Team Name: Crimson Wing
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Progress Report: Smartphone Price Prediction using Classification Algorithms

****Project Overview:****

- The goal of this project is to develop a smartphone price prediction model using classification algorithms. The project aims to leverage machine learning techniques to accurately predict the price range of smartphones based on various features. This progress report provides an update on the current status of the project, including the tasks completed, challenges encountered, and next steps.

****Accomplishments:****

- Data Collection: A diverse dataset of smartphone specifications and prices has been collected from reliable sources. The dataset includes features such as brand, display size, RAM, internal storage, camera specifications, battery capacity, and other relevant attributes.

- Data Preprocessing: The collected dataset underwent preprocessing steps to handle missing values, outliers, and data inconsistencies. Feature engineering techniques were applied to extract meaningful information from the raw data. Categorical variables were encoded, and numerical features were scaled to ensure compatibility with classification algorithms.

- Algorithm Selection: Several classification algorithms were explored, including Logistic Regression, Decision Trees, Random Forest, KNN and SVM. Each algorithm's strengths, weaknesses, and suitability for smartphone price prediction were considered. Based on initial experimentation, it was determined that these algorithms hold promise for accurate price range prediction.

- Model Development: The selected classification algorithms were implemented and trained on the pre-processed dataset. The models were fine-tuned using appropriate hyperparameters to optimize their performance. Cross-validation techniques were employed to assess model generalization and prevent overfitting.

- Model Evaluation: Multiple evaluation metrics, such as accuracy, precision, recall, and F1 score, were used to assess the performance of the developed models. The models were tested on a holdout dataset to measure their ability to generalize to unseen smartphone instances. Preliminary evaluation results indicate promising performance across multiple algorithms.

Challenges Faced:

- Imbalanced Data: The dataset exhibited class imbalance, where certain price ranges had significantly fewer instances than others. Handling this imbalance was a challenge during model training and evaluation. Techniques like oversampling, undersampling, or using class weights were explored to address this issue.

- Feature Selection: Determining the most relevant features for smartphone price prediction posed a challenge. Extensive feature analysis and domain knowledge were required to select the optimal subset of features that contribute significantly to the model's predictive performance.

- Algorithm Complexity: Some classification algorithms, such as XGBoost, have a complex parameter space, making it challenging to find the best hyperparameter configuration. Careful tuning and experimentation were necessary to strike a balance between model complexity and performance.

Next Steps:

- Fine-tuning Models: The hyperparameter tuning process will be refined to optimize the performance of the selected algorithms. Techniques like grid search or Bayesian optimization will be employed to efficiently explore the hyperparameter space and identify the best configuration.
- Applying ANN model to further boost accuracy.

Conclusion:

The project has made significant progress in developing a smartphone price prediction model using classification algorithms. Data collection, preprocessing, algorithm selection, model development, and evaluation have been accomplished.

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Code:

