Problem Statement: The task is to build a predictive model that can accurately classify mobile phones into predefined price ranges based on various attributes such as battery power, camera features, memory, connectivity options, and more. The dataset provided contains information about several mobile phones, including their specifications and corresponding price ranges.

In [1]:
```
#importing libraries
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


sns.set()
%matplotlib inline

import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
dataset = pd.read_csv("train.csv")
dataset.head()
```

Out[2]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_wt	n_cores	...	px_height	px_width	ra
0	842	0	2.2	0	1	0	7	0.6	188	2	...	20	756	254
1	1021	1	0.5	1	0	1	53	0.7	136	3	...	905	1988	263
2	563	1	0.5	1	2	1	41	0.9	145	5	...	1263	1716	260
3	615	1	2.5	0	0	0	10	0.8	131	6	...	1216	1786	276
4	1821	1	1.2	0	13	1	44	0.6	141	2	...	1208	1212	141

5 rows × 21 columns

In [3]:
```
# To avoid data loss
dataset2 = dataset.copy()
```

In [4]:
```
#checking information abour data
dataset.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
```

EDA

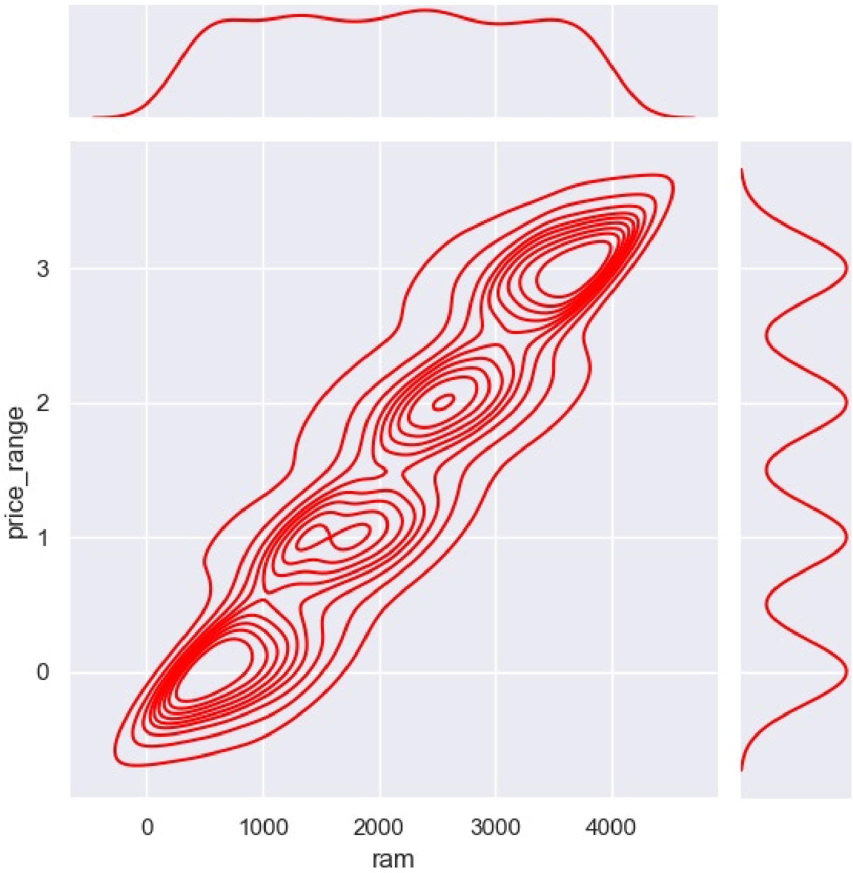
In [5]:
```
#statistical analysis
dataset.describe()
```

Out[5]:

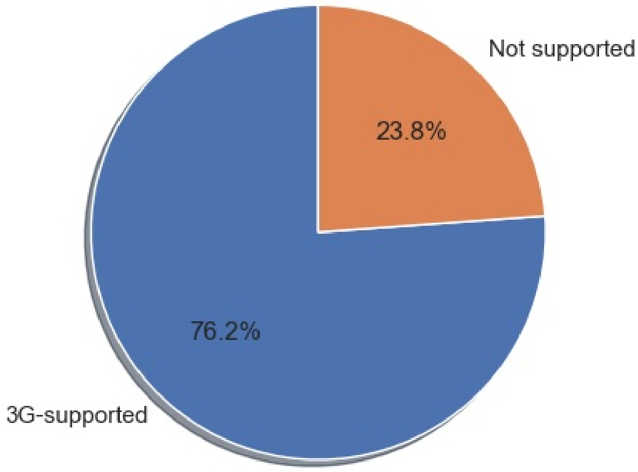
	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_wt	
count	2000.000000	2000.0000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	200
mean	1238.518500	0.4950	1.522250	0.509500	4.309500	0.521500	32.046500	0.501750	140.249000	
std	439.418206	0.5001	0.816004	0.500035	4.341444	0.499662	18.145715	0.288416	35.399655	
min	501.000000	0.0000	0.500000	0.000000	0.000000	0.000000	2.000000	0.100000	80.000000	
25%	851.750000	0.0000	0.700000	0.000000	1.000000	0.000000	16.000000	0.200000	109.000000	
50%	1226.000000	0.0000	1.500000	1.000000	3.000000	1.000000	32.000000	0.500000	141.000000	
75%	1615.250000	1.0000	2.200000	1.000000	7.000000	1.000000	48.000000	0.800000	170.000000	
max	1998.000000	1.0000	3.000000	1.000000	19.000000	1.000000	64.000000	1.000000	200.000000	

8 rows × 21 columns

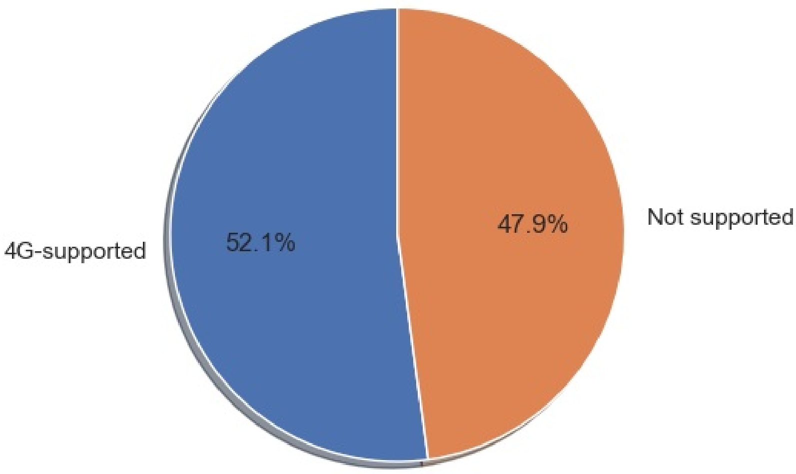
In [6]:
```python
sns.jointplot(x='ram',y='price_range',data=dataset,color='red',kind='kde');
```



In [7]:
```python
#3G support
labels = ["3G-supported",'Not supported']
values=dataset['three_g'].value_counts().values
fig1, ax1 = plt.subplots()
ax1.pie(values, labels=labels, autopct='%1.1f%%',shadow=True,startangle=90)
plt.show()
```

