#importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from google.colab import drive
drive.mount('/content/drive')

→ Mounted at /content/drive

data= pd.read_csv("/content/dataset_traffic_accident_prediction1.csv")

data.head(15)

→ *			_				
``		Weather	Road_Type	Time_of_Day	Traffic_Density	Speed_Limit	Number_of_Vehicles
	0	Rainy	City Road	Morning	1.0	100.0	5.0
	1	Clear	Rural Road	Night	NaN	120.0	3.0
	2	Rainy	Highway	Evening	1.0	60.0	4.0
	3	Clear	City Road	Afternoon	2.0	60.0	3.0
	4	Rainy	Highway	Morning	1.0	195.0	11.0
	5	Clear	Rural Road	Night	0.0	120.0	3.0
	6	Foggy	Highway	Afternoon	0.0	60.0	4.0
	7	Rainy	City Road	Afternoon	0.0	60.0	4.0
	8	Stormy	Highway	Morning	1.0	60.0	2.0
	9	Rainy	City Road	Afternoon	2.0	30.0	2.0
	10	Foggy	NaN	Evening	NaN	60.0	2.0
	11	Clear	Mountain Road	Night	2.0	100.0	5.0
	12	NaN	Rural Road	Afternoon	0.0	60.0	4.0
	13	Rainy	City Road	Night	0.0	30.0	1.0
	14	Clear	Rural Road	Morning	0.0	NaN	1.0

data.drop_duplicates(inplace=True)

data

→		Weather	Road_Type	Time_of_Day	Traffic_Density	Speed_Limit	Number_of_Vehicle
	0	Rainy	City Road	Morning	1.0	100.0	5.
	1	Clear	Rural Road	Night	NaN	120.0	3.
	2	Rainy	Highway	Evening	1.0	60.0	4.
	3	Clear	City Road	Afternoon	2.0	60.0	3.
	4	Rainy	Highway	Morning	1.0	195.0	11.
	835	Clear	Highway	Night	2.0	30.0	4.
	836	Rainy	Rural Road	Evening	2.0	60.0	4.
	837	Foggy	Highway	Evening	NaN	30.0	4.
	838	Foggy	Highway	Afternoon	2.0	60.0	3.
	839	Clear	Highway	Afternoon	1.0	60.0	4.

826 rows × 14 columns

data.columns

data.info()

<<class 'pandas.core.frame.DataFrame'>
 Index: 826 entries, 0 to 839
 Data columns (total 14 columns):

#	Column	Non-Null Count	Dtype
0	Weather	784 non-null	object
1	Road_Type	784 non-null	object
2	Time_of_Day	785 non-null	object
3	Traffic_Density	784 non-null	float64
4	Speed_Limit	784 non-null	float64
5	Number_of_Vehicles	784 non-null	float64
6	Driver_Alcohol	784 non-null	float64
7	Accident_Severity	785 non-null	object
8	Road_Condition	784 non-null	object
9	Vehicle_Type	784 non-null	object
10	Driver_Age	784 non-null	float64
11	Driver Experience	784 non-null	float64

12 Road_Light_Condition 784 non-null object
13 Accident 784 non-null float64

dtypes: float64(7), object(7)

memory usage: 96.8+ KB

#finding missing values
data.isnull().sum()



	0
Weather	42
Road_Type	42
Time_of_Day	41
Traffic_Density	42
Speed_Limit	42
Number_of_Vehicles	42
Driver_Alcohol	42
Accident_Severity	41
Road_Condition	42
Vehicle_Type	42
Driver_Age	42
Driver_Experience	42
Road_Light_Condition	42
Accident	42

dtype: int64

data.duplicated().sum()

→ np.int64(0)

#dropping missing values
data.dropna()



