```
### Network Slicing Recognition
```

The telecom industry is going through a massive digital transformation with the adoption of ML, AI, feedback-based automation and advanced analytics to handle the next generation applications and services. AI concepts are not new; the algorithms used by Machine Learning and Deep Learning are being currently implemented in various industries and technology verticals. With growing data and immense volume

of information over 5G, the ability to predict data proactively, swiftly and with accuracy, is critically important. Data-driven decision making will be vital in future communication networks due to the traffic explosion and Artificial Intelligence (AI) will accelerate the 5G network performance.

Mobile operators are looking for a programmable solution that will allow them to accommodate multiple independent tenants on the same physical infrastructure and 5G networks allow for end-to-end network resource allocation using the concept of Network Slicing (NS).

Network Slicing will play a vital role in enabling a multitude of 5G applications, use cases, and services. Network slicing functions will provide an end-to-end isolation between slices with an ability to customize each slice based on the service demands (bandwidth, coverage, security, latency, reliability, etc).

Your Task is to build a Machine Learning model that will be able to to proactively detect and eliminate threats based on incoming connections thereby selecting the most appropriate network slice, even in case of a network failure.

LTE/5g - User Equipment categories or classes to define the performance specifications
Packet Loss Rate - number of packets not received divided by the total number of packets sent.
Packet Delay - The time for a packet to be received.
Slice type - network configuration that allows multiple networks (virtualized and independent)
GBR - Guaranteed Bit Rate
Healthcare - Usage in Healthcare (1 or 0)
Industry 4.0 - Usage in Digital Enterprises(1 or 0)
IoT Devices - Usage
Public Safety - Usage for public welfare and safety purposes (1 or 0)
Smart City & Home - usage in daily household chores
Smart Transportation - usage in public transportation
Smartphone - whether used for smartphone cellular data

```
###! pip install neattext
```

```
import pandas as pd
import numpy as np
import neattext.functions as nfx
import seaborn as sn

from sklearn.feature_extraction.text import TfidfVectorizer,CountVectorizer
from sklearn.metrics.pairwise import cosine_similarity,linear_kernel
```

```
##! pip uninstall numpy
##! pip install numpy==1.20
```

```
###!mkdir ~/.kaggle
```

```
###!cp /kaggle.json ~/.kaggle/
```

```
##! pip install kaggle
##!pip install keras-tuner
```

```
###!kaggle datasets download -d gauravduttakiit/network-slicing-recognition
```

```
###!unzip /content/network-slicing-recognition.zip
```

```
train_dataset = pd.read_csv("/content/train_dataset.csv")
test_dataset = pd.read_csv("/content/test_dataset.csv")
```

```
print(train_dataset.shape, test_dataset.shape)
```

```
(31583, 17) (31584, 16)
```

```
test_dataset['slice Type'] = 0
```

```
train_dataset = train_dataset.reset_index()
test_dataset = test_dataset.reset_index()
#train_dataset.rename(columns = { "index" : "ID"}, inplace = True)
#test_dataset.rename(columns = { "index" : "ID"}, inplace = True)
```

```
print(train_dataset.columns, train_dataset.shape)
```

```
Index(['index', 'LTE/5g Category', 'Time', 'Packet Loss Rate', 'Packet delay',
       'IoT', 'LTE/5G', 'GBR', 'Non-GBR', 'AR/VR/Gaming', 'Healthcare',
       'Industry 4.0', 'IoT Devices', 'Public Safety', 'Smart City & Home',
       'Smart Transportation', 'Smartphone', 'slice Type'],
      dtype='object') (31583, 18)
```

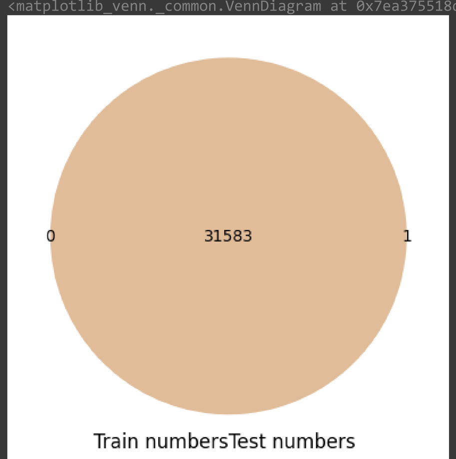
```
train_dataset['slice Type'].value_counts()
```

```
1    16799
3     7392
2     7392
Name: slice Type, dtype: int64
```

```
from matplotlib_venn import venn2, venn2_circles, venn2_unweighted
from matplotlib_venn import venn3, venn3_circles
```

```
set_numbers_train = set(train_dataset[['index']].drop_duplicates().sort_values(by = 'index')['index'].tolist())
set_numbers_test = set(test_dataset[['index']].drop_duplicates().sort_values(by = 'index')['index'].tolist())
venn2((set_numbers_train, set_numbers_test), set_labels = ('Train numbers', 'Test numbers'))
```

```
<matplotlib_venn._common.VennDiagram at 0x7ea375518d90>
```




```
train_dataset.columns
```

```
Index(['index', 'LTE/5g Category', 'Time', 'Packet Loss Rate', 'Packet delay',
       'IoT', 'LTE/5G', 'GBR', 'Non-GBR', 'AR/VR/Gaming', 'Healthcare',
       'Industry 4.0', 'IoT Devices', 'Public Safety', 'Smart City & Home',
       'Smart Transportation', 'Smartphone', 'slice Type'],
      dtype='object')
```

```
###! pip install klib
```

```
import klib
```

```
train_dataset = klib.clean_column_names(train_dataset)
test_dataset = klib.clean_column_names(test_dataset)
```

```
train_dataset = klib.convert_datatypes(train_dataset)
test_dataset = klib.convert_datatypes(test_dataset)
```

```
train_dataset.columns
```

```
Index(['index', 'lte_5g_category', 'time', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone', 'slice_type'],
      dtype='object')
```

