Multi-Label Text Sentiment Classification and Word Embedding Analysis For "Thread" Social Media Appliaction Reviews

In this project, we delve into the world of sentiment analysis and word embedding to gain valuable insights from user-generated content in the context of the popular "Thread" social media application. With over 37,000 user reviews collected from the Google Play Store and Apple App Store, our comprehensive dataset offers a rich and diverse range of sentiments and opinions.

The primary objectives of this project are:

Sentiment Analysis: We aim to develop a multi-label text sentiment classification model to categorize user sentiments into positive, negative, or neutral. The analysis provides valuable insights into user satisfaction, app usability, feature preferences, and potential areas for improvement.

Word Embedding with Word2Vec: Leveraging Word2Vec, we perform word embedding analysis to explore the intricacies of user language, writing styles, and expressions of sentiment. By transforming text data into dense vector representations, we enable advanced NLP tasks and extract meaningful patterns and trends.

In [1]:

```
import gensim
from gensim.models import word2vec
from gensim.models.word2vec import Word2Vec
import gensim.downloader as api

from IPython.display import display
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import string
import os

from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score, confusion_matrix, roc_curve, auc
from sklearn.svm import SVC
from sklearn.preprocessing import MultiLabelBinarizer
from sklearn.multioutput import MultiOutputClassifier
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler


import spacy
from wordcloud import WordCloud

from nltk.sentiment.vader import SentimentIntensityAnalyzer
from nltk.tokenize import word_tokenize, sent_tokenize
from nltk.stem import WordNetLemmatizer
import nltk

nltk.download('punkt')
nltk.download('wordnet')

import warnings

# Ignore all warnings
warnings.filterwarnings("ignore")
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

In [2]:

```
gensim.__version__
```

Out[2]:

```
'4.3.2'
```

In [3]:

```
print(list(gensim.downloader.info()['models'].keys()))
```

```
['fasttext-wiki-news-subwords-300', 'conceptnet-numberbatch-17-06-300', 'word2vec-ruscorpora-300', 'word2vec-google-news-300', 'glove-wiki-gigaword-50', 'glove-wiki-gigaword-100', 'glove-wiki-gigaword-200', 'glove-wiki-gigaword-300', 'glove-twitter-25', 'glove-twitter-50', 'glove-twitter-100', 'glove-twitter-200', '__testing_word2vec-matrix-synopsis']
```

In [4]:

```
data = pd.read_csv("37000_reviews_of_thread_app.csv")
```

New Section

New Section

In [5]:
```
display(data)
```

	Unnamed: 0	source	review_id	user_name	review_title	review_description	rating	thumbs_up	review_date	developer_respo
0	0	Google Play	7cd90e5b-4829-43b9-9fb4-c8c6d1e339c1	Eddie Clark Jr.	NaN	Good	5	0.0	2023-08-07 19:14:36	
1	1	Google Play	6deb8265-2bac-4524-bcb6-f90829fa4e69	Rasa RT	NaN	Weak copy of Twitter	1	0.0	2023-08-07 19:07:04	
2	2	Google Play	91ef61ce-0f05-4f3b-b3d3-5d19cd408ab8	SITI NUR HAFIZA BINTI AZIZ	NaN	i wish threads have a save button for images a...	3	0.0	2023-08-07 18:57:07	
3	3	Google Play	b7721b78-6b77-4f8c-a1d3-a854af4c1f0f	Asap Khalifah	NaN	Love it	5	0.0	2023-08-07 18:37:16	
4	4	Google Play	c89ef522-c94c-4171-878f-1d672dce7f11	Syed Hussein	NaN	Very god	5	0.0	2023-08-07 18:14:15	
...	...	...	...	...	...	...	...	...	...	
36938	1995	App Store	d0503900-7c8b-4cf3-8f16-1a628f25d99b	Ileila888	Hybrid of IG and Twitter with 0 UVP	Threads have mediocre UX with 0 unique value p...	2	NaN	2023-07-06 00:37:57	
36939	1996	App Store	d55529a3-42b9-4a55-a17c-b49f30d7b419	MaxW239	Outstanding	Twitter (Instagram's Version)	5	NaN	2023-07-06 00:00:39	
36940	1997	App Store	8818ddd0-1ce4-4d82-b0df-b43a6c68ff81	Anne Marie C	Let the battle begin!	😂😂😂	5	NaN	2023-07-05 23:16:15	
36941	1998	App Store	81561238-d8c1-467d-b9dc-be25d64a1aa7	alexcookiedough92	No search bar??	How do you expect a social media app to succee...	1	NaN	2023-08-06 12:31:54	
36942	1999	App Store	af10f81b-c974-401f-8668-a3fbd79667be	cncfan	Needs new features	Desperately needs new features.	2	NaN	2023-08-01 06:37:45	

36943 rows × 14 columns

In [6]:
```python
lemmatizer = WordNetLemmatizer()