Weather	Road_Type	Time_of_Day	Traffic_Density	Speed_Limit	Number_of_Vehicle:
Rainy	Highway	Evening	1.0	60.0	4.(
Clear	City Road	Afternoon	2.0	60.0	3.0
Rainy	Highway	Morning	1.0	195.0	11.0
Foggy	Highway	Afternoon	0.0	60.0	4.0
Rainy	City Road	Afternoon	0.0	60.0	4.0
Clear	Highway	Morning	1.0	100.0	2.0
Clear	Highway	Night	2.0	30.0	4.0
Rainy	Rural Road	Evening	2.0	60.0	4.(
Foggy	Highway	Afternoon	2.0	60.0	3.0
Clear	Highway	Afternoon	1.0	60.0	4.0

```
#filling the null values
data["Traffic_Density"].fillna(data["Traffic_Density"].mean(), inplace=True)
data["Speed_Limit"].fillna(data["Speed_Limit"].mean(), inplace=True)
data["Number_of_Vehicles"].fillna(data["Number_of_Vehicles"].mean(), inplace=True)
data["Driver_Alcohol"].fillna(data["Driver_Alcohol"].mean(), inplace=True)
data["Accident_Severity"].fillna(data["Accident_Severity"].mode()[0], inplace=True)
data["Road_Condition"].fillna(data["Road_Condition"].mode()[0], inplace=True)
data["Vehicle_Type"].fillna(data["Vehicle_Type"].mode()[0], inplace=True)
data["Driver_Age"].fillna(data["Driver_Age"].mean(), inplace=True)
data["Broad_Light_Condition"].fillna(data["Broad_Light_Condition"].mode()[0], inplace=True)
data["Accident"].fillna(data["Accident"].mean(), inplace=True)
data["Weather"].fillna(data["Weather"].mode()[0], inplace=True)
data["Road_Type"].fillna(data["Road_Type"].mode()[0], inplace=True)
data["Time_of_Day"].fillna(data["Time_of_Day"].mode()[0], inplace=True)
```



```
For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method
  data["Road_Condition"].fillna(data["Road_Condition"].mode()[0], inplace=True)
<ipython-input-24-230c89790859>:8: FutureWarning: A value is trying to be set on a
The behavior will change in pandas 3.0. This inplace method will never work because
For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method
  data["Vehicle_Type"].fillna(data["Vehicle_Type"].mode()[0], inplace=True)
<ipython-input-24-230c89790859>:9: FutureWarning: A value is trying to be set on a
The behavior will change in pandas 3.0. This inplace method will never work because
For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method
  data["Driver_Age"].fillna(data["Driver_Age"].mean(), inplace=True)
<ipython-input-24-230c89790859>:10: FutureWarning: A value is trying to be set on
The behavior will change in pandas 3.0. This inplace method will never work because
For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method'
  data["Driver_Experience"].fillna(data["Driver_Experience"].mean(), inplace=True)
<ipython-input-24-230c89790859>:11: FutureWarning: A value is trying to be set on
The behavior will change in pandas 3.0. This inplace method will never work because
For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method'
  data["Road_Light_Condition"].fillna(data["Road_Light_Condition"].mode()[0], inpl
<ipython-input-24-230c89790859>:12: FutureWarning: A value is trying to be set on
The behavior will change in pandas 3.0. This inplace method will never work because
For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method
  data["Accident"].fillna(data["Accident"].mean(), inplace=True)
<ipython-input-24-230c89790859>:15: FutureWarning: A value is trying to be set on
The behavior will change in pandas 3.0. This inplace method will never work because
For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method
 data["Time of Dav"].fillna(data["Time of Dav"].mode()[0]. inplace=True)
```

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	Weather	Road_Type	Time_of_Day	Traffic_Density	Speed_Limit	Number_of_Vehicle
0	Rainy	City Road	Morning	1.000000	100.0	5.
1	Clear	Rural Road	Night	0.998724	120.0	3.
2	Rainy	Highway	Evening	1.000000	60.0	4.
3	Clear	City Road	Afternoon	2.000000	60.0	3.
4	Rainy	Highway	Morning	1.000000	195.0	11.
835	Clear	Highway	Night	2.000000	30.0	4.
836	Rainy	Rural Road	Evening	2.000000	60.0	4.
837	Foggy	Highway	Evening	0.998724	30.0	4.
838	Foggy	Highway	Afternoon	2.000000	60.0	3.
839	Clear	Highway	Afternoon	1.000000	60.0	4.