Anomaly Detection Using One-Class SVM

```
from sklearn import svm
```

```
clf = svm.OneClassSVM(nu=0.05, kernel="rbf", gamma=0.1)
clf.fit(train_dataset)
```

```
▾         OneClassSVM
OneClassSVM(gamma=0.1, nu=0.05)
```

```
pred = clf.predict(train_dataset)

# inliers are labeled 1, outliers are labeled -1
normal = train_dataset[pred == 1]
abnormal = train_dataset[pred == -1]
```

```
print(normal.shape, abnormal.shape)
```

```
(18373, 18) (13210, 18)
```

```
normal.columns
```

```
Index(['index', 'lte_5g_category', 'time', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone', 'slice_type'],
      dtype='object')
```

```
train_dataset = normal
```

```
print(train_dataset.shape)
print(train_dataset.columns)
```

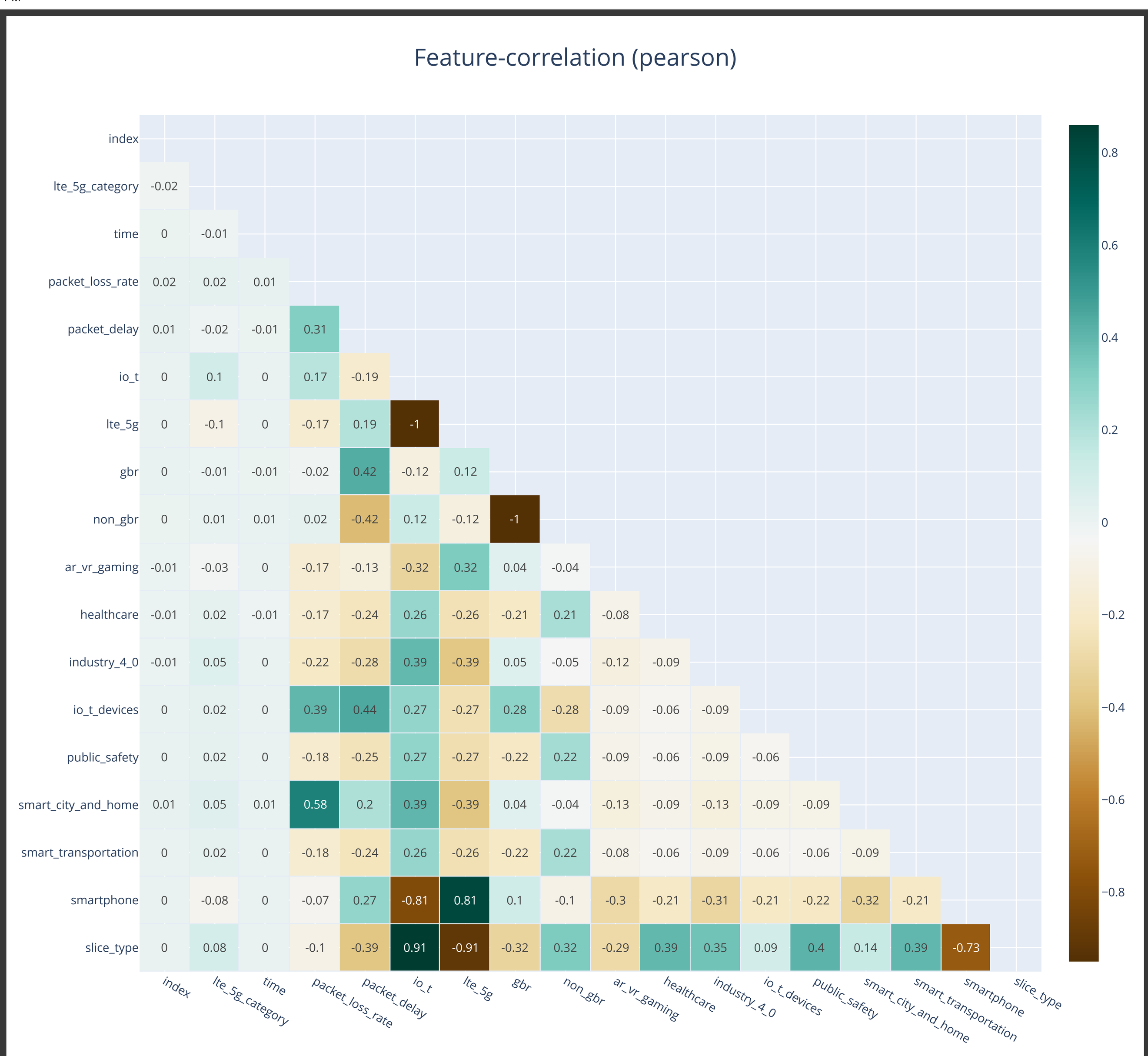
```
(18373, 18)
Index(['index', 'lte_5g_category', 'time', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone', 'slice_type'],
      dtype='object')
```

```
test_dataset['slice_type'] = 0
```

```
klib.cat_plot(train_dataset)
```

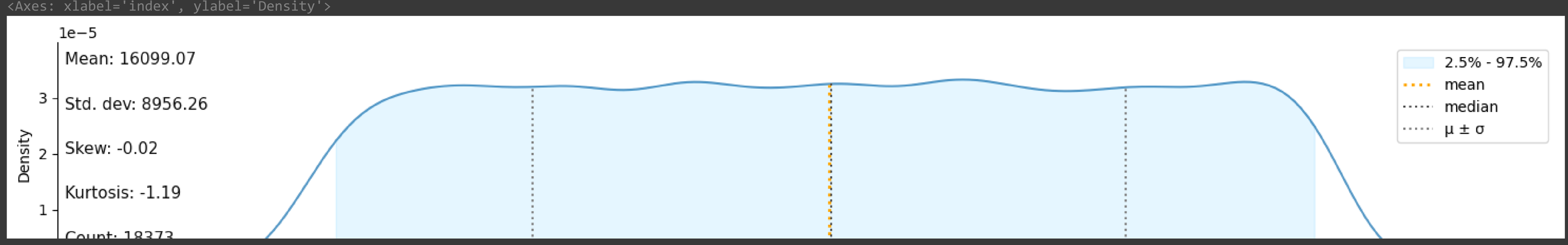
```
No columns with categorical data were detected.
```

```
klib.corr_interactive_plot(train_dataset)
```




```
klib.dist_plot(train_dataset)
```

```
Large dataset detected, using 10000 random samples for the plots. Summary statistics are still based on the entire dataset.
<Axes: xlabel='index', ylabel='Density'>
```




```
klib.missingval_plot(train_dataset)
```

```
No missing values found in the dataset.
```

```
klib.corr_mat(train_dataset)
```

