In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sb
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score, confusion
from sklearn.model_selection import GridSearchCV

# Disable scientific notation for large numbers
pd.options.display.float_format = '{:.0f}'.format

# Setting display options for Pandas to show three decimal places for floati
pd.set_option('display.float_format', lambda x: '%.2f' % x)
```

# Data Loading

In [3]:
```
# import data
mobile_df = pd.read_csv('/content/drive/MyDrive/dataset.csv')
```

# Data Exploration

In [4]:
```
mobile_df.info()  # Display information about the DataFrame, including data
```

```
<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: 328.3 KB
```

In [5]:
```
mobile_df.head()  # Display the first 5 rows of the DataFrame
```

Out[5]:

| | battery_power | blue | clock_speed | dual_sim | fc | four_g | int_memory | m_de |
|---|---|---|---|---|---|---|---|---|
| **0** | 842 | 0 | 2.20 | 0 | 1 | 0 | 7 | 0.6 |
| **1** | 1021 | 1 | 0.50 | 1 | 0 | 1 | 53 | 0.7 |
| **2** | 563 | 1 | 0.50 | 1 | 2 | 1 | 41 | 0.9 |
| **3** | 615 | 1 | 2.50 | 0 | 0 | 0 | 10 | 0.8 |
| **4** | 1821 | 1 | 1.20 | 0 | 13 | 1 | 44 | 0.6 |

5 rows × 21 columns

In [6]:
```
mobile_df.describe()  # Display statistical information about Dataframe
```

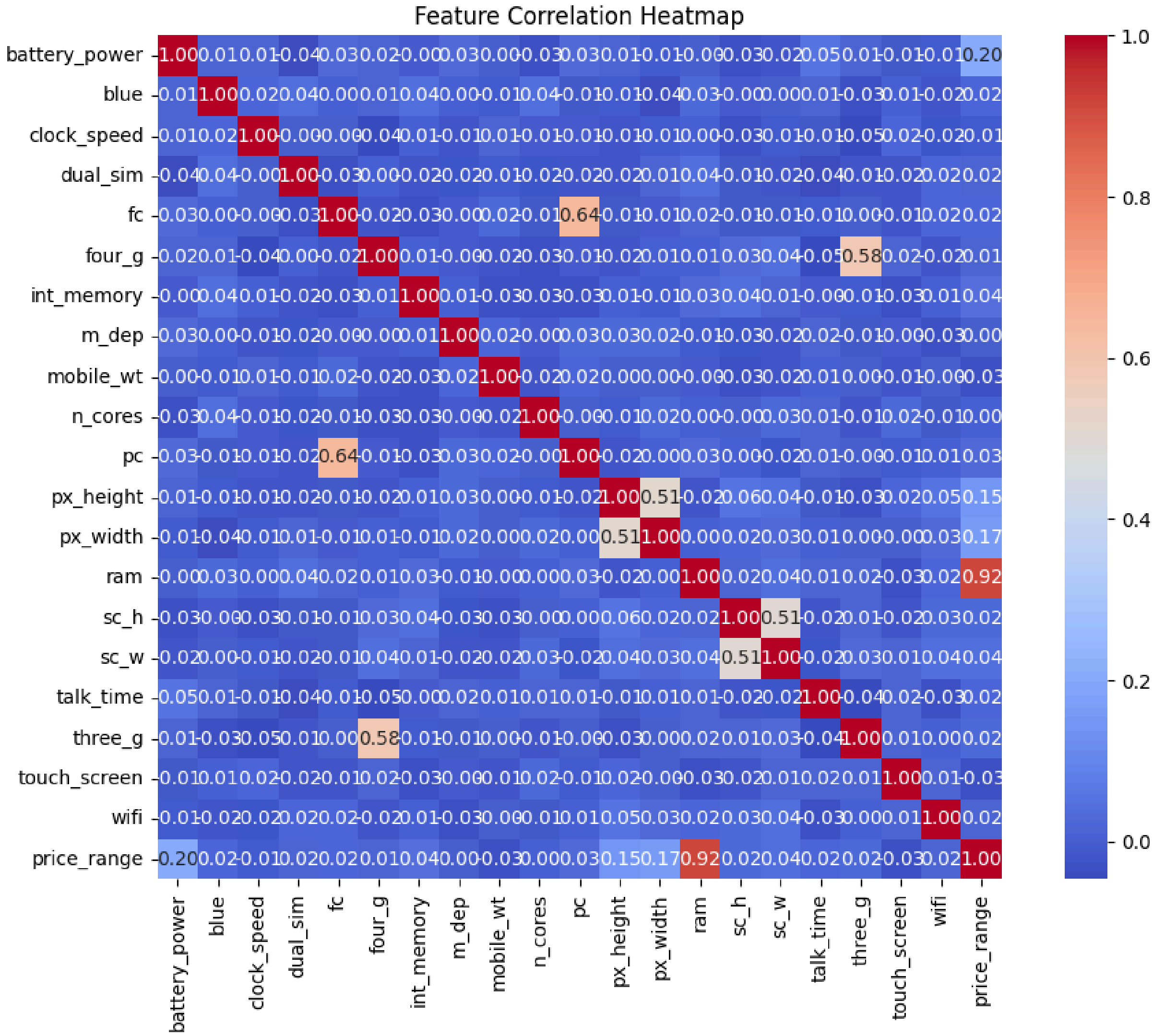
Out[6]:

| | battery_power | blue | clock_speed | dual_sim | fc | four_g | int_m |
|---|---|---|---|---|---|---|---|
| **count** | 2000.00 | 2000.00 | 2000.00 | 2000.00 | 2000.00 | 2000.00 | 2 |
| **mean** | 1238.52 | 0.49 | 1.52 | 0.51 | 4.31 | 0.52 | |
| **std** | 439.42 | 0.50 | 0.82 | 0.50 | 4.34 | 0.50 | |
| **min** | 501.00 | 0.00 | 0.50 | 0.00 | 0.00 | 0.00 | |
| **25%** | 851.75 | 0.00 | 0.70 | 0.00 | 1.00 | 0.00 | |
| **50%** | 1226.00 | 0.00 | 1.50 | 1.00 | 3.00 | 1.00 | |
| **75%** | 1615.25 | 1.00 | 2.20 | 1.00 | 7.00 | 1.00 | |
| **max** | 1998.00 | 1.00 | 3.00 | 1.00 | 19.00 | 1.00 | |

8 rows × 21 columns

In [7]:

```
# Visualize feature distributions
plt.figure(figsize=(12,8))
sb.heatmap(mobile_df.corr(), annot=True, fmt=".2f", cmap="coolwarm", square=
plt.title("Feature Correlation Heatmap")
plt.show()
```




# Data Cleaning

In [8]:

```
mobile_df.isna().sum()  # Find sum of missing values
```

Out[8]:

| | 0 |
|---|---|
| **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

Since missing data is 0, so handling missing data is not required

In [9]:
```
print(mobile_df.duplicated().sum())  # Find sum of duplicate rows
```

```
0
```

Since, sum of duplicated values is zero, so there is no need to drop duplicates.

# Model Training and Evaluation

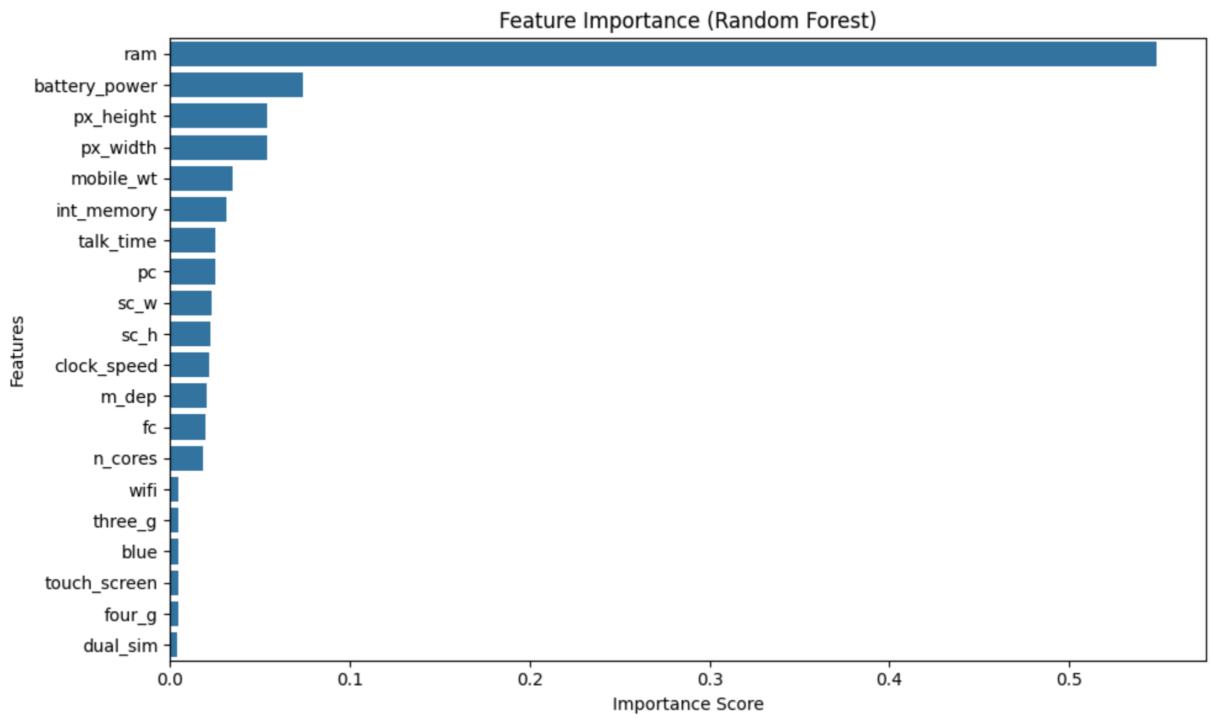
In [15]:
```
# Feature Engineering
X = mobile_df.drop('price_range', axis=1)
y = mobile_df['price_range']
```

