Nompumelelo Ngwenya

Training a machine learning model using the Employee Attrition data.

Introduction and Overview:

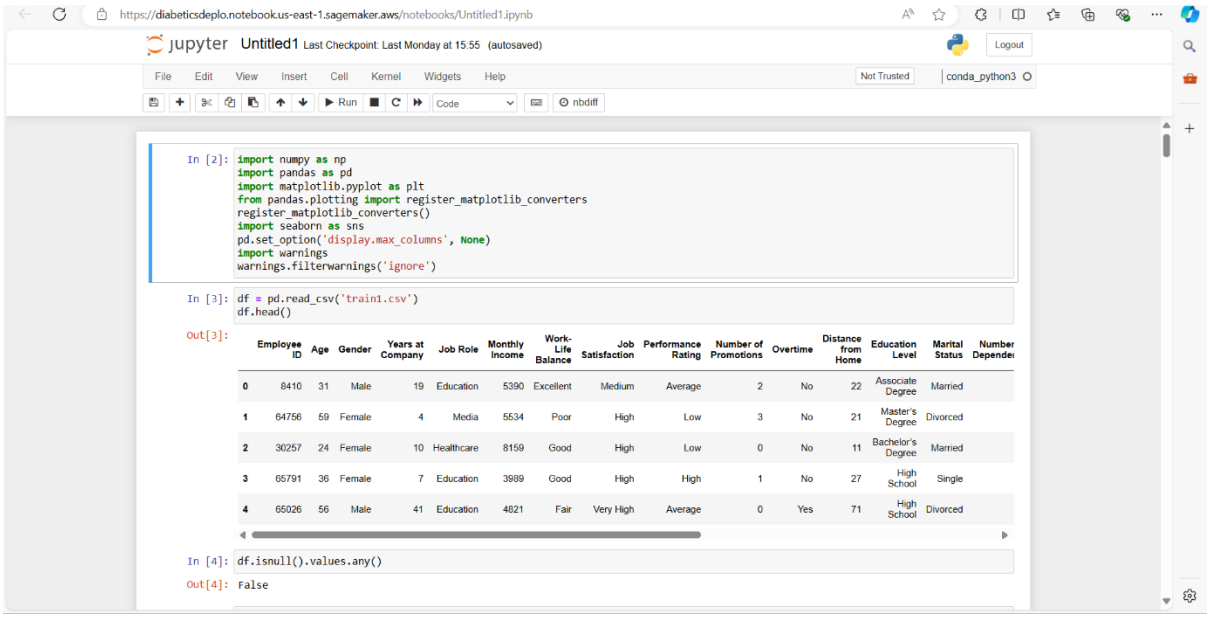
This document aims to guide stakeholders through the process of deploying a machine learning model trained on the Employees Attrition (Train) dataset on AWS.

The dataset comprises 74,498 samples and It contains detailed information about various aspects of an employee's profile, including demographics, job-related features, and personal circumstances. Each record includes a unique Employee ID and features that influence employee attrition. The aim is to understand the factors contributing to attrition and develop predictive models to identify at-risk employees.

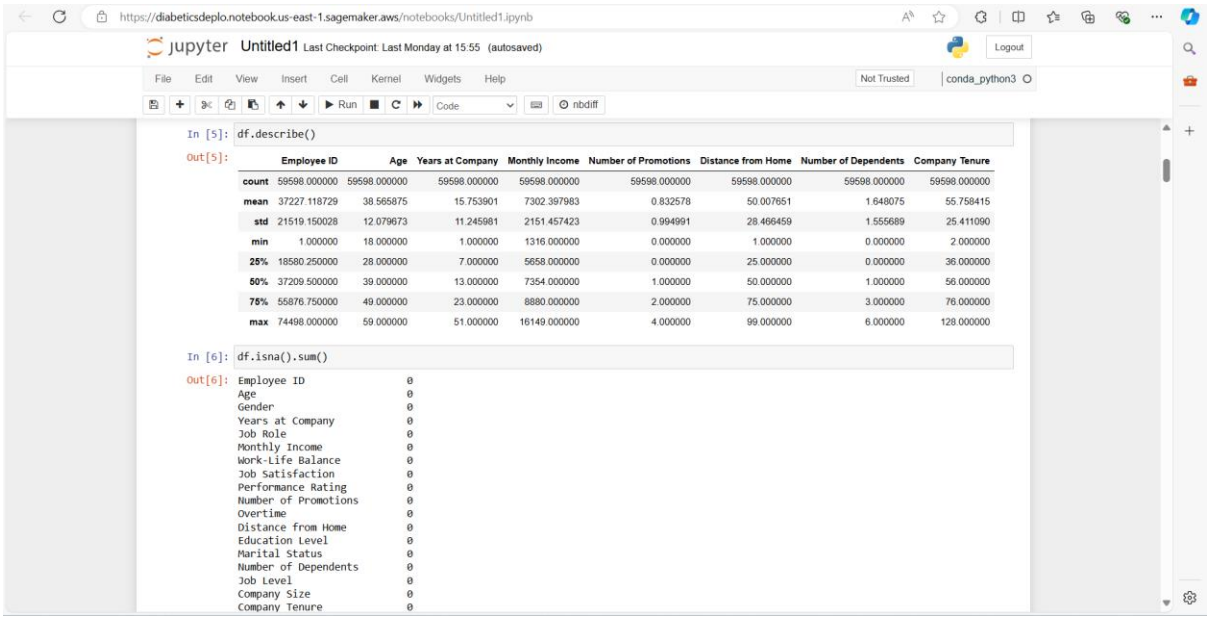
This dataset is ideal for HR analytics, machine learning model development, and demonstrating advanced data analysis techniques. It provides a comprehensive and realistic view of the factors affecting employee retention, making it a valuable resource for researchers and practitioners in the field of human resources and organizational development.

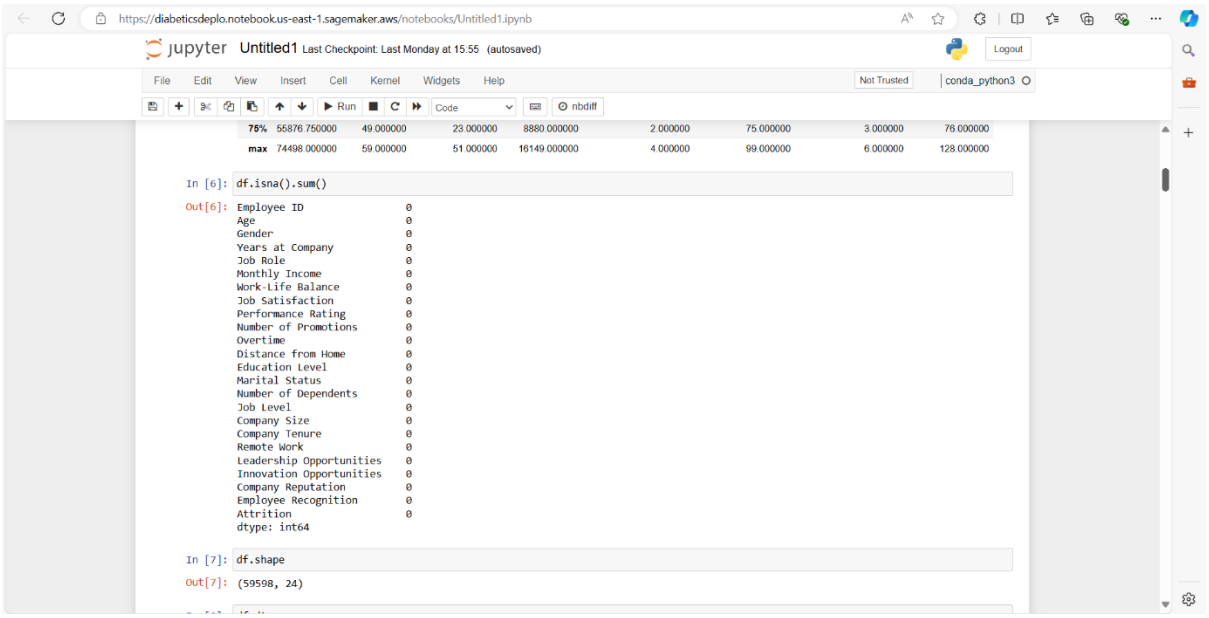
Data source: (Employee Attrition Classification Dataset (kaggle.com))

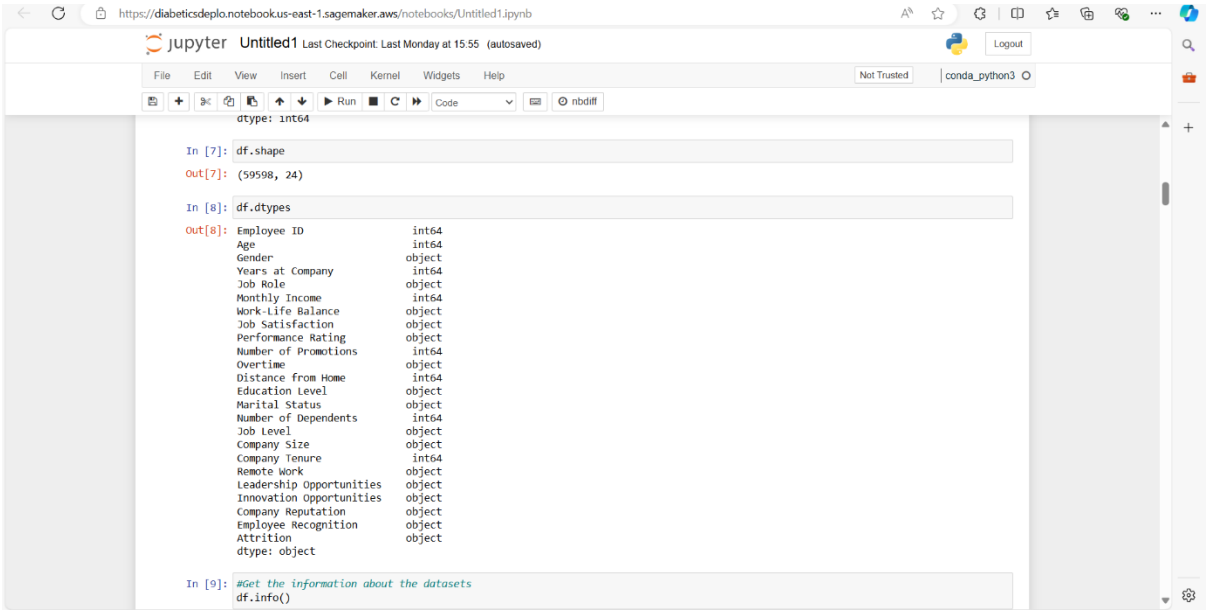
Importing the necessary python libraries and data extracting from the data source



Exploratory data analysis(EDA) and data cleaning by checking for any null values



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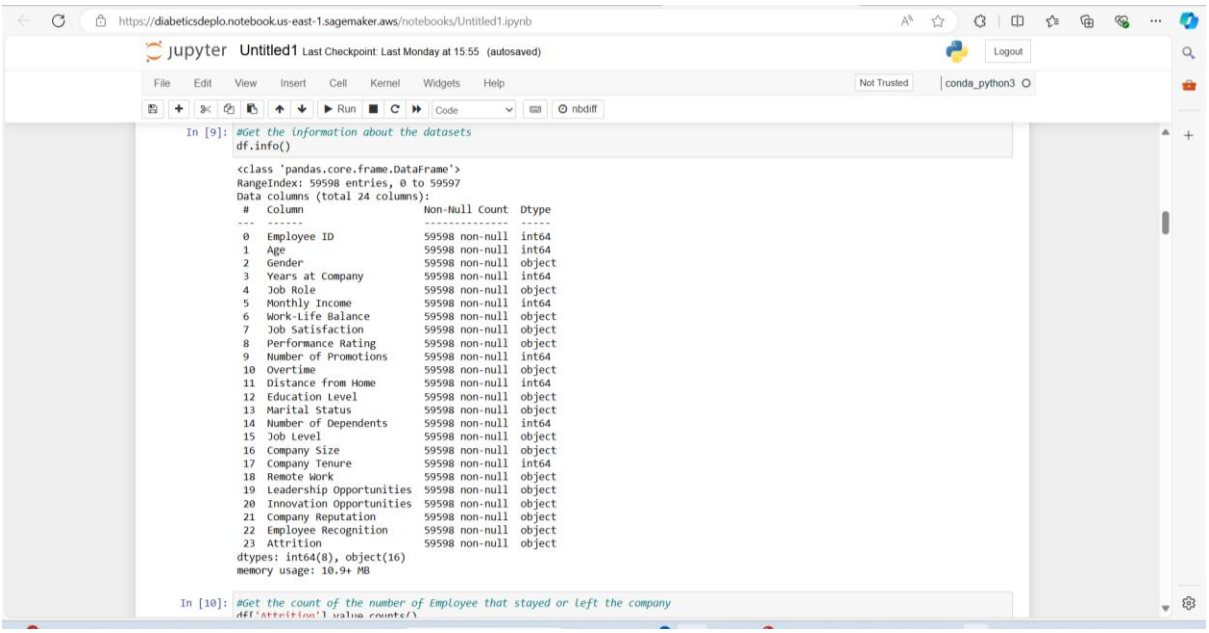
File Edit View Insert Cell Kernel Widgets Help
Not Trusted
conda_python3
Run
Code
nbdiff
dtype: int64
In [7]: df.shape
Out[7]: (59598, 24)
In [8]: df.dtypes
Out[8]: Employee ID int64
Age int64
Gender object
Years at Company int64
Job Role object
Monthly Income int64
Work-Life Balance object
Job Satisfaction object
Performance Rating object
Number of Promotions int64
Overtime object
Distance from Home int64
Education Level object
Marital Status object
Number of Dependents int64
Job Level object
Company Size object
Company Tenure int64
Remote Work object
Leadership Opportunities object
Innovation Opportunities object
Company Reputation object
Employee Recognition object
Attrition object
dtype: object
In [9]: #Get the information about the datasets
df.info()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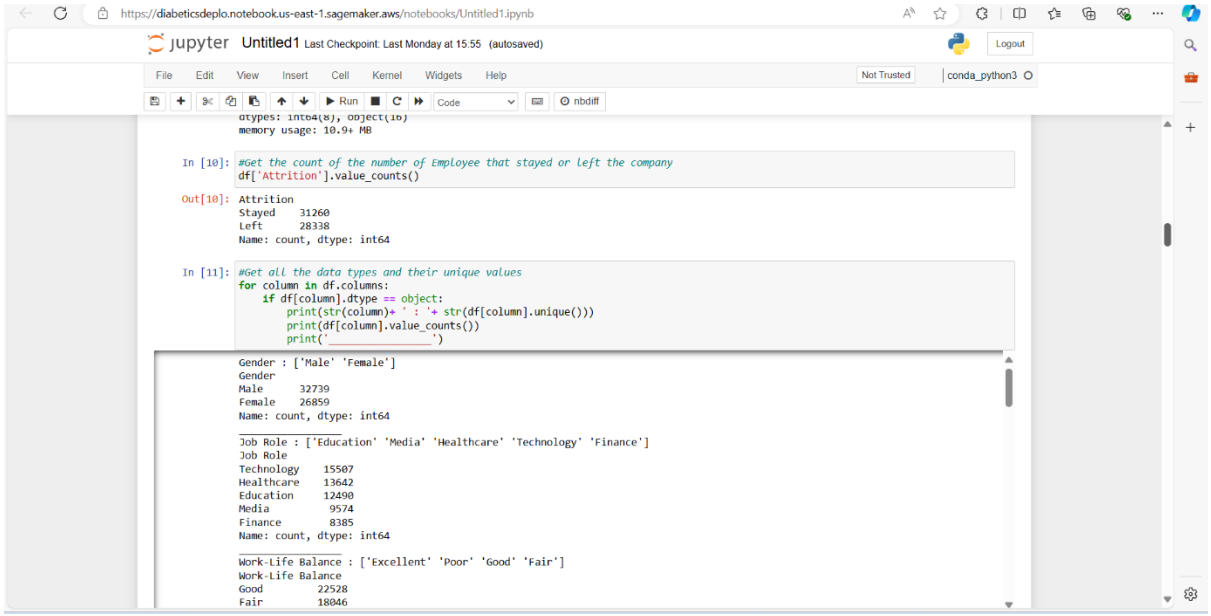
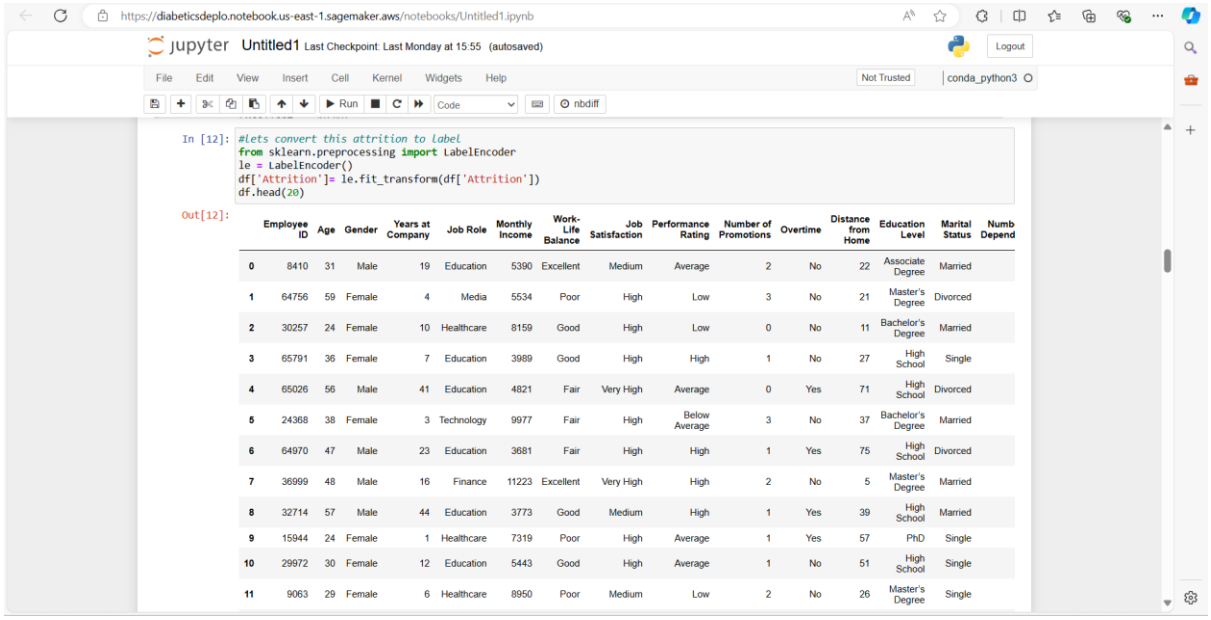
Not Trusted
conda_python3
Run
Code
nbdiff
In [9]: #Get the information about the datasets
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59598 entries, 0 to 59597
Data columns (total 24 columns):
Column Non-Null Count Dtype
--- ------ -------------- -----
0 Employee ID 59598 non-null int64
1 Age 59598 non-null int64
2 Gender 59598 non-null object
3 Years at Company 59598 non-null int64
4 Job Role 59598 non-null object
5 Monthly Income 59598 non-null int64
6 Work-Life Balance 59598 non-null object
7 Job Satisfaction 59598 non-null object
8 Performance Rating 59598 non-null object
9 Number of Promotions 59598 non-null int64
10 Overtime 59598 non-null object
11 Distance from Home 59598 non-null int64
12 Education Level 59598 non-null object
13 Marital Status 59598 non-null object
14 Number of Dependents 59598 non-null int64
15 Job Level 59598 non-null object
16 Company Size 59598 non-null object
17 Company Tenure 59598 non-null int64
18 Remote Work 59598 non-null object
19 Leadership Opportunities 59598 non-null object
20 Innovation Opportunities 59598 non-null object
21 Company Reputation 59598 non-null object
22 Employee Recognition 59598 non-null object
23 Attrition 59598 non-null object
dtypes: int64(8), object(16)
memory usage: 10.9+ MB
In [10]: #Get the count of the number of Employee that stayed or left the company



Encoding the attrition. Employees that stayed as 1, employees who left as 0



	Employee ID	Age	Gender	Years at Company	Job Role	Monthly Income	Work-Life Balance	Job Satisfaction	Performance Rating	Number of Promotions	Overtime	Distance from Home	Education Level	Marital Status	Numb Depend
0	8410	31	Male	19	Education	5390	Excellent	Medium	Average	2	No	22	Associate Degree	Married	
1	64756	59	Female	4	Media	5534	Poor	High	Low	3	No	21	Master's Degree	Divorced	
2	30257	24	Female	10	Healthcare	8159	Good	High	Low	0	No	11	Bachelor's Degree	Married	
3	65791	36	Female	7	Education	3989	Good	High	High	1	No	27	High School	Single	
4	65026	56	Male	41	Education	4821	Fair	Very High	Average	0	Yes	71	High School	Divorced	
5	24368	38	Female	3	Technology	9977	Fair	High	Below Average	3	No	37	Bachelor's Degree	Married	
6	64970	47	Male	23	Education	3681	Fair	High	High	1	Yes	75	High School	Divorced	
7	36999	48	Male	16	Finance	11223	Excellent	Very High	High	2	No	5	Master's Degree	Married	
8	32714	57	Male	44	Education	3773	Good	Medium	High	1	Yes	39	High School	Married	
9	15944	24	Female	1	Healthcare	7319	Poor	High	Average	1	Yes	57	PhD	Single	
10	29972	30	Female	12	Education	5443	Good	High	Average	1	No	51	High School	Single	
11	9063	29	Female	6	Healthcare	8950	Poor	Medium	Low	2	No	26	Master's Degree	Single	

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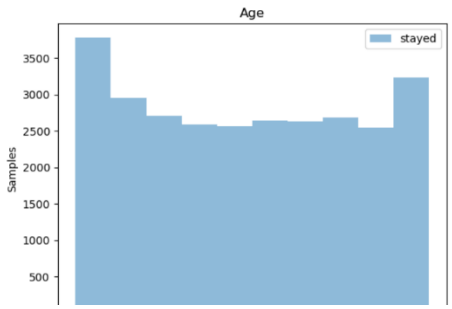
19	9697	29	Male	9	Healthcare	7538	Fair	Medium	Average	0	No	10	Bachelor's Degree	Married

In [13]:
```
stayed = df.Attrition == 0
left = df.Attrition ==1
```

In [14]:
```
plt.hist(df[stayed].Age, alpha=0.5, label='stayed')
plt.title('Age')
plt.xlabel ('Age')
plt.ylabel('Samples')
plt.legend()
plt.show()
```



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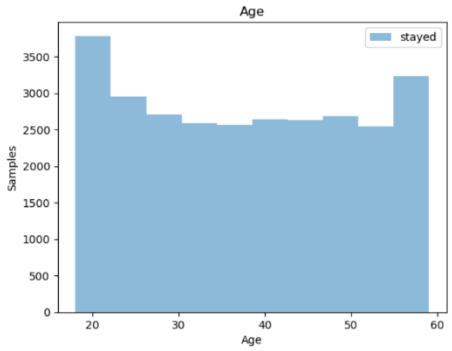
Run Code nbdiff

In [14]:
```
plt.hist(df[stayed].Age, alpha=0.5, label='stayed')
plt.title('Age')
plt.xlabel ('Age')
plt.ylabel('Samples')
plt.legend()
plt.show()
```



In [15]:
```
plt.hist(df[left].Age, alpha=0.5, label='left')
plt.title('Age')
```

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Run Code nbdiff

In [16]:
```
le.classes_
```

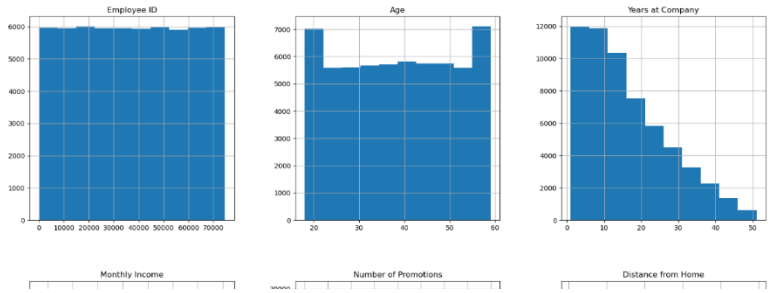
Out[16]:
```
array(['Left', 'Stayed'], dtype=object)
```

In [17]:
```
#Attrition{stayed=1, left=1}
Attrition_employee=le.classes_
print(Attrition_employee)
```

```
['Left' 'Stayed']
```

In [18]:
```
#plotting the distributions

p = df.hist(figsize=(20,20))
```



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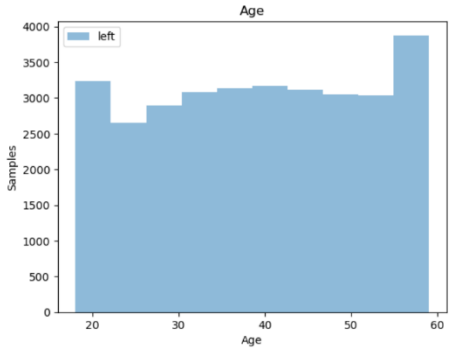
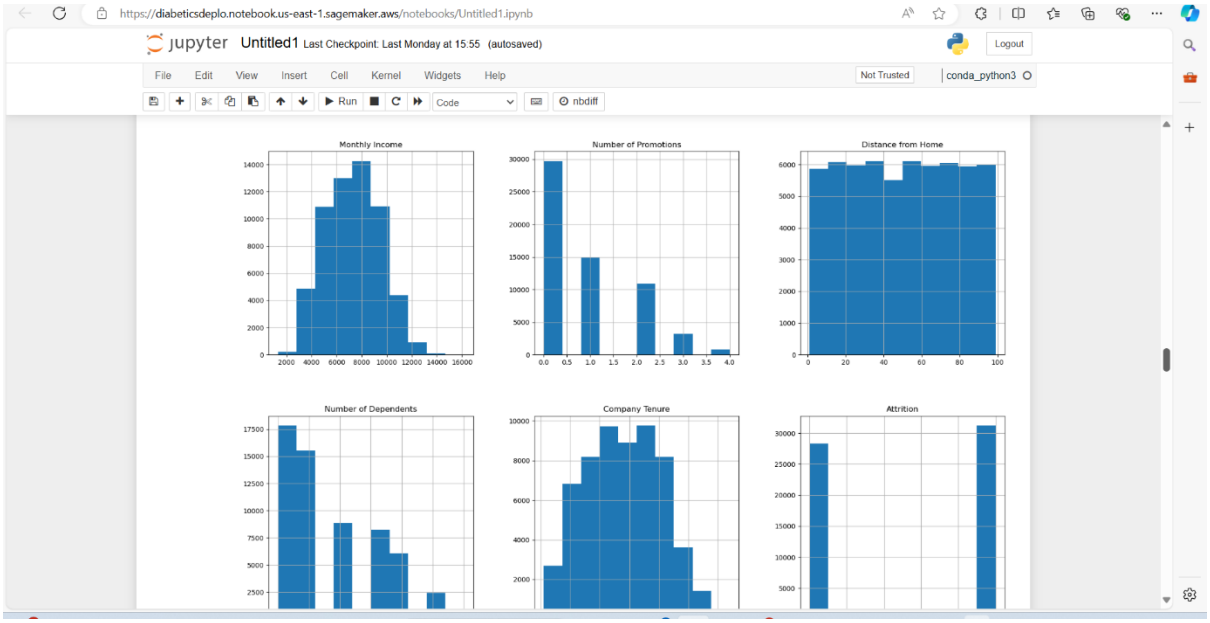
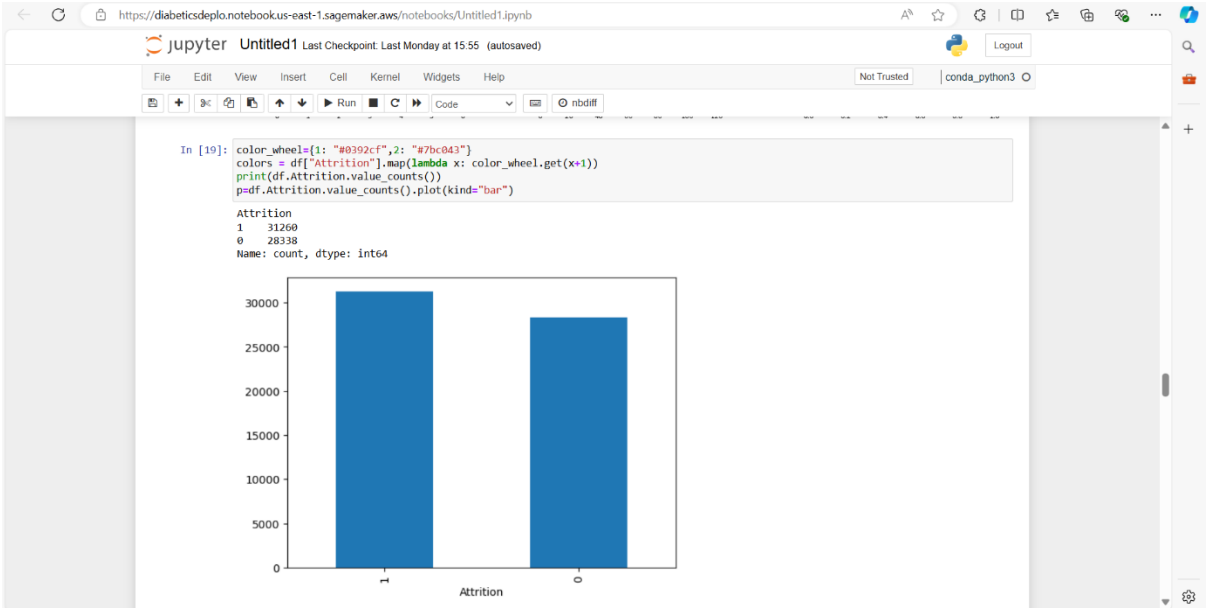
Run Code nbdiff

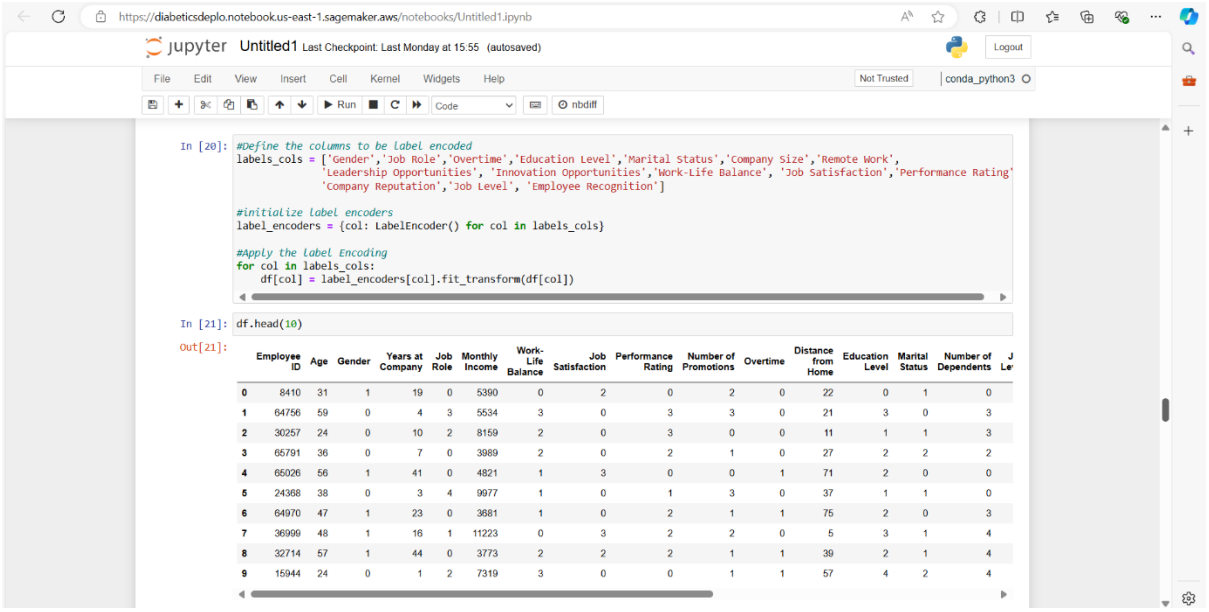
In [15]:
```
plt.hist(df[left].Age, alpha=0.5, label='left')
plt.title('Age')
plt.xlabel ('Age')
plt.ylabel('Samples')
plt.legend()
plt.show()
```





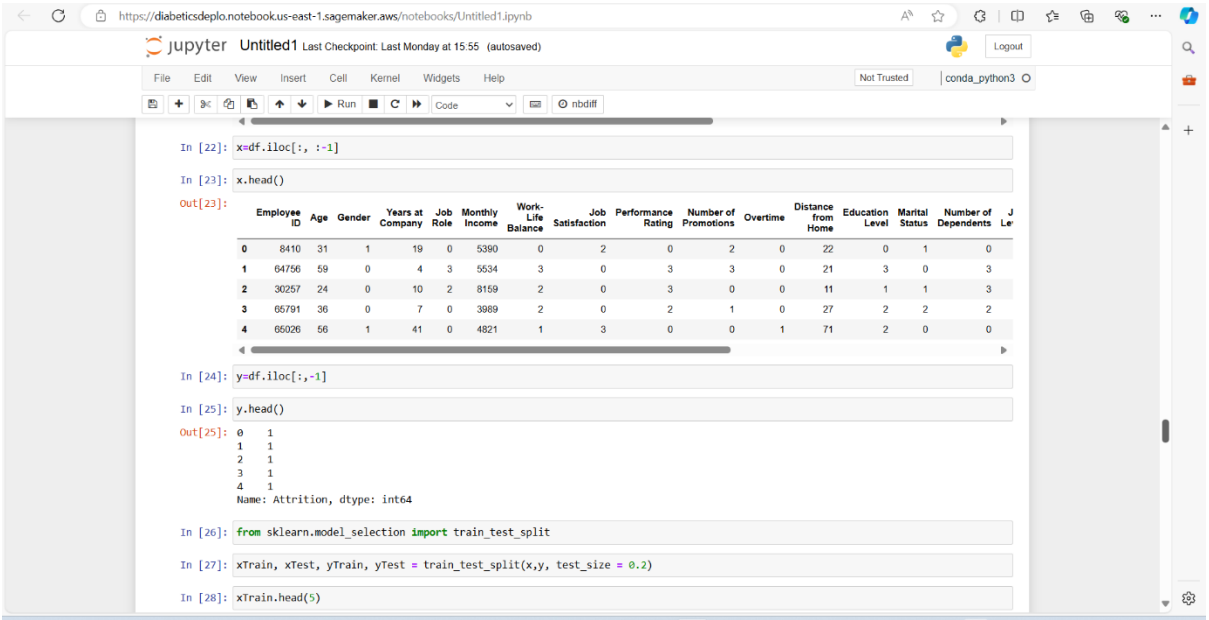


Encoding the columns to prepare for training.



	Employee ID	Age	Gender	Years at Company	Job Role	Monthly Income	Work-Life Balance	Job Satisfaction	Performance Rating	Number of Promotions	Overtime	Distance from Home	Education Level	Marital Status	Number of Dependents	J Le
0	8410	31	1	19	0	5390	0	2	0	2	0	22	0	1	0	
1	64756	59	0	4	3	5534	3	0	3	3	0	21	3	0	3	
2	30257	24	0	10	2	8159	2	0	3	0	0	11	1	1	3	
3	65791	36	0	7	0	3989	2	0	2	1	0	27	2	2	2	
4	65026	56	1	41	0	4821	1	3	0	0	1	71	2	0	0	
5	24368	38	0	3	4	9977	1	0	1	3	0	37	1	1	0	
6	64970	47	1	23	0	3681	1	0	2	1	1	75	2	0	3	
7	36999	48	1	16	1	11223	0	3	2	2	0	5	3	1	4	
8	32714	57	1	44	0	3773	2	2	2	1	1	39	2	1	4	
9	15944	24	0	1	2	7319	3	0	0	1	1	57	4	2	4	

Splitting data as X and Y, to prepare for training.



	Employee ID	Age	Gender	Years at Company	Job Role	Monthly Income	Work-Life Balance	Job Satisfaction	Performance Rating	Number of Promotions	Overtime	Distance from Home	Education Level	Marital Status	Number of Dependents	J Le
0	8410	31	1	19	0	5390	0	2	0	2	0	22	0	1	0	
1	64756	59	0	4	3	5534	3	0	3	3	0	21	3	0	3	
2	30257	24	0	10	2	8159	2	0	3	0	0	11	1	1	3	
3	65791	36	0	7	0	3989	2	0	2	1	0	27	2	2	2	
4	65026	56	1	41	0	4821	1	3	0	0	1	71	2	0	0	

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Run Code nbdiff

In [30]:
```
trainDF=xTrain.join(yTrain)
trainDF.head(5)
```

Out[30]:

	Employee ID	Age	Gender	Years at Company	Job Role	Monthly Income	Work-Life Balance	Job Satisfaction	Performance Rating	Number of Promotions	Overtime	Distance from Home	Education Level	Marital Status	Number of Dependents
48722	73255	29	1	8	4	7870	1	3	0	3	0	96	3	2	4
1768	29901	26	0	8	0	3685	2	0	0	0	0	57	2	2	0
1516	4409	39	0	25	3	5980	0	2	0	1	0	31	3	0	1
23326	53341	28	1	14	1	7857	2	2	0	0	1	54	1	2	1
7246	56311	55	1	6	2	7678	3	3	0	3	0	55	2	0	1

In [31]:
```
testDF = xTest.join(yTest)
testDF.head(5)
```

Out[31]:

	Employee ID	Age	Gender	Years at Company	Job Role	Monthly Income	Work-Life Balance	Job Satisfaction	Performance Rating	Number of Promotions	Overtime	Distance from Home	Education Level	Marital Status	Number of Dependents
22101	15182	39	0	12	1	12931	3	0	1	0	1	99	0	1	1
17205	62820	55	0	25	2	6623	0	3	3	3	0	41	2	1	1
49282	17777	33	1	1	0	4264	1	0	2	1	0	54	1	1	0
26225	1824	45	0	35	1	7434	2	3	3	1	0	22	0	2	1
8047	70265	51	0	11	3	6240	3	0	0	0	1	84	0	1	2

In [32]:
```
column = ['Attrition',
          'Age','Gender',
          'Years at Company',
          'Job Role','Marital Status',
```

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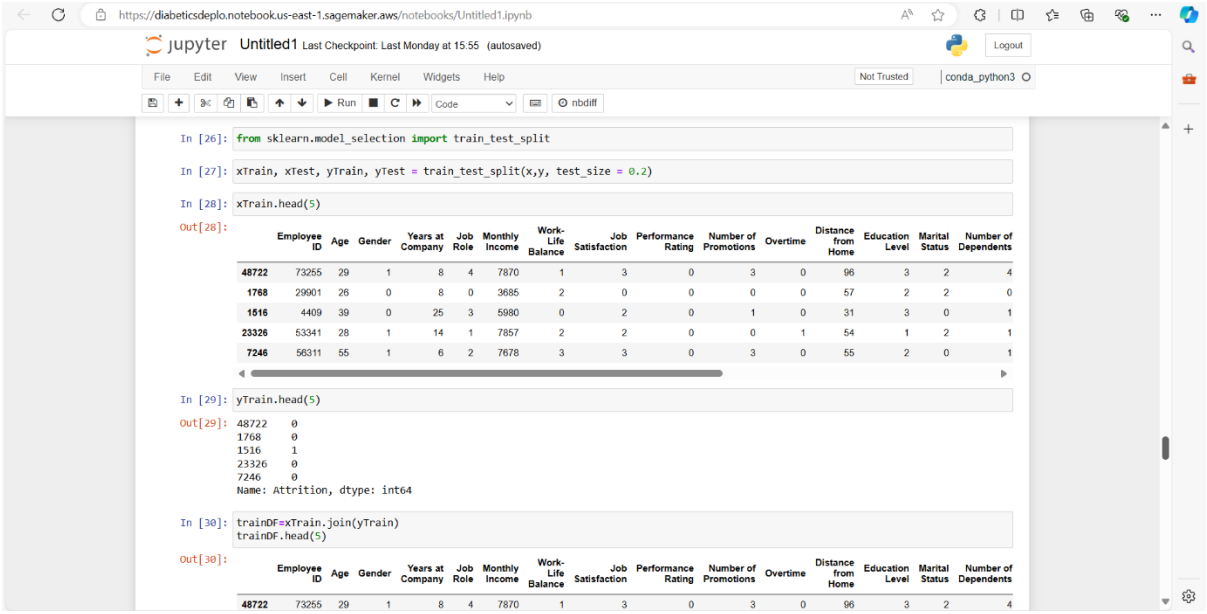
Run Code nbdiff

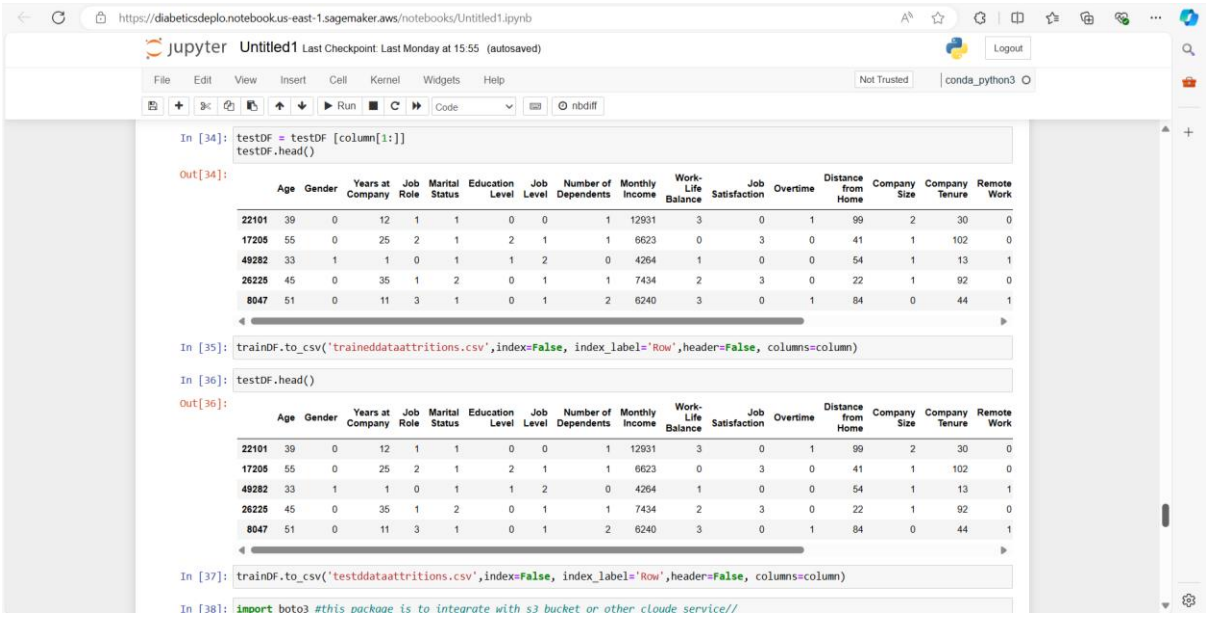
In [32]:
```
column = ['Attrition',
          'Age','Gender',
          'Years at Company',
          'Job Role','Marital Status',
          'Education Level',
          'Job Level',
          'Number of Dependents',
          'Monthly Income',
          'Work-Life Balance',
          'Job Satisfaction','Overtime',
          'Distance from Home','Company Size',
          'Company Tenure','Remote Work',
          'Leadership Opportunities',
          'Innovation Opportunities',
          'Company Reputation',
          'Employee Recognition',
         ]
```

In [33]:
```
trainDF= trainDF[column]
trainDF.head(10)
```

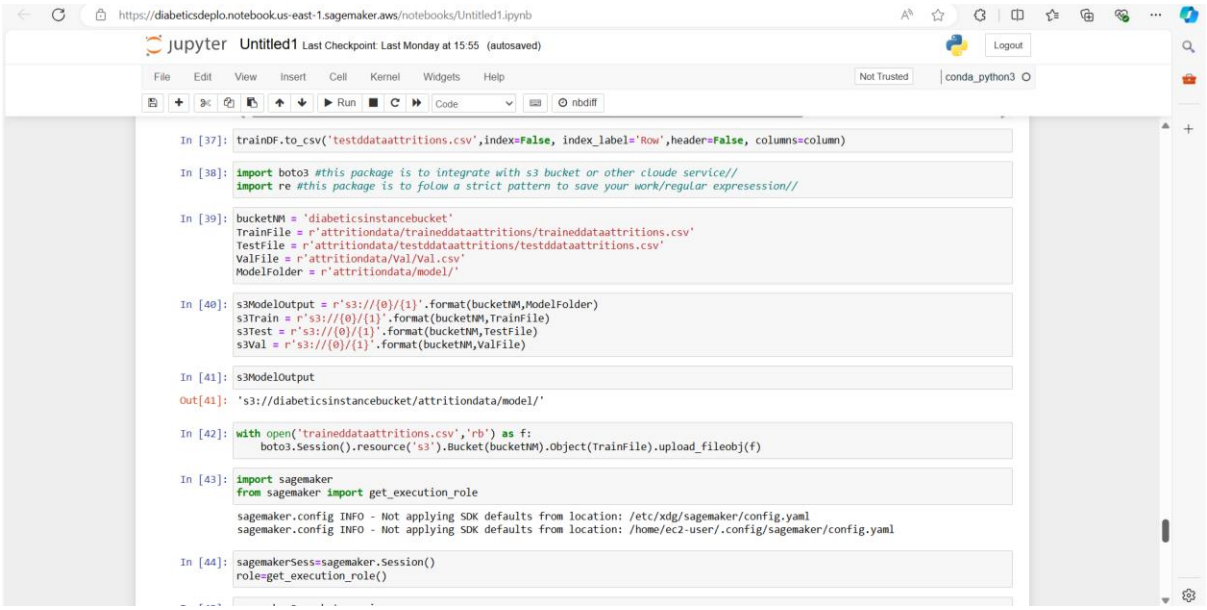
Out[33]:

	Attrition	Age	Gender	Years at Company	Job Role	Marital Status	Education Level	Job Level	Number of Dependents	Monthly Income	Work-Life Balance	Job Satisfaction	Overtime	Distance from Home	Company Size	Company Tenure
48722	0	29	1	8	4	2	3	0	4	7870	1	3	0	96	2	37
1768	0	26	0	8	0	2	2	0	0	3685	2	0	0	57	1	65
1516	1	39	0	25	3	0	3	0	1	5980	0	2	0	31	1	67
23326	0	28	1	14	1	2	1	0	1	7857	2	2	1	54	1	50
7246	0	55	1	6	2	0	2	0	1	7678	3	3	0	55	2	37
3645	0	25	1	13	3	1	1	0	2	5385	0	3	0	69	1	90
11086	1	38	0	27	2	1	1	0	4	7074	0	0	1	83	1	86
33008	1	32	1	3	2	1	3	0	4	10464	2	3	0	55	2	69

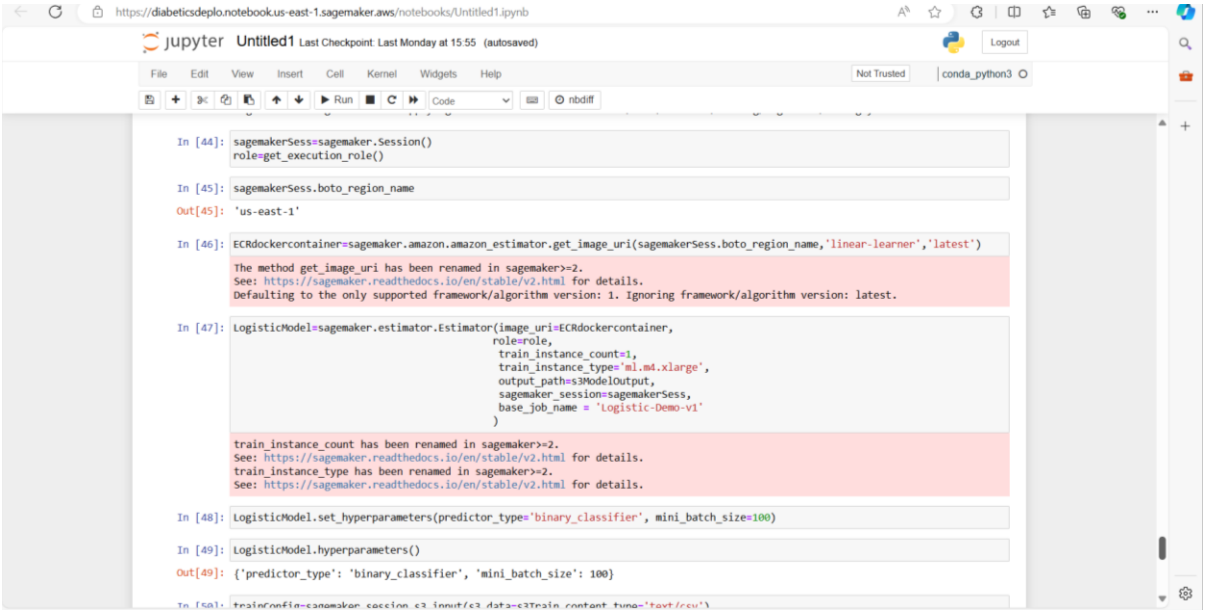




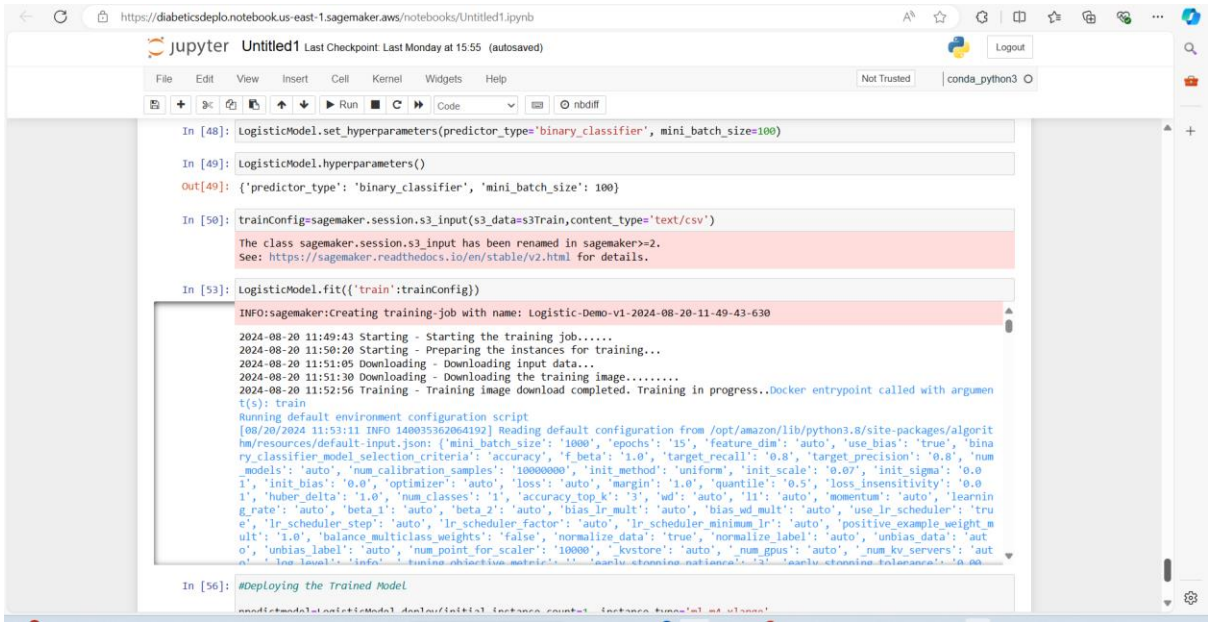
Creating an s3 storage and moving the trained and test data to the s3 object storage



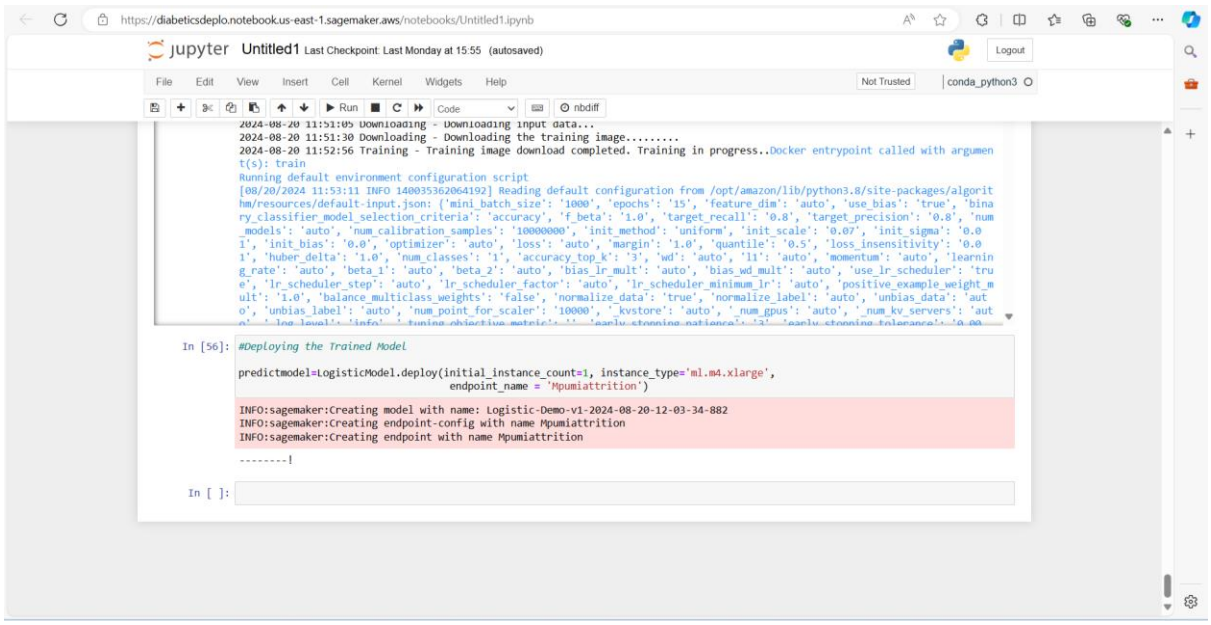
Setting up the hyperparameter for tuning/optimization



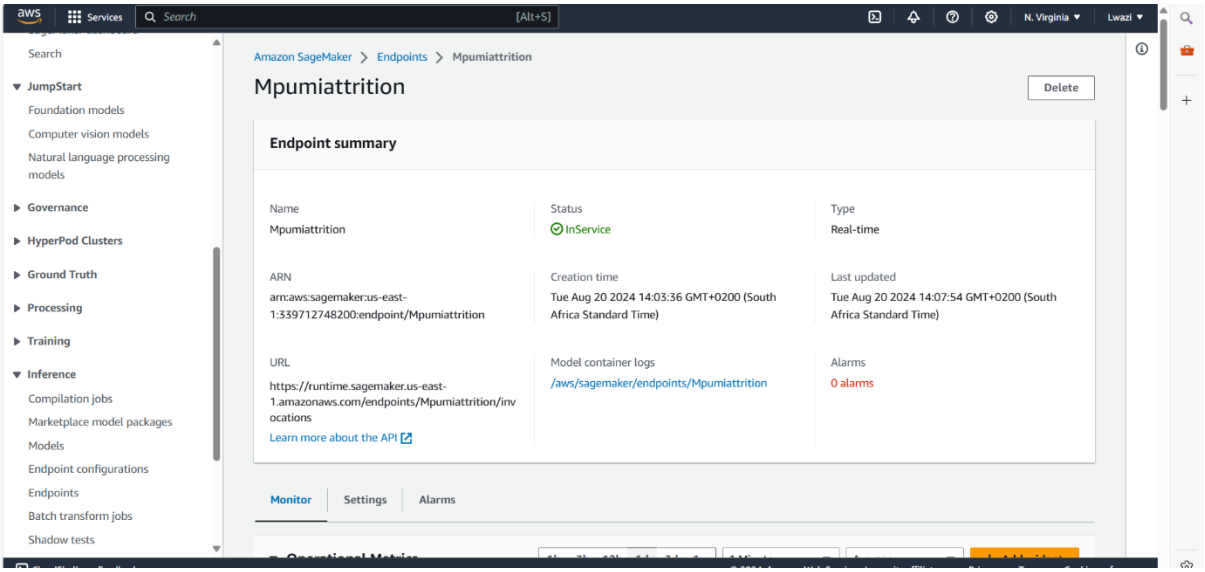
Building and Training the model on sagemaker

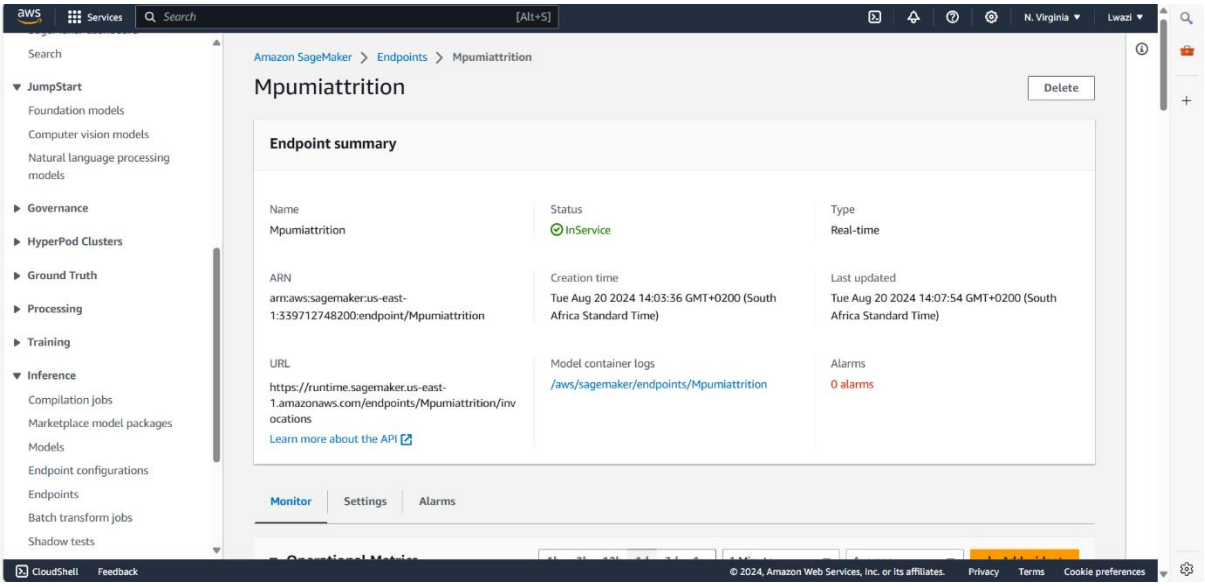


Deploying the model after training

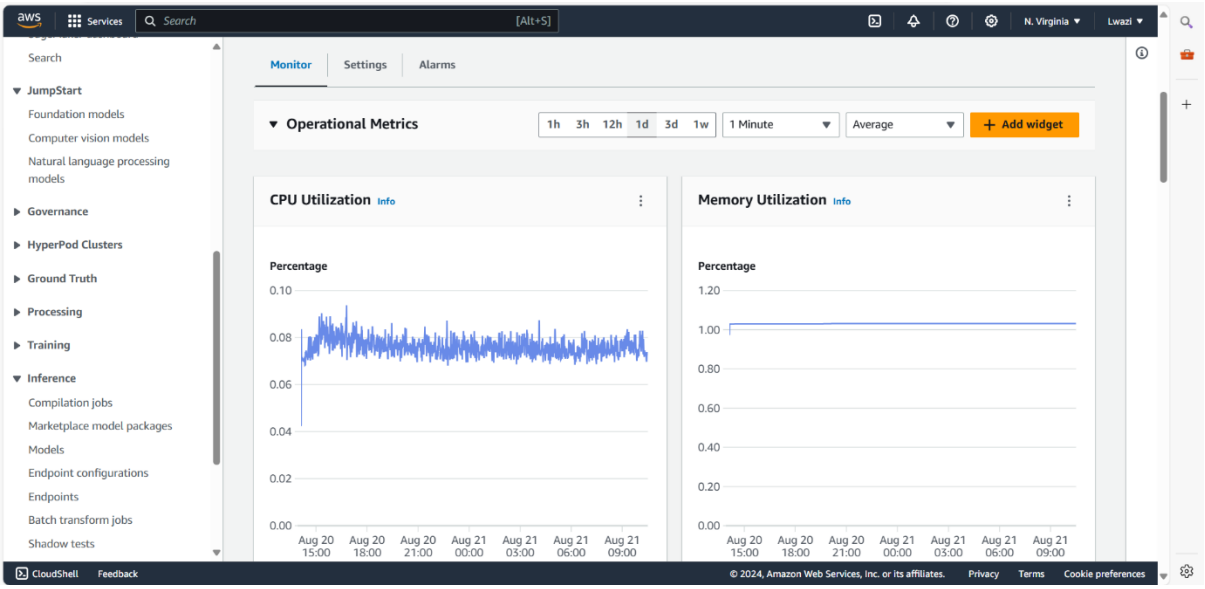


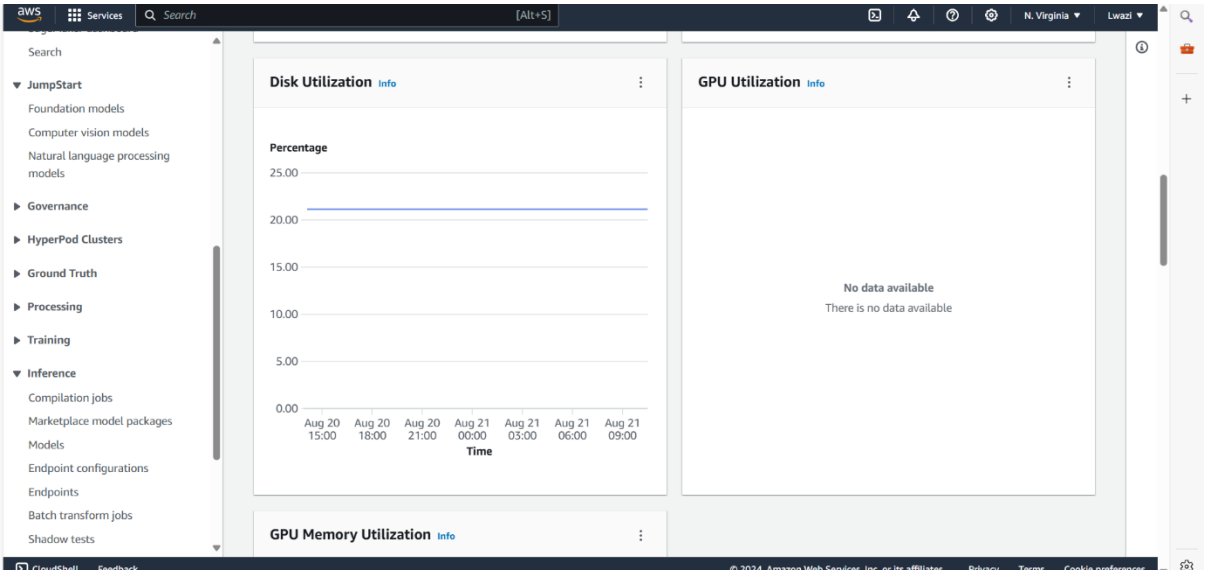
The deployed model on AWS sagemaker





The metrics and monitoring of resources

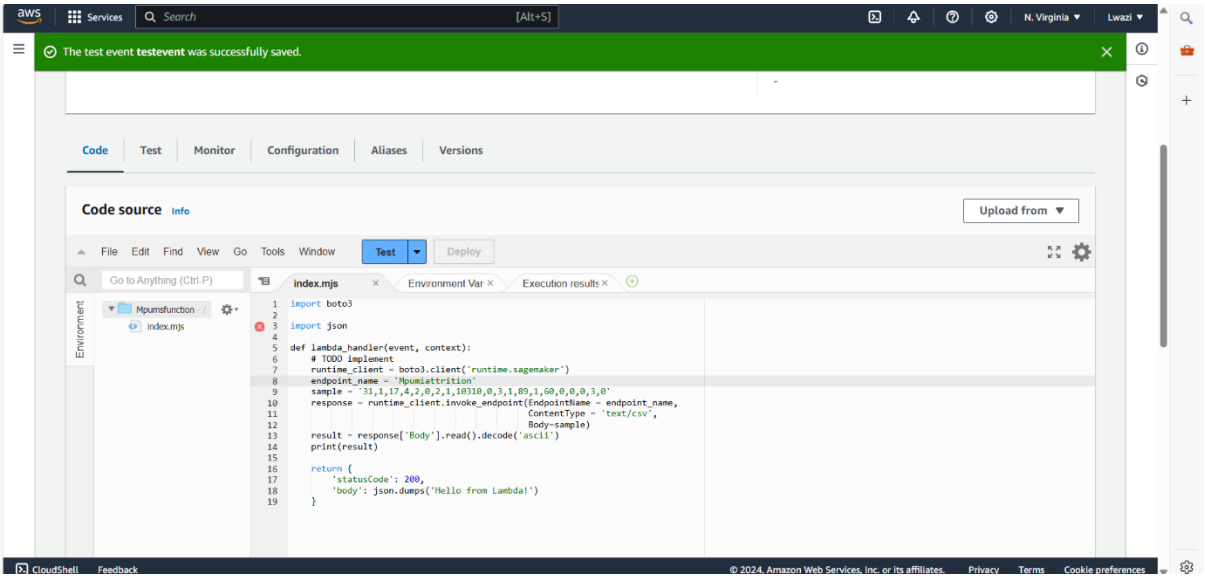




The end point link:

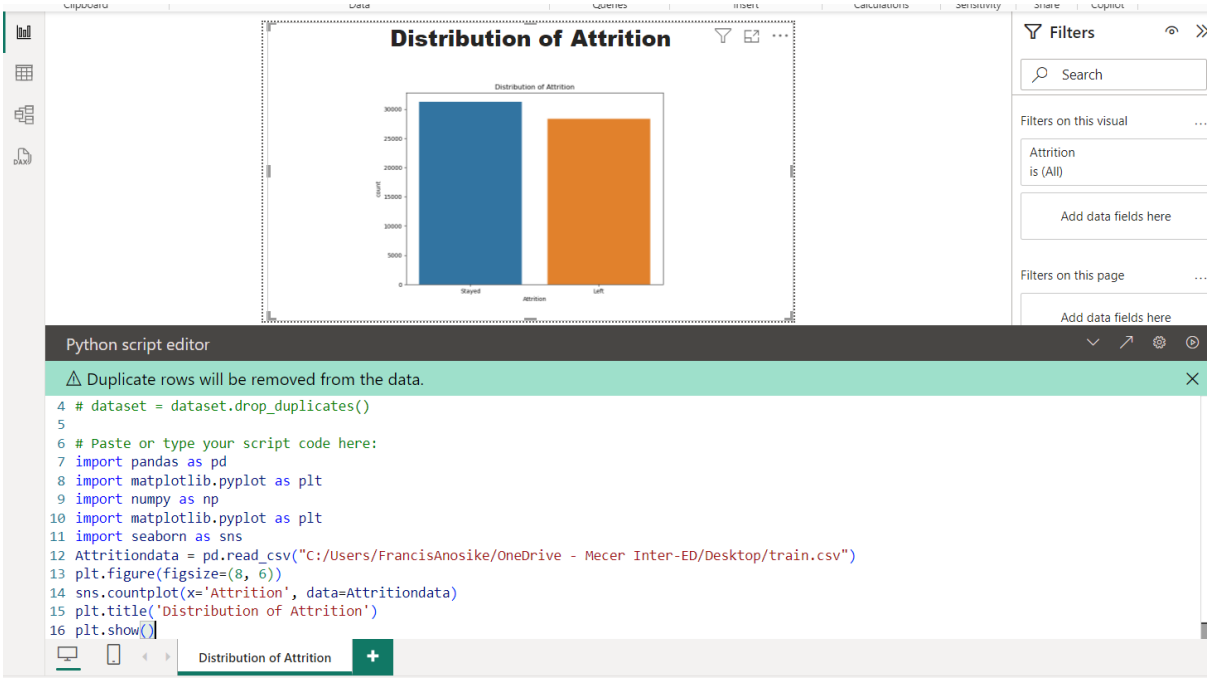
https://runtime.sagemaker.us-east-1.amazonaws.com/endpoints/Mpumiattrition/invocations

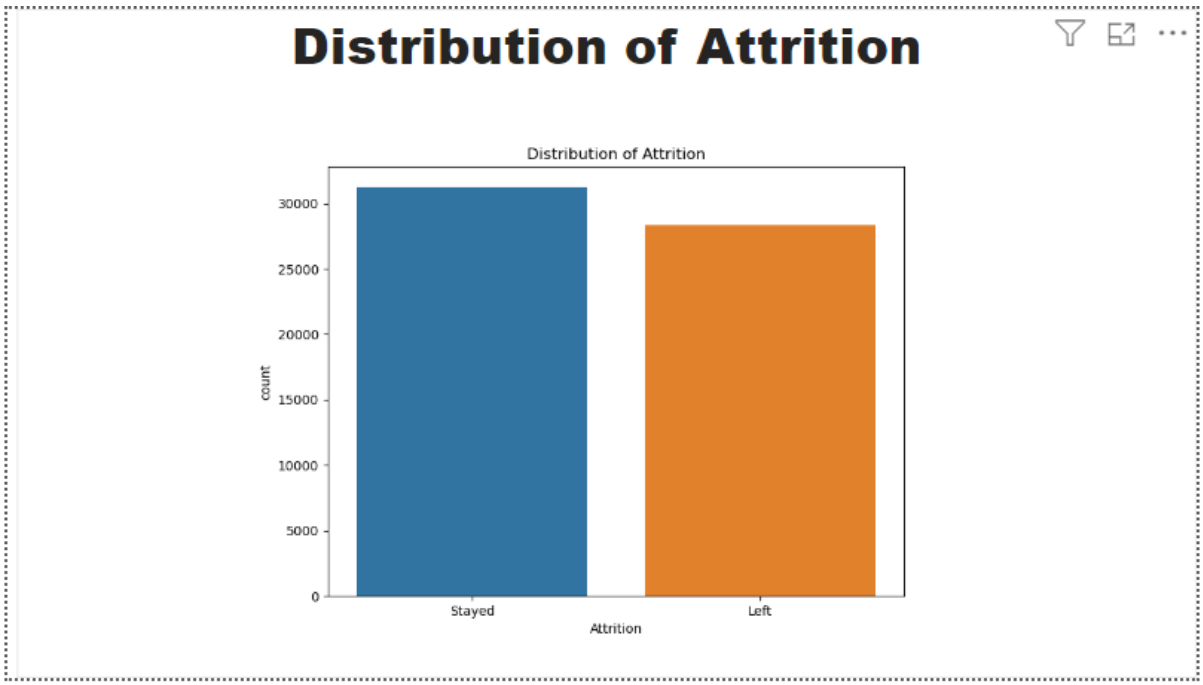
Testing the model on the lambda service on AWS:



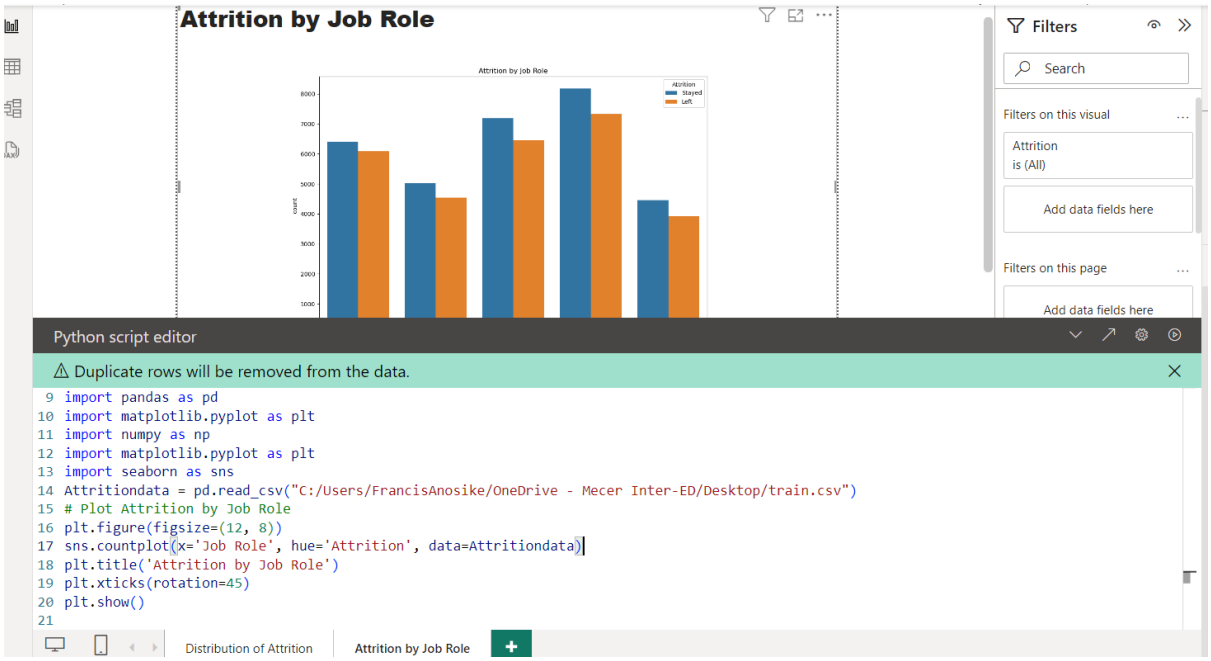
Visualizing the dataset using python scripts embedded in PowerBI

