```
import numpy as np
import pandas as pd
```

```
df=pd.read_csv('/content/tweets.csv')
```

```
df.head()
```

	token	date	reply_count	like_count	retweet_count	quote_count	text	sentiment_label	sentiment_score
0	bitcoin	2022-01-01 00:00:00.000	20	207	31	3	Most people underestimate the impact #Bitcoin ...	Neutral	0.717482
1	bitcoin	2022-01-01 00:00:00.000	232	3405	286	27	#Bitcoin has started a new yearly candle https...	Neutral	0.810814
2	bitcoin	2022-01-01	2	861	12	0	@DESTROYBINARY did people forget that	Neutral	0.606978

```
!pip install contractions
!pip install emoji
```

```
Collecting contractions
  Downloading contractions-0.1.73-py2.py3-none-any.whl.metadata (1.2 kB)
Collecting textsearch>=0.0.21 (from contractions)
  Downloading textsearch-0.0.24-py2.py3-none-any.whl.metadata (1.2 kB)
Collecting anyascii (from textsearch>=0.0.21->contractions)
  Downloading anyascii-0.3.2-py3-none-any.whl.metadata (1.5 kB)
Collecting pyahocorasick (from textsearch>=0.0.21->contractions)
  Downloading pyahocorasick-2.1.0-cp310-cp310-manylinux_2_5_x86_64.manylinux1_x86_64.manylinux_2_12_x86_64.manylinux2010_x86_64.whl
Downloading contractions-0.1.73-py2.py3-none-any.whl (8.7 kB)
Downloading textsearch-0.0.24-py2.py3-none-any.whl (7.6 kB)
Downloading anyascii-0.3.2-py3-none-any.whl (289 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 289.9/289.9 kB 4.0 MB/s eta 0:00:00
Downloading pyahocorasick-2.1.0-cp310-cp310-manylinux_2_5_x86_64.manylinux1_x86_64.manylinux_2_12_x86_64.manylinux2010_x86_64.whl (1
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 110.7/110.7 kB 8.4 MB/s eta 0:00:00
Installing collected packages: pyahocorasick, anyascii, textsearch, contractions
Successfully installed anyascii-0.3.2 contractions-0.1.73 pyahocorasick-2.1.0 textsearch-0.0.24
Collecting emoji
  Downloading emoji-2.14.0-py3-none-any.whl.metadata (5.7 kB)
Downloading emoji-2.14.0-py3-none-any.whl (586 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 586.9/586.9 kB 5.2 MB/s eta 0:00:00
Installing collected packages: emoji
Successfully installed emoji-2.14.0
```

```
import nltk
nltk.download('vader_lexicon')
```

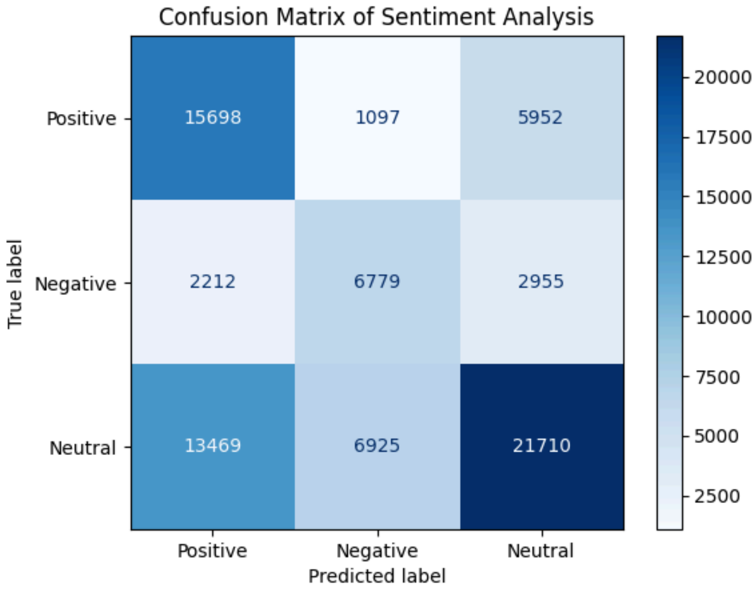
```
[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
True
```