def preprocess_text(text):

  if isinstance(text, str):

    text = ''.join([char for char in text if char not in string.punctuation and not char.isdigit()])
    text = text.lower()

    words = [lemmatizer.lemmatize(word) for word in word_tokenize(text) if word.isalpha()]
    sentences = sent_tokenize(text)

    word_count = len(words)
    sentence_count = len(sentences)

    tokens = [word.lower() for word in word_tokenize(text) if word.isalpha()]

    return {
        'tokens': tokens,
        'lemmatized_tokens': words,
        'sentences': sentences,
        'word_count': word_count,
        'sentence_count': sentence_count
    }
```

In [7]:
```python
data['processed_description'] = data['review_description'].apply(preprocess_text)
data['processed_title'] = data['review_title'].apply(preprocess_text)
```

In [8]:
```python
data
```

Out[8]:

	Unnamed: 0	source	review_id	user_name	review_title	review_description	rating	thumbs_up	review_date	developer_respo
0	0	Google Play	7cd90e5b-4829-43b9-9fb4-c8c6d1e339c1	Eddie Clark Jr.	NaN	Good	5	0.0	2023-08-07 19:14:36	
1	1	Google Play	6deb8265-2bac-4524-bcb6-f90829fa4e69	Rasa RT	NaN	Weak copy of Twitter	1	0.0	2023-08-07 19:07:04	
2	2	Google Play	91ef61ce-0f05-4f3b-b3d3-5d19cd408ab8	SITI NUR HAFIZA BINTI AZIZ	NaN	i wish threads have a save button for images a...	3	0.0	2023-08-07 18:57:07	
3	3	Google Play	b7721b78-6b77-4f8c-a1d3-a854af4c1f0f	Asap Khalifah	NaN	Love it	5	0.0	2023-08-07 18:37:16	
4	4	Google Play	c89ef522-c94c-4171-878f-1d672dce7f11	Syed Hussein	NaN	Very god	5	0.0	2023-08-07 18:14:15	
...	...	...	...	...	...	...	...	...	...	
36938	1995	App Store	d0503900-7c8b-4cf3-8f16-1a628f25d99b	Ileila888	Hybrid of IG and Twitter with 0 UVP	Threads have mediocre UX with 0 unique value p...	2	NaN	2023-07-06 00:37:57	
36939	1996	App Store	d55529a3-42b9-4a55-a17c-b49f30d7b419	MaxW239	Outstanding	Twitter (Instagram's Version)	5	NaN	2023-07-06 00:00:39	
36940	1997	App Store	8818ddd0-1ce4-4d82-b0df-b43a6c68ff81	Anne Marie C	Let the battle begin!	😂😂😂	5	NaN	2023-07-05 23:16:15	
36941	1998	App Store	81561238-d8c1-467d-b9dc-be25d64a1aa7	alexcookiedough92	No search bar??	How do you expect a social media app to succee...	1	NaN	2023-08-06 12:31:54	
36942	1999	App Store	af10f81b-c974-401f-8668-a3fbd79667be	cncfan	Needs new features	Desperately needs new features.	2	NaN	2023-08-01 06:37:45	

36943 rows × 16 columns

In [9]:

```python
display(data['processed_description'][0:10])
```

```
0    {'tokens': ['good'], 'lemmatized_tokens': ['go...
1    {'tokens': ['weak', 'copy', 'of', 'twitter'], ...
2    {'tokens': ['i', 'wish', 'threads', 'have', 'a...
3    {'tokens': ['love', 'it'], 'lemmatized_tokens'...
4    {'tokens': ['very', 'god'], 'lemmatized_tokens...
5    {'tokens': ['nice'], 'lemmatized_tokens': ['ni...
6    {'tokens': ['vain'], 'lemmatized_tokens': ['va...
7    {'tokens': ['not', 'satisfied', 'why', 'this',...
8    {'tokens': ['people', 'want', 'to', 'leave', '...
9    {'tokens': ['copy', 'of', 'twitter', 'hahaha',...
Name: processed_description, dtype: object
```

In [10]:

```python
tokens_df = pd.DataFrame({
    'tokens_text': data['processed_description'].apply(lambda x: x['tokens'] if x is not None else []),
    'tokens_title': data['processed_title'].apply(lambda x: x['tokens'] if x is not None else [])
})
```

In [11]:

```python
tokens_df['tokens_text']
```

Out[11]:

```
0                                                [good]
1                              [weak, copy, of, twitter]
2         [i, wish, threads, have, a, save, button, for,...
3                                            [love, it]
4                                           [very, god]
                              ...
36938    [threads, have, mediocre, ux, with, unique, va...
36939                      [twitter, instagram, s, version]
36940                                                    []
36941    [how, do, you, expect, a, social, media, app, ...
36942                   [desperately, needs, new, features]
Name: tokens_text, Length: 36943, dtype: object
```

Sentiment Analysis for Tokens

In [12]:
```python
# Create a Word2Vec model for 'tokens_text'
model_text = Word2Vec(tokens_df['tokens_text'], vector_size=100, window=5, min_count=1, sg=0, hs=0, negative=10
model_text.build_vocab(tokens_df["tokens_text"])
```

```
WARNING:gensim.models.keyedvectors:sorting after vectors have been allocated is expensive & error-prone
```

In [13]:
```python
# Train the Word2Vec models
model_text.train(tokens_df['tokens_text'], total_examples=len(tokens_df['tokens_text']), epochs=model_text.epoc
```

```
WARNING:gensim.models.word2vec:Effective 'alpha' higher than previous training cycles
```

Out[13]:
```
(6506426, 8817580)
```

In [14]:
```python
model_text
```

Out[14]:
```
<gensim.models.word2vec.Word2Vec at 0x7b9686d9b550>
```

In [15]:
```python
similar_word = model_text.wv.most_similar(["good", "excellent", "great"], topn=16)