	index	lte_5g_category	time	packet_loss_rate	packet_delay	io_t	lte_5g	gbr	non_gbr	ar_vr_gaming	healthcare	industry_4_0	io_t_devices	public_safety	smart_city_and_home	smart_transportation	smartphone	slice_type
index	1.00	-0.02	-0.00	0.02	0.01	0.00	-0.00	0.00	-0.00	-0.01	-0.01	-0.01	0.00	0.00	0.01	-0.00	0.00	-0.00
lte_5g_category	-0.02	1.00	-0.01	0.02	-0.02	0.10	-0.10	-0.01	0.01	-0.03	0.02	0.05	0.02	0.02	0.05	0.02	-0.08	0.08
time	-0.00	-0.01	1.00	0.01	-0.01	0.00	-0.00	-0.01	0.01	-0.00	-0.01	0.00	-0.00	0.00	0.01	-0.00	0.00	-0.00
packet_loss_rate	0.02	0.02	0.01	1.00	0.31	0.17	-0.17	-0.02	0.02	-0.17	-0.17	-0.22	0.39	-0.18	0.58	-0.18	-0.07	-0.10
packet_delay	0.01	-0.02	-0.01	0.31	1.00	-0.19	0.19	0.42	-0.42	-0.13	-0.24	-0.28	0.44	-0.25	0.20	-0.24	0.27	-0.39
io_t	0.00	0.10	0.00	0.17	-0.19	1.00	-1.00	-0.12	0.12	-0.32	0.26	0.39	0.27	0.27	0.39	0.26	-0.81	0.91
lte_5g	-0.00	-0.10	-0.00	-0.17	0.19	-1.00	1.00	0.12	-0.12	0.32	-0.26	-0.39	-0.27	-0.27	-0.39	-0.26	0.81	-0.91
gbr	0.00	-0.01	-0.01	-0.02	0.42	-0.12	0.12	1.00	-1.00	0.04	-0.21	0.05	0.28	-0.22	0.04	-0.22	0.10	-0.32
non_gbr	-0.00	0.01	0.01	0.02	-0.42	0.12	-0.12	-1.00	1.00	-0.04	0.21	-0.05	-0.28	0.22	-0.04	0.22	-0.10	0.32
ar_vr_gaming	-0.01	-0.03	-0.00	-0.17	-0.13	-0.32	0.32	0.04	-0.04	1.00	-0.08	-0.12	-0.09	-0.09	-0.13	-0.08	-0.30	-0.29
healthcare	-0.01	0.02	-0.01	-0.17	-0.24	0.26	-0.26	-0.21	0.21	-0.08	1.00	-0.09	-0.06	-0.06	-0.09	-0.06	-0.21	0.39
industry_4_0	-0.01	0.05	0.00	-0.22	-0.28	0.39	-0.39	0.05	-0.05	-0.12	-0.09	1.00	-0.09	-0.09	-0.13	-0.09	-0.31	0.35
io_t_devices	0.00	0.02	-0.00	0.39	0.44	0.27	-0.27	0.28	-0.28	-0.09	-0.06	-0.09	1.00	-0.06	-0.09	-0.06	-0.21	0.09
public_safety	0.00	0.02	0.00	-0.18	-0.25	0.27	-0.27	-0.22	0.22	-0.09	-0.06	-0.09	-0.06	1.00	-0.09	-0.06	-0.22	0.40
smart_city_and_home	0.01	0.05	0.01	0.58	0.20	0.39	-0.39	0.04	-0.04	-0.13	-0.09	-0.13	-0.09	-0.09	1.00	-0.09	-0.32	0.14
smart_transportation	-0.00	0.02	-0.00	-0.18	-0.24	0.26	-0.26	-0.22	0.22	-0.08	-0.06	-0.09	-0.06	-0.06	-0.09	1.00	-0.21	0.39
smartphone	0.00	-0.08	0.00	-0.07	0.27	-0.81	0.81	0.10	-0.10	-0.30	-0.21	-0.31	-0.21	-0.22	-0.32	-0.21	1.00	-0.73
slice_type	-0.00	0.08	-0.00	-0.10	-0.39	0.91	-0.91	-0.32	0.32	-0.29	0.39	0.35	0.09	0.40	0.14	0.39	-0.73	1.00

```
train_dataset.columns
```

```
Index(['index', 'lte_5g_category', 'time', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone', 'slice_type'],
      dtype='object')
```

```
# Checking for outliers in the continuous variables
num_train_dataset = train_dataset[['index', 'lte_5g_category', 'time', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone', 'slice_type']]
```

```
train_dataset['slice_type'].value_counts()
```

```
1    9839
2    4294
3    4240
Name: slice_type, dtype: int64
```

```
y_train = train_dataset['slice_type']
x_train = train_dataset.drop('slice_type', axis = 1)
y_test = test_dataset['slice_type']
x_test = test_dataset.drop('slice_type', axis = 1)
```