data.isnull().sum()



	0
Weather	0
Road_Type	0
Time_of_Day	0
Traffic_Density	0
Speed_Limit	0
Number_of_Vehicles	0
Driver_Alcohol	0
Accident_Severity	0
Road_Condition	0
Vehicle_Type	0
Driver_Age	0
Driver_Experience	0
Road_Light_Condition	0
Accident	0

dtype: int64

#categorical data
data["Road_Light_Condition"].fillna(data["Road_Light_Condition"].mode()[0], inplace = Tru

<ipython-input-26-8de2997c5d88>:2: FutureWarning: A value is trying to be set on a co The behavior will change in pandas 3.0. This inplace method will never work because t

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({

data["Road_Light_Condition"].fillna(data["Road_Light_Condition"].mode()[0], inplace



	Weather	Road_Type	Time_of_Day	Traffic_Density	Speed_Limit	Number_of_Vehicle
0	Rainy	City Road	Morning	1.000000	100.0	5.
1	Clear	Rural Road	Night	0.998724	120.0	3.
2	Rainy	Highway	Evening	1.000000	60.0	4.
3	Clear	City Road	Afternoon	2.000000	60.0	3.
4	Rainy	Highway	Morning	1.000000	195.0	11.
835	Clear	Highway	Night	2.000000	30.0	4.
836	Rainy	Rural Road	Evening	2.000000	60.0	4.
837	Foggy	Highway	Evening	0.998724	30.0	4.
838	Foggy	Highway	Afternoon	2.000000	60.0	3.
839	Clear	Highway	Afternoon	1.000000	60.0	4.

#removing duplicates
data.drop_duplicates(inplace=True)

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
data_scaled = data.copy()
data_scaled[["Traffic_Density","Speed_Limit"]] =scaler.fit_transform(data[["Traffic_Densidata_scaled"])
```



	Weather	Road_Type	Time_of_Day	Traffic_Density	Speed_Limit	Number_of_Vehicle
0	Rainy	City Road	Morning	0.001672	0.918165	5.
1	Clear	Rural Road	Night	0.000002	1.555111	3.
2	Rainy	Highway	Evening	0.001672	-0.355726	4.
3	Clear	City Road	Afternoon	1.311322	-0.355726	3.
4	Rainy	Highway	Morning	0.001672	3.943656	11.
835	Clear	Highway	Night	1.311322	-1.311144	4.
836	Rainy	Rural Road	Evening	1.311322	-0.355726	4.
837	Foggy	Highway	Evening	0.000002	-1.311144	4.
838	Foggy	Highway	Afternoon	1.311322	-0.355726	3.
839	Clear	Highway	Afternoon	0.001672	-0.355726	4.

from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

data_scaled[["Traffic_Density","Speed_Limit"]] =scaler.fit_transform(data[["Traffic_Densi
data_scaled

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	Weather	Road_Type	Time_of_Day	Traffic_Density	Speed_Limit	Number_of_Vehicle
0	Rainy	City Road	Morning	0.500000	0.382514	5.
1	Clear	Rural Road	Night	0.499362	0.491803	3.
2	Rainy	Highway	Evening	0.500000	0.163934	4.
3	Clear	City Road	Afternoon	1.000000	0.163934	3.
4	Rainy	Highway	Morning	0.500000	0.901639	11.
835	Clear	Highway	Night	1.000000	0.000000	4.
836	Rainy	Rural Road	Evening	1.000000	0.163934	4.
837	Foggy	Highway	Evening	0.499362	0.000000	4.
838	Foggy	Highway	Afternoon	1.000000	0.163934	3.
839	Clear	Highway	Afternoon	0.500000	0.163934	4.

data_encoded = pd.get_dummies(data, columns=["Road_Light_Condition"],drop_first=True)
print(data_encoded)

0 1 2 3 4 835 836 837 838	Rainy Foggy Foggy	City Road Rural Road Highway City Road Highway Highway Rural Road Highway Highway	Morning Night Evening Afternoon Morning Night Evening	Traffic_Density	Speed_Limit		
0 1 2 3 4 835 836 837 838		of_Vehicles 5.0 3.0 4.0 3.0 11.0 4.0 4.0 3.0 4.0 4.0		hol Accident_Seve 0.0 0.0 Mode 0.0 0.0 0.0 0.0 1.0 0.0	Low rate Low	nd_Condition Wet Wet Icy Construction Dry Dry Dry Dry Dry Dry Dry Dry	\

Vehicle_Type Driver_Age Driver_Experience Accident \

