Employee Attrition Prediction

The IBM HR Analytics Employee Attrition & Performance dataset is a large dataset that contains a plethora of information about employees at a fictitious company. It contains a wide range of demographic, work-related, and performance-related characteristics that can be used to investigate the factors that influence employee attrition and job performance.

In [1]:
```
#IMPORT LIBRARIES
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

#import the necessary modelling algorithm
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier

#model(training & testing)
from sklearn.model_selection import train_test_split

#preprocess.
from sklearn.preprocessing import StandardScaler,LabelEncoder
from sklearn.metrics import accuracy_score

import tensorflow as tf
import random as rn
```

In [2]:
```
ibm=pd.read_csv('C:\\Users\\darsh\\Downloads\\ML Scripts\\IBM-Employee-Attrit
ibm.head()
```

Out[2]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Edu
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Li
1	49	No	Travel_Frequently	279	Research & Development	8	1	Li
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Li
4	27	No	Travel_Rarely	591	Research & Development	2	1	

5 rows × 35 columns

In [3]:
```
#Missing Values
ibm.info()  # no null or NAN values.
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 35 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   Age                       1470 non-null   int64 
 1   Attrition                 1470 non-null   object
 2   BusinessTravel            1470 non-null   object
 3   DailyRate                 1470 non-null   int64 
 4   Department                1470 non-null   object
 5   DistanceFromHome          1470 non-null   int64 
 6   Education                 1470 non-null   int64 
 7   EducationField            1470 non-null   object
 8   EmployeeCount             1470 non-null   int64 
 9   EmployeeNumber            1470 non-null   int64 
 10  EnvironmentSatisfaction   1470 non-null   int64 
 11  Gender                    1470 non-null   object
 12  HourlyRate                1470 non-null   int64 
 13  JobInvolvement            1470 non-null   int64 
 14  JobLevel                  1470 non-null   int64 
 15  JobRole                   1470 non-null   object
 16  JobSatisfaction           1470 non-null   int64 
 17  MaritalStatus             1470 non-null   object
 18  MonthlyIncome             1470 non-null   int64 
 19  MonthlyRate               1470 non-null   int64 
 20  NumCompaniesWorked        1470 non-null   int64 
 21  Over18                    1470 non-null   object
 22  OverTime                  1470 non-null   object
 23  PercentSalaryHike         1470 non-null   int64 
 24  PerformanceRating         1470 non-null   int64 
 25  RelationshipSatisfaction  1470 non-null   int64 
 26  StandardHours             1470 non-null   int64 
 27  StockOptionLevel          1470 non-null   int64 
 28  TotalWorkingYears         1470 non-null   int64 
 29  TrainingTimesLastYear     1470 non-null   int64 
 30  WorkLifeBalance           1470 non-null   int64 
 31  YearsAtCompany            1470 non-null   int64 
 32  YearsInCurrentRole        1470 non-null   int64 
 33  YearsSinceLastPromotion   1470 non-null   int64 
 34  YearsWithCurrManager      1470 non-null   int64 
dtypes: int64(26), object(9)
memory usage: 402.1+ KB
```

In [4]:
```
ibm.isnull().sum()
```

Out[4]:
```
Age                         0
Attrition                   0
BusinessTravel              0
DailyRate                   0
Department                  0
DistanceFromHome            0
Education                   0
EducationField              0
EmployeeCount               0
EmployeeNumber              0
EnvironmentSatisfaction     0
Gender                      0
HourlyRate                  0
JobInvolvement              0
JobLevel                    0
JobRole                     0
JobSatisfaction             0
MaritalStatus               0
MonthlyIncome               0
MonthlyRate                 0
NumCompaniesWorked          0
Over18                      0
OverTime                    0
PercentSalaryHike           0
PerformanceRating           0
RelationshipSatisfaction    0
StandardHours               0
StockOptionLevel            0
TotalWorkingYears           0
TrainingTimesLastYear       0
WorkLifeBalance             0
YearsAtCompany              0
YearsInCurrentRole          0
YearsSinceLastPromotion     0
YearsWithCurrManager        0
dtype: int64
```