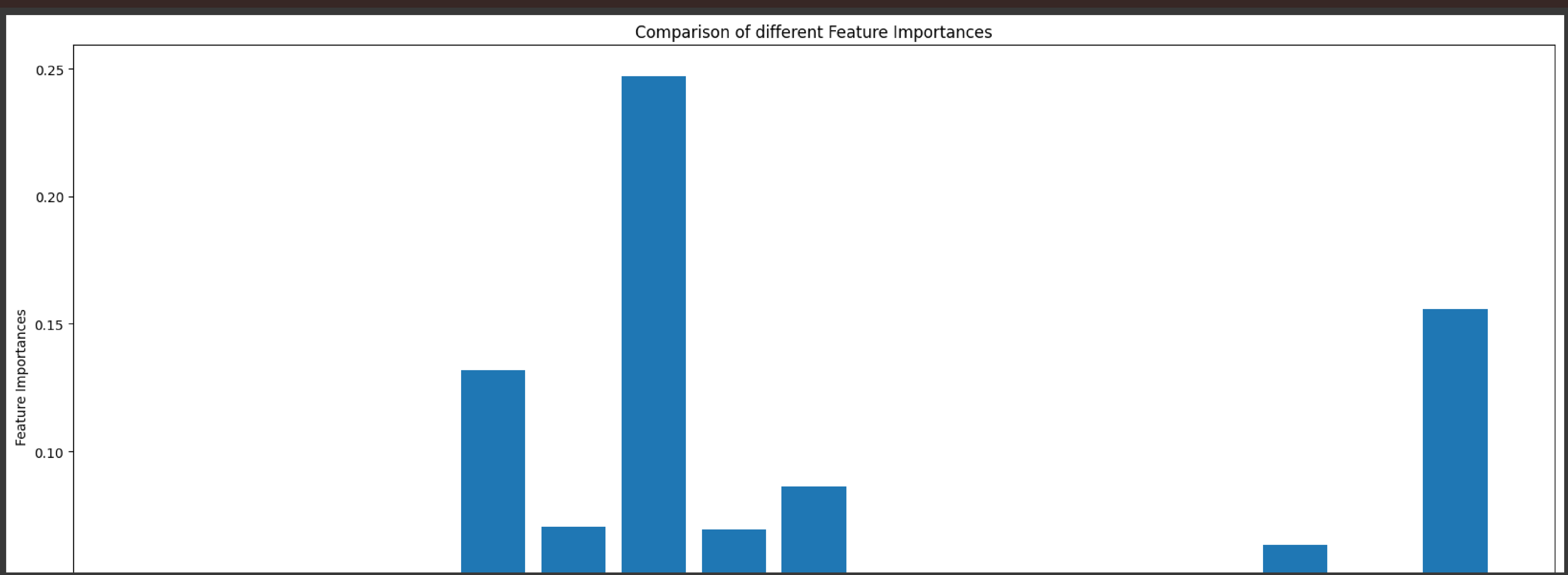
```
from sklearn.ensemble import ExtraTreesClassifier
extra_tree_forest = ExtraTreesClassifier(n_estimators = 5,
                                        criterion ='entropy', max_features = 2)
extra_tree_forest.fit(x_train, y_train)
feature_importance = extra_tree_forest.feature_importances_
feature_importance_normalized = np.std([tree.feature_importances_ for tree in
                                        extra_tree_forest.estimators_],
                                        axis = 0)
```

```
import matplotlib.pyplot as plt
```

```
feature_importance_normalized
```

```
array([2.23385989e-05, 5.35038464e-04, 5.80663207e-05, 2.63614706e-02,
       1.31715736e-01, 7.04401988e-02, 2.46897826e-01, 6.95286066e-02,
       8.62630973e-02, 3.79345537e-03, 7.44487335e-03, 2.30854823e-02,
       2.71210850e-02, 3.25027780e-02, 6.35507569e-02, 3.85865774e-02,
       1.55860310e-01])
```

```
plt.figure(figsize = [20,9])
plt.bar(x_train.columns, feature_importance_normalized)
plt.xlabel('Feature Labels')
plt.ylabel('Feature Importances')
plt.xticks(rotation = 90)
plt.title('Comparison of different Feature Importances')
plt.show()
```




```
x_train.columns
```

```
Index(['index', 'lte_5g_category', 'time', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone'],
      dtype='object')
```

```
x_train2 = x_train[['lte_5g_category', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone']]
```

```
x_test2 = x_test[['lte_5g_category', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone']]
```

```
print(x_train2.shape, x_test2.shape)
print(y_train.shape, y_test.shape)
```

```
(18373, 15) (31584, 15)
(18373,) (31584,)
```

```
y_train.value_counts()
```

```
1    9839
2    4294
3    4240
Name: slice_type, dtype: int64
```

```
x_train2 = pd.DataFrame(x_train2)
```

```
x_train2.head(4)
```

	lte_5g_category	packet_loss_rate	packet_delay	io_t	lte_5g	gbr	non_gbr	ar_vr_gaming	healthcare	industry_4_0	io_t_devices	public_safety	smart_city_and_home	smart_transportation	smartphone
0	14	0.000001	10	1	0	0	1	0	0	0	0	1	0	0	0
4	9	0.010000	50	1	0	0	1	0	0	0	0	0	1	0	0
5	19	0.000001	10	1	0	0	1	0	0	1	0	0	0	0	0
8	8	0.001000	150	0	1	0	1	0	0	0	0	0	0	0	1