```
15/05/2025, 20:25
                                                   phase 3 ankitha - Colab
         a
                       Car
                              51.000000
                                                        48.0 0.000000
         1
                     Truck
                              49.000000
                                                        43.0 0.000000
         2
                              54.000000
                                                        52.0 0.000000
                       Car
         3
                       Bus
                              34.000000
                                                        31.0 0.000000
         4
                       Car
                              62.000000
                                                        55.0 1.000000
                       . . .
                                    . . .
                                                        . . .
         835
                       Car
                             23.000000
                                                        15.0 0.000000
         836
               Motorcycle
                             52.000000
                                                        46.0 1.000000
         837
                                                        34.0 0.298469
                       Car
                             43.153061
         838
                       Car
                              25.000000
                                                       19.0 0.000000
         839
               Motorcycle
                              29.000000
                                                        21.0
                                                              0.000000
              Road_Light_Condition_Daylight Road_Light_Condition_No Light
         0
                                        False
                                                                          False
         1
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         2
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         3
                                         True
                                                                          False
         4
                                        False
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         . .
         835
                                         True
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         836
                                         True
                                                                          False
         837
                                        False
                                                                          False
         838
                                        False
                                                                          False
         839
                                        False
                                                                          False
         [825 rows x 15 columns]
    from sklearn.preprocessing import LabelEncoder
    encoder = LabelEncoder()
    data["Road_Light_Condition"] = encoder.fit_transform(data["Road_Light_Condition"])
    def performance_category(Speed_Limit):
        if Speed Limit >= 10:
          return "High"
        elif Speed Limit >= 5:
          return "Medium"
        else:
          return "Low"
    data["Performance"] = data["Speed_Limit"].apply(performance_category)
    print(data)
    \rightarrow
             Weather
                        Road Type Time of Day
                                                 Traffic Density
                                                                   Speed Limit
                Rainy
                        City Road
                                       Morning
                                                         1.000000
                                                                          100.0
         0
         1
               Clear
                       Rural Road
                                         Night
                                                         0.998724