```python
# Split data (training data 80% test data 20%)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar

# Scale features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Model Training
model = RandomForestClassifier(random_state=42)

# Hyperparameter tuning
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5]
}

grid_search = GridSearchCV(model, param_grid, cv=3)
grid_search.fit(X_train, y_train)

best_model = grid_search.best_estimator_

# Model Evaluation
y_pred = best_model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}\n")
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

```
Accuracy: 0.89


Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.96      0.95       105
           1       0.88      0.86      0.87        91
           2       0.81      0.85      0.83        92
           3       0.93      0.89      0.91       112

    accuracy                           0.89       400
   macro avg       0.89      0.89      0.89       400
weighted avg       0.89      0.89      0.89       400


Confusion Matrix:
[[101   4   0   0]
 [  7  78   6   0]
 [  0   7  78   7]
 [  0   0  12 100]]
```

Feature Importance Analysis

In [11]:
```
features = X.columns
importances = best_model.feature_importances_
feature_names = X.columns
feat_imp = pd.Series(importances, index=feature_names).sort_values(ascending

plt.figure(figsize=(10, 6))
sb.barplot(x=feat_imp, y=feat_imp.index)
plt.title("Feature Importance (Random Forest)")
plt.xlabel("Importance Score")
plt.ylabel("Features")
plt.tight_layout()
plt.show()
```




Key insights from the analysis:

1. Feature Importance: RAM shows the highest correlation with price range, followed by battery power and pixel resolution
2. Class Distribution: The dataset contains balanced classes (500 samples each)
3. Model Performance: Random Forest achieves 89% accuracy with proper tuning
4. Critical Features: o RAM (most significant predictor) o Battery capacity o Pixel resolution dimensions o Internal memory

Predicting if the mobile can be priced low/med/high/very high.

In [14]:
```
# Map 0 -> "Low", 1 -> "Medium", 2 -> "High", 3 ->"Very High"
price_map = {0: "Low", 1: "Medium", 2: "High", 3: "Very High"}
```

```python
# Prediction function
def predict_mobile_price(features_dict):
  feature_order = X.columns.tolist()
  input_data = np.array([[features_dict[feat] for feat in feature_order]])
  prediction = grid_search.predict(input_data)[0]
  return price_map[prediction]

# Example prediction
features = {
    "battery_power": 850, "blue": 1, "clock_speed": 2.0, "dual_sim": 1,
    "fc": 3, "four_g": 1, "int_memory": 64, "m_dep": 0.6,
    "mobile_wt": 140, "n_cores": 4, "pc": 16, "px_height": 1000,
    "px_width": 1300, "ram": 3000, "sc_h": 14, "sc_w": 8,
    "talk_time": 15, "three_g": 1, "touch_screen": 1, "wifi": 1
}

result = predict_mobile_price(features)
print("Predicted Price Range:", result)
```

```
Predicted Price Range: Very High
```