In [5]:
```
ibm.columns
```

Out[5]:
```
Index(['Age', 'Attrition', 'BusinessTravel', 'DailyRate', 'Department',
       'DistanceFromHome', 'Education', 'EducationField', 'EmployeeCount',
       'EmployeeNumber', 'EnvironmentSatisfaction', 'Gender', 'HourlyRate',
       'JobInvolvement', 'JobLevel', 'JobRole', 'JobSatisfaction',
       'MaritalStatus', 'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorke
d',
       'Over18', 'OverTime', 'PercentSalaryHike', 'PerformanceRating',
       'RelationshipSatisfaction', 'StandardHours', 'StockOptionLevel',
       'TotalWorkingYears', 'TrainingTimesLastYear', 'WorkLifeBalance',
       'YearsAtCompany', 'YearsInCurrentRole', 'YearsSinceLastPromotion',
       'YearsWithCurrManager'],
      dtype='object')
```

In all we have 34 features consisting of both the categorical as well as the numerical features. The target variable is the 'Attrition' of the employee which can be either a Yes or a No.

In [6]:
```
#Univariate Analysis
ibm.describe()
```

Out[6]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNu
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1470.0
mean	36.923810	802.485714	9.192517	2.912925	1.0	1024.8
std	9.135373	403.509100	8.106864	1.024165	0.0	602.0
min	18.000000	102.000000	1.000000	1.000000	1.0	1.0
25%	30.000000	465.000000	2.000000	2.000000	1.0	491.2
50%	36.000000	802.000000	7.000000	3.000000	1.0	1020.5
75%	43.000000	1157.000000	14.000000	4.000000	1.0	1555.7
max	60.000000	1499.000000	29.000000	5.000000	1.0	2068.0

