Natural Language Processing using NLTK and Scikit

In [6]:

```
import pip
pip.main(["install", "openpyxl"])
```

```
WARNING: pip is being invoked by an old script wrapper. This will fail in a future version of pip.
Please see https://github.com/pypa/pip/issues/5599 for advice on fixing the underlying issue.
To avoid this problem you can invoke Python with '-m pip' instead of running pip directly.
Collecting openpyxl

  Downloading openpyxl-3.1.2-py2.py3-none-any.whl (249 kB)

 Output()

Collecting et-xmlfile (from openpyxl)

  Downloading et_xmlfile-1.1.0-py3-none-any.whl (4.7 kB)

Installing collected packages: et-xmlfile, openpyxl

Successfully installed et-xmlfile-1.1.0 openpyxl-3.1.2

[notice] A new release of pip is available: 23.1.2 -> 24.0
[notice] To update, run: C:\Users\nasru\AppData\Local\Programs\Python\Python3
```

Out[6]:

```
0
```

In [17]:

```
!pip install --upgrade pip
```

```
Requirement already satisfied: pip in c:\users\nasru\anaconda3\envs\nlp\lib\site-packages (23.3.1)
Collecting pip
  Using cached pip-24.0-py3-none-any.whl.metadata (3.6 kB)
Using cached pip-24.0-py3-none-any.whl (2.1 MB)
ERROR: To modify pip, please run the following command:
C:\Users\nasru\anaconda3\envs\NLP\python.exe -m pip install --upgrade pip
```

1. Importing Data and Converting XLSX to CSV

In [20]:

```
import pandas as pd

# Assuming you're running this in an environment where 'openpyxl' is installed
# Load the dataset from an Excel file
file_path = 'combined_text_labelled.xlsx'
data = pd.read_excel(file_path)

# Convert the loaded DataFrame to a CSV file in the current working directory
csv_file_path = 'combined_text_labelled.csv'  # Save in the current directory
```

```
data.to_csv(csv_file_path, index=False)

# Print the path to the newly created CSV file
print(csv_file_path)
```

```
combined_text_labelled.csv
```

2. Reading data

In [ ]:

```
import pandas as pd

# Load the dataset
file_path = 'combined_text_labelled.csv'
data = pd.read_csv(file_path)

# Display the first few rows of the dataset to understand its structure
data.head()
```

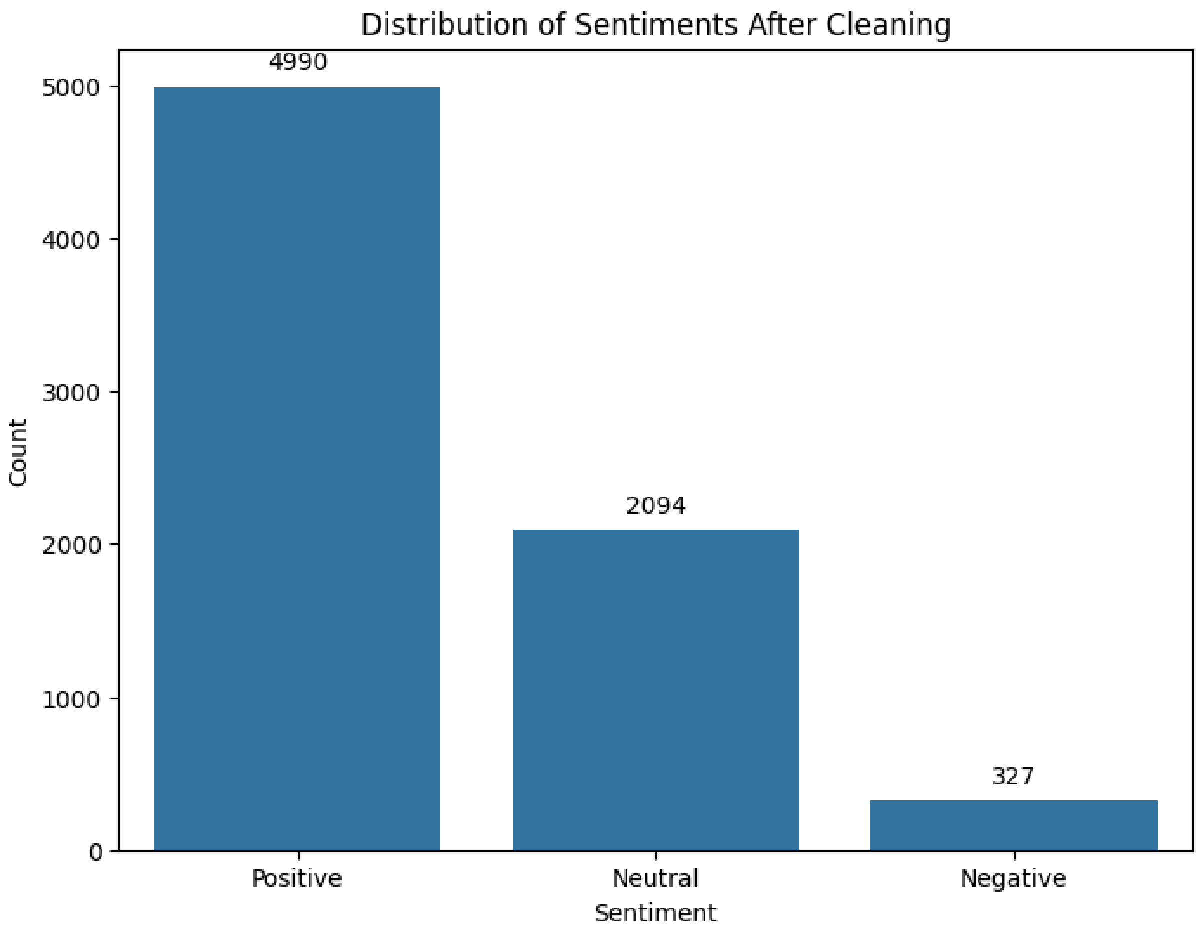
In [ ]:

```
# Distribution of the "Sentiment" column
sentiment_distribution = data['Sentiment'].value_counts(normalize=True) * 100

sentiment_distribution
```

