Mobile_Price_Classification

July 19, 2024

1 IMPORT LIBRARY

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
# Split dataset
from sklearn.model_selection import train_test_split
# Standardscaller
from sklearn.preprocessing import StandardScaler, LabelBinarizer
# Cross validation
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
# Evaluation metric
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, ConfusionMatrixDisplay
from sklearn.metrics import confusion_matrix, classification_report,␣
↪roc_auc_score, roc_curve, auc
# Tuning parameter
from sklearn.model_selection import GridSearchCV
# XGBOOST
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
# TensorFlow
import tensorflow as tf
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import Adam
```

2 IMPORT DATA

2.0.1 Read Data

[2]:
```
data_train = pd.read_csv("train.csv")
data_test = pd.read_csv("test.csv")
```

[3]:
```
data_train.head()
```

[3]:
```
   battery_power  blue  clock_speed  dual_sim  fc  four_g  int_memory  m_dep  \
0            842     0          2.2         0   1       0           7    0.6
1           1021     1          0.5         1   0       1          53    0.7
2            563     1          0.5         1   2       1          41    0.9
3            615     1          2.5         0   0       0          10    0.8
4           1821     1          1.2         0  13       1          44    0.6

   mobile_wt  n_cores  …  px_height  px_width   ram  sc_h  sc_w  talk_time  \
0        188        2  …         20       756  2549     9     7         19
1        136        3  …        905      1988  2631    17     3          7
2        145        5  …       1263      1716  2603    11     2          9
3        131        6  …       1216      1786  2769    16     8         11
4        141        2  …       1208      1212  1411     8     2         15

   three_g  touch_screen  wifi  price_range
0        0             0     1            1
1        1             1     0            2
2        1             1     0            2
3        1             0     0            2
4        1             1     0            1

[5 rows x 21 columns]
```

[4]:
```python
data_test.head()
```

[4]:
```
   id  battery_power  blue  clock_speed  dual_sim  fc  four_g  int_memory  \
0   1           1043     1          1.8         1  14       0           5
1   2            841     1          0.5         1   4       1          61
2   3           1807     1          2.8         0   1       0          27
3   4           1546     0          0.5         1  18       1          25
4   5           1434     0          1.4         0  11       1          49

   m_dep  mobile_wt  …  pc  px_height  px_width   ram  sc_h  sc_w  \
0    0.1        193  …  16        226      1412  3476    12     7
1    0.8        191  …  12        746       857  3895     6     0
2    0.9        186  …   4       1270      1366  2396    17    10
3    0.5         96  …  20        295      1752  3893    10     0
4    0.5        108  …  18        749       810  1773    15     8

   talk_time  three_g  touch_screen  wifi
0          2        0             1     0
1          7        1             0     0
2         10        0             1     1
3          7        1             1     0
4          7        1             0     1

[5 rows x 21 columns]
```

2.0.2 Data Information

[5]:
```
data_train.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
```

[6]:
```
data_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             1000 non-null   int64
 1   battery_power  1000 non-null   int64
 2   blue           1000 non-null   int64
 3   clock_speed    1000 non-null   float64
 4   dual_sim       1000 non-null   int64
 5   fc             1000 non-null   int64
 6   four_g         1000 non-null   int64
 7   int_memory     1000 non-null   int64
 8   m_dep          1000 non-null   float64
```

```
 9   mobile_wt       1000 non-null   int64
 10  n_cores         1000 non-null   int64
 11  pc              1000 non-null   int64
 12  px_height       1000 non-null   int64
 13  px_width        1000 non-null   int64
 14  ram             1000 non-null   int64
 15  sc_h            1000 non-null   int64
 16  sc_w            1000 non-null   int64
 17  talk_time       1000 non-null   int64
 18  three_g         1000 non-null   int64
 19  touch_screen    1000 non-null   int64
 20  wifi            1000 non-null   int64
dtypes: float64(2), int64(19)
memory usage: 164.2 KB
```

3 EXPLORATORY DATA ANALYSIS

In data exploration, there are 3 important things that need to be done to find out the initial overview of the data, i.e.: - Checking for missing values - Data distribution check - Correlation

3.1 Missing Value

[7]:
```
data_train.isnull().sum()
```

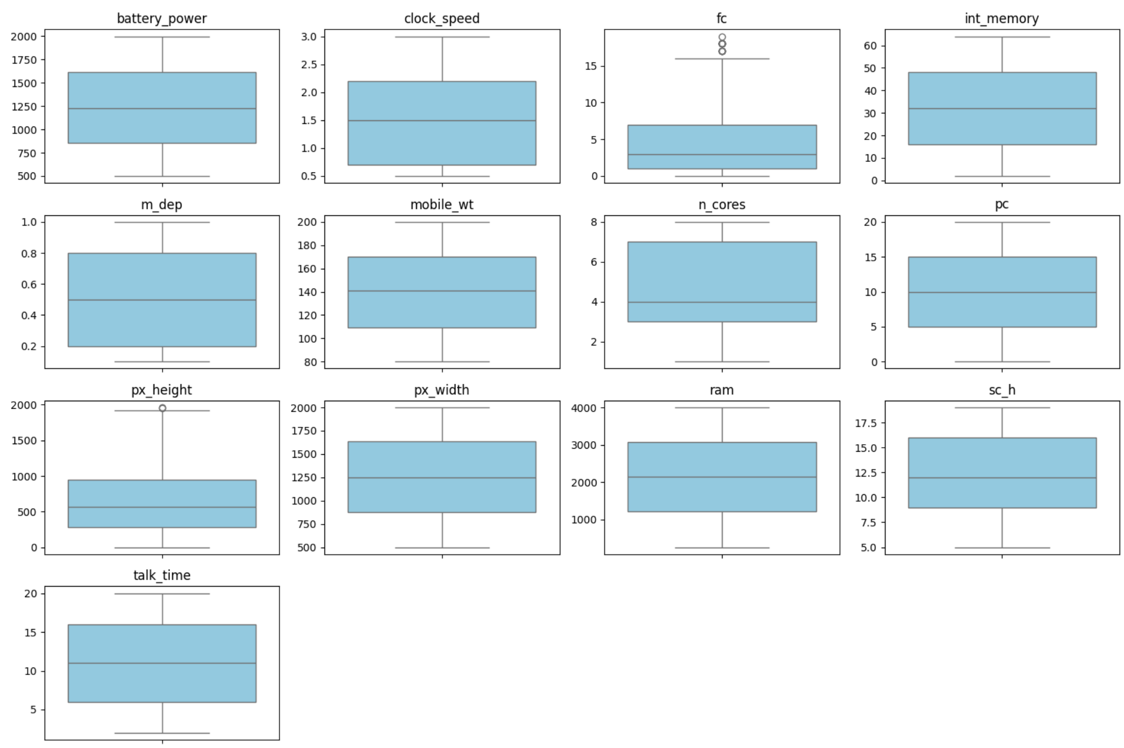
[7]:
```
battery_power    0
blue             0
clock_speed      0
dual_sim         0
fc               0
four_g           0
int_memory       0
m_dep            0
mobile_wt        0
n_cores          0
pc               0
px_height        0
px_width         0
ram              0
sc_h             0
sc_w             0
talk_time        0
three_g          0
touch_screen     0
wifi             0
price_range      0
dtype: int64
```

3.2 Data Distribution

3.2.1 Box-plot

[8]:
```
# List numerical column
col_num = ['battery_power', 'clock_speed', 'fc', 'int_memory', 'm_dep',␣
↪'mobile_wt',
           'n_cores', 'pc', 'px_height', 'px_width', 'ram', 'sc_h', 'talk_time']

plt.figure(figsize=(15,10))
for i, column in enumerate(col_num):
  plt.subplot(4,4,i+1)
  sns.boxplot(data = data_train, y=column, color='skyblue')
  plt.title(column, fontsize = 12)
  plt.xlabel('')
  plt.ylabel('')
  plt.tight_layout();
```

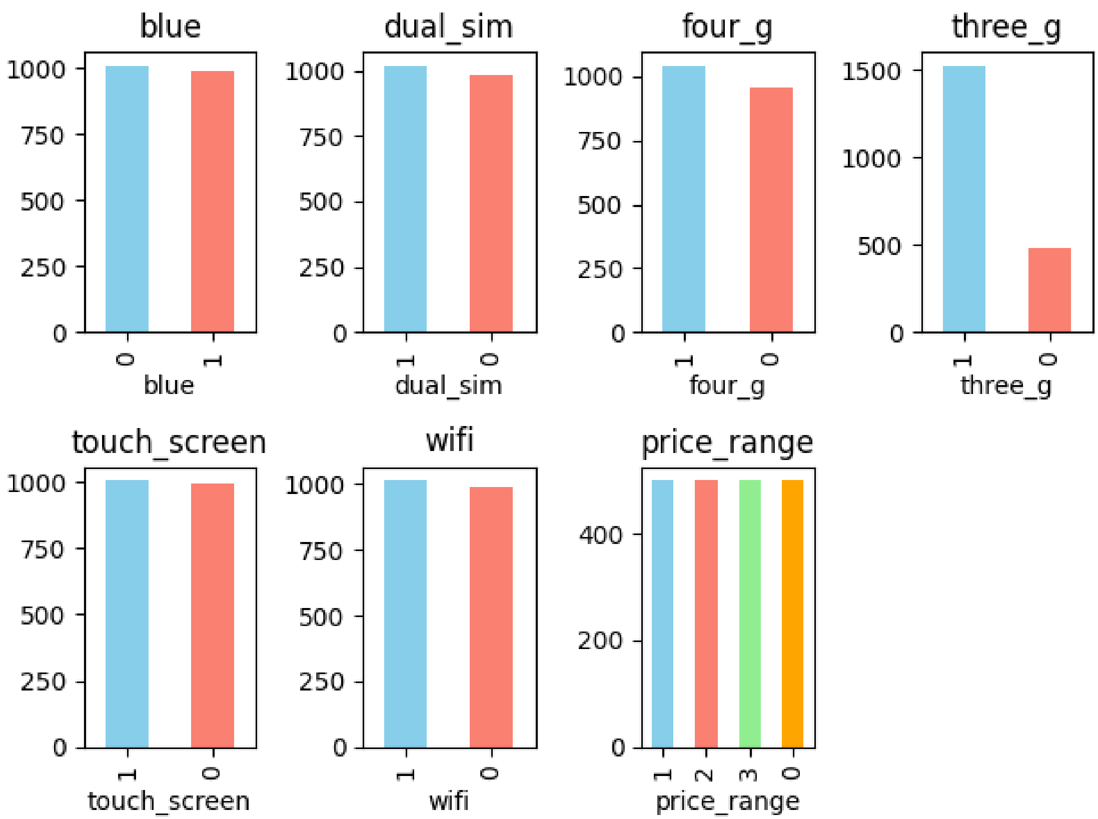


3.2.2 Bar-plot

[9]:
```
# List categorical column
col_cat = ['blue', 'dual_sim', 'four_g', 'three_g', 'touch_screen', 'wifi',␣
↪'price_range']
```