                                                                          120.0
         2
                Rainy
                          Highway
                                       Evening
                                                         1.000000
                                                                           60.0
         3
               Clear
                        City Road
                                     Afternoon
                                                         2.000000
                                                                           60.0
         4
                Rainy
                          Highway
                                       Morning
                                                         1.000000
                                                                          195.0
                  . . .
                                            . . .
                                                                            . . .
         835
               Clear
                          Highway
                                         Night
                                                         2.000000
                                                                           30.0
         836
               Rainy
                       Rural Road
                                       Evening
                                                         2.000000
                                                                           60.0
         837
                Foggy
                          Highway
                                       Evening
                                                         0.998724
                                                                           30.0
                                                                           60.0
         838
                          Highway
                                     Afternoon
                                                         2.000000
                Foggy
         839
               Clear
                          Highway
                                     Afternoon
                                                         1.000000
                                                                           60.0
               Number_of_Vehicles
                                    Driver_Alcohol Accident_Severity
                                                                             Road_Condition \
                                                                                         Wet
```

55.0

. . .

15.0

46.0

34.0

19.0

21.0

0

1

1

0

0

0

4

835

836

837

838

839

1	3.0	0.0	Moderate	Wet
2	4.0	0.0	Low	Icy
3	3.0	0.0	Low	Under Construction
4	11.0	0.0	Low	Dry
• •	• • •	• • •		• • •
835	4.0	0.0	Low	Dry
836	4.0	0.0	Low	Dry
837	4.0	1.0	High	Dry
838	3.0	0.0	Low	Dry
839	4.0	0.0	Low	Dry
Vehicle_T	ype Driver Age	Driver Experience	Road Ligh	t Condition \
0	Car 51.000000		_ 0	_ 0
1 Tr	uck 49.000000	43.0		0
2	Car 54.000000	52.0		0
3	Bus 34.000000	31.0		1

Accident	Performance

Motorcycle

. . .

Car

Car

Motorcycle 52.000000

Car 62.000000

Car 23.000000

43.153061

25.000000

29.000000

	Accident	Performance
0	0.000000	High
1	0.000000	High
2	0.000000	High
3	0.000000	High
4	1.000000	High
• •	• • •	• • •
835	0.000000	High
835 836	0.000000 1.000000	High High
		•
836	1.000000	High

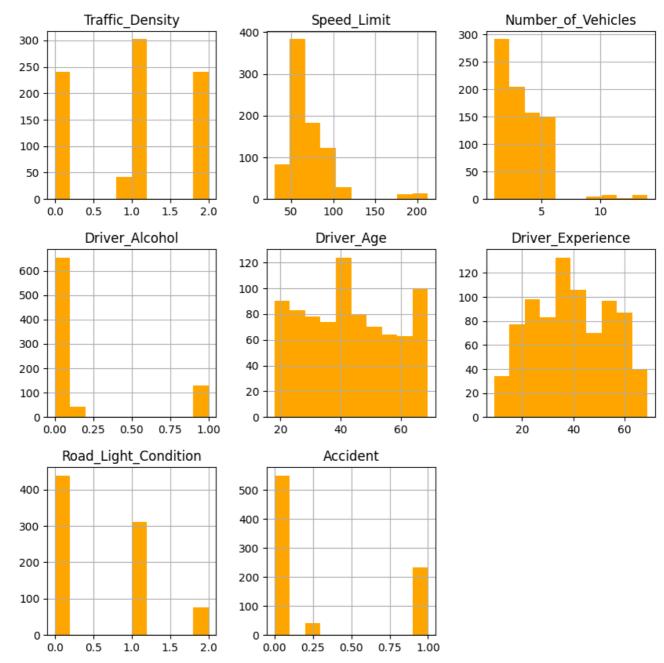
[825 rows x 15 columns]



	Weather	Road_Type	Time_of_Day	Traffic_Density	Speed_Limit	Number_of_Vehicle
0	Rainy	City Road	Morning	1.000000	100.0	5.
1	Clear	Rural Road	Night	0.998724	120.0	3.
2	Rainy	Highway	Evening	1.000000	60.0	4.
3	Clear	City Road	Afternoon	2.000000	60.0	3.
4	Rainy	Highway	Morning	1.000000	195.0	11.
835	Clear	Highway	Night	2.000000	30.0	4.
836	Rainy	Rural Road	Evening	2.000000	60.0	4.
837	Foggy	Highway	Evening	0.998724	30.0	4.
838	Foggy	Highway	Afternoon	2.000000	60.0	3.
839	Clear	Highway	Afternoon	1.000000	60.0	4.

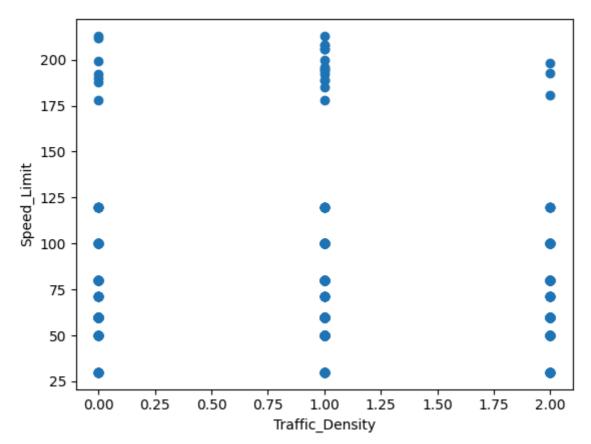
#univariate analysis
data.hist(figsize=(10,10), color="Orange")
plt.show()





