Configuration Manual

MSc Research Project
Data Analytics

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MSc Project Submission Sheet

School of Computing

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Programme:	…MSc in Data Analytics…………………………… **Year:** …2022……………..
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Lecturer:	…Dr. Catherine Mulwa…………………………………………………….………
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Configuration Manual

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1 Introduction

In this Configuration Manual all the perquisites required to reproduce the research and its outcomes on individual environment are mentioned. The software and the hardware requirement along with a snapshot of code for Data Import and Exploratory Data Analysis, Data Pre-processing, Label Encoding, Feature Selection, all the models-built and Evaluation are included. The structure of the report is as follows, Section 2, gives the information about environment configuration.
Section 3, provides detail about data collection. Section 4 is data exploration consists of Data Pre-processing and Exploratory Data Analysis. Label Encoding is explained in section 5. Section 6 provides the details about Class Balancing. Section 7 provides the details about Feature Selection. The train test splits for the data for model training and testing are covered in this section. Section 8 provides the details about the models built. Section 9, explains how results are computed and visualized.

2 Environment

This section provides the details of Software and Hardware requirements to implement the research done.

2.1 Hardware Requirements

Below Figure 1, provides the hardware specifications required. AMD Ryzen 5 2600 Six-Core Processor @ 3.40 GHz, 16 GB installed DDR4 RAM Memory at speed of 3200 Mhz, 64 Bit Windows 11 Pro operating System, 1024 GB SSD.

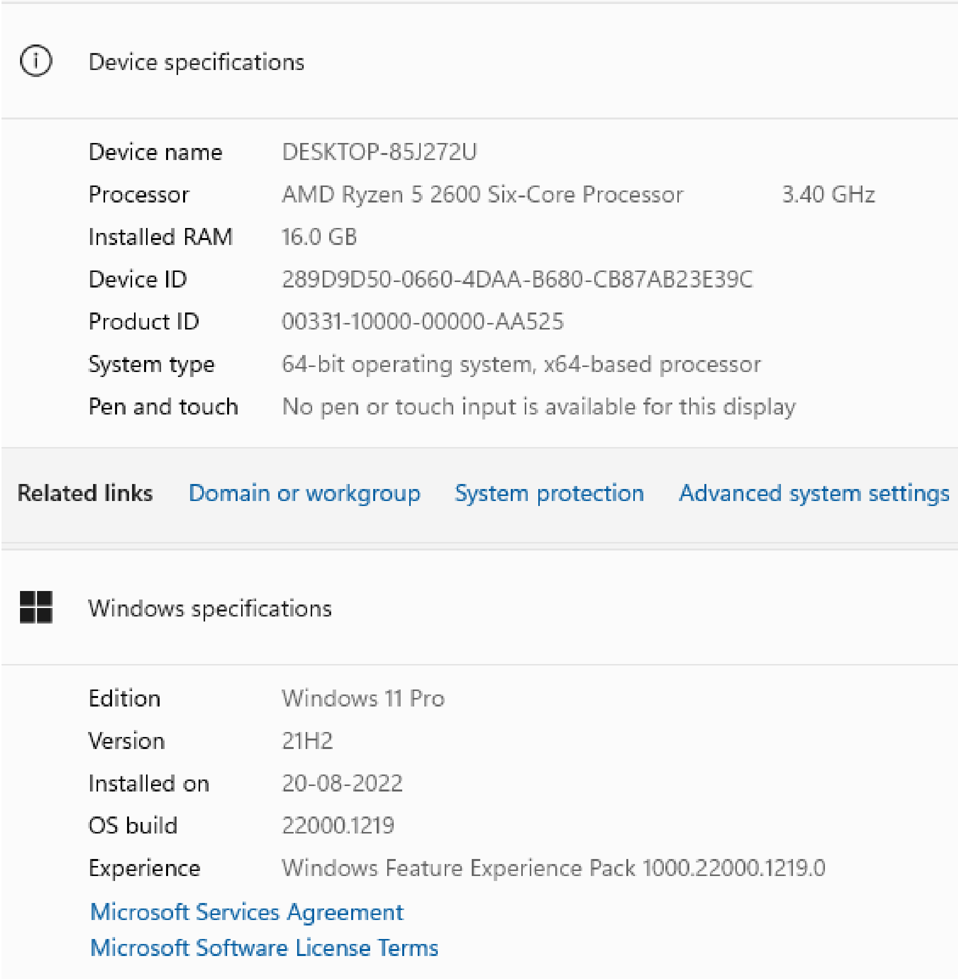


Figure 1: Hardware Requirements2

2.2 Software Requirements

- Anaconda 3 for Windows (Version 4.8.0)
- Jupyter Notebook (Version 6.0.3)
- Python (Version 3.7.6)

3 Data Collection

The data is taken from https://github.com/rlilojr/Detecting-Malicious-URL-Machine-Learning.

4 Data Exploration

All the Python libraries required to implement the entire project are listed in Figure 2.

```python
import matplotlib.pyplot as plt
import matplotlib.ticker as mtick
import pandas as pd
import numpy as np
from sklearn import preprocessing
from sklearn.feature_selection import chi2, SelectKBest
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import accuracy_score,f1_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier
```

Figure 2: Required Python Libraries

The Figure 3 represents the code to import data.

```python
# importing the data file
data = pd.read_excel("employee attrition final dataset.xlsx")
```

```python
# printing the top 10 rows of data
data.head(10)
```

	Employee_ID	Gender	Age	Education_Level	Relationship_Status	Hometown	Unit	Decision_skill_possess	Time_of_service	Time_since_promotion
0	EID_23371	F	42.0	4	Married	Franklin	IT	Conceptual	4.0	4
1	EID_18000	M	24.0	3	Single	Springfield	Logistics	Analytical	5.0	4
2	EID_3891	F	58.0	3	Married	Clinton	Quality	Conceptual	27.0	3
3	EID_17492	F	26.0	3	Single	Lebanon	Human Resource Management	Behavioral	4.0	3
4	EID_22534	F	31.0	1	Married	Springfield	Logistics	Conceptual	5.0	4
5	EID_2278	M	54.0	3	Married	Lebanon	Purchasing	Conceptual	19.0	1
6	EID_18588	F	21.0	4	Married	Springfield	Purchasing	Directive	2.0	1
7	EID_1235	F	NaN	3	Married	Springfield	Sales	Directive	34.0	4
8	EID_10197	M	40.0	4	Single	Springfield	Production	Analytical	13.0	1
9	EID_21262	M	45.0	3	Married	Lebanon	IT	Directive	21.0	4

10 rows × 24 columns

Figure 3: Data import

The Figure 4 represents the code to check data columns and statistical information about the data.

```python
# column name
data.columns
```

```
Index(['Employee_ID', 'Gender', 'Age', 'Education_Level',
       'Relationship_Status', 'Hometown', 'Unit', 'Decision_skill_possess',
       'Time_of_service', 'Time_since_promotion', 'growth_rate', 'Travel_Rate',
       'Post_Level', 'Pay_Scale', 'Compensation_and_Benefits',
       'Work_Life_balance', 'VAR1', 'VAR2', 'VAR3', 'VAR4', 'VAR5', 'VAR6',
       'VAR7', 'Attrition_rate'],
      dtype='object')
```

```python
# understanding the data structure
data.describe()
```

	Age	Education_Level	Time_of_service	Time_since_promotion	growth_rate	Travel_I
count	4713.000000	4999.000000	4903.000000	4999.000000	4999.000000	4999.00(
mean	39.632930	3.169834	13.378748	2.356071	46.964593	0.81{
std	13.715201	1.074162	10.363130	1.150377	15.844159	0.64{
min	19.000000	1.000000	0.000000	0.000000	20.000000	0.00(
25%	27.000000	3.000000	5.000000	1.000000	33.000000	0.00(
50%	37.000000	3.000000	10.000000	2.000000	47.000000	1.00(
75%	52.000000	4.000000	21.000000	3.000000	61.000000	1.00(
max	65.000000	5.000000	43.000000	4.000000	74.000000	2.00(

Figure 4: Data Description

The Figure 5 represents the code to check data information and the count of missing values for each feature column.

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4999 entries, 0 to 4998
Data columns (total 24 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   Employee_ID                 4999 non-null   object 
 1   Gender                      4999 non-null   object 
 2   Age                         4713 non-null   float64
 3   Education_Level             4999 non-null   int64  
 4   Relationship_Status         4999 non-null   object 
 5   Hometown                    4999 non-null   object 
 6   Unit                        4999 non-null   object 
 7   Decision_skill_possess      4999 non-null   object 
 8   Time_of_service             4903 non-null   float64
 9   Time_since_promotion        4999 non-null   int64  
 10  growth_rate                 4999 non-null   int64  
 11  Travel_Rate                 4999 non-null   int64  
 12  Post_Level                  4999 non-null   int64  
 13  Pay_Scale                   4992 non-null   float64
 14  Compensation_and_Benefits   4999 non-null   object 
 15  Work_Life_balance           4989 non-null   float64
 16  VAR1                        4999 non-null   int64  
 17  VAR2                        4595 non-null   float64
 18  VAR3                        4999 non-null   float64
 19  VAR4                        4524 non-null   float64
 20  VAR5                        4999 non-null   int64  
 21  VAR6                        4999 non-null   int64  
 22  VAR7                        4999 non-null   int64  
 23  Attrition_rate              4999 non-null   float64
dtypes: float64(8), int64(9), object(7)
memory usage: 937.4+ KB
```

Figure 5: Data Information

Figure 6 represents the code top count the missing values present in each column. The missing values are fixed in figure 7. The figure also shows the code to convert the float type attrition_rate to integer by rounding off the digits.

```
# checking if data has null values
data.isnull().sum()
```

```
Employee_ID                    0
Gender                         0
Age                          286
Education_Level                0
Relationship_Status            0
Hometown                       0
Unit                           0
Decision_skill_possess         0
Time_of_service               96
Time_since_promotion           0
growth_rate                    0
Travel_Rate                    0
Post_Level                     0
Pay_Scale                      7
Compensation_and_Benefits      0
Work_Life_balance             10
VAR1                           0
VAR2                         404
VAR3                           0
VAR4                         475
VAR5                           0
VAR6                           0
VAR7                           0
Attrition_rate                 0
dtype: int64
```

Figure 6: Missing Values

```
data['Work_Life_balance'] = data['Work_Life_balance'].fillna(1.0)
data = data.fillna(0)
```

```
data['Attrition_rate'] = np.round(data['Attrition_rate'],0)
```

Figure 7: For missing value

The Figure 8, illustrate the code to count the data points for each class.

```
# Checking valvue count for class balance
data['Attrition_rate'].value_counts()
```

```
0.0    4611
1.0     388
Name: Attrition_rate, dtype: int64
```

Figure 8: Class count

The Figure 9, illustrate the code to plot the gender distribution graph showing the percentage of male and female employees.

```
# To see attrition percentage by gender
ax = (data['Gender'].value_counts()*100.0 /len(data)).plot(kind='bar',sta
ax.yaxis.set_major_formatter(mtick.PercentFormatter())
ax.set_ylabel('% Customers')
ax.set_xlabel('Gender')
ax.set_ylabel('% Employee')
ax.set_title('Gender Distribution')

# create a list to collect the plt.patches data
totals = []

# find the values and append to list
for i in ax.patches:
    totals.append(i.get_width())

# set individual bar lables using above list
total = sum(totals)

for i in ax.patches:
    # get_width pulls left or right; get_y pushes up or down
    ax.text(i.get_x()+.15, i.get_height()-3.5, \
            str(round((i.get_height()/total), 1))+'%',
            fontsize=12,
            color='white',
           weight = 'bold')
```

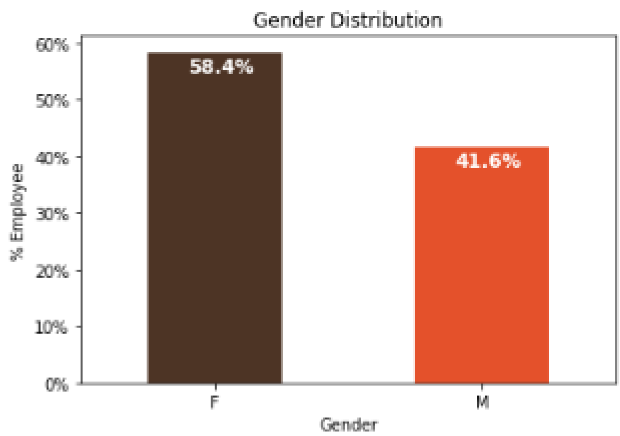


Figure 9: Plot for gender distribution

The Figure 10, illustrate the code to generate the value count for work life balance and plot a pie chart for work life balance based on attrition rate.

```
data['Work_Life_balance'].value_counts()
```

```
1.0    1492
3.0    1424
2.0    1138
4.0     870
5.0      75
Name: Work_Life_balance, dtype: int64
```

```
# To see attrition percentage by Work_Life_balance
ax = (data['Work_Life_balance'].value_counts()*100.0 /len(data))\
.plot.pie(autopct='%.1f%%', labels = [5.0,4.0,3.0,2.0,1.0],figsize =(5,5), fontsize = 12 )
ax.yaxis.set_major_formatter(mtick.PercentFormatter())
ax.set_ylabel('Work_Life_balance',fontsize = 12)
ax.set_title('% of Employees', fontsize = 12)
```

```
Text(0.5, 1.0, '% of Employees')
```

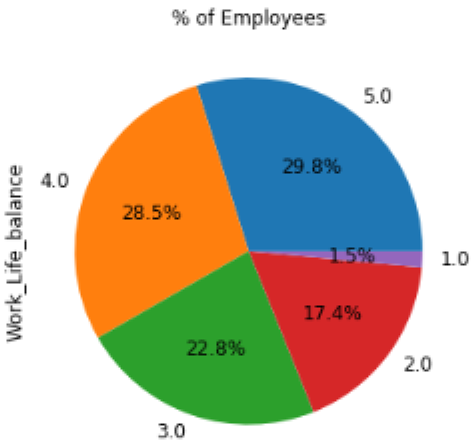


Figure 10: Plot for Work life balance

The Figure 11, illustrate the code to find the data points present for each department and the code showed in figure (12-23) is showing the sub setting of data for each department.

```
data.Unit.value_counts()
```

```
IT                              1008
Logistics                        841
Sales                            675
Operarions                       482
R&D                              480
Accounting and Finance           362
Purchasing                       358
Human Resource Management        245
Marketing                        157
Production                       151
Quality                          139
Security                         101
Name: Unit, dtype: int64
```

Figure 11: Department wise data count

```python
dataIT = data[data.Unit == "IT"].drop('Unit', axis=1)
dataIT.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1008 entries, 0 to 4998
Data columns (total 23 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Employee_ID               1008 non-null   object 
 1   Gender                    1008 non-null   object 
 2   Age                       1008 non-null   float64
 3   Education_Level           1008 non-null   int64  
 4   Relationship_Status       1008 non-null   object 
 5   Hometown                  1008 non-null   object 
 6   Decision_skill_possess    1008 non-null   object 
 7   Time_of_service           1008 non-null   float64
 8   Time_since_promotion      1008 non-null   int64  
 9   growth_rate               1008 non-null   int64  
 10  Travel_Rate               1008 non-null   int64  
 11  Post_Level                1008 non-null   int64  
 12  Pay_Scale                 1008 non-null   float64
 13  Compensation_and_Benefits 1008 non-null   object 
 14  Work_Life_balance         1008 non-null   float64
 15  VAR1                      1008 non-null   int64  
 16  VAR2                      1008 non-null   float64
 17  VAR3                      1008 non-null   float64
 18  VAR4                      1008 non-null   float64
 19  VAR5                      1008 non-null   int64  
 20  VAR6                      1008 non-null   int64  
 21  VAR7                      1008 non-null   int64  
 22  Attrition_rate            1008 non-null   float64
dtypes: float64(8), int64(9), object(6)
memory usage: 189.0+ KB
```

Figure 12: Sub setting for IT department

```python
dataLogistics = data[data.Unit == "Logistics"].drop('Unit', axis=1)
dataLogistics.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 841 entries, 1 to 4989
Data columns (total 23 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Employee_ID               841 non-null    object 
 1   Gender                    841 non-null    object 
 2   Age                       841 non-null    float64
 3   Education_Level           841 non-null    int64  
 4   Relationship_Status       841 non-null    object 
 5   Hometown                  841 non-null    object 
 6   Decision_skill_possess    841 non-null    object 
 7   Time_of_service           841 non-null    float64
 8   Time_since_promotion      841 non-null    int64  
 9   growth_rate               841 non-null    int64  
 10  Travel_Rate               841 non-null    int64  
 11  Post_Level                841 non-null    int64  
 12  Pay_Scale                 841 non-null    float64
 13  Compensation_and_Benefits 841 non-null    object 
 14  Work_Life_balance         841 non-null    float64
 15  VAR1                      841 non-null    int64  
 16  VAR2                      841 non-null    float64
 17  VAR3                      841 non-null    float64
 18  VAR4                      841 non-null    float64
 19  VAR5                      841 non-null    int64  
 20  VAR6                      841 non-null    int64  
 21  VAR7                      841 non-null    int64  
 22  Attrition_rate            841 non-null    float64
dtypes: float64(8), int64(9), object(6)
memory usage: 157.7+ KB
```

Figure 13: Sub setting for Logitics department

```python
dataQuality = data[data.Unit == "Quality"].drop('Unit', axis=1)
dataQuality.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 139 entries, 2 to 4975
Data columns (total 23 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   Employee_ID                 139 non-null    object 
 1   Gender                      139 non-null    object 
 2   Age                         139 non-null    float64
 3   Education_Level             139 non-null    int64  
 4   Relationship_Status         139 non-null    object 
 5   Hometown                    139 non-null    object 
 6   Decision_skill_possess      139 non-null    object 
 7   Time_of_service             139 non-null    float64
 8   Time_since_promotion        139 non-null    int64  
 9   growth_rate                 139 non-null    int64  
 10  Travel_Rate                 139 non-null    int64  
 11  Post_Level                  139 non-null    int64  
 12  Pay_Scale                   139 non-null    float64
 13  Compensation_and_Benefits   139 non-null    object 
 14  Work_Life_balance           139 non-null    float64
 15  VAR1                        139 non-null    int64  
 16  VAR2                        139 non-null    float64
 17  VAR3                        139 non-null    float64
 18  VAR4                        139 non-null    float64
 19  VAR5                        139 non-null    int64  
 20  VAR6                        139 non-null    int64  
 21  VAR7                        139 non-null    int64  
 22  Attrition_rate              139 non-null    float64
dtypes: float64(8), int64(9), object(6)
memory usage: 26.1+ KB
```

Figure 14: Sub setting for Quality department

```python
dataHR = data[data.Unit == "Human Resource Management"].drop('Unit', axis=1)
dataHR.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 245 entries, 3 to 4985
Data columns (total 23 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   Employee_ID                 245 non-null    object 
 1   Gender                      245 non-null    object 
 2   Age                         245 non-null    float64
 3   Education_Level             245 non-null    int64  
 4   Relationship_Status         245 non-null    object 
 5   Hometown                    245 non-null    object 
 6   Decision_skill_possess      245 non-null    object 
 7   Time_of_service             245 non-null    float64
 8   Time_since_promotion        245 non-null    int64  
 9   growth_rate                 245 non-null    int64  
 10  Travel_Rate                 245 non-null    int64  
 11  Post_Level                  245 non-null    int64  
 12  Pay_Scale                   245 non-null    float64
 13  Compensation_and_Benefits   245 non-null    object 
 14  Work_Life_balance           245 non-null    float64
 15  VAR1                        245 non-null    int64  
 16  VAR2                        245 non-null    float64
 17  VAR3                        245 non-null    float64
 18  VAR4                        245 non-null    float64
 19  VAR5                        245 non-null    int64  
 20  VAR6                        245 non-null    int64  
 21  VAR7                        245 non-null    int64  
 22  Attrition_rate              245 non-null    float64
dtypes: float64(8), int64(9), object(6)
memory usage: 45.9+ KB
```

Figure 15: Sub setting for HR department