```
colors = ['skyblue', 'salmon', 'lightgreen', 'orange']

for i, column in enumerate(col_cat):
    plt.subplot(2, 4, i + 1)
    data_train[column].value_counts().plot(kind='bar', color=colors)
    plt.title(column, fontsize=12)
    plt.ylabel('')
    plt.tight_layout()
```

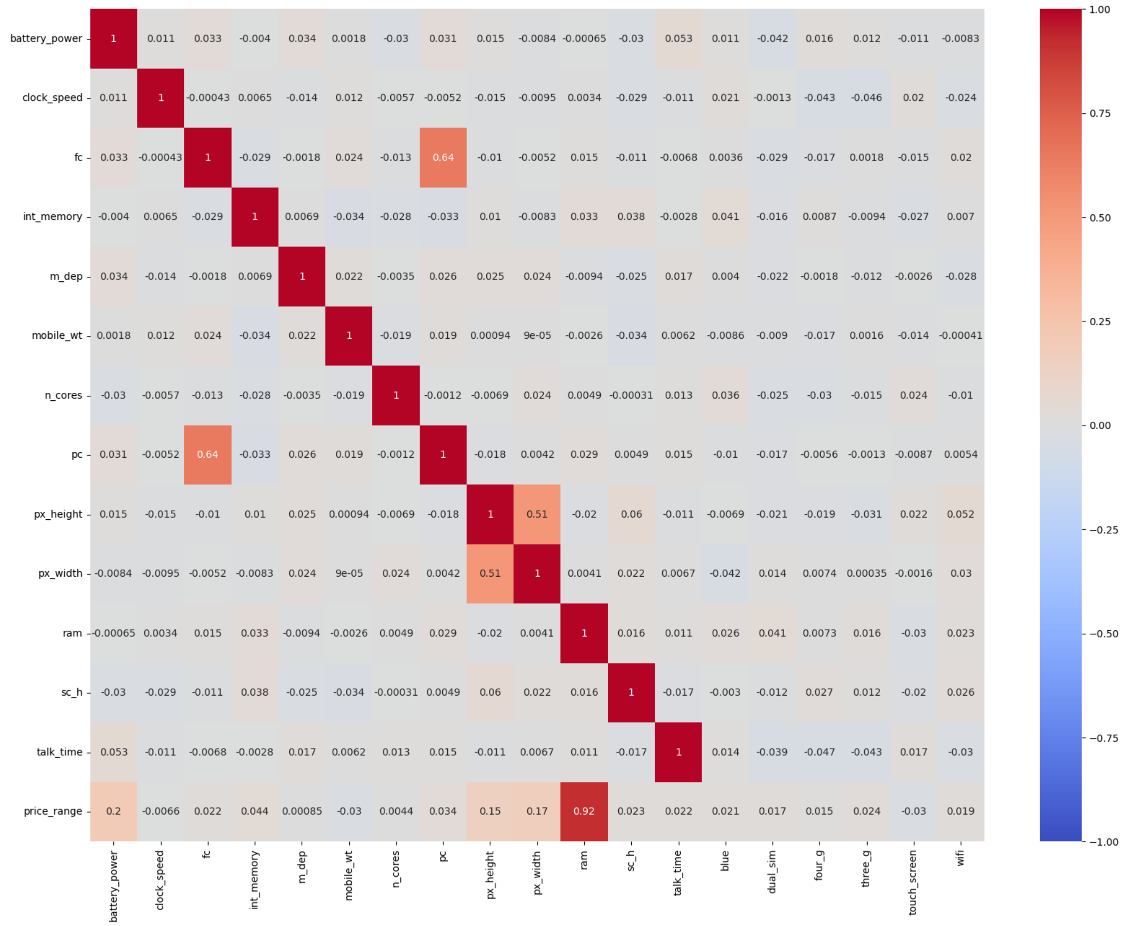


3.3 Correlation

[10]:
```
# List numerical column
col_num = ['battery_power', 'clock_speed', 'fc', 'int_memory', 'm_dep',␣
 ↪'mobile_wt', 'n_cores', 'pc',
           'px_height', 'px_width', 'ram', 'sc_h', 'talk_time']
# List categorical column
col_cat = ['blue', 'dual_sim', 'four_g', 'three_g', 'touch_screen', 'wifi']
# Merge column
variables = col_num + col_cat
```

```python
# Correlation
cor = data_train[variables + ['price_range']].corr()

# Heatmap
plt.figure(figsize=(20, 15))
sns.heatmap(cor.loc[col_num + ['price_range'], variables], annot=True,␣
    ↪cmap='coolwarm', vmin=-1, vmax=1)
plt.title('')
plt.show()
```



4 DATA PROCESSING

Then conduct data processing. In this stage, it is categorized into 3 sections, namely: - Data standardization - Feature engineering - Split data

4.1 Standardization

[12]:
```python
# Function to scaling data
def scale_data(data_train):
    # Make copy data
    scaled_data_train = data_train.copy()
    num_fit = ['battery_power', 'clock_speed', 'fc', 'int_memory', 'm_dep', 'mobile_wt',
               'n_cores', 'pc', 'px_height', 'px_width', 'ram', 'sc_h', 'talk_time']
    # Standardscaler (Z score)
    scaler = StandardScaler()
    scaled_data_train[num_fit] = scaler.fit_transform(scaled_data_train[num_fit])
    return scaled_data_train

scaled_data_train = scale_data(data_train)
print(scaled_data_train)
```

```
      battery_power  blue  clock_speed  dual_sim        fc  four_g  \
0         -0.902597     0     0.830779         0 -0.762495       0
1         -0.495139     1    -1.253064         1 -0.992890       1
2         -1.537686     1    -1.253064         1 -0.532099       1
3         -1.419319     1     1.198517         0 -0.992890       0
4          1.325906     1    -0.395011         0  2.002254       1
…               …   …          …       …       …     …
1995      -1.011860     1    -1.253064         1 -0.992890       1
1996       1.653694     1     1.321096         1 -0.992890       0
1997       1.530773     0    -0.762748         1 -0.762495       1
1998       0.622527     0    -0.762748         0 -0.071307       1
1999      -1.658331     1     0.585621         1  0.159088       1

      int_memory     m_dep  mobile_wt   n_cores  …  px_height  px_width  \
0      -1.380644  0.340740   1.349249 -1.101971  …  -1.408949 -1.146784
1       1.155024  0.687548  -0.120059 -0.664768  …   0.585778  1.704465
2       0.493546  1.381165   0.134244  0.209639  …   1.392684  1.074968
3      -1.215274  1.034357  -0.261339  0.646842  …   1.286750  1.236971
4       0.658915  0.340740   0.021220 -1.101971  …   1.268718 -0.091452
…            …        …         …        …  …       …        …
1995   -1.656260  1.034357  -0.967737  0.646842  …   1.300273  1.477661
1996    0.383299 -1.046495   1.320993 -0.227564  …   0.608317  1.651235
1997    0.217930  0.687548  -0.911225  1.521249  …   0.502383  0.880565
1998    0.769162 -1.393304   0.134244  0.209639  …  -0.696707 -1.345816
1999    0.714039  1.381165   0.784130  0.646842  …  -0.365380 -1.151413

           ram      sc_h  sc_w  talk_time  three_g  touch_screen  wifi  \
0     0.391703 -0.784983     7   1.462493        0             0     1
1     0.467317  1.114266     3  -0.734267        1             1     0
```

```
2     0.441498 -0.310171     2  -0.368140        1             1     0
3     0.594569  0.876859     8  -0.002014        1             0     0
4    -0.657666 -1.022389     2   0.730240        1             1     0
…          …        …    …       …        …          …    …
1995 -1.342799  0.164641     4   1.462493        1             1     0
1996 -0.085031 -0.310171    10   0.913303        1             1     1
1997  0.860139 -0.784983     1  -1.100394        1             1     0
1998 -1.157454  1.351672    10   1.462493        1             1     1
1999  1.655004  1.589078     4  -1.649584        1             1     1

      price_range
0               1
1               2
2               2
3               2
4               1
…             …
1995            0
1996            2
1997            3
1998            0
1999            3

[2000 rows x 21 columns]
```

4.2 Feature Engineering

[13]:
```
# Make feature column to numerical and categorical column
feature_columns = []

# Numerical column
num_fit = ['battery_power', 'clock_speed', 'fc', 'int_memory', 'm_dep',␣
 ↪'mobile_wt', 'n_cores', 'pc',
           'px_height', 'px_width', 'ram', 'sc_h', 'talk_time']

for col in num_fit:
  feature_num = tf.feature_column.numeric_column(col)
  feature_columns.append(feature_num)

# Categorical column
cat_fit = ['blue', 'dual_sim', 'four_g', 'three_g', 'touch_screen', 'wifi']

for col in cat_fit:
    feature_cat = tf.feature_column.categorical_column_with_vocabulary_list(
        key=col,
        vocabulary_list=scaled_data_train[col].unique().tolist()
    )
```