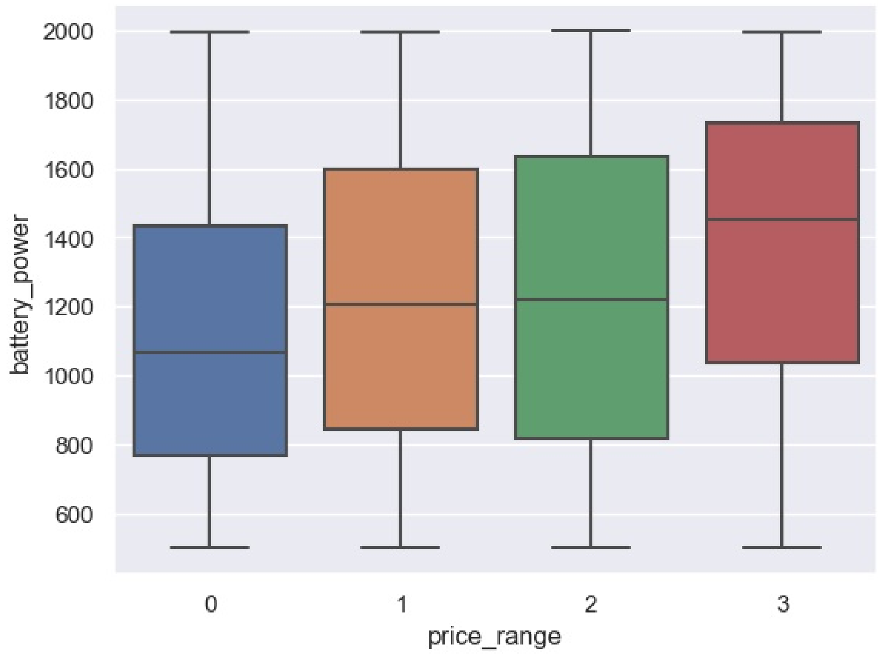


In [8]:
```
#4G support
labels4g = ["4G-supported",'Not supported']
values4g = dataset['four_g'].value_counts().values
fig1, ax1 = plt.subplots()
ax1.pie(values4g, labels=labels4g, autopct='%1.1f%%',shadow=True,startangle=90)
plt.show()
```



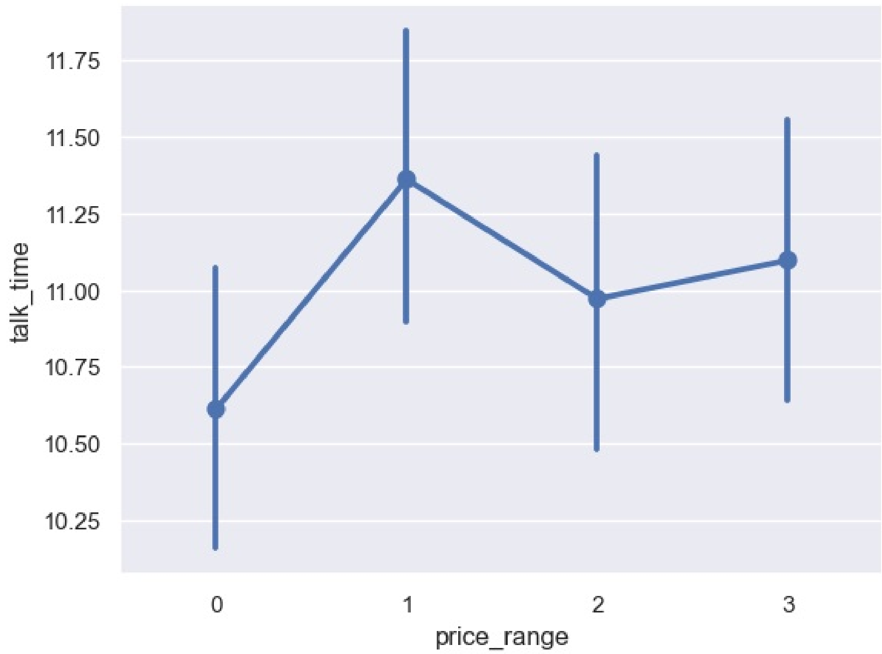
In [9]:
```
#battery power vs price_range
sns.boxplot(x="price_range", y="battery_power", data=dataset)
```