Next steps: Generate code with x_train2 View recommended plots

```
x_train2 = pd.DataFrame(x_train2)
x_test2 = pd.DataFrame(x_test2)
```

```
x_train2.astype(float).corr()
```

	lte_5g_category	packet_loss_rate	packet_delay	io_t	lte_5g	gbr	non_gbr	ar_vr_gaming	healthcare	industry_4_0	io_t_devices	public_safety	smart_city_and_home	smart_transportation	smartphone
lte_5g_category	1.000000	0.022254	-0.015085	0.095605	-0.095605	-0.007156	0.007156	-0.034010	0.018408	0.045106	0.019458	0.019485	0.047347	0.019787	-0.075152
packet_loss_rate	0.022254	1.000000	0.306436	0.170858	-0.170858	-0.022315	0.022315	-0.168172	-0.174050	-0.216202	0.389878	-0.182358	0.578743	-0.176111	-0.067416
packet_delay	-0.015085	0.306436	1.000000	-0.187910	0.187910	0.424124	-0.424124	-0.127614	-0.238384	-0.284384	0.437355	-0.249763	0.200818	-0.241206	0.268831
io_t	0.095605	0.170858	-0.187910	1.000000	-1.000000	-0.122402	0.122402	-0.321284	0.260863	0.385515	0.265817	0.273314	0.394585	0.263951	-0.807524
lte_5g	-0.095605	-0.170858	0.187910	-1.000000	1.000000	0.122402	-0.122402	0.321284	-0.260863	-0.385515	-0.265817	-0.273314	-0.394585	-0.263951	0.807524
gbr	-0.007156	-0.022315	0.424124	-0.122402	0.122402	1.000000	-1.000000	0.037476	-0.213782	0.045353	0.281337	-0.223986	0.035940	-0.216313	0.099995
non_gbr	0.007156	0.022315	-0.424124	0.122402	-0.122402	-1.000000	1.000000	-0.037476	0.213782	-0.045353	-0.281337	0.223986	-0.035940	0.216313	-0.099995
ar_vr_gaming	-0.034010	-0.168172	-0.127614	-0.321284	0.321284	0.037476	-0.037476	1.000000	-0.083811	-0.123860	-0.085403	-0.087812	-0.126774	-0.084803	-0.299119
healthcare	0.018408	-0.174050	-0.238384	0.260863	-0.260863	-0.213782	0.213782	-0.083811	1.000000	-0.087228	-0.060145	-0.061841	-0.089280	-0.059722	-0.210653
industry_4_0	0.045106	-0.216202	-0.284384	0.385515	-0.385515	0.045353	-0.045353	-0.123860	-0.087228	1.000000	-0.088885	-0.091391	-0.131942	-0.088261	-0.311313
io_t_devices	0.019458	0.389878	0.437355	0.265817	-0.265817	0.281337	-0.281337	-0.085403	-0.060145	-0.088885	1.000000	-0.063016	-0.090976	-0.060857	-0.214654
public_safety	0.019485	-0.182358	-0.249763	0.273314	-0.273314	-0.223986	0.223986	-0.087812	-0.061841	-0.091391	-0.063016	1.000000	-0.093542	-0.062573	-0.220708
smart_city_and_home	0.047347	0.578743	0.200818	0.394585	-0.394585	0.035940	-0.035940	-0.126774	-0.089280	-0.131942	-0.090976	-0.093542	1.000000	-0.090337	-0.318637
smart_transportation	0.019787	-0.176111	-0.241206	0.263951	-0.263951	-0.216313	0.216313	-0.084803	-0.059722	-0.088261	-0.060857	-0.062573	-0.090337	1.000000	-0.213147
smartphone	-0.075152	-0.067416	0.268831	-0.807524	0.807524	0.099995	-0.099995	-0.299119	-0.210653	-0.311313	-0.214654	-0.220708	-0.318637	-0.213147	1.000000

```
def correlation(dataset, threshold):
    col_corr = set() # Set of all the names of deleted columns
    corr_matrix = dataset.corr()
    for i in range(len(corr_matrix.columns)):
        for j in range(i):
            if (corr_matrix.iloc[i, j] >= threshold) and (corr_matrix.columns[j] not in col_corr):
                colname = corr_matrix.columns[i] # getting the name of column
                col_corr.add(colname)
                if colname in dataset.columns:
                    del dataset[colname] # deleting the column from the dataset

    print(dataset.columns)
    print(dataset.shape)
```

```
correlation(x_train2, 0.95)
```

```
Index(['lte_5g_category', 'packet_loss_rate', 'packet_delay', 'io_t', 'lte_5g',
       'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare', 'industry_4_0',
       'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone'],
      dtype='object')
(18373, 15)
```

```
print(x_train2.columns, x_train2.shape)
print(x_test2.columns, x_test2.shape)
```

```
Index(['lte_5g_category', 'packet_loss_rate', 'packet_delay', 'io_t', 'lte_5g',
       'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare', 'industry_4_0',
       'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone'],
      dtype='object') (18373, 15)
Index(['lte_5g_category', 'packet_loss_rate', 'packet_delay', 'io_t', 'lte_5g',
       'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare', 'industry_4_0',
       'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone'],
      dtype='object') (31584, 15)
```

Standard Scaler

```
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
x_train_scaled=pd.DataFrame(scaler.fit_transform(x_train2),columns=x_train2.columns)
x_train_scaled.head()
```

	lte_5g_category	packet_loss_rate	packet_delay	io_t	lte_5g	gbr	non_gbr	ar_vr_gaming	healthcare	industry_4_0	io_t_devices	public_safety	smart_city_and_home	smart_transportation	smartphone
0	0.496569	-0.716409	-0.981216	1.073740	-1.073740	-0.87995	0.87995	-0.344976	-0.242948	-0.359040	-0.247562	3.928589	-0.367487	-0.245824	-0.867071
1	-0.319527	1.574868	-0.602200	1.073740	-1.073740	-0.87995	0.87995	-0.344976	-0.242948	-0.359040	-0.247562	-0.254544	2.721185	-0.245824	-0.867071
2	1.312664	-0.716409	-0.981216	1.073740	-1.073740	-0.87995	0.87995	-0.344976	-0.242948	2.785209	-0.247562	-0.254544	-0.367487	-0.245824	-0.867071
3	-0.482746	-0.487488	0.345339	-0.931324	0.931324	-0.87995	0.87995	-0.344976	-0.242948	-0.359040	-0.247562	-0.254544	-0.367487	-0.245824	1.153308
4	-0.645965	-0.716409	-0.981216	1.073740	-1.073740	-0.87995	0.87995	-0.344976	4.116113	-0.359040	-0.247562	-0.254544	-0.367487	-0.245824	-0.867071

Next steps: Generate code with x_train_scaled View recommended plots

```
x_test_scaled=pd.DataFrame(scaler.fit_transform(x_test2),columns=x_test2.columns)
x_test_scaled.head()
```

	lte_5g_category	packet_loss_rate	packet_delay	io_t	lte_5g	gbr	non_gbr	ar_vr_gaming	healthcare	industry_4_0	io_t_devices	public_safety	smart_city_and_home	smart_transportation	smartphone
0	0.664781	-0.482940	-0.136290	-0.938083	0.938083	1.124027	-1.124027	2.896828	-0.25058	-0.365662	-0.250722	-0.246559	-0.362819	-0.248791	-0.860496
1	0.500168	-0.712444	-0.982767	1.066004	-1.066004	-0.889658	0.889658	-0.345205	-0.25058	-0.365662	-0.250722	-0.246559	-0.362819	4.019440	-0.860496
2	0.006327	-0.482940	-0.606555	1.066004	-1.066004	1.124027	-1.124027	-0.345205	-0.25058	2.734762	-0.250722	-0.246559	-0.362819	-0.248791	-0.860496
3	1.487848	-0.482940	-0.606555	1.066004	-1.066004	1.124027	-1.124027	-0.345205	-0.25058	2.734762	-0.250722	-0.246559	-0.362819	-0.248791	-0.860496
4	-1.475194	-0.482940	-0.606555	-0.938083	0.938083	-0.889658	0.889658	2.896828	-0.25058	-0.365662	-0.250722	-0.246559	-0.362819	-0.248791	-0.860496

Next steps: Generate code with x_test_scaled View recommended plots

```
print(x_train_scaled.shape, x_test_scaled.shape)
```

```
(18373, 15) (31584, 15)
```

```
y_train = pd.DataFrame(y_train)
y_test = pd.DataFrame(y_test)
```

```
# Install libraries
#!pip install boostaroota
#!pip install h2o
#!pip install ppscore
#!pip install imblearn
```

```
#! pip install optuna
#! pip install shap
```

```
###! pip install catboost
```

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import os
from ipywidgets import interact, interactive, fixed, interact_manual
import ipywidgets as widgets
import plotly.express as px
import matplotlib.pyplot as plt
import plotly.graph_objs as go
from tqdm import tqdm
from sklearn.metrics import mean_squared_error
import tensorflow as tf
from sklearn import model_selection as sk_model_selection
from xgboost.sklearn import XGBRegressor
from sklearn.metrics import mean_squared_error,roc_auc_score,precision_score
from sklearn import metrics
import optuna
from boostaroota import BoostARoota
from sklearn.metrics import log_loss
from optuna.samplers import TPESampler
import functools
from functools import partial
import xgboost as xgb
import joblib
from matplotlib_venn import venn2, venn2_circles, venn2_unweighted
from matplotlib_venn import venn3, venn3_circles
import statsmodels.api as sm
import pylab
from xgboost import plot_tree
import shap
from xgboost.sklearn import XGBClassifier
from sklearn.metrics import mean_squared_error,roc_auc_score,precision_score
from sklearn import metrics
from sklearn.metrics import log_loss
from sklearn.metrics import confusion_matrix, recall_score, precision_score, precision_recall_curve, auc, f1_score, \
    average_precision_score, accuracy_score, roc_curve
from sklearn.preprocessing import LabelEncoder
import h2o
from h2o.automl import H2OAutoML
from catboost import Pool, CatBoostRegressor, cv
import tensorflow as tf
from tensorflow.keras.utils import plot_model
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.callbacks import ModelCheckpoint
from tensorflow.keras.callbacks import ReduceLROnPlateau
from tensorflow.keras.layers import BatchNormalization
from tensorflow.keras.layers import Dense, Dropout, Input
from tensorflow.keras.layers import Concatenate, LSTM, GRU
from tensorflow.keras.layers import Bidirectional, Multiply
import seaborn as sns
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC


SEED = 42
```

```
x_train_scaled.columns
```

```
Index(['lte_5g_category', 'packet_loss_rate', 'packet_delay', 'io_t', 'lte_5g',
       'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare', 'industry_4_0',
       'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone'],
      dtype='object')
```

```
x_test_scaled.columns
```

```
Index(['lte_5g_category', 'packet_loss_rate', 'packet_delay', 'io_t', 'lte_5g',
       'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare', 'industry_4_0',
       'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone'],
      dtype='object')
```

```
feature_cols = ['lte_5g_category', 'packet_loss_rate', 'packet_delay', 'io_t', 'lte_5g',
       'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare', 'industry_4_0',
       'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone']
```

```
from sklearn.metrics import  precision_recall_curve, roc_auc_score, confusion_matrix, accuracy_score, recall_score, precision_score, f1_score,auc, roc_curve
try:
    from imblearn.over_sampling import ADASYN
except:
    pass
try:
    import ppscore as pps
except:
    pass

from imblearn.over_sampling import ADASYN
```

```
h2o.init(
    nthreads=-1,     # number of threads when launching a new H2O server
    max_mem_size=12  # in gigabytes
)
```

```
Checking whether there is an H2O instance running at http://localhost:54321. connected.
```

H2O_cluster_uptime:	13 mins 48 secs
H2O_cluster_timezone:	Etc/UTC
H2O_data_parsing_timezone:	UTC
H2O_cluster_version:	3.44.0.3
H2O_cluster_version_age:	2 months
H2O_cluster_name:	H2O_from_python_unknownUser_wqymo5
H2O_cluster_total_nodes:	1
H2O_cluster_free_memory:	23.99 Gb
H2O_cluster_total_cores:	2
H2O_cluster_allowed_cores:	2
H2O_cluster_status:	locked, healthy
H2O_connection_url:	http://localhost:54321
H2O_connection_proxy:	{"http": null, "https": null, "colab_language_server": "/usr/colab/bin/language_service"}
H2O_internal_security:	False
Python_version:	3.10.12 final

```
print(train_dataset.shape, test_dataset.shape)
```

```
(18373, 18) (31584, 18)
```

```
h2o_train_df = h2o.H2OFrame(train_dataset)
h2o_test_df = h2o.H2OFrame(test_dataset)
```

```
Parse progress: |████████████████████████████████████████| (done) 100%
Parse progress: |████████████████████████████████████████| (done) 100%
```

```
aml = H2OAutoML(max_models = 35, seed = 100, exclude_algos = ["StackedEnsemble"], verbosity="info", nfolds=0, balance_classes=True, max_after_balance_size=0.3)
```

```
train_dataset.columns
```

```
Index(['index', 'lte_5g_category', 'time', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone', 'slice_type'],
      dtype='object')
```

```
features = ['index', 'lte_5g_category', 'time', 'packet_loss_rate', 'packet_delay',
       'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming', 'healthcare',
       'industry_4_0', 'io_t_devices', 'public_safety', 'smart_city_and_home',
       'smart_transportation', 'smartphone']
output = 'slice_type'
```

```
aml = H2OAutoML(max_models = 30, max_runtime_secs=300, seed = 1)
```

```
aml.train(x = features, y = output, training_frame = h2o_train_df)
```

```
AutoML progress: |████████████████████████████████████████| (done) 100%

Model Details
=============
H2ORandomForestEstimator : Distributed Random Forest
Model Key: DRF_1_AutoML_2_20240221_95129
```

Model Summary:

number_of_trees	number_of_internal_trees	model_size_in_bytes	min_depth	max_depth	mean_depth	min_leaves	max_leaves	mean_leaves
50.0	50.0	5461.0	2.0	6.0	2.94	3.0	7.0	4.02

```
ModelMetricsRegression: drf
** Reported on train data. **

MSE: 0.0
RMSE: 0.0
MAE: 0.0
RMSLE: 0.0
Mean Residual Deviance: 0.0

ModelMetricsRegression: drf
** Reported on cross-validation data. **

MSE: 0.0
RMSE: 0.0
MAE: 0.0
RMSLE: 0.0
Mean Residual Deviance: 0.0
```

Cross-Validation Metrics Summary:

	mean	sd	cv_1_valid	cv_2_valid	cv_3_valid	cv_4_valid	cv_5_valid
mae	0.0	0.0	0.0	0.0	0.0	0.0	0.0
mean_residual_deviance	0.0	0.0	0.0	0.0	0.0	0.0	0.0
mse	0.0	0.0	0.0	0.0	0.0	0.0	0.0
r2	1.0	0.0	1.0	1.0	1.0	1.0	1.0
residual_deviance	0.0	0.0	0.0	0.0	0.0	0.0	0.0
rmse	0.0	0.0	0.0	0.0	0.0	0.0	0.0
rmsle	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Scoring History:

timestamp	duration	number_of_trees	training_rmse	training_mae	training_deviance
2024-02-21 09:52:18	4.930 sec	0.0	nan	nan	nan
2024-02-21 09:52:18	4.976 sec	5.0	0.0	0.0	0.0
2024-02-21 09:52:18	5.029 sec	10.0	0.0	0.0	0.0
2024-02-21 09:52:18	5.072 sec	15.0	0.0	0.0	0.0
2024-02-21 09:52:18	5.127 sec	20.0	0.0	0.0	0.0
2024-02-21 09:52:18	5.204 sec	25.0	0.0	0.0	0.0
2024-02-21 09:52:18	5.267 sec	30.0	0.0	0.0	0.0
2024-02-21 09:52:18	5.344 sec	35.0	0.0	0.0	0.0
2024-02-21 09:52:18	5.413 sec	40.0	0.0	0.0	0.0
2024-02-21 09:52:18	5.483 sec	45.0	0.0	0.0	0.0
2024-02-21 09:52:19	5.560 sec	50.0	0.0	0.0	0.0

Variable Importances:

variable	relative_importance	scaled_importance	percentage
lte_5g	174344.5937500	1.0	0.3286021
io_t	145182.75	0.8327345	0.2736383
packet_delay	116860.8515625	0.6702866	0.2202576
smartphone	34613.1914062	0.1985332	0.0652384
public_safety	15720.8300781	0.0901710	0.0296304
packet_loss_rate	13198.0820312	0.0757011	0.0248755
smart_transportation	7059.2353516	0.0404901	0.0133051
gbr	5947.2958984	0.0341123	0.0112094
smart_city_and_home	4591.7216797	0.0263370	0.0086544
industry_4_0	4192.8383789	0.0240491	0.0079026
healthcare	3875.0671387	0.0222265	0.0073037
non_gbr	2510.5192871	0.0143998	0.0047318
ar_vr_gaming	2276.3232422	0.0130565	0.0042904
io_t_devices	190.8676453	0.0010948	0.0003597
lte_5g_category	0.3425862	0.0000020	0.0000006
index	0.0	0.0	0.0
time	0.0	0.0	0.0

```
[tips]
Use `model.explain()` to inspect the model.
--
Use `h2o.display.toggle_user_tips()` to switch on/off this section.
```

Model leaderboard