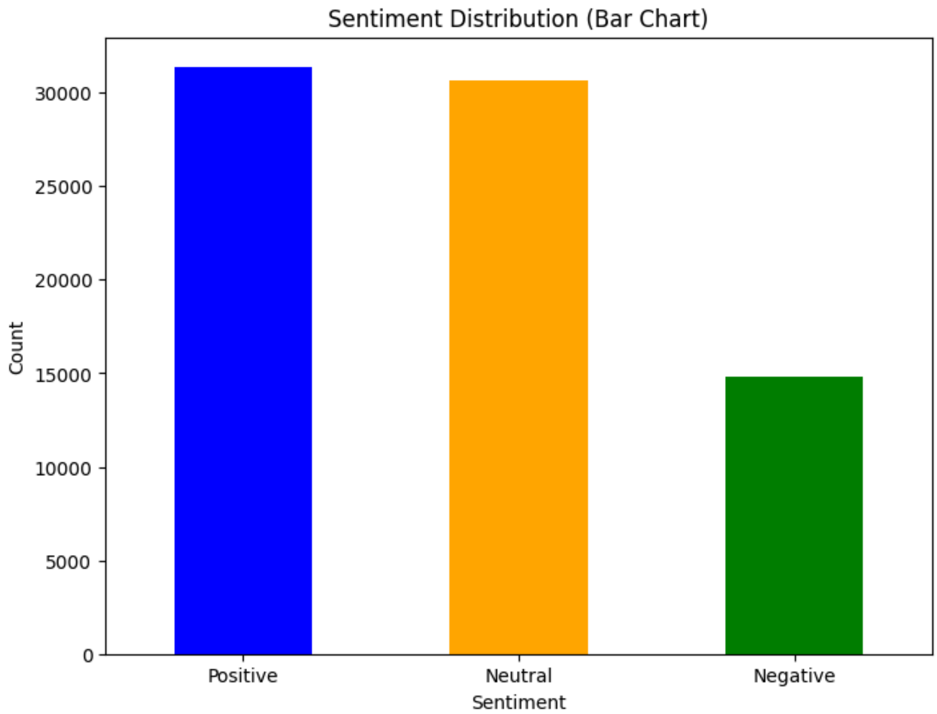
```
import pandas as pd
import numpy as np
import re
import emoji
from nltk.sentiment import SentimentIntensityAnalyzer
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
from wordcloud import WordCloud

# Convert 'date' column to datetime
df['date'] = pd.to_datetime(df['date'])

# Enhanced text cleaning function
def clean_tweet(text):
    text = re.sub(r"http\S+|www\S+|https\S+", "", text)  # Remove URLs
    text = re.sub(r"@\w+", "", text)  # Remove mentions
    text = re.sub(r"[^a-zA-Z#\s]", "", text)  # Remove special characters but keep hashtags
    text = emoji.demojize(text)  # Convert emojis to descriptive text
    text = re.sub(r"_", " ", text)  # Replace underscores in demojized text
    return text.lower().strip()

df['cleaned_text'] = df['text'].apply(clean_tweet)

# Initialize VADER SentimentIntensityAnalyzer
sia = SentimentIntensityAnalyzer()

# Add custom domain-specific words to VADER
custom_lexicon = {
    'bullish': 3.0,
```