8 rows × 26 columns

In [7]:
```
#Analysis using subplots
fig,ax = plt.subplots(5,2, figsize=(9,9))
sns.distplot(ibm['TotalWorkingYears'], ax = ax[0,0])
sns.distplot(ibm['MonthlyIncome'], ax = ax[0,1])
sns.distplot(ibm['YearsAtCompany'], ax = ax[1,0])
sns.distplot(ibm['DistanceFromHome'], ax = ax[1,1])
sns.distplot(ibm['YearsInCurrentRole'], ax = ax[2,0])
sns.distplot(ibm['YearsWithCurrManager'], ax = ax[2,1])
sns.distplot(ibm['YearsSinceLastPromotion'], ax = ax[3,0])
sns.distplot(ibm['PercentSalaryHike'], ax = ax[3,1])
sns.distplot(ibm['YearsSinceLastPromotion'], ax = ax[4,0])
sns.distplot(ibm['TrainingTimesLastYear'], ax = ax[4,1])
plt.tight_layout()
plt.show()
```

```
C:\Users\darsh\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu
tureWarning: `distplot` is a deprecated function and will be removed in a fu
ture version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\darsh\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Fu
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ture version. Please adapt your code to use either `displot` (a figure-level
```
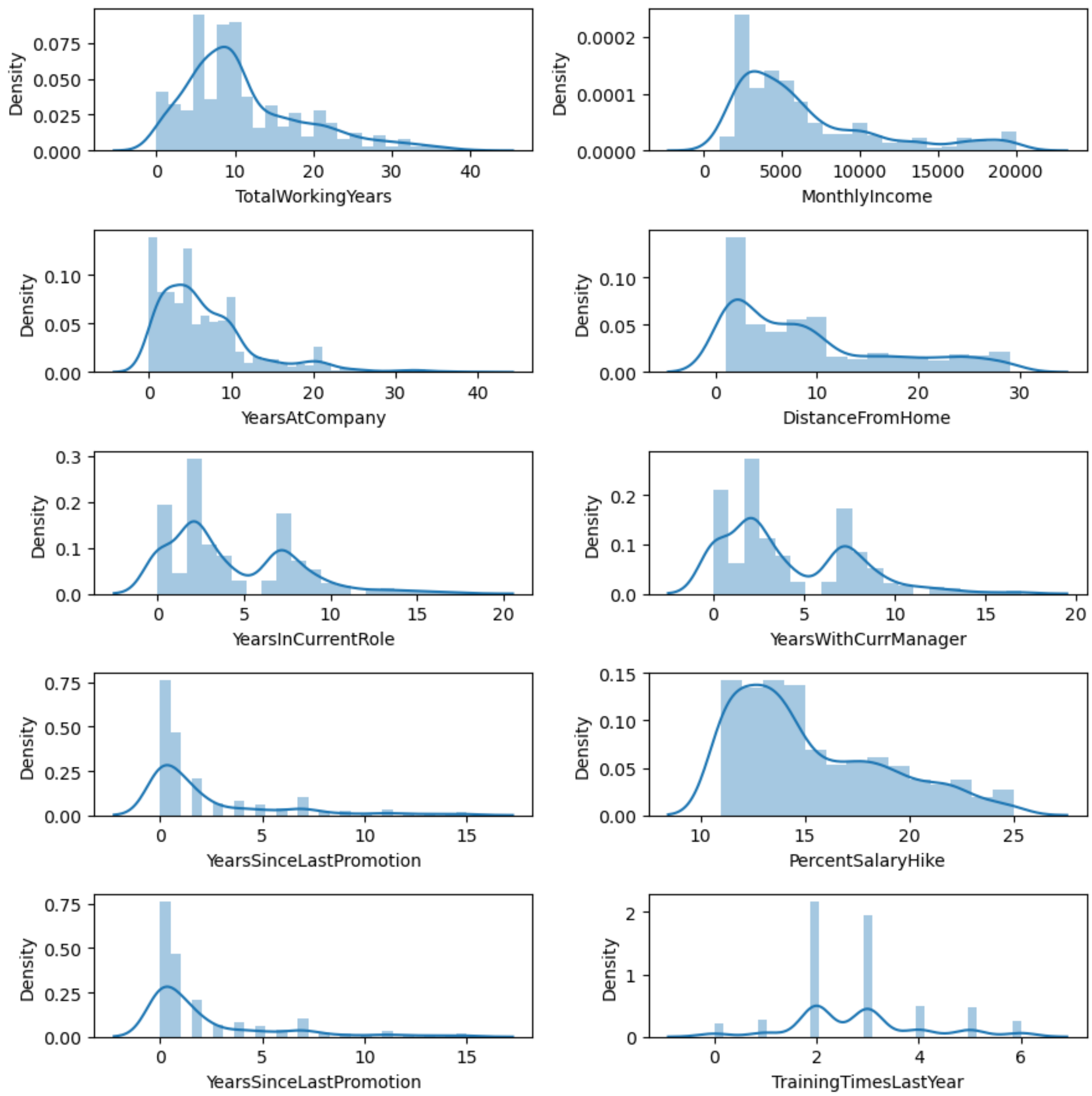

```
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```



In [14]:
```
le = LabelEncoder()
for col in ibm.columns:
    if ibm[col].dtype == 'object':
        ibm[col] = le.fit_transform(ibm[col])
ibm.head()
```

Out[14]:

	Age	Attrition	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisf
0	41	1	2	1	2	1	
1	49	0	1	8	1	1	
2	37	1	1	2	2	4	
3	33	0	1	3	4	1	
4	27	0	1	2	1	3	

5 rows × 24 columns

The feature Selection is one of the main steps of the preprocessing phase as the features which we choose directly effects the model performance. While some of the features seem to be less useful in terms of the context; others seem to equally useful. The better features we use the better our model will perform.

We can also use the Recusrive Feature Elimination technique (a wrapper method) to choose the desired number of most important features. The Recursive Feature Elimination (or RFE) works by recursively removing attributes and building a model on those attributes that remain.

It uses the model accuracy to identify which attributes (and combination of attributes) contribute the most to predicting the target attribute.

In [15]:
```
#Dropping Unneccesary Columns
ibm.drop(['BusinessTravel','DailyRate','EmployeeCount','EmployeeNumber',
          'HourlyRate','MonthlyRate','NumCompaniesWorked','Over18','StandardH
          'StockOptionLevel','TrainingTimesLastYear'],axis=1,inplace=True)
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_31112\1282314506.py in <module>
      1 #Dropping Unneccesary Columns
----> 2 ibm.drop(['BusinessTravel','DailyRate','EmployeeCount','EmployeeNumb
er',
      3            'HourlyRate','MonthlyRate','NumCompaniesWorked','Over1
8','StandardHours',
      4            'StockOptionLevel','TrainingTimesLastYear'],axis=1,inplace
=True)

~\anaconda3\lib\site-packages\pandas\util\_decorators.py in wrapper(*args, *
*kwargs)
    309                     stacklevel=stacklevel,
    310                 )
--> 311             return func(*args, **kwargs)
    312 
    313         return wrapper

