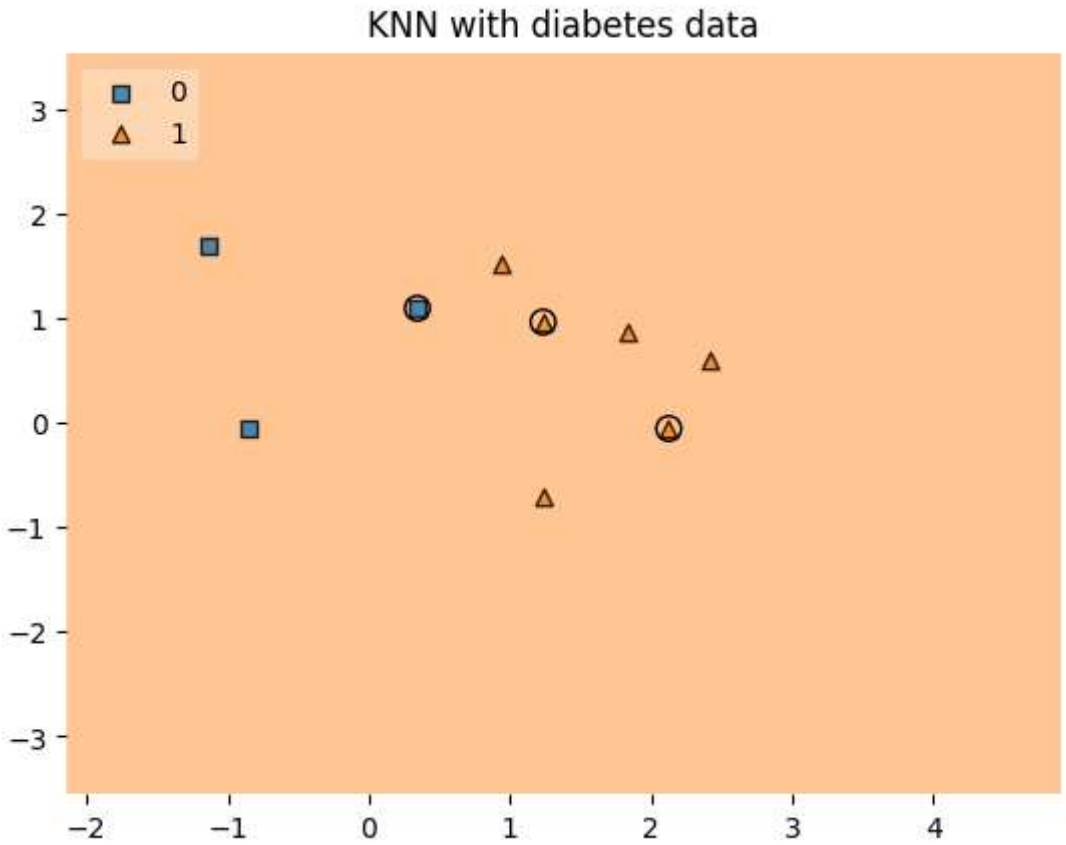


In [24]:
```
# K=11
#Setup a knn classifier with k neighbors
knn = KNeighborsClassifier(11)

knn.fit(X_train,y_train)
knn.score(X_test,y_test)
```

Out[24]: 0.765625

In [25]:
```
from mlxtend.plotting import plot_decision_regions
value = 20000
width  =20000

plot_decision_regions(X.values, y.values, clf = knn, legend =2,filler_feature_
                      filler_feature_ranges={2: width, 3: width, 4: width, 5:
                      X_highlight=X_test.values)
plt.title("KNN with diabetes data")
plt.show()
```