```
    feature_cat_onehot = tf.feature_column.indicator_column(feature_cat)
    feature_columns.append(feature_cat_onehot)
```

```
WARNING:tensorflow:From <ipython-input-13-111c80208b70>:9: numeric_column (from
tensorflow.python.feature_column.feature_column_v2) is deprecated and will be
removed in a future version.
Instructions for updating:
Use Keras preprocessing layers instead, either directly or via the
`tf.keras.utils.FeatureSpace` utility. Each of `tf.feature_column.*` has a
functional equivalent in `tf.keras.layers` for feature preprocessing when
training a Keras model.
WARNING:tensorflow:From <ipython-input-13-111c80208b70>:16:
categorical_column_with_vocabulary_list (from
tensorflow.python.feature_column.feature_column_v2) is deprecated and will be
removed in a future version.
Instructions for updating:
Use Keras preprocessing layers instead, either directly or via the
`tf.keras.utils.FeatureSpace` utility. Each of `tf.feature_column.*` has a
functional equivalent in `tf.keras.layers` for feature preprocessing when
training a Keras model.
WARNING:tensorflow:From <ipython-input-13-111c80208b70>:20: indicator_column
(from tensorflow.python.feature_column.feature_column_v2) is deprecated and will
be removed in a future version.
Instructions for updating:
Use Keras preprocessing layers instead, either directly or via the
`tf.keras.utils.FeatureSpace` utility. Each of `tf.feature_column.*` has a
functional equivalent in `tf.keras.layers` for feature preprocessing when
training a Keras model.
```

4.2.1 Feature Layer

[14]:
```
feature_layer = tf.keras.layers.DenseFeatures(feature_columns)
```

4.2.2 Change to TensorFlow

[15]:
```
# Function to convert dataframe to Tensorflow dataset
def data_to_dataset(dataframe, shuffle=True, batch_size=32):
  dataframe = dataframe.copy()
  labels = dataframe.pop('price_range')
  ds = tf.data.Dataset.from_tensor_slices((dict(dataframe),labels))

  if shuffle:
    ds = ds.shuffle(buffer_size=len(dataframe))

  ds = ds.batch(batch_size=batch_size)

  return ds
```

4.3 Split Data

Partitioned data into training data and testing data randomly. The training data is 80% of the total data, while the testing data is 20% of the overall data.

4.3.1 Neural Network

[16]:
```
# Partition data for Neural Network #
train, test = train_test_split(scaled_data_train, test_size=0.2,␣
↪random_state=42)
```

[17]:
```
# Convert dataframe to tfds dataset
train_ds = data_to_dataset(train, shuffle = True, batch_size=32)
test_ds = data_to_dataset(test, shuffle=False, batch_size=32)
```

[18]:
```
X = scale_data(data_train.drop('price_range', axis=1))
y = scaled_data_train['price_range']
```

[19]:
```
X
```

[19]:
```
      battery_power  blue  clock_speed  dual_sim        fc  four_g  \
0         -0.902597     0     0.830779         0 -0.762495       0
1         -0.495139     1    -1.253064         1 -0.992890       1
2         -1.537686     1    -1.253064         1 -0.532099       1
3         -1.419319     1     1.198517         0 -0.992890       0
4          1.325906     1    -0.395011         0  2.002254       1
…               …   …          …         …       …     …
1995      -1.011860     1    -1.253064         1 -0.992890       1
1996       1.653694     1     1.321096         1 -0.992890       0
1997       1.530773     0    -0.762748         1 -0.762495       1
1998       0.622527     0    -0.762748         0 -0.071307       1
1999      -1.658331     1     0.585621         1  0.159088       1

      int_memory     m_dep  mobile_wt   n_cores        pc  px_height  \
0      -1.380644  0.340740   1.349249 -1.101971 -1.305750  -1.408949
1       1.155024  0.687548  -0.120059 -0.664768 -0.645989   0.585778
2       0.493546  1.381165   0.134244  0.209639 -0.645989   1.392684
3      -1.215274  1.034357  -0.261339  0.646842 -0.151168   1.286750
4       0.658915  0.340740   0.021220 -1.101971  0.673534   1.268718
…            …       …         …        …        …         …
1995   -1.656260  1.034357  -0.967737  0.646842  0.673534   1.300273
1996    0.383299 -1.046495   1.320993 -0.227564 -1.140810   0.608317
1997    0.217930  0.687548  -0.911225  1.521249 -1.140810   0.502383
1998    0.769162 -1.393304   0.134244  0.209639 -0.810929  -0.696707
1999    0.714039  1.381165   0.784130  0.646842  1.003414  -0.365380

      px_width       ram      sc_h  sc_w  talk_time  three_g  touch_screen  \
0    -1.146784  0.391703 -0.784983     7   1.462493        0             0
```

```
1      1.704465  0.467317  1.114266     3  -0.734267        1             1
2      1.074968  0.441498 -0.310171     2  -0.368140        1             1
3      1.236971  0.594569  0.876859     8  -0.002014        1             0
4     -0.091452 -0.657666 -1.022389     2   0.730240        1             1
…         …        …        …    …      …       …        …
1995   1.477661 -1.342799  0.164641     4   1.462493        1             1
1996   1.651235 -0.085031 -0.310171    10   0.913303        1             1
1997   0.880565  0.860139 -0.784983     1  -1.100394        1             1
1998  -1.345816 -1.157454  1.351672    10   1.462493        1             1
1999  -1.151413  1.655004  1.589078     4  -1.649584        1             1

      wifi
0        1
1        0
2        0
3        0
4        0
…     …
1995     0
1996     1
1997     0
1998     1
1999     1

[2000 rows x 20 columns]
```

[20]:
```
y
```

[20]:
```
0       1
1       2
2       2
3       2
4       1
       ..
1995    0
1996    2
1997    3
1998    0
1999    3
Name: price_range, Length: 2000, dtype: int64
```

4.3.2 XGBoost

[21]:
```
# Partition data for XGBoost #
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,␣
 ↪random_state=42)
print(f"X_train : {X_train.shape}")
```

```
print(f"X_test : {X_test.shape}")
print(f"y_train : {y_train.shape}")
print(f"y_test : {y_test.shape}")
```

```
X_train : (1600, 20)
X_test : (400, 20)
y_train : (1600,)
y_test : (400,)
```

[22]:
```
X_train
```

[22]:
```
      battery_power  blue  clock_speed  dual_sim        fc  four_g  \
968        1.558089     0    -1.253064         1  0.619880       0
240       -1.378345     1     0.830779         0 -0.992890       1
819       -0.005733     0    -0.762748         1 -0.532099       1
692       -1.041452     0    -0.517590         0 -0.532099       0
420        0.495054     1    -1.253064         1  0.619880       0
…               …   …         …         …       …       …
1130       1.676457     1     0.463042         1 -0.532099       0
1294      -1.478503     1    -1.253064         0 -0.762495       1
860        1.344116     1    -1.253064         0 -0.992890       1
1459       1.567194     0    -0.762748         1 -0.301703       0
1126      -1.373793     1    -1.130485         1 -0.762495       1

      int_memory     m_dep  mobile_wt   n_cores        pc  px_height  \
968     0.769162 -0.006069   1.434017 -1.539175  0.013773   0.274736
240     0.934531 -1.393304  -0.035292  1.521249 -1.470690  -0.261699
819     1.375517 -1.393304   1.349249 -1.539175  0.673534  -0.288746
692     0.328176 -0.352878   1.631808  0.209639 -0.481048  -0.768833
420    -1.380644 -0.352878  -0.995993  0.209639  0.343653   0.400956
…            …         …         …         …         …         …
1130   -0.057686  1.381165   0.303779 -1.539175  1.168355   0.292767
1294    1.485763  0.687548   0.162500  1.521249 -0.975869   0.256704
860    -0.939658 -0.352878   0.558083  0.209639 -0.481048   0.189087
1459   -1.160151 -0.352878   1.405761  1.521249  0.343653  -0.347348
1126    0.989655 -0.699686  -1.222041  0.209639  0.508594  -1.019019

      px_width       ram      sc_h  sc_w  talk_time  three_g  touch_screen  \
968   1.174484 -0.585741 -0.547577     9  -1.466521        1             1
240  -0.561260  1.323964 -0.310171     1   0.913303        1             1
819  -1.024125 -0.662277  0.402047    12   1.645557        1             0
692   0.977767  1.276014  0.164641     8  -1.100394        0             0
420  -0.341399 -0.495373 -1.497202     5   1.645557        1             0
…          …         …         …   …         …       …
1130  0.822707  0.827865  0.164641     5   1.462493        0             0
1294  1.403602 -1.624967  0.876859    10  -0.917331        1             1
860   0.035836 -0.040770  0.876859    11   0.181050        1             0
1459  0.588960  0.730120  0.876859    11   1.279430        0             1
```

```
1126 -0.607546 -0.015872  0.164641    12   0.181050        1             0

      wifi
968      1
240      1
819      1
692      1
420      1
…    …
1130     1
1294     1
860      1
1459     1
1126     0

[1600 rows x 20 columns]
```

[23]:
```
y_train
```

[23]:
```
968     1
240     2
819     0
692     3
420     1
       ..
1130    3
1294    0
860     2
1459    3
1126    1
Name: price_range, Length: 1600, dtype: int64
```

[24]:
```
X_test
```

[24]:
```
      battery_power  blue  clock_speed  dual_sim        fc  four_g  \
1860       0.927552     0     1.198517         0 -0.301703       1
353       -0.128653     0    -1.253064         0  0.619880       1
1333       1.669628     0     1.688833         0  1.080671       0
905       -0.567980     1     0.585621         0 -0.071307       0
1289      -1.419319     1    -1.253064         1  0.619880       0
…                 …   …            …         …       …
965        0.319779     0    -1.253064         1 -0.762495       0
1284      -0.563428     0     0.585621         0 -0.532099       1
1739      -0.442784     0     0.340463         0 -0.071307       1
261       -1.162096     0     1.443675         1 -0.992890       0
535       -0.121824     0     0.463042         0 -0.992890       0
```