```
dataPurchasing = data[data.Unit == "Purchasing"].drop('Unit', axis=1)
dataPurchasing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 358 entries, 5 to 4995
Data columns (total 23 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Employee_ID                358 non-null    object
 1   Gender                     358 non-null    object
 2   Age                        358 non-null    float64
 3   Education_Level            358 non-null    int64
 4   Relationship_Status        358 non-null    object
 5   Hometown                   358 non-null    object
 6   Decision_skill_possess     358 non-null    object
 7   Time_of_service            358 non-null    float64
 8   Time_since_promotion       358 non-null    int64
 9   growth_rate                358 non-null    int64
 10  Travel_Rate                358 non-null    int64
 11  Post_Level                 358 non-null    int64
 12  Pay_Scale                  358 non-null    float64
 13  Compensation_and_Benefits  358 non-null    object
 14  Work_Life_balance          358 non-null    float64
 15  VAR1                       358 non-null    int64
 16  VAR2                       358 non-null    float64
 17  VAR3                       358 non-null    float64
 18  VAR4                       358 non-null    float64
 19  VAR5                       358 non-null    int64
 20  VAR6                       358 non-null    int64
 21  VAR7                       358 non-null    int64
 22  Attrition_rate             358 non-null    float64
dtypes: float64(8), int64(9), object(6)
memory usage: 67.1+ KB
```

Figure 16: Sub setting for Purchasing department

```
dataSales = data[data.Unit == "Sales"].drop('Unit', axis=1)
dataSales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 675 entries, 7 to 4996
Data columns (total 23 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Employee_ID              675 non-null    object 
 1   Gender                   675 non-null    object 
 2   Age                      675 non-null    float64
 3   Education_Level          675 non-null    int64  
 4   Relationship_Status      675 non-null    object 
 5   Hometown                 675 non-null    object 
 6   Decision_skill_possess   675 non-null    object 
 7   Time_of_service          675 non-null    float64
 8   Time_since_promotion     675 non-null    int64  
 9   growth_rate              675 non-null    int64  
 10  Travel_Rate              675 non-null    int64  
 11  Post_Level               675 non-null    int64  
 12  Pay_Scale                675 non-null    float64
 13  Compensation_and_Benefits 675 non-null   object 
 14  Work_Life_balance        675 non-null    float64
 15  VAR1                     675 non-null    int64  
 16  VAR2                     675 non-null    float64
 17  VAR3                     675 non-null    float64
 18  VAR4                     675 non-null    float64
 19  VAR5                     675 non-null    int64  
 20  VAR6                     675 non-null    int64  
 21  VAR7                     675 non-null    int64  
 22  Attrition_rate           675 non-null    float64
dtypes: float64(8), int64(9), object(6)
memory usage: 126.6+ KB
```

Figure 17: Sub setting for Sales department

```
dataProduction = data[data.Unit == "Production"].drop('Unit', axis=1)
dataProduction.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 151 entries, 8 to 4971
Data columns (total 23 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   Employee_ID                 151 non-null    object
 1   Gender                      151 non-null    object
 2   Age                         151 non-null    float64
 3   Education_Level             151 non-null    int64
 4   Relationship_Status         151 non-null    object
 5   Hometown                    151 non-null    object
 6   Decision_skill_possess      151 non-null    object
 7   Time_of_service             151 non-null    float64
 8   Time_since_promotion        151 non-null    int64
 9   growth_rate                 151 non-null    int64
 10  Travel_Rate                 151 non-null    int64
 11  Post_Level                  151 non-null    int64
 12  Pay_Scale                   151 non-null    float64
 13  Compensation_and_Benefits   151 non-null    object
 14  Work_Life_balance           151 non-null    float64
 15  VAR1                        151 non-null    int64
 16  VAR2                        151 non-null    float64
 17  VAR3                        151 non-null    float64
 18  VAR4                        151 non-null    float64
 19  VAR5                        151 non-null    int64
 20  VAR6                        151 non-null    int64
 21  VAR7                        151 non-null    int64
 22  Attrition_rate              151 non-null    float64
dtypes: float64(8), int64(9), object(6)
memory usage: 28.3+ KB
```

Figure 18: Sub setting for Production department

```
dataOperarions = data[data.Unit == "Operarions"].drop('Unit', axis=1)
dataOperarions.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 482 entries, 11 to 4986
Data columns (total 23 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Employee_ID              482 non-null    object 
 1   Gender                   482 non-null    object 
 2   Age                      482 non-null    float64
 3   Education_Level          482 non-null    int64  
 4   Relationship_Status      482 non-null    object 
 5   Hometown                 482 non-null    object 
 6   Decision_skill_possess   482 non-null    object 
 7   Time_of_service          482 non-null    float64
 8   Time_since_promotion     482 non-null    int64  
 9   growth_rate              482 non-null    int64  
 10  Travel_Rate              482 non-null    int64  
 11  Post_Level               482 non-null    int64  
 12  Pay_Scale                482 non-null    float64
 13  Compensation_and_Benefits  482 non-null    object 
 14  Work_Life_balance        482 non-null    float64
 15  VAR1                     482 non-null    int64  
 16  VAR2                     482 non-null    float64
 17  VAR3                     482 non-null    float64
 18  VAR4                     482 non-null    float64
 19  VAR5                     482 non-null    int64  
 20  VAR6                     482 non-null    int64  
 21  VAR7                     482 non-null    int64  
 22  Attrition_rate           482 non-null    float64
dtypes: float64(8), int64(9), object(6)
memory usage: 90.4+ KB
```

Figure 19: Sub setting for Operations department

```
dataAcconting = data[data.Unit == "Accounting and Finance"].drop('Unit', axis=1)
dataAcconting.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 362 entries, 17 to 4997
Data columns (total 23 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Employee_ID              362 non-null    object 
 1   Gender                   362 non-null    object 
 2   Age                      362 non-null    float64
 3   Education_Level          362 non-null    int64  
 4   Relationship_Status      362 non-null    object 
 5   Hometown                 362 non-null    object 
 6   Decision_skill_possess   362 non-null    object 
 7   Time_of_service          362 non-null    float64
 8   Time_since_promotion     362 non-null    int64  
 9   growth_rate              362 non-null    int64  
 10  Travel_Rate              362 non-null    int64  
 11  Post_Level               362 non-null    int64  
 12  Pay_Scale                362 non-null    float64
 13  Compensation_and_Benefits  362 non-null    object 
 14  Work_Life_balance        362 non-null    float64
 15  VAR1                     362 non-null    int64  
 16  VAR2                     362 non-null    float64
 17  VAR3                     362 non-null    float64
 18  VAR4                     362 non-null    float64
 19  VAR5                     362 non-null    int64  
 20  VAR6                     362 non-null    int64  
 21  VAR7                     362 non-null    int64  
 22  Attrition_rate           362 non-null    float64
dtypes: float64(8), int64(9), object(6)
memory usage: 67.9+ KB
```

Figure 20: Sub setting for Accounting and Finance department

```python
dataMarketing = data[data.Unit == "Marketing"].drop('Unit', axis=1)
dataMarketing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 157 entries, 25 to 4958
Data columns (total 23 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   Employee_ID                157 non-null    object 
 1   Gender                     157 non-null    object 
 2   Age                        157 non-null    float64
 3   Education_Level            157 non-null    int64  
 4   Relationship_Status        157 non-null    object 
 5   Hometown                   157 non-null    object 
 6   Decision_skill_possess     157 non-null    object 
 7   Time_of_service            157 non-null    float64
 8   Time_since_promotion       157 non-null    int64  
 9   growth_rate                157 non-null    int64  
 10  Travel_Rate                157 non-null    int64  
 11  Post_Level                 157 non-null    int64  
 12  Pay_Scale                  157 non-null    float64
 13  Compensation_and_Benefits  157 non-null    object 
 14  Work_Life_balance          157 non-null    float64
 15  VAR1                       157 non-null    int64  
 16  VAR2                       157 non-null    float64
 17  VAR3                       157 non-null    float64
 18  VAR4                       157 non-null    float64
 19  VAR5                       157 non-null    int64  
 20  VAR6                       157 non-null    int64  
 21  VAR7                       157 non-null    int64  
 22  Attrition_rate             157 non-null    float64
dtypes: float64(8), int64(9), object(6)
memory usage: 29.4+ KB
```

Figure 21: Sub setting for Marketing department

```
dataRnD = data[data.Unit == "R&D"].drop('Unit', axis=1)
dataRnD.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 480 entries, 26 to 4992
Data columns (total 23 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   Employee_ID                 480 non-null    object 
 1   Gender                      480 non-null    object 
 2   Age                         480 non-null    float64
 3   Education_Level             480 non-null    int64  
 4   Relationship_Status         480 non-null    object 
 5   Hometown                    480 non-null    object 
 6   Decision_skill_possess      480 non-null    object 
 7   Time_of_service             480 non-null    float64
 8   Time_since_promotion        480 non-null    int64  
 9   growth_rate                 480 non-null    int64  
 10  Travel_Rate                 480 non-null    int64  
 11  Post_Level                  480 non-null    int64  
 12  Pay_Scale                   480 non-null    float64
 13  Compensation_and_Benefits   480 non-null    object 
 14  Work_Life_balance           480 non-null    float64
 15  VAR1                        480 non-null    int64  
 16  VAR2                        480 non-null    float64
 17  VAR3                        480 non-null    float64
 18  VAR4                        480 non-null    float64
 19  VAR5                        480 non-null    int64  
 20  VAR6                        480 non-null    int64  
 21  VAR7                        480 non-null    int64  
 22  Attrition_rate              480 non-null    float64
dtypes: float64(8), int64(9), object(6)
memory usage: 90.0+ KB
```

Figure 22: Sub setting for R&D department

```
dataSecurity = data[data.Unit == "Security"].drop('Unit', axis=1)
dataSecurity.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 101 entries, 61 to 4932
Data columns (total 23 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Employee_ID              101 non-null    object 
 1   Gender                   101 non-null    object 
 2   Age                      101 non-null    float64
 3   Education_Level          101 non-null    int64  
 4   Relationship_Status      101 non-null    object 
 5   Hometown                 101 non-null    object 
 6   Decision_skill_possess   101 non-null    object 
 7   Time_of_service          101 non-null    float64
 8   Time_since_promotion     101 non-null    int64  
 9   growth_rate              101 non-null    int64  
 10  Travel_Rate              101 non-null    int64  
 11  Post_Level               101 non-null    int64  
 12  Pay_Scale                101 non-null    float64
 13  Compensation_and_Benefits 101 non-null   object 
 14  Work_Life_balance        101 non-null    float64
 15  VAR1                     101 non-null    int64  
 16  VAR2                     101 non-null    float64
 17  VAR3                     101 non-null    float64
 18  VAR4                     101 non-null    float64
 19  VAR5                     101 non-null    int64  
 20  VAR6                     101 non-null    int64  
 21  VAR7                     101 non-null    int64  
 22  Attrition_rate           101 non-null    float64
dtypes: float64(8), int64(9), object(6)
memory usage: 18.9+ KB
```

Figure 23: Sub setting for Security department

5 Label Encoding

The Figure 24, illustrate the code to encode the data and all the department wise subset of the data.

```
data = pd.get_dummies(data)
dataIT = pd.get_dummies(dataIT)
dataLogistics = pd.get_dummies(dataLogistics)
dataQuality = pd.get_dummies(dataQuality)
dataHR = pd.get_dummies(dataHR)
dataPurchasing = pd.get_dummies(dataPurchasing)
dataSales = pd.get_dummies(dataSales)
dataProduction = pd.get_dummies(dataProduction)
dataOperarions = pd.get_dummies(dataOperarions)
dataAcconting = pd.get_dummies(dataAcconting)
dataMarketing = pd.get_dummies(dataMarketing)
dataRnD = pd.get_dummies(dataRnD)
dataSecurity = pd.get_dummies(dataSecurity)
```

Figure 24: Label Encoding

6 Class Balancing

Figure 25 below, shows the function generate to balance the classes in the data and the below figures 102 & Figures from (26-35) shows the department wise implementation.

```
def class_balancing(data):
    count_class_0, count_class_1 = data.Attrition_rate.value_counts()

    # Divide by class
    df_class_0 = data[data['Attrition_rate'] == 0]
    df_class_1 = data[data['Attrition_rate'] == 1]
    df_class_1_over = df_class_1.sample(count_class_0, replace=True)
    df_test_over = pd.concat([df_class_0, df_class_1_over], axis=0)

    print('Random over-sampling:')
    print(df_test_over.Attrition_rate.value_counts())

    df_test_over.Attrition_rate.value_counts().plot(kind='bar', title='Count (target)')
    return df_test_over
```

```
data = class_balancing(data)
```

```
Random over-sampling:
0.0    4611
1.0    4611
Name: Attrition_rate, dtype: int64
```

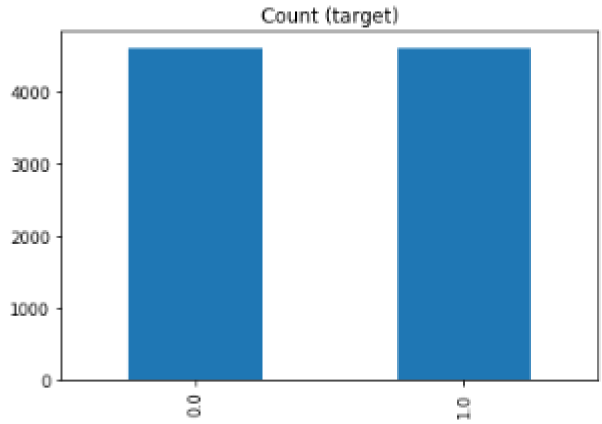


Figure 25: Class Balancing

```
dataIT = class_balancing(dataIT)
```

```
Random over-sampling:
0.0    946
1.0    946
Name: Attrition_rate, dtype: int64
```

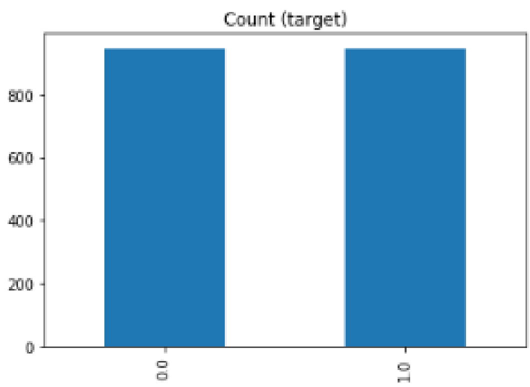


Figure 102: Class balancing Department wise (IT)

```
dataLogistics = class_balancing(dataLogistics)
```

```
Random over-sampling:
0.0    778
1.0    778
Name: Attrition_rate, dtype: int64
```

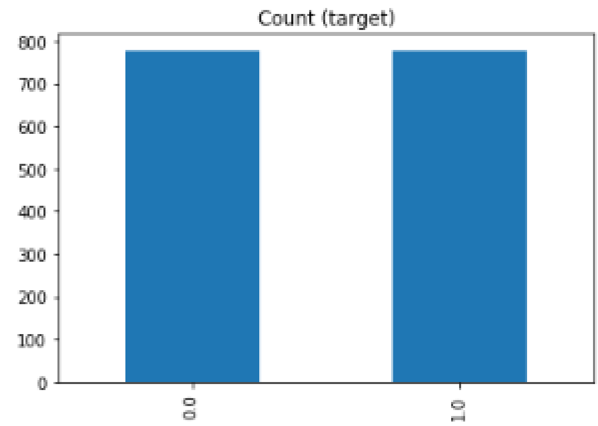


Figure 26: Class Balancing for department (Logistics)

```
dataQuality = class_balancing(dataQuality)
```

```
Random over-sampling:
0.0    129
1.0    129
Name: Attrition_rate, dtype: int64
```

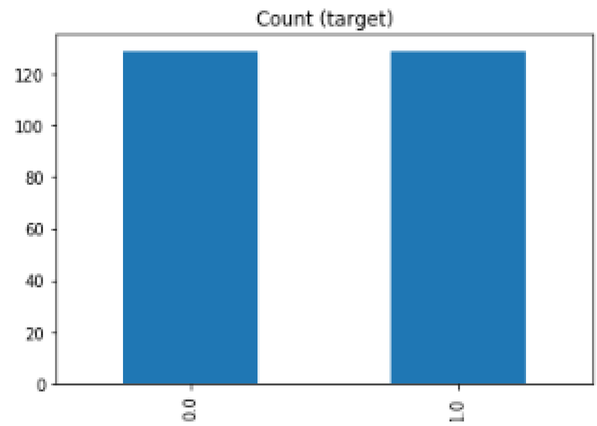


Figure 27: Class Balancing for department (Quality)

```
dataHR = class_balancing(dataHR)
```

```
Random over-sampling:
0.0    229
1.0    229
Name: Attrition_rate, dtype: int64
```

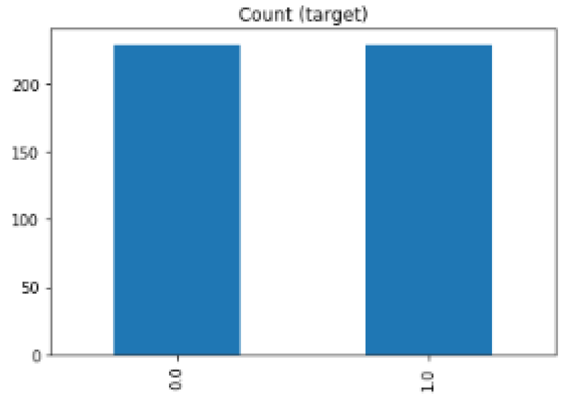


Figure 28: Class Balancing for department (HR)

```
dataPurchasing = class_balancing(dataPurchasing)
```

```
Random over-sampling:
0.0    329
1.0    329
Name: Attrition_rate, dtype: int64
```

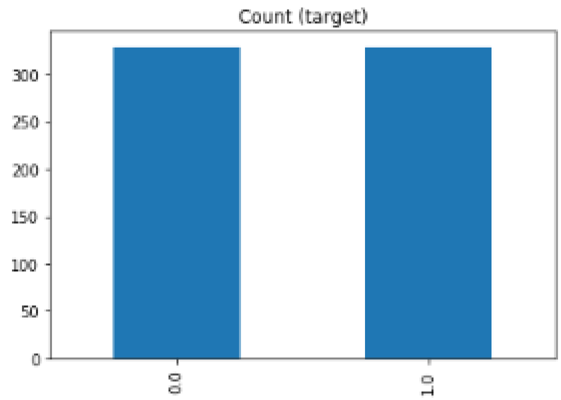


Figure 29: Class Balancing for department (Purchasing)

