Deliverable 1

Importing Dependecies

```
import numpy as np
import pandas as pd
```

Importing the dataset

```
df=pd.read_csv('neo_v2.csv')
```

Taking inputs from user

```
def findStandardisedValues(df):
  l1=[]
  # relative_velocity
  min_X = df["relative_velocity"].min()
  max_X = df["relative_velocity"].max()
  x_new = input("Enter Value for Relative Velocity")
  x_new_normalized = (x_new - min_X) / (max_X - min_X)
  l1.push(x_new_normalized)

  #miss_distance
  min_X = df["miss_distance"].min()
  max_X = df["miss_distance"].max()
  x_new = input("Enter Value for Miss Distance")
  x_new_normalized = (x_new - min_X) / (max_X - min_X)
  l1.push(x_new_normalized)

  #absolute_magnitude
  min_X = df["absolute_magnitude"].min()
  max_X = df["absolute_magnitude"].max()
  x_new = input("Enter Value for Absolute Magnitude")
  x_new_normalized = (x_new - min_X) / (max_X - min_X)
  l1.push(x_new_normalized)


  #   est_diameter_max
  min_X = df["est_diameter_max"].min()
  max_X = df["est_diameter_max"].max()
  x_new = input("Enter Value forEstimated Diameter")
  x_new_normalized = (x_new - min_X) / (max_X - min_X)
  l1.push(x_new_normalized)

  return l1
```

```
df.shape
```

```
(90836, 10)
```

```
df.head()
```

```
        id                 name  est_diameter_min  est_diameter_max  \
0  2162635  162635 (2000 SS164)          1.198271          2.679415
1  2277475    277475 (2005 WK4)          0.265800          0.594347
2  2512244   512244 (2015 YE18)          0.722030          1.614507
3  3596030          (2012 BV13)          0.096506          0.215794
4  3667127          (2014 GE35)          0.255009          0.570217

   relative_velocity  miss_distance orbiting_body  sentry_object  \
0       13569.249224   5.483974e+07         Earth          False
1       73588.726663   6.143813e+07         Earth          False
2      114258.692129   4.979872e+07         Earth          False
3       24764.303138   2.543497e+07         Earth          False
4       42737.733765   4.627557e+07         Earth          False

   absolute_magnitude  hazardous
0               16.73      False
1               20.00       True
2               17.83      False
3               22.20      False
4               20.09       True
```

Checking for null values

```
df.isnull().sum()
```

```
id                    0
name                  0
est_diameter_min      0
est_diameter_max      0
relative_velocity     0
miss_distance         0
orbiting_body         0
sentry_object         0
absolute_magnitude    0
hazardous             0
dtype: int64
```

Validating Datatypes

```
df.dtypes
```

```
id                      int64
name                   object
est_diameter_min      float64
```

```
est_diameter_max      float64
relative_velocity     float64
miss_distance         float64
orbiting_body          object
sentry_object            bool
absolute_magnitude    float64
hazardous                bool
dtype: object
```

```
df.describe()
```

```
                 id  est_diameter_min  est_diameter_max
relative_velocity  \
count  9.083600e+04      90836.000000      90836.000000
90836.000000
mean   1.438288e+07          0.127432          0.284947
48066.918918
std    2.087202e+07          0.298511          0.667491
25293.296961
min    2.000433e+06          0.000609          0.001362
203.346433
25%    3.448110e+06          0.019256          0.043057
28619.020645
50%    3.748362e+06          0.048368          0.108153
44190.117890
75%    3.884023e+06          0.143402          0.320656
62923.604633
max    5.427591e+07         37.892650         84.730541
236990.128088

       miss_distance  absolute_magnitude
count   9.083600e+04        90836.000000
mean    3.706655e+07           23.527103
std     2.235204e+07            2.894086
min     6.745533e+03            9.230000
25%     1.721082e+07           21.340000
50%     3.784658e+07           23.700000
75%     5.654900e+07           25.700000
max     7.479865e+07           33.200000
```

Dropping Columns

```
df.orbiting_body.unique()
```

```
----------------------------------------------------------------------
-----
AttributeError                            Traceback (most recent call
last)
<ipython-input-10-8edbcf88be91> in <cell line: 1>()
----> 1 df.orbiting_body.unique()
```

```
/usr/local/lib/python3.10/dist-packages/pandas/core/generic.py in
__getattr__(self, name)
   5900         ):
   5901             return self[name]
-> 5902         return object.__getattribute__(self, name)
   5903
   5904     def __setattr__(self, name: str, value) -> None:

AttributeError: 'DataFrame' object has no attribute 'orbiting_body'
```

```
colunms_to_drop=['orbiting_body','id','sentry_object']
df.drop(columns=colunms_to_drop,inplace=True)

df.head()
```

```
                  name  est_diameter_min  est_diameter_max
relative_velocity  \
0  162635 (2000 SS164)          1.198271          2.679415
13569.249224
1    277475 (2005 WK4)          0.265800          0.594347
73588.726663
2   512244 (2015 YE18)          0.722030          1.614507
114258.692129
3          (2012 BV13)          0.096506          0.215794
24764.303138
4          (2014 GE35)          0.255009          0.570217
42737.733765

   miss_distance  absolute_magnitude  hazardous
0   5.483974e+07               16.73      False
1   6.143813e+07               20.00       True
2   4.979872e+07               17.83      False
3   2.543497e+07               22.20      False
4   4.627557e+07               20.09       True
```

Creating a new column to calculate the errors in 'est_diameter'

```
df['est_diameter_error']=(df['est_diameter_max']-
df['est_diameter_min'])/2
df.head()
```

```
                  name  est_diameter_min  est_diameter_max
relative_velocity  \
0  162635 (2000 SS164)          1.198271          2.679415
13569.249224
1    277475 (2005 WK4)          0.265800          0.594347
73588.726663
2   512244 (2015 YE18)          0.722030          1.614507
114258.692129
```

```
3         (2012 BV13)          0.096506          0.215794
24764.303138
4         (2014 GE35)          0.255009          0.570217
42737.733765

   miss_distance  absolute_magnitude hazardous  est_diameter_error
0   5.483974e+07               16.73     False            0.740572
1   6.143813e+07               20.00      True            0.164273
2   4.979872e+07               17.83     False            0.446239
3   2.543497e+07               22.20     False            0.059644
4   4.627557e+07               20.09      True            0.157604
```

Binary Encoding of 'hazardous' column

```
df['hazardous']=df['hazardous'].astype("category").cat.codes

df.head()

                  name  est_diameter_min  est_diameter_max
relative_velocity  \
0  162635 (2000 SS164)          1.198271          2.679415
13569.249224
1    277475 (2005 WK4)          0.265800          0.594347
73588.726663
2   512244 (2015 YE18)          0.722030          1.614507
114258.692129
3         (2012 BV13)          0.096506          0.215794
24764.303138
4         (2014 GE35)          0.255009          0.570217
42737.733765

   miss_distance  absolute_magnitude  hazardous  est_diameter_error
0   5.483974e+07               16.73          0            0.740572
1   6.143813e+07               20.00          1            0.164273
2   4.979872e+07               17.83          0            0.446239
3   2.543497e+07               22.20          0            0.059644
4   4.627557e+07               20.09          1            0.157604

df.describe()

       est_diameter_min  est_diameter_max  relative_velocity
miss_distance  \
count      90836.000000      90836.000000       90836.000000
9.083600e+04
mean           0.127432          0.284947       48066.918918
3.706655e+07
std            0.298511          0.667491       25293.296961
2.235204e+07
min            0.000609          0.001362         203.346433
6.745533e+03
```

```
25%              0.019256          0.043057       28619.020645
1.721082e+07
50%              0.048368          0.108153       44190.117890
3.784658e+07
75%              0.143402          0.320656       62923.604633
5.654900e+07
max             37.892650         84.730541      236990.128088
7.479865e+07

       absolute_magnitude     hazardous  est_diameter_error
count        90836.000000  90836.000000        90836.000000
mean            23.527103      0.097318            0.078757
std              2.894086      0.296392            0.184490
min              9.230000      0.000000            0.000376
25%             21.340000      0.000000            0.011901
50%             23.700000      0.000000            0.029893
75%             25.700000      0.000000            0.088627
max             33.200000      1.000000           23.418946
```

Scaling Columns

```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
columns_to_scale=['relative_velocity','miss_distance','absolute_magnit
ude','est_diameter_min','est_diameter_max','est_diameter_error']
df[columns_to_scale]=scaler.fit_transform(df[columns_to_scale])

df.describe()

       est_diameter_min  est_diameter_max  relative_velocity
miss_distance  \
count      90836.000000      90836.000000       90836.000000
90836.000000
mean           0.003347          0.003347           0.202138
0.495505
std            0.007878          0.007878           0.106819
0.298856
min            0.000000          0.000000           0.000000
0.000000
25%            0.000492          0.000492           0.120005
0.230026
50%            0.001260          0.001260           0.185765
0.505935
75%            0.003768          0.003768           0.264881
0.755994
max            1.000000          1.000000           1.000000
1.000000

       absolute_magnitude     hazardous  est_diameter_error
count        90836.000000  90836.000000        90836.000000
```

```
mean                 0.596458      0.097318             0.003347
std                  0.120738      0.296392             0.007878
min                  0.000000      0.000000             0.000000
25%                  0.505215      0.000000             0.000492
50%                  0.603671      0.000000             0.001260
75%                  0.687109      0.000000             0.003768
max                  1.000000      1.000000             1.000000
```

Principal Component Analysis

```
df2=df.copy()
df2.drop(columns=['name'],inplace=True)
df2.head()
```

```
   est_diameter_min  est_diameter_max  relative_velocity
miss_distance  \
0          0.261620          0.261620           0.067458
0.733286
1          0.057824          0.057824           0.378721
0.821537
2          0.157535          0.157535           0.589637
0.665865
3          0.020824          0.020824           0.125516
0.340010
4          0.055465          0.055465           0.218727
0.618744

   absolute_magnitude  hazardous  est_diameter_error
0            0.162952          0           0.261620
1            0.346063          1           0.057824
2            0.224549          0           0.157535
3            0.469257          0           0.020824
4            0.351103          1           0.055465
```

```
from sklearn.decomposition import PCA
pca=PCA(n_components=3)
df3= pca.fit_transform(df2)
df4 = pd.DataFrame(df3 , columns= ['PC1','PC2','PC3'])
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call
last)
<ipython-input-15-39a2a4fd9a19> in <cell line: 3>()
      1 from sklearn.decomposition import PCA
      2 pca=PCA(n_components=3)
----> 3 df3= pca.fit_transform(df2)
      4 df4 = pd.DataFrame(df3 , columns= ['PC1','PC2','PC3'])

/usr/local/lib/python3.10/dist-packages/sklearn/utils/_set_output.py
```

```
in wrapped(self, X, *args, **kwargs)
    138     @wraps(f)
    139     def wrapped(self, X, *args, **kwargs):
--> 140         data_to_wrap = f(self, X, *args, **kwargs)
    141         if isinstance(data_to_wrap, tuple):
    142             # only wrap the first output for cross
decomposition

/usr/local/lib/python3.10/dist-packages/sklearn/decomposition/_pca.py
in fit_transform(self, X, y)
    460         self._validate_params()
    461
--> 462         U, S, Vt = self._fit(X)
    463         U = U[:, : self.n_components_]
    464

/usr/local/lib/python3.10/dist-packages/sklearn/decomposition/_pca.py
in _fit(self, X)
    483             )
    484
--> 485         X = self._validate_data(
    486             X, dtype=[np.float64, np.float32], ensure_2d=True,
copy=self.copy
    487         )

/usr/local/lib/python3.10/dist-packages/sklearn/base.py in
_validate_data(self, X, y, reset, validate_separately, **check_params)
    563             raise ValueError("Validation should be done on X,
y or both.")
    564         elif not no_val_X and no_val_y:
--> 565             X = check_array(X, input_name="X", **check_params)
    566             out = X
    567         elif no_val_X and not no_val_y:

/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py in
check_array(array, accept_sparse, accept_large_sparse, dtype, order,
copy, force_all_finite, ensure_2d, allow_nd, ensure_min_samples,
ensure_min_features, estimator, input_name)
    919
    920         if force_all_finite:
--> 921             _assert_all_finite(
    922                 array,
    923                 input_name=input_name,

/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py in
_assert_all_finite(X, allow_nan, msg_dtype, estimator_name,
input_name)
    159                 "#estimators-that-handle-nan-values"
    160             )
--> 161         raise ValueError(msg_err)
```

```
    162
    163

ValueError: Input X contains NaN.
PCA does not accept missing values encoded as NaN natively. For
supervised learning, you might want to consider
sklearn.ensemble.HistGradientBoostingClassifier and Regressor which
accept missing values encoded as NaNs natively. Alternatively, it is
possible to preprocess the data, for instance by using an imputer
transformer in a pipeline or drop samples with missing values. See
https://scikit-learn.org/stable/modules/impute.html You can find a
list of all estimators that handle NaN values at the following page:
https://scikit-learn.org/stable/modules/impute.html#estimators-that-
handle-nan-values
```

```
df4
```

```
            PC1       PC2       PC3
0      0.143398 -0.213701  0.124930
1      0.863812  0.454322 -0.035872
2      0.146692 -0.183983  0.333868
3     -0.178893  0.037477  0.032489
4      0.697724  0.593852 -0.077204
...         ...       ...       ...
90831 -0.311956  0.146109  0.032565
90832  0.082650 -0.230882 -0.108223
90833 -0.180086  0.008697 -0.094084
90834  0.221086 -0.365859 -0.146019
90835  0.138957 -0.273596 -0.102580

[90836 rows x 3 columns]
```

