```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from plotly.offline import iplot , plot
from plotly.subplots import make_subplots
from sklearn.model_selection import train_test_split , GridSearchCV
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.preprocessing import MinMaxScaler
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
import warnings
warnings.filterwarnings('ignore')
```

```
df = pd.read_csv("/content/train.csv")
```

```
df.sample(5)
```

```
print(f"Number of Row : {df.shape[0]}\nNumber of Columns : {df.shape[1]}")
```

```
Number of Row : 2000
Number of Columns : 21
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   battery_power  2000 non-null   int64  
 1   blue           2000 non-null   int64  
 2   clock_speed    2000 non-null   float64
 3   dual_sim       2000 non-null   int64  
 4   fc             2000 non-null   int64  
 5   four_g         2000 non-null   int64  
 6   int_memory     2000 non-null   int64  
 7   m_dep          2000 non-null   float64
 8   mobile_wt      2000 non-null   int64  
 9   n_cores        2000 non-null   int64  
 10  pc             2000 non-null   int64  
 11  px_height      2000 non-null   int64  
 12  px_width       2000 non-null   int64  
 13  ram            2000 non-null   int64  
 14  sc_h           2000 non-null   int64  
 15  sc_w           2000 non-null   int64  
 16  talk_time      2000 non-null   int64  
 17  three_g        2000 non-null   int64  
 18  touch_screen   2000 non-null   int64  
 19  wifi           2000 non-null   int64  
 20  price_range    2000 non-null   int64  
dtypes: float64(2), int64(19)
memory usage: 328.2 KB
```

```
df.isna().sum()
```

```
battery_power    0
blue             0
clock_speed      0
dual_sim         0
fc               0
four_g           0
int_memory       0
m_dep            0
mobile_wt        0
n_cores          0
pc               0
px_height        0
px_width         0
ram              0
sc_h             0
sc_w             0
talk_time        0
three_g          0
touch_screen     0
wifi             0
price_range      0
dtype: int64
```

```
df.describe()
```

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_wt	n_cores
count	2000.000000	2000.0000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	1238.518500	0.4950	1.522250	0.509500	4.309500	0.521500	32.046500	0.501750	140.249000	4.520500
std	439.418206	0.5001	0.816004	0.500035	4.341444	0.499662	18.145715	0.288416	35.399655	2.287837
min	501.000000	0.0000	0.500000	0.000000	0.000000	0.000000	2.000000	0.100000	80.000000	1.000000
25%	851.750000	0.0000	0.700000	0.000000	1.000000	0.000000	16.000000	0.200000	109.000000	3.000000
50%	1226.000000	0.0000	1.500000	1.000000	3.000000	1.000000	32.000000	0.500000	141.000000	4.000000
75%	1615.250000	1.0000	2.200000	1.000000	7.000000	1.000000	48.000000	0.800000	170.000000	7.000000
max	1998.000000	1.0000	3.000000	1.000000	19.000000	1.000000	64.000000	1.000000	200.000000	8.000000

8 rows × 21 columns

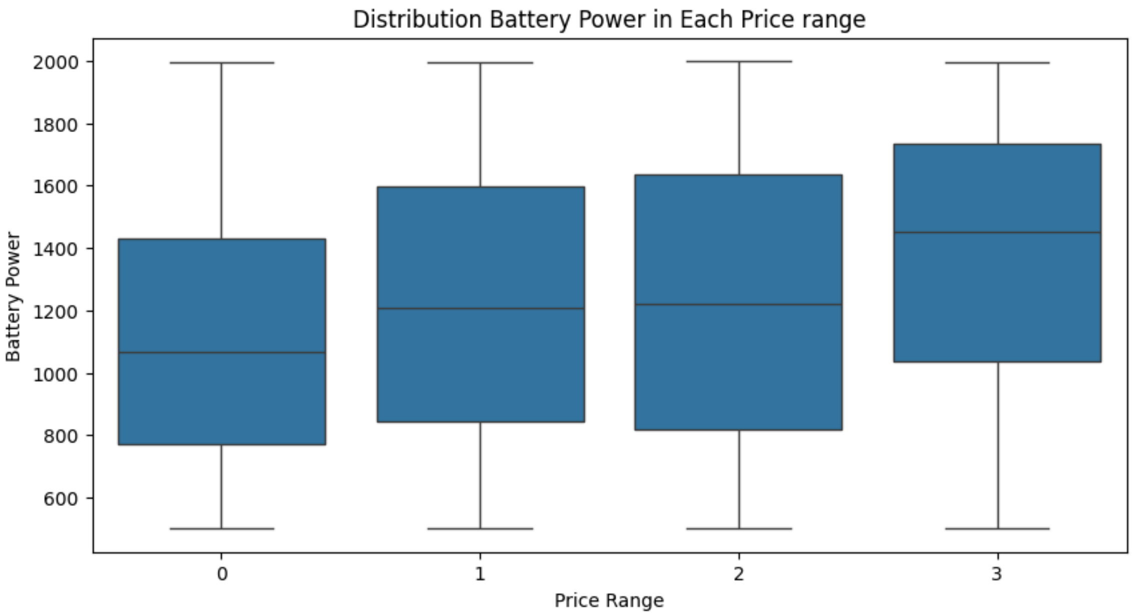
```
df.duplicated().any()
```

```
False
```

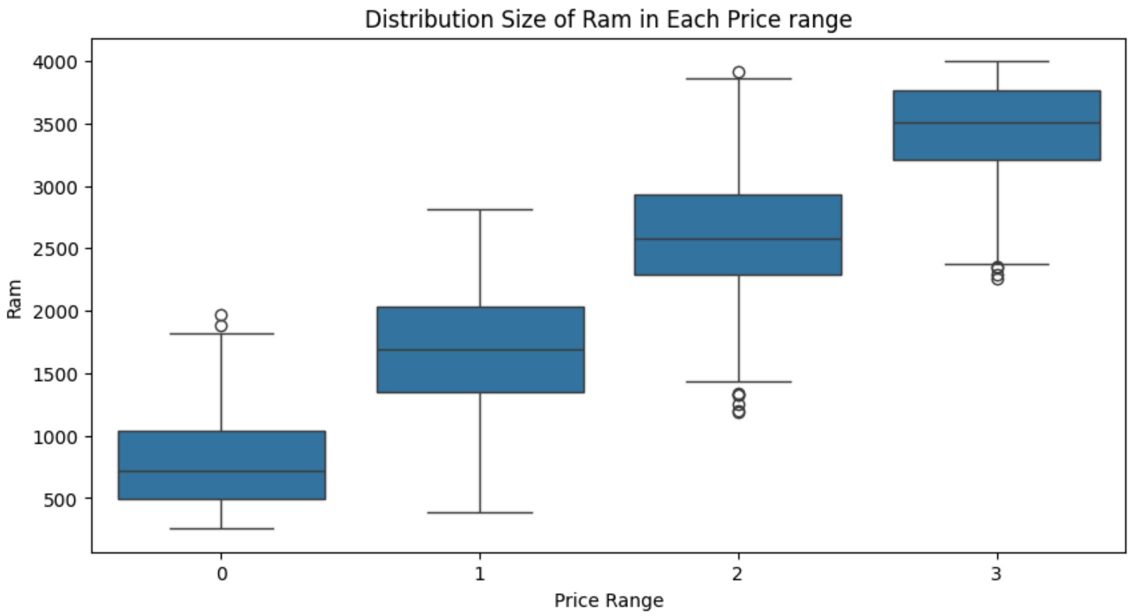
```
df_battery_price = df.groupby('price_range')['battery_power'].mean()
```

```
iplot(px.line(df_battery_price,
              labels={'value':'Mean of Battery Capacity','price_range':'Price Range'},
              color_discrete_sequence=['red']
              ))
```

```
plt.figure(figsize=(10,5))
plt.title('Distribution Battery Power in Each Price range')
sns.boxplot(x=df['price_range'],y=df['battery_power'])
plt.xlabel('Price Range')
plt.ylabel('Battery Power')
plt.show()
```




```
plt.figure(figsize=(10,5))
plt.title('Distribution Size of Ram in Each Price range')
sns.boxplot(x=df['price_range'],y=df['ram'])
plt.xlabel('Price Range')
plt.ylabel('Ram')
plt.show()
```




```
df_4g = df['four_g'].value_counts()
iplot(px.pie(values=df_4g,
             names=['Support 4G','Not Support 4G'],
             template='plotly_dark',
             title='Is Support 4G ?'
             ).update_traces(textinfo='label+percent'))
```

```
df_3g = df['three_g'].value_counts()
iplot(px.pie(values=df_3g,
             names=['Support 3G','Not Support 3G'],
             template='plotly_dark',
             title='Is Support 3G ?'
             ).update_traces(textinfo='label+percent'))
```

```
x = df.drop(columns='price_range')
y = df.price_range
```

```
scaler = MinMaxScaler()
x = scaler.fit_transform(x)
```

```
x_train , x_test , y_train , y_test = train_test_split(x,y,test_size=0.2)
```

```
print(f'Shape of X_Train {x_train.shape}')
print(f'Shape of X_Test {x_test.shape}')
print(f'Shape of Y_Train {y_train.shape}')
print(f'Shape of Y_Test {y_test.shape}')
```

```
Shape of X_Train (1600, 20)
Shape of X_Test (400, 20)
Shape of Y_Train (1600,)
Shape of Y_Test (400,)
```

```
model_params = {
    'svm':{
        'model' : SVC(gamma='auto'),
        'params':{
            'C':[1,10,20],
            'kernel':['rbf','linear']
        }
    },
    'random_forest':{
        'model':RandomForestClassifier(),
        'params':{
            'n_estimators':[1,5,10]
        }
    },
    'logistic_regression':{
        'model':LogisticRegression(solver='liblinear',multi_class='auto'),
        'params':{
            'C':[1,5,10]
        }
    }
}
```

```
scores = []

for model_name , mp in model_params.items():
    clf = GridSearchCV(mp['model'],mp['params'],cv=5,return_train_score=False)
    clf.fit(x,y)
    scores.append({
            'model':model_name,
            'best_scores':clf.best_score_,
            'best_params':clf.best_params_
        }
    )
pd.DataFrame(scores,columns=['model','best_scores','best_params'])
```

	model	best_scores	best_params
0	svm	0.9675	{'C': 20, 'kernel': 'linear'}
1	random_forest	0.8080	{'n_estimators': 10}
2	logistic_regression	0.8375	{'C': 10}

```
model_svm = SVC(kernel='linear',C=20)
model_svm.fit(x_train,y_train)
```

```
▾ SVC
SVC(C=20, kernel='linear')
```

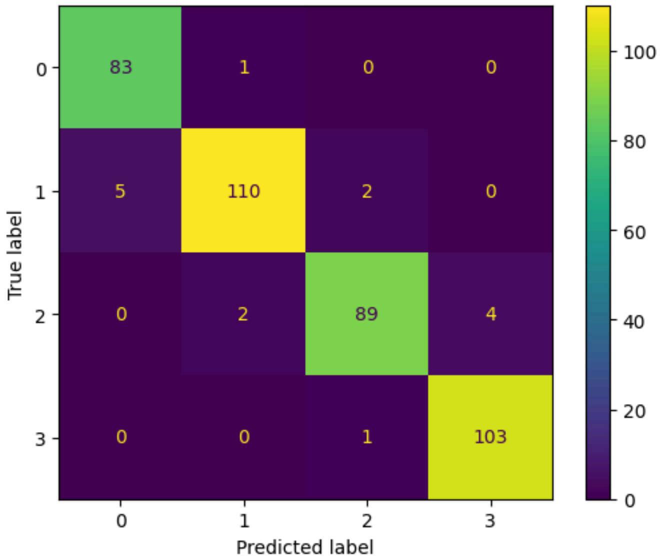
```
score_svm_train = model_svm.score(x_train,y_train)
print(f"Train accuracy: {score_svm_train}")
```

```
Train accuracy: 0.976875
```

```
score_svm_test = model_svm.score(x_test,y_test)
print(f"Test accuracy: {score_svm_test}")
```

```
Test accuracy: 0.9625
```

```
ConfusionMatrixDisplay.from_estimator(model_svm,
                                      x_test,
                                      y_test);
```




```
model_LR = LogisticRegression(C=10)
model_LR.fit(x_train,y_train)
```

```
▾ LogisticRegression
LogisticRegression(C=10)
```

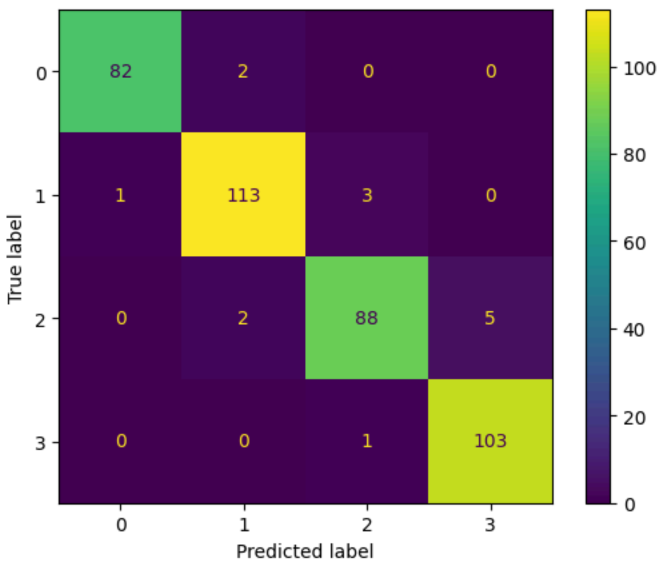
```
score_LR_train = model_LR.score(x_train,y_train)
print(f"Train accuracy: {score_LR_train}")
```

```
Train accuracy: 0.974375
```

```
score_LR_test = model_LR.score(x_test,y_test)
print(f"Test accuracy: {score_LR_test}")
```

```
Test accuracy: 0.965
```

```
ConfusionMatrixDisplay.from_estimator(model_LR,
                                      x_test,
                                      y_test);
```




```
model_RFC = RandomForestClassifier(n_estimators=10,random_state=42)
model_RFC.fit(x_train,y_train)
```

```
▾ RandomForestClassifier
RandomForestClassifier(n_estimators=10, random_state=42)
```

```
score_RFC_train = model_RFC.score(x_train,y_train)
print(f"Train accuracy: {score_RFC_train}")
```

```
Train accuracy: 0.995625
```

```
score_RFC_test = model_RFC.score(x_test,y_test)
print(f"Test accuracy: {score_RFC_test}")
```

```
Test accuracy: 0.7625
```

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import GradientBoostingRegressor
import xgboost as xgb
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
# Training Gradient Boosting model
gb_model = GradientBoostingRegressor(n_estimators=100, learning_rate=0.1, max_depth=3, random_state=42)
gb_model.fit(x_train, y_train)
# Training XGBoost model
xgb_model = xgb.XGBRegressor(n_estimators=100, learning_rate=0.1, max_depth=3, random_state=42)
xgb_model.fit(x_train, y_train)
# Making predictions on the testing set
gb_predictions = gb_model.predict(x_test)
xgb_predictions = xgb_model.predict(x_test)
```

```
mae = mean_absolute_error(y_test, gb_predictions)
print("Mean Absolute Error (MAE):", mae)
# Calculate Mean Squared Error (MSE)
mse = mean_squared_error(y_test, gb_predictions)
print("Mean Squared Error (MSE):", mse)
# Calculate Root Mean Squared Error (RMSE)
rmse = mean_squared_error(y_test, gb_predictions, squared=False)
print("Root Mean Squared Error (RMSE):", rmse)
# Calculate R-squared (R2) score
r2 = r2_score(y_test, gb_predictions)
print("R-squared (R2) Score:", r2)
```

```
Mean Absolute Error (MAE): 0.22347228527141083
Mean Squared Error (MSE): 0.07961726983879017
```