```
dataSales = class_balancing(dataSales)
```

```
Random over-sampling:
0.0    618
1.0    618
Name: Attrition_rate, dtype: int64
```

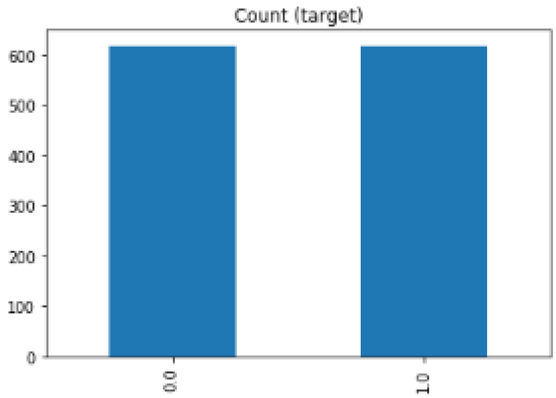


Figure 30: Class Balancing for department (Sales)

```
dataProduction = class_balancing(dataProduction)
```

```
Random over-sampling:
0.0    138
1.0    138
Name: Attrition_rate, dtype: int64
```

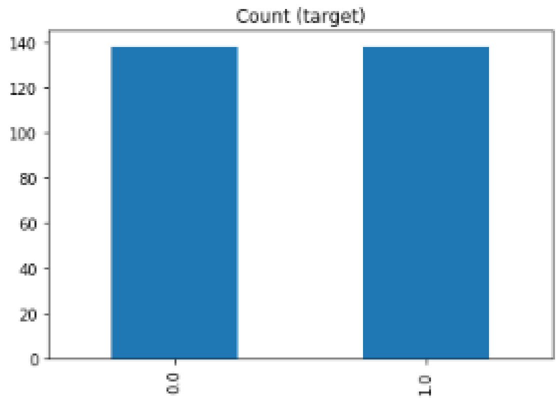


Figure 31: Class Balancing for department (Production)

```
dataOperarions = class_balancing(dataOperarions)
```

```
Random over-sampling:
0.0    438
1.0    438
Name: Attrition_rate, dtype: int64
```

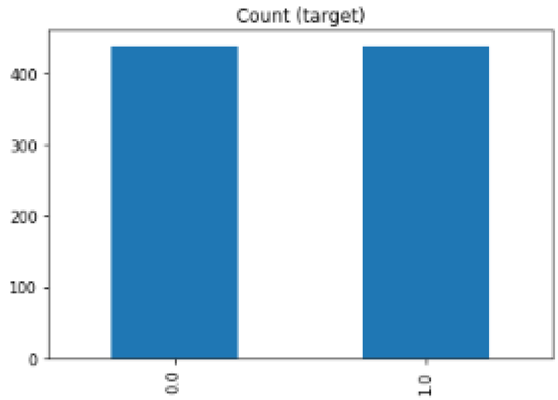


Figure 32: Class Balancing for department (Operations)

```
dataAcconting = class_balancing(dataAcconting)
```

```
Random over-sampling:
0.0    341
1.0    341
Name: Attrition_rate, dtype: int64
```

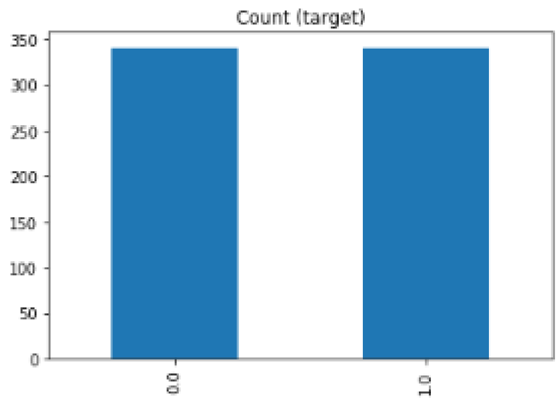
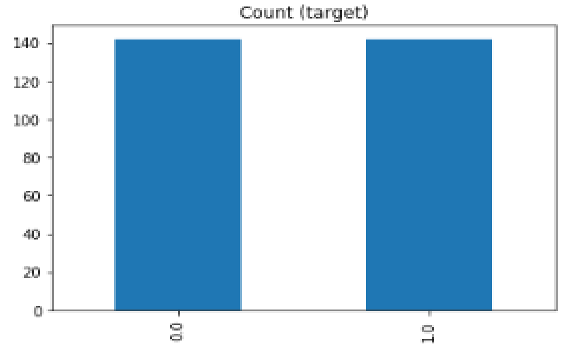


Figure 33: Class Balancing for department (Accounting)

```
dataMarketing = class_balancing(dataMarketing)
```

```
Random over-sampling:
0.0    142
1.0    142
Name: Attrition_rate, dtype: int64
```




```
dataRnD = class_balancing(dataRnD)
```

```
Random over-sampling:
0.0    429
1.0    429
Name: Attrition_rate, dtype: int64
```

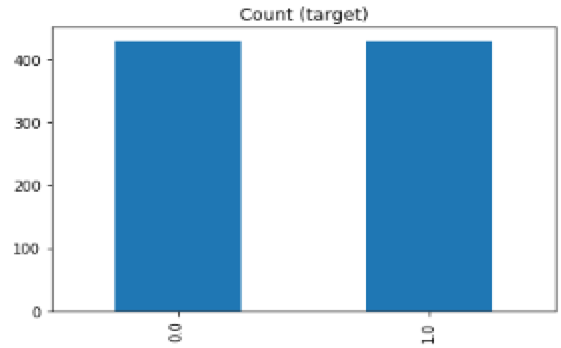


Figure 34: Class Balancing for department (Marketing & RnD)

```
dataSecurity = class_balancing(dataSecurity)
```

```
Random over-sampling:
0.0    94
1.0    94
Name: Attrition_rate, dtype: int64
```

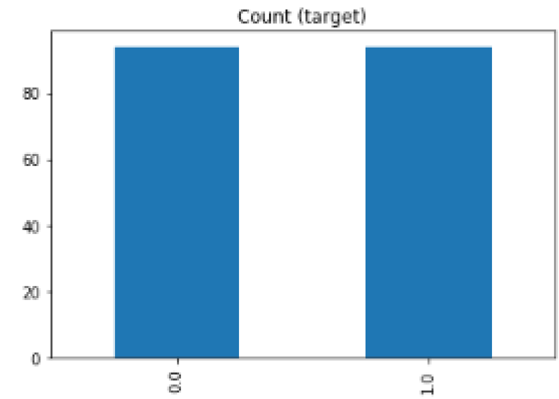


Figure 35: Class Balancing for department (Security)

7 Feature Selection

Figure 36 below, shows the function generate to separate the target and feature set of the data and finding the features which are important. The figures(37-44) below shows the department wise implementation. Figure 45 represents performance metrics for departments.

```
def feature_selection(data):
    x = data.drop('Attrition_rate',axis=1)
    y = data['Attrition_rate']
    # Generating chi score for all features
    chi_scores = chi2(np.abs(x),y)
    # Probality values
    p_values = pd.Series(chi_scores[1],index = x.columns)
    p_values.sort_values(ascending = False , inplace = True)
    print(p_values)
    x = SelectKBest(chi2, k=20).fit_transform(np.abs(x), y)
    return x,y
```

```
x, y = feature_selection(data)
XTrain, XTest, YTrain, YTest = train_test_split(x,y, test_size=0.2)
XTrain.shape, XTest.shape, YTrain.shape, YTest.shape
```

```
Compensation_and_Benefits_type2      8.782351e-01
Decision_skill_possess_Conceptual    8.696895e-01
VAR1                                 7.949371e-01
Unit_Quality                         7.532573e-01
Unit_Security                        7.116726e-01
                                         ...
Employee_ID_EID_10978                4.592834e-06
Unit_IT                              4.115381e-06
Employee_ID_EID_7146                 2.726505e-06
Compensation_and_Benefits_type0      3.359719e-08
Age                                  2.185039e-12
Length: 5045, dtype: float64

((7377, 20), (1845, 20), (7377,), (1845,))
```

Figure 36: Feature selection

```
x, y = feature_selection(dataIT)
XTraindataIT, XTestdataIT, YTraindataIT, YTestdataIT = train_test_split(x,y, test_size=0.2)
XTraindataIT.shape, XTestdataIT.shape, YTraindataIT.shape, YTestdataIT.shape
```

```
Hometown_Franklin                  7.680826e-01
Relationship_Status_Married        6.129342e-01
Post_Level                         6.100392e-01
Pay_Scale                          5.796980e-01
VAR5                               4.997942e-01
                                       ...
Employee_ID_EID_2738               2.726505e-06
Employee_ID_EID_15300              2.726505e-06
Compensation_and_Benefits_type3    1.122713e-09
growth_rate                        1.288580e-24
Age                                2.183443e-30
Length: 1042, dtype: float64

((1513, 20), (379, 20), (1513,), (379,))
```

Figure 37: Feature selection for department (IT)

```
x, y = feature_selection(dataLogistics)
XTraindataLogistics, XTestdataLogistics, YTraindataLogistics, YTestdataLogistics = train_test_split(x,y, test_size=0.2)
XTraindataLogistics.shape, XTestdataLogistics.shape, YTraindataLogistics.shape, YTestdataLogistics.shape
```

```
Compensation_and_Benefits_type2       9.734530e-01
Hometown_Franklin                     9.171891e-01
VAR4                                  8.458596e-01
Decision_skill_possess_Behavioral     8.369957e-01
growth_rate                           7.751463e-01
                                          ...
Employee_ID_EID_19564                 2.209050e-05
Work_Life_balance                     2.006313e-05
Employee_ID_EID_21072                 7.744216e-06
Decision_skill_possess_Directive      1.877765e-06
Time_of_service                       4.381861e-08
Length: 875, dtype: float64

((1244, 20), (312, 20), (1244,), (312,))
```

Figure 38: Feature selection for department (Logistics)

```
x, y = feature_selection(dataQuality)
XTraindataQuality, XTestdataQuality, YTraindataQuality,YTestdataQuality = train_test_split(x,y, test_size=0.2)
XTraindataQuality.shape, XTestdataQuality.shape, YTraindataQuality.shape, YTestdataQuality.shape
```

```
VAR2                        8.429088e-01
Pay_Scale                   8.213745e-01
Education_Level             7.519777e-01
VAR6                        7.427869e-01
VAR5                        5.774687e-01
                                ...
Employee_ID_EID_3331        1.075112e-04
Travel_Rate                 1.955081e-05
Employee_ID_EID_20117       1.307185e-05
Hometown_Franklin           2.726505e-06
Age                         9.861541e-07
Length: 173, dtype: float64

((206, 20), (52, 20), (206,), (52,))
```

```
x, y = feature_selection(dataHR)
XTraindataHR, XTestdataHR, YTraindataHR, YTestdataHR = train_test_split(x,y, test_size=0.2)
XTraindataHR.shape, XTestdataHR.shape, YTraindataHR.shape, YTestdataHR.shape
```

```
Compensation_and_Benefits_type2        1.000000e+00
Post_Level                             8.864030e-01
Time_of_service                        8.861931e-01
Hometown_Washington                    8.161534e-01
Decision_skill_possess_Analytical      8.045709e-01
                                           ...
Hometown_Franklin                      1.416965e-05
Employee_ID_EID_1174                   1.307185e-05
Employee_ID_EID_8226                   7.744216e-06
Employee_ID_EID_6691                   1.620014e-06
Age                                    9.370874e-18
Length: 279, dtype: float64

((366, 20), (92, 20), (366,), (92,))
```

Figure 39: Feature selection for department (Quality)

```
x, y = feature_selection(dataPurchasing)
XTraindataPurchasing, XTestdataPurchasing, YTraindataPurchasing, YTestdataPurchasing = train_test_split(x,y, test_size=0.2)
XTraindataPurchasing.shape, XTestdataPurchasing.shape, YTraindataPurchasing.shape, YTestdataPurchasing.shape
```

```
VAR4                                  9.764648e-01
Gender_F                              7.544542e-01
Gender_M                              7.245892e-01
Hometown_Franklin                     6.521086e-01
Compensation_and_Benefits_type0       6.373519e-01
                                          ...
Employee_ID_EID_10774                 3.737982e-05
Employee_ID_EID_13380                 4.592834e-06
Decision_skill_possess_Directive      2.143518e-08
Age                                   3.668689e-09
Time_of_service                       1.233285e-41
Length: 392, dtype: float64

((526, 20), (132, 20), (526,), (132,))
```

Figure 40: Feature selection for department (Purchasing)

```
x, y = feature_selection(dataSales)
XTraindataSales, XTestdataSales, YTraindataSales, YTestdataSales = train_test_split(x,y, test_size=0.2)
XTraindataSales.shape, XTestdataSales.shape, YTraindataSales.shape, YTestdataSales.shape
```

```
Compensation_and_Benefits_type2    9.696104e-01
VAR1                               9.612310e-01
Hometown_Franklin                  9.519149e-01
Hometown_Lebanon                   8.800180e-01
VAR5                               8.009287e-01
                                       ...
Employee_ID_EID_5033               6.334248e-05
Employee_ID_EID_7146               3.737982e-05
Employee_ID_EID_2434               2.209050e-05
growth_rate                        3.365845e-16
Time_of_service                    2.692500e-16
Length: 709, dtype: float64

((988, 20), (248, 20), (988,), (248,))
```

```
x, y = feature_selection(dataProduction)
XTraindataProduction, XTestdataProduction, YTraindataProduction, YTestdataProduction = train_test_split(x,y, test_size=0.2)
XTraindataProduction.shape, XTestdataProduction.shape, YTraindataProduction.shape, YTestdataProduction.shape
```

```
Hometown_Washington                1.000000e+00
VAR7                               8.653142e-01
Hometown_Lebanon                   8.330289e-01
Time_of_service                    8.269712e-01
Education_Level                    7.351710e-01
                                       ...
Employee_ID_EID_10978              1.075112e-04
Employee_ID_EID_13896              6.334248e-05
Compensation_and_Benefits_type3    1.628658e-05
Time_since_promotion               1.683315e-06
Hometown_Franklin                  9.215887e-09
Length: 185, dtype: float64

((220, 20), (56, 20), (220,), (56,))
```

Figure 41: Feature selection for department (Sales)

```
x, y = feature_selection(dataOperarions)
XTraindataOperarions, XTestdataOperarions, YTraindataOperarions, YTestdataOperarions = train_test_split(x,y, test_size=0.2)
XTraindataOperarions.shape, XTestdataOperarions.shape, YTraindataOperarions.shape, YTestdataOperarions.shape
```

```
VAR7                                  9.555356e-01
Decision_skill_possess_Conceptual     8.912543e-01
Education_Level                       8.801685e-01
VAR1                                  8.476680e-01
Time_since_promotion                  5.038242e-01
                                          ...
Gender_M                              4.530325e-05
Compensation_and_Benefits_type0       2.336033e-05
Gender_F                              2.233998e-05
growth_rate                           1.496701e-05
Time_of_service                       9.497941e-07
Length: 516, dtype: float64

((700, 20), (176, 20), (700,), (176,))
```

```
x, y = feature_selection(dataAcconting)
XTraindataAcconting, XTestdataAcconting, YTraindataAcconting, YTestdataAcconting = train_test_split(x,y, test_size=0.2)
XTraindataAcconting.shape, XTestdataAcconting.shape, YTraindataAcconting.shape, YTestdataAcconting.shape
```

```
Relationship_Status_Married        7.353909e-01
Compensation_and_Benefits_type4    7.150007e-01
Post_Level                         6.827826e-01
Time_since_promotion               6.647672e-01
Relationship_Status_Single         6.598747e-01
                                       ...
Hometown_Franklin                  6.738559e-06
Employee_ID_EID_16850              4.592834e-06
Employee_ID_EID_18305              2.726505e-06
Age                                1.663196e-07
Hometown_Washington                9.264885e-09
Length: 396, dtype: float64

((545, 20), (137, 20), (545,), (137,))
```

Figure 42: Feature selection for department (Operations)

```
x, y = feature_selection(dataMarketing)
XTraindataMarketing, XTestdataMarketing, YTraindataMarketing, YTestdataMarketing = train_test_split(x,y, test_size=0.2)
XTraindataMarketing.shape, XTestdataMarketing.shape, YTraindataMarketing.shape, YTestdataMarketing.shape
```

```
VAR2                      0.946289
Pay_Scale                 0.922760
VAR5                      0.889310
Hometown_Springfield      0.829248
Post_Level                0.726608
                            ...
Employee_ID_EID_7811      0.000311
Employee_ID_EID_11191     0.000311
Employee_ID_EID_7940      0.000311
Employee_ID_EID_14773     0.000063
Hometown_Clinton          0.000063
Length: 191, dtype: float64

((227, 20), (57, 20), (227,), (57,))
```

```
x, y = feature_selection(dataRnD)
XTraindataRnD, XTestdataRnD, YTraindataRnD, YTestdataRnD = train_test_split(x,y, test_size=0.2)
XTraindataRnD.shape, XTestdataRnD.shape, YTraindataRnD.shape, YTestdataRnD.shape
```

```
Decision_skill_possess_Directive    1.000000e+00
Work_Life_balance                   1.000000e+00
VAR3                                9.844124e-01
VAR4                                9.793112e-01
VAR5                                9.356960e-01
                                        ...
Hometown_Franklin                   1.887297e-04
Employee_ID_EID_23944               3.737982e-05
Compensation_and_Benefits_type3     2.656752e-05
Compensation_and_Benefits_type4     4.302779e-06
growth_rate                         1.071302e-17
Length: 514, dtype: float64

((686, 20), (172, 20), (686,), (172,))
```

Figure 43: Feature selection for department (Marketing & RnD)

```
x, y = feature_selection(dataSecurity)
XTraindataSecurity, XTestdataSecurity, YTraindataSecurity, YTestdataSecurity = train_test_split(x,y, test_size=0.2)
XTraindataSecurity.shape, XTestdataSecurity.shape, YTraindataSecurity.shape, YTestdataSecurity.shape
```

```
Hometown_Springfield                8.864030e-01
VAR5                                8.604904e-01
Decision_skill_possess_Analytical   7.630246e-01
Compensation_and_Benefits_type3     7.179817e-01
Gender_F                            7.172452e-01
                                        ...
Post_Level                          3.031459e-05
Travel_Rate                         3.414174e-07
Decision_skill_possess_Behavioral   3.414174e-07
growth_rate                         1.409768e-07
Pay_Scale                           9.522231e-12
Length: 134, dtype: float64

((150, 20), (38, 20), (150,), (38,))
```

Figure 44: Feature selection for department (Security)

```
orgMetrics = pd.DataFrame()
ITMetrics = pd.DataFrame()
LogisticsMetrics = pd.DataFrame()
QualityMetrics = pd.DataFrame()
HRMetrics = pd.DataFrame()
PurchasingMetrics = pd.DataFrame()
SalesMetrics = pd.DataFrame()
ProductionMetrics = pd.DataFrame()
OperarionsMetrics = pd.DataFrame()
AccontingMetrics = pd.DataFrame()
MarketingMetrics = pd.DataFrame()
RnDMetrics = pd.DataFrame()
SecurityMetrics = pd.DataFrame()
```

Figure 45: Performance Metrics for department

8 Machine Learning Models

8.1 Decision Trees

```
dt_metrics = pd.DataFrame()

def decision_tree(xtrain, xtest, ytrain, ytest):
    dt = DecisionTreeClassifier()
    dt.fit(xtrain, ytrain)
    pred =  dt.predict(xtest)
    acc = accuracy_score(ytest, pred)
    f1 = f1_score(ytest, pred)
    return acc, f1
```

Figure 46: Implementation of Decision Trees