# We found that Upto the 16 entity, their vector are greater thatn .5 which indicates connectedness of thee wor
```

In [16]:
```python
similar_word
```

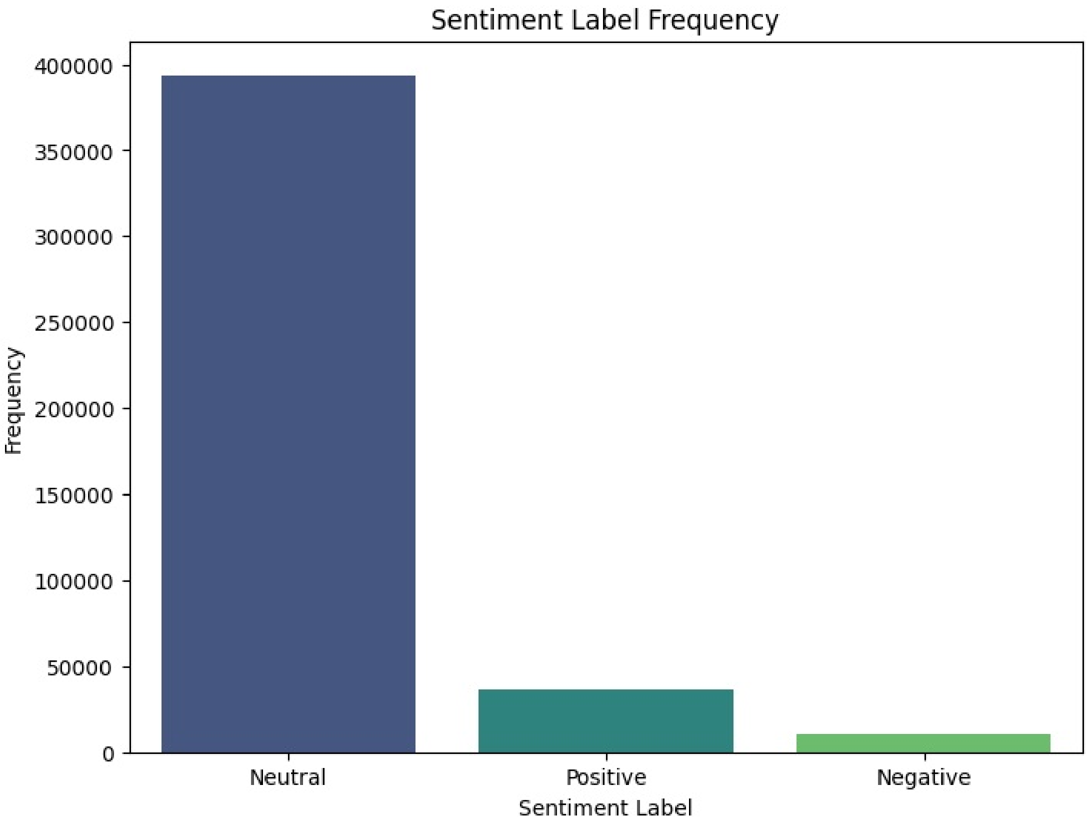
Out[16]:
```
[('perfect', 0.6139432191848755),
 ('nice', 0.6085947155952454),
 ('awesome', 0.5647971034049988),
 ('amazing', 0.5541619062423706),
 ('wonderful', 0.4926517605781555),
 ('smooth', 0.4902808666229248),
 ('love', 0.48485925793647766),
 ('solid', 0.46117129921913147),
 ('best', 0.45708802342414856),
 ('overall', 0.45396432280540466),
 ('better', 0.428947776556015),
 ('definitely', 0.42502084374427795),
 ('cool', 0.41920655965805054),
 ('fantastic', 0.4050028622150421),
 ('this', 0.3917708396911621),
 ('happy', 0.3859647214412689)]
```

In [17]:
```python
from textblob import TextBlob

def analyze_token_sentiment(token):
  analysis = TextBlob(token)
  if analysis.sentiment.polarity > 0:
    return "Positive"
  elif analysis.sentiment.polarity == 0:
    return "Neutral"
  else:
    return "Negative"

tokens_df['Sentiments'] = tokens_df['tokens_text'].apply(lambda tokens: [analyze_token_sentiment(token) for tok
print(tokens_df)
```

```
                                     tokens_text  \
0                                         [good]
1                     [weak, copy, of, twitter]
2      [i, wish, threads, have, a, save, button, for,...
3                                     [love, it]
4                                    [very, god]
...                                          ...
36938  [threads, have, mediocre, ux, with, unique, va...
36939                [twitter, instagram, s, version]
36940                                             []
36941  [how, do, you, expect, a, social, media, app, ...
36942             [desperately, needs, new, features]

                              tokens_title  \
0                                       []
1                                       []
2                                       []
3                                       []
4                                       []
...                                    ...
36938  [hybrid, of, ig, and, twitter, with, uvp]
36939                          [outstanding]
36940                  [let, the, battle, begin]
36941                      [no, search, bar]
36942                 [needs, new, features]