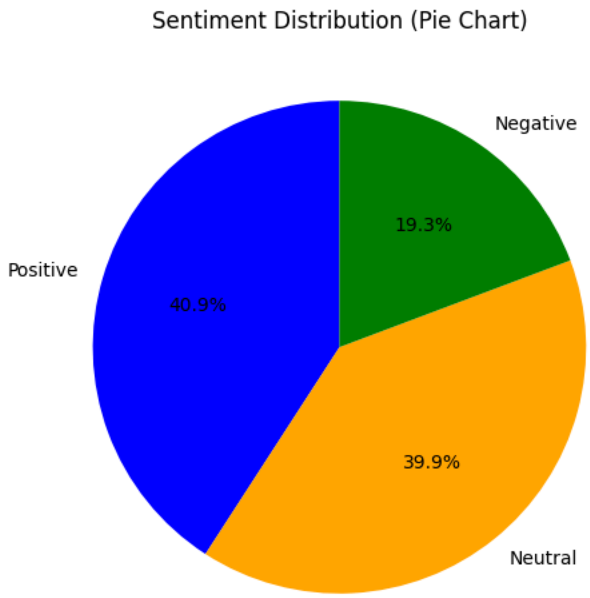
```
    'bearish': -3.0,
    'HODL': 2.0,
    'moon': 2.5,
    'dump': -2.5,
    'pump': 2.0,
    'rekt': -3.0,
}
sia.lexicon.update(custom_lexicon)

# Define a custom VADER sentiment function
def vader_sentiment_analysis(text):
    scores = sia.polarity_scores(text)
    compound = scores['compound']
    # Adjust thresholds for sentiment labeling
    if compound >= 0.2:  # Higher threshold for positive sentiment
        return 'Positive'
    elif compound <= -0.2:  # Lower threshold for negative sentiment
        return 'Negative'
    else:
        return 'Neutral'

# Apply VADER sentiment analysis
df['vader_sentiment'] = df['cleaned_text'].apply(vader_sentiment_analysis)

# Evaluate accuracy
accuracy = accuracy_score(df['sentiment_label'], df['vader_sentiment'])
print(f"Accuracy of VADER predictions: {accuracy * 100:.2f}%")

# Confusion matrix
cm = confusion_matrix(df['sentiment_label'], df['vader_sentiment'], labels=['Positive', 'Negative', 'Neutral'])
cm_display = ConfusionMatrixDisplay(cm, display_labels=['Positive', 'Negative', 'Neutral'])
cm_display.plot(cmap=plt.cm.Blues)
plt.title("Confusion Matrix of Sentiment Analysis")
plt.show()

# Plot sentiment distribution (Bar chart)
sentiment_counts = df['vader_sentiment'].value_counts()
plt.figure(figsize=(8, 6))
sentiment_counts.plot(kind='bar', color=['blue', 'orange', 'green'])
plt.title('Sentiment Distribution (Bar Chart)')
plt.xlabel('Sentiment')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.show()

# Plot sentiment distribution (Pie chart)
plt.figure(figsize=(8, 6))
sentiment_counts.plot(kind='pie', autopct='%1.1f%%', colors=['blue', 'orange', 'green'], startangle=90, legend=False)
plt.title('Sentiment Distribution (Pie Chart)')
plt.ylabel('')
plt.show()

# Highlight most positive and most negative tweets
df['compound_score'] = df['cleaned_text'].apply(lambda x: sia.polarity_scores(x)['compound'])
most_positive = df.loc[df['compound_score'].idxmax()]
most_negative = df.loc[df['compound_score'].idxmin()]

print("\nMost Positive Tweet:")
print(most_positive[['text', 'compound_score']])

print("\nMost Negative Tweet:")
print(most_negative[['text', 'compound_score']])

# Word clouds for positive and negative tweets
positive_words = ' '.join(df[df['vader_sentiment'] == 'Positive']['cleaned_text'])
negative_words = ' '.join(df[df['vader_sentiment'] == 'Negative']['cleaned_text'])

wordcloud_positive = WordCloud(width=800, height=400, background_color='white').generate(positive_words)
wordcloud_negative = WordCloud(width=800, height=400, background_color='black').generate(negative_words)

# Display word clouds
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.imshow(wordcloud_positive, interpolation='bilinear')
plt.title('Positive Tweets Word Cloud')
plt.axis('off')

plt.subplot(1, 2, 2)
plt.imshow(wordcloud_negative, interpolation='bilinear')
plt.title('Negative Tweets Word Cloud')
plt.axis('off')
```

```
plt.tight_layout()
plt.show()
```

```
Accuracy of VADER predictions: 57.54%
```








```
Most Positive Tweet:
```

```
text              UPDATE: #Bitcoin time frames 👇\n\nMonthly is b...
compound_score                                            0.9958
Name: 68048, dtype: object

Most Negative Tweet:
text              #Ethereum is a premined scam\n#BNB is a centra...
compound_score                                           -0.9875
Name: 35650, dtype: object
```