```
acc, f1 = decision_tree(XTrain, XTest, YTrain, YTest)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
dt_metrics = dt_metrics.append([['Organisation', acc*100, f1*100]])
orgMetrics = orgMetrics.append([['Decision Tree', acc*100, f1*100]])
```

```
Accuracy Score :  64.17
F1-Score :  63.62
```

```
acc, f1 = decision_tree(XTraindataIT, XTestdataIT, YTraindataIT, YTestdataIT)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
dt_metrics = dt_metrics.append([['IT', acc*100, f1*100]])
ITMetrics = ITMetrics.append([['Decision Tree', acc*100, f1*100]])
```

```
Accuracy Score :  96.83
F1-Score :  96.94
```

Figure 47: Implementation of Model training and prediction Scores and saving model and department score

```
acc, f1 = decision_tree(XTraindataLogistics, XTestdataLogistics, YTraindataLogistics, YTestdataLogistics)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
dt_metrics = dt_metrics.append([['Logistics', acc*100, f1*100]])
LogisticsMetrics = LogisticsMetrics.append([['Decision Tree', acc*100, f1*100]])
```

```
Accuracy Score :  91.35
F1-Score :  91.79
```

```
acc, f1 = decision_tree(XTraindataQuality, XTestdataQuality, YTraindataQuality,YTestdataQuality)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
dt_metrics = dt_metrics.append([['Quality', acc*100, f1*100]])
QualityMetrics = QualityMetrics.append([['Decision Tree', acc*100, f1*100]])
```

```
Accuracy Score :  96.15
F1-Score :  96.15
```

Figure 48: Implementation of Model training and prediction Scores and saving model and department score

```
acc, f1 = decision_tree(XTraindataHR, XTestdataHR, YTraindataHR, YTestdataHR)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
dt_metrics = dt_metrics.append([['HR', acc*100, f1*100]])
HRMetrics = HRMetrics.append([['Decision Tree', acc*100, f1*100]])
```

```
Accuracy Score :  97.83
F1-Score :  98.25
```

```
acc, f1 = decision_tree(XTraindataPurchasing, XTestdataPurchasing, YTraindataPurchasing, YTestdataPurchasing)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
dt_metrics = dt_metrics.append([['Purchasing', acc*100, f1*100]])
PurchasingMetrics = PurchasingMetrics.append([['Decision Tree', acc*100, f1*100]])
```

```
Accuracy Score :  96.21
F1-Score :  95.5
```

```
acc, f1 = decision_tree(XTraindataSales, XTestdataSales, YTraindataSales, YTestdataSales)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100))
dt_metrics = dt_metrics.append([['Sales', acc*100, f1*100]])
SalesMetrics = SalesMetrics.append([['Decision Tree', acc*100, f1*100]])
```

```
Accuracy Score :  95.97
F1-Score :  96.0
```

Figure 49: Implementation of Model training and prediction Scores and saving model and department score

```
acc, f1 = decision_tree(XTraindataOperarions, XTestdataOperarions, YTraindataOperarions, YTestdataOperarions)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
dt_metrics = dt_metrics.append([['Operations', acc*100, f1*100]])
OperarionsMetrics = OperarionsMetrics.append([['Decision Tree', acc*100, f1*100]])
```

```
Accuracy Score :  94.32
F1-Score :  95.05
```

```
acc, f1 = decision_tree(XTraindataProduction, XTestdataProduction, YTraindataProduction, YTestdataProduction)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
dt_metrics = dt_metrics.append([['Production', acc*100, f1*100]])
ProductionMetrics = ProductionMetrics.append([['Decision Tree', acc*100, f1*100]])
```

```
Accuracy Score :  96.43
F1-Score :  96.15
```

```
acc, f1 = decision_tree(XTraindataAcconting, XTestdataAcconting, YTraindataAcconting, YTestdataAcconting)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
dt_metrics = dt_metrics.append([['Accounting', acc*100, f1*100]])
AccontingMetrics = AccontingMetrics.append([['Decision Tree', acc*100, f1*100]])
```

```
Accuracy Score :  97.08
F1-Score :  97.01
```

Figure 50: Implementation of Model training and prediction Scores and saving model and department score

```
acc, f1 = decision_tree(XTraindataMarketing, XTestdataMarketing, YTraindataMarketing, YTestdataMarketing)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
dt_metrics = dt_metrics.append([['Marketing', acc*100, f1*100]])
MarketingMetrics = MarketingMetrics.append([['Decision Tree', acc*100, f1*100]])
```

```
Accuracy Score :  91.23
F1-Score :  92.06
```

```
acc, f1 = decision_tree(XTraindataRnD, XTestdataRnD, YTraindataRnD, YTestdataRnD)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
dt_metrics = dt_metrics.append([['RnD', acc*100, f1*100]])
RnDMetrics = RnDMetrics.append([['Decision Tree', acc*100, f1*100]])
```

```
Accuracy Score :  89.53
F1-Score :  91.0
```

```
acc, f1 = decision_tree(XTraindataSecurity, XTestdataSecurity, YTraindataSecurity, YTestdataSecurity)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
dt_metrics = dt_metrics.append([['Security', acc*100, f1*100]])
SecurityMetrics = SecurityMetrics.append([['Decision Tree', acc*100, f1*100]])
```

```
Accuracy Score :  89.47
F1-Score :  90.48
```

Figure 51: Implementation of Model training and prediction Scores and saving model and department score

8.2 Random Forest Trees

```
rf_metrics = pd.DataFrame()

def rf_tree(xtrain, xtest, ytrain, ytest):
    rf = RandomForestClassifier()
    rf.fit(xtrain, ytrain)
    pred =  rf.predict(xtest)
    acc = accuracy_score(ytest, pred)
    f1 = f1_score(ytest, pred)
    return acc, f1
```

Figure 52: Implementation of Random Forest Trees

```
acc, f1 = rf_tree(XTrain, XTest, YTrain, YTest)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
rf_metrics = rf_metrics.append([['Organisation', acc*100, f1*100]])
orgMetrics = orgMetrics.append([['Random Forest', acc*100, f1*100]])
```

```
Accuracy Score :  64.39
F1-Score :  63.96
```

```
acc, f1 = rf_tree(XTraindataIT, XTestdataIT, YTraindataIT, YTestdataIT)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
rf_metrics = rf_metrics.append([['IT', acc*100, f1*100]])
ITMetrics = ITMetrics.append([['Random Forest', acc*100, f1*100]])
```

```
Accuracy Score :  98.15
F1-Score :  98.19
```

Figure 53: Implementation of Model training and prediction Scores and saving model and department score

```
acc, f1 = rf_tree(XTraindataLogistics, XTestdataLogistics, YTraindataLogistics, YTestdataLogistics)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
rf_metrics = rf_metrics.append([['Logistics', acc*100, f1*100]])
LogisticsMetrics = LogisticsMetrics.append([['Random Forest', acc*100, f1*100]])
```

```
Accuracy Score :  91.67
F1-Score :  92.07
```

```
acc, f1 = rf_tree(XTraindataQuality, XTestdataQuality, YTraindataQuality,YTestdataQuality)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
rf_metrics = rf_metrics.append([['Quality', acc*100, f1*100]])
QualityMetrics = QualityMetrics.append([['Random Forest', acc*100, f1*100]])
```

```
Accuracy Score :  100.0
F1-Score :  100.0
```

```
acc, f1 = rf_tree(XTraindataHR, XTestdataHR, YTraindataHR, YTestdataHR)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
rf_metrics = rf_metrics.append([['HR', acc*100, f1*100]])
HRMetrics = HRMetrics.append([['Random Forest', acc*100, f1*100]])
```

```
Accuracy Score :  100.0
F1-Score :  100.0
```

```
acc, f1 = rf_tree(XTraindataPurchasing, XTestdataPurchasing, YTraindataPurchasing, YTestdataPurchasing)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
rf_metrics = rf_metrics.append([['Purchasing', acc*100, f1*100]])
PurchasingMetrics = PurchasingMetrics.append([['Random Forest', acc*100, f1*100]])
```

```
Accuracy Score :  97.73
F1-Score :  97.25
```

Figure 54: Implementation of Model training and prediction Scores and saving model and department score

```
acc, f1 = rf_tree(XTraindataSales, XTestdataSales, YTraindataSales, YTestdataSales)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
rf_metrics = rf_metrics.append([['Sales', acc*100, f1*100]])
SalesMetrics = SalesMetrics.append([['Random Forest', acc*100, f1*100]])
```

```
Accuracy Score :  97.58
F1-Score :  97.54
```

```
acc, f1 = rf_tree(XTraindataOperarions, XTestdataOperarions, YTraindataOperarions, YTestdataOperarions)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
rf_metrics = rf_metrics.append([['Operations', acc*100, f1*100]])
OperarionsMetrics = OperarionsMetrics.append([['Random Forest', acc*100, f1*100]])
```

```
Accuracy Score :  96.59
F1-Score :  96.97
```

```
acc, f1 = rf_tree(XTraindataProduction, XTestdataProduction, YTraindataProduction, YTestdataProduction)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
rf_metrics = rf_metrics.append([['Production', acc*100, f1*100]])
ProductionMetrics = ProductionMetrics.append([['Random Forest', acc*100, f1*100]])
```

```
Accuracy Score :  98.21
F1-Score :  98.04
```

Figure 55: Implementation of Model training and prediction Scores and saving model and department score

```
acc, f1 = rf_tree(XTraindataAcconting, XTestdataAcconting, YTraindataAcconting, YTestdataAcconting)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
rf_metrics = rf_metrics.append([['Accounting', acc*100, f1*100]])
AccontingMetrics = AccontingMetrics.append([['Random Forest', acc*100, f1*100]])
```

```
Accuracy Score :  97.08
F1-Score :  97.01
```

```
acc, f1 = rf_tree(XTraindataMarketing, XTestdataMarketing, YTraindataMarketing, YTestdataMarketing)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
rf_metrics = rf_metrics.append([['Marketing', acc*100, f1*100]])
MarketingMetrics = MarketingMetrics.append([['Random Forest', acc*100, f1*100]])
```

```
Accuracy Score :  98.25
F1-Score :  98.31
```

```
acc, f1 = rf_tree(XTraindataRnD, XTestdataRnD, YTraindataRnD, YTestdataRnD)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
rf_metrics = rf_metrics.append([['RnD', acc*100, f1*100]])
RnDMetrics = RnDMetrics.append([['Random Forest', acc*100, f1*100]])
```

```
Accuracy Score :  91.28
F1-Score :  92.39
```

```
acc, f1 = rf_tree(XTraindataSecurity, XTestdataSecurity, YTraindataSecurity, YTestdataSecurity)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
rf_metrics = rf_metrics.append([['Security', acc*100, f1*100]])
SecurityMetrics = SecurityMetrics.append([['Random Forest', acc*100, f1*100]])
```

```
Accuracy Score :  100.0
F1-Score :  100.0
```

Figure 56: Implementation of Model training and prediction Scores and saving model and department score

8.3 SVM

```
svm_metrics = pd.DataFrame()

def svm_model(xtrain, xtest, ytrain, ytest):
    svm = SVC()
    svm.fit(xtrain, ytrain)
    pred =  svm.predict(xtest)
    acc = accuracy_score(ytest, pred)
    f1 = f1_score(ytest, pred)
    return acc, f1
```

Figure 46: Implementation of SVM

```
acc, f1 = svm_model(XTrain, XTest, YTrain, YTest)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
svm_metrics = svm_metrics.append([['Organisation', acc*100, f1*100]])
orgMetrics = orgMetrics.append([['SVM', acc*100, f1*100]])
```

```
Accuracy Score :  50.03
F1-Score :  65.72
```

```
acc, f1 = svm_model(XTraindataIT, XTestdataIT, YTraindataIT, YTestdataIT)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
svm_metrics = svm_metrics.append([['IT', acc*100, f1*100]])
ITMetrics = ITMetrics.append([['SVM', acc*100, f1*100]])
```

```
Accuracy Score :  55.41
F1-Score :  59.67
```

```
acc, f1 = svm_model(XTraindataLogistics, XTestdataLogistics, YTraindataLogistics, YTestdataLogistics)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
svm_metrics = svm_metrics.append([['Logistics', acc*100, f1*100]])
LogisticsMetrics = LogisticsMetrics.append([['SVM', acc*100, f1*100]])
```

```
Accuracy Score :  62.82
F1-Score :  63.98
```

Figure 47: Implementation of Model training and prediction Scores and saving model and department score

```
acc, f1 = svm_model(XTraindataQuality, XTestdataQuality, YTraindataQuality,YTestdataQuality)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
svm_metrics = svm_metrics.append([['Quality', acc*100, f1*100]])
QualityMetrics = QualityMetrics.append([['SVM', acc*100, f1*100]])
```

```
Accuracy Score :  50.0
F1-Score :  53.57
```

```
acc, f1 = svm_model(XTraindataHR, XTestdataHR, YTraindataHR, YTestdataHR)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
svm_metrics = svm_metrics.append([['HR', acc*100, f1*100]])
HRMetrics = HRMetrics.append([['SVM', acc*100, f1*100]])
```

```
Accuracy Score :  72.83
F1-Score :  80.62
```

```
acc, f1 = svm_model(XTraindataPurchasing, XTestdataPurchasing, YTraindataPurchasing, YTestdataPurchasing)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
svm_metrics = svm_metrics.append([['Purchasing', acc*100, f1*100]])
PurchasingMetrics = PurchasingMetrics.append([['SVM', acc*100, f1*100]])
```

```
Accuracy Score :  55.3
F1-Score :  59.31
```

```
acc, f1 = svm_model(XTraindataSales, XTestdataSales, YTraindataSales, YTestdataSales)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
svm_metrics = svm_metrics.append([['Sales', acc*100, f1*100]])
SalesMetrics = SalesMetrics.append([['SVM', acc*100, f1*100]])
```

```
Accuracy Score :  59.27
F1-Score :  62.45
```

Figure 48: Implementation of Model training and prediction Scores and saving model and department score

```
acc, f1 = svm_model(XTraindataProduction, XTestdataProduction, YTraindataProduction, YTestdataProduction)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
svm_metrics = svm_metrics.append([['Production', acc*100, f1*100]])
ProductionMetrics = ProductionMetrics.append([['ProductionMetrics', acc*100, f1*100]])
```

```
Accuracy Score :  51.79
F1-Score :  55.74
```

```
acc, f1 = svm_model(XTraindataOperarions, XTestdataOperarions, YTraindataOperarions, YTestdataOperarions)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
svm_metrics = svm_metrics.append([['Operations', acc*100, f1*100]])
OperarionsMetrics = OperarionsMetrics.append([['SVM', acc*100, f1*100]])
```

```
Accuracy Score :  54.55
F1-Score :  43.66
```

```
acc, f1 = svm_model(XTraindataAcconting, XTestdataAcconting, YTraindataAcconting, YTestdataAcconting)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
svm_metrics = svm_metrics.append([['Accounting', acc*100, f1*100]])
AccontingMetrics = AccontingMetrics.append([['SVM', acc*100, f1*100]])
```

```
Accuracy Score :  54.74
F1-Score :  52.31
```

Figure 49: Implementation of Model training and prediction Scores and saving model and department score

```
acc, f1 = svm_model(XTraindataMarketing, XTestdataMarketing, YTraindataMarketing, YTestdataMarketing)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
svm_metrics = svm_metrics.append([['Marketing', acc*100, f1*100]])
MarketingMetrics = MarketingMetrics.append([['SVM', acc*100, f1*100]])
```

```
Accuracy Score :  59.65
F1-Score :  68.49
```

```
acc, f1 = svm_model(XTraindataRnD, XTestdataRnD, YTraindataRnD, YTestdataRnD)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
svm_metrics = svm_metrics.append([['RnD', acc*100, f1*100]])
RnDMetrics = RnDMetrics.append([['SVM', acc*100, f1*100]])
```

```
Accuracy Score :  58.72
F1-Score :  59.89
```

```
acc, f1 = svm_model(XTraindataSecurity, XTestdataSecurity, YTraindataSecurity, YTestdataSecurity)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
svm_metrics = svm_metrics.append([['Security', acc*100, f1*100]])
SecurityMetrics = SecurityMetrics.append([['SVM', acc*100, f1*100]])
```

```
Accuracy Score :  60.53
F1-Score :  66.67
```

Figure 50: Implementation of Model training and prediction Scores and saving model and department score

8.4 Neural Network

```
nn_metrics = pd.DataFrame()

def neural_network(xtrain, xtest, ytrain, ytest):
    nn = MLPClassifier(hidden_layer_sizes=(150,100,50), max_iter=600,activation = 'tanh',solver='adam',random_state=1)
    nn.fit(xtrain, ytrain)
    pred =  nn.predict(xtest)
    acc = accuracy_score(ytest, pred)
    f1 = f1_score(ytest, pred)
    return acc, f1
```

Figure 51: Implementation of Neural Network

```
acc, f1 = neural_network(XTrain, XTest, YTrain, YTest)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
nn_metrics = nn_metrics.append([['Organisation', acc*100, f1*100]])
orgMetrics = orgMetrics.append([['Neural Network', acc*100, f1*100]])
```

```
Accuracy Score :  54.25
F1-Score :  62.62
```

```
acc, f1 = neural_network(XTraindataIT, XTestdataIT, YTraindataIT, YTestdataIT)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
nn_metrics = nn_metrics.append([['IT', acc*100, f1*100]])
ITMetrics = ITMetrics.append([['Neural Network', acc*100, f1*100]])
```

```
Accuracy Score :  77.84
F1-Score :  81.9
```

```
acc, f1 = neural_network(XTraindataLogistics, XTestdataLogistics, YTraindataLogistics, YTestdataLogistics)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
nn_metrics = nn_metrics.append([['Logistics', acc*100, f1*100]])
LogisticsMetrics = LogisticsMetrics.append([['Neural Network', acc*100, f1*100]])
```

```
Accuracy Score :  85.26
F1-Score :  86.39
```

Figure 52: Implementation of Model training and prediction Scores and saving model and department score

```
acc, f1 = neural_network(XTraindataQuality, XTestdataQuality, YTraindataQuality,YTestdataQuality)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
nn_metrics = nn_metrics.append([['Quality', acc*100, f1*100]])
QualityMetrics = QualityMetrics.append([['Neural Network', acc*100, f1*100]])
```

```
Accuracy Score :  98.08
F1-Score :  98.04
```

```
acc, f1 = neural_network(XTraindataHR, XTestdataHR, YTraindataHR, YTestdataHR)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
nn_metrics = nn_metrics.append([['HR', acc*100, f1*100]])
HRMetrics = HRMetrics.append([['Neural Network', acc*100, f1*100]])
```

```
Accuracy Score :  98.91
F1-Score :  99.12
```

```
acc, f1 = neural_network(XTraindataPurchasing, XTestdataPurchasing, YTraindataPurchasing, YTestdataPurchasing)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
nn_metrics = nn_metrics.append([['Purchasing', acc*100, f1*100]])
PurchasingMetrics = PurchasingMetrics.append([['Neural Network', acc*100, f1*100]])
```

```
Accuracy Score :  89.39
F1-Score :  87.04
```

Figure 53: Implementation of Model training and prediction Scores and saving model and department score

```
acc, f1 = neural_network(XTraindataSales, XTestdataSales, YTraindataSales, YTestdataSales)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
nn_metrics = nn_metrics.append([['Sales', acc*100, f1*100]])
SalesMetrics = SalesMetrics.append([['Neural Network', acc*100, f1*100]])
```