                                      Sentiments
0                                     [Positive]
1               [Negative, Neutral, Neutral, Neutral]
2      [Neutral, Neutral, Neutral, Neutral, Neutral, ...
3                            [Positive, Neutral]
4                            [Positive, Neutral]
...                                          ...
36938  [Neutral, Neutral, Negative, Neutral, Neutral,...
36939            [Neutral, Neutral, Neutral, Neutral]
36940                                             []
36941  [Neutral, Neutral, Neutral, Neutral, Neutral, ...
36942           [Negative, Neutral, Positive, Neutral]

[36943 rows x 3 columns]
```

In [18]:

```python
sentiments = [sentiment for sentiments_list in tokens_df['Sentiments'] for sentiment in sentiments_list]


sentiment_counts = pd.Series(sentiments).value_counts()

# Create a bar plot
plt.figure(figsize=(8, 6))
sns.barplot(x=sentiment_counts.index, y=sentiment_counts.values, palette="viridis")
plt.title("Sentiment Label Frequency")
plt.xlabel("Sentiment Label")
plt.ylabel("Frequency")
plt.show()
```



In [19]:
```
def calculate_document_vector(doc, model):
    words = [word for word in doc if word in model.wv.key_to_index]
    if words:
        word_vectors = [model.wv[word] for word in words]
        return np.mean(word_vectors, axis=0)
    else:
        return np.zeros(model.vector_size)
```

In [33]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(tokens_df['tokens_text'], tokens_df['Sentiments'], test_siz

mlb = MultiLabelBinarizer()
y_train_encoded = mlb.fit_transform(y_train)
y_test_encoded = mlb.transform(y_test)

# Calculate document vectors for training and testing data
X_train_vectors = [calculate_document_vector(doc, model_text) for doc in X_train]
X_test_vectors = [calculate_document_vector(doc, model_text) for doc in X_test]

# Create and train a MultiOutputClassifier with an SVM classifier
clf = MultiOutputClassifier(SVC())
clf.fit(X_train_vectors, y_train_encoded)


y_pred_encoded = clf.predict(X_test_vectors)

accuracies = [accuracy_score(y_test_encoded[:, i], y_pred_encoded[:, i]) for i in range(len(mlb.classes_))]
mean_accuracy = sum(accuracies) / len(accuracies)

print(f"Label-wise accuracies: {accuracies}")
print(f"Mean accuracy: {mean_accuracy}")
```

```
Label-wise accuracies: [0.8825280822844769, 0.9820002706726214, 0.9100013533631073]
Mean accuracy: 0.9248432354400684
```