~\anaconda3\lib\site-packages\pandas\core\frame.py in drop(self, labels, axi
s, index, columns, level, inplace, errors)
   4955                 weight  1.0     0.8
   4956         """
-> 4957         return super().drop(
   4958             labels=labels,
   4959             axis=axis,

~\anaconda3\lib\site-packages\pandas\core\generic.py in drop(self, labels, a
xis, index, columns, level, inplace, errors)
   4265         for axis, labels in axes.items():
   4266             if labels is not None:
-> 4267                 obj = obj._drop_axis(labels, axis, level=level, erro
rs=errors)
   4268 
   4269         if inplace:

~\anaconda3\lib\site-packages\pandas\core\generic.py in _drop_axis(self, lab
els, axis, level, errors, consolidate, only_slice)
   4309                 new_axis = axis.drop(labels, level=level, errors=err
ors)
   4310             else:
-> 4311                 new_axis = axis.drop(labels, errors=errors)
   4312             indexer = axis.get_indexer(new_axis)
   4313 

~\anaconda3\lib\site-packages\pandas\core\indexes\base.py in drop(self, labe
ls, errors)
   6659         if mask.any():
   6660             if errors != "ignore":
-> 6661                 raise KeyError(f"{list(labels[mask])} not found in a
xis")
   6662             indexer = indexer[~mask]
   6663         return self.delete(indexer)

KeyError: "['BusinessTravel', 'DailyRate', 'EmployeeCount', 'EmployeeNumbe
r', 'HourlyRate', 'MonthlyRate', 'NumCompaniesWorked', 'Over18', 'StandardHo
```

```
urs', 'StockOptionLevel', 'TrainingTimesLastYear'] not found in axis"
```

In this code snippet, the ibm dataset is being modified by dropping several columns using the drop() function. The dropped columns are:

BusinessTravel: It may not be relevant for predicting employee attrition or performance as it just indicates the frequency of travel of employees.

DailyRate, HourlyRate, MonthlyRate: These columns contain information about employee's pay rate, which may not be directly related to employee attrition or performance.

EmployeeCount, EmployeeNumber, Over18, StandardHours: These columns contain information that is constant for all employees, so they do not provide any useful information for predicting employee attrition or performance.

NumCompaniesWorked: This column contains information about the number of companies an employee has worked for prior to joining the current company. While it may be relevant, it is also highly correlated with other columns such as TotalWorkingYears and JobInvolvement, so it may not be necessary to keep it.

StockOptionLevel, TrainingTimesLastYear: These columns may not have a significant impact on employee attrition or performance.

In [ ]:

```
corr_matrix = ibm.corr()

# Set the threshold for selecting highly correlated features
threshold = 0.5

# Select the most highly correlated features
corr_features = set()
for i in range(len(corr_matrix.columns)):
    for j in range(len(corr_matrix.index)):
        if abs(corr_matrix.iloc[i, j]) > threshold and i != j:
            colname_i = corr_matrix.columns[i]
            colname_j = corr_matrix.index[j]
            corr_features.add(colname_i)
            corr_features.add(colname_j)