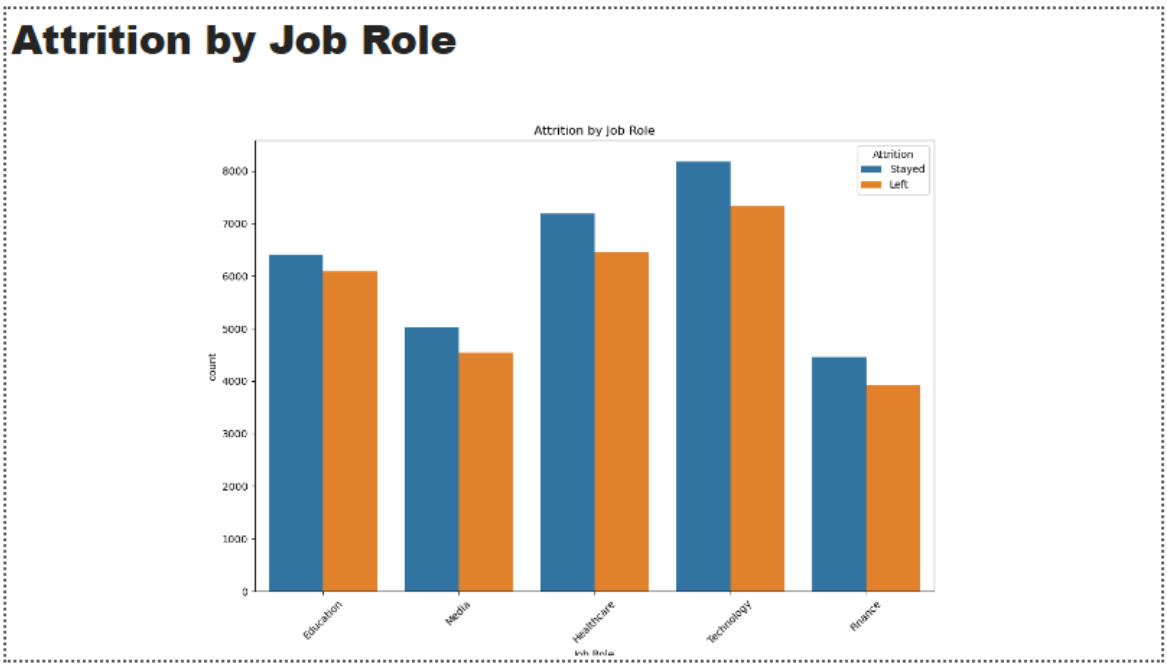
The employee attrition visual



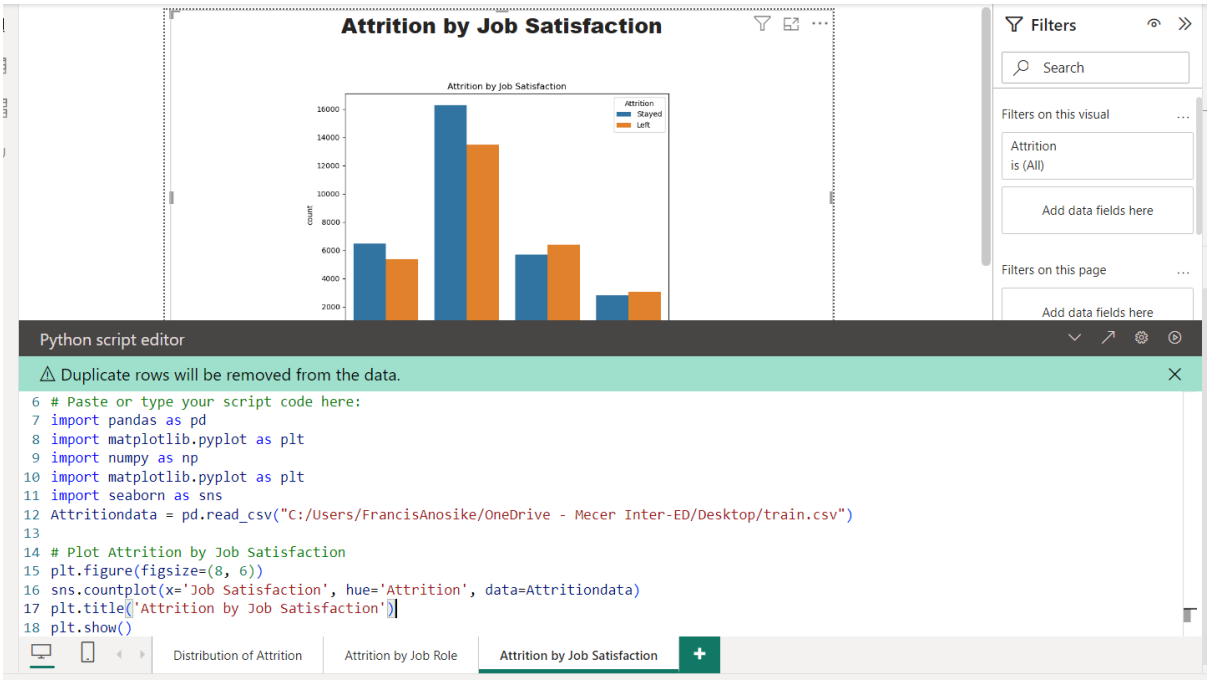


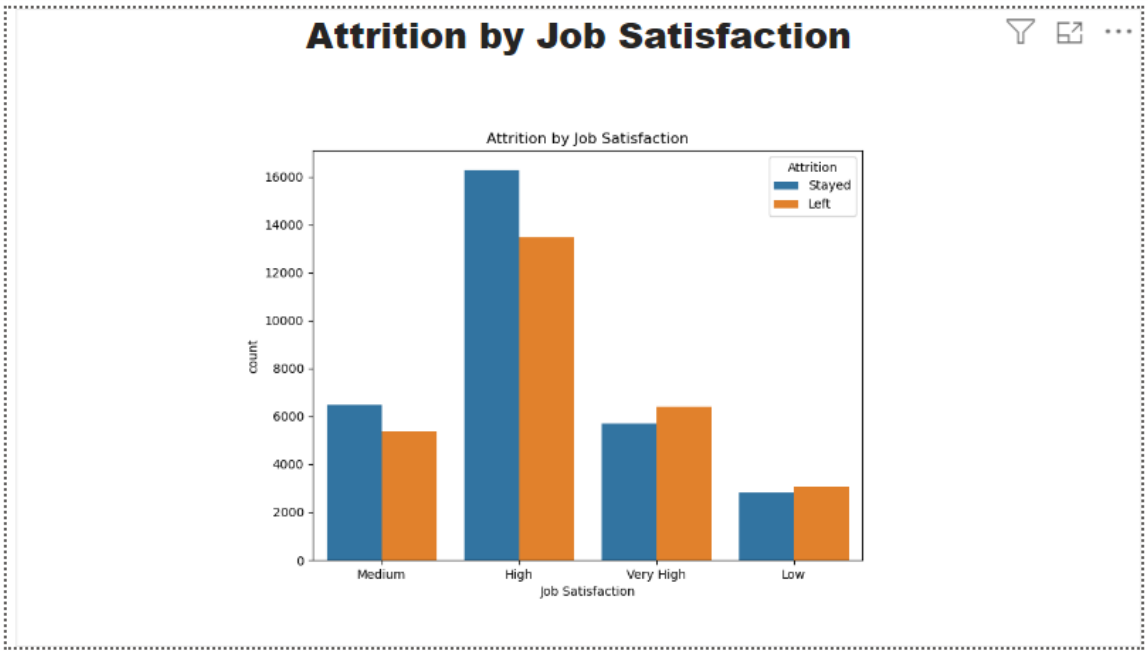
Employee Attrition by job role



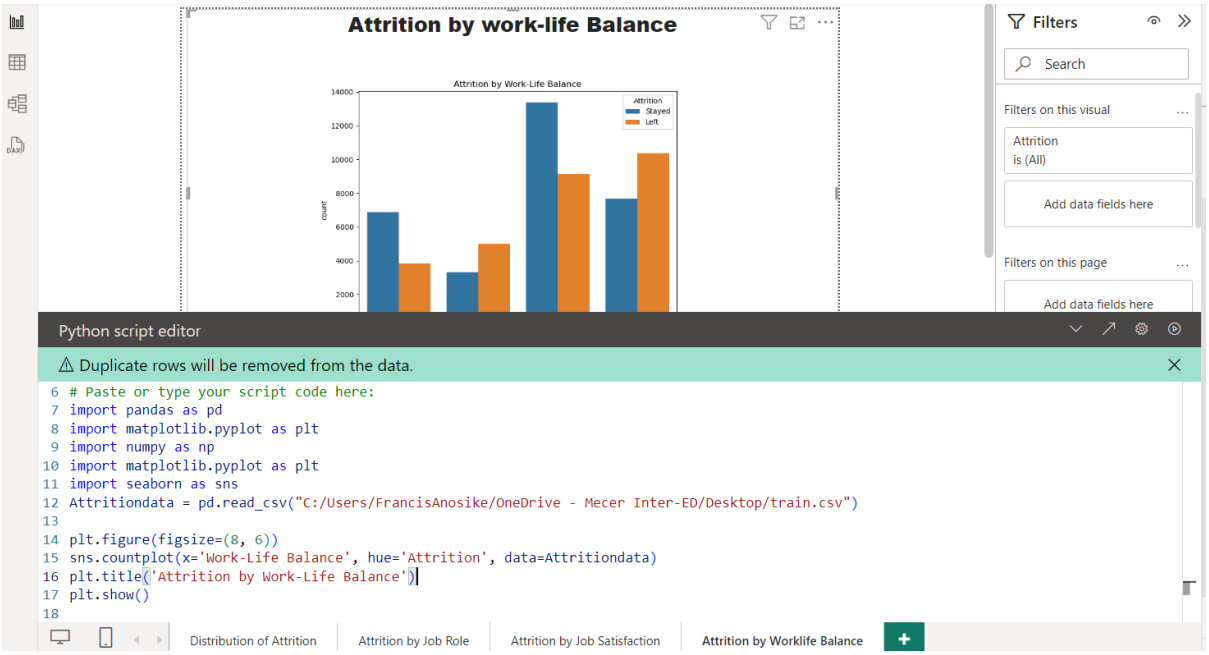


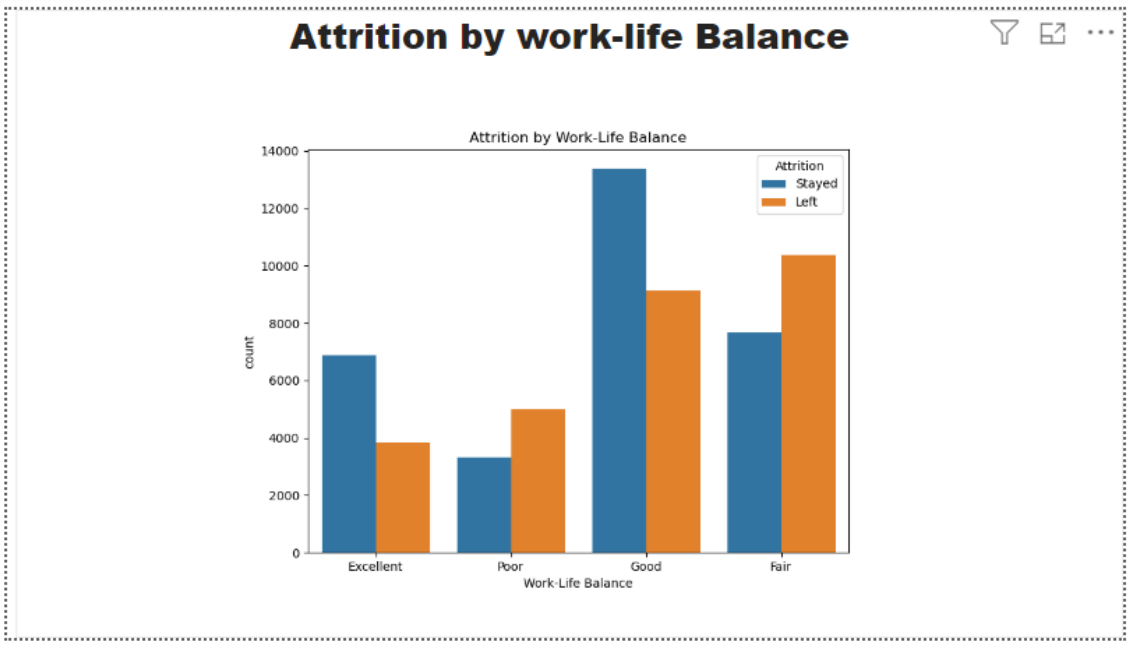
Employee attrition by job satisfaction.



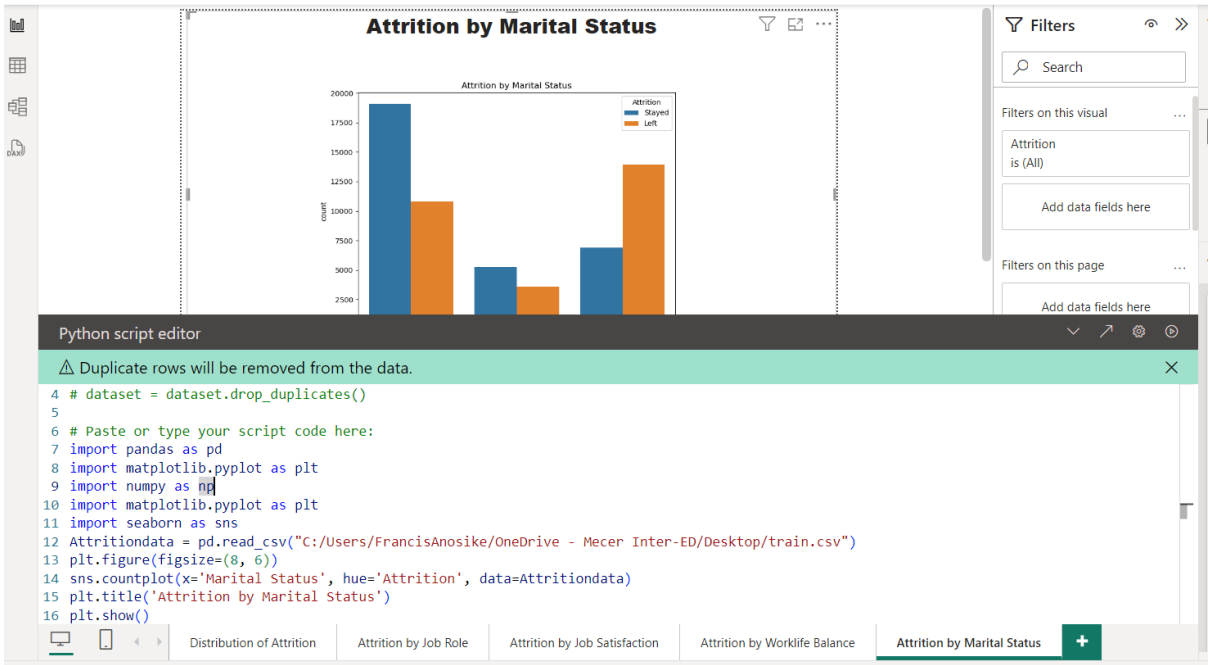


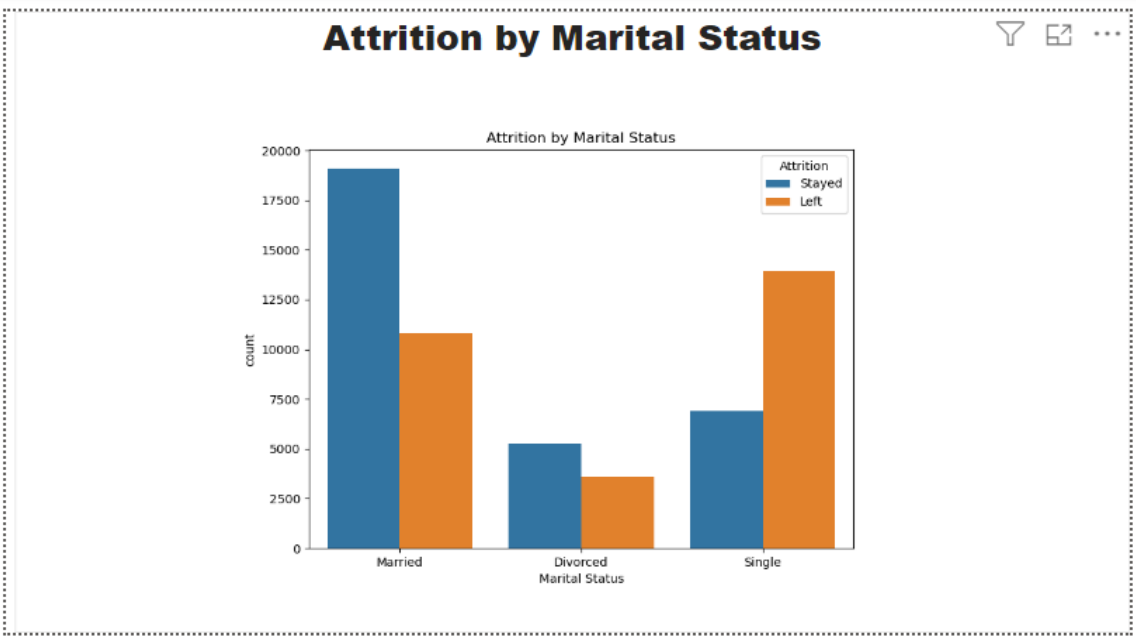
Employee attrition by work-life balance.





Employee attrition by marital status.

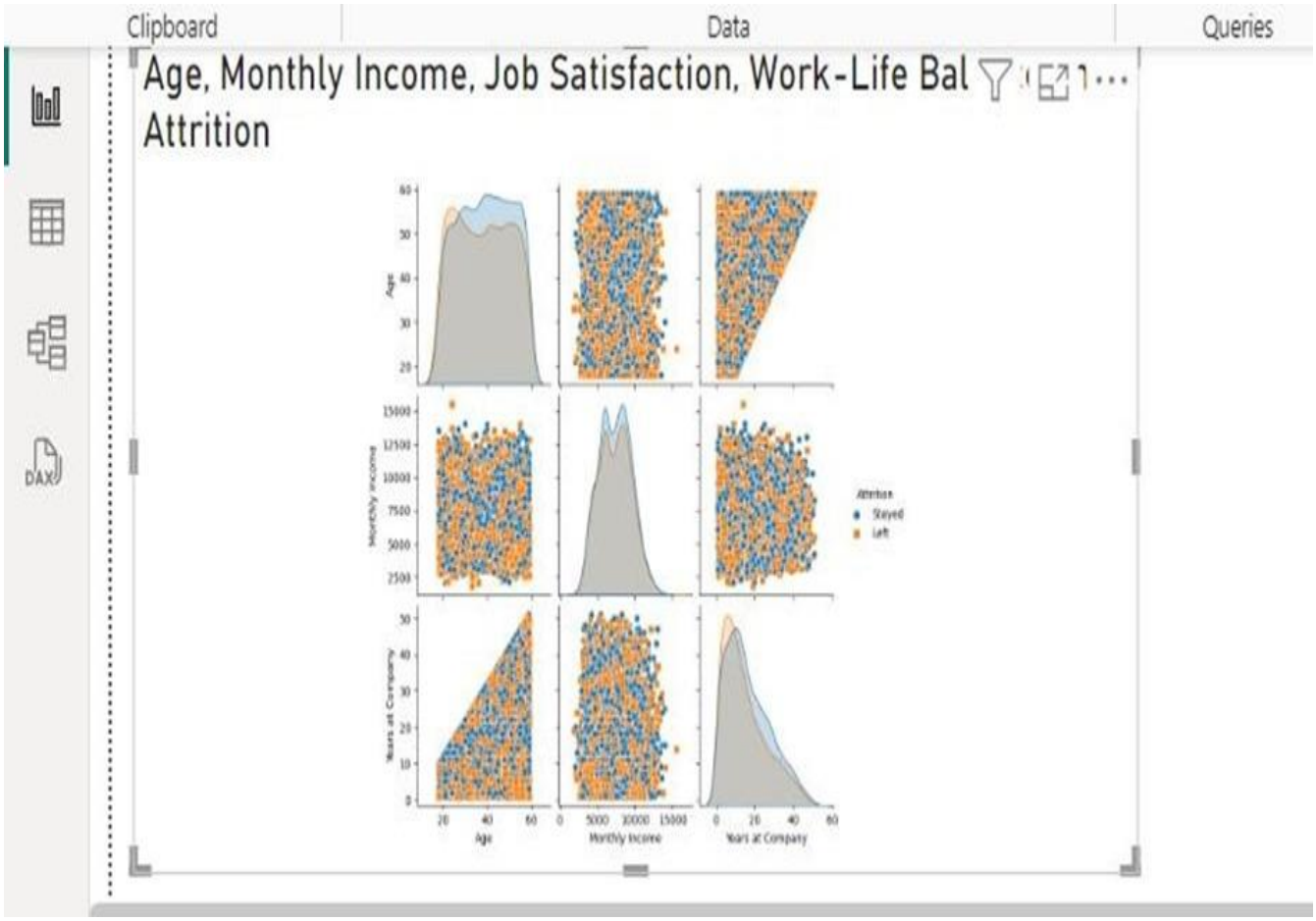





```python
import statsmodels.api as sm
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder

df = pd.read_csv(r"C:\Users\Tesserai\Desktop\Train Project\train.csv")

# Pair plot for selected features
selected_features = ['Age', 'Monthly Income', 'Years at Company', 'Job Satisfaction', 'Work-Life Balance', 'Attrition']
sns.pairplot(df[selected_features], hue='Attrition', diag_kind='kde', markers=["o", "s"])
plt.show()
```



Monitoring and Maintenance:

Once deployed, the model's performance needs to be monitored regularly to ensure that it continues to provide accurate predictions over time. This may involve updating the model with new data or retraining it periodically to maintain its accuracy.

Deployment Environment used for the deployment of the model:

Frameworks and Libraries:

NumPy: For numerical computations and array manipulations.

Pandas: For data manipulation and analysis, particularly useful for handling datasets like the Iris dataset.

Scikit-learn: For machine learning algorithms and model training. It includes logistic regression and utilities for model evaluation.

Development Tools:

IDEs: PowerBI, VS Code, or Jupyter notebook for coding and testing.

Version Control: Git for managing code versions.

Package Management: pip or conda for managing Python packages and dependencies.

Security Considerations:

Access Control: Restrict access to the deployed model and its endpoints. Implement role-based access control (RBAC) to ensure only authorized personnel can interact with the model.

Encryption: Use encryption mechanisms (e.g., HTTPS/TLS) to secure data transmission between clients and the deployed model, preventing eavesdropping and data tampering.

Input Validation: Validate input data to prevent injection attacks and ensure that only expected and sanitized data is processed by the model.