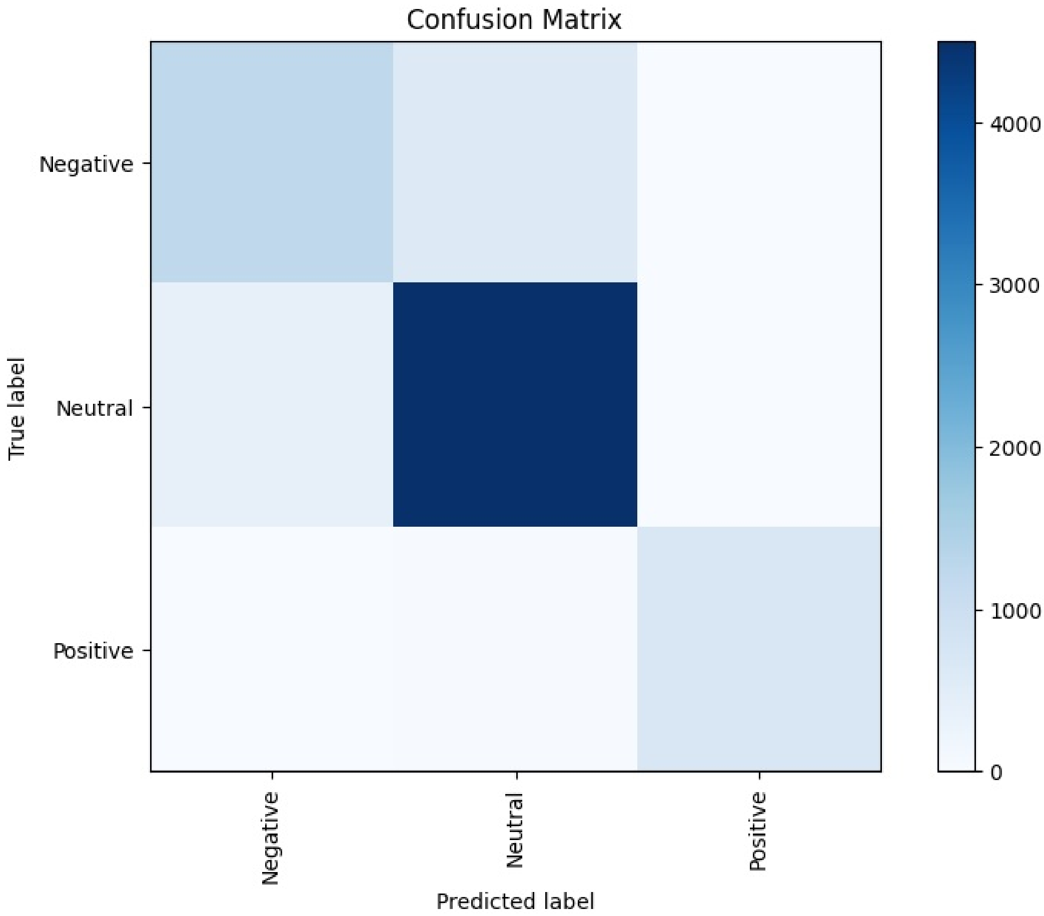
In [34]:
```
accuracy = accuracy_score(y_test_encoded, y_pred_encoded)
print(f"Accuracy Rate: {accuracy}")
```

```
Accuracy Rate: 0.7990255785627284
```

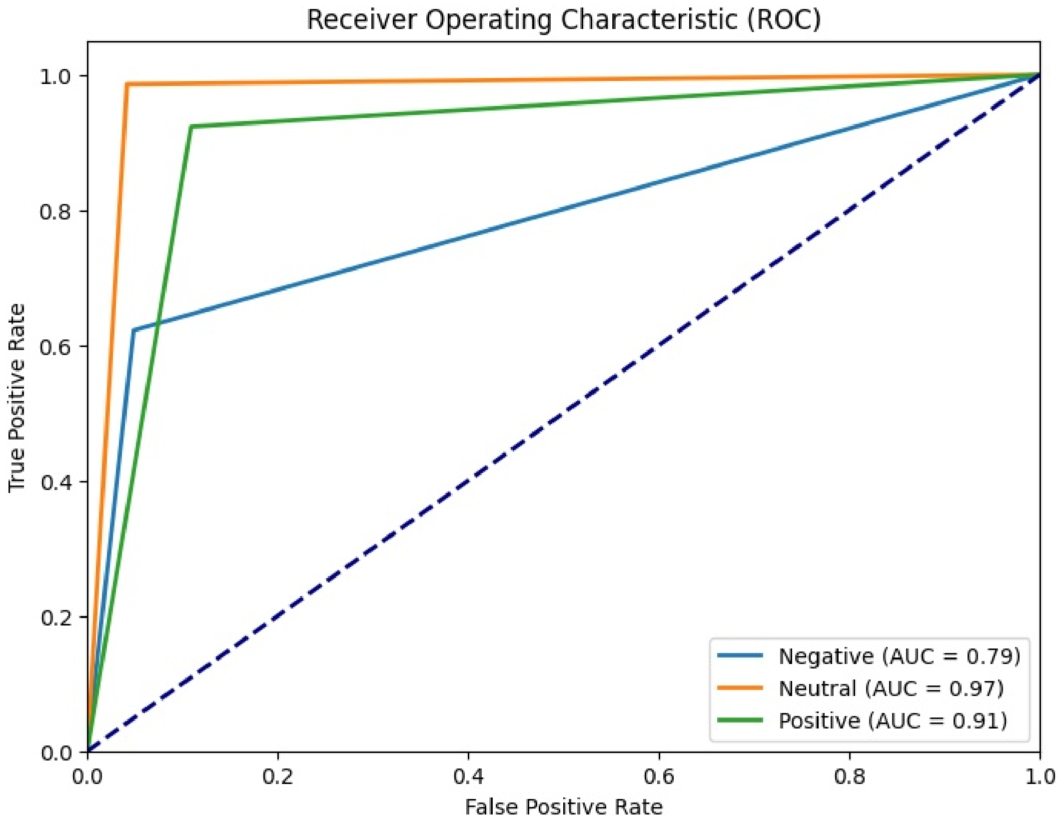
In [35]:
```
# Calculate precision, recall, and F1-score
precision = precision_score(y_test_encoded, y_pred_encoded, average='weighted')
recall = recall_score(y_test_encoded, y_pred_encoded, average='weighted')
print(f"Precision: {precision}")
print(f"Recall: {recall}")
```

```
Precision: 0.9406388841284368
Recall: 0.9177075679647319
```