Exporting the cleaned dataset

```
df.to_csv('cleaned_neo_v2.csv',index=False)
```

Deliverable 2

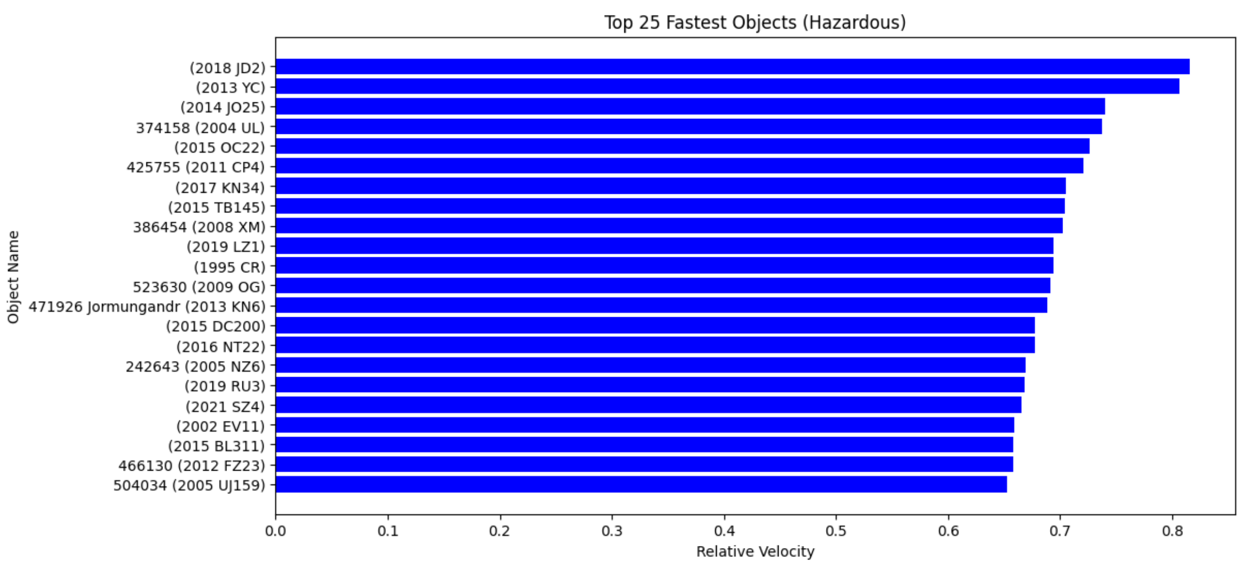
```
import matplotlib.pyplot as plt
import pandas as pd

df=pd.read_csv('cleaned_neo_v2.csv')

df.head()
```

```
                  name  est_diameter_min  est_diameter_max
relative_velocity  \
0  162635 (2000 SS164)          0.031607          0.031607
```

```
0.056447
1    277475 (2005 WK4)         0.006999         0.006999
0.309922
2   512244 (2015 YE18)         0.019039         0.019039
0.481680
3          (2012 BV13)         0.002531         0.002531
0.103726
4          (2014 GE35)         0.006714         0.006714
0.179632

   miss_distance  absolute_magnitude  hazardous  est_diameter_error
0       0.733141            0.312891          0            0.031607
1       0.821364            0.449312          1            0.006999
2       0.665740            0.358782          0            0.019039
3       0.339986            0.541093          0            0.002531
4       0.618634            0.453066          1            0.006714

df.describe()

       est_diameter_min  est_diameter_max  relative_velocity
miss_distance  \
count      90836.000000      90836.000000       90836.000000
90836.000000
mean           0.003347          0.003347           0.202138
0.495505
std            0.007878          0.007878           0.106819
0.298856
min            0.000000          0.000000           0.000000
0.000000
25%            0.000492          0.000492           0.120005
0.230026
50%            0.001260          0.001260           0.185765
0.505935
75%            0.003768          0.003768           0.264881
0.755994
max            1.000000          1.000000           1.000000
1.000000

       absolute_magnitude     hazardous  est_diameter_error
count        90836.000000  90836.000000        90836.000000
mean             0.596458      0.097318            0.003347
std              0.120738      0.296392            0.007878
min              0.000000      0.000000            0.000000
25%              0.505215      0.000000            0.000492
50%              0.603671      0.000000            0.001260
75%              0.687109      0.000000            0.003768
max              1.000000      1.000000            1.000000
```

Top 25 hazardous fastest objects

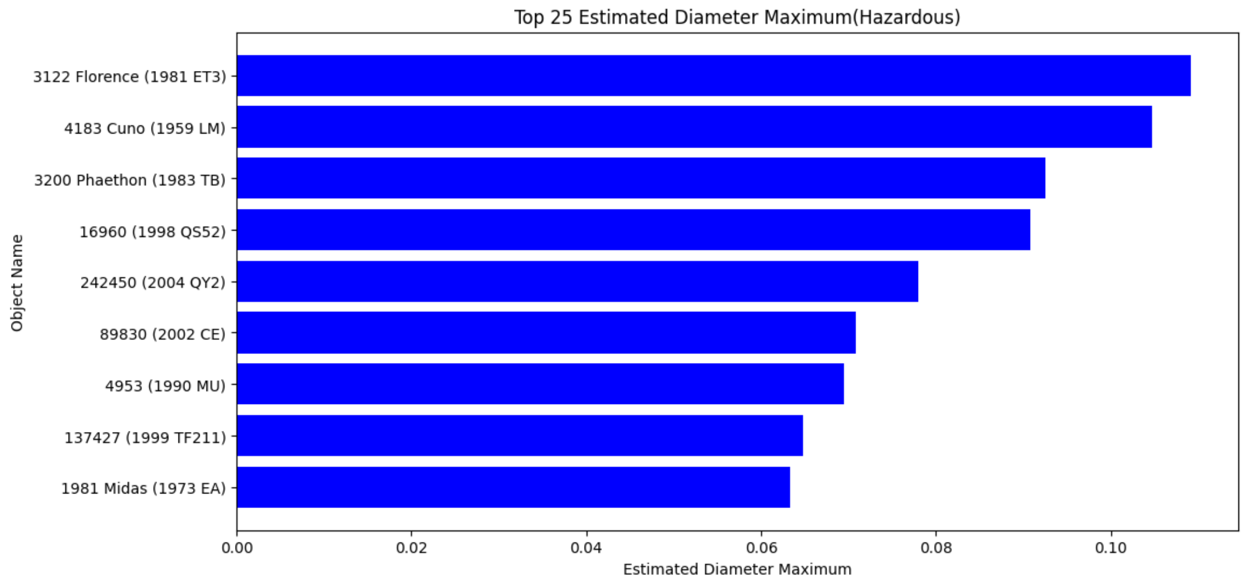
```python
hazardous_df = df[df['hazardous'] == 1]

# Sort the hazardous objects by relative velocity in descending order
sorted_df = hazardous_df.sort_values('relative_velocity',
ascending=False)

# Select the top 25 objects with the highest relative velocity
top_25_df = sorted_df.head(25)

plt.figure(figsize=(12, 6))
plt.barh(top_25_df['name'], top_25_df['relative_velocity'],
color='blue')


plt.xlabel('Relative Velocity')
plt.ylabel('Object Name')
plt.title('Top 25 Fastest Objects (Hazardous)')
plt.gca().invert_yaxis()


plt.show()
```



Top 25 Hazardous Estd diameter maximum

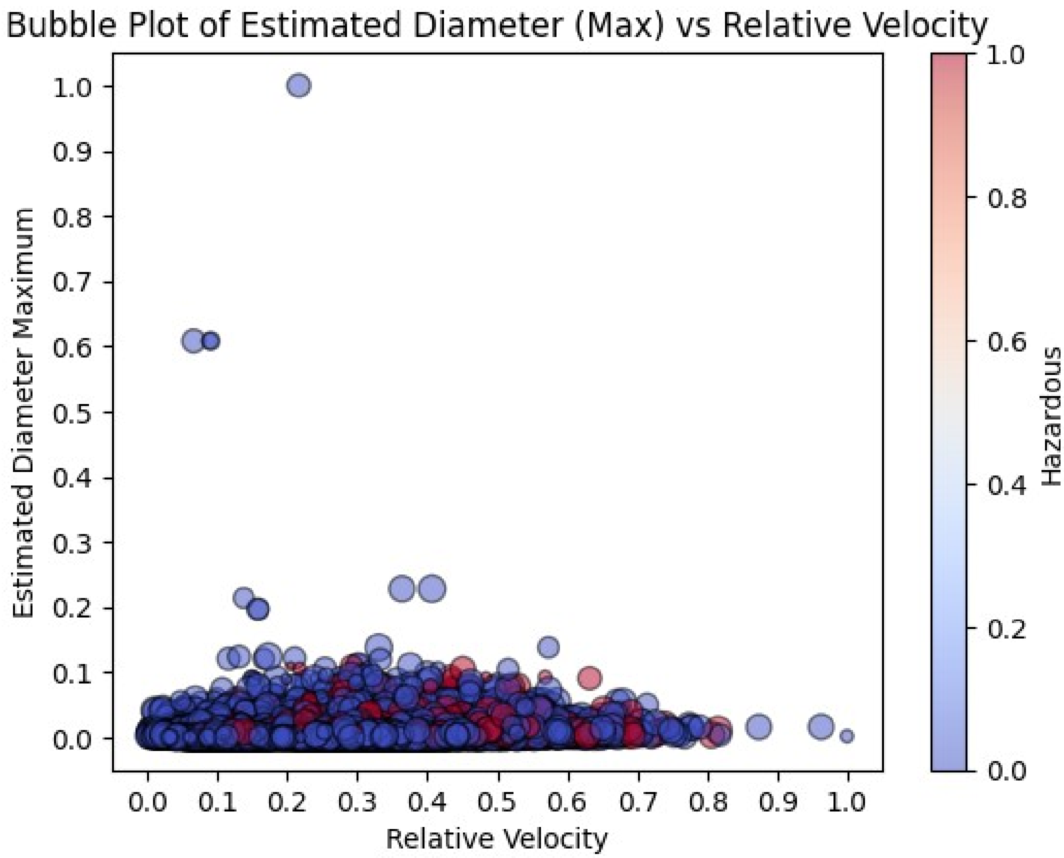
```python
hazardous_df = df[df['hazardous'] == 1]

# Sort the hazardous objects by relative velocity in descending order
sorted_df = hazardous_df.sort_values('est_diameter_max',
ascending=False)
top_25_df = sorted_df.head(25)
plt.figure(figsize=(12, 6))
plt.barh(top_25_df['name'], top_25_df['est_diameter_max'],
```

```
color='blue')

plt.xlabel('Estimated Diameter Maximum')
plt.ylabel('Object Name')
plt.title('Top 25 Estimated Diameter Maximum(Hazardous)')
plt.gca().invert_yaxis()
plt.show()
```



Bubble Plot of Absolute magnitude vs Relative velocity with hazardous and miss distance