```
      int_memory     m_dep  mobile_wt   n_cores        pc  px_height  \
1860   -0.388426  0.340740   1.688320 -1.101971 -0.810929  -0.978448
353    -1.325520 -0.006069  -0.063548  1.521249  1.003414  -0.834197
1333   -0.994781 -0.352878   1.575296  1.084046  1.333295  -0.793626
905    -0.829411 -1.046495   0.727618 -0.664768  1.498235  -0.877022
1289    1.430640 -0.006069  -0.289595  0.209639 -0.316108   0.847234
…           …        …        …         …         …         …
965    -0.719165 -0.699686  -0.176571  1.521249  1.168355  -0.581757
1284   -1.105027 -0.699686   0.501571  0.209639 -0.645989   1.270972
1739   -1.105027  0.687548  -1.024249  0.646842 -0.810929   1.318305
261    -0.388426 -1.046495  -1.476344 -0.227564 -1.470690  -0.268461
535    -0.057686 -0.352878   0.332035  1.521249 -0.481048   0.432511

      px_width       ram      sc_h  sc_w  talk_time  three_g  touch_screen  \
1860  0.825021 -1.326201 -1.022389     6  -0.002014        1             1
353  -0.614489  0.404613  1.589078    17   1.462493        1             0
1333 -0.693176 -0.745267 -1.022389     1  -0.551204        1             1
905   0.329755  1.630107  1.351672     7   1.462493        1             1
1289  1.635035 -0.201218  0.402047     5  -1.100394        1             0
…         …         …        …   …        …        …           …
965  -1.343502  1.648549 -0.310171     2   1.462493        0             1
1284  0.987024 -0.101629 -0.310171     9  -0.185077        1             0
1739  0.026579 -0.304495  1.351672     7   1.462493        1             1
261   0.642189 -0.078576 -1.734608     1   0.181050        1             1
535   0.903708  0.297647  0.876859     2  -1.466521        1             1

      wifi
1860     0
353      0
1333     0
905      0
1289     0
…     …
965      1
1284     0
1739     1
261      1
535      1

[400 rows x 20 columns]
```

[25]:
```
y_test
```

[25]:
```
1860    0
353     2
1333    1
905     3
```

```
1289    1
        ..
965     3
1284    2
1739    1
261     1
535     2
Name: price_range, Length: 400, dtype: int64
```

5 MODELLING

The machine learning models used are Neural Network and XGBoost.

5.0.1 Neural Network

This code snippet builds, compiles, and trains a neural network model using TensorFlow's Keras API for a multi-class classification problem with four classes. Key steps include:

- **Building the Model**: Adding layers sequentially including preprocessing, dense, dropout, and regularization layers.
- **Compiling the Model**: Defining the optimizer, loss function, and evaluation metric.
- **Training the Model**: Fitting the model on the training dataset and validating it using the validation dataset over a specified number of epochs.

[26]:

```
## Build NN model ##
model_nn = tf.keras.Sequential([
    feature_layer,
    tf.keras.layers.Dense(units=512, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(units=256, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(units=128, activation='relu', kernel_regularizer=tf.
 ↪keras.regularizers.l2(0.05)),
    tf.keras.layers.Dense(units=64, activation='relu', kernel_regularizer=tf.
 ↪keras.regularizers.l2(0.01)),
    tf.keras.layers.Dense(units=4, activation='softmax')  # 4 class␣
 ↪('price_range')
])

# Compile Model
model_nn.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# Train model
history = model_nn.fit(train_ds, validation_data=test_ds, epochs=20)
```

```
Epoch 1/20
```

```
50/50 [==============================] - 4s 17ms/step - loss: 6.8101 - accuracy:
0.4856 - val_loss: 3.5117 - val_accuracy: 0.8575
Epoch 2/20
50/50 [==============================] - 0s 8ms/step - loss: 2.3807 - accuracy:
0.7575 - val_loss: 1.3754 - val_accuracy: 0.8650
Epoch 3/20
50/50 [==============================] - 0s 8ms/step - loss: 1.1202 - accuracy:
0.8300 - val_loss: 0.7267 - val_accuracy: 0.9425
Epoch 4/20
50/50 [==============================] - 0s 8ms/step - loss: 0.7430 - accuracy:
0.8600 - val_loss: 0.5253 - val_accuracy: 0.9525
Epoch 5/20
50/50 [==============================] - 0s 8ms/step - loss: 0.5962 - accuracy:
0.8694 - val_loss: 0.4253 - val_accuracy: 0.9550
Epoch 6/20
50/50 [==============================] - 0s 9ms/step - loss: 0.5231 - accuracy:
0.8694 - val_loss: 0.4411 - val_accuracy: 0.8950
Epoch 7/20
50/50 [==============================] - 0s 8ms/step - loss: 0.4730 - accuracy:
0.8825 - val_loss: 0.3551 - val_accuracy: 0.9350
Epoch 8/20
50/50 [==============================] - 0s 8ms/step - loss: 0.4624 - accuracy:
0.8650 - val_loss: 0.3561 - val_accuracy: 0.9300
Epoch 9/20
50/50 [==============================] - 0s 8ms/step - loss: 0.3759 - accuracy:
0.9125 - val_loss: 0.3397 - val_accuracy: 0.9050
Epoch 10/20
50/50 [==============================] - 1s 13ms/step - loss: 0.3811 - accuracy:
0.9050 - val_loss: 0.2937 - val_accuracy: 0.9525
Epoch 11/20
50/50 [==============================] - 1s 13ms/step - loss: 0.3580 - accuracy:
0.9069 - val_loss: 0.2962 - val_accuracy: 0.9275
Epoch 12/20
50/50 [==============================] - 0s 8ms/step - loss: 0.3403 - accuracy:
0.9156 - val_loss: 0.2837 - val_accuracy: 0.9375
Epoch 13/20
50/50 [==============================] - 0s 8ms/step - loss: 0.3331 - accuracy:
0.9119 - val_loss: 0.3228 - val_accuracy: 0.9100
Epoch 14/20
50/50 [==============================] - 0s 8ms/step - loss: 0.3169 - accuracy:
0.9200 - val_loss: 0.3314 - val_accuracy: 0.8975
Epoch 15/20
50/50 [==============================] - 0s 8ms/step - loss: 0.3105 - accuracy:
0.9144 - val_loss: 0.2797 - val_accuracy: 0.9200
Epoch 16/20
50/50 [==============================] - 0s 8ms/step - loss: 0.3067 - accuracy:
0.9181 - val_loss: 0.2367 - val_accuracy: 0.9450
Epoch 17/20
```

```
50/50 [==============================] - 0s 8ms/step - loss: 0.2850 - accuracy:
0.9256 - val_loss: 0.2455 - val_accuracy: 0.9450
Epoch 18/20
50/50 [==============================] - 0s 8ms/step - loss: 0.2695 - accuracy:
0.9306 - val_loss: 0.2776 - val_accuracy: 0.9250
Epoch 19/20
50/50 [==============================] - 0s 9ms/step - loss: 0.2634 - accuracy:
0.9325 - val_loss: 0.2393 - val_accuracy: 0.9475
Epoch 20/20
50/50 [==============================] - 0s 8ms/step - loss: 0.2520 - accuracy:
0.9306 - val_loss: 0.2218 - val_accuracy: 0.9450
```

5.1 XGBoost

This code snippet builds, tunes, and trains an XGBoost classifier for a multi-class classification task. The steps include:

- **Building the model**: Creating an XGBoost classifier with specific settings.
- **Hyperparameter Tuning**: Specifying the hyperparameters and their ranges for grid search.
- **Grid Search CV**: Configuring the grid search with cross-validation to find the best hyperparameters.
- **Model Training**: Training the model using grid search to find the optimal hyperparameters.
- **Best Parameter**: Extracting and printing the best model and its parameters after the grid search.

[27]:
```
# Build Model XGBoost
model_xgb = XGBClassifier(use_label_encoder=False, eval_metric='mlogloss')

# Parameter grid
param_grid = {
    'learning_rate': [0.1, 0.01, 0.001],
    'max_depth': [3, 5, 7],
    'n_estimators': [100, 200, 300],
}

# Grid search CV hyperparameter tuning
grid_search = GridSearchCV(model_xgb, param_grid, cv=5, n_jobs=-1, verbose=2)

# Train model
grid_search.fit(X_train, y_train)

# Best parameter
best_xgb = grid_search.best_estimator_
print('Best combination parameter:', grid_search.best_params_)
```

```
Fitting 5 folds for each of 27 candidates, totalling 135 fits
```

```
/usr/local/lib/python3.10/dist-
packages/joblib/externals/loky/backend/fork_exec.py:38: RuntimeWarning:
```

```
os.fork() was called. os.fork() is incompatible with multithreaded code, and JAX
is multithreaded, so this will likely lead to a deadlock.
  pid = os.fork()
/usr/local/lib/python3.10/dist-
packages/joblib/externals/loky/backend/fork_exec.py:38: RuntimeWarning:
os.fork() was called. os.fork() is incompatible with multithreaded code, and JAX
is multithreaded, so this will likely lead to a deadlock.
  pid = os.fork()
```