# Create the truncated heatmap
plt.figure(figsize=(10,8))
sns.heatmap(ibm[corr_features].corr(), cmap='coolwarm', annot=True, fmt='.2f'
plt.title('Truncated Correlation Matrix of IBM Dataset')
plt.show()
```

SOME INFERENCES FROM THE ABOVE HEATMAP

Self relation ie of a feature to itself is equal to 1 as expected.

JobLevel is highly related to Age as expected as aged employees will generally tend to occupy higher positions in the company.

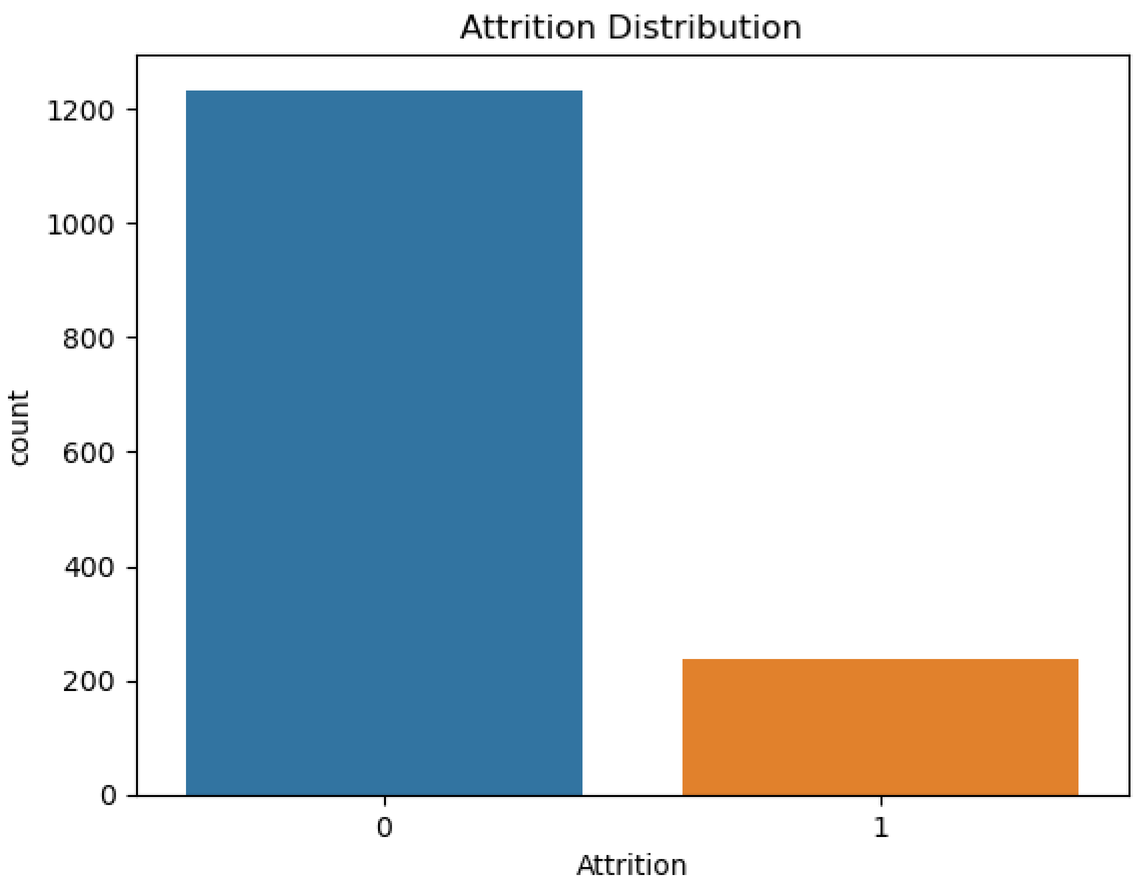
MonthlyIncome is very strongly related to joblevel as expected as senior employees will definately earn more.

Also note that TotalWorkingYears is highly related to JobLevel which is expected as senior employees must have worked for a larger span of time.

YearsWithCurrManager is highly related to YearsAtCompany.

YearsAtCompany is related to YearsInCurrentRole

In [16]:
```
sns.countplot(x='Attrition', data=ibm)
plt.title('Attrition Distribution')
plt.show()
```



Note that the number of observations belonging to the 'No' category is way greater than that belonging to 'Yes' category. Hence we have skewed classes and this is a typical example of the 'Imbalanced Classification Problem'. To handle such types of problems we need to use the over-sampling or under-sampling techniques.

STANDARDIZATION

In [17]:
```
# Feature Scaling.
# I have used the StandardScaler to scale the data.

scaler=StandardScaler()
scaled_ibm=scaler.fit_transform(ibm.drop('Attrition',axis=1))
X=scaled_ibm
Y=ibm['Attrition']
```

In [18]:
```
#Splitting the data into training and validation sets
x_train,x_test,y_train,y_test=train_test_split(X,Y,test_size=0.25,random_stat
```

In an imbalanced dataset the main problem is that the data is highly skewed ie the number of observations of certain class is more than that of the other. Therefore what we do in this approach is to either increase the number of observations corressponding to the minority class (oversampling) or decrease the number of observations for the majority class (undersampling).

Note that in our case the number of observations is already pretty low and so oversampling will be more appropriate.

Below I have used an oversampling technique known as the SMOTE(Synthetic Minority Oversampling Technique) which randomly creates some 'Synthetic' instances of the minority class so that the net observations of both the class get balanced out.

One thing more to take of is to use the SMOTE before the cross validation step; just to ensure that our model does not overfit the data; just as in the case of feature selection.

In [19]:
```
from imblearn.over_sampling import SMOTE
oversampler=SMOTE(random_state=42)
x_train_smote,  y_train_smote = oversampler.fit_resample(x_train,y_train)
```

RANDOM-FOREST CLASSIFIER

In [20]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
# create an instance of RandomForestClassifier
rfc = RandomForestClassifier(n_estimators=100, random_state=42)

# fit the model on the training data
rfc.fit(x_train_smote, y_train_smote)

# make predictions on the test data
y_pred = rfc.predict(x_test)

# evaluate the performance of the model
print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.8369565217391305
              precision    recall  f1-score   support

           0       0.85      0.97      0.91       304
           1       0.59      0.20      0.30        64

    accuracy                           0.84       368
   macro avg       0.72      0.59      0.61       368
weighted avg       0.81      0.84      0.80       368
```