In [2]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
import matplotlib.pylab as plt
%matplotlib inline
```

In [3]:
```
train_data=pd.read_csv("New Dataset/train.csv")
train_data.head()
```

Out[3]:

	Battery_Power	Clock_Speed	FC	Int_Memory	Mobile_D	Mobile_W	Cores	PC	Pixel_H	Pixel_W	...	Screen_H	Screen_W	Talk_Time	Four_G	Three_G	T
0	842	2.2	1	7	0.6	188	2	2	20	756	...	9	7	19	0	0	
1	1021	0.5	0	53	0.7	136	3	6	905	1988	...	17	3	7	1	1	
2	563	0.5	2	41	0.9	145	5	6	1263	1716	...	11	2	9	1	1	
3	615	2.5	0	10	0.8	131	6	9	1216	1786	...	16	8	11	0	1	
4	1821	1.2	13	44	0.6	141	2	14	1208	1212	...	8	2	15	1	1	

5 rows × 21 columns

In [4]:
```
train_data.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   Clock_Speed    2000 non-null   float64
 2   FC             2000 non-null   int64
 3   Int_Memory     2000 non-null   int64
 4   Mobile_D       2000 non-null   float64
 5   Mobile_W       2000 non-null   int64
 6   Cores          2000 non-null   int64
 7   PC             2000 non-null   int64
 8   Pixel_H        2000 non-null   int64
 9   Pixel_W        2000 non-null   int64
 10  Ram            2000 non-null   int64
 11  Screen_H       2000 non-null   int64
 12  Screen_W       2000 non-null   int64
 13  Talk_Time      2000 non-null   int64
 14  Four_G         2000 non-null   int64
 15  Three_G        2000 non-null   int64
 16  Touch_Screen   2000 non-null   int64
 17  Dual_SIM       2000 non-null   int64
 18  Bluetooth      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
```

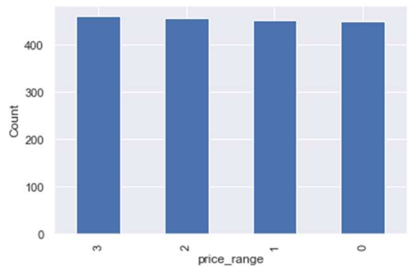
In [6]:
```
train_data_f = train_data[train_data['Screen_W'] != 0]
train_data_f.shape
```

Out[6]: (1820, 21)

In [6]:
```
train_data_f = train_data[train_data['Screen_W'] != 0]
train_data_f.shape
```

Out[6]: (1820, 21)

In [9]:
```
#classes
sns.set()
price_plot=train_data_f['Price_Range'].value_counts().plot(kind='bar')
plt.xlabel('price_range')
plt.ylabel('Count')
plt.show()
```



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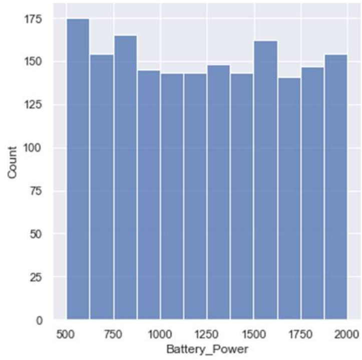
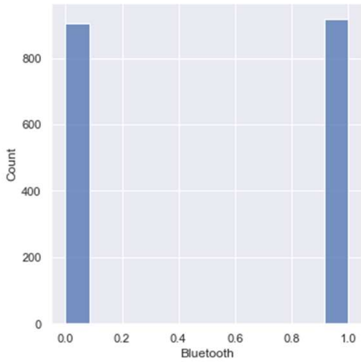
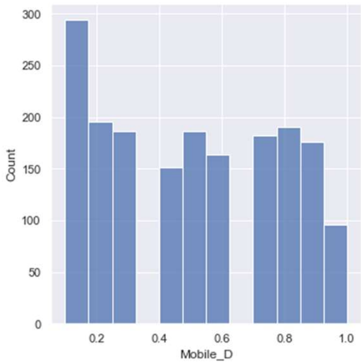
In [11]:
```
sns.set(rc={'figure.figsize':(5,5)})
ax=sns.displot(data=train_data_f["Battery_Power"])
plt.show()
```



In [13]:
```
sns.set(rc={'figure.figsize':(5,5)})
ax=sns.displot(data=train_data_f["Bluetooth"])
plt.show()
```



In [14]:
```
sns.set(rc={'figure.figsize':(5,5)})
ax=sns.displot(data=train_data_f["Mobile_D"])
plt.show()
```



In [15]:
```
X=train_data_f.drop(['Price_Range'], axis=1)
y=train_data_f['Price_Range']
#missing values
X.isna().any()
```

Out[15]:
```
Battery_Power    False
Clock_Speed      False
FC               False
Int_Memory       False
Mobile_D         False
Mobile_W         False
Cores            False
PC               False
Pixel_H          False
Pixel_W          False
Ram              False
Screen_H         False
Screen_W         False
Talk_Time        False
Four_G           False
Three_G          False
Touch_Screen     False
Dual_SIM         False
Bluetooth        False
WiFi             False
dtype: bool
```

In [16]:
```
#train test split of data
from sklearn.model_selection import train_test_split
X_train, X_valid, y_train, y_valid= train_test_split(X, y, test_size=0.2, random_state=7)
```

In [16]:
```
#train test split of data
from sklearn.model_selection import train_test_split
X_train, X_valid, y_train, y_valid= train_test_split(X, y, test_size=0.2, random_state=7)
```


In [17]:
```
#confusion matrix
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
def my_confusion_matrix(y_test, y_pred, plt_title):
    cm=confusion_matrix(y_test, y_pred)
    print(classification_report(y_test, y_pred))
    sns.heatmap(cm, annot=True, fmt='g', cbar=False, cmap='BuPu')
    plt.xlabel('Predicted Values')
    plt.ylabel('Actual Values')
    plt.title(plt_title)
    plt.show()
    return cm
```

In [18]:
```
#building the model
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier(bootstrap= True,
                           max_depth= 7,
                           max_features= 15,
                           min_samples_leaf= 3,
                           min_samples_split= 10,
                           n_estimators= 200,
                           random_state=7)
```

In [19]:
```
rfc.fit(X_train, y_train)
y_pred_rfc=rfc.predict(X_valid)
```

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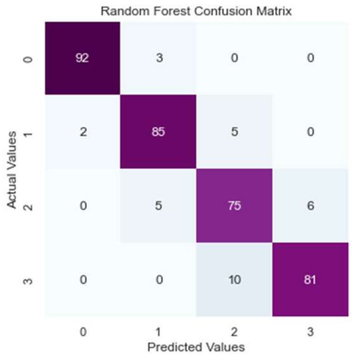
Random Forest Classifier

In [20]:
```
print('Random Forest Classifier Accuracy Score: ',accuracy_score(y_valid,y_pred_rfc))
cm_rfc=my_confusion_matrix(y_valid, y_pred_rfc, 'Random Forest Confusion Matrix')
```

```
Random Forest Classifier Accuracy Score:  0.9148351648351648
              precision    recall  f1-score   support

           0       0.98      0.97      0.97        95
           1       0.91      0.92      0.92        92
           2       0.83      0.87      0.85        86
           3       0.93      0.89      0.91        91

    accuracy                           0.91       364
   macro avg       0.91      0.91      0.91       364
weighted avg       0.92      0.91      0.92       364
```



Naive Bayes

In [21]:
```
from sklearn.naive_bayes import GaussianNB
gnb = GaussianNB()
```

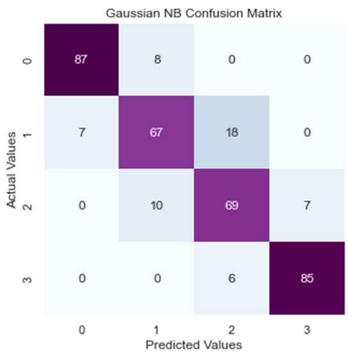
In [22]:
```
gnb.fit(X_train, y_train)
y_pred_gnb=gnb.predict(X_valid)
```

In [23]:
```
print('Gaussian NB Classifier Accuracy Score: ',accuracy_score(y_valid,y_pred_gnb))
cm_rfc=my_confusion_matrix(y_valid, y_pred_gnb, 'Gaussian NB Confusion Matrix')
```

```
Gaussian NB Classifier Accuracy Score:  0.8461538461538461
              precision    recall  f1-score   support

           0       0.93      0.92      0.92        95
           1       0.79      0.73      0.76        92
           2       0.74      0.80      0.77        86
           3       0.92      0.93      0.93        91

    accuracy                           0.85       364
   macro avg       0.84      0.85      0.84       364
weighted avg       0.85      0.85      0.85       364
```



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KNN Classifier

In [24]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=3,leaf_size=25)
```

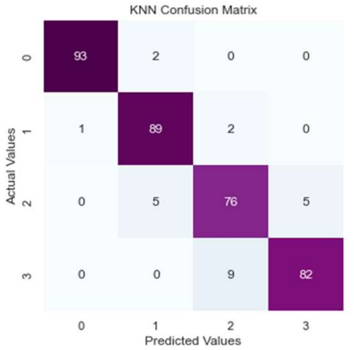
In [25]:
```
knn.fit(X_train, y_train)
y_pred_knn=knn.predict(X_valid)
```

In [26]:
```
print('KNN Classifier Accuracy Score: ',accuracy_score(y_valid,y_pred_knn))
cm_rfc=my_confusion_matrix(y_valid, y_pred_knn, 'KNN Confusion Matrix')
```

```
KNN Classifier Accuracy Score:  0.9340659340659341
              precision    recall  f1-score   support

           0       0.99      0.98      0.98        95
           1       0.93      0.97      0.95        92
           2       0.87      0.88      0.88        86
           3       0.94      0.90      0.92        91

    accuracy                           0.93       364
   macro avg       0.93      0.93      0.93       364
weighted avg       0.93      0.93      0.93       364
```



SVM Classifier

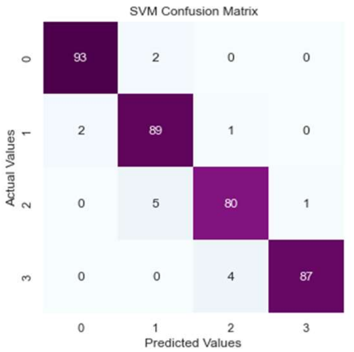
In [27]:
```
from sklearn import svm
svm_clf = svm.SVC(decision_function_shape='ovo')
svm_clf.fit(X_train, y_train)
y_pred_svm=svm_clf.predict(X_valid)
```

In [28]:
```
print('SVM Classifier Accuracy Score: ',accuracy_score(y_valid,y_pred_svm))
cm_rfc=my_confusion_matrix(y_valid, y_pred_svm, 'SVM Confusion Matrix')
```

```
SVM Classifier Accuracy Score:  0.9587912087912088
              precision    recall  f1-score   support

           0       0.98      0.98      0.98        95
           1       0.93      0.97      0.95        92
           2       0.94      0.93      0.94        86
           3       0.99      0.96      0.97        91

    accuracy                           0.96       364
   macro avg       0.96      0.96      0.96       364
weighted avg       0.96      0.96      0.96       364
```



-Made by Manish Kumar (Crimson Wing)