```
Best combination parameter: {'learning_rate': 0.1, 'max_depth': 5,
'n_estimators': 300}
```

5.1.1 Features Importance

Extract and display feature importance from the trained XGBoost model

[28]:
```python
# Feature importance XGBoost
feature_importance = best_xgb.feature_importances_
feature_importance = pd.DataFrame({'Feature': X_train.columns, 'Importance':
 ↪feature_importance})
feature_importance = feature_importance.sort_values(by='Importance',
 ↪ascending=False)
feature_importance = feature_importance.set_index('Feature')
feature_importance
```

[28]:

Feature	Importance
ram	0.421694
battery_power	0.134269
px_height	0.096689
px_width	0.077731
m_dep	0.030650
mobile_wt	0.025206
n_cores	0.021878
pc	0.019198
fc	0.018655
int_memory	0.018039
sc_h	0.017958
dual_sim	0.017684
clock_speed	0.017016
touch_screen	0.015846
talk_time	0.014842
sc_w	0.013548
four_g	0.011630
blue	0.011510
three_g	0.008912
wifi	0.007045

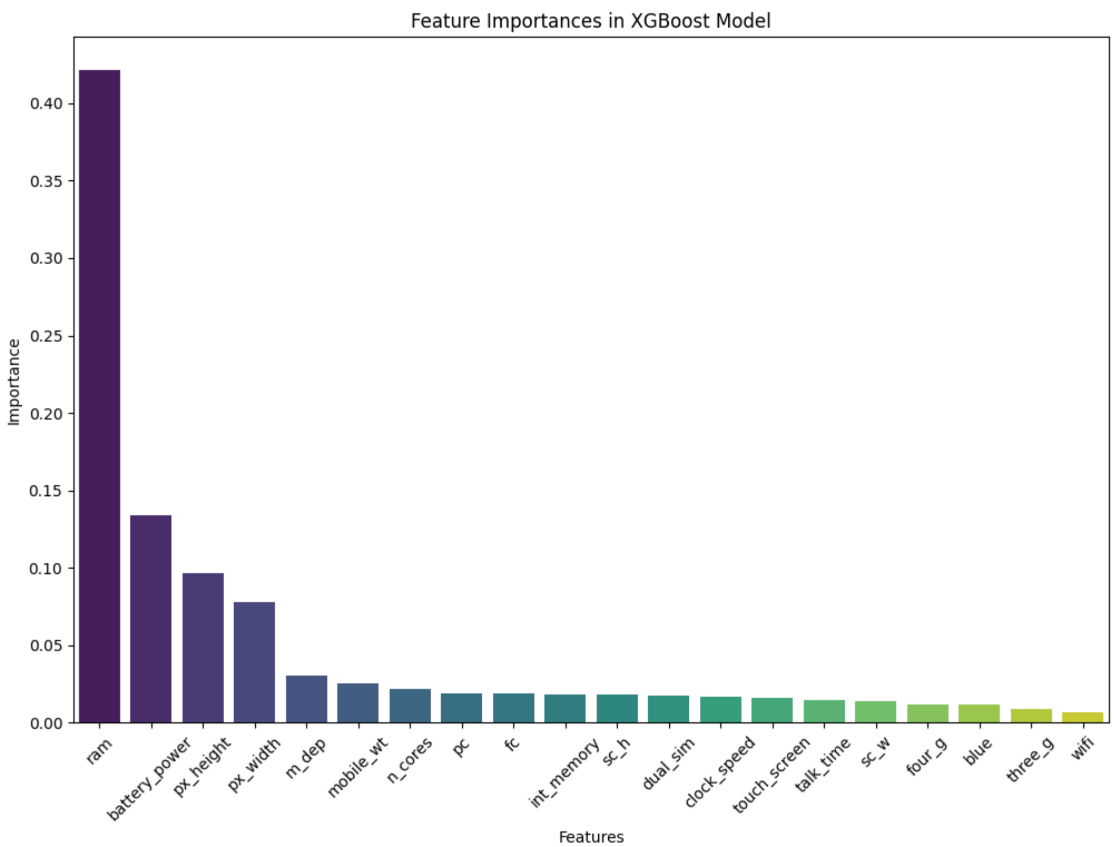
5.1.2 Plot

[29]:
```
plt.figure(figsize=(12, 8))
sns.barplot(x=feature_importance.index, y=feature_importance['Importance'],␣
    ↪palette="viridis")
plt.title('Feature Importances in XGBoost Model')
plt.xlabel('Features')
plt.ylabel('Importance')
plt.xticks(rotation=45)
plt.show()
```

```
<ipython-input-29-ba0ccd030aac>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=feature_importance.index, y=feature_importance['Importance'],
palette="viridis")
```



[30]:
```python
top_features = feature_importance.head(5)
print("Top 5 Important Features:")
print(top_features)
```

```
Top 5 Important Features:
               Importance
Feature
ram              0.421694
battery_power    0.134269
px_height        0.096689
px_width         0.077731
m_dep            0.030650
```

6 MODEL EVALUATION

6.1 NEURAL NETWORK

6.1.1 Accuracy

[31]:
```python
accuracy = model_nn.evaluate(test_ds)
print(f'Accuracy: {accuracy}')
```

```
13/13 [==============================] - 0s 6ms/step - loss: 0.2218 - accuracy:
0.9450
Accuracy: [0.2218443751335144, 0.9449999928474426]
```

6.1.2 Predict

The steps in making predictions are as follows: - Input data is passed into the network to be processed step by step. - Forward propagation, where the input data will be processed in a forward direction through each network to produce an output. - The softmax activation function is applied to the output of the final dense layer to get probabilities for each class. - The predicted class is the one with the highest probability.

[32]:
```python
# Predict
y_pred_probs_nn = model_nn.predict(test_ds)
y_pred_nn = tf.argmax(y_pred_probs_nn, axis=1)
```

```
13/13 [==============================] - 2s 8ms/step
```

[55]:
```python
y_pred_probs_nn
```

[55]:
```
array([[1.1764974e-11, 5.7305338e-06, 2.9299134e-01, 7.0700294e-01],
       [1.6081386e-14, 1.0920873e-08, 5.8020917e-03, 9.9419785e-01],
       [2.1041899e-09, 3.0209581e-04, 9.4689518e-01, 5.2802693e-02],
       …,
       [7.8229952e-01, 2.1767491e-01, 2.5416541e-05, 8.1559915e-12],
       [2.8675852e-06, 4.4830784e-02, 9.5438033e-01, 7.8595895e-04],
       [2.4422516e-07, 1.2284250e-02, 9.8691291e-01, 8.0256991e-04]],
```

```
       dtype=float32)
```

[33]:
```
y_pred_nn
```

[33]:
```
<tf.Tensor: shape=(400,), dtype=int64, numpy=
array([0, 2, 1, 3, 1, 1, 2, 0, 3, 1, 0, 0, 2, 3, 3, 2, 3, 3, 1, 0, 0, 2,
       0, 2, 0, 1, 3, 3, 2, 0, 0, 0, 3, 0, 1, 1, 2, 0, 3, 0, 2, 3, 2, 0,
       2, 3, 2, 1, 3, 1, 3, 1, 0, 0, 1, 0, 1, 3, 0, 0, 1, 3, 3, 1, 0, 0,
       3, 3, 1, 2, 2, 2, 0, 1, 2, 0, 1, 3, 2, 2, 3, 2, 1, 0, 1, 3, 1, 3,
       3, 0, 3, 3, 2, 1, 3, 2, 2, 3, 1, 1, 0, 0, 1, 0, 0, 3, 2, 0, 1, 1,
       0, 0, 3, 1, 3, 2, 3, 2, 0, 2, 1, 3, 2, 1, 3, 3, 0, 3, 0, 2, 3, 0,
       2, 2, 0, 3, 1, 0, 0, 2, 3, 1, 3, 2, 0, 0, 0, 1, 1, 2, 3, 1, 1, 0,
       2, 2, 0, 1, 0, 2, 2, 3, 3, 3, 1, 0, 0, 2, 2, 3, 3, 0, 0, 0, 3, 1,
       1, 2, 1, 0, 0, 0, 0, 0, 3, 2, 0, 3, 0, 0, 0, 0, 1, 3, 3, 1, 0, 1,
       2, 1, 1, 2, 2, 3, 3, 3, 1, 2, 0, 0, 0, 2, 1, 1, 3, 1, 0, 2, 1, 1,
       3, 2, 3, 0, 0, 2, 1, 3, 0, 1, 1, 0, 1, 3, 2, 0, 1, 3, 3, 0, 1, 3,
       3, 3, 0, 3, 1, 2, 3, 3, 2, 1, 1, 3, 3, 1, 3, 3, 3, 2, 3, 0, 2, 2,
       3, 2, 3, 0, 2, 3, 2, 3, 2, 1, 0, 2, 0, 2, 3, 1, 3, 1, 0, 3, 1, 2,
       0, 0, 3, 0, 1, 2, 3, 3, 3, 1, 0, 0, 1, 3, 3, 0, 1, 2, 2, 0, 3, 3,
       2, 3, 2, 3, 2, 0, 2, 1, 1, 1, 0, 0, 0, 2, 3, 3, 1, 0, 1, 0, 2, 2,
       3, 0, 3, 3, 2, 1, 3, 0, 0, 3, 1, 3, 2, 0, 1, 1, 1, 0, 1, 3, 1, 0,
       0, 3, 3, 0, 3, 0, 0, 2, 0, 1, 2, 2, 2, 3, 0, 3, 2, 3, 3, 3, 3, 2,
       1, 1, 0, 3, 1, 3, 3, 0, 2, 3, 2, 3, 3, 3, 0, 0, 2, 3, 0, 0, 2, 3,
       2, 1, 1, 2])>
```

6.1.3 Evaluation Metric

[34]:
```
# Evaluation Metric
print(f'Accuracy: {accuracy_score(y_test, y_pred_nn)}')
print(f'Precision: {precision_score(y_test, y_pred_nn, average="weighted")}')
print(f'Recall: {recall_score(y_test, y_pred_nn, average="weighted")}')
print(f'F1-Score: {f1_score(y_test, y_pred_nn, average="weighted")}')
```

```
Accuracy: 0.945
Precision: 0.9451004143368664
Recall: 0.945
F1-Score: 0.9445358010257542
```

6.1.4 Confussion Matrix

[35]:
```
# Confusion Matrix
cm_nn = confusion_matrix(y_test, y_pred_nn)
print("Confusion Matrix NN:")
print(cm_nn)
```

```
Confusion Matrix NN:
[[104   1   0   0]
 [  5  84   2   0]
```

```
[  0   3  81   8]
 [  0   0   3 109]]
```

6.1.5 Classification Report

[37]:
```
# Classification Report
cr_nn = classification_report(y_test, y_pred_nn)
print("\nClassification Report Neural Network:")
print(cr_nn)
```

```
Classification Report Neural Network:
              precision    recall  f1-score   support

           0       0.95      0.99      0.97       105
           1       0.95      0.92      0.94        91
           2       0.94      0.88      0.91        92
           3       0.93      0.97      0.95       112

    accuracy                           0.94       400
   macro avg       0.95      0.94      0.94       400
weighted avg       0.95      0.94      0.94       400
```

6.1.6 ROC Score

[38]:
```
# ROC Score
roc_auc_scores = roc_auc_score(y_test, y_pred_probs_nn, multi_class='ovo')
print("ROC AUC Score:", roc_auc_scores)
```

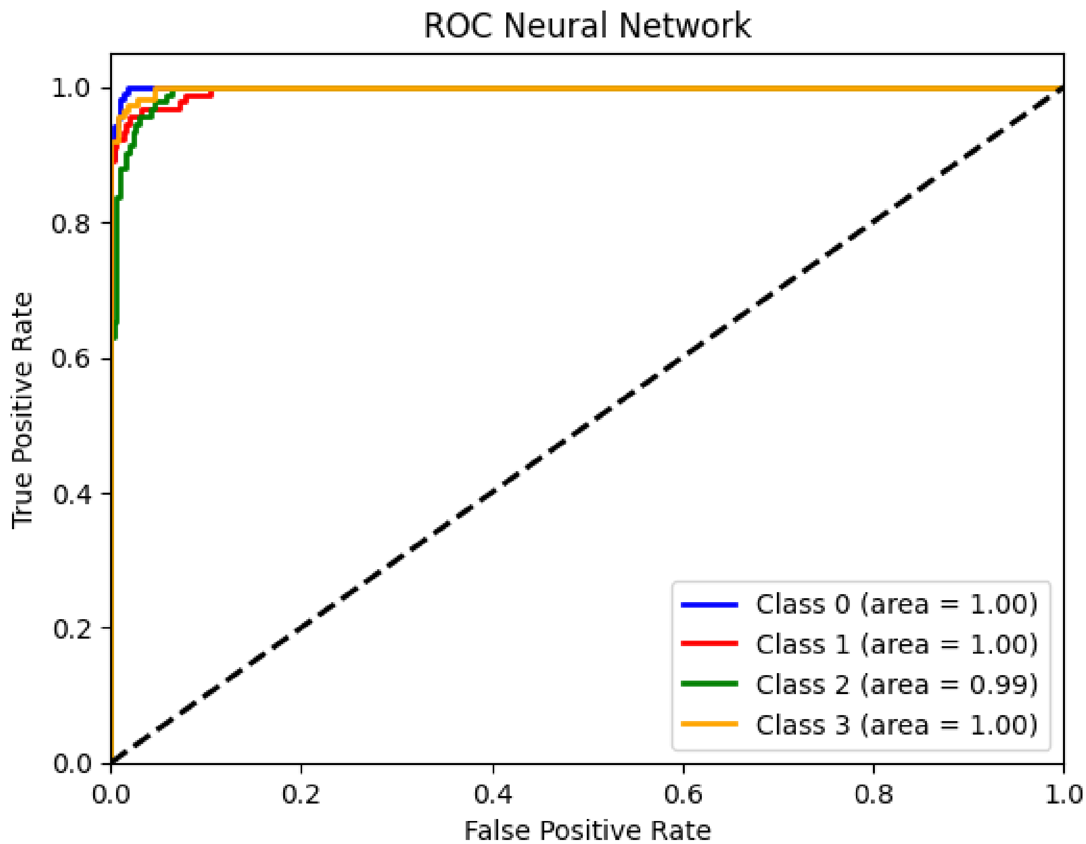
```
ROC AUC Score: 0.9969261080965274
```

6.1.7 Plot ROC

[39]:
```
# Plot ROC
plt.figure()
colors = ['blue', 'red', 'green', 'orange']
for i in range(4):
    fpr, tpr, _ = roc_curve(y_test, y_pred_probs_nn[:, i], pos_label=i)
    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, color=colors[i], lw=2, label=f'Class {i} (area =␣
 ↪{roc_auc:.2f})')

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Neural Network')
```

```
plt.legend(loc='lower right')
plt.show()
```



6.2 XGBOOST

6.2.1 Predict

The process involves making predictions using each tree in the ensemble and then aggregating these predictions. The steps in making predictions are as follows: - For each sample in X_test, each tree makes a prediction. - XGBoost uses boosting, which means each tree's prediction is added to the previous trees' predictions. - After all tree predictions are added, the final prediction is obtained. If the model is for classification, this final value is used to determine the class label (softmax function).

[40]:
```
# Predict
y_pred_xgb = best_xgb.predict(X_test)
y_pred_xgb
```

[40]:
```
array([0, 2, 1, 3, 1, 1, 2, 0, 3, 1, 0, 1, 2, 3, 2, 2, 3, 3, 1, 0, 0, 1,
       1, 2, 0, 1, 3, 2, 2, 0, 0, 0, 3, 0, 1, 1, 2, 0, 3, 0, 2, 3, 2, 0,
       3, 2, 1, 1, 3, 1, 3, 1, 0, 0, 0, 1, 1, 2, 0, 0, 1, 3, 3, 1, 0, 0,
```

```
3, 3, 1, 2, 2, 2, 0, 1, 2, 0, 0, 3, 2, 2, 3, 2, 1, 0, 1, 3, 1, 3,
3, 0, 3, 3, 2, 1, 3, 2, 2, 3, 1, 1, 0, 0, 1, 0, 0, 3, 2, 0, 1, 1,
0, 0, 3, 1, 2, 2, 3, 2, 0, 2, 1, 3, 2, 1, 3, 3, 0, 3, 0, 2, 3, 0,
2, 2, 0, 3, 1, 0, 0, 2, 3, 0, 2, 2, 0, 0, 0, 1, 1, 2, 3, 1, 1, 0,
2, 2, 0, 1, 0, 1, 2, 3, 2, 2, 1, 0, 0, 2, 2, 3, 3, 1, 1, 0, 3, 1,
2, 2, 1, 0, 0, 0, 0, 0, 3, 2, 0, 3, 0, 0, 0, 0, 1, 3, 3, 1, 0, 1,
1, 1, 1, 1, 2, 2, 3, 3, 1, 2, 0, 0, 0, 2, 1, 1, 3, 1, 0, 2, 1, 1,
3, 2, 3, 0, 0, 2, 1, 3, 0, 1, 2, 0, 2, 3, 2, 1, 1, 3, 3, 0, 1, 3,
3, 3, 0, 3, 1, 2, 3, 3, 2, 1, 1, 3, 3, 1, 3, 3, 3, 3, 3, 0, 1, 2,
2, 1, 2, 0, 2, 3, 2, 2, 2, 1, 0, 1, 0, 3, 3, 1, 3, 1, 0, 3, 1, 2,
0, 0, 3, 0, 1, 2, 3, 3, 3, 1, 0, 0, 1, 3, 3, 0, 1, 2, 2, 0, 3, 3,
2, 3, 2, 3, 2, 0, 2, 1, 1, 1, 0, 0, 0, 3, 2, 3, 1, 0, 1, 0, 1, 3,
3, 0, 3, 3, 2, 1, 3, 0, 0, 3, 1, 3, 2, 0, 1, 1, 1, 0, 1, 3, 2, 0,
0, 3, 3, 0, 3, 0, 0, 2, 0, 1, 2, 2, 2, 3, 0, 3, 2, 2, 3, 3, 3, 2,
1, 2, 0, 3, 2, 3, 3, 0, 2, 3, 2, 3, 3, 3, 0, 0, 2, 3, 0, 0, 2, 3,
2, 1, 1, 2])
```

6.2.2 Probability

[41]:
```
# Probability
y_pred_probs_xgb = best_xgb.predict_proba(X_test)
print(y_pred_probs_xgb)
```

```
[[9.9930334e-01 6.8816036e-04 5.6351510e-06 2.8256468e-06]
 [2.0649713e-04 4.4723582e-03 9.9521613e-01 1.0506645e-04]
 [1.6548836e-03 9.9751830e-01 6.1345228e-04 2.1338854e-04]
 …
 [1.0245005e-03 9.7667056e-01 2.1862783e-02 4.4214181e-04]
 [1.7009232e-04 9.9034750e-01 9.3114236e-03 1.7090060e-04]
 [5.1436735e-05 6.1962113e-04 9.9374098e-01 5.5879410e-03]]
```

6.2.3 Evaluation Metric

[42]:
```
# Evaluation Metric
print(f'Accuracy: {accuracy_score(y_test, y_pred_xgb)}')
print(f'Precision: {precision_score(y_test, y_pred_xgb, average="weighted")}')
print(f'Recall: {recall_score(y_test, y_pred_xgb, average="weighted")}')
print(f'F1-Score: {f1_score(y_test, y_pred_xgb, average="weighted")}')
```

```
Accuracy: 0.9075
Precision: 0.9080434006869172
Recall: 0.9075
F1-Score: 0.9076272051888165
```

6.2.4 Confussion Matrix

[43]:
```
# Confusion Matrix
cm_xgb = confusion_matrix(y_test, y_pred_xgb)
print("Confusion Matrix XGBOOST:")
print(cm_xgb)
```

```
Confusion Matrix XGBOOST:
[[100   5   0   0]
 [  6  82   3   0]
 [  0   7  79   6]
 [  0   0  10 102]]
```

6.2.5 Classification Report

[44]:
```
# Classification Report
cr_xgb = classification_report(y_test, y_pred_xgb)
print("\nClassification Report XGBOOST:")
print(cr_xgb)
```

```

Classification Report XGBOOST:
              precision    recall  f1-score   support

           0       0.94      0.95      0.95       105
           1       0.87      0.90      0.89        91
           2       0.86      0.86      0.86        92
           3       0.94      0.91      0.93       112

    accuracy                           0.91       400
   macro avg       0.90      0.91      0.91       400
weighted avg       0.91      0.91      0.91       400

```

6.2.6 ROC Score

[45]:
```
# ROC Score
xgb_roc_auc = roc_auc_score(y_test, y_pred_probs_xgb, multi_class='ovr')
print(f'ROC AUC Score: {xgb_roc_auc}')
```