Out[9]:
```
<AxesSubplot:xlabel='price_range', ylabel='battery_power'>
```



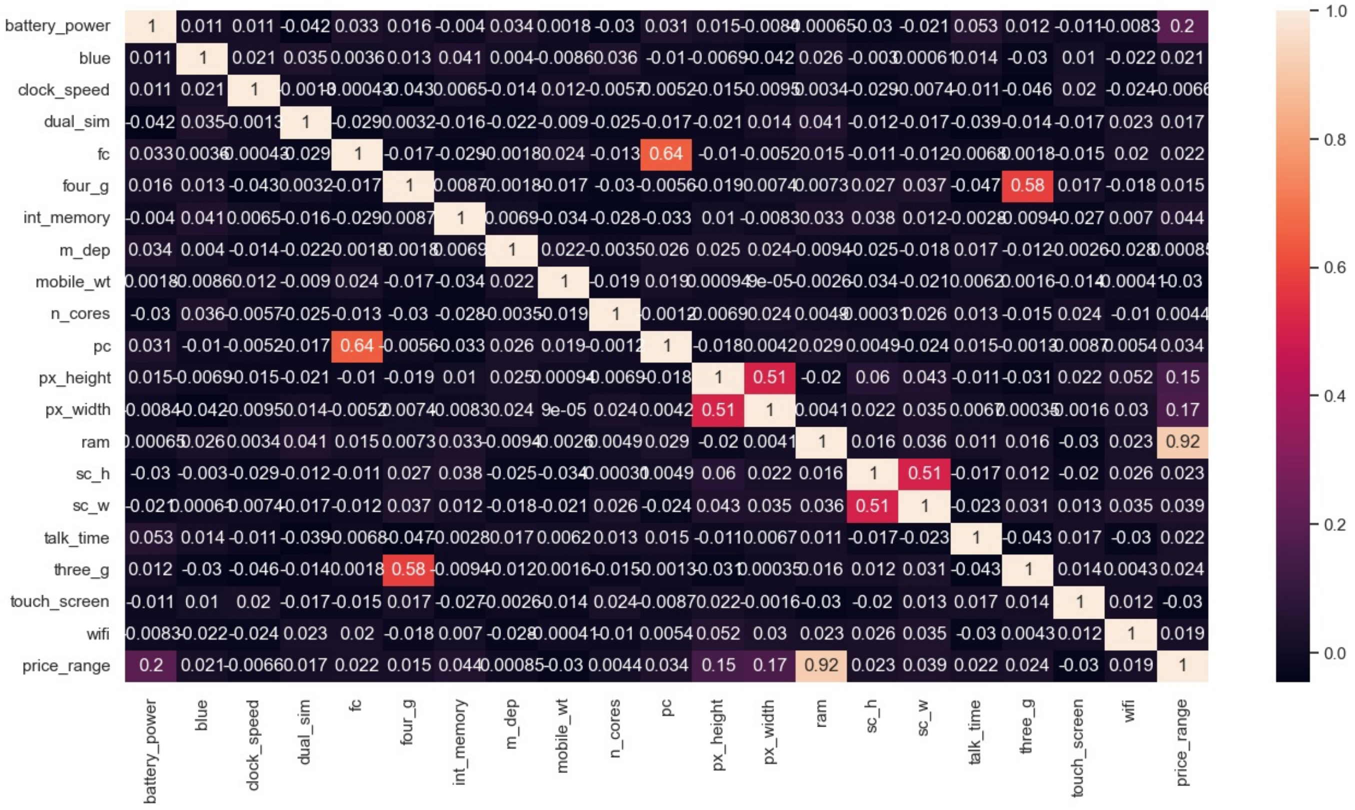

```
In [10]: sns.pointplot(y="talk_time", x="price_range", data=dataset)
```

```
Out[10]: <AxesSubplot:xlabel='price_range', ylabel='talk_time'>
```




```
In [11]: #correlation among columns
plt.figure(figsize=(16,8))
```

```python
sns.heatmap(dataset.corr(), annot = True)
plt.show()
```



dependent and independent variable

In [12]:
```python
x=dataset.drop('price_range',axis=1)
```

In [13]:
```python
x.head()
```

Out[13]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_wt	n_cores	pc	px_height	px_width	ra
0	842	0	2.2	0	1	0	7	0.6	188	2	2	20	756	25
1	1021	1	0.5	1	0	1	53	0.7	136	3	6	905	1988	26
2	563	1	0.5	1	2	1	41	0.9	145	5	6	1263	1716	26
3	615	1	2.5	0	0	0	10	0.8	131	6	9	1216	1786	27
4	1821	1	1.2	0	13	1	44	0.6	141	2	14	1208	1212	14

In [14]:
```python
y=dataset['price_range']
```

In [15]:
```python
y.head()
```

Out[15]:
```
0    1
1    2
2    2
3    2
4    1
Name: price_range, dtype: int64
```

Train Test split

In [16]:
```python
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.33, random_state=101)
```

Model

In [17]:
```python
#logistic regression
from sklearn.linear_model import LogisticRegression
logit_model = LogisticRegression()
logit_model.fit(x_train, y_train)
```

Out[17]:
```
LogisticRegression()
```

In [18]:
```
#creating function to check models performance
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
def model_report(model):
    y_pred_train = model.predict(x_train)
    y_pred_test = model.predict(x_test)
    print("Accuracy Score Train:", accuracy_score(y_train,y_pred_train))
    print("Accuracy score test:", accuracy_score(y_test,y_pred_test))
    print("******"*9)

    print("Confusion Matrix train:\n ", confusion_matrix(y_train,y_pred_train))
    print("Confusion matrix test: \n", confusion_matrix(y_test,y_pred_test))
    print("*****"*9)

    print("classification report train: \n", classification_report(y_train,y_pred_train ))
    print("classification report test: \n", classification_report(y_test,y_pred_test ))
```

In [19]:
```
model_report(logit_model)
```

```
Accuracy Score Train: 0.6455223880597015
Accuracy score test: 0.6181818181818182
******************************************************
Confusion Matrix train:
  [[270  68   4   0]
 [ 57 194  71  26]
 [  1  81 123  96]
 [  0   4  67 278]]
Confusion matrix test:
 [[122  35   1   0]
 [ 25  89  32   6]
 [  0  47  78  74]
 [  0   1  31 119]]
*********************************************
classification report train:
               precision    recall  f1-score   support

           0       0.82      0.79      0.81       342
           1       0.56      0.56      0.56       348
           2       0.46      0.41      0.43       301
           3       0.69      0.80      0.74       349

    accuracy                           0.65      1340
   macro avg       0.64      0.64      0.64      1340
weighted avg       0.64      0.65      0.64      1340

classification report test:
               precision    recall  f1-score   support

           0       0.83      0.77      0.80       158
           1       0.52      0.59      0.55       152
           2       0.55      0.39      0.46       199
           3       0.60      0.79      0.68       151

    accuracy                           0.62       660
   macro avg       0.62      0.63      0.62       660
weighted avg       0.62      0.62      0.61       660
```

In [20]:
```
## Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
rfc.fit(x_train, y_train)
```

Out[20]:
```
RandomForestClassifier()
```

In [21]:
```
model_report(rfc)
```

```
Accuracy Score Train: 1.0
Accuracy score test: 0.8636363636363636
*******************************************************
Confusion Matrix train:
  [[342   0   0   0]
 [  0 348   0   0]
 [  0   0 301   0]
 [  0   0   0 349]]
Confusion matrix test:
 [[147  11   0   0]
 [ 13 133   6   0]
 [  0  26 151  22]
 [  0   0  12 139]]
**********************************************
classification report train:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       342
           1       1.00      1.00      1.00       348
           2       1.00      1.00      1.00       301
           3       1.00      1.00      1.00       349

    accuracy                           1.00      1340
   macro avg       1.00      1.00      1.00      1340
weighted avg       1.00      1.00      1.00      1340

classification report test:
               precision    recall  f1-score   support

           0       0.92      0.93      0.92       158
           1       0.78      0.88      0.83       152
           2       0.89      0.76      0.82       199
           3       0.86      0.92      0.89       151

    accuracy                           0.86       660
   macro avg       0.86      0.87      0.87       660
weighted avg       0.87      0.86      0.86       660
```

In [22]:

```python
#above model is overfitted so we need to understand why it happens and then adjust hyperparameters
#hyperparameter tunning
from sklearn.model_selection import GridSearchCV
rf_param_grid = {
    'n_estimators': [100, 200,15],
    'max_depth': [6,8,9],
    'min_samples_split': [2, 5, 10]
}
random_forest_instance = RandomForestClassifier()
rf_grid = GridSearchCV(estimator=random_forest_instance, param_grid=rf_param_grid, cv=5)
rf_grid.fit(x_train,y_train)
print("Best parameters for Random Forest Regressor:", rf_grid.best_params_)
print("Best score for Random Forest Regressor:", rf_grid.best_score_)
```

```
Best parameters for Random Forest Regressor: {'max_depth': 9, 'min_samples_split': 2, 'n_estimators': 200}
Best score for Random Forest Regressor: 0.864179104477612
```

In [23]:

```python
#from above code we get a new model of rfc which is rf_grid, so we will check accuracy for that model
model_report(rf_grid)
```

```
Accuracy Score Train: 0.9992537313432835
Accuracy score test: 0.8621212121212121
*******************************************************
Confusion Matrix train:
  [[342   0   0   0]
 [  0 347   1   0]
 [  0   0 301   0]
 [  0   0   0 349]]
Confusion matrix test:
 [[150   8   0   0]
 [ 12 134   6   0]
 [  0  30 146  23]
 [  0   0  12 139]]
*********************************************
classification report train:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       342
           1       1.00      1.00      1.00       348
           2       1.00      1.00      1.00       301
           3       1.00      1.00      1.00       349

    accuracy                           1.00      1340
   macro avg       1.00      1.00      1.00      1340
weighted avg       1.00      1.00      1.00      1340

classification report test:
               precision    recall  f1-score   support

           0       0.93      0.95      0.94       158
           1       0.78      0.88      0.83       152
           2       0.89      0.73      0.80       199
           3       0.86      0.92      0.89       151

    accuracy                           0.86       660
   macro avg       0.86      0.87      0.86       660
weighted avg       0.87      0.86      0.86       660
```

In [24]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=10)
knn.fit(x_train,y_train)
```

Out[24]:
```
KNeighborsClassifier(n_neighbors=10)
```

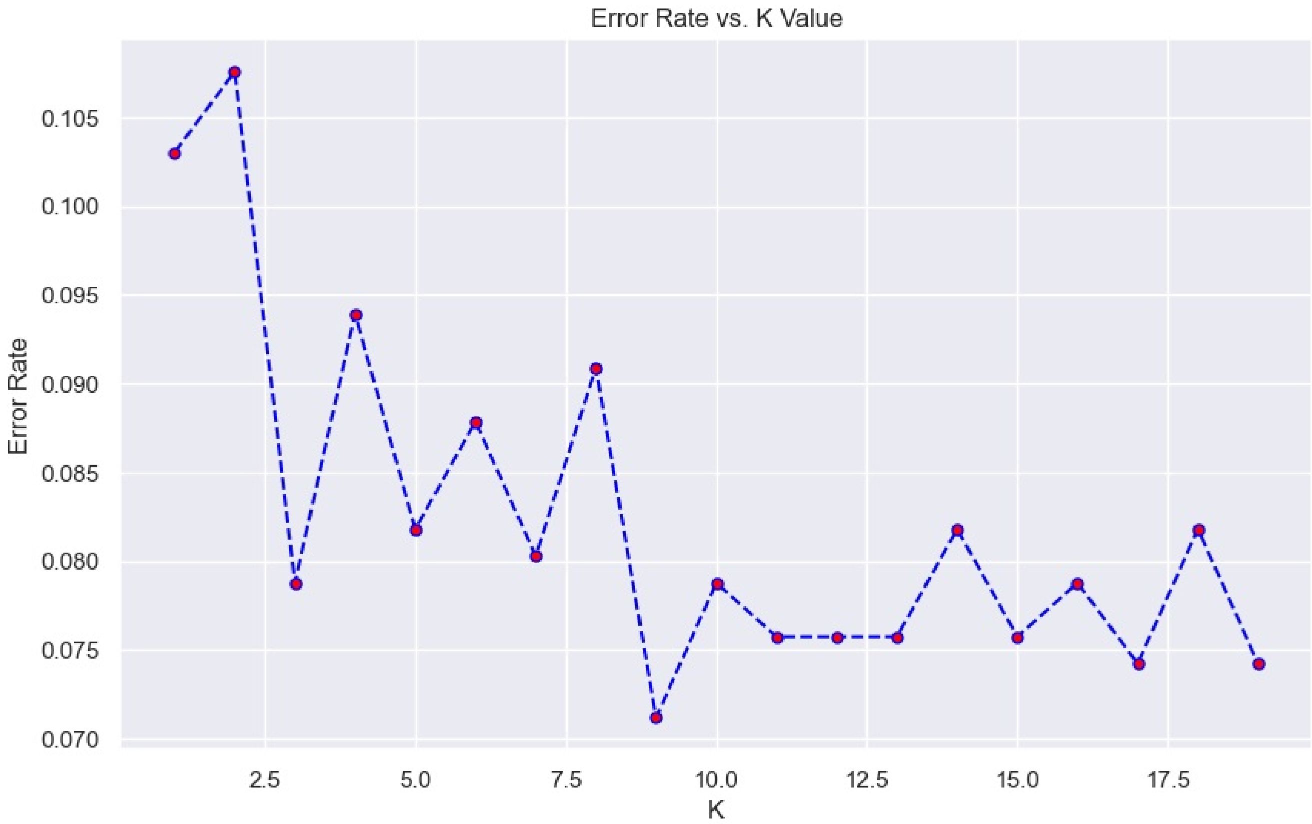
In [25]:
```
model_report(knn)
```

```
Accuracy Score Train: 0.9462686567164179
Accuracy score test: 0.9212121212121213
*******************************************************
Confusion Matrix train:
  [[334   8   0   0]
 [ 14 331   3   0]
 [  0  18 271  12]
 [  0   0  17 332]]
Confusion matrix test:
 [[157   1   0   0]
 [  6 143   3   0]
 [  0  20 169  10]
 [  0   0  12 139]]
**********************************************
classification report train:
               precision    recall  f1-score   support

           0       0.96      0.98      0.97       342
           1       0.93      0.95      0.94       348
           2       0.93      0.90      0.92       301
           3       0.97      0.95      0.96       349

    accuracy                           0.95      1340
   macro avg       0.95      0.94      0.95      1340
weighted avg       0.95      0.95      0.95      1340

classification report test:
               precision    recall  f1-score   support

           0       0.96      0.99      0.98       158
           1       0.87      0.94      0.91       152
           2       0.92      0.85      0.88       199
           3       0.93      0.92      0.93       151

    accuracy                           0.92       660
   macro avg       0.92      0.93      0.92       660
weighted avg       0.92      0.92      0.92       660
```

In [26]:
```
#using elbow method to get best values of hyperparameter- n_neighbors

error_rate = []
for i in range(1,20):

    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(x_train,y_train)
    pred_i = knn.predict(x_test)
    error_rate.append(np.mean(pred_i != y_test))
```

In [27]:
```
#lets visualize these neighbors to get clear picture

plt.figure(figsize=(10,6))
plt.plot(range(1,20),error_rate,color='blue', linestyle='dashed', marker='o',
         markerfacecolor='red', markersize=5)
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')
```

Out[27]:
```
Text(0, 0.5, 'Error Rate')
```



Result is KNN model performs best by comparing their accuracies

In [28]:
```
test=pd.read_csv('test.csv')
test.head()
```

Out[28]:

	id	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_wt	...	pc	px_height	px_width	ram
0	1	1043	1	1.8	1	14	0	5	0.1	193	...	16	226	1412	3476
1	2	841	1	0.5	1	4	1	61	0.8	191	...	12	746	857	3895
2	3	1807	1	2.8	0	1	0	27	0.9	186	...	4	1270	1366	2396
3	4	1546	0	0.5	1	18	1	25	0.5	96	...	20	295	1752	3893
4	5	1434	0	1.4	0	11	1	49	0.5	108	...	18	749	810	1773

5 rows × 21 columns

In [29]:
```
test=test.drop('id',axis=1)
test.head()
```

Out[29]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_wt	n_cores	pc	px_height	px_width	ra
0	1043	1	1.8	1	14	0	5	0.1	193	3	16	226	1412	34
1	841	1	0.5	1	4	1	61	0.8	191	5	12	746	857	38
2	1807	1	2.8	0	1	0	27	0.9	186	3	4	1270	1366	23
3	1546	0	0.5	1	18	1	25	0.5	96	8	20	295	1752	38
4	1434	0	1.4	0	11	1	49	0.5	108	6	18	749	810	17

In [30]:

```
# lets predict price by feeding data to best model i.e., KNN
predict_price = knn.predict(test)
```

In [31]:

```
predict_price
```

Out[31]:

```
array([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, 0, 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,
       2, 3, 1, 2, 1, 2, 2, 3, 3, 0, 2, 0, 2, 3, 0, 3, 3, 0, 3, 0, 3, 1,
       3, 0, 1, 2, 2, 1, 2, 1, 0, 2, 1, 2, 1, 0, 0, 3, 0, 2, 0, 1, 2, 3,
       3, 3, 1, 3, 3, 3, 3, 1, 3, 0, 0, 3, 2, 1, 2, 0, 3, 2, 3, 1, 0, 2,
       1, 1, 3, 1, 1, 0, 3, 2, 1, 3, 1, 3, 2, 3, 3, 3, 2, 3, 2, 3, 1, 0,
       3, 2, 3, 3, 3, 3, 2, 2, 3, 3, 3, 3, 1, 0, 3, 0, 0, 0, 2, 1, 0, 1,
       0, 0, 1, 2, 1, 0, 0, 1, 1, 2, 2, 1, 0, 0, 0, 0, 0, 3, 1, 0, 2, 2,
       3, 3, 1, 1, 3, 3, 3, 2, 2, 1, 1, 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, 2, 0, 3, 0, 3, 1, 2, 0,
       0, 2, 1, 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, 1, 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, 1, 2, 0, 0, 0, 1, 3, 2, 0, 0, 0, 3, 2, 0,
       2, 3, 1, 2, 2, 2, 3, 1, 3, 3, 1, 2, 3, 3, 3, 0, 3, 0, 3, 1, 3, 1,
       2, 3, 0, 1, 0, 3, 1, 3, 1, 3, 0, 0, 0, 0, 2, 0, 0, 2, 1, 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, 3,
       0, 3, 0, 1, 1, 1, 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, 2, 0, 0, 3, 1, 1, 0, 3, 2,
       3, 0, 3, 0, 2, 3, 3, 3, 0, 2, 0, 2, 3, 0, 1, 1, 0, 0, 1, 1, 1, 3,
       3, 3, 2, 3, 1, 1, 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, 2, 2, 2, 3, 0, 1, 2, 3, 1,
       3, 2, 3, 1, 1, 1, 0, 3, 1, 0, 3, 2, 3, 2, 0, 3, 3, 3, 2, 3, 3, 1,
       2, 0, 2, 3, 3, 1, 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, 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, 3, 0, 1, 1,
       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, 2, 1, 1, 3, 0, 1, 0, 1, 2, 1, 0, 0, 1,
       0, 0, 3, 0, 1, 2, 0, 0, 1, 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, 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, 2, 3, 2, 0, 1, 1,
       2, 1, 0, 3, 2, 0, 3, 1, 2, 1, 1, 1, 3, 1, 1, 1, 2, 1, 0, 1, 2, 0,
       3, 0, 0, 0, 0, 2, 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, 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, 2, 0, 2,
       3, 0, 2, 3, 2, 2, 2, 3, 2, 0, 1, 2, 0, 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, 1, 1, 3, 2, 0, 3, 0, 2, 3, 0, 3, 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, 0, 1, 3, 0, 1, 0, 0, 3, 3, 2, 0, 0, 0, 0, 3,
       2, 3, 3, 0, 0, 2, 1, 0, 2, 2], dtype=int64)
```

In [32]:

```
#let's concatenate with test data
test['price_range']=predict_price
```

In [33]:

```
test.head()
```

Out[33]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_wt	n_cores	...	px_height	px_width	ra
0	1043	1	1.8	1	14	0	5	0.1	193	3	...	226	1412	347
1	841	1	0.5	1	4	1	61	0.8	191	5	...	746	857	389
2	1807	1	2.8	0	1	0	27	0.9	186	3	...	1270	1366	239
3	1546	0	0.5	1	18	1	25	0.5	96	8	...	295	1752	389
4	1434	0	1.4	0	11	1	49	0.5	108	6	...	749	810	177

5 rows × 21 columns

In [ ]:

In [ ]:

In [ ]:

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