Random forest is an ensemble learning method that combines multiple decision trees and uses a majority vote to make predictions. This can help to reduce overfitting and improve the accuracy of the model.Random forest can also handle a larger number of features than decision tree, which can be useful for datasets with many features.Actually i have also used decision tree before it give me 78% accuracy.hence,Random Forest is better than decision tree.

DECISION TREE

In [21]:
```
from sklearn.tree import DecisionTreeClassifier

# Create an instance of DecisionTreeClassifier
dt = DecisionTreeClassifier(random_state=42)

# Fit the model to the training data
dt.fit(x_train, y_train)

# Make predictions on the test data
y_pred = dt.predict(x_test)

# Evaluate the performance of the model
print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.7771739130434783
              precision    recall  f1-score   support

           0       0.87      0.87      0.87       304
           1       0.36      0.36      0.36        64

    accuracy                           0.78       368
   macro avg       0.61      0.61      0.61       368
weighted avg       0.78      0.78      0.78       368
```

ANN

In [22]:
```
np.random.seed(42)
rn.seed(42)
tf.random.set_seed(42)
```

In [27]:
```
#BUILDING KERAS MODEL
from keras.models import Sequential
from keras.layers import Dense
from keras.optimizers import Adam
from tensorflow import keras
from tensorflow.keras import layers


np.random.seed(42)
rn.seed(42)
tf.random.set_seed(42)
model = keras.Sequential([
    layers.Dense(32, activation='relu', input_shape=[x_train.shape[1]]),
    layers.Dense(16, activation='relu'),
    layers.Dense(1, activation='sigmoid')
])

model.compile(optimizer=Adam(lr=0.01),loss='binary_crossentropy',metrics=['ac
History=model.fit(x_train_smote,y_train_smote,validation_data=(x_test,y_test)
```

```
Epoch 1/9
59/59 [==============================] - 1s 9ms/step - loss: 0.4973 - acc
uracy: 0.7481 - val_loss: 0.5346 - val_accuracy: 0.7663
Epoch 2/9
59/59 [==============================] - 0s 5ms/step - loss: 0.3820 - acc
uracy: 0.8186 - val_loss: 0.5244 - val_accuracy: 0.7880
Epoch 3/9
59/59 [==============================] - 0s 5ms/step - loss: 0.3181 - acc
uracy: 0.8638 - val_loss: 0.5532 - val_accuracy: 0.7799
Epoch 4/9
59/59 [==============================] - 0s 5ms/step - loss: 0.2775 - acc
uracy: 0.8854 - val_loss: 0.5932 - val_accuracy: 0.7690
Epoch 5/9
59/59 [==============================] - 0s 4ms/step - loss: 0.2525 - acc
uracy: 0.8956 - val_loss: 0.5811 - val_accuracy: 0.7636
Epoch 6/9
59/59 [==============================] - 0s 5ms/step - loss: 0.2277 - acc
uracy: 0.9128 - val_loss: 0.6362 - val_accuracy: 0.7799
Epoch 7/9
```

First we need to build a model. For this we use the Sequential model provided by the Keras which is nothing but a linear stack of layers.

Next we need to add the layers to our Sequential model. For this we use the model.add() function.

Note that for each layer we need to specify the number of units (or the number of neurons) and also the activation function used by the neurons.

Note that activation function is used to model complex non-linear relationships and their are many choices. But generally it is preferred to use 'relu' function for the hidden layers and the 'sigmoid' or the 'logistic' function for the output layer. For a multi-class classification problem we can use the 'softmax' function as the activation function for the output layer.

Note that the first layer and ONLY the first layer expects the input dimensions in order to know the shape of the input numpy array.

Finally note that the number of units or neurons in the final layer is equal to the number of classes of the target variable. In other words for a 'n' class classification problem we shall have 'n' neurons in the output layer.

Each neuron represents a specific target class. The output of each neuron in the final layer thus represents the probability of given observation being classified to that target class. The observation is classified to the target class; the neuron corressponding to which has the

BREAKING IT DOWN Now we need to compile the model. We have to specify the optimizer used by the model We have many choices like Adam, RMSprop etc.. Rfer to Keras doc for a comprehensive list of the optimizers available.

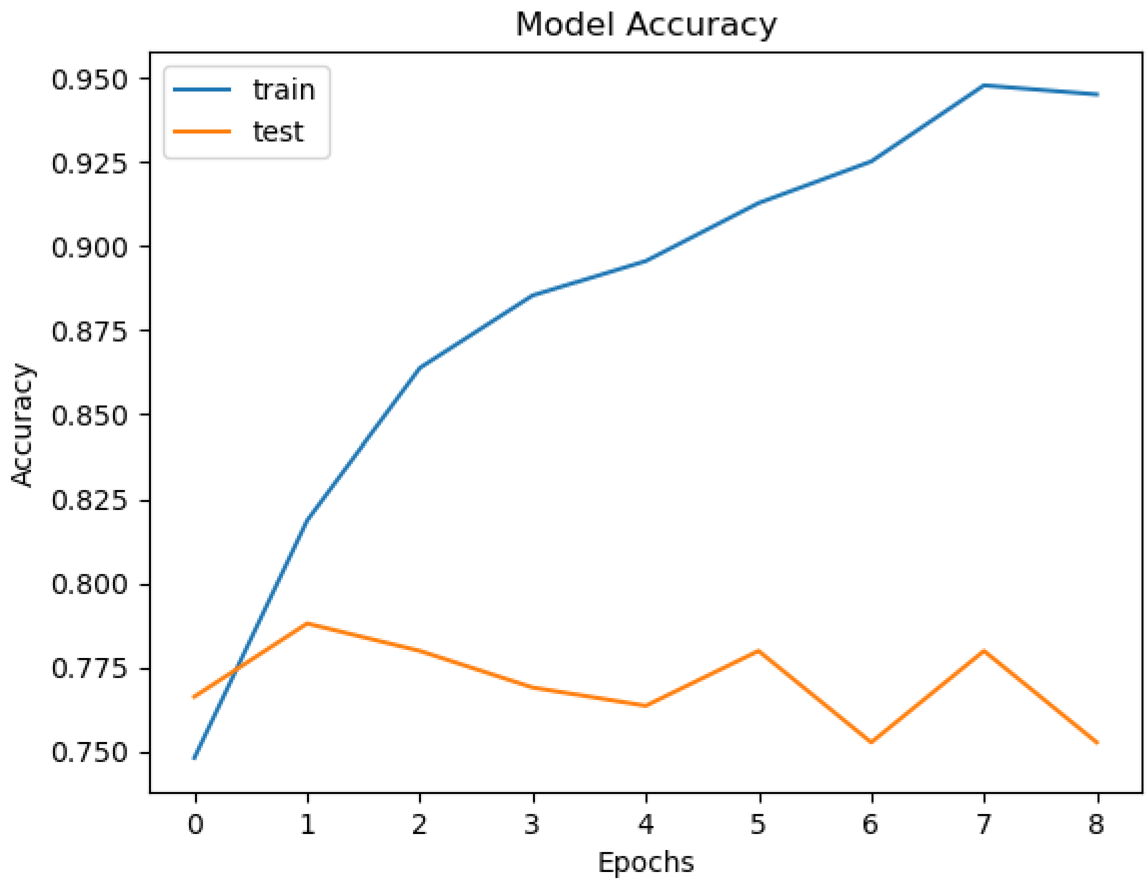
Next we need to specify the loss function for the neural network which we seek to minimize.

I have used the 'binary_crossentropy' loss function since this is a binary classification problem. For a multi-class classification problems we may use the 'categorical_crossentropy'.

Next we need to specify the metric to evaluate our models performance. Here I have used accuracy.

EVALUTION

In [28]:
```
plt.plot(History.history['accuracy'])
plt.plot(History.history['val_accuracy'])
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epochs')
plt.legend(['train', 'test'])
plt.show()
```



In [ ]: