```python
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)
```

{"type":"dataframe"}

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

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

```python
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()
```

{"type":"dataframe"}

```
pd.DataFrame({'Count':df.shape[0],
              'Null':df.isnull().sum(),
              'Null %':df.isnull().mean() * 100,
              'Cardinality':df.nunique()
})
```

{"summary":"{\n \"name\": \"})\",\n \"rows\": 21,\n \"fields\": [\n   {\n   \"column\": \"Count\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 0,\n   \"min\": 2000,\n   \"max\": 2000,\n   \"num_unique_values\": 1,\n   \"samples\": [\n   2000\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"Null\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 0,\n   \"min\": 0,\n

\"max\": 0,\n   \"num_unique_values\": 1,\n   \"samples\": [\n   0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"Null %\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 0.0,\n   \"min\": 0.0,\n   \"max\": 0.0,\n   \"num_unique_values\": 1,\n   \"samples\": [\n   0.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"Cardinality\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 493,\n   \"min\": 2,\n   \"max\": 1562,\n   \"num_unique_values\": 15,\n   \"samples\": [\n   1137\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe"}

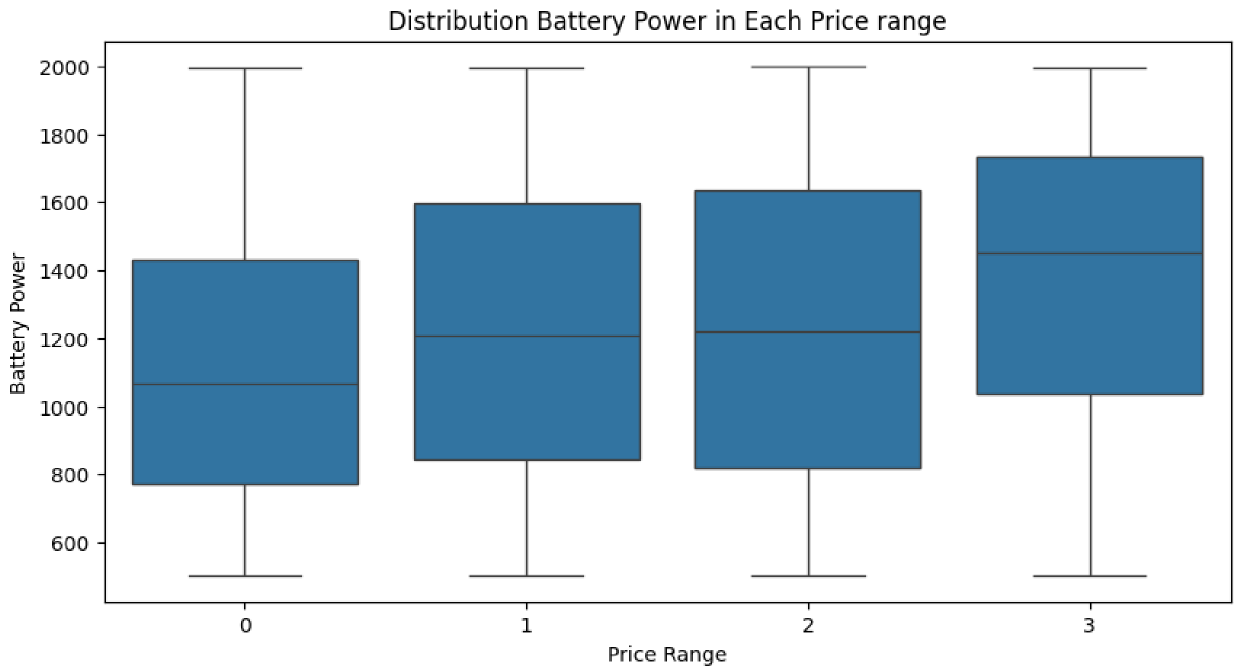
```
df.duplicated().any()
```

```
False
```

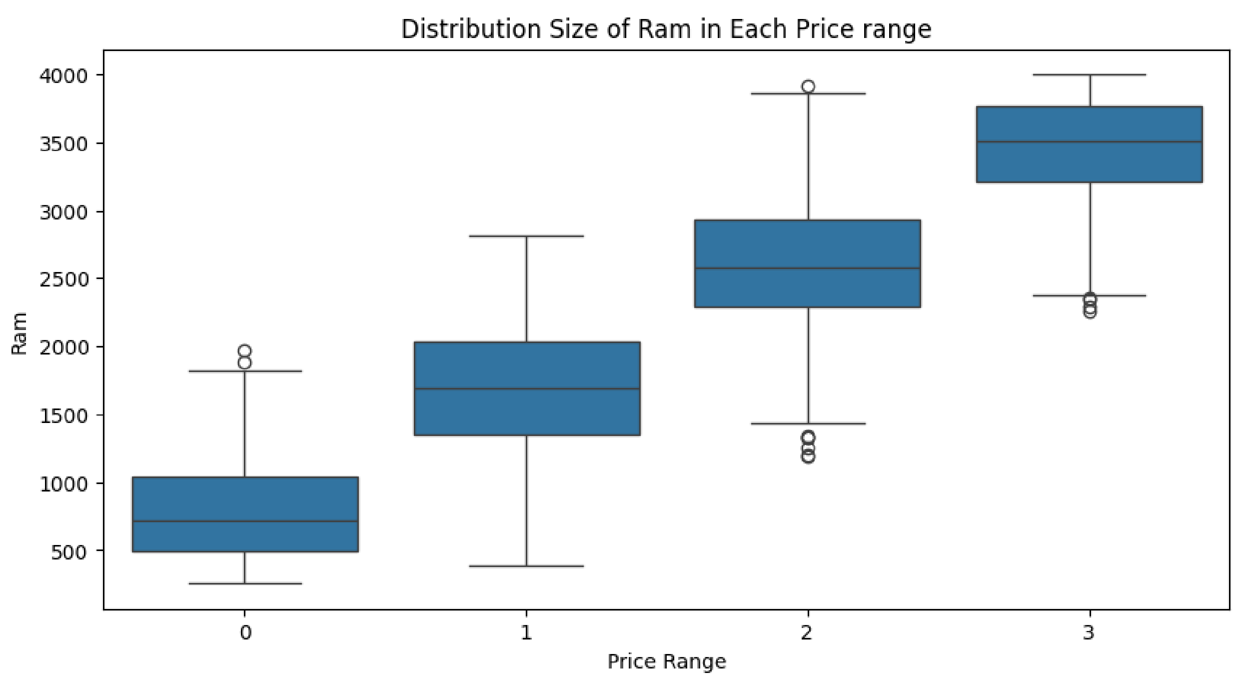
```
df_battery_price = df.groupby('price_range')['battery_power'].mean()

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'])
```


```
{"summary":"{\n  \"name\": \"pd\",\n  \"rows\": 3,\n  \"fields\": [\n
{\n      \"column\": \"model\",\n      \"properties\": {\n
\"dtype\": \"string\",\n        \"num_unique_values\": 3,\n
\"samples\": [\n          \"svm\",\n          \"random_forest\",\n
\"logistic_regression\"\n        ],\n        \"semantic_type\": \"\",\
n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"best_scores\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0.08927672335683767,\n
\"min\": 0.7965,\n        \"max\": 0.9674999999999999,\n
\"num_unique_values\": 3,\n        \"samples\": [\n
0.9674999999999999,\n          0.7965,\n          0.8375\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"best_params\",\n
\"properties\": {\n        \"dtype\": \"object\",\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    }\n  ]\n}","type":"dataframe"}
```


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

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

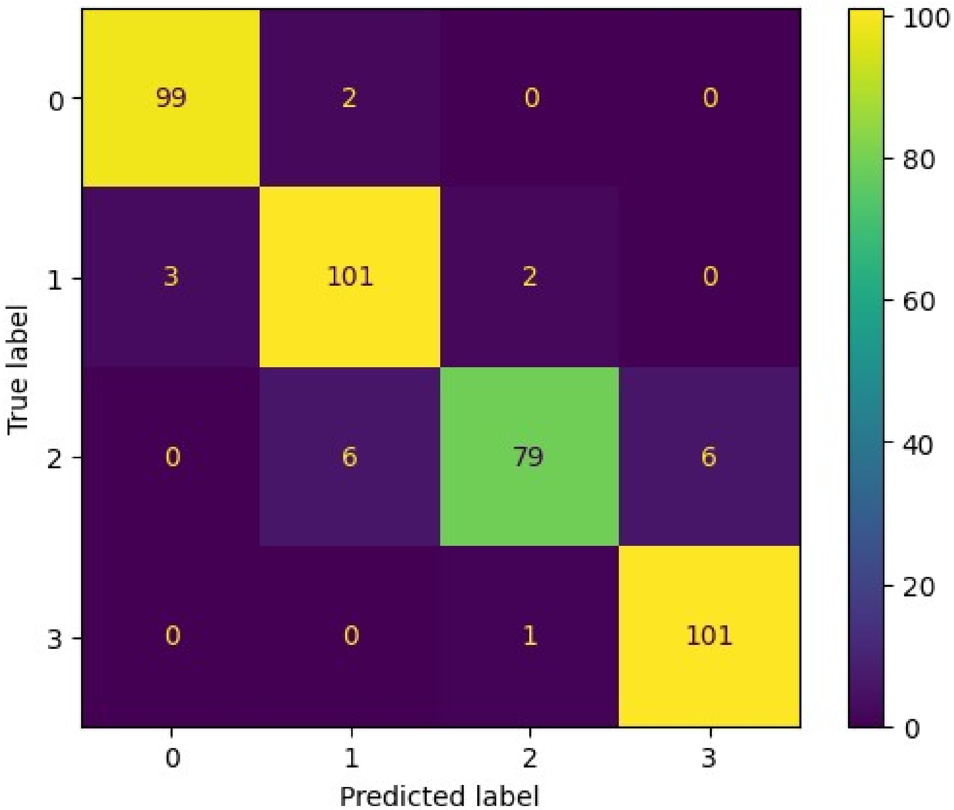
```
score_svm_train = model_svm.score(x_train,y_train)
print(f"Train accuracy: {score_svm_train}")
```

```
Train accuracy: 0.9825
```

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

```
Test accuracy: 0.95
```

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




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

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

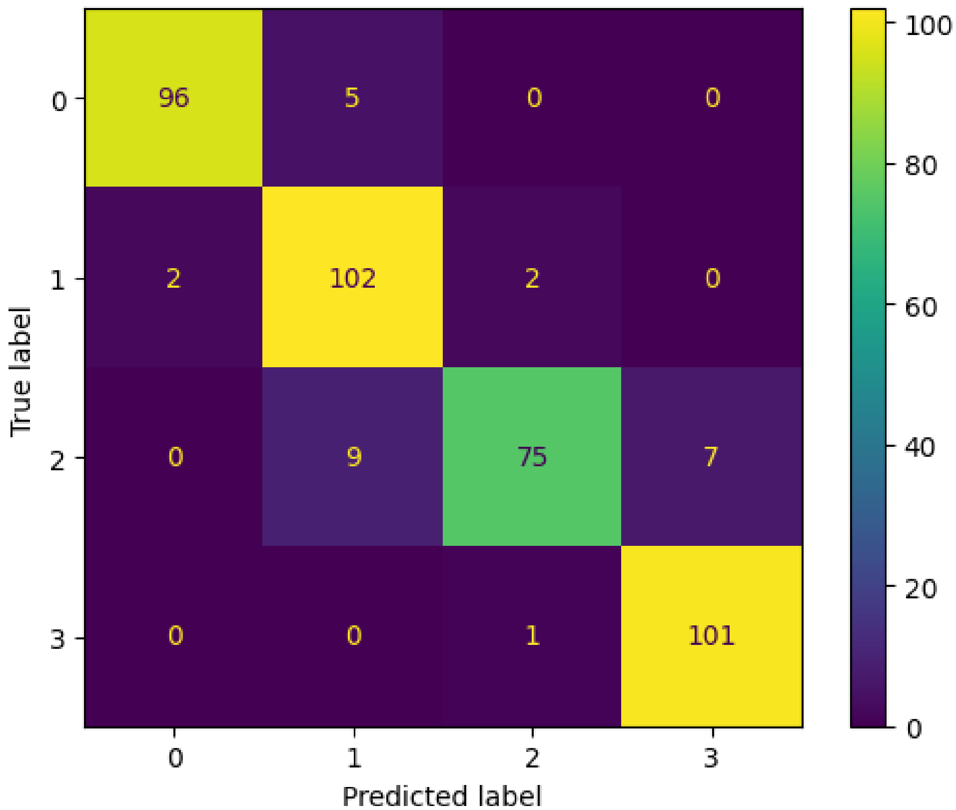
```
score_LR_train = model_LR.score(x_train,y_train)
print(f"Train accuracy: {score_LR_train}")
```

```
Train accuracy: 0.979375
```

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

```
Test accuracy: 0.935
```

```
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(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: 0.996875
```

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

```
Test accuracy: 0.8125
```

```
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): 0.2210071896344121
Mean Squared Error (MSE): 0.07875900850305091
Root Mean Squared Error (RMSE): 0.280640354373798
R-squared (R2) Score: 0.9377288383285162
```

```
# Calculate Mean Absolute Error (MAE)
mae = mean_absolute_error(y_test, xgb_predictions)
print("Mean Absolute Error (MAE):", mae)

# Calculate Mean Squared Error (MSE)
mse = mean_squared_error(y_test, xgb_predictions)
print("Mean Squared Error (MSE):", mse)

# Calculate Root Mean Squared Error (RMSE)
rmse = mean_squared_error(y_test, xgb_predictions, squared=False)
print("Root Mean Squared Error (RMSE):", rmse)

# Calculate R-squared (R2) score
r2 = r2_score(y_test, xgb_predictions)
print("R-squared (R2) Score:", r2)
```

```
Mean Absolute Error (MAE): 0.21938442243495956
Mean Squared Error (MSE): 0.07824639518480786
Root Mean Squared Error (RMSE): 0.2797255712029343
R-squared (R2) Score: 0.9381341383370102
```