```
#scatter chart
plt.scatter(data["Traffic_Density"], data["Speed_Limit"])
plt.xlabel("Traffic_Density")
plt.ylabel("Speed_Limit")
plt.show()
```





```
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
data["Road_Light_Condition"] = encoder.fit_transform(data["Road_Light_Condition"])
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
data["Accident"] = encoder.fit_transform(data["Accident"])
data["Accident_Severity"]=encoder.fit_transform(data["Accident_Severity"])
data["Road_Condition"]=encoder.fit_transform(data["Road_Condition"])
data["Vehicle_Type"]=encoder.fit_transform(data["Vehicle_Type"])
data["Driver_Alcohol"]=encoder.fit_transform(data["Driver_Alcohol"])
data["Road_Type"]=encoder.fit_transform(data["Road_Type"])
data["Time_of_Day"]=encoder.fit_transform(data["Time_of_Day"])
data["Weather"]=encoder.fit_transform(data["Weather"])
data["Performance"]=encoder.fit_transform(data["Performance"])
#model building
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
#random forest
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
#select target data
X = data.drop("Accident", axis=1)
```

```
y = data["Accident"]
x_test,x_train,y_test,y_train = train_test_split(X,y,test_size=0.2,random_state=42)
#logistic regression
model = LogisticRegression()
model.fit(x_train,y_train)
 /usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:465: Conver
  STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.
  Increase the number of iterations (max iter) or scale the data as shown in:
   https://scikit-learn.org/stable/modules/preprocessing.html
  Please also refer to the documentation for alternative solver options:
   https://scikit-learn.org/stable/modules/linear model.html#logistic-regression
  n_iter_i = _check_optimize_result(
  ▼ LogisticRegression ① ??
  LogisticRegression()
#prediction
y_pred = model.predict(x_test)
print("y_pred",y_pred)
#random forest classifier
model = RandomForestClassifier()
model.fit(x_train,y_train)
→
  RandomForestClassifier (i) ??
  RandomForestClassifier()
```

```
#prediction
y_pred_random = model.predict(x_test)
print("y_pred_random",y_pred_random)
```

```
#Evaluation logistic regression
accuracy = accuracy_score(y_test,y_pred)
print("accuracy",accuracy)
classification_rep = classification_report(y_test,y_pred)
print("classification_rep",classification_rep)
confusion_mat = confusion_matrix(y_test,y_pred)
print("confusion_mat",confusion_mat)
```

```
accuracy 0.6454545454545455
classification rep
                                   precision
                                                 recall f1-score
                                                                      support
                               0.96
                                          0.78
                                                     438
           0
                    0.66
           1
                    0.06
                               0.03
                                          0.04
                                                      37
                    0.57
                               0.02
                                          0.04
                                                     185
                                         0.65
    accuracy
                                                     660
                               0.34
                                         0.29
   macro avg
                    0.43
                                                     660
weighted avg
                    0.60
                               0.65
                                         0.53
                                                     660
confusion mat [[421 14
                            31
 [ 36
        1
            0]
 [178
        3
            4]]
```

```
#evaluation random forest
accuracy_random = accuracy_score(y_test,y_pred_random)
print("accuracy_random",accuracy_random)
classification_rep_random = classification_report(y_test,y_pred_random)
print("classification_rep_random",classification_rep_random)
confusion_mat_random = confusion_matrix(y_test,y_pred_random)
print("confusion_mat_random",confusion_mat_random)
```

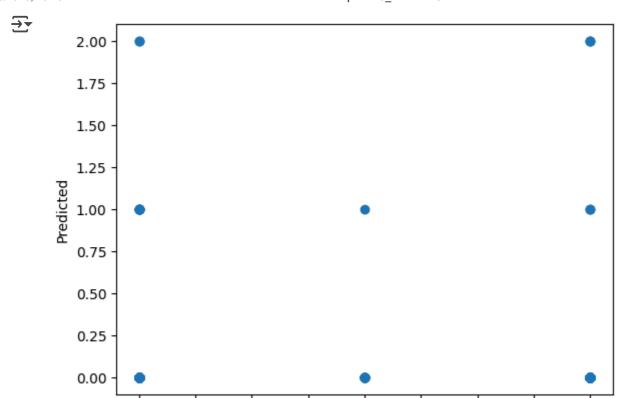
```
accuracy_random 0.646969696969697
    classification_rep_random
                                            precision
                                                         recall f1-score
                                                                             support
                       0.67
                                 0.95
                                           0.78
                                                      438
               1
                       0.00
                                 0.00
                                           0.00
                                                       37
               2
                       0.29
                                 0.05
                                           0.08
                                                      185
                                           0.65
                                                      660
        accuracy
                       0.32
                                 0.33
                                           0.29
                                                      660
       macro avg
    weighted avg
                       0.52
                                 0.65
                                           0.54
                                                      660
    confusion_mat_random [[418
                                 1 19]
                3]
     [ 34
     [176
            0
                9]]
```

#prediction analysis
prediction_analysis = pd.DataFrame({"Actual":y_test,"Predicted":y_pred})
print(prediction_analysis)

→		Actual	Predicted
	239	0	0
	701	0	0
	655	2	0
	345	0	0
	302	2	0
	• •		
	71	2	0
	106	0	0
	272	0	0
	441	0	0
	102	0	0

[660 rows x 2 columns]

```
#visualization prediction and actual value
plt.scatter(y_test,y_pred)
plt.xlabel("Actual")
plt.ylabel("Predicted")
plt.show()
```



0.75

1.00

Actual

1.25

1.50

1.75

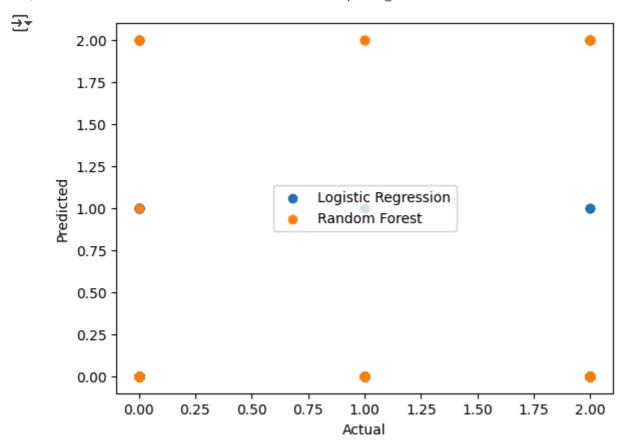
2.00

```
#visualization an two models
plt.scatter(y_test,y_pred,label="Logistic Regression")
plt.scatter(y_test,y_pred_random,label="Random Forest")
plt.xlabel("Actual")
plt.ylabel("Predicted")
plt.legend()
plt.show()
```

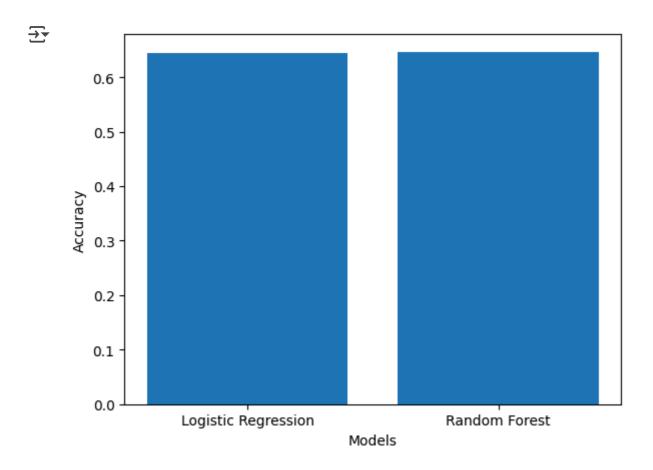
0.25

0.50

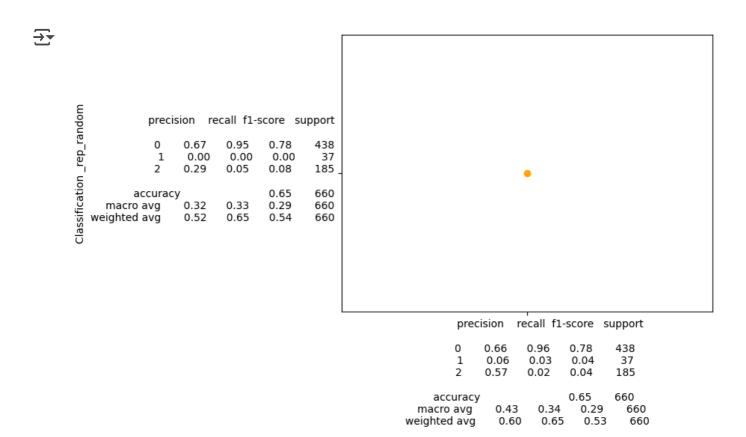
0.00



#visualization on evaluation two models
plt.bar(["Logistic Regression","Random Forest"],[accuracy,accuracy_random])
plt.xlabel("Models")
plt.ylabel("Accuracy")
plt.show()

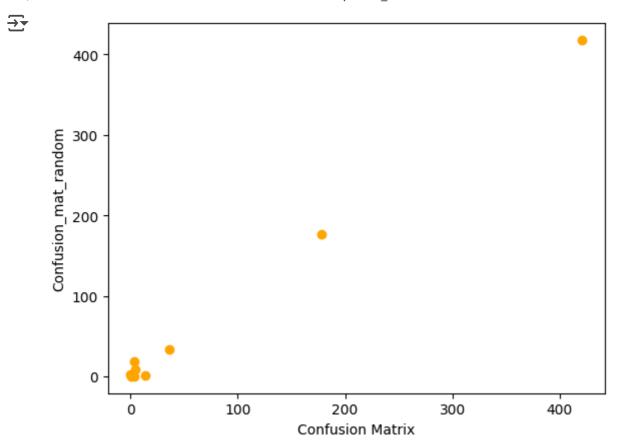


```
#chart classification report
plt.scatter(classification_rep,classification_rep_random,color="Orange")
plt.xlabel("Classification Report")
plt.ylabel("Classification _rep_random")
plt.show()
```



Classification Report

#confusion matrix chart
plt.scatter(confusion_mat,confusion_mat_random,color="Orange")
plt.xlabel("Confusion Matrix")
plt.ylabel("Confusion_mat_random")
plt.show()



#final output prediction
final_output = pd.DataFrame({"Actual":y_test,"Logistic Regression":y_pred,"Random Forest"
print(final_output)

<u> </u>		Actual	Logistic Regression	Random Forest
<u>~</u>		ACCUAL	LUGISCIC NEGIESSION	Kandom Torest
	239	0	0	0
	701	0	0	0
	655	2	0	0
	345	0	0	0
	302	2	0	0
			• • •	• • •
	71	2	0	0
	106	0	0	0
	272	0	0	2
	441	0	0	0
	102	0	0	0

[660 rows x 3 columns]

Start coding or generate with AI.

Start coding or generate with AI.