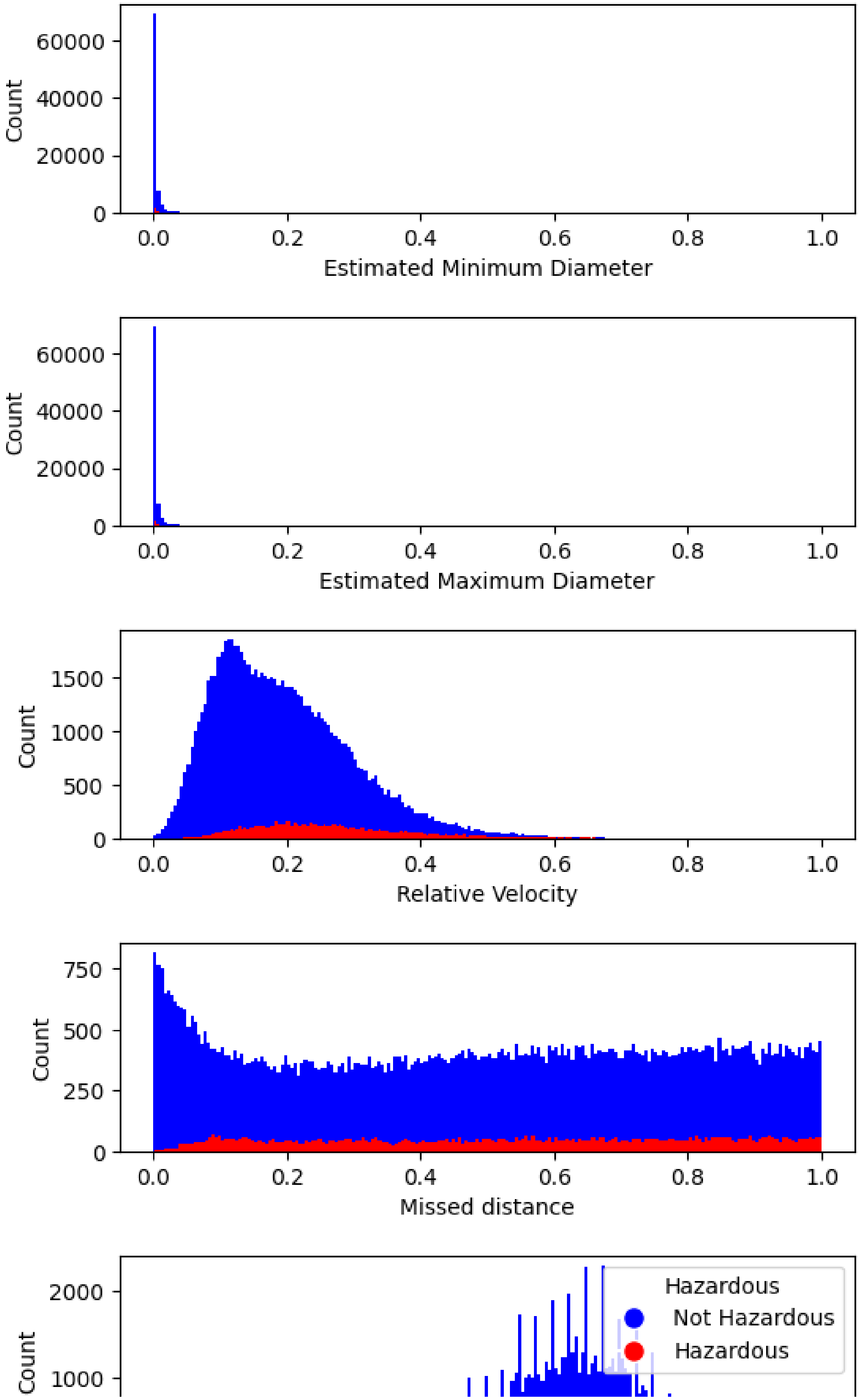
```
# Bubble plot of absolute magnitude vs relative velocity with
hazardous and miss distance
plt.scatter(df['relative_velocity'], df['est_diameter_max'],
c=df['hazardous'], s=(df['miss_distance']*100),
cmap='coolwarm',alpha=0.5,edgecolors='k')
plt.xlabel('Relative Velocity')
plt.ylabel('Estimated Diameter Maximum')
plt.colorbar(label='Hazardous')
plt.yticks([0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0])
plt.xticks([0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0])
plt.title('Bubble Plot of Estimated Diameter (Max) vs Relative
Velocity')
plt.show()
```



Histograms

```
#all histograms red shows hazardous while blue shows non-hazardous
fig, axs = plt.subplots(5, 1, figsize=(6, 12), sharex=False)
fig.subplots_adjust(hspace=0.5)  # Adjust the vertical spacing

hazardous = df[df.hazardous == 1]
non_hazardous = df[df.hazardous == 0]

axs[0].hist(non_hazardous["est_diameter_min"], bins=200, color='blue',
alpha = 1)
axs[0].hist(hazardous["est_diameter_min"], bins=200, color='red',
alpha = 1)

axs[0].set_xlabel("Estimated Minimum Diameter")
axs[0].set_ylabel("Count")


axs[1].hist(non_hazardous["est_diameter_max"], bins=200, color='blue',
alpha = 1)
axs[1].hist(hazardous["est_diameter_max"], bins=200, color='red',
alpha = 1)

axs[1].set_xlabel("Estimated Maximum Diameter")
```

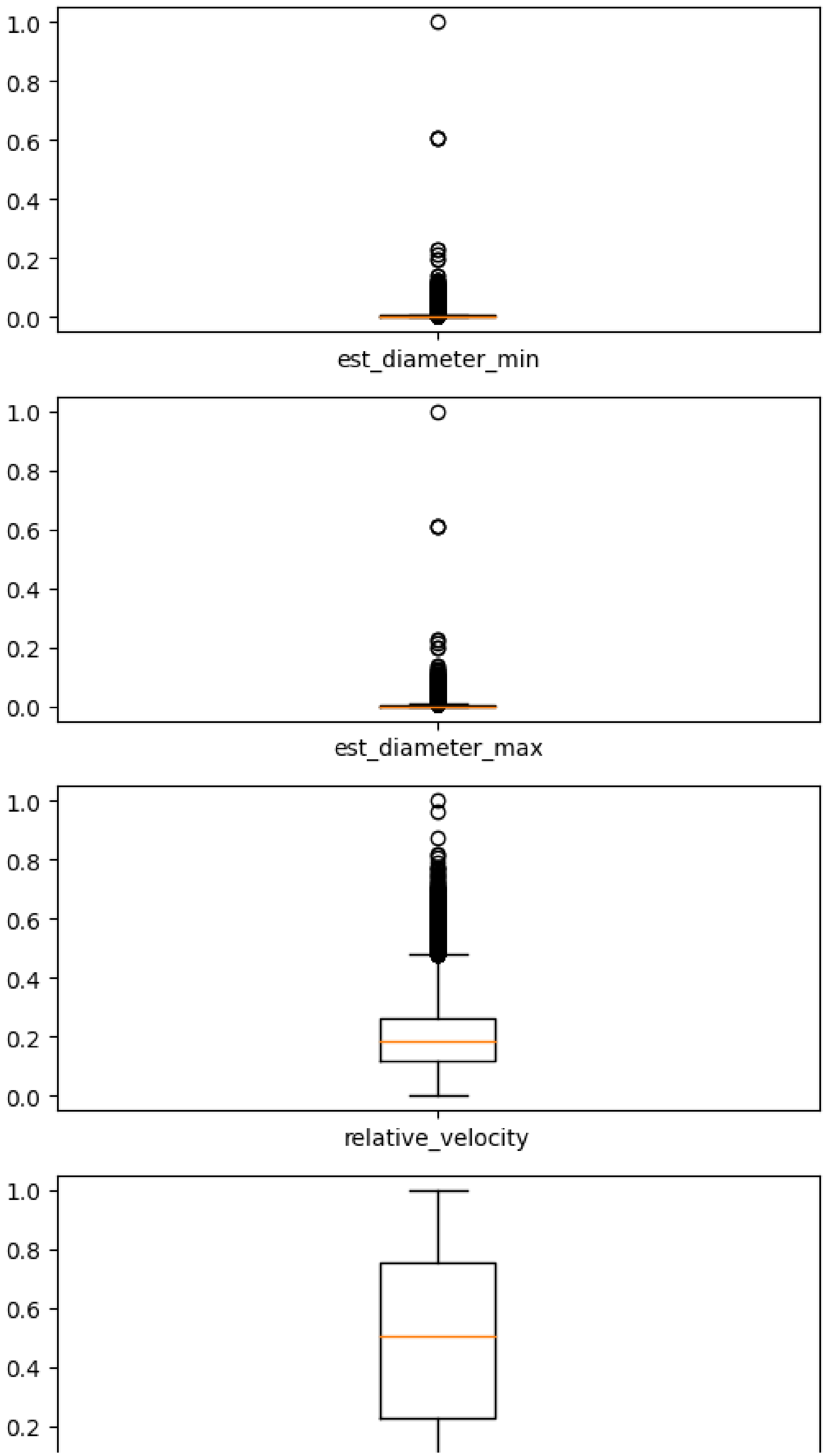
```
axs[1].set_ylabel("Count")

axs[2].hist(non_hazardous["relative_velocity"], bins=200,
color='blue', alpha = 1)
axs[2].hist(hazardous["relative_velocity"], bins=200, color='red',
alpha = 1)

axs[2].set_xlabel("Relative Velocity")
axs[2].set_ylabel("Count")

axs[3].hist(non_hazardous["miss_distance"], bins=200, color='blue',
alpha = 1)
axs[3].hist(hazardous["miss_distance"], bins=200, color='red', alpha =
1)

axs[3].set_xlabel("Missed distance")
axs[3].set_ylabel("Count")

axs[4].hist(non_hazardous["absolute_magnitude"], bins=200,
color='blue', alpha = 1)
axs[4].hist(hazardous["absolute_magnitude"], bins=200, color='red',
alpha = 1)

axs[4].set_xlabel("Absolute Magnitude")
axs[4].set_ylabel("Count")

legend_labels = ['Not Hazardous', 'Hazardous']
legend = [plt.Line2D([0], [0], marker='o', color='w', label=label,
markerfacecolor=color, markersize=10) for color, label in zip(['blue',
'red'], legend_labels)]
plt.legend(handles=legend, title='Hazardous', loc='upper right')
plt.show()


plt.show()
```



Count
60000
40000
20000
0
0.0
0.2
0.4
0.6
0.8
1.0
Estimated Minimum Diameter
Count
60000
40000
20000
0
0.0
0.2
0.4
0.6
0.8
1.0
Estimated Maximum Diameter
Count
1500
1000
500
0
0.0
0.2
0.4
0.6
0.8
1.0
Relative Velocity
Count
750
500
250
0
0.0
0.2
0.4
0.6
0.8
1.0
Missed distance
Count
2000
1000
Hazardous
Not Hazardous
Hazardous

Boxplot of Every Variable

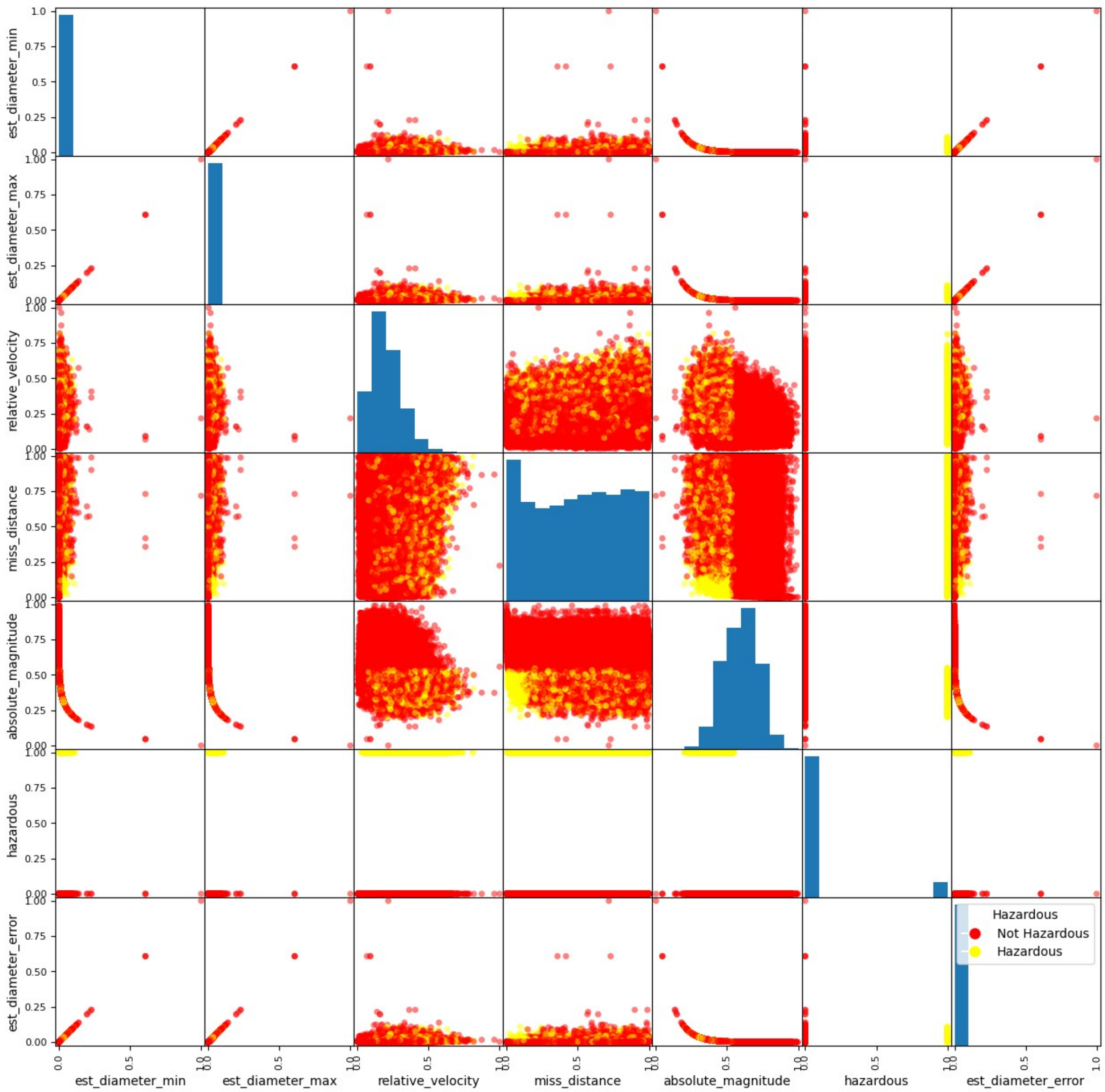
```
#all boxplots
import matplotlib.gridspec as gridspec

fig = plt.figure(figsize=(6, 18))  # Increase the figure height
gs = gridspec.GridSpec(6, 1, height_ratios=[1, 1, 1, 1, 1, 1])  #
Adjust height ratios

axs = [plt.subplot(gs[i]) for i in range(6)]


axs[0].boxplot(df['est_diameter_min'])
axs[0].set_xticklabels(["est_diameter_min"])


axs[1].boxplot(df['est_diameter_max'])
axs[1].set_xticklabels(["est_diameter_max"])


axs[2].boxplot(df['relative_velocity'])
axs[2].set_xticklabels(["relative_velocity"])


axs[3].boxplot(df['miss_distance'])
axs[3].set_xticklabels(["miss_distance"])


axs[4].boxplot(df['absolute_magnitude'])
axs[4].set_xticklabels(["absolute_magnitude"])


axs[5].boxplot(df['est_diameter_error'])
axs[5].set_xticklabels(["est_diameter_error"])

plt.show()
```



