

Mobile Phone Price Prediction

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**Objective:** Build a system that predicts mobile phone pricing categories (low, medium, high, very high) based on features like battery power, RAM, processor speed, etc.

**Step 1: Import Necessary Libraries** Libraries like pandas for data manipulation, sklearn for preprocessing, model building, and evaluation, and matplotlib and seaborn for visualization.

```
# Importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

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**Step** executed by yuvashree magesh  
20:32 (22 minutes ago)  
**Load** executed in 4.622 s ; structure to understand the features.

```
# Load the dataset
df = pd.read_csv('dataset.csv')

# Display basic information and summary statistics
print(df.head())
print(df.info())
print(df.describe())

# Check for missing values
print(df.isnull().sum())
```

	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]
<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
None
battery_power    blue  clock_speed    dual_sim    fc  \
count  2000.000000  2000.0000  2000.000000  2000.000000  2000.000000
mean    1238.518500    0.4950    1.522250    0.509500    4.309500
std     439.418206    0.5001    0.816004    0.500035    4.341444
min     501.000000    0.0000    0.500000    0.000000    0.000000
25%     851.750000    0.0000    0.700000    0.000000    1.000000
50%     1226.000000    0.0000    1.500000    1.000000    3.000000

```

**Step 3: Data Preprocessing** Some preprocessing steps may be necessary, like scaling the features or encoding categorical data

```

# Splitting the dataset into features (X) and target (y)
X = df.drop('price_range', axis=1)
y = df['price_range']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Scaling (scaling)
scale = StandardScaler()
X_train_scaled = scale.fit_transform(X_train)
X_test_scaled = scale.transform(X_test)

```

#### Step 4: Model Building

```

# Initialize and train the Random Forest model
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train_scaled, y_train)

# Make predictions
y_pred = model.predict(X_test_scaled)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy*100:.2f}%")

# Display confusion matrix and classification report
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d')
plt.show()

print(classification_report(y_test, y_pred))

```



## Step 5: Hyperparameter Tuning

Further optimize the model using techniques like GridSearchCV for hyperparameter tuning.

```
from sklearn.model_selection import GridSearchCV

# Define a grid of parameters to test
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 20, None],
    'min_samples_split': [2, 5, 10]
}

# Grid search for the best parameters
grid_search = GridSearchCV(RandomForestClassifier(random_state=42), param_grid, cv=5, scoring='accuracy')
grid_search.fit(X_train_scaled, y_train)

# Best parameters and score
print(f"Best Params: {grid_search.best_params_}")
print(f"Best Score: {grid_search.best_score_}")

# Train and evaluate the best model
best_estimator = grid_search.best_estimator_
y_pred_best = best_estimator.predict(X_test_scaled)

# Evaluate the tuned model
accuracy_best = accuracy_score(y_test, y_pred_best)
print(f"Tuned Accuracy: {accuracy_best*100:.2f}%")
```

Best Params: {'max\_depth': 20, 'min\_samples\_split': 2, 'n\_estimators': 200}  
 Best Score: 0.878125  
 Tuned Accuracy: 89.50%