```
Accuracy Score :  73.39
F1-Score :  65.26
```

```
acc, f1 = neural_network(XTraindataOperarions, XTestdataOperarions, YTraindataOperarions, YTestdataOperarions)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
nn_metrics = nn_metrics.append([['Operations', acc*100, f1*100]])
OperarionsMetrics = OperarionsMetrics.append([['Neural Network', acc*100, f1*100]])
```

```
Accuracy Score :  84.66
F1-Score :  86.15
```

```
acc, f1 = neural_network(XTraindataProduction, XTestdataProduction, YTraindataProduction, YTestdataProduction)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
nn_metrics = nn_metrics.append([['Production', acc*100, f1*100]])
ProductionMetrics = ProductionMetrics.append([['Neural Network', acc*100, f1*100]])
```

```
Accuracy Score :  100.0
F1-Score :  100.0
```

```
acc, f1 = neural_network(XTraindataAcconting, XTestdataAcconting, YTraindataAcconting, YTestdataAcconting)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
nn_metrics = nn_metrics.append([['Accounting', acc*100, f1*100]])
AccontingMetrics = AccontingMetrics.append([['Neural Network', acc*100, f1*100]])
```

```
Accuracy Score :  94.89
F1-Score :  94.31
```

Figure 54: Implementation of Model training and prediction Scores and saving model and department score

```
acc, f1 = neural_network(XTraindataMarketing, XTestdataMarketing, YTraindataMarketing, YTestdataMarketing)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
nn_metrics = nn_metrics.append([['Marketing', acc*100, f1*100]])
MarketingMetrics = MarketingMetrics.append([['Neural Network', acc*100, f1*100]])
```

```
Accuracy Score :  94.74
F1-Score :  94.74
```

```
acc, f1 = neural_network(XTraindataRnD, XTestdataRnD, YTraindataRnD, YTestdataRnD)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
nn_metrics = nn_metrics.append([['RnD', acc*100, f1*100]])
RnDMetrics = RnDMetrics.append([['Neural Network', acc*100, f1*100]])
```

```
Accuracy Score :  73.26
F1-Score :  75.79
```

```
acc, f1 = neural_network(XTraindataSecurity, XTestdataSecurity, YTraindataSecurity, YTestdataSecurity)
print('Accuracy Score : ', np.round(acc*100, 2))
print('F1-Score : ', np.round(f1*100, 2))
nn_metrics = nn_metrics.append([['Security', acc*100, f1*100]])
SecurityMetrics = SecurityMetrics.append([['Neural Network', acc*100, f1*100]])
```

```
Accuracy Score :  94.74
F1-Score :  95.0
```

Figure 55: Implementation of Model training and prediction Scores and saving model and department score

9 Model result

This section explains the performance of the models.

9.1 Model Scores

9.1.1 Decision Trees

```
dt_metrics.columns = ['Department', 'Accuracy', 'F1-Score']
```

```
dt_metrics
```

	Department	Accuracy	F1-Score
0	Organisation	64.173442	63.621354
0	IT	96.833773	96.938776
0	Logistics	91.346154	91.793313
0	Quality	96.153846	96.153846
0	HR	97.826087	98.245614
0	Purchasing	96.212121	95.495495
0	Sales	95.967742	95.967742
0	Operations	94.318182	95.049505
0	Production	96.428571	96.153846
0	Accounting	97.080292	97.014925
0	Marketing	91.228070	92.063492
0	RnD	89.534884	91.000000
0	Security	89.473684	90.476190

Figure 56: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(dt_metrics['Department'], dt_metrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(dt_metrics['Department'], dt_metrics['Accuracy'])
ax.set_xticklabels(dt_metrics.Department, rotation=45)
plt.show()
```

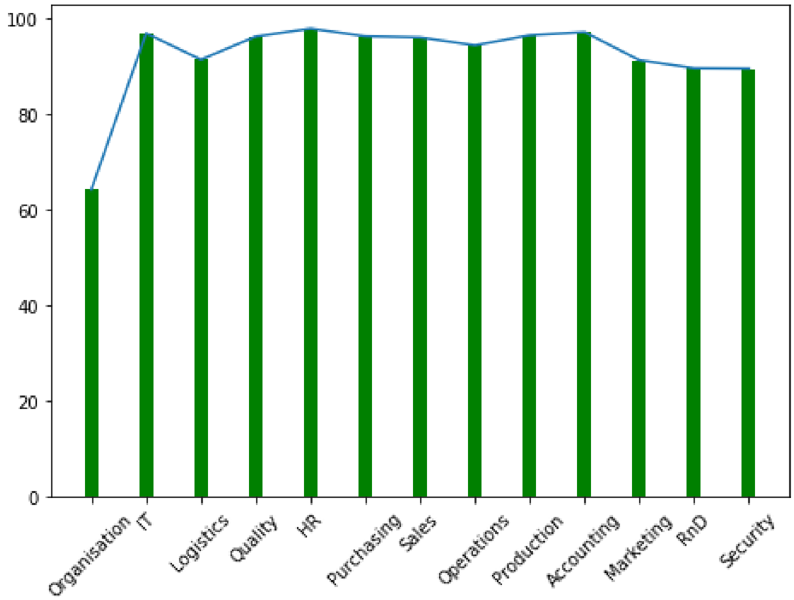


Figure 57: Model Accuracy Score Plot

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(dt_metrics['Department'], dt_metrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(dt_metrics['Department'], dt_metrics['F1-Score'])
ax.set_xticklabels(dt_metrics.Department, rotation=45)
plt.show()
```

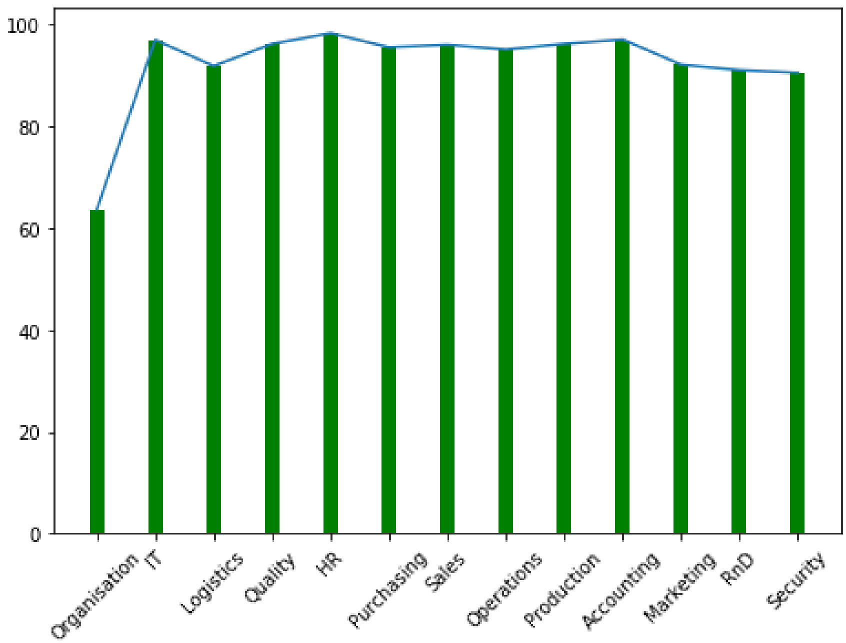


Figure 58: Model F1-Score Plot

9.1.2 Random Forest Trees

```
rf_metrics.columns = ['Department', 'Accuracy', 'F1-Score']
rf_metrics
```

	Department	Accuracy	F1-Score
0	Organisation	64.390244	63.960505
0	IT	98.153034	98.191214
0	Logistics	91.666667	92.073171
0	Quality	100.000000	100.000000
0	HR	100.000000	100.000000
0	Purchasing	97.727273	97.247706
0	Sales	97.580645	97.540984
0	Operations	96.590909	96.969697
0	Production	98.214286	98.039216
0	Accounting	97.080292	97.014925
0	Marketing	98.245614	98.305085
0	RnD	91.279070	92.385787
0	Security	100.000000	100.000000

Figure 59: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(rf_metrics['Department'], rf_metrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(rf_metrics['Department'], rf_metrics['Accuracy'])
ax.set_xticklabels(rf_metrics.Department, rotation=45)
plt.show()
```

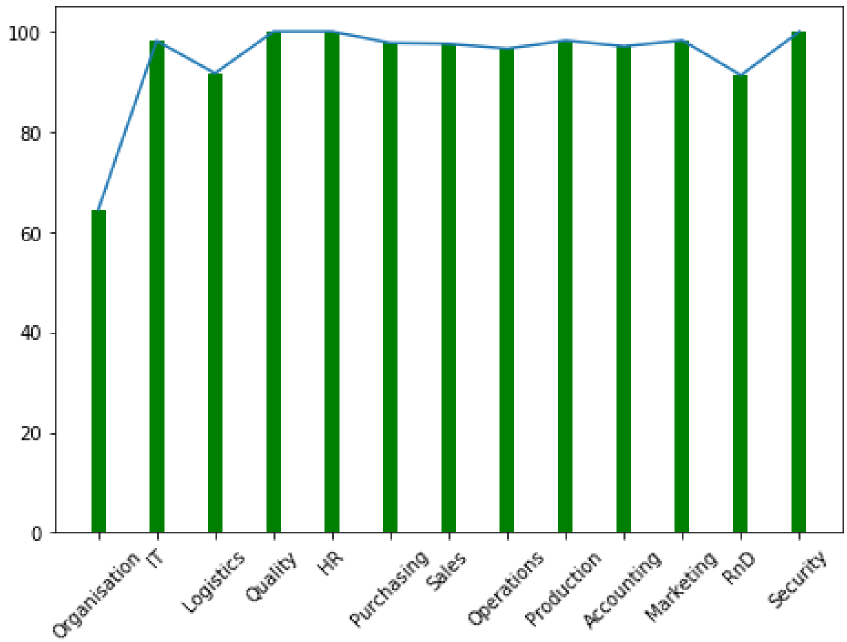


Figure 60: Model Accuracy Score Plot

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(rf_metrics['Department'], rf_metrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(rf_metrics['Department'], rf_metrics['F1-Score'])
ax.set_xticklabels(rf_metrics.Department, rotation=45)
plt.show()
```

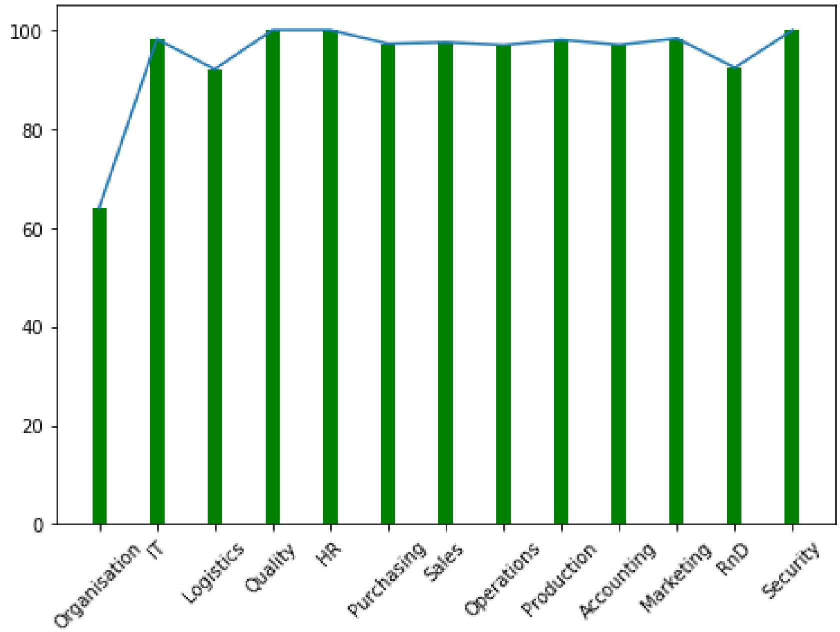


Figure 61: Model F1-Score Plot

9.1.3 SVM

```
svm_metrics.columns = ['Department', 'Accuracy', 'F1-Score']
svm_metrics.info
```

```
<bound method DataFrame.info of      Department   Accuracy   F1-Score
0  Organisation  50.027100  65.724907
0            IT  55.408971  59.665871
0     Logistics  62.820513  63.975155
0       Quality  50.000000  53.571429
0            HR  72.826087  80.620155
0    Purchasing  55.303030  59.310345
0         Sales  59.274194  62.453532
0    Production  51.785714  55.737705
0    Operations  54.545455  43.661972
0    Accounting  54.744526  52.307692
0     Marketing  59.649123  68.493151
0           RnD  58.720930  59.887006
0      Security  60.526316  66.666667>
```

Figure 62: Model Performance

```python
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(svm_metrics['Department'], svm_metrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(svm_metrics['Department'], svm_metrics['Accuracy'])
ax.set_xticklabels(svm_metrics.Department, rotation=45)
plt.show()
```

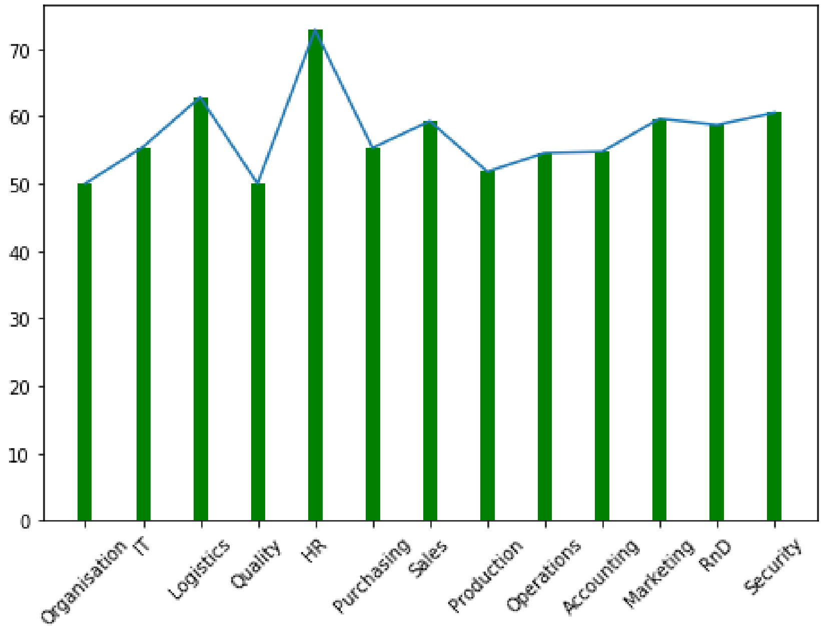


Figure 63: Model Accuracy Score Plot

```python
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(svm_metrics['Department'], svm_metrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(svm_metrics['Department'], svm_metrics['F1-Score'])
ax.set_xticklabels(svm_metrics.Department, rotation=45)
plt.show()
```

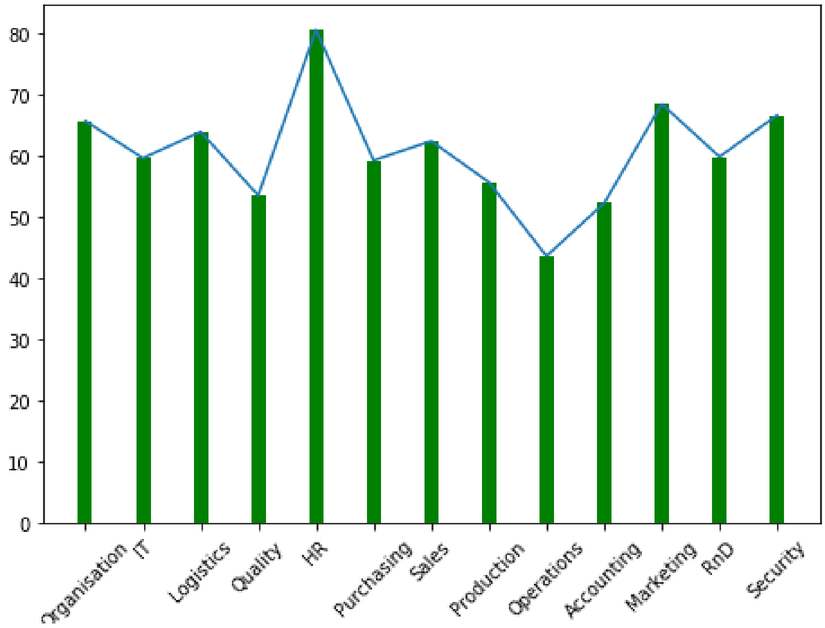


Figure 64: Model F1-Score Plot

9.1.4 Neural Network

```
nn_metrics.columns = ['Department', 'Accuracy', 'F1-Score']
nn_metrics
```

	Department	Accuracy	F1-Score
0	Organisation	54.254743	62.621789
0	IT	77.836412	81.896552
0	Logistics	85.256410	86.390533
0	Quality	98.076923	98.039216
0	HR	98.913043	99.115044
0	Purchasing	89.393939	87.037037
0	Sales	73.387097	65.263158
0	Operations	84.659091	86.153846
0	Production	100.000000	100.000000
0	Accounting	94.890511	94.308943
0	Marketing	94.736842	94.736842
0	RnD	73.255814	75.789474
0	Security	94.736842	95.000000

Figure 65: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(nn_metrics['Department'], nn_metrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(nn_metrics['Department'], nn_metrics['Accuracy'])
ax.set_xticklabels(nn_metrics.Department, rotation=45)
plt.show()
```

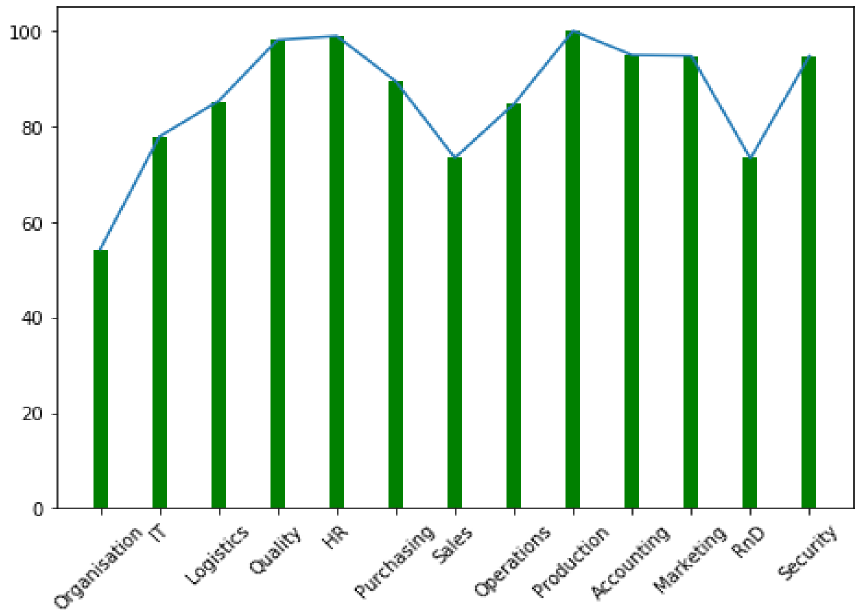


Figure 66: Model Accuracy Score Plot

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(nn_metrics['Department'], nn_metrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(nn_metrics['Department'], nn_metrics['F1-Score'])
ax.set_xticklabels(nn_metrics.Department, rotation=45)
plt.show()
```

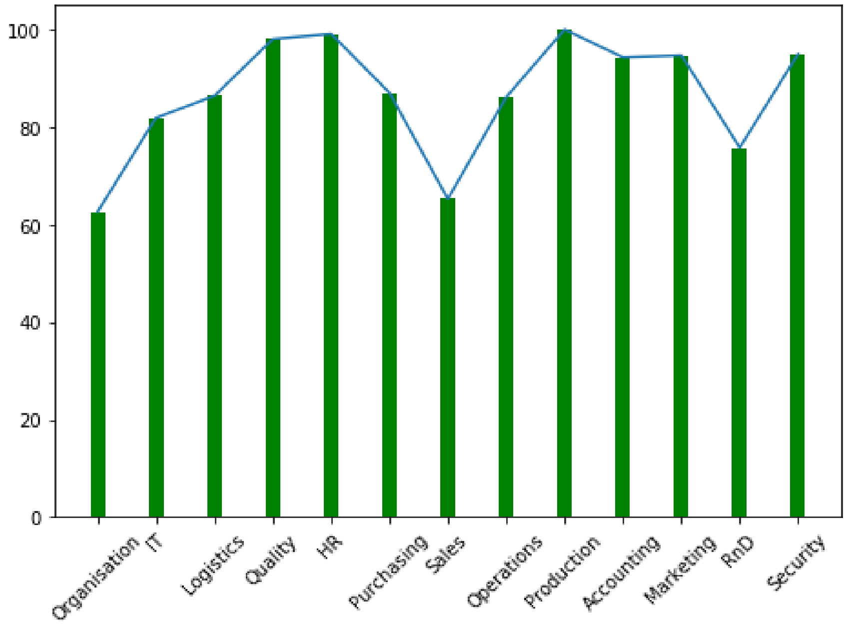


Figure 67: Model F1-Score Plot

9.2 Department Analysis

9.2.1 Organization

```
orgMetrics.columns = ['Model', 'Accuracy', 'F1-Score']
orgMetrics
```

	Model	Accuracy	F1-Score
0	Decision Tree	64.173442	63.621354
0	Random Forest	64.390244	63.960505
0	SVM	50.027100	65.724907
0	Neural Network	54.254743	62.621789

Figure 68: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(orgMetrics['Model'], orgMetrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(orgMetrics['Model'], orgMetrics['Accuracy'])
ax.set_xticklabels(orgMetrics.Model, rotation=45)
plt.show()
```

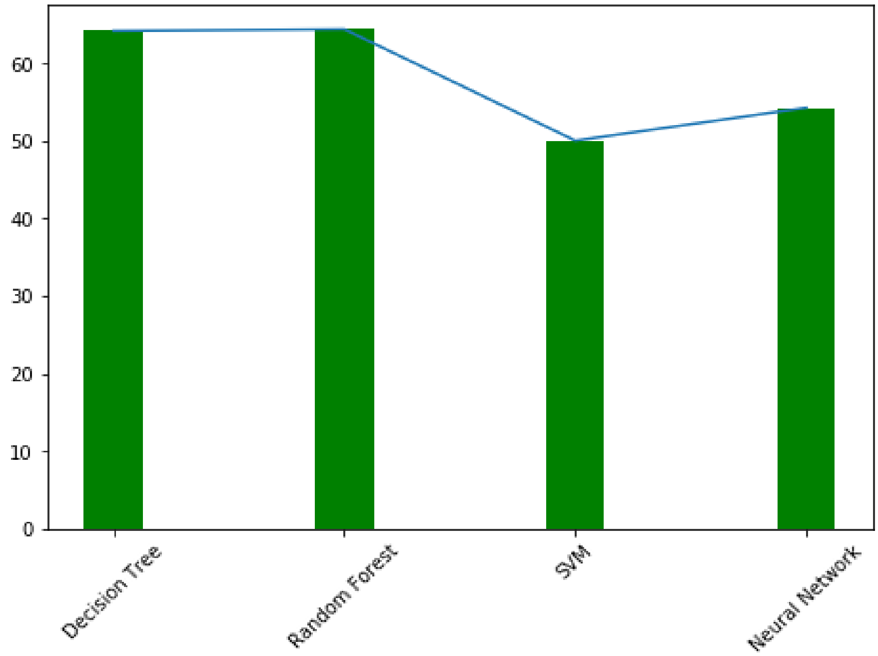


Figure 69: Model Accuracy Score Plot

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(orgMetrics['Model'], orgMetrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(orgMetrics['Model'], orgMetrics['F1-Score'])
ax.set_xticklabels(orgMetrics.Model, rotation=45)
plt.show()
```

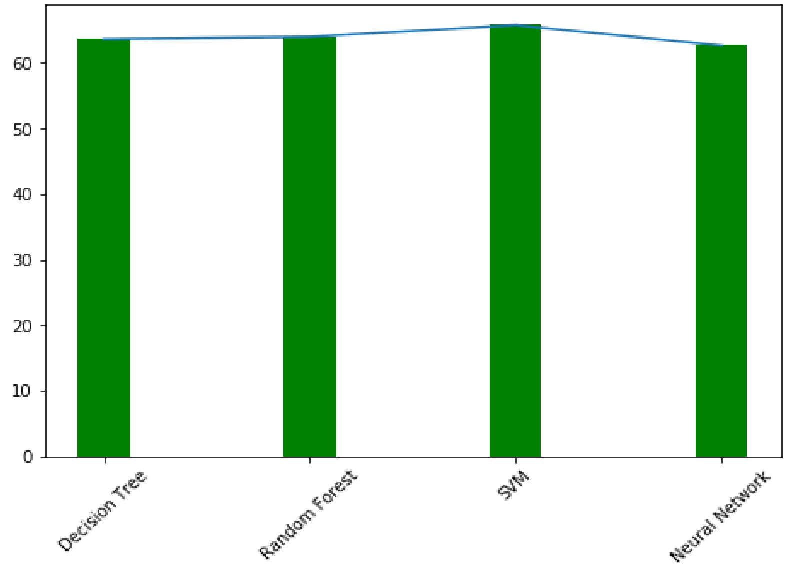


Figure 70: Model F1-Score Plot

9.2.2 IT Department

```
ITMetrics.columns = ['Model', 'Accuracy', 'F1-Score']
ITMetrics
```

	Model	Accuracy	F1-Score
0	Decision Tree	96.833773	96.938776
0	Random Forest	98.153034	98.191214
0	SVM	55.408971	59.665871
0	Neural Network	77.836412	81.896552

Figure 71: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(ITMetrics['Model'], ITMetrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(ITMetrics['Model'], ITMetrics['Accuracy'])
ax.set_xticklabels(ITMetrics.Model, rotation=45)
plt.show()
```

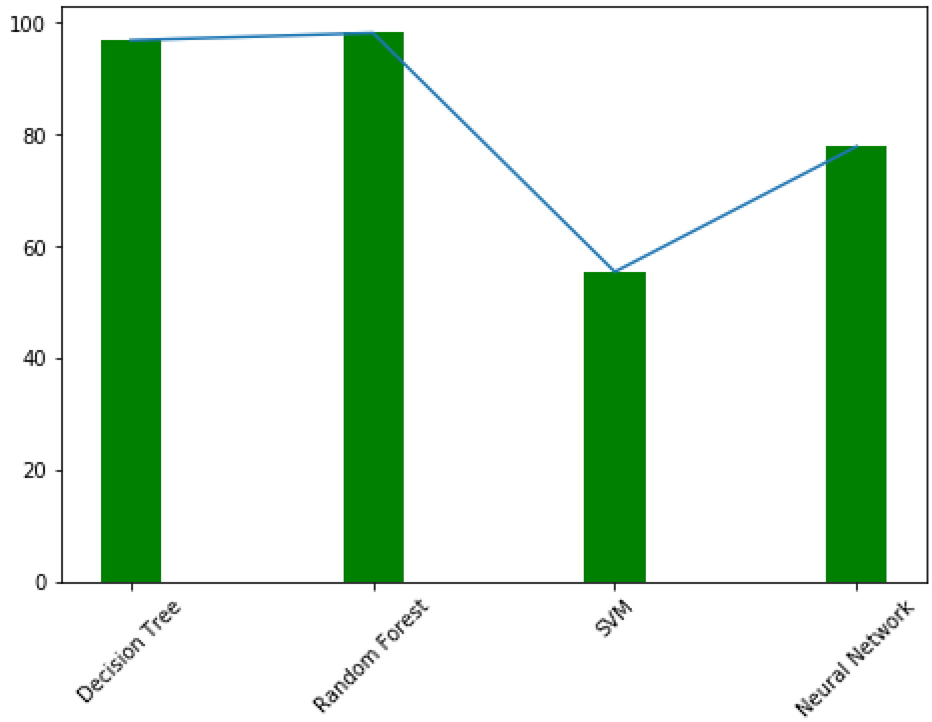


Figure 72: Model Accuracy Score Plot

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(ITMetrics['Model'], ITMetrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(ITMetrics['Model'], ITMetrics['F1-Score'])
ax.set_xticklabels(ITMetrics.Model, rotation=45)
plt.show()
```

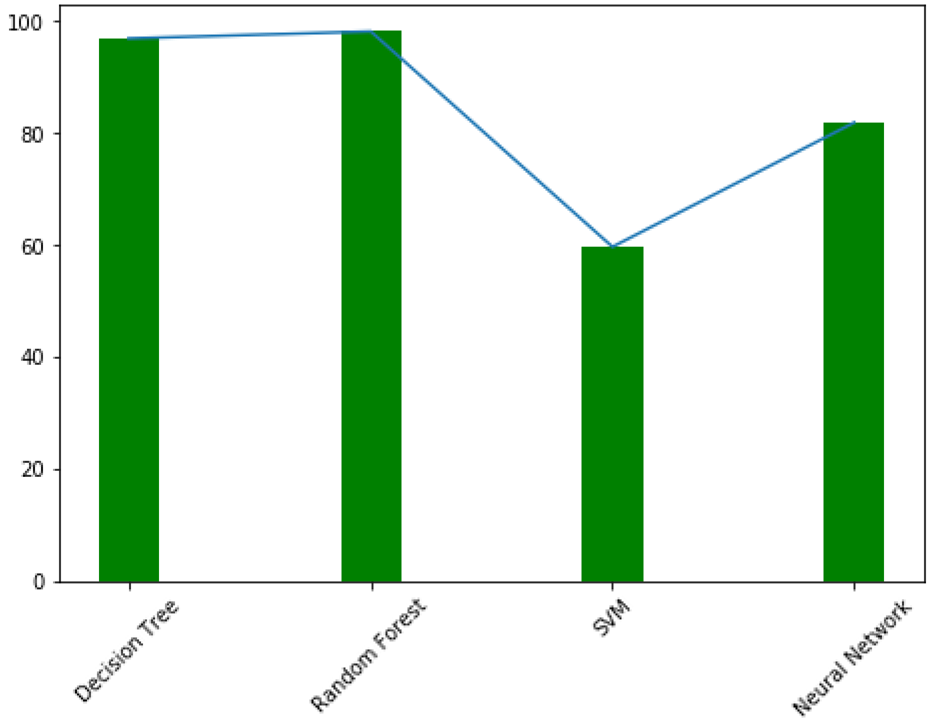


Figure 73: Model F1-Score Plot

9.2.3 Logistics Department

```
LogisticsMetrics.columns = ['Model', 'Accuracy', 'F1-Score']
LogisticsMetrics
```

	Model	Accuracy	F1-Score
0	Decision Tree	91.346154	91.793313
0	Random Forest	91.666667	92.073171
0	SVM	62.820513	63.975155
0	Neural Network	85.256410	86.390533

Figure 74: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(LogisticsMetrics['Model'], LogisticsMetrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(LogisticsMetrics['Model'], LogisticsMetrics['Accuracy'])
ax.set_xticklabels(LogisticsMetrics.Model, rotation=45)
plt.show()
```

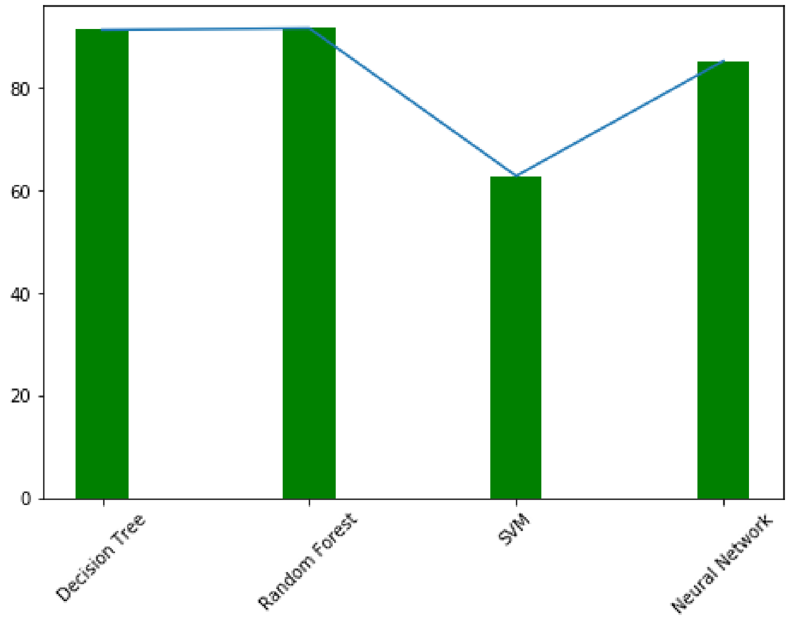


Figure 75: Model Accuracy Score Plot

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(LogisticsMetrics['Model'], LogisticsMetrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(LogisticsMetrics['Model'], LogisticsMetrics['F1-Score'])
ax.set_xticklabels(LogisticsMetrics.Model, rotation=45)
plt.show()
```

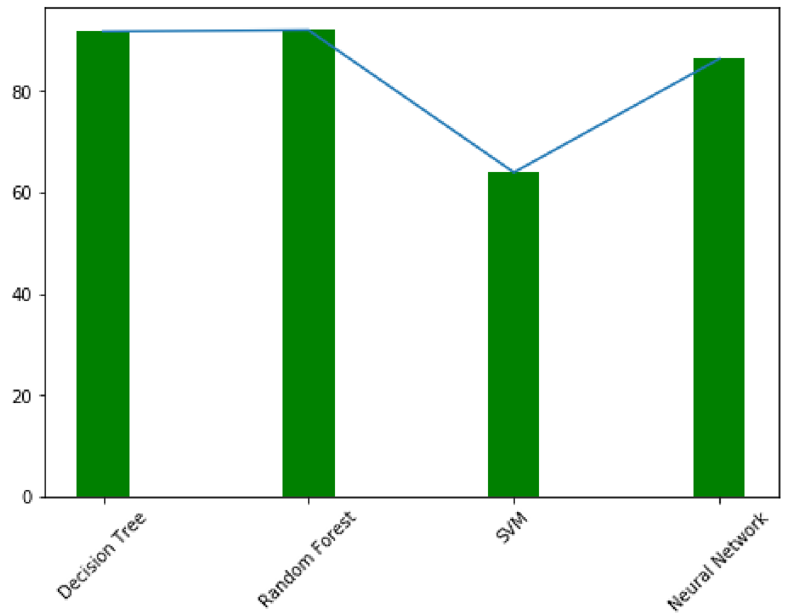


Figure 76: Model F1-Score Plot

9.2.4 Quality Department

```
QualityMetrics.columns = ['Model', 'Accuracy', 'F1-Score']
QualityMetrics
```

	Model	Accuracy	F1-Score
0	Decision Tree	96.153846	96.153846
0	Random Forest	100.000000	100.000000
0	SVM	50.000000	53.571429
0	Neural Network	98.076923	98.039216

Figure 77: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(QualityMetrics['Model'], QualityMetrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(QualityMetrics['Model'], QualityMetrics['Accuracy'])
ax.set_xticklabels(QualityMetrics.Model, rotation=45)
plt.show()
```

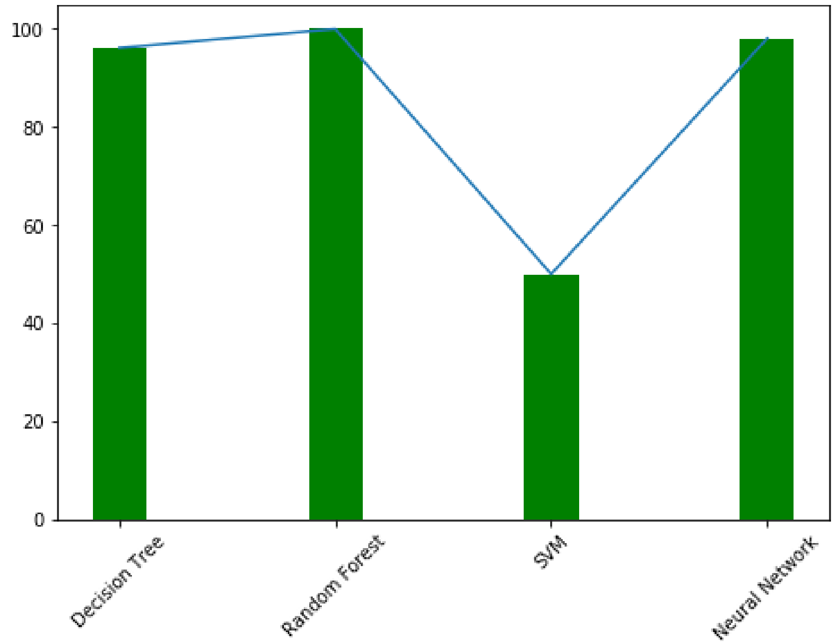


Figure 78: Model Accuracy Score Plot

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(QualityMetrics['Model'], QualityMetrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(QualityMetrics['Model'], QualityMetrics['F1-Score'])
ax.set_xticklabels(QualityMetrics.Model, rotation=45)
plt.show()
```

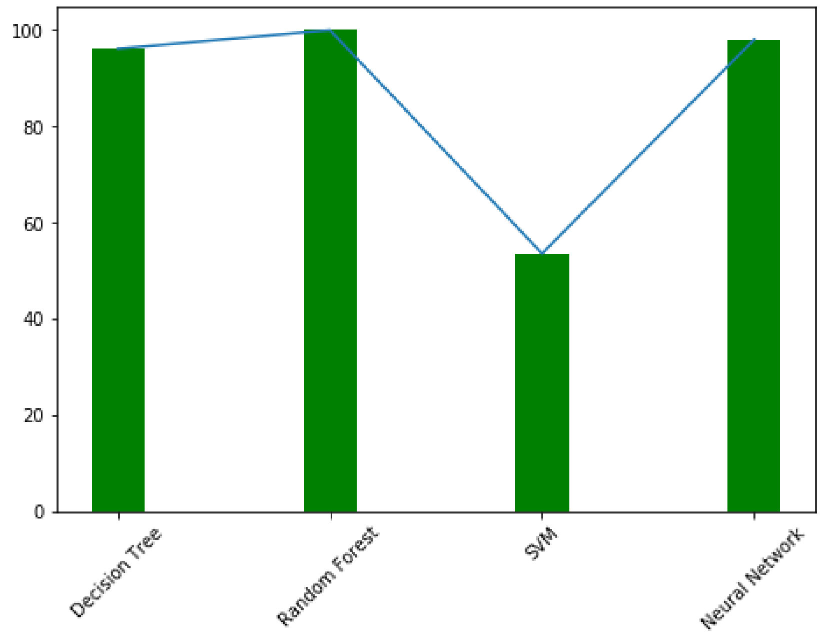


Figure 79: Model F1-Score Plot

9.2.5 HR Department

```
HRMetrics.columns = ['Model', 'Accuracy', 'F1-Score']
HRMetrics
```

	Model	Accuracy	F1-Score
0	Decision Tree	97.826087	98.245614
0	Random Forest	100.000000	100.000000
0	SVM	72.826087	80.620155
0	Neural Network	98.913043	99.115044

Figure 80: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(HRMetrics['Model'], HRMetrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(HRMetrics['Model'], HRMetrics['Accuracy'])
ax.set_xticklabels(HRMetrics.Model, rotation=45)
plt.show()
```

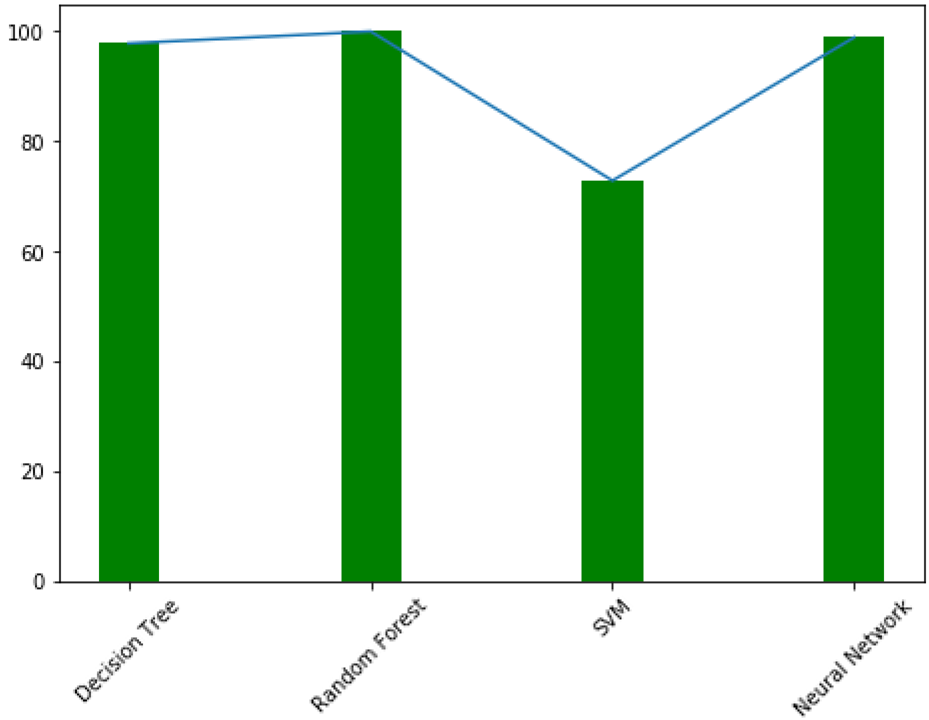


Figure 81: Model Accuracy Score Plot

```python
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(HRMetrics['Model'], HRMetrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(HRMetrics['Model'], HRMetrics['F1-Score'])
ax.set_xticklabels(HRMetrics.Model, rotation=45)
plt.show()
```

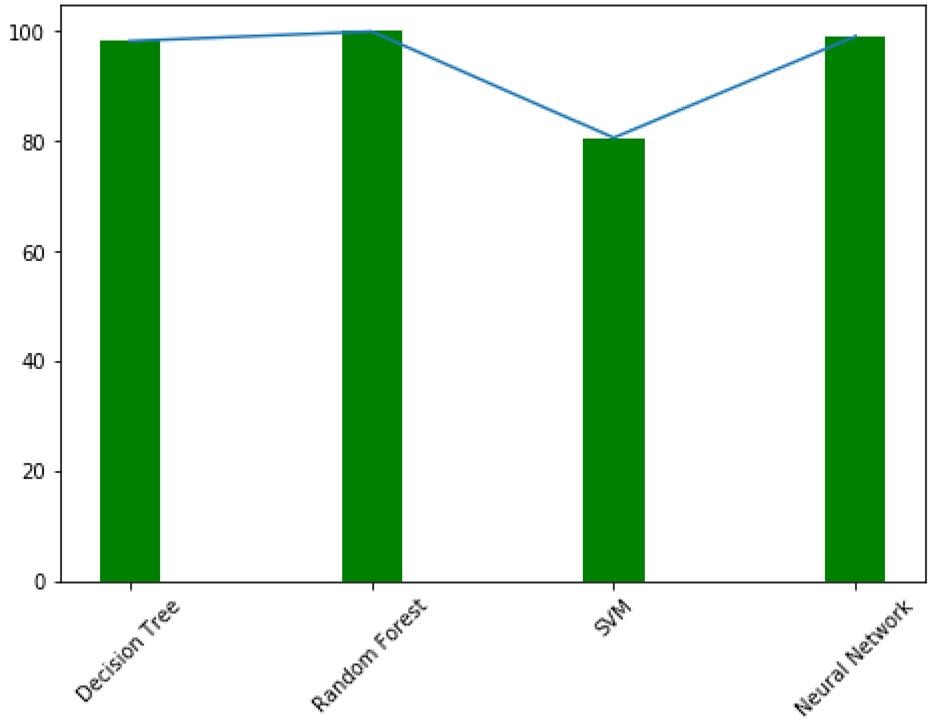


Figure 82: Model F1-Score Plot

9.2.6 Purchasing Department

```python
PurchasingMetrics.columns = ['Model', 'Accuracy', 'F1-Score']
PurchasingMetrics
```

	Model	Accuracy	F1-Score
0	Decision Tree	96.212121	95.495495
0	Random Forest	97.727273	97.247706
0	SVM	55.303030	59.310345
0	Neural Network	89.393939	87.037037

Figure 83: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(PurchasingMetrics['Model'], PurchasingMetrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(PurchasingMetrics['Model'], PurchasingMetrics['Accuracy'])
ax.set_xticklabels(PurchasingMetrics.Model, rotation=45)
plt.show()
```

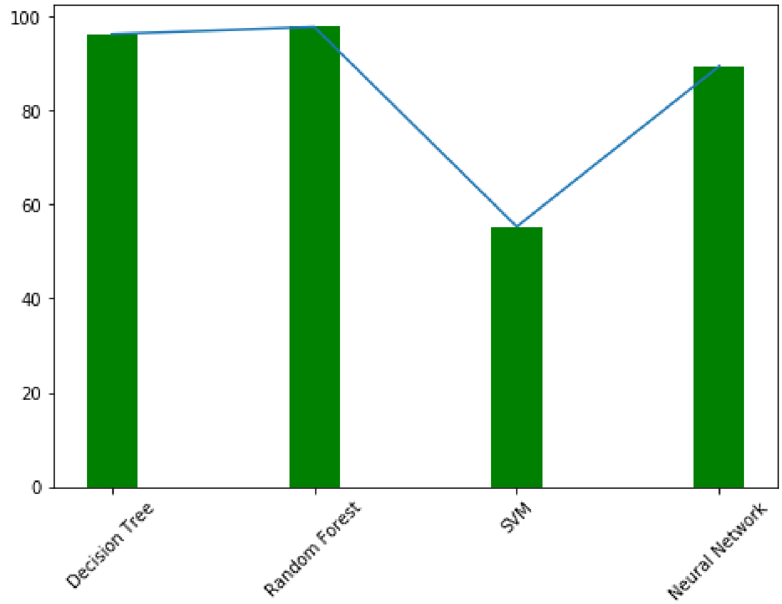


Figure 84: Model Accuracy Score Plot

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(PurchasingMetrics['Model'], PurchasingMetrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(PurchasingMetrics['Model'], PurchasingMetrics['F1-Score'])
ax.set_xticklabels(PurchasingMetrics.Model, rotation=45)
plt.show()
```

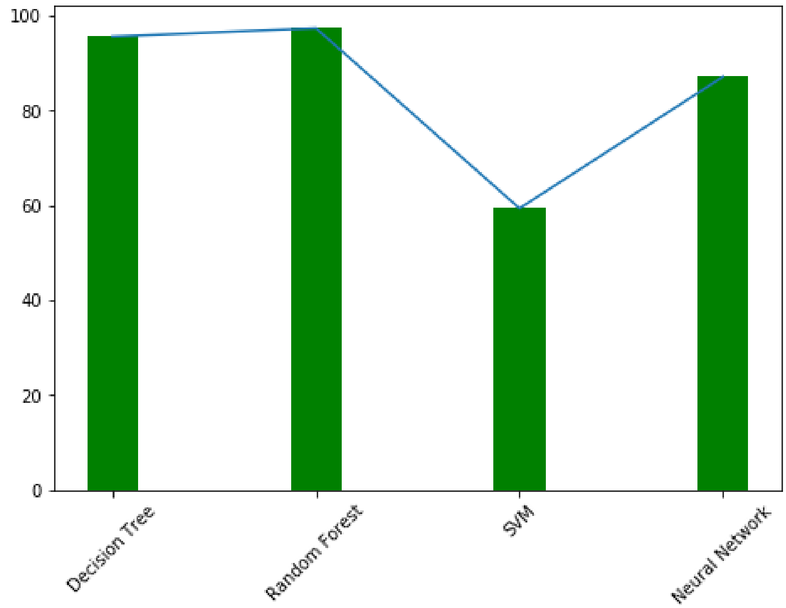


Figure 85: Model F1-Score Plot

9.2.7 Sales Department

```
SalesMetrics.columns = ['Model', 'Accuracy', 'F1-Score']
SalesMetrics
```

	Model	Accuracy	F1-Score
0	Decision Tree	95.967742	95.967742
0	Random Forest	97.580645	97.540984
0	SVM	59.274194	62.453532
0	Neural Network	73.387097	65.263158

Figure 86: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(SalesMetrics['Model'], SalesMetrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(SalesMetrics['Model'], SalesMetrics['Accuracy'])
ax.set_xticklabels(SalesMetrics.Model, rotation=45)
plt.show()
```

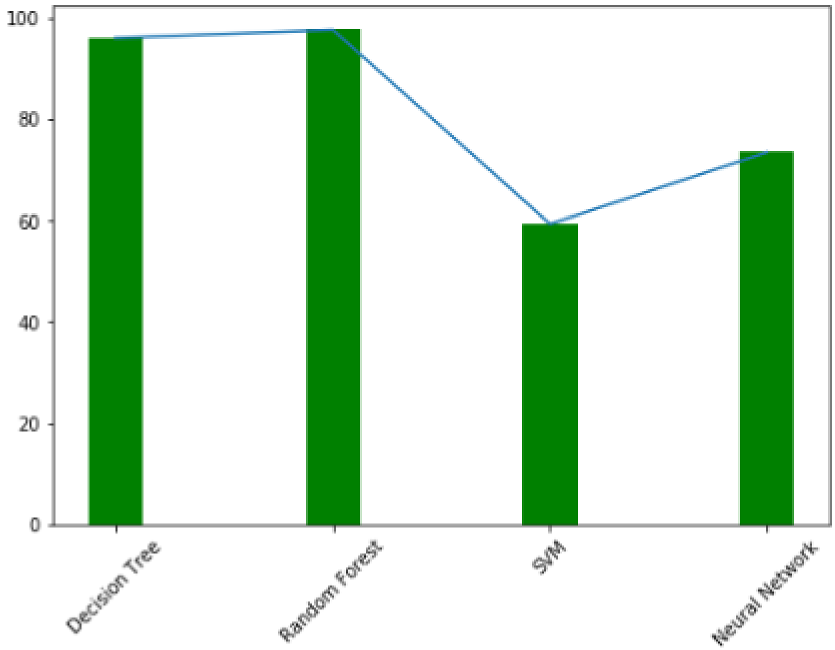


Figure 87: Model Accuracy Score Plot

```python
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(SalesMetrics['Model'], SalesMetrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(SalesMetrics['Model'], SalesMetrics['F1-Score'])
ax.set_xticklabels(SalesMetrics.Model, rotation=45)
plt.show()
```

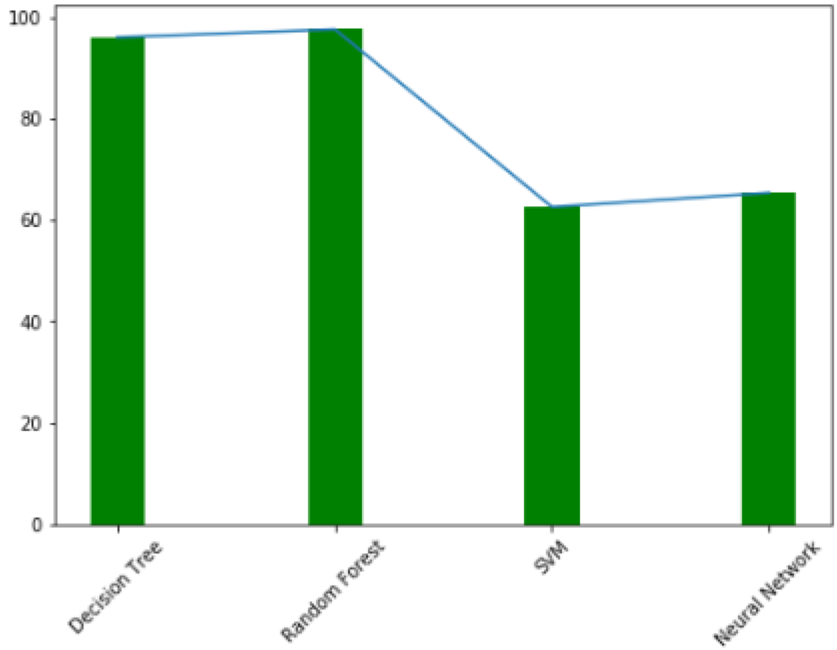


Figure 88: Model F1-Score Plot

9.2.8 Operations Department

```python
OperarionsMetrics.columns = ['Model', 'Accuracy', 'F1-Score']
OperarionsMetrics
```

	Model	Accuracy	F1-Score
0	Decision Tree	94.318182	95.049505
0	Random Forest	96.590909	96.969697
0	SVM	54.545455	43.661972
0	Neural Network	84.659091	86.153846

Figure 89: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(OperarionsMetrics['Model'], OperarionsMetrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(OperarionsMetrics['Model'], OperarionsMetrics['Accuracy'])
ax.set_xticklabels(OperarionsMetrics.Model, rotation=45)
plt.show()
```

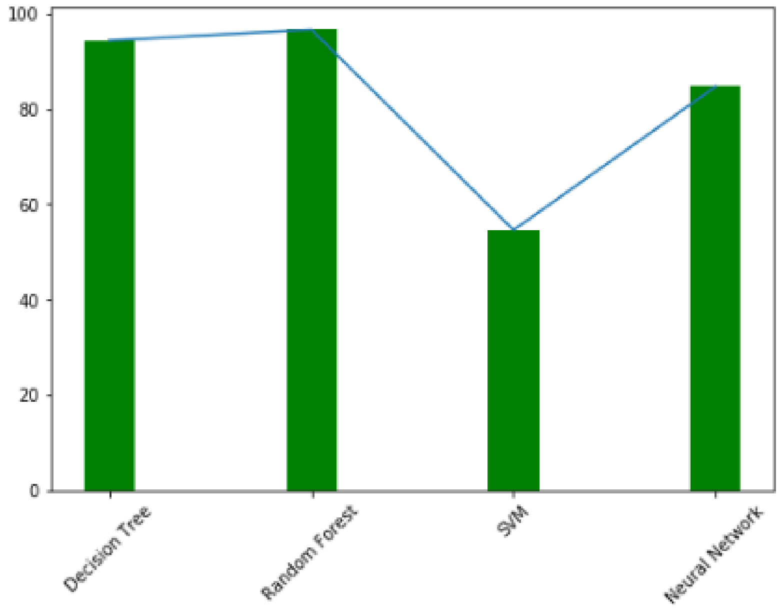


Figure 90: Model Accuracy Score Plot

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(OperarionsMetrics['Model'], OperarionsMetrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(OperarionsMetrics['Model'], OperarionsMetrics['F1-Score'])
ax.set_xticklabels(OperarionsMetrics.Model, rotation=45)
plt.show()
```

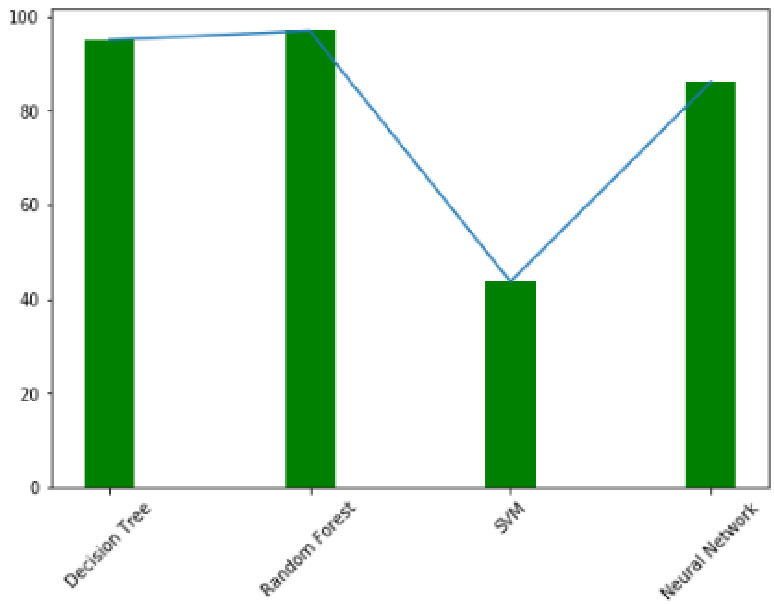


Figure 91: Model F1-Score Plot

9.2.9 Production Department

```
ProductionMetrics.columns = ['Model', 'Accuracy', 'F1-Score']
ProductionMetrics
```

	Model	Accuracy	F1-Score
0	Decision Tree	96.428571	96.153846
0	Random Forest	98.214286	98.039216
0	ProductionMetrics	51.785714	55.737705
0	Neural Network	100.000000	100.000000

Figure 92: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(ProductionMetrics['Model'], ProductionMetrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(ProductionMetrics['Model'], ProductionMetrics['Accuracy'])
ax.set_xticklabels(ProductionMetrics.Model, rotation=45)
plt.show()
```

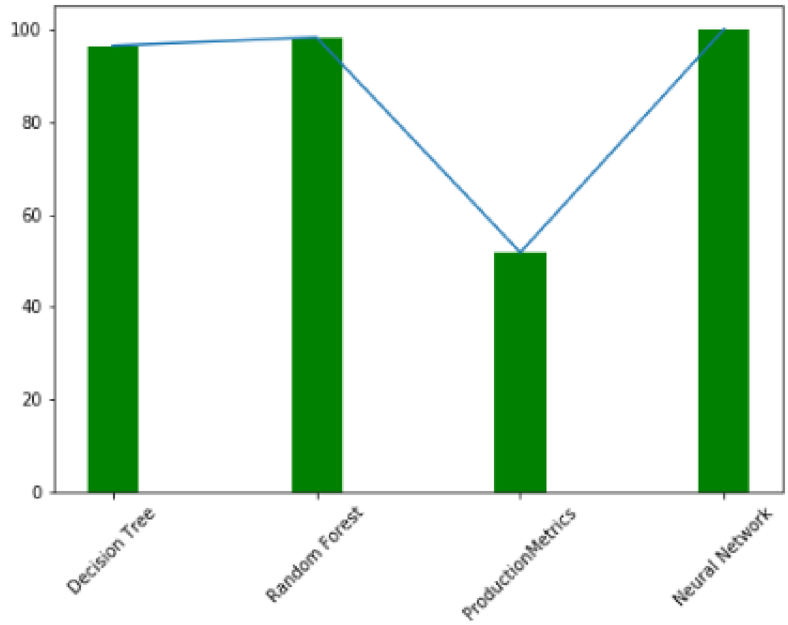


Figure 93: Model Accuracy Score Plot

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(ProductionMetrics['Model'], ProductionMetrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(ProductionMetrics['Model'], ProductionMetrics['F1-Score'])
ax.set_xticklabels(ProductionMetrics.Model, rotation=45)
plt.show()
```

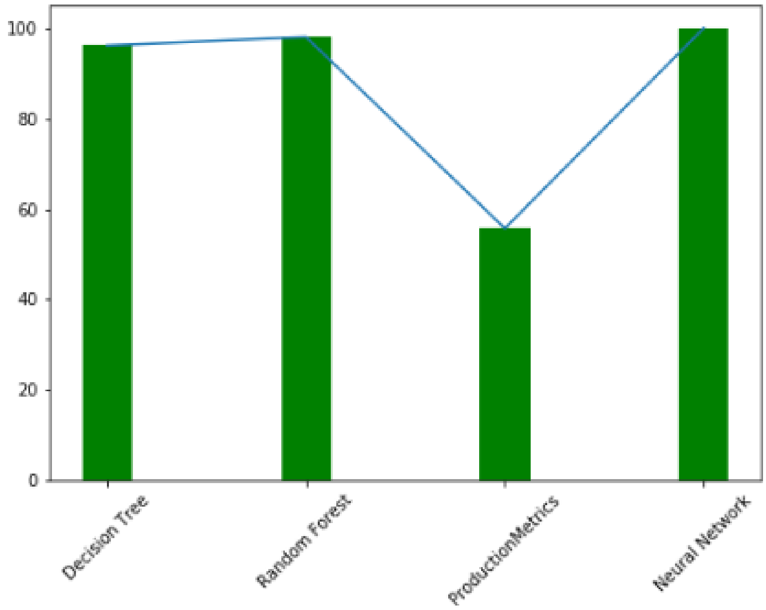


Figure 94: Model F1-Score Plot

9.2.10 Accounting Department

```
AccontingMetrics.columns = ['Model', 'Accuracy', 'F1-Score']
AccontingMetrics
```

	Model	Accuracy	F1-Score
0	Decision Tree	97.080292	97.014925
0	Random Forest	97.080292	97.014925
0	SVM	54.744526	52.307692
0	Neural Network	94.890511	94.308943

Figure 95: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(AccontingMetrics['Model'], AccontingMetrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(AccontingMetrics['Model'], AccontingMetrics['Accuracy'])
ax.set_xticklabels(AccontingMetrics.Model, rotation=45)
plt.show()
```

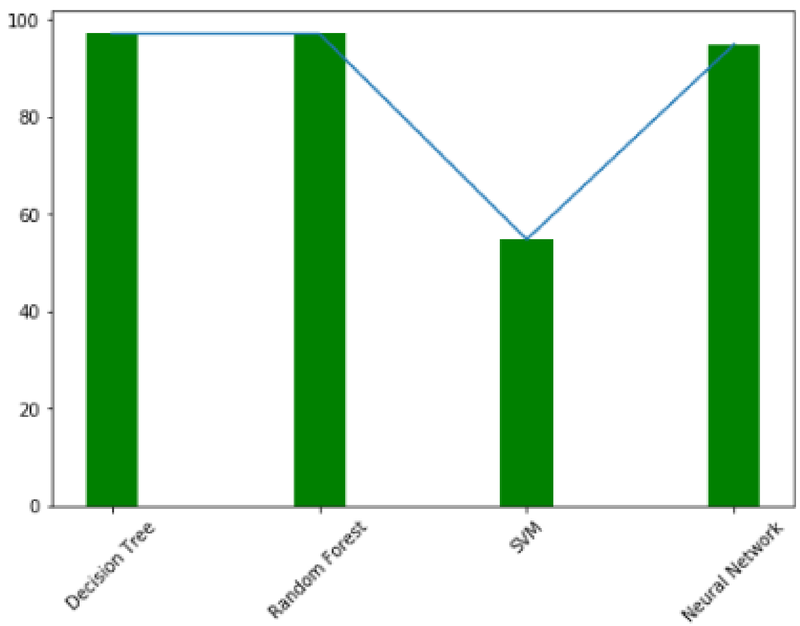


Figure 96: Model Accuracy Score Plot

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(AccontingMetrics['Model'], AccontingMetrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(AccontingMetrics['Model'], AccontingMetrics['F1-Score'])
ax.set_xticklabels(AccontingMetrics.Model, rotation=45)
plt.show()
```

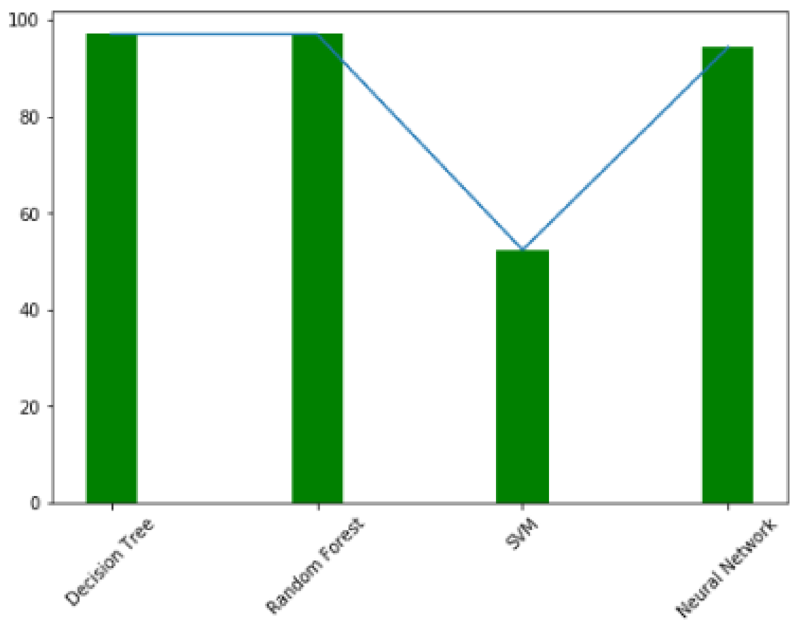


Figure 97: Model F1-Score Plot

9.2.11 Marketing Department

```
MarketingMetrics.columns = ['Model', 'Accuracy', 'F1-Score']
MarketingMetrics
```

	Model	Accuracy	F1-Score
0	Decision Tree	91.228070	92.063492
0	Random Forest	98.245614	98.305085
0	SVM	59.649123	68.493151
0	Neural Network	94.736842	94.736842

Figure 98: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(MarketingMetrics['Model'], MarketingMetrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(MarketingMetrics['Model'], MarketingMetrics['Accuracy'])
ax.set_xticklabels(MarketingMetrics.Model, rotation=45)
plt.show()
```

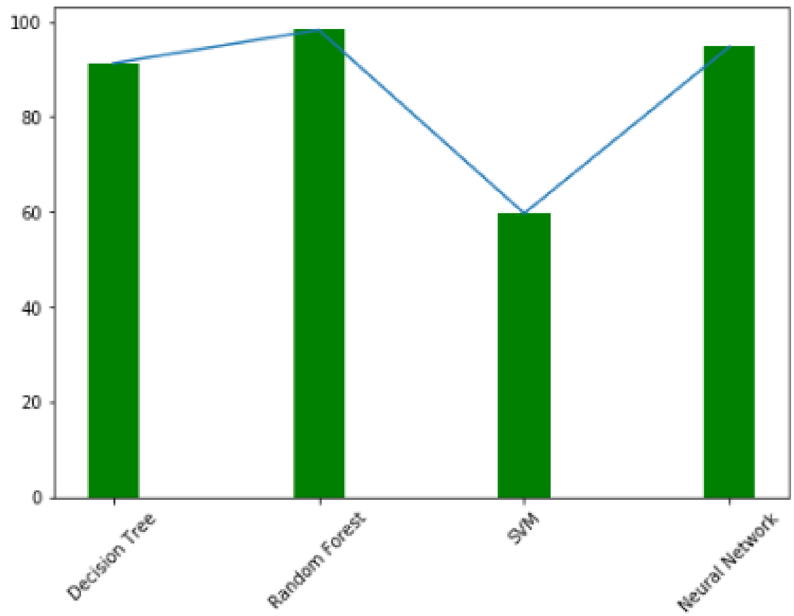


Figure 99: Model Accuracy Score Plot

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(MarketingMetrics['Model'], MarketingMetrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(MarketingMetrics['Model'], MarketingMetrics['F1-Score'])
ax.set_xticklabels(MarketingMetrics.Model, rotation=45)
plt.show()
```

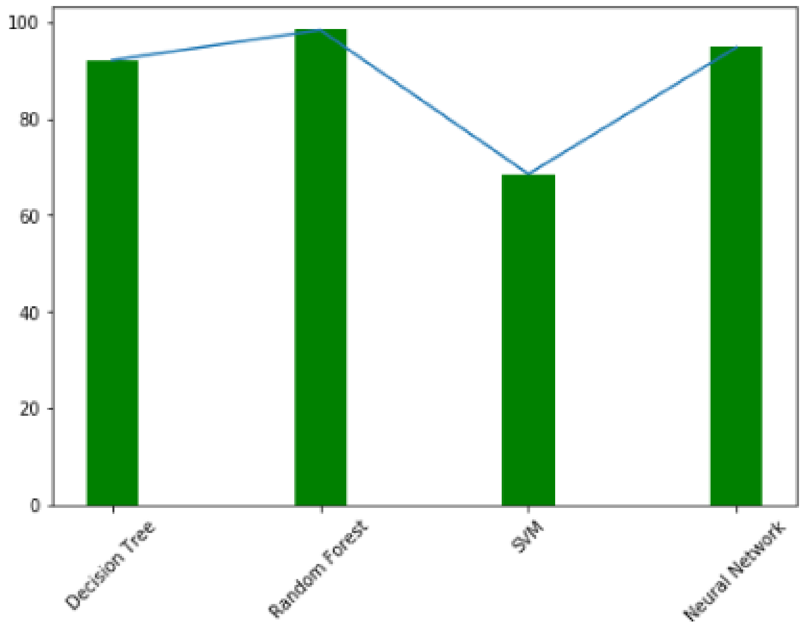


Figure 100: Model F1-Score Plot

9.2.12 R&D Department

```
RnDMetrics.columns = ['Model', 'Accuracy', 'F1-Score']
RnDMetrics
```

	Model	Accuracy	F1-Score
0	Decision Tree	89.534884	91.000000
0	Random Forest	91.279070	92.385787
0	SVM	58.720930	59.887006
0	Neural Network	73.255814	75.789474

Figure 101: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(RnDMetrics['Model'], RnDMetrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(RnDMetrics['Model'], RnDMetrics['Accuracy'])
ax.set_xticklabels(RnDMetrics.Model, rotation=45)
plt.show()
```

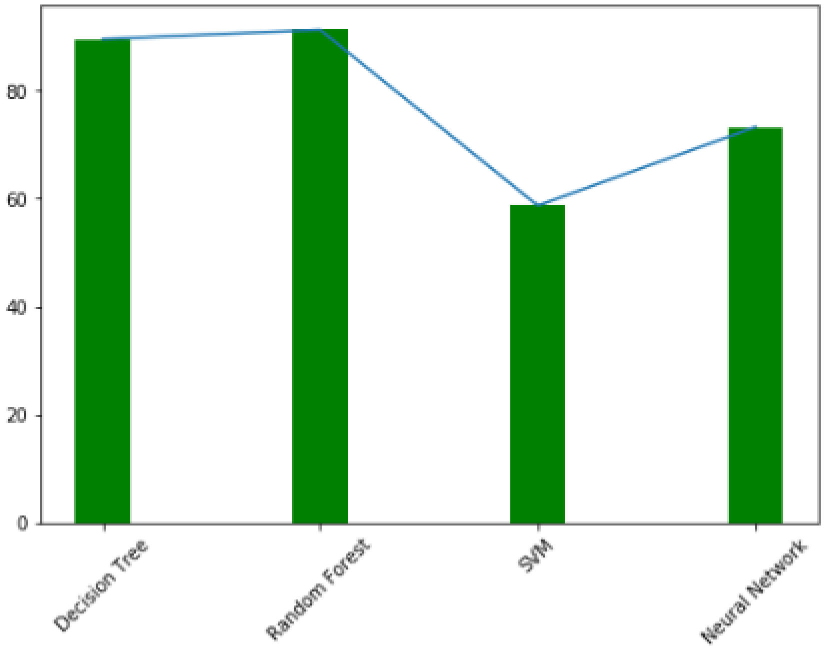


Figure 102: Model Accuracy Score Plot

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(RnDMetrics['Model'], RnDMetrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(RnDMetrics['Model'], RnDMetrics['F1-Score'])
ax.set_xticklabels(RnDMetrics.Model, rotation=45)
plt.show()
```

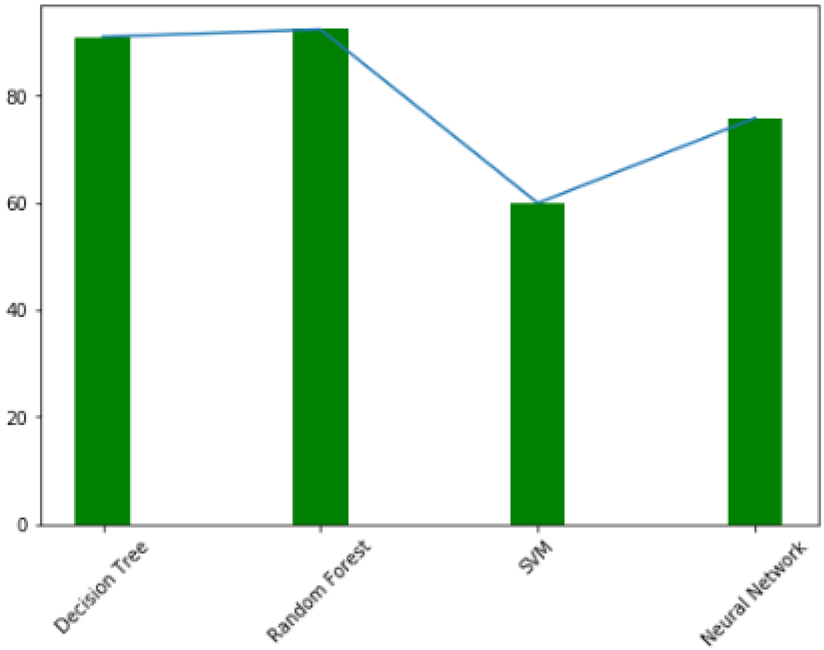


Figure 103: Model F1-Score Plot

9.2.13 Security Department

```
SecurityMetrics.columns = ['Model', 'Accuracy', 'F1-Score']
SecurityMetrics
```

	Model	Accuracy	F1-Score
0	Decision Tree	89.473684	90.476190
0	Random Forest	100.000000	100.000000
0	SVM	60.526316	66.666667
0	Neural Network	94.736842	95.000000

Figure 104: Model Performance

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(SecurityMetrics['Model'], SecurityMetrics['Accuracy'], color = 'g', width = 0.25)
ax.plot(SecurityMetrics['Model'], SecurityMetrics['Accuracy'])
ax.set_xticklabels(SecurityMetrics.Model, rotation=45)
plt.show()
```

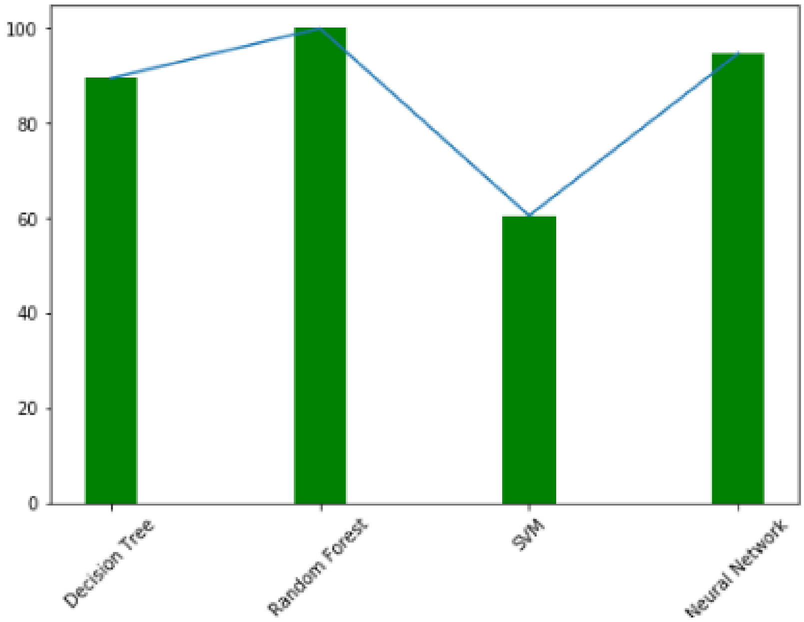


Figure 105: Model Accuracy Score Plot

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(SecurityMetrics['Model'], SecurityMetrics['F1-Score'], color = 'g', width = 0.25)
ax.plot(SecurityMetrics['Model'], SecurityMetrics['F1-Score'])
ax.set_xticklabels(SecurityMetrics.Model, rotation=45)
plt.show()
```

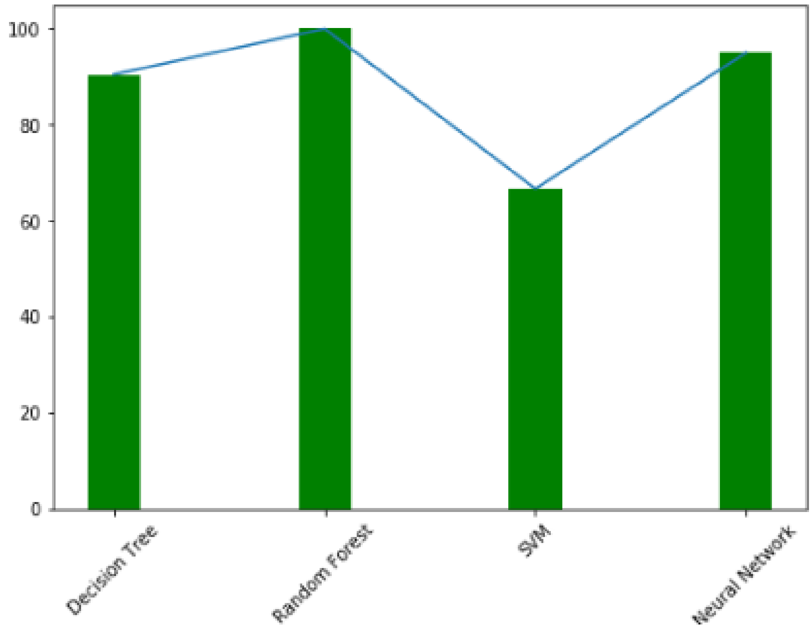


Figure 106: Model F1-Score Plot

References

https://scikit-learn.org/stable/modules/tree.html

https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html#sklearn.tree.DecisionTreeClassifier

https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html

https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html

https://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPClassifier.html#sklearn.neural_network.MLPClassifier