1.0
0.8
0.6
0.4
0.2
0.0
est_diameter_min
1.0
0.8
0.6
0.4
0.2
0.0
est_diameter_max
1.0
0.8
0.6
0.4
0.2
0.0
relative_velocity
1.0
0.8
0.6
0.4
0.2

Scatter Matrix Based with Hazardous Attribute

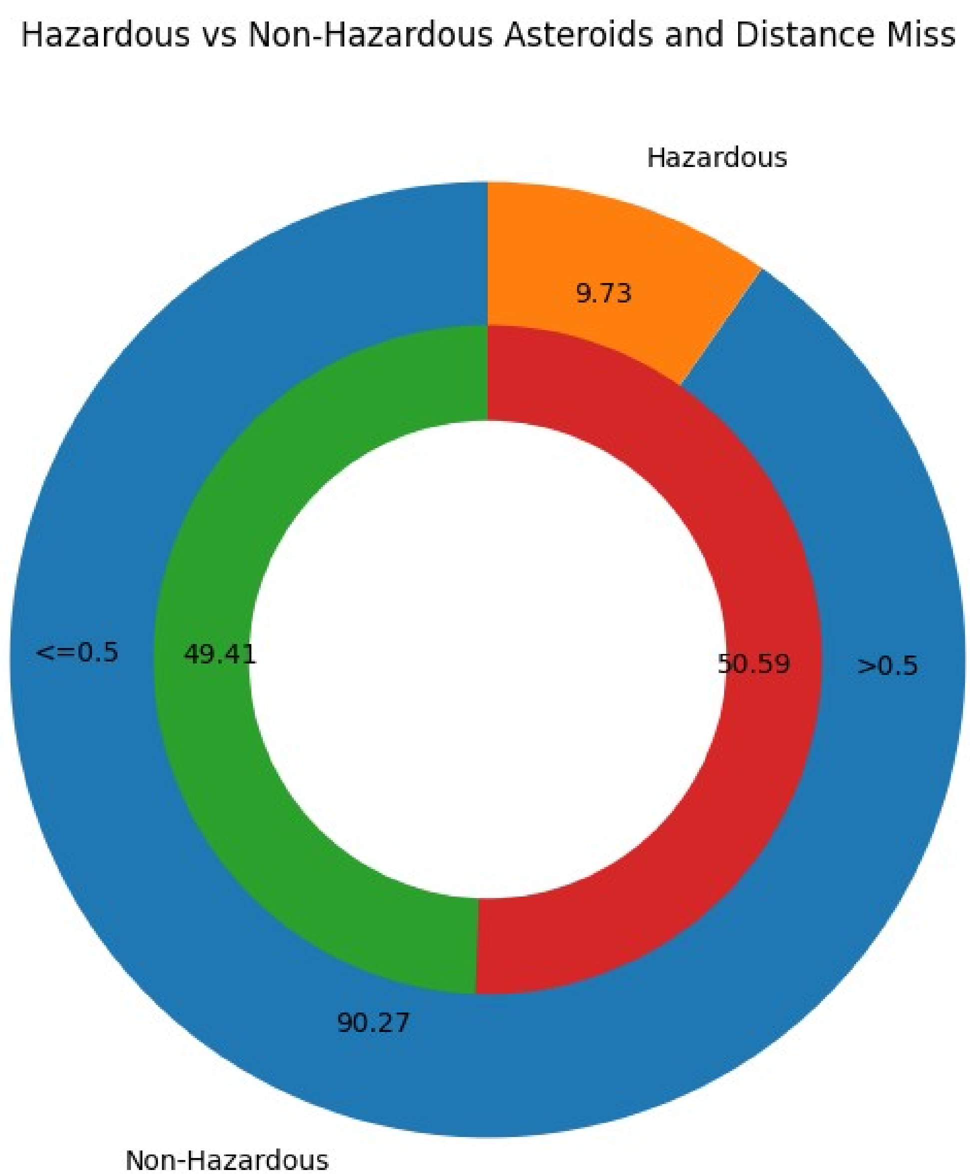
```
#multivariant analysis between each variable with all other. coloring based on hazardous attribute
colors = df['hazardous'].map({0: 'red', 1: 'yellow'})
scatter_matrix = pd.plotting.scatter_matrix(df, figsize=(15, 15), marker='.', s=100,color=colors)
legend_labels = ['Not Hazardous', 'Hazardous']
legend = [plt.Line2D([0], [0], marker='o', color='w', label=label, markerfacecolor=color, markersize=10) for color, label in zip(['red', 'yellow'], legend_labels)]
plt.legend(handles=legend, title='Hazardous', loc='upper right')
plt.show()
```



```python
import numpy as np
```

Donut Plot b/w Hazardous and Miss Distance

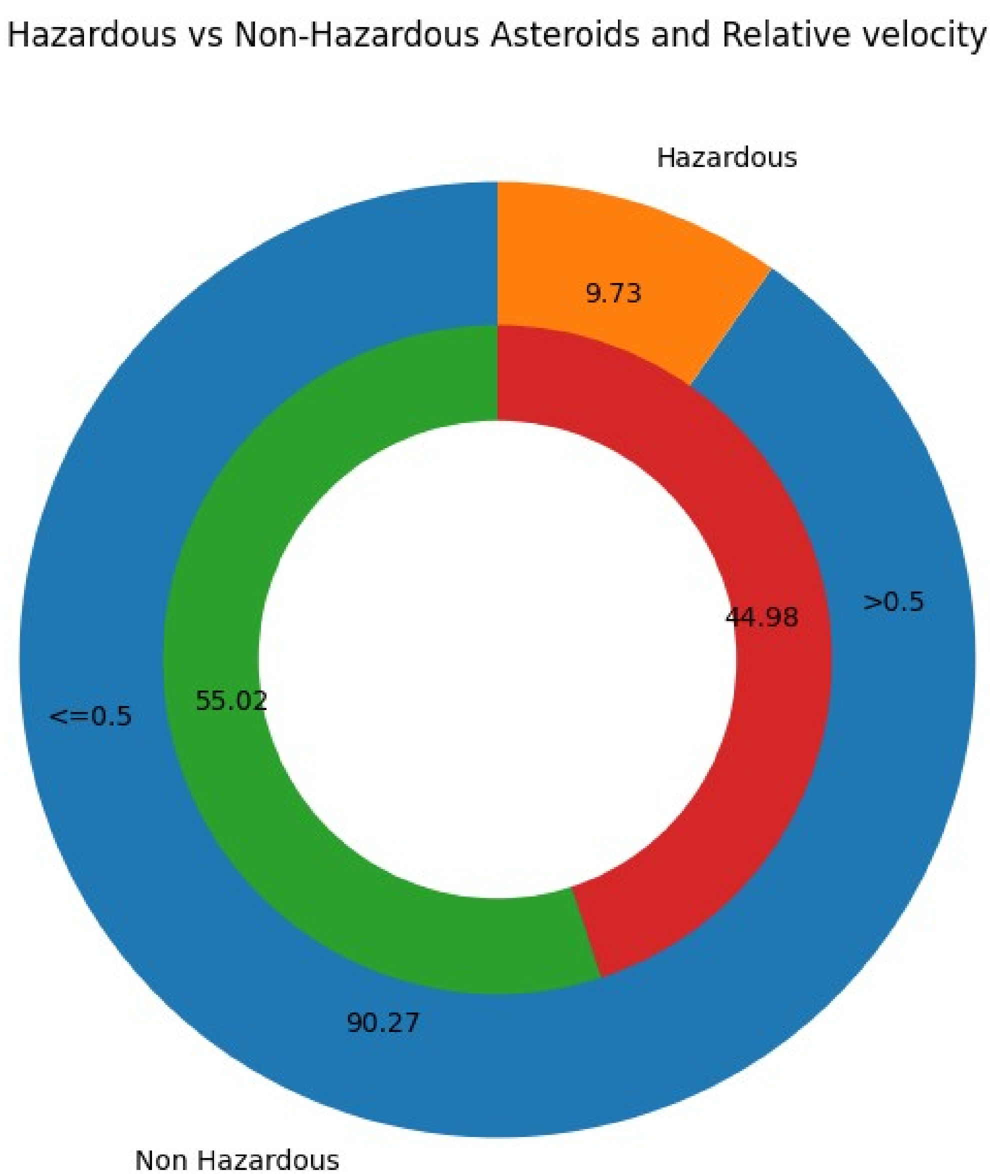
```python
#donut plot b/w hazardous and miss_distance attributes
plt.figure(figsize=(8,8))
#outside donut tells hazardous or not
outs=plt.pie(df.hazardous.value_counts().values,
              labels=["Non-Hazardous","Hazardous"],
              autopct="%0.2f",
              pctdistance=0.80,
              startangle=90)

less_than_half = df[df['miss_distance'] <= 0.5].shape[0]
greater_than_half = df[df['miss_distance'] > 0.5].shape[0]

#inside donut tells us miss_distance
ins=plt.pie([less_than_half, greater_than_half],
              labels=["<=0.5",">0.5"],
              autopct="%0.2f",
              radius=0.7,
              pctdistance=0.80,
              startangle=90)

hole=plt.Circle((0,0),0.5,fc='white')
fig = plt.gcf()
fig.gca().add_artist(hole)
plt.title('Hazardous vs Non-Hazardous Asteroids and Distance Miss')
plt.show()
```



Donut Plot b/w Hazardous and Relative Velocity

```
plt.figure(figsize=(8,8))
#outside donut tells hazardous or not
outs=plt.pie(df.hazardous.value_counts().values,
              labels=["Non Hazardous","Hazardous"],
              autopct="%0.2f",
              pctdistance=0.80,
              startangle=90)

less_than_half = df[df['relative_velocity'] <= 0.2].shape[0]
```

```
greater_than_half = df[df['relative_velocity'] > 0.2].shape[0]

#inside donut tells us relative_velocity
ins=plt.pie([less_than_half, greater_than_half],
              labels=["<=0.5",">0.5"],
              autopct="%0.2f",
              radius=0.7,
              pctdistance=0.80,
              startangle=90)

hole=plt.Circle((0,0),0.5,fc='white')
fig = plt.gcf()
fig.gca().add_artist(hole)
plt.title('Hazardous vs Non-Hazardous Asteroids and Relative
velocity')
plt.show()
```