In [37]:
```
cm = confusion_matrix(y_test_encoded.argmax(axis=1), y_pred_encoded.argmax(axis=1))
plt.figure(figsize=(8, 6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(mlb.classes_))
plt.xticks(tick_marks, mlb.classes_, rotation=90)
plt.yticks(tick_marks, mlb.classes_)
plt.tight_layout()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()
```



In [38]:
```
# Calculate and plot ROC curves and AUC for each class
fpr = dict()
tpr = dict()
roc_auc = dict()

for i in range(len(mlb.classes_)):
    fpr[i], tpr[i], _ = roc_curve(y_test_encoded[:, i], y_pred_encoded[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

plt.figure(figsize=(8, 6))
for i in range(len(mlb.classes_)):
    plt.plot(fpr[i], tpr[i], lw=2, label=f'{mlb.classes_[i]} (AUC = {roc_auc[i]:.2f})')

plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc='lower right')
plt.show()
```



Label-wise Accuracies: These values represent the accuracy of each sentiment label individually. For each sentiment class (e.g., positive, negative, neutral), the classification model achieves the following accuracies:

`Positive Sentiment:` 88.25%

`Negative Sentiment:` 98.20%

`Neutral Sentiment:` 91.00%

Mean Accuracy: The mean accuracy is the average of the label-wise accuracies, and it provides an overall view of how well the model performs across all sentiment classes. In this case, the mean accuracy is approximately 92.48%, indicating that the model is performing well on average.

Accuracy Rate: The accuracy rate measures the overall classification accuracy without considering specific labels. An accuracy rate of 79.90% suggests that the majority of the reviews are being correctly classified into their respective sentiment categories.

Precision: Precision measures the ratio of true positive predictions to the total positive predictions. A precision of 94.06% for this model suggests that when it predicts a sentiment label (e.g., positive), it is correct 94.06% of the time.

Recall: Recall, also known as sensitivity, measures the ratio of true positive predictions to the actual positive instances. A recall of 91.77% indicates that the model is effective at capturing most of the actual positive reviews.

In [39]:
```
text = " ".join([" ".join(tokens) for tokens in tokens_df['tokens_text']])

wordcloud = WordCloud(width=800, height=400, background_color='white').generate(text)

# Display the word cloud using matplotlib
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()
```


app
thread
twitter
good
instagram
better
account
people
post
feed
feature
follow
nice
will
need
love
great
option
see
want
one
use
dont
nice app
instagram account
make
delete
good
app
first
far
best
still
thank
user
new
really
using
work
add
please
application
copy
thing
think
content
amazing
lot
way
hope
meta
update
look
much
im
try
s
problem
easy
twitter

In [ ]: