Title

Flipkart Reviews Sentiment Analysis

Overview of Problem Statement

Customer reviews play a crucial role in shaping buyer decisions on e-commerce platforms. With thousands of reviews, it becomes challenging for customers to read and interpret sentiment. This aims to perform sentiment analysis on Flipkart product reviews to classify them into positive and categories, helping both customers and businesses gain quick insights.

Objective

To analyze customer reviews from Flipkart and classify them as Positive or Negative.

To apply different machine learning models to evaluate their performance on sentiment classifica

To identify the best-performing model for future deployment

Importing necessary libraries

In [1]:
```
import numpy as np
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt
from wordcloud import WordCloud
import nltk
from nltk.corpus import stopwords
import string
import re
import datetime

from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer



from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier,BaggingClassifier, ExtraT
from xgboost import XGBClassifier


from nltk.corpus import stopwords
from wordcloud import WordCloud



from sklearn.metrics import confusion_matrix, accuracy_score, classificat
```

In [2]:
```
import warnings
warnings.filterwarnings('ignore')
```

Data collection

In [3]:
```
# Loading the dataset
file_path = 'flipkart_data.csv'
df = pd.read_csv(file_path)
```

In [4]:
```
df
```

Out[4]:

	review	rating
0	It was nice produt. I like it's design a lot. ...	5
1	awesome sound....very pretty to see this nd th...	5
2	awesome sound quality. pros 7-8 hrs of battery...	4
3	I think it is such a good product not only as ...	5
4	awesome bass sound quality very good bettary l...	5
...	...	...
9971	GoodREAD MORE	5
9972	Everything is amazimg but the built is very li...	5
9973	GoodREAD MORE	5
9974	Best headphone i have ever used....READ MORE	5
9975	NiceREAD MORE	5

9976 rows × 2 columns

Data Description

In [5]:
```
df.shape
```

Out[5]:
```
(9976, 2)
```

EDA

In [6]:
```
# Get a summary of the dataset
df.info
```

Out[6]:
```
<bound method DataFrame.info of
review  rating
0     It was nice produt. I like it's design a lot. ...       5
1     awesome sound....very pretty to see this nd th...       5
2     awesome sound quality. pros 7-8 hrs of battery...       4
3     I think it is such a good product not only as ...       5
4     awesome bass sound quality very good bettary l...       5
...                                                 ...     ...
9971                                      GoodREAD MORE       5
9972  Everything is amazimg but the built is very li...       5
9973                                      GoodREAD MORE       5
9974       Best headphone i have ever used....READ MORE       5
9975                                      NiceREAD MORE       5

[9976 rows x 2 columns]>
```

In [7]:
```
# Display statistical summary for all columns within the dataFram
df.describe(include='all')
```

Out[7]:

	review	rating
count	9976	9976.000000
unique	7694	NaN
top	GoodREAD MORE	NaN
freq	264	NaN
mean	NaN	4.215417
std	NaN	1.167911
min	NaN	1.000000
25%	NaN	4.000000
50%	NaN	5.000000
75%	NaN	5.000000
max	NaN	5.000000

In [8]:
```
df.duplicated().sum()
```

Out[8]:
```
2108
```

In [9]:
```
df.isnull().sum()
```

Out[9]:
```
review    0
rating    0
dtype: int64
```

Preprocessing

In [10]:
```
# Remove duplicate rows
df = df.drop_duplicates()
```

In [11]:
```
df.shape
```

Out[11]:
```
(7868, 2)
```

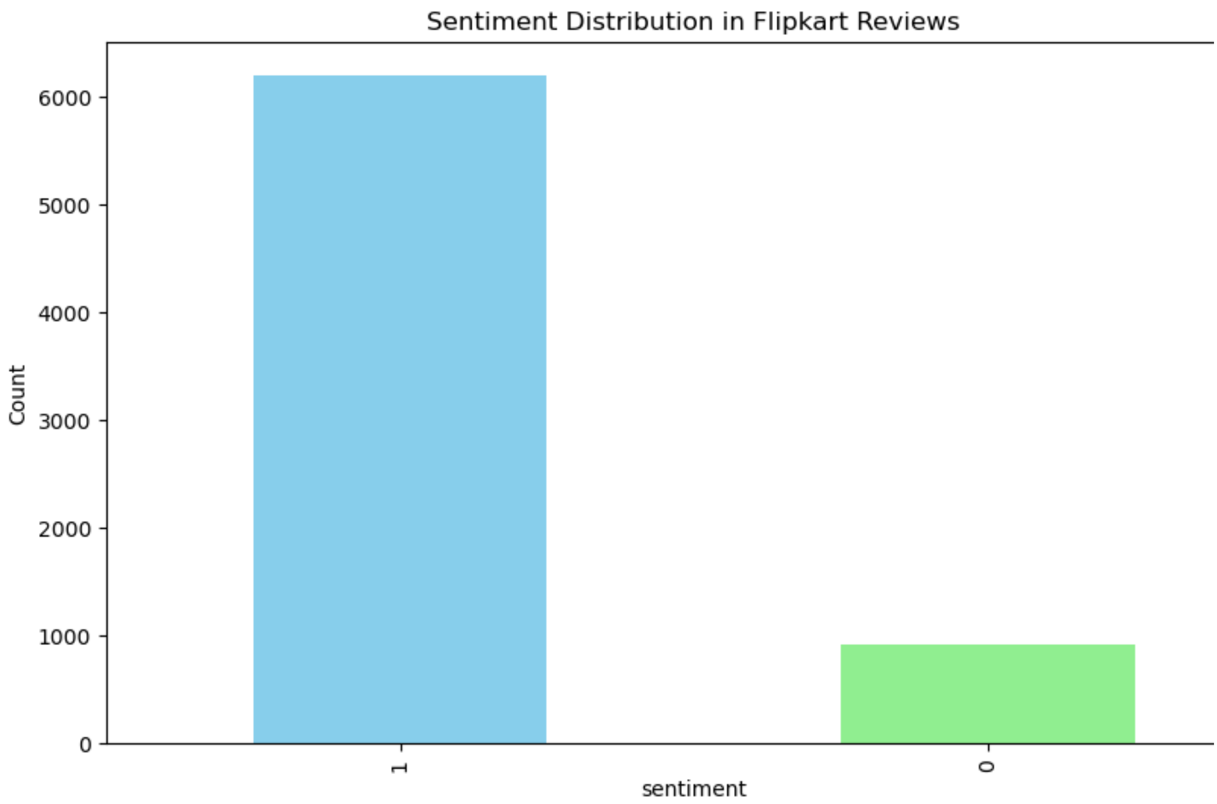
In [12]:
```
##  Create Sentiment Labels (Positive vs Negative)
# Ratings 4-5 → Positive (1), Ratings 1-2 → Negative (0), Rating 3 → Drop
df = df[df['rating'] != 3]
df['sentiment'] = df['rating'].apply(lambda x: 1 if x > 3 else 0)
df = df[['review', 'sentiment']]
```

In [13]:
```
# Text Preprocessing Function with Enhancements
def preprocess_text(text):
    text = text.lower()  # Lowercasing
    text = text.translate(str.maketrans('', '', string.punctuation))  # R
    text = re.sub(r"\d+", "", text)  # Removing numerical values
    text = re.sub(r"\s+", " ", text).strip()  # Removing extra spaces
    words = text.split()  # Tokenizing
    words = [word for word in words if word not in stopwords.words('engli
    return ' '.join(words)
```

```
In [14]: # Applying text preprocessing
         # Applying text preprocessing and renaming the column to 'Cleaned_Text'
         df['Cleaned_review'] = df['review'].apply(preprocess_text)
         df.drop(columns=['review'], inplace=True)
```