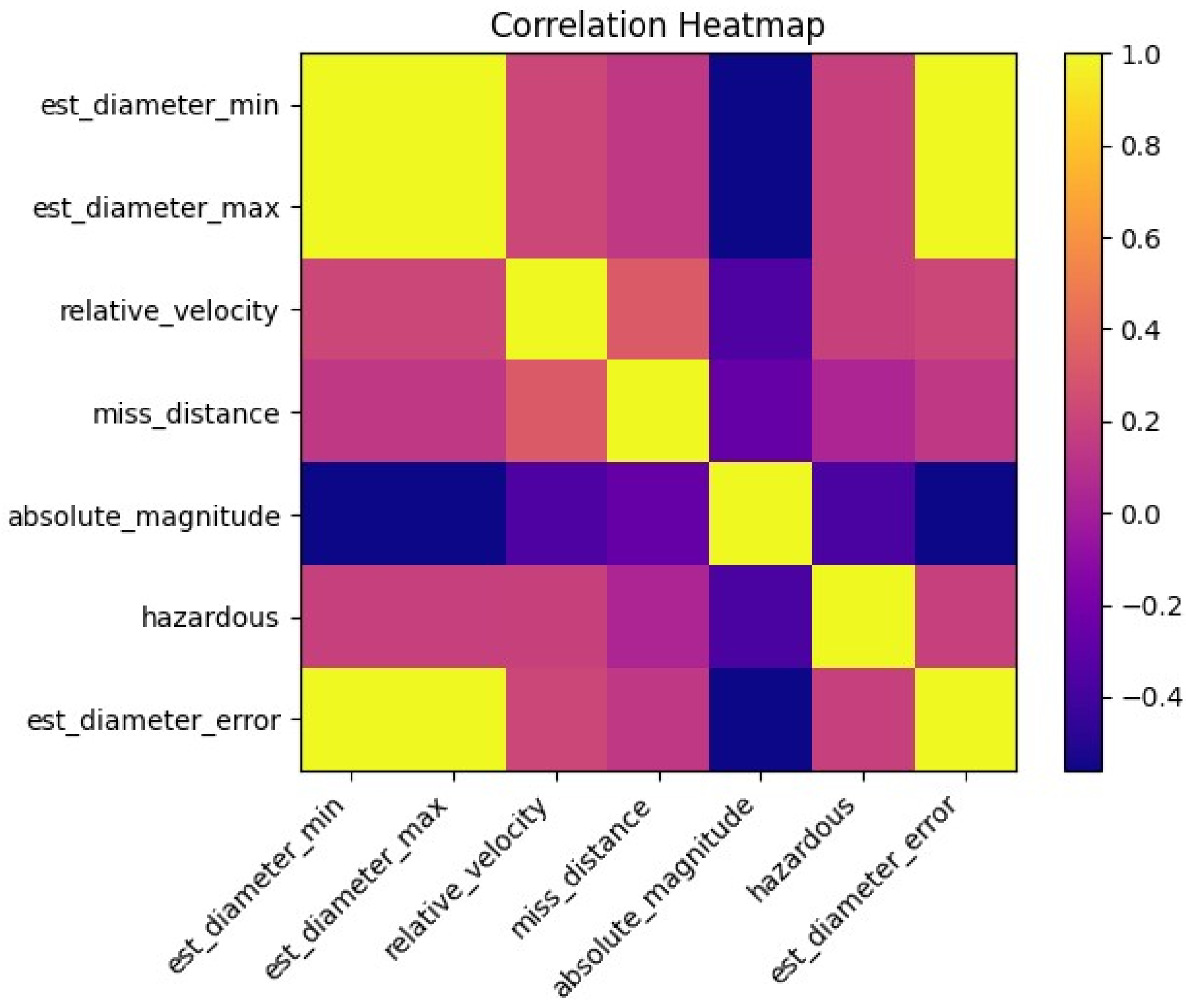


Correlation

```
df2=df.copy()
df2=df2.drop(['name'],axis=1)
df2.head()
corr_matrix=df2.corr()
corr_matrix

                    est_diameter_min  est_diameter_max
relative_velocity  \
est_diameter_min            1.000000          1.000000
0.221553
```

```
est_diameter_max             1.000000         1.000000
0.221553
relative_velocity            0.221553         0.221553
1.000000
miss_distance                0.142241         0.142241
0.327169
absolute_magnitude          -0.560188        -0.560188          -
0.353863
hazardous                    0.183363         0.183363
0.191185
est_diameter_error           1.000000         1.000000
0.221553

                    miss_distance  absolute_magnitude  hazardous  \
est_diameter_min         0.142241           -0.560188   0.183363
est_diameter_max         0.142241           -0.560188   0.183363
relative_velocity        0.327169           -0.353863   0.191185
miss_distance            1.000000           -0.264168   0.042302
absolute_magnitude      -0.264168            1.000000  -0.365267
hazardous                0.042302           -0.365267   1.000000
est_diameter_error       0.142241           -0.560188   0.183363

                    est_diameter_error
est_diameter_min              1.000000
est_diameter_max              1.000000
relative_velocity             0.221553
miss_distance                 0.142241
absolute_magnitude           -0.560188
hazardous                     0.183363
est_diameter_error            1.000000
```

```
heatmap=plt.imshow(corr_matrix, cmap='plasma', interpolation='none',
aspect='equal')
plt.title("Correlation Heatmap")
plt.title("Correlation Heatmap")
plt.title("Correlation Heatmap")
plt.yticks(np.arange(len(corr_matrix.columns)), corr_matrix.columns)

# Set x-ticks and labels (column names) on the x-axis
plt.xticks(np.arange(len(corr_matrix.columns)), corr_matrix.columns,
rotation=45, ha='right')
plt.colorbar(heatmap)
plt.show()
```



Deliverable 3

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.figure as fig
from matplotlib.backends.backend_tkagg import FigureCanvasTkAgg
import sklearn
from sklearn.model_selection import train_test_split
import keras
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout

df=pd.read_csv("cleaned_neo_v2.csv")

df.head()
```

```
                    name  est_diameter_min  est_diameter_max
relative_velocity  \
0  162635 (2000 SS164)          0.031607          0.031607
0.056447
1    277475 (2005 WK4)          0.006999          0.006999
0.309922
2   512244 (2015 YE18)          0.019039          0.019039
0.481680
3          (2012 BV13)          0.002531          0.002531
0.103726
4          (2014 GE35)          0.006714          0.006714
0.179632

   miss_distance  absolute_magnitude  hazardous  est_diameter_error
0       0.733141            0.312891          0            0.031607
1       0.821364            0.449312          1            0.006999
2       0.665740            0.358782          0            0.019039
3       0.339986            0.541093          0            0.002531
4       0.618634            0.453066          1            0.006714

X =
df.drop(columns=['name','est_diameter_min','est_diameter_error','hazar
dous'], axis=1)
y = df['hazardous']
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

model = keras.Sequential([
    keras.layers.Dense(81, input_dim=4, activation='relu'),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.Dense(16, activation='relu'),
    keras.layers.Dense(1, activation='sigmoid')
])
opt = keras.optimizers.Adam(learning_rate=0.01)
model.compile(optimizer=opt, loss='binary_crossentropy',
metrics=['accuracy'])

history = model.fit(X_train, y_train, epochs=5, batch_size=256,
validation_data=(X_test, y_test))

loss, accuracy = model.evaluate(X_test, y_test)
loss2, accuracy2 =model.evaluate(X_train,y_train)
print(f'Training dataset loss: {loss2}, validation: {accuracy2}')
print(f'Validation dataset Loss: {loss}, Test Accuracy: {accuracy}')

Epoch 1/5
284/284 [==============================] - 3s 5ms/step - loss: 0.2230
- accuracy: 0.9014 - val_loss: 0.1981 - val_accuracy: 0.9113
Epoch 2/5
```

```
284/284 [==============================] - 2s 6ms/step - loss: 0.1991
- accuracy: 0.9095 - val_loss: 0.1901 - val_accuracy: 0.9129
Epoch 3/5
284/284 [==============================] - 2s 7ms/step - loss: 0.1949
- accuracy: 0.9109 - val_loss: 0.1887 - val_accuracy: 0.9135
Epoch 4/5
284/284 [==============================] - 2s 6ms/step - loss: 0.1941
- accuracy: 0.9108 - val_loss: 0.1974 - val_accuracy: 0.9136
Epoch 5/5
284/284 [==============================] - 1s 4ms/step - loss: 0.1934
- accuracy: 0.9110 - val_loss: 0.1889 - val_accuracy: 0.9124
568/568 [==============================] - 1s 2ms/step - loss: 0.1889
- accuracy: 0.9124
2271/2271 [==============================] - 4s 2ms/step - loss:
0.1895 - accuracy: 0.9105
Training dataset loss: 0.18954584002494812, validation:
0.9105383157730103
Validation dataset Loss: 0.1889345347881317, Test Accuracy:
0.9124284386634827
```

```
model.save("model.h5")
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/engine/
training.py:3079: UserWarning: You are saving your model as an HDF5
file via `model.save()`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')`.
```

```
from tensorflow.keras.models import load_model
sample_data = [[0.031607,  0.056447,  0.733141,  0.312891   ]]
load_model("model.h5")
model.predict(sample_data)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call
last)
<ipython-input-6-39bab5a27c7d> in <cell line: 4>()
      2 sample_data = [[0.031607,       0.056447,       0.733141,
0.312891        ]]
      3 load_model("model.h5")
----> 4 model.predict(sample_data)

NameError: name 'model' is not defined
```

```
# Assuming your model is already trained and compiled
loss, accuracy = model.evaluate(X_test, y_test)
print(f'Accuracy: {accuracy}')
print(f'Loss: {loss}')
```

```
568/568 [==============================] - 1s 2ms/step - loss: 0.1889
- accuracy: 0.9124
Accuracy: 0.9124284386634827
Loss: 0.1889345347881317
```

```
import joblib

joblib.dump(model, 'model.pkl')
```

```
['model.pkl']
```

```
# Load the model from the .pkl file
loaded_model = joblib.load('model.pkl')

sample_data = [[0.031607,  0.056447,  0.733141,  0.312891   ]]  #
Replace with actual data
predictions = loaded_model.predict(sample_data)
print(predictions)
```

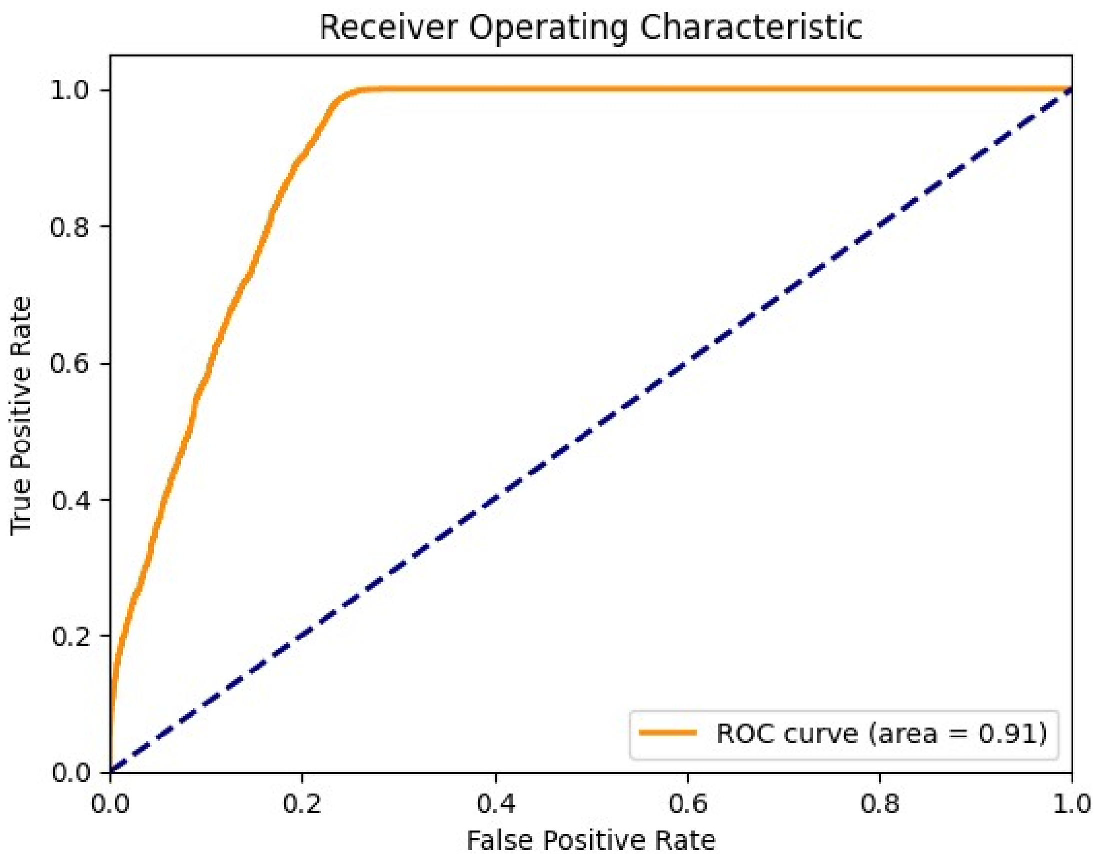
```
1/1 [==============================] - 0s 41ms/step
[[0.26265946]]
```

```
y_pred_binary = (predictions > 0.034).astype(int)

print(y_pred_binary)
```

```
[[1]]
```

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
from plotnine import *
import plotnine


predicted_probabilities = model.predict(X_test)
positive_probabilities = predicted_probabilities[:, 0]

fpr, tpr, thresholds = roc_curve(y_test, positive_probabilities)
roc_auc = auc(fpr, tpr)
df_fpr_tpr = pd.DataFrame({'FPR':fpr, 'TPR':tpr,
'Threshold':thresholds})
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area =
%0.2f)' % roc_auc)

plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])

plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
```

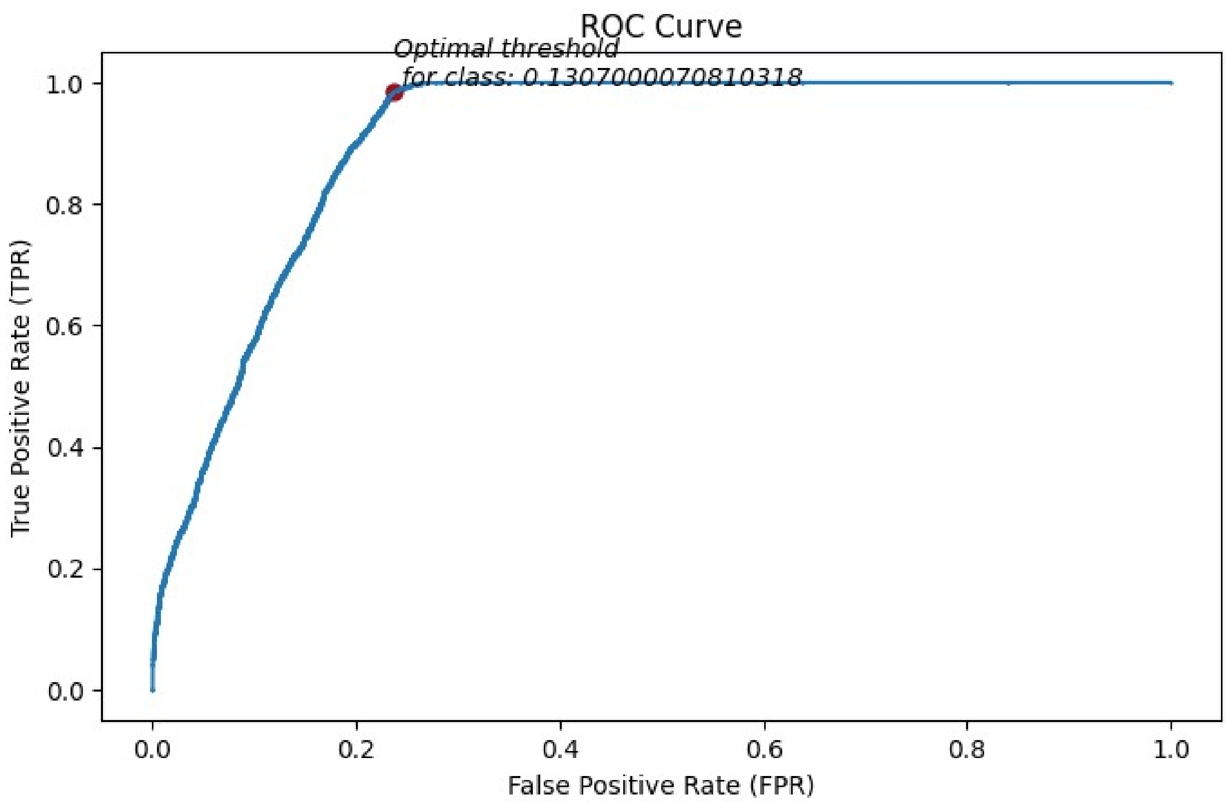
```
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()


568/568 [==============================] - 1s 2ms/step
```




```
df_fpr_tpr = pd.DataFrame({'FPR':fpr, 'TPR':tpr,
'Threshold':thresholds})
g_mean = np.sqrt(tpr * (1 - fpr))

index = np.argmax(g_mean)

thresholdOpt = round(thresholds[index], ndigits = 4)

gmeanOpt = round(g_mean[index], ndigits = 4)
fprOpt = round(fpr[index], ndigits = 4)

tprOpt = round(tpr[index], ndigits = 4)

print('Best Threshold: {} with G-Mean: {}'.format(thresholdOpt,
gmeanOpt))
```

```
print('FPR: {}, TPR: {}'.format(fprOpt, tprOpt))


import matplotlib.pyplot as plt
plt.figure(figsize=(8, 4.8))
plt.scatter(df_fpr_tpr['FPR'], df_fpr_tpr['TPR'], s=0.4)
plt.scatter(fprOpt, tprOpt, color='#981220', s=40)
plt.plot(df_fpr_tpr['FPR'], df_fpr_tpr['TPR'])
plt.text(fprOpt, tprOpt, 'Optimal threshold \n for class:
{}'.format(thresholdOpt),ha='left', va='bottom', fontsize=10,
style='italic')
plt.title('ROC Curve')
plt.xlabel('False Positive Rate (FPR)')
plt.ylabel('True Positive Rate (TPR)')
plt.show()
```

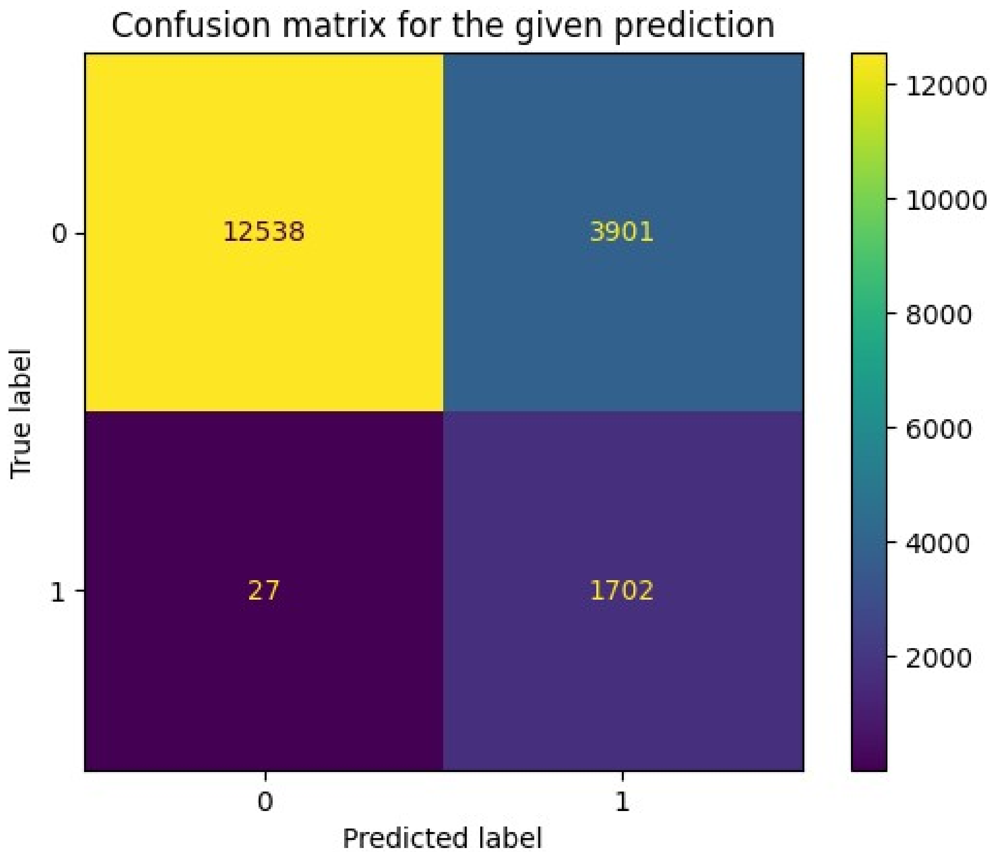
```
Best Threshold: 0.1307000070810318 with G-Mean: 0.8665
FPR: 0.2372, TPR: 0.9844
```




```
from sklearn.metrics import
f1_score,accuracy_score,confusion_matrix,ConfusionMatrixDisplay,classi
fication_report
from sklearn.metrics import recall_score,precision_score
y_pred = model.predict(X_test)
```

```
y_true_classes = y_test
#thresholding for binary classification
y_pred_binary = (y_pred > 0.13).astype(int)

def evaluation(y_test,y_pred):

    print('Accuracy Score:',accuracy_score(y_test,y_pred))
    print('f1_score:',f1_score(y_test,y_pred))
    print('Precision:',precision_score(y_test,y_pred))
    print('Recall:',recall_score(y_test,y_pred))
    print('Classification report:\
n',classification_report(y_test,y_pred))
    cm=confusion_matrix(y_test,y_pred)
    ConfusionMatrixDisplay(cm).plot()
    plt.title('Confusion matrix for the given prediction')
    plt.show()

evaluation(y_true_classes,y_pred_binary)
```

```
568/568 [==============================] - 1s 2ms/step
Accuracy Score: 0.7837956847203875
f1_score: 0.46426623022367697
Precision: 0.30376583972871674
Recall: 0.9843840370156159
Classification report:
               precision    recall  f1-score   support

           0       1.00      0.76      0.86     16439
           1       0.30      0.98      0.46      1729

    accuracy                           0.78     18168
   macro avg       0.65      0.87      0.66     18168
weighted avg       0.93      0.78      0.83     18168
```

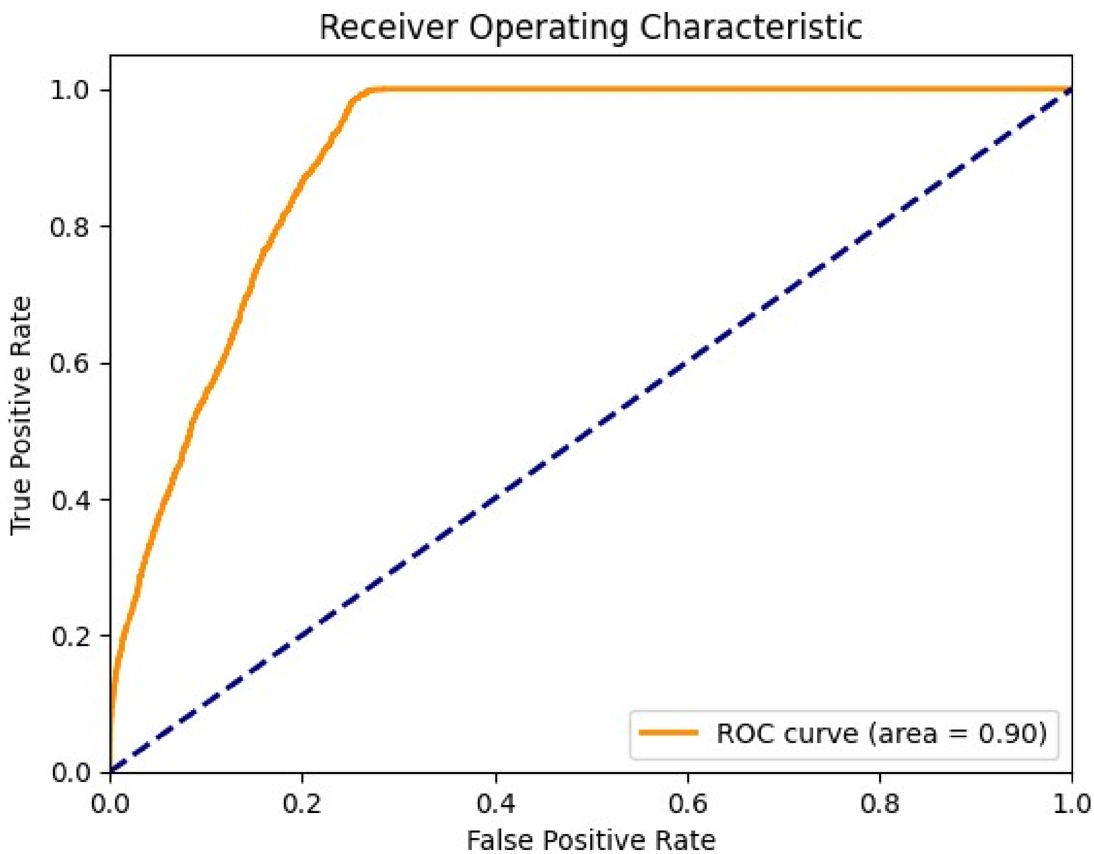


Alternative Approaches Tried

```
model = keras.Sequential([
    keras.layers.Dense(256, input_dim=4, activation='relu'),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.Dense(32, activation='relu'),
    keras.layers.Dense(16, activation='relu'),
    keras.layers.Dense(1, activation='sigmoid')
])
opt = keras.optimizers.Adam(learning_rate=0.01)
model.compile(optimizer=opt, loss='binary_crossentropy',
metrics=['accuracy'])

history = model.fit(X_train, y_train, epochs=5, batch_size=256,
validation_data=(X_test, y_test))

loss, accuracy = model.evaluate(X_test, y_test)
loss2, accuracy2 =model.evaluate(X_train,y_train)
```

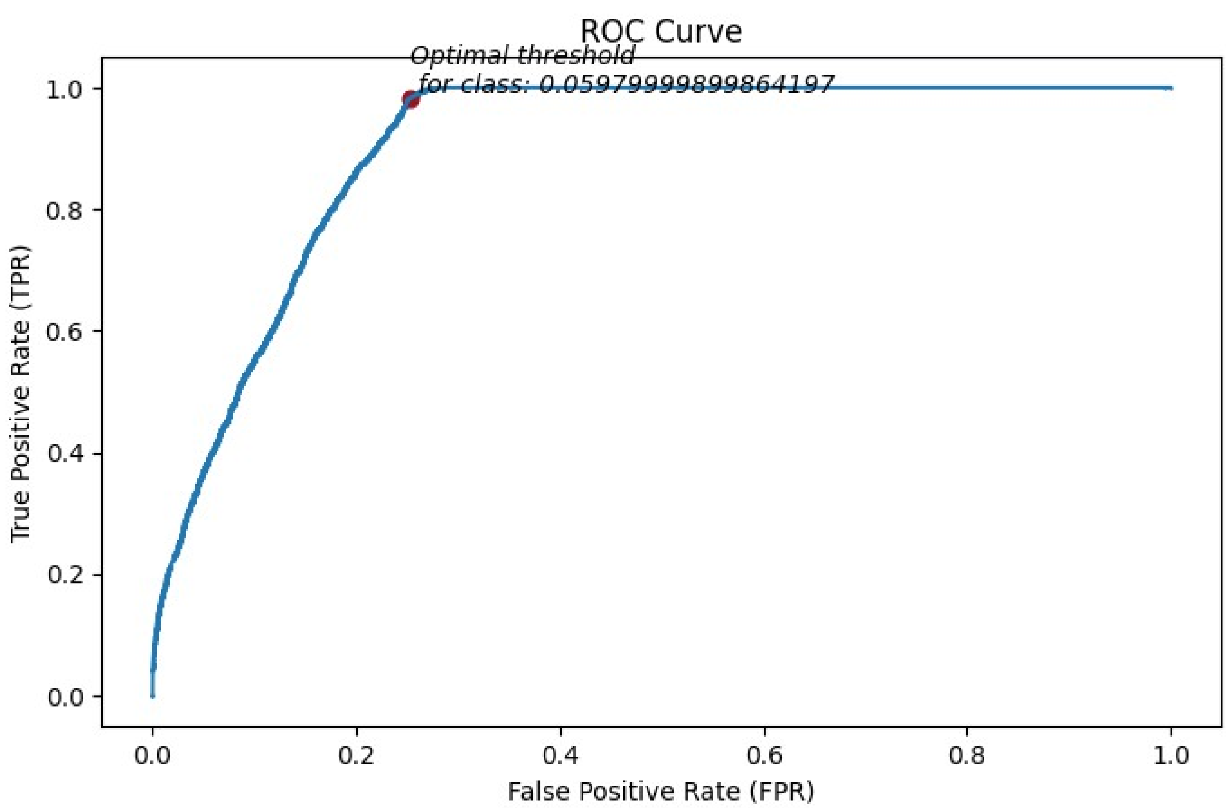
```
print(f'Training dataset loss: {loss2}, validation: {accuracy2}')
print(f'Validation dataset Loss: {loss}, Test Accuracy: {accuracy}')

Epoch 1/5
284/284 [==============================] - 5s 10ms/step - loss: 0.2242
- accuracy: 0.9014 - val_loss: 0.1938 - val_accuracy: 0.9111
Epoch 2/5
284/284 [==============================] - 3s 10ms/step - loss: 0.1990
- accuracy: 0.9088 - val_loss: 0.2043 - val_accuracy: 0.9052
Epoch 3/5
284/284 [==============================] - 3s 11ms/step - loss: 0.1985
- accuracy: 0.9091 - val_loss: 0.1944 - val_accuracy: 0.9053
Epoch 4/5
284/284 [==============================] - 4s 14ms/step - loss: 0.1958
- accuracy: 0.9091 - val_loss: 0.1948 - val_accuracy: 0.9057
Epoch 5/5
284/284 [==============================] - 3s 10ms/step - loss: 0.1948
- accuracy: 0.9099 - val_loss: 0.1912 - val_accuracy: 0.9122
568/568 [==============================] - 1s 2ms/step - loss: 0.1912
- accuracy: 0.9122
2271/2271 [==============================] - 6s 3ms/step - loss:
0.1913 - accuracy: 0.9104
Training dataset loss: 0.19132466614246368, validation:
0.9104282259941101
Validation dataset Loss: 0.19118881225585938, Test Accuracy:
0.9121532440185547

import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
from plotnine import *
import plotnine


predicted_probabilities = model.predict(X_test)
positive_probabilities = predicted_probabilities[:, 0]

fpr, tpr, thresholds = roc_curve(y_test, positive_probabilities)
roc_auc = auc(fpr, tpr)
df_fpr_tpr = pd.DataFrame({'FPR':fpr, 'TPR':tpr,
'Threshold':thresholds})
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area =
%0.2f)' % roc_auc)

plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])

plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
```

```
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()


568/568 [==============================] - 1s 2ms/step
```




```
df_fpr_tpr = pd.DataFrame({'FPR':fpr, 'TPR':tpr,
'Threshold':thresholds})
g_mean = np.sqrt(tpr * (1 - fpr))

index = np.argmax(g_mean)

thresholdOpt = round(thresholds[index], ndigits = 4)

gmeanOpt = round(g_mean[index], ndigits = 4)
fprOpt = round(fpr[index], ndigits = 4)

tprOpt = round(tpr[index], ndigits = 4)

print('Best Threshold: {} with G-Mean: {}'.format(thresholdOpt,
gmeanOpt))
```

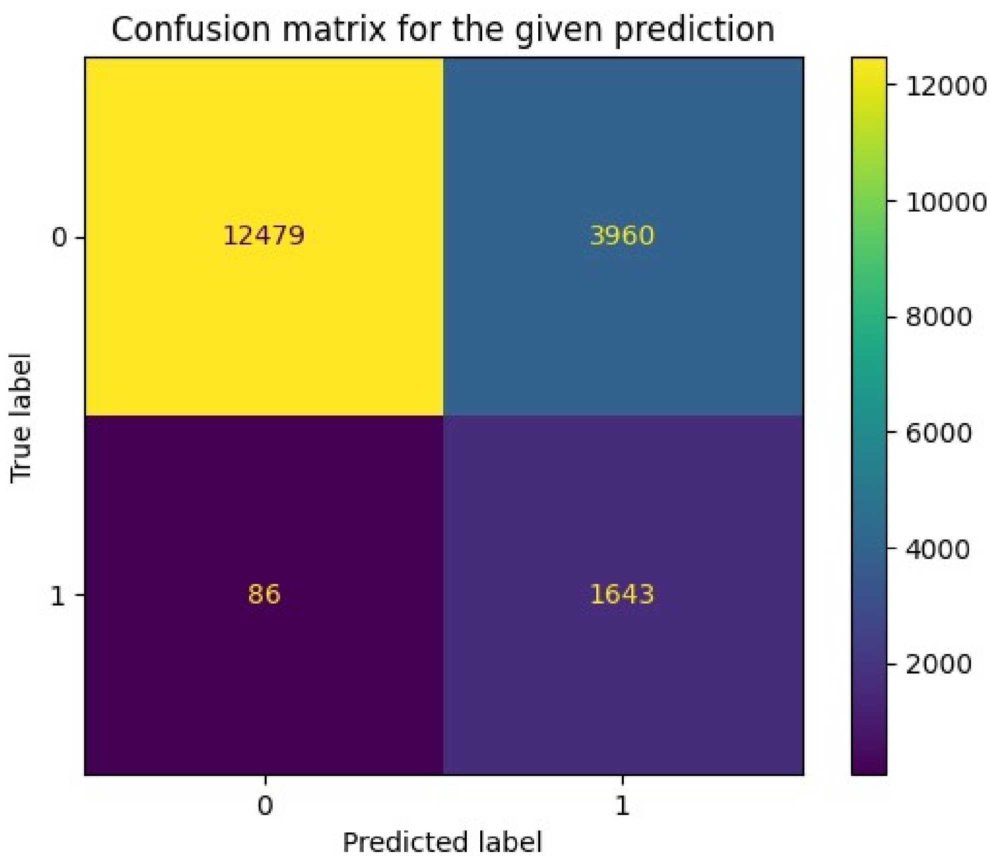
```
print('FPR: {}, TPR: {}'.format(fprOpt, tprOpt))


import matplotlib.pyplot as plt
plt.figure(figsize=(8, 4.8))
plt.scatter(df_fpr_tpr['FPR'], df_fpr_tpr['TPR'], s=0.4)
plt.scatter(fprOpt, tprOpt, color='#981220', s=40)
plt.plot(df_fpr_tpr['FPR'], df_fpr_tpr['TPR'])
plt.text(fprOpt, tprOpt, 'Optimal threshold \n for class:
{}'.format(thresholdOpt),ha='left', va='bottom', fontsize=10,
style='italic')
plt.title('ROC Curve')
plt.xlabel('False Positive Rate (FPR)')
plt.ylabel('True Positive Rate (TPR)')
plt.show()

Best Threshold: 0.05979999899864197 with G-Mean: 0.857
FPR: 0.2521, TPR: 0.9821
```




```
from sklearn.metrics import
f1_score,accuracy_score,confusion_matrix,ConfusionMatrixDisplay,classi
fication_report
from sklearn.metrics import recall_score,precision_score
y_pred = model.predict(X_test)
```

```
y_true_classes = y_test
#thresholding for binary classification
y_pred_binary = (y_pred > 0.14).astype(int)

evaluation(y_true_classes,y_pred_binary)
```

```
568/568 [==============================] - 1s 2ms/step
Accuracy Score: 0.7773007485689124
f1_score: 0.4481723949809056
Precision: 0.293235766553632
Recall: 0.9502602660497398
Classification report:
              precision    recall  f1-score   support

           0       0.99      0.76      0.86     16439
           1       0.29      0.95      0.45      1729

    accuracy                           0.78     18168
   macro avg       0.64      0.85      0.65     18168
weighted avg       0.93      0.78      0.82     18168
```



Trying with SMOTE

```
y.value_counts()
```

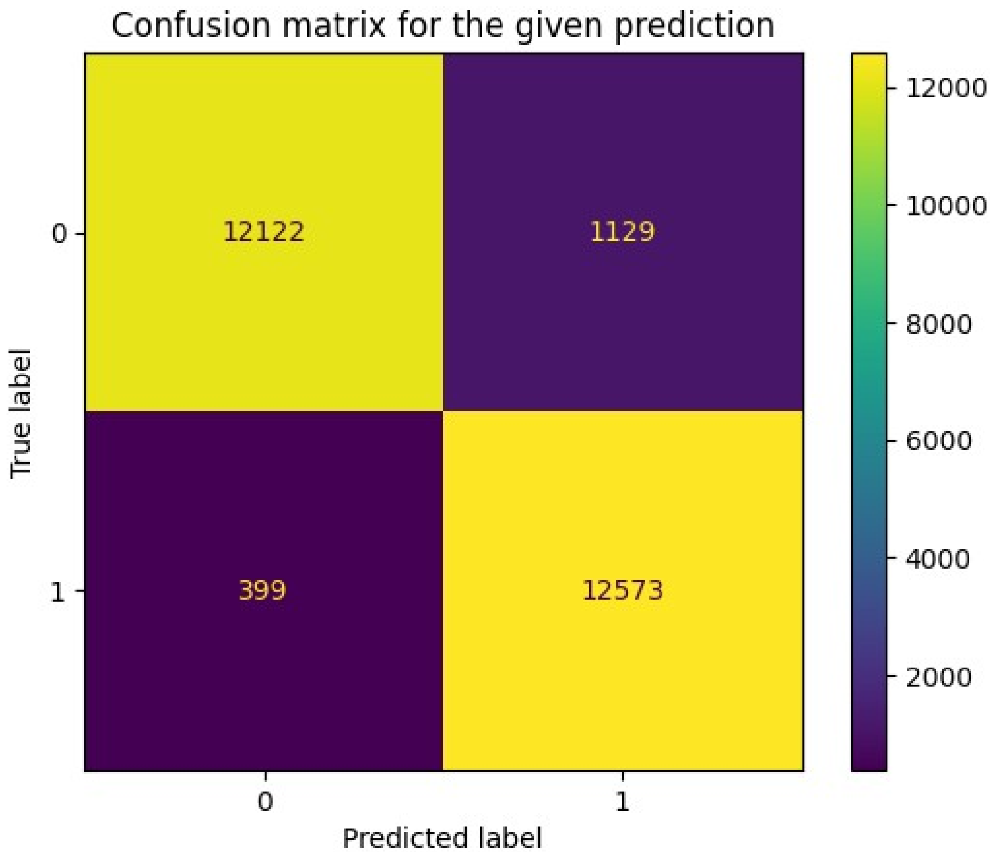
```
0    81996
1     8840
Name: hazardous, dtype: int64
```

```
from imblearn.over_sampling import SMOTE
smote = SMOTE(random_state=42)
X =
df.drop(columns=['name','est_diameter_min','est_diameter_error','hazar
dous'], axis=1)
y = df['hazardous']
X_resampled, y_resampled = smote.fit_resample(X_train, y_train)
X_train, X_test, y_train, y_test = train_test_split(X_resampled,
y_resampled, test_size=0.2, random_state=42)
```

Random Forest Classifier

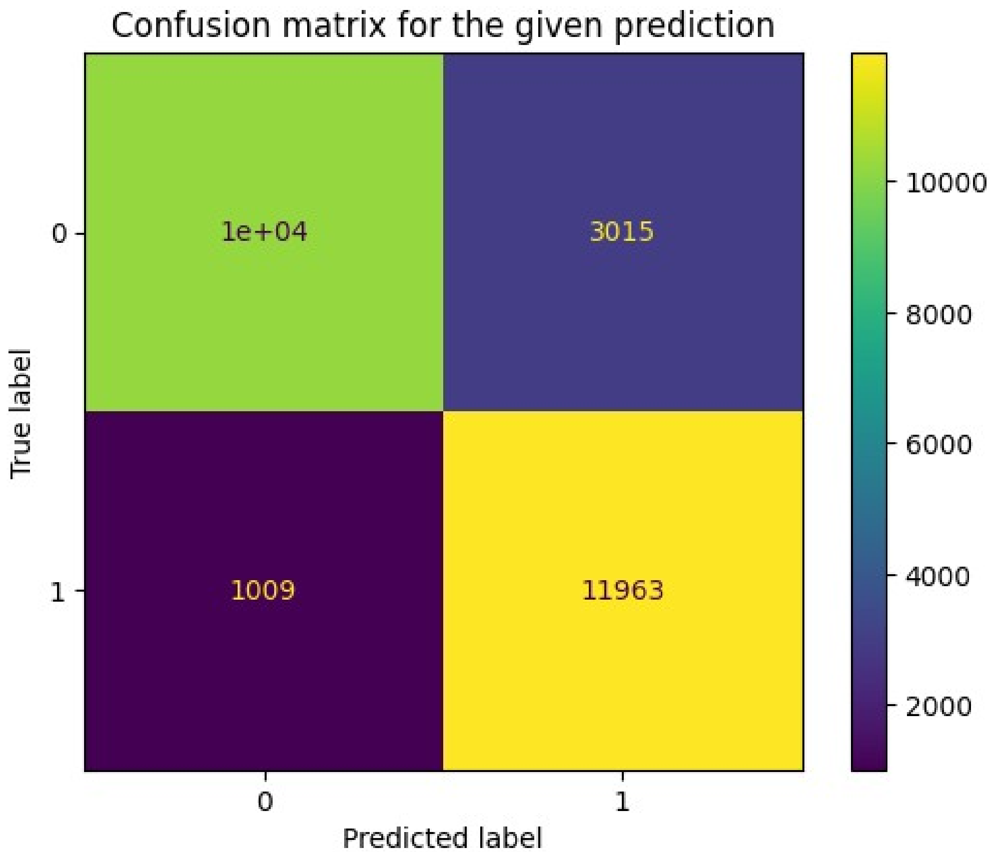
```
from sklearn.ensemble import
RandomForestClassifier,GradientBoostingClassifier
rf=RandomForestClassifier()
y_pred=rf.fit(X_train,y_train).predict(X_test)
evaluation(y_test,y_pred)
```

```
Accuracy Score: 0.9417305418907066
f1_score: 0.9427157531678788
Precision: 0.9176032695956795
Recall: 0.9692414431082331
Classification report:
               precision    recall  f1-score   support

           0       0.97      0.91      0.94     13251
           1       0.92      0.97      0.94     12972

    accuracy                           0.94     26223
   macro avg       0.94      0.94      0.94     26223
weighted avg       0.94      0.94      0.94     26223
```



Linear Regression

```
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression() # Machine instance
lr_model=lr.fit(X_train,y_train)
y_pred=lr_model.predict(X_test)
evaluation(y_test,y_pred)

Accuracy Score: 0.8465469244556305
f1_score: 0.8560286225402505
Precision: 0.7987047669915877
Recall: 0.9222170829478877
Classification report:
               precision    recall  f1-score   support

           0       0.91      0.77      0.84     13251
           1       0.80      0.92      0.86     12972

    accuracy                           0.85     26223
   macro avg       0.85      0.85      0.85     26223
weighted avg       0.86      0.85      0.85     26223
```



Custom Neural network

```
# model = keras.Sequential([
#     keras.layers.Dense(512, input_dim=4, activation='relu'),
#      keras.layers.Dense(512, activation='relu'),
#     keras.layers.Dense(512, activation='relu'),
#     keras.layers.Dense(512, activation='relu'),
#     keras.layers.Dense(256, activation='relu'),
#     keras.layers.Dense(256, activation='relu'),
#     keras.layers.Dense(64, activation='relu'),
#     keras.layers.Dense(64, activation='relu'),
#     keras.layers.Dense(128, activation='relu'),
#     keras.layers.Dense(128, activation='relu'),
#     keras.layers.Dense(128, activation='relu'),
#     keras.layers.Dense(1, activation='sigmoid')
# ])
model = keras.Sequential([
    keras.layers.Dense(512, input_dim=4, activation='relu',
kernel_initializer='he_normal'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(512, activation='relu',
kernel_initializer='he_normal'),
```

```
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(512, activation='relu',
kernel_initializer='he_normal'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(512, activation='relu',
kernel_initializer='he_normal'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(256, activation='relu',
kernel_initializer='he_normal'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(256, activation='relu',
kernel_initializer='he_normal'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(512, activation='relu',
kernel_initializer='he_normal'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(512, activation='relu',
kernel_initializer='he_normal'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(128, activation='relu',
kernel_initializer='he_normal'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(128, activation='relu',
kernel_initializer='he_normal'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(128, activation='relu',
kernel_initializer='he_normal'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.2),
     keras.layers.Dense(128, activation='relu',
kernel_initializer='he_normal'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(128, activation='relu',
kernel_initializer='he_normal'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(128, activation='relu',
kernel_initializer='he_normal'),
    keras.layers.BatchNormalization(),
```

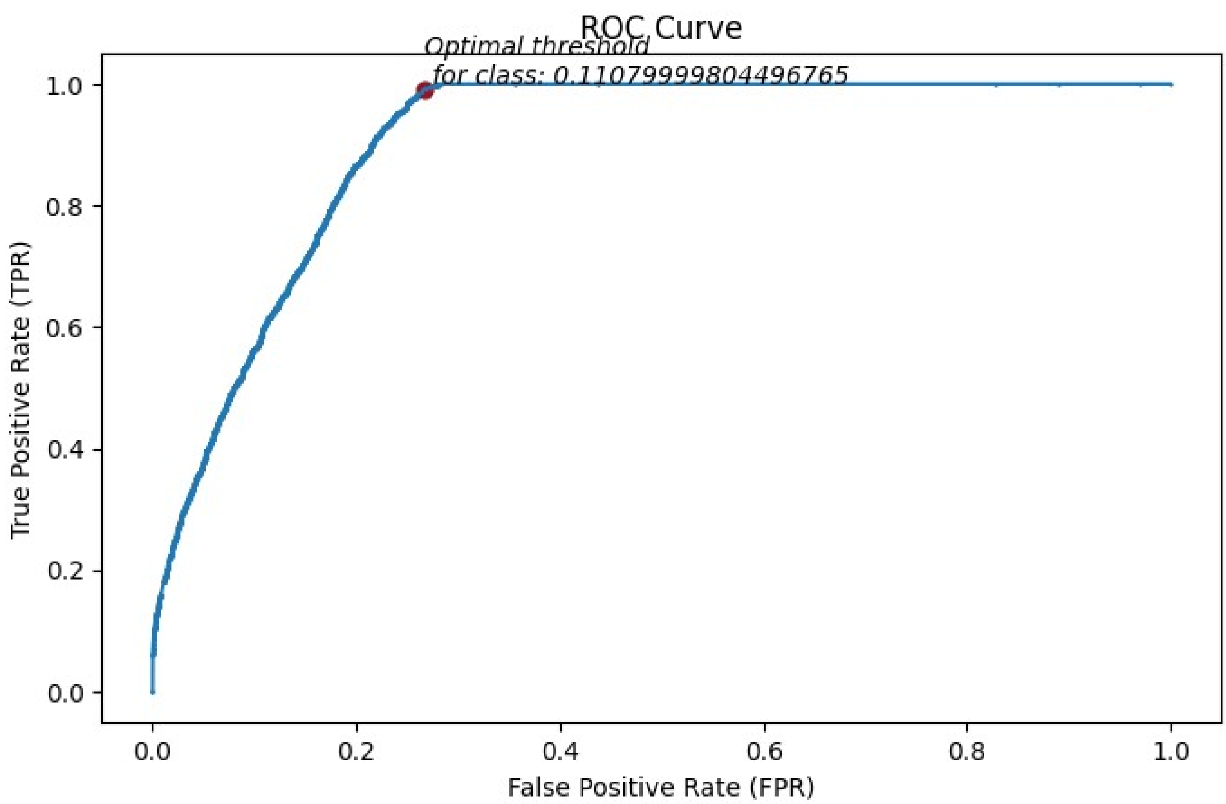
```
    keras.layers.Dropout(0.2),
    keras.layers.Dense(1, activation='sigmoid')
])

opt = keras.optimizers.Adam(learning_rate=0.01)
model.compile(optimizer=opt, loss='binary_crossentropy',
metrics=['accuracy'])

history = model.fit(X_train, y_train, epochs=5, batch_size=512,
validation_data=(X_test, y_test))

loss, accuracy = model.evaluate(X_test, y_test)
loss2, accuracy2 =model.evaluate(X_train,y_train)
print(f'Training dataset loss: {loss2}, validation: {accuracy2}')
print(f'Validation dataset Loss: {loss}, Test Accuracy: {accuracy}')
```

```
Epoch 1/5
205/205 [==============================] - 52s 194ms/step - loss:
0.3624 - accuracy: 0.8429 - val_loss: 3.4445 - val_accuracy: 0.6936
Epoch 2/5
205/205 [==============================] - 44s 214ms/step - loss:
0.3247 - accuracy: 0.8633 - val_loss: 0.8903 - val_accuracy: 0.8243
Epoch 3/5
205/205 [==============================] - 43s 209ms/step - loss:
0.3200 - accuracy: 0.8657 - val_loss: 0.3432 - val_accuracy: 0.8636
Epoch 4/5
205/205 [==============================] - 39s 189ms/step - loss:
0.3132 - accuracy: 0.8693 - val_loss: 0.5525 - val_accuracy: 0.8123
Epoch 5/5
205/205 [==============================] - 41s 200ms/step - loss:
0.3131 - accuracy: 0.8698 - val_loss: 0.5234 - val_accuracy: 0.8116
820/820 [==============================] - 8s 10ms/step - loss: 0.5234
- accuracy: 0.8116
3278/3278 [==============================] - 31s 10ms/step - loss:
0.5212 - accuracy: 0.8172
Training dataset loss: 0.5211853384971619, validation:
0.8172388672828674
Validation dataset Loss: 0.5234202742576599, Test Accuracy:
0.8116157650947571
```

```
df_fpr_tpr = pd.DataFrame({'FPR':fpr, 'TPR':tpr,
'Threshold':thresholds})
g_mean = np.sqrt(tpr * (1 - fpr))

index = np.argmax(g_mean)

thresholdOpt = round(thresholds[index], ndigits = 4)

gmeanOpt = round(g_mean[index], ndigits = 4)
fprOpt = round(fpr[index], ndigits = 4)
```

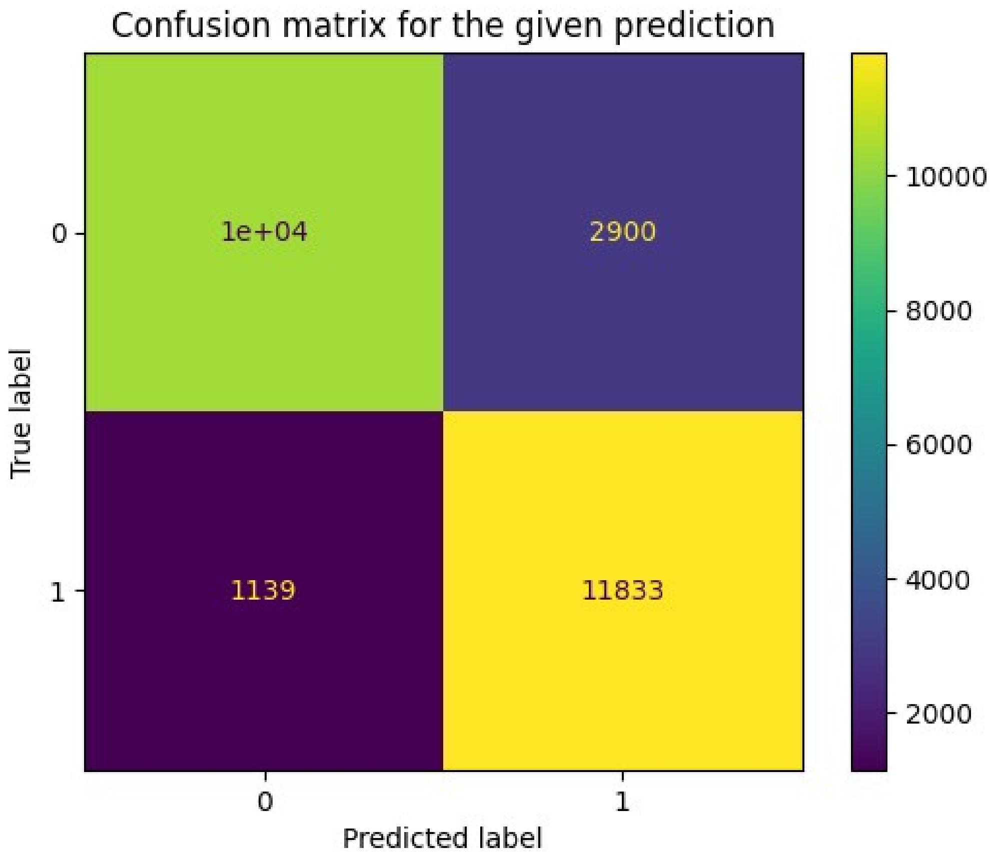
```
tprOpt = round(tpr[index], ndigits = 4)

print('Best Threshold: {} with G-Mean: {}'.format(thresholdOpt,
gmeanOpt))
print('FPR: {}, TPR: {}'.format(fprOpt, tprOpt))


import matplotlib.pyplot as plt
plt.figure(figsize=(8, 4.8))
plt.scatter(df_fpr_tpr['FPR'], df_fpr_tpr['TPR'], s=0.4)
plt.scatter(fprOpt, tprOpt, color='#981220', s=40)
plt.plot(df_fpr_tpr['FPR'], df_fpr_tpr['TPR'])
plt.text(fprOpt, tprOpt, 'Optimal threshold \n for class:
{}'.format(thresholdOpt),ha='left', va='bottom', fontsize=10,
style='italic')
plt.title('ROC Curve')
plt.xlabel('False Positive Rate (FPR)')
plt.ylabel('True Positive Rate (TPR)')
plt.show()
```

```
Best Threshold: 0.11079999804496765 with G-Mean: 0.8525
FPR: 0.2664, TPR: 0.9907
```



```
from sklearn.metrics import
f1_score,accuracy_score,confusion_matrix,ConfusionMatrixDisplay,classi
fication_report
from sklearn.metrics import recall_score,precision_score
y_pred = model.predict(X_test)
y_true_classes = y_test
#thresholding for binary classification
y_pred_binary = (y_pred > 0.14).astype(int)

evaluation(y_true_classes,y_pred_binary)
```

```
820/820 [==============================] - 9s 11ms/step
Accuracy Score: 0.8459749075239293
f1_score: 0.8542140407868616
Precision: 0.8031629674879522
Recall: 0.912195497995683
Classification report:
              precision    recall  f1-score   support

           0       0.90      0.78      0.84     13251
           1       0.80      0.91      0.85     12972

    accuracy                           0.85     26223
   macro avg       0.85      0.85      0.85     26223
weighted avg       0.85      0.85      0.85     26223
```


Confusion matrix for the given prediction
True label
Predicted label
0
1
0
1
1e+04
2900
1139
11833
10000
8000
6000
4000
2000