```
ROC AUC Score: 0.991549070627018
```

6.2.7 Plot ROC

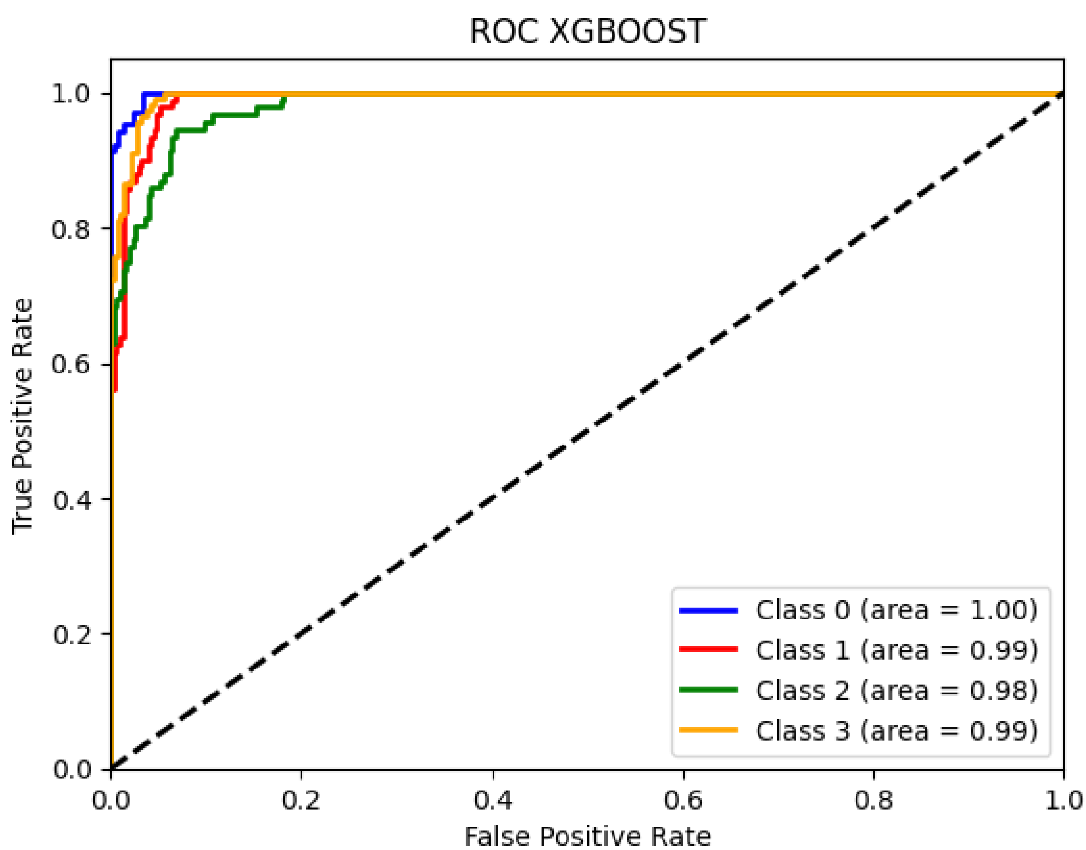
[46]:
```
fpr = {}
tpr = {}
roc_auc = {}

for i in range(4):  # 4 CLASS
```

```python
    fpr[i], tpr[i], _ = roc_curve(y_test, y_pred_probs_xgb[:, i], pos_label=i)
    roc_auc[i] = auc(fpr[i], tpr[i])

# Plot ROC
plt.figure()
colors = ['blue', 'red', 'green', 'orange']
for i in range(4):
    plt.plot(fpr[i], tpr[i], color=colors[i], lw=2, label=f'Class {i} (area =␣
 ↪{roc_auc[i]:0.2f})')

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC XGBOOST')
plt.legend(loc="lower right")
plt.show()
```



7 PREDICTION

7.1 Read Data

[47]:
```
data_testing = pd.read_csv("test.csv")
```

7.2 Data Preprocessing

7.2.1 Standardize

[48]:
```
def scale_data(data_testing):
    scaled_data_testing = data_testing.copy()
    num_fit = ['battery_power', 'clock_speed', 'fc', 'int_memory', 'm_dep',␣
  ↪'mobile_wt',
               'n_cores', 'pc', 'px_height', 'px_width', 'ram', 'sc_h',␣
  ↪'talk_time']
    scaler = StandardScaler()
    scaled_data_testing[num_fit] = scaler.
  ↪fit_transform(scaled_data_testing[num_fit])
    return scaled_data_testing

scaled_data_testing = scale_data(data_testing)
print(scaled_data_testing)
```

```
       id  battery_power  blue  clock_speed  dual_sim        fc  four_g  \
0       1      -0.475451     1     0.312601         1  2.108676       0
1       2      -0.942782     1    -1.255832         1 -0.132927       1
2       3       1.292077     1     1.519087         0 -0.805408       0
3       4       0.688249     0    -1.255832         1  3.005317       1
4       5       0.429135     0    -0.169994         0  1.436195       1
..    …            …   …          …       …        …     …
995   996       1.044531     1     0.433249         0 -1.029568       1
996   997      -1.479519     0     0.312601         1 -1.029568       0
997   998      -0.146932     0    -0.169994         0 -0.805408       1
998   999       0.658173     1    -1.255832         1 -1.029568       0
999  1000       0.049718     1    -1.255832         0 -0.132927       1

     int_memory     m_dep  mobile_wt  …        pc  px_height  px_width  \
0     -1.581269 -1.487247   1.535535  …  0.976026  -0.926990  0.391912
1      1.509303  1.006341   1.478120  …  0.319433   0.274729 -0.871028
2     -0.367116  1.362567   1.334582  … -0.993754   1.485693  0.287236
3     -0.477493 -0.062340  -1.249091  …  1.632619  -0.767532  1.165604
4      0.847037 -0.062340  -0.904602  …  1.304323   0.281662 -0.977979
..          …        …        …  …     …       …        …
995    1.122981 -0.062340   0.875263  …  1.140174   0.039007 -0.743596
996   -1.139759  1.362567   1.334582  … -1.322051   1.212995  0.892536
997   -1.415702 -0.062340  -1.708411  …  0.319433  -0.346930 -0.943846
998    0.902226 -0.418566   0.903970  …  0.319433  -1.361458 -0.927917
999    0.074394 -1.487247   0.014038  …  1.468471  -0.393150 -1.437643
```

```
          ram      sc_h  sc_w  talk_time  three_g  touch_screen  wifi
0    1.229373  0.001158     7  -1.653355        0             1     0
1    1.614643 -1.388231     0  -0.743418        1             0     0
2    0.236313  1.158982    10  -0.197456        0             1     1
3    1.612804 -0.461972     0  -0.743418        1             1     0
4   -0.336535  0.695852     8  -0.743418        1             0     1
..        …         …    …          …       …             …   …
995 -0.016549  0.464287     8   0.712481        1             1     0
996 -0.189415 -0.925101     1   1.440430        0             1     1
997 -0.842260 -1.619796     0   0.530493        1             0     0
998  0.340217  0.695852    11  -0.925406        0             1     0
999  0.633537 -0.693537     2  -1.471368        1             0     1

[1000 rows x 21 columns]
```

7.3 Neural Network

7.3.1 Data Convertion

[49]:
```python
def data_to_dataset(dataframe, batch_size=32):
    dataframe = dataframe.copy()
    ds = tf.data.Dataset.from_tensor_slices(dict(dataframe))
    ds = ds.batch(batch_size)
    return ds

test_ds = data_to_dataset(scaled_data_testing)
```

7.3.2 Predict

[56]:
```python
y_pred_probs_nn = model_nn.predict(test_ds)
y_pred_nn = tf.argmax(y_pred_probs_nn, axis=1).numpy()

print("Neural Network Predict:")
print(y_pred_nn)
```

```
32/32 [==============================] - 0s 6ms/step
Neural Network Predict:
[3 3 2 3 1 3 3 1 3 0 3 3 0 0 2 0 2 1 3 2 1 3 1 1 3 0 2 0 2 0 2 0 3 0 1 1 3
 1 2 1 1 2 0 0 0 1 0 3 1 2 1 0 3 0 3 0 3 1 0 3 3 3 0 1 0 1 2 3 1 2 1 2 2 3
 3 0 2 0 1 3 0 3 3 0 3 0 3 1 3 0 1 2 2 1 2 2 0 2 1 3 1 0 0 3 0 2 0 1 2 3 3
 3 1 3 3 3 3 2 3 0 0 3 2 1 2 0 3 2 2 2 0 2 1 1 3 1 1 0 3 2 1 2 1 2 2 3 3 3
 2 3 2 3 1 0 3 2 3 3 3 3 3 2 3 3 3 3 1 0 3 0 0 0 2 0 0 1 0 0 1 2 1 0 0 1 1
 2 2 1 0 0 0 1 0 3 1 0 2 2 3 3 1 1 3 3 3 2 2 1 0 0 1 3 0 2 3 3 0 2 0 3 2 3
 3 1 0 1 0 3 0 1 0 2 2 1 3 0 3 0 3 1 2 0 0 2 0 3 3 3 1 1 3 0 0 2 3 3 1 3 1
 1 3 2 1 2 3 3 3 1 0 1 2 3 1 1 3 2 0 3 0 0 2 0 0 3 2 3 3 2 0 3 3 2 3 1 2 1
 2 0 2 3 1 0 0 3 0 3 0 1 2 0 2 3 1 3 2 2 0 2 0 0 0 1 3 2 0 0 0 3 2 0 2 3 1
 2 2 2 3 1 3 3 2 2 2 3 3 0 3 0 3 1 3 1 2 3 0 1 0 3 1 3 2 3 0 0 0 0 2 0 0 2
 2 0 2 2 2 0 1 0 0 3 2 0 3 1 2 2 1 2 3 1 1 2 2 1 2 0 1 1 0 3 2 0 0 1 0 0 1
```

```
1 0 0 0 2 2 3 2 3 0 3 0 3 0 1 1 0 2 0 3 2 3 3 1 3 1 3 1 3 2 0 1 2 1 1 0 0
0 1 2 1 0 3 2 0 2 3 0 0 3 1 2 0 2 2 3 0 3 0 2 3 2 3 0 2 0 2 3 0 1 1 0 0 1
1 1 3 3 3 1 3 1 2 2 3 3 3 2 0 2 1 2 2 1 0 2 2 0 0 0 3 1 0 2 2 2 0 3 0 2 2
0 3 0 2 3 0 1 1 3 3 1 1 1 3 2 0 3 1 2 0 3 3 1 3 2 2 3 0 1 2 3 1 3 2 3 1 1
0 0 3 1 0 3 2 3 2 1 3 3 3 2 3 3 1 2 0 2 3 3 0 0 1 1 2 2 2 0 0 2 2 3 2 0 2
1 3 3 0 1 3 0 2 1 1 0 0 2 1 0 1 2 2 2 0 2 2 1 0 3 0 0 3 2 0 0 0 0 0 3 0 3
0 3 2 1 3 2 0 1 0 3 2 3 2 0 3 0 2 0 2 0 0 1 1 1 2 1 3 1 3 2 2 1 3 2 0 1 2
0 3 3 0 2 1 1 2 0 3 2 0 3 2 3 0 0 3 0 2 2 3 2 2 2 3 1 2 3 0 0 0 1 2 1 0 0
1 0 0 3 0 1 2 0 0 0 1 3 0 3 2 3 0 0 1 2 2 1 0 1 2 0 1 1 0 0 3 3 0 3 1 1 3
0 1 0 2 2 0 3 1 0 3 0 1 0 3 3 3 2 3 0 3 2 0 0 0 3 3 2 0 2 1 3 0 0 2 2 0 3
1 2 1 1 1 3 1 1 1 2 0 0 2 2 0 2 0 0 0 0 3 3 3 3 0 1 2 1 1 0 0 2 1 0 2 0 3
2 2 1 2 0 2 1 3 0 0 3 2 3 0 0 2 3 3 1 3 2 1 0 0 3 3 0 3 0 0 0 2 2 1 2 0 3
3 1 2 3 3 0 1 1 2 1 2 2 0 1 3 1 1 3 0 2 3 2 1 1 1 3 3 0 2 3 0 2 3 2 2 2 3
2 0 1 2 1 2 1 1 2 2 2 1 2 1 0 1 3 1 0 1 2 3 1 0 0 3 2 2 3 0 3 3 2 1 3 0 1
3 1 1 0 1 3 2 0 3 0 2 3 0 3 1 3 3 1 0 2 3 1 0 2 1 2 1 2 0 2 3 0 2 3 2 3 0
2 1 1 2 2 3 3 0 2 1 2 1 3 0 0 3 0 2 0 0 3 3 2 0 0 0 0 3 2 3 3 0 0 2 1 0 2
2]
```

7.4 XGBOOST

7.4.1 Preparing Data

[52]:
```python
data_predict = scaled_data_testing[['battery_power', 'blue', 'clock_speed',␣
↪'dual_sim', 'fc',
                                    'four_g', 'int_memory', 'm_dep',␣
↪'mobile_wt', 'n_cores', 'pc', 'px_height', 'px_width', 'ram', 'sc_h',␣
↪'sc_w', 'talk_time', 'three_g', 'touch_screen', 'wifi']]
```

[53]:
```python
data_predict.head()
```

[53]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	\
0	-0.475451	1	0.312601	1	2.108676	0	-1.581269	
1	-0.942782	1	-1.255832	1	-0.132927	1	1.509303	
2	1.292077	1	1.519087	0	-0.805408	0	-0.367116	
3	0.688249	0	-1.255832	1	3.005317	1	-0.477493	
4	0.429135	0	-0.169994	0	1.436195	1	0.847037	

	m_dep	mobile_wt	n_cores	pc	px_height	px_width	ram	\
0	-1.487247	1.535535	-0.580671	0.976026	-0.926990	0.391912	1.229373	
1	1.006341	1.478120	0.293833	0.319433	0.274729	-0.871028	1.614643	
2	1.362567	1.334582	-0.580671	-0.993754	1.485693	0.287236	0.236313	
3	-0.062340	-1.249091	1.605590	1.632619	-0.767532	1.165604	1.612804	
4	-0.062340	-0.904602	0.731085	1.304323	0.281662	-0.977979	-0.336535	

	sc_h	sc_w	talk_time	three_g	touch_screen	wifi
0	0.001158	7	-1.653355	0	1	0
1	-1.388231	0	-0.743418	1	0	0
2	1.158982	10	-0.197456	0	1	1

```
3 -0.461972     0  -0.743418        1            1     0
4  0.695852     8  -0.743418        1            0     1
```

7.4.2 Predict

[57]:
```python
y_pred_xgb = best_xgb.predict(data_predict)

print("XGBoost Predict:")
print(y_pred_xgb)
```

```
XGBoost Predict:
[3 3 2 3 1 3 3 1 3 0 3 3 0 0 2 0 2 1 3 2 1 3 1 1 3 0 2 0 3 0 2 0 3 0 1 1 3
 1 2 1 1 2 0 0 0 1 0 3 1 2 1 0 3 0 3 1 3 1 1 3 3 2 0 1 1 1 1 3 1 2 1 2 2 3
 3 0 2 0 2 3 1 3 3 0 3 0 3 1 3 0 1 2 2 0 2 2 1 2 1 2 1 0 0 3 0 2 0 1 2 3 3
 2 1 3 3 3 3 2 3 0 0 3 1 1 2 0 3 2 3 1 0 2 1 1 3 1 1 0 3 2 1 2 1 2 2 3 3 2
 2 3 2 3 0 0 3 2 3 3 3 3 2 2 3 3 3 3 1 0 3 0 0 0 1 1 0 1 0 0 1 2 0 0 0 1 1
 2 2 1 0 0 0 1 0 3 2 0 2 2 2 3 1 2 2 3 3 2 2 1 0 0 1 2 0 2 3 3 0 2 0 3 2 3
 3 1 0 1 0 3 0 1 0 2 2 1 3 1 3 0 3 1 2 0 0 2 1 3 2 3 1 1 3 0 0 2 3 3 1 3 1
 1 3 2 1 2 3 3 3 1 0 1 2 3 1 1 3 2 0 3 0 1 2 0 0 3 2 3 3 2 1 3 3 2 3 2 2 1
 2 0 2 3 1 0 0 3 0 3 0 1 2 0 2 3 1 3 2 2 1 2 0 0 0 1 3 2 0 0 0 3 2 0 2 3 1
 2 3 2 3 1 3 3 2 2 2 3 3 0 3 0 3 1 3 1 3 3 0 1 0 3 1 3 2 3 0 0 0 0 2 0 0 2
 2 1 2 2 2 0 1 0 0 3 2 0 3 1 2 2 1 2 3 1 1 2 2 1 2 0 1 1 0 3 2 1 0 1 0 0 1
 1 0 0 0 2 2 3 2 3 0 2 0 3 0 1 1 1 1 0 3 2 3 3 1 3 1 3 1 3 2 0 1 2 1 1 0 0
 0 1 2 1 0 3 2 0 2 3 0 0 3 1 1 0 2 2 3 0 3 0 2 3 3 3 0 2 0 2 2 0 1 2 0 0 1
 1 1 3 3 3 2 3 1 2 2 3 3 3 2 0 2 1 2 2 1 0 2 2 0 0 0 3 1 1 2 2 2 0 3 0 2 2
 0 3 0 2 3 0 1 1 3 3 1 1 1 3 2 0 2 1 2 0 3 3 1 2 2 2 3 0 1 2 3 1 3 2 3 1 1
 0 0 3 1 0 3 2 3 2 0 3 3 3 2 3 3 1 2 1 2 3 3 1 0 1 1 2 2 1 0 0 2 2 3 2 0 2
 1 3 3 0 1 3 0 2 1 1 0 0 2 1 0 1 1 2 2 0 2 2 1 0 3 0 0 3 2 0 0 0 0 0 3 0 3
 1 3 1 1 3 2 0 1 1 3 2 2 2 1 3 0 2 0 2 0 0 1 1 1 2 2 3 1 3 2 2 1 3 2 0 1 2
 0 3 3 0 2 1 1 2 0 3 2 0 3 2 3 0 0 3 0 2 2 3 2 2 2 2 1 2 3 0 1 1 1 2 2 0 0
 1 0 0 3 0 1 1 0 0 1 1 3 0 3 2 3 0 0 1 2 1 1 0 1 1 0 1 1 0 0 3 3 0 3 1 2 3
 0 1 0 2 2 0 3 1 0 3 0 1 0 3 3 3 2 3 0 3 2 0 0 0 3 3 2 0 2 1 2 1 0 3 2 0 3
 1 2 1 1 1 3 1 1 1 2 1 0 1 2 0 2 0 0 0 0 3 3 3 3 0 1 2 2 1 0 0 2 1 0 2 0 2
 2 2 1 2 0 2 1 3 0 0 3 1 3 0 0 2 2 3 1 2 2 1 0 0 2 3 0 3 0 0 0 2 2 1 2 0 3
 2 1 2 3 3 0 1 1 2 1 2 2 0 1 3 1 1 3 1 2 3 1 1 1 1 3 3 0 2 3 0 2 3 2 2 2 3
 2 0 1 2 1 2 1 1 2 2 2 1 2 1 1 1 3 1 0 1 2 3 1 0 0 2 2 2 3 0 3 3 2 1 3 0 1
 3 1 2 1 2 3 2 0 3 0 2 3 0 2 2 2 3 1 0 2 3 1 0 2 1 2 1 2 0 2 2 0 2 3 2 3 0
 2 1 1 2 2 3 3 0 2 1 2 1 3 1 1 3 0 1 0 0 3 2 2 0 0 0 0 3 2 3 3 0 0 2 1 0 2
 2]
```