Visualization

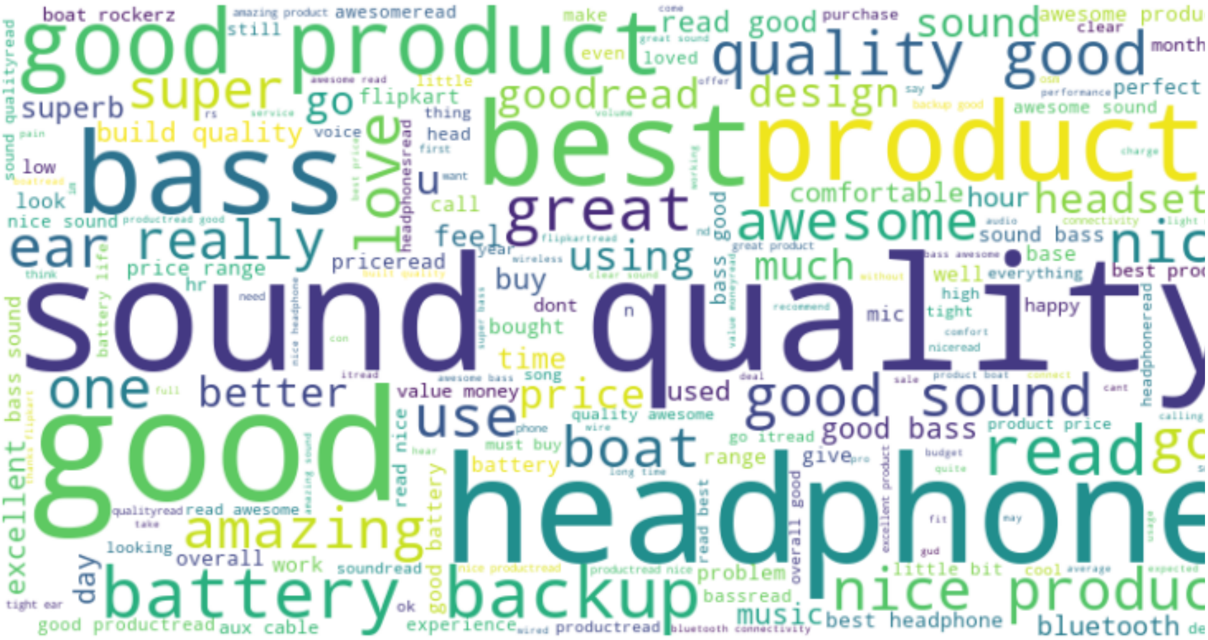
```
In [15]: # Visualizing the distribution of sentiments
         plt.figure(figsize=(10,6))
         df['sentiment'].value_counts().plot(kind='bar', color=['skyblue', 'lightg
         plt.title('Sentiment Distribution in Flipkart Reviews')
         plt.xlabel('sentiment')
         plt.ylabel('Count')
         plt.show()
```



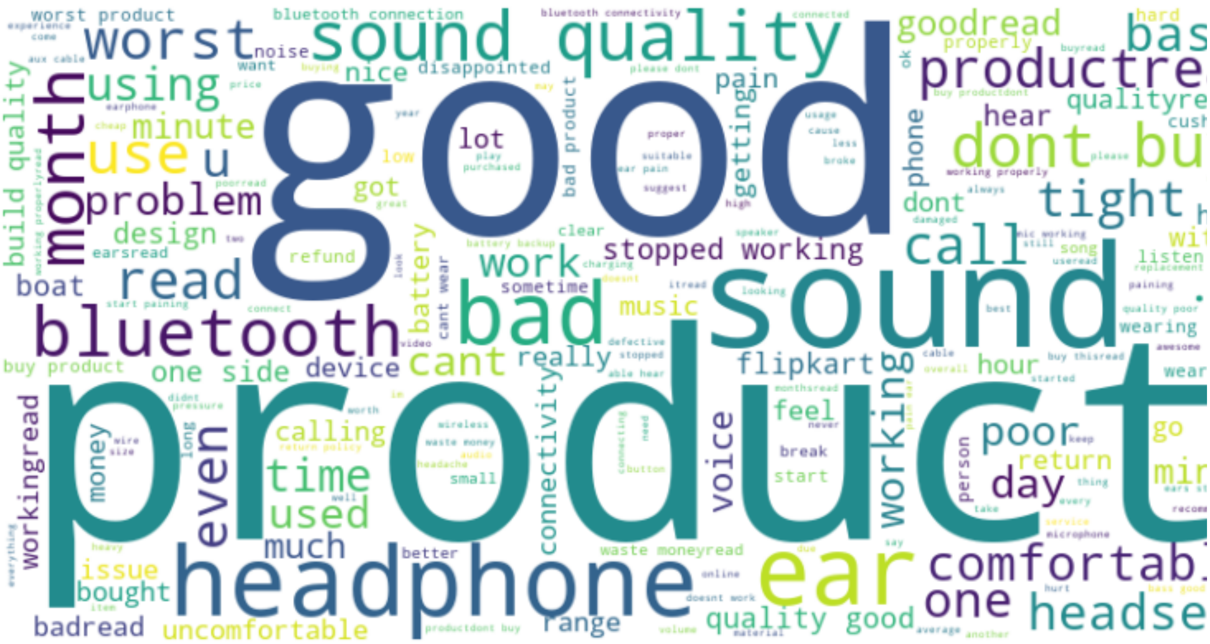

```
In [16]: # Function for Word Cloud Generation
         def generate_wordcloud(text, title):
             wordcloud = WordCloud(width=800, height=400, background_color='white'
             plt.figure(figsize=(10,5))
             plt.imshow(wordcloud, interpolation='bilinear')
             plt.title(title)
             plt.axis('off')
             plt.show()
```

```
In [17]: # Generating Word Clouds for each sentiment
         for sentiment in df['sentiment'].unique():
             sentiment_text = ' '.join(df[df['sentiment'] == sentiment]['Cleaned_re
             generate_wordcloud(sentiment_text, f'{sentiment} Sentiment Word Cloud
```

1 Sentiment Word Cloud



0 Sentiment Word Cloud



Data Splitting

```
In [18]: X = df['Cleaned_review']
         y  = df['sentiment']
```

Vectorize the text data using TF-IDF

```
In [19]: ##  Vectorization
         vectorizer = TfidfVectorizer(max_features=5000)
         X = vectorizer.fit_transform(df['Cleaned_review'])
         y = df['sentiment']
```

```
In [20]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

Building Model

In [21]:
```
models_dict = {
    'LogisticRegression': LogisticRegression(max_iter=10_000),
    'KNeighborsClassifier': KNeighborsClassifier(),
    'DecisionTreeClassifier': DecisionTreeClassifier(),
    'RandomForestClassifier': RandomForestClassifier(),
    'BaggingClassifier': BaggingClassifier(),
    'ExtraTreesClassifier': ExtraTreesClassifier(),
    'AdaBoostClassifier': AdaBoostClassifier(),
    'XGBClassifier': XGBClassifier()
}
```

Find the best Model

In [22]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, classificat

results = []

for name, model in models_dict.items():
    print(f"\nTraining: {name}")
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)

    results.append({
        'Model': name,
        'Accuracy': acc,
        'Confusion Matrix': confusion_matrix(y_test, y_pred)
    })

    print(f"Accuracy: {acc:.4f}")
    print(classification_report(y_test, y_pred))
```

```
Training: LogisticRegression
Accuracy: 0.9276
              precision    recall  f1-score   support

           0       0.91      0.40      0.55       161
           1       0.93      1.00      0.96      1261

    accuracy                           0.93      1422
   macro avg       0.92      0.70      0.76      1422
weighted avg       0.93      0.93      0.91      1422


Training: KNeighborsClassifier
Accuracy: 0.8966
              precision    recall  f1-score   support

           0       0.77      0.12      0.21       161
           1       0.90      1.00      0.94      1261

    accuracy                           0.90      1422
   macro avg       0.83      0.56      0.58      1422
weighted avg       0.88      0.90      0.86      1422


Training: DecisionTreeClassifier
Accuracy: 0.8966
              precision    recall  f1-score   support

           0       0.54      0.59      0.56       161
           1       0.95      0.94      0.94      1261

    accuracy                           0.90      1422
   macro avg       0.74      0.76      0.75      1422
weighted avg       0.90      0.90      0.90      1422


Training: RandomForestClassifier
Accuracy: 0.9311
              precision    recall  f1-score   support

           0       0.82      0.50      0.62       161
           1       0.94      0.99      0.96      1261

    accuracy                           0.93      1422
   macro avg       0.88      0.74      0.79      1422
weighted avg       0.93      0.93      0.92      1422


Training: BaggingClassifier
Accuracy: 0.9093
              precision    recall  f1-score   support

           0       0.61      0.53      0.57       161
           1       0.94      0.96      0.95      1261

    accuracy                           0.91      1422
   macro avg       0.78      0.75      0.76      1422
weighted avg       0.90      0.91      0.91      1422


Training: ExtraTreesClassifier
```