Positive Tweets Word Cloud

Negative Tweets Word Cloud


```
# prompt: compare the accuracy of predicted and original dataset

from sklearn.metrics import accuracy_score, classification_report

# Assuming 'sentiment_label' contains the actual sentiment labels
# and 'vader_sentiment' contains the predicted sentiment
if 'sentiment_label' in df.columns and 'vader_sentiment' in df.columns:
    accuracy = accuracy_score(df['sentiment_label'], df['vader_sentiment'])  # Changed to 'vader_sentiment'
    print(f"Accuracy: {accuracy}")

    # Classification report for more detailed metrics
    print(classification_report(df['sentiment_label'], df['vader_sentiment'], labels=['Positive', 'Negative', 'Neutral'])) # Changed to
else:
    print("No 'sentiment_label' or 'vader_sentiment' column found. Cannot calculate accuracy.")
```

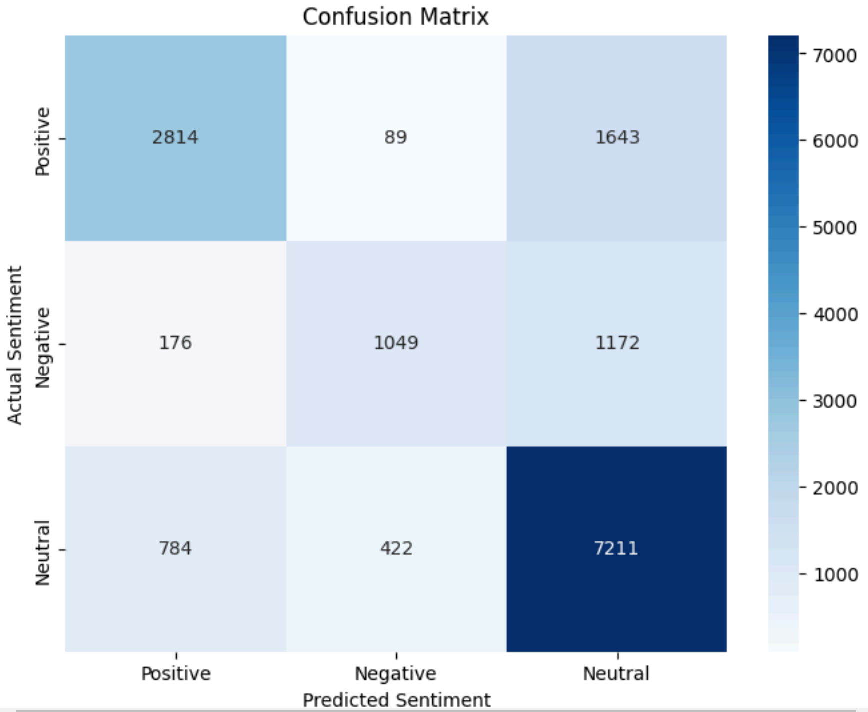
```
Accuracy: 0.5753740380483613
              precision    recall  f1-score   support

    Positive       0.50      0.69      0.58     22747
    Negative       0.46      0.57      0.51     11946
     Neutral       0.71      0.52      0.60     42104

    accuracy                           0.58     76797
   macro avg       0.56      0.59      0.56     76797
weighted avg       0.61      0.58      0.58     76797
```

```
import numpy as np
import pandas as pd
import re
import matplotlib.pyplot as plt
from wordcloud import WordCloud, STOPWORDS
from sklearn.metrics import confusion_matrix
import seaborn as sns
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression


# Install contractions library if not already installed
!pip install contractions

import contractions

# Load your dataset
df = pd.read_csv('/content/tweets.csv')

def clean_tweet(tweet):
    tweet = contractions.fix(tweet)  # Expand contractions
    tweet = re.sub(r"@[A-Za-z0-9]+", "", tweet)  # Remove mentions
    tweet = re.sub(r"#", "", tweet)  # Remove '#' symbol
    tweet = re.sub(r"RT[\s]+", "", tweet)  # Remove RT
    tweet = re.sub(r"https?:\/\/\S+", "", tweet)  # Remove hyperlinks
    tweet = re.sub(r"\s+", " ", tweet).strip()  # Remove excessive whitespace
    tweet = re.sub(r"[^a-zA-Z\s]", "", tweet) # Remove special characters
    tweet = tweet.lower()  # Convert to lowercase
```

```
    return tweet

df['clean_tweet'] = df['text'].apply(clean_tweet)

# Split data into training and testing sets
X = df['clean_tweet']
y = df['sentiment_label']  # Assuming you have a 'sentiment_label' column
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


# TF-IDF vectorization
vectorizer = TfidfVectorizer(max_features=5000) # Adjust max_features if needed
X_train_vec = vectorizer.fit_transform(X_train)
X_test_vec = vectorizer.transform(X_test)

# Logistic Regression Model
model = LogisticRegression(max_iter=1000) # Increased max_iter
model.fit(X_train_vec, y_train)

# Prediction and Evaluation
y_pred = model.predict(X_test_vec)
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")
print(classification_report(y_test, y_pred))
```

```
Requirement already satisfied: contractions in /usr/local/lib/python3.10/dist-packages (0.1.73)
Requirement already satisfied: textsearch>=0.0.21 in /usr/local/lib/python3.10/dist-packages (from contractions) (0.0.24)
Requirement already satisfied: anyascii in /usr/local/lib/python3.10/dist-packages (from textsearch>=0.0.21->contractions) (0.3.2)
Requirement already satisfied: pyahocorasick in /usr/local/lib/python3.10/dist-packages (from textsearch>=0.0.21->contractions) (2.:
Accuracy: 0.7209635416666667
              precision    recall  f1-score   support

    Negative       0.67      0.44      0.53      2397
     Neutral       0.72      0.86      0.78      8417
    Positive       0.75      0.62      0.68      4546

    accuracy                           0.72     15360
   macro avg       0.71      0.64      0.66     15360
weighted avg       0.72      0.72      0.71     15360
```

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# Assuming y_test and y_pred are defined from your model's prediction
cm = confusion_matrix(y_test, y_pred, labels=['Positive', 'Negative', 'Neutral'])
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
            xticklabels=['Positive', 'Negative', 'Neutral'],
            yticklabels=['Positive', 'Negative', 'Neutral'])
plt.xlabel('Predicted Sentiment')
plt.ylabel('Actual Sentiment')
plt.title('Confusion Matrix')
plt.show()
```




```
!pip install vaderSentiment
```

```
Collecting vaderSentiment
  Downloading vaderSentiment-3.3.2-py2.py3-none-any.whl.metadata (572 bytes)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from vaderSentiment) (2.32.3)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->vaderSentiment)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->vaderSentiment) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->vaderSentiment) (2.2.3
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->vaderSentiment) (2024.8
Downloading vaderSentiment-3.3.2-py2.py3-none-any.whl (125 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 126.0/126.0 kB 2.9 MB/s eta 0:00:00
Installing collected packages: vaderSentiment
Successfully installed vaderSentiment-3.3.2
```

```
import numpy as np
import pandas as pd
import re
import contractions
import matplotlib.pyplot as plt
from wordcloud import WordCloud, STOPWORDS
from sklearn.metrics import confusion_matrix
import seaborn as sns
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression


# Convert 'date' column to datetime
df['date'] = pd.to_datetime(df['date'])

# Enhanced tweet cleaning function
def clean_tweet(tweet):
    tweet = contractions.fix(tweet)  # Expand contractions
    tweet = re.sub(r"@[A-Za-z0-9]+", "", tweet)  # Remove mentions
    tweet = re.sub(r"#", "", tweet)  # Remove '#' symbol
    tweet = re.sub(r"RT[\s]+", "", tweet)  # Remove RT
    tweet = re.sub(r"https?:\/\/\S+", "", tweet)  # Remove hyperlinks
    tweet = re.sub(r"\s+", " ", tweet).strip()  # Remove excessive whitespace
    tweet = re.sub(r"[^a-zA-Z\s]", "", tweet)  # Remove special characters
    tweet = tweet.lower()  # Convert to lowercase
    return tweet

df['clean_tweet'] = df['text'].apply(clean_tweet)

# Initialize VADER SentimentIntensityAnalyzer
sia = SentimentIntensityAnalyzer()

# Define a custom VADER sentiment function
def vader_sentiment_analysis(text):
```

```
        scores = sia.polarity_scores(text)
        compound = scores['compound']
        # Adjust thresholds for sentiment labeling
        if compound >= 0.2:  # Higher threshold for positive sentiment
            return 'Positive'
        elif compound <= -0.2:  # Lower threshold for negative sentiment
            return 'Negative'
        else:
            return 'Neutral'

    # Apply VADER sentiment analysis
    df['vader_sentiment'] = df['clean_tweet'].apply(vader_sentiment_analysis)

    # Split data into training and testing sets
    X = df['clean_tweet']
    y = df['vader_sentiment']  # Use VADER sentiment labels for training
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    # TF-IDF vectorization
    vectorizer = TfidfVectorizer(max_features=5000)  # Adjust max_features if needed
    X_train_vec = vectorizer.fit_transform(X_train)
    X_test_vec = vectorizer.transform(X_test)

    # Logistic Regression Model
    model = LogisticRegression(max_iter=1000)  # Increased max_iter
    model.fit(X_train_vec, y_train)

    # Prediction and Evaluation
    y_pred = model.predict(X_test_vec)
    accuracy = accuracy_score(y_test, y_pred)
    print(f"Accuracy: {accuracy}")
    print(classification_report(y_test, y_pred))

    # Confusion Matrix
    cm = confusion_matrix(y_test, y_pred, labels=['Positive', 'Negative', 'Neutral'])
    cm_display = ConfusionMatrixDisplay(cm, display_labels=['Positive', 'Negative', 'Neutral'])
    cm_display.plot(cmap=plt.cm.Blues)
    plt.title("Confusion Matrix of Sentiment Analysis")
    plt.show()
    print("\n")
    # Plot sentiment distribution (Pie chart)
    sentiment_counts = df['vader_sentiment'].value_counts()
    plt.figure(figsize=(8, 6))
    sentiment_counts.plot(kind='pie', autopct='%1.1f%%', colors=['blue', 'orange', 'green'], startangle=90, legend=False)
    plt.title('Sentiment Distribution (Pie Chart)')
    plt.ylabel('')
    plt.show()
    print("\n")

    # Word clouds for positive and negative tweets
    positive_words = ' '.join(df[df['vader_sentiment'] == 'Positive']['clean_tweet'])
    negative_words = ' '.join(df[df['vader_sentiment'] == 'Negative']['clean_tweet'])

    wordcloud_positive = WordCloud(width=800, height=400, background_color='white').generate(positive_words)
    wordcloud_negative = WordCloud(width=800, height=400, background_color='black').generate(negative_words)

    # Display word clouds
    plt.figure(figsize=(10, 5))
    plt.subplot(1, 2, 1)
    plt.imshow(wordcloud_positive, interpolation='bilinear')
    plt.title('Positive Tweets Word Cloud')
    plt.axis('off')
    print("\n")
    plt.subplot(1, 2, 2)
    plt.imshow(wordcloud_negative, interpolation='bilinear')
    plt.title('Negative Tweets Word Cloud')
    plt.axis('off')
    print("\n")
    plt.tight_layout()
    plt.show()
```

```
Accuracy: 0.8199869791666666
              precision    recall  f1-score   support

    Negative       0.79      0.65      0.71      2932
     Neutral       0.80      0.86      0.83      6347
    Positive       0.86      0.86      0.86      6081
```