```
lb = aml.leaderboard
lb.head(rows=lb.nrows)
```

model_id	rmse	mse	mae	rmsle	mean_residual_deviance
DRF_1_AutoML_2_20240221_95129	0	0	0	0	0
GBM_5_AutoML_2_20240221_95129	7.54682e-07	5.69545e-13	6.21247e-07	2.70514e-07	5.69545e-13
GBM_grid_1_AutoML_2_20240221_95129_model_2	7.54682e-07	5.69545e-13	6.21247e-07	2.70514e-07	5.69545e-13
GBM_1_AutoML_2_20240221_95129	7.54682e-07	5.69545e-13	6.21247e-07	2.70514e-07	5.69545e-13
GBM_4_AutoML_2_20240221_95129	7.54682e-07	5.69545e-13	6.21247e-07	2.70514e-07	5.69545e-13
GBM_2_AutoML_2_20240221_95129	7.54682e-07	5.69545e-13	6.21247e-07	2.70514e-07	5.69545e-13
XGBoost_grid_1_AutoML_2_20240221_95129_model_3	8.13005e-06	6.60978e-11	6.70222e-06	2.79717e-06	6.60978e-11
XGBoost_grid_1_AutoML_2_20240221_95129_model_4	8.13615e-06	6.6197e-11	6.69312e-06	2.79782e-06	6.6197e-11
XGBoost_grid_1_AutoML_2_20240221_95129_model_6	1.08735e-05	1.18233e-10	9.58954e-06	3.66615e-06	1.18233e-10
XGBoost_3_AutoML_2_20240221_95129	1.08934e-05	1.18666e-10	8.55583e-06	3.52064e-06	1.18666e-10
XGBoost_1_AutoML_2_20240221_95129	1.15087e-05	1.32449e-10	9.95931e-06	4.14199e-06	1.32449e-10
XGBoost_2_AutoML_2_20240221_95129	1.17968e-05	1.39164e-10	1.04852e-05	4.23955e-06	1.39164e-10
XGBoost_grid_1_AutoML_2_20240221_95129_model_7	2.10875e-05	4.44682e-10	1.67334e-05	7.28113e-06	4.44682e-10
XGBoost_grid_1_AutoML_2_20240221_95129_model_2	2.97055e-05	8.82416e-10	2.08393e-05	8.4723e-06	8.82416e-10
GBM_grid_1_AutoML_2_20240221_95129_model_3	0.000186748	3.4875e-08	1.55002e-05	5.46401e-05	3.4875e-08
GBM_3_AutoML_2_20240221_95129	0.000256323	6.57015e-08	4.43435e-05	7.2183e-05	6.57015e-08
XGBoost_grid_1_AutoML_2_20240221_95129_model_5	0.00177365	3.14584e-06	0.000292366	0.000488191	3.14584e-06
XGBoost_grid_1_AutoML_2_20240221_95129_model_1	0.00178665	3.19212e-06	0.00063747	0.000539846	3.19212e-06
DeepLearning_1_AutoML_2_20240221_95129	0.00648694	4.20804e-05	0.00525655	0.00239027	4.20804e-05
GBM_grid_1_AutoML_2_20240221_95129_model_1	0.0132094	0.000174488	0.0097893	0.00510195	0.000174488
GLM_1_AutoML_2_20240221_95129	0.150152	0.0225456	0.0957561	0.0495642	0.0225456
XRT_1_AutoML_2_20240221_95129	0.323965	0.104953	0.278212	0.105518	0.104953

[22 rows x 6 columns]

```
preds = aml.predict(h2o_test_df)
```

```
drf prediction progress: |████████████████████████████████████████| (done) 100%
```

```
preds.columns
```

```
['predict']
```

```
preds.head(2)
```

predict
1
3

[2 rows x 1 column]

```
print(test_dataset.shape)
```

```
(31584, 18)
```

```
test_dataset.to_csv("/content/test.csv")
```

```
test2 = pd.read_csv("/content/test.csv")
```

```
sub = preds[0].as_data_frame()
test2['Prediction_Value'] = sub
test2.to_csv('h20.ai-automl.csv',index = False)
```

```
Export File progress: |████████████████████████████████████████| (done) 100%
```

```
test2.columns
```

```
Index(['Unnamed: 0', 'index', 'lte_5g_category', 'time', 'packet_loss_rate',
       'packet_delay', 'io_t', 'lte_5g', 'gbr', 'non_gbr', 'ar_vr_gaming',
       'healthcare', 'industry_4_0', 'io_t_devices', 'public_safety',
       'smart_city_and_home', 'smart_transportation', 'smartphone',
       'slice_type', 'Prediction_Value'],
      dtype='object')
```

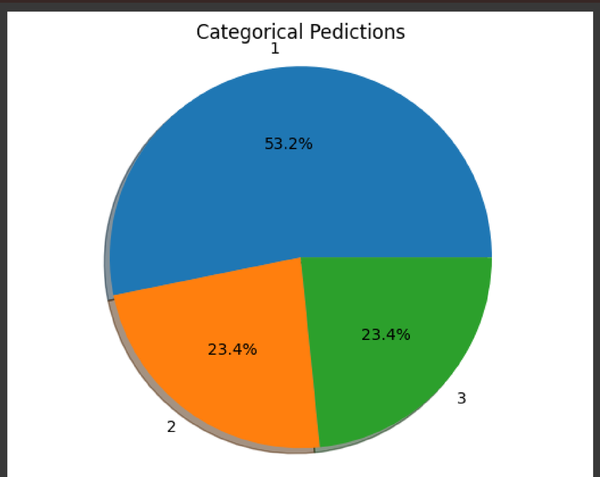
```
test2["Prediction_Value_int"] = test2.Prediction_Value.apply(np.round)
```

```
test2["Prediction_Value_int"] = test2["Prediction_Value_int"].astype(int)
```

```
print(test2["Prediction_Value_int"].value_counts())
```

```
1    16800
3     7392
2     7392
Name: Prediction_Value_int, dtype: int64
```

```
labels = test2['Prediction_Value_int'].astype('category').cat.categories.tolist()
counts = test2['Prediction_Value_int'].value_counts()
sizes = [counts[var_cat] for var_cat in labels]
fig1, ax1 = plt.subplots()
plt.title("Categorical Pedictions")
ax1.pie(sizes, labels=labels, autopct='%1.1f%%', shadow=True) #autopct is show the % on plot
ax1.axis('equal')
plt.show()
```




```
from sklearn import metrics
```

```
hamming_loss = metrics.hamming_loss(y_test, test2["Prediction_Value_int"])
```