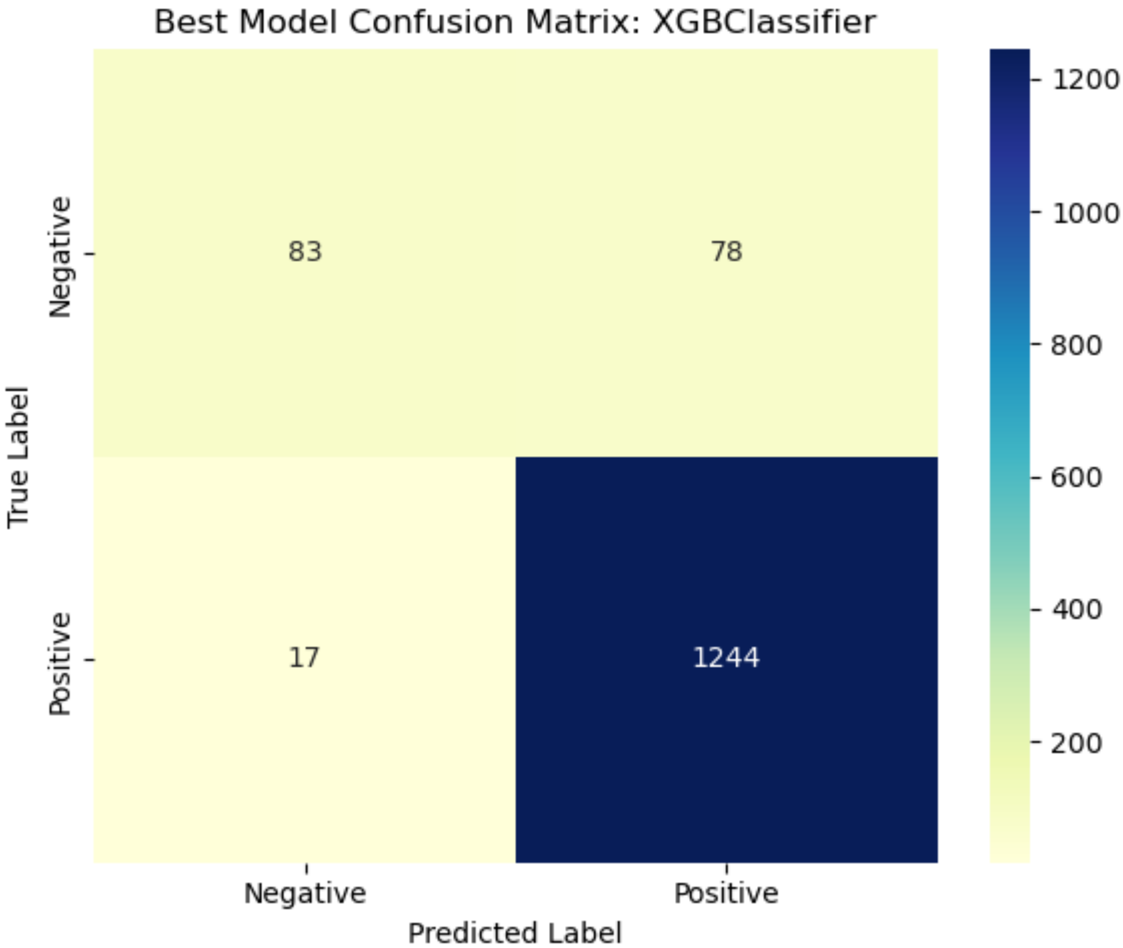
In [23]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

#  Find the best model (highest accuracy)
best_model_result = max(results, key=lambda x: x['Accuracy'])

#  Extract the confusion matrix and model name
best_model_name = best_model_result['Model']
best_cm = best_model_result['Confusion Matrix']

# Plot the heatmap
plt.figure(figsize=(6, 5))
sns.heatmap(best_cm, annot=True, fmt='d', cmap='YlGnBu',
            xticklabels=['Negative', 'Positive'],
            yticklabels=['Negative', 'Positive'])

plt.title(f'Best Model Confusion Matrix: {best_model_name}')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.tight_layout()
plt.show()
```



Results

Best Performing Models: Gradient Boosting / XGBoost with highest accuracy and balanced preci recall.

Observation: Ensemble methods outperform single classifiers due to their ability to handle non-li features.

Conclusion

Sentiment analysis on Flipkart reviews provides a reliable system to classify opinions as positive negative.

Ensemble classifiers such as Gradient Boosting and XGBoost deliver the best results.

This system can help businesses improve product quality and customer experience by focusing negative feedback.

```
In [ ]:
```