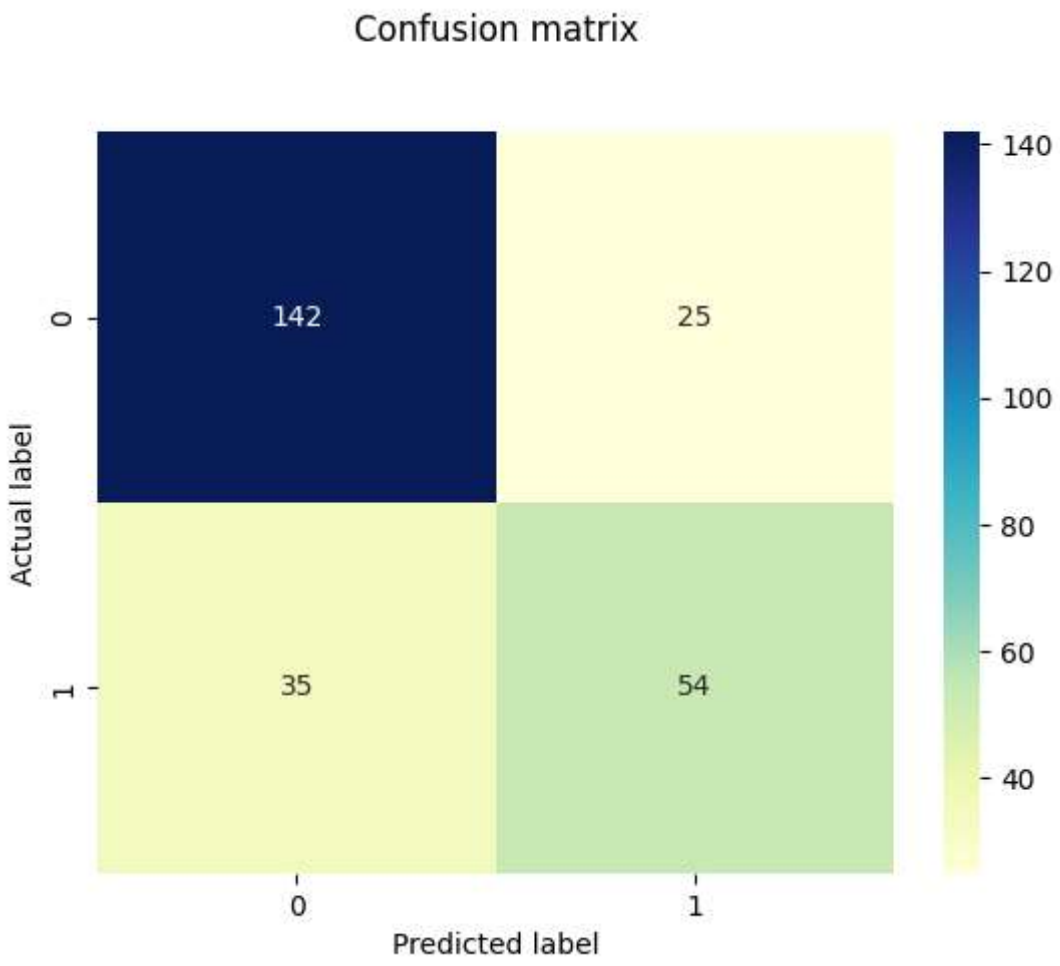
```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X d
oes not have valid feature names, but KNeighborsClassifier was fitted with fe
ature names
  warnings.warn(
```



In [26]:
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_
y_pred = knn.predict(X_test)

cnf_matrix = confusion_matrix(y_test, y_pred)
```

In [27]:
```
p = sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[27]: Text(0.5, 23.52222222222222, 'Predicted label')



In [28]:
```
def model_evaluation(y_test, y_pred, model_name):
    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred)
    rec = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    f2 = fbeta_score(y_test, y_pred, beta = 2.0)

    results = pd.DataFrame([[model_name, acc, prec, rec, f1, f2]],
                      columns = ["Model", "Accuracy", "Precision", "Recall",
                                 "F1 SCore", "F2 Score"])
    results = results.sort_values(["Precision", "Recall", "F2 Score"], ascendi
    return results



model_evaluation(y_test, y_pred, "KNN")
```

Out[28]:

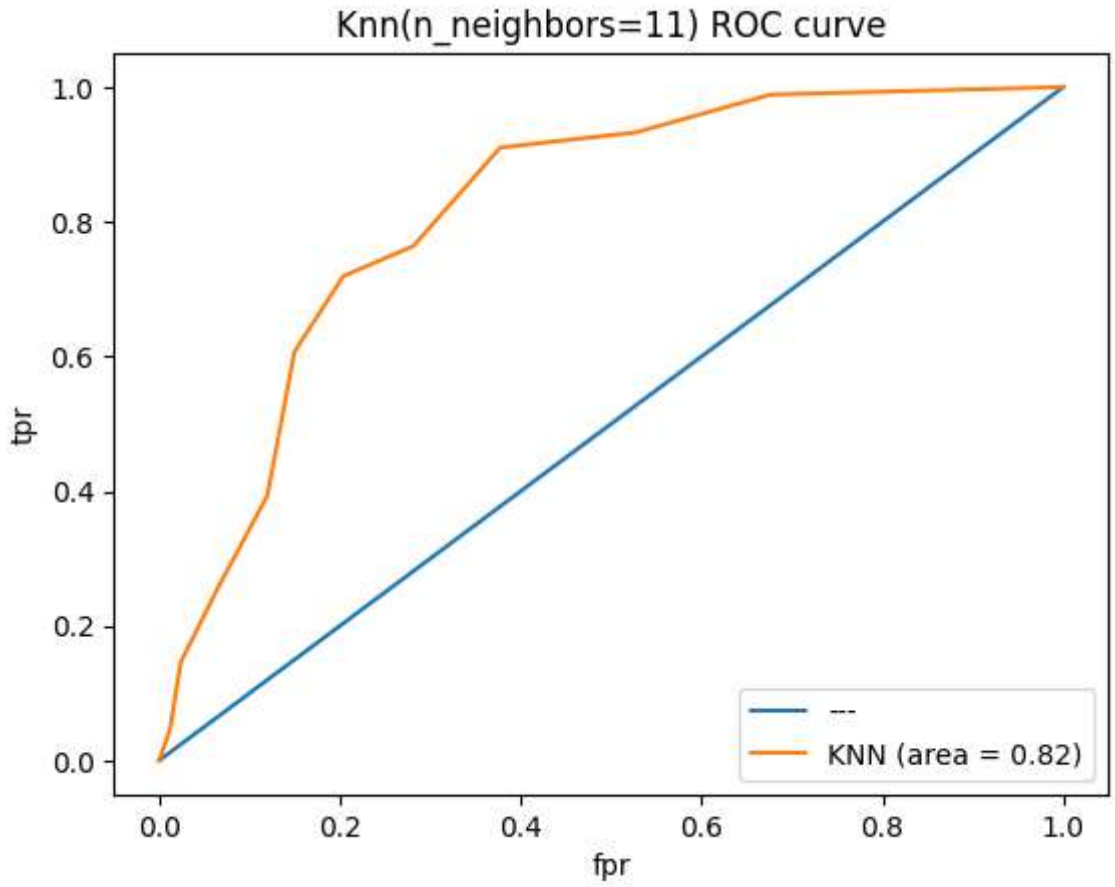
	Model	Accuracy	Precision	Recall	F1 SCore	F2 Score
0	KNN	0.765625	0.683544	0.606742	0.642857	0.62069

In [29]:
```
# Alternate way
from sklearn.metrics import classification_report
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.80      0.85      0.83       167
           1       0.68      0.61      0.64        89

    accuracy                           0.77       256
   macro avg       0.74      0.73      0.73       256
weighted avg       0.76      0.77      0.76       256
```

In [30]:
```
from sklearn.metrics import auc, roc_auc_score, roc_curve

y_pred_proba = knn.predict_proba(X_test)[:,-1]
fpr, tpr, threshold = roc_curve(y_test, y_pred_proba)
```

In [31]:
```
classifier_roc_auc = roc_auc_score(y_test, y_pred_proba)
plt.plot([0,1],[0,1], label = "---")

plt.plot(fpr, tpr, label ='KNN (area = %0.2f)' % classifier_roc_auc)
plt.xlabel("fpr")
plt.ylabel("tpr")
plt.title('Knn(n_neighbors=11) ROC curve')
plt.legend(loc="lower right", fontsize = "medium")
plt.xticks(rotation=0, horizontalalignment="center")
plt.yticks(rotation=0, horizontalalignment="right")
plt.show()
```



In [32]:
```
#Hyper parameters tuning using GridSearchCV
from sklearn.model_selection import GridSearchCV
parameters_grid = {"n_neighbors": np.arange(0,50)}
knn= KNeighborsClassifier()
knn_GSV = GridSearchCV(knn, param_grid=parameters_grid, cv = 5)
knn_GSV.fit(X, y)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.p
y:378: FitFailedWarning:
5 fits failed out of a total of 250.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting erro
r_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
---
5 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_vali
dation.py", line 686, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.10/dist-packages/sklearn/neighbors/_classifica
tion.py", line 213, in fit
    self._validate_params()
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 600, i
n _validate_params
    validate_parameter_constraints(
  File "/usr/local/lib/python3.10/dist-packages/sklearn/utils/_param_validati
on.py", line 97, in validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'n_neighbors' para
meter of KNeighborsClassifier must be an int in the range [1, inf) or None. G
ot 0 instead.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_search.py:95
2: UserWarning: One or more of the test scores are non-finite: [       nan 0.
68759019 0.71362363 0.73312962 0.7369663  0.73441134
 0.73700025 0.74609965 0.74870554 0.75395977 0.74743231 0.76436635
 0.75787285 0.76699771 0.75524998 0.76306765 0.76828792 0.76698073
 0.77086835 0.76698073 0.76438333 0.76696376 0.76307614 0.76566505
 0.76176895 0.77218403 0.76566505 0.76958662 0.77088532 0.76568203
 0.76045327 0.76306765 0.76305916 0.76047874 0.7696036  0.76437484
 0.76046176 0.76047874 0.76046176 0.75526696 0.76176895 0.76438333
 0.75655717 0.75916306 0.75785587 0.75525847 0.75264409 0.75135387
 0.75265258 0.75136236]
  warnings.warn(
```

Out[32]:
```
GridSearchCV(cv=5, estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': array([ 0,  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])})
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [33]:
```
print("Best Params" ,knn_GSV.best_params_)
print("Best score" ,knn_GSV.best_score_)
```

```
Best Params {'n_neighbors': 25}
Best score 0.7721840251252015
```

In [ ]:
```

```