3. Data Cleaning

In [12]:

```
# Data Cleaning
# Correcting the sentiment labels
data['Sentiment'] = data['Sentiment'].str.strip()

# Removing rows with empty values in 'Text' and 'Sentiment' columns
data_cleaned = data.dropna(subset=['Text', 'Sentiment'])

# Checking for any remaining empty strings in 'Text'
data_cleaned = data_cleaned[data_cleaned['Text'].str.strip() != '']

# Now, let's visualize the corrected distribution of sentiments using Seaborn
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(8, 6))
ax = sns.countplot(x='Sentiment', data=data_cleaned)
plt.title('Distribution of Sentiments After Cleaning')
plt.xlabel('Sentiment')
plt.ylabel('Count')

# Adding the count above each bar
for p in ax.patches:
    ax.annotate(f'{int(p.get_height())}', (p.get_x() + p.get_width() / 2., p.get_he

plt.show()
```



4. Data Preprocessing

1. Download NLTK stop words

In [30]:
```
pip.main(["install", "nltk"])
pip.main(["install", "wordcloud"])
pip.main(["install", "scikit-learn"])

import nltk
nltk.download('stopwords')
nltk.download('punkt')
```

```
WARNING: pip is being invoked by an old script wrapper. This will fail in a future v
ersion of pip.
Please see https://github.com/pypa/pip/issues/5599 for advice on fixing the underlyi
ng issue.
To avoid this problem you can invoke Python with '-m pip' instead of running pip dir
ectly.
```

```
Requirement already satisfied: nltk in c:\users\nasru\appdata\local\programs\
Requirement already satisfied: click in c:\users\nasru\appdata\local\programs
Requirement already satisfied: joblib in c:\users\nasru\appdata\local\program
Requirement already satisfied: regex>=2021.8.3 in c:\users\nasru\appdata\loca
Requirement already satisfied: tqdm in c:\users\nasru\appdata\local\programs\

Requirement already satisfied: colorama in c:\users\nasru\appdata\local\progr

[notice] A new release of pip is available: 23.1.2 -> 24.0
[notice] To update, run: C:\Users\nasru\AppData\Local\Programs\Python\Python3
```

```
WARNING: pip is being invoked by an old script wrapper. This will fail in a future v
ersion of pip.
Please see https://github.com/pypa/pip/issues/5599 for advice on fixing the underlyi
ng issue.
To avoid this problem you can invoke Python with '-m pip' instead of running pip dir
ectly.
```

```
Requirement already satisfied: wordcloud in c:\users\nasru\appdata\local\prog

Requirement already satisfied: numpy>=1.6.1 in c:\users\nasru\appdata\local\p

Requirement already satisfied: pillow in c:\users\nasru\appdata\roaming\pytho

Requirement already satisfied: matplotlib in c:\users\nasru\appdata\local\pro

Requirement already satisfied: contourpy>=1.0.1 in c:\users\nasru\appdata\loc

Requirement already satisfied: cycler>=0.10 in c:\users\nasru\appdata\local\p

Requirement already satisfied: fonttools>=4.22.0 in c:\users\nasru\appdata\lo

Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\nasru\appdata\lo

Requirement already satisfied: packaging>=20.0 in c:\users\nasru\appdata\roam

Requirement already satisfied: pyparsing>=2.2.1 in c:\users\nasru\appdata\roa

Requirement already satisfied: python-dateutil>=2.7 in c:\users\nasru\appdata

Requirement already satisfied: six>=1.5 in c:\users\nasru\appdata\roaming\pyt

[notice] A new release of pip is available: 23.1.2 -> 24.0
[notice] To update, run: C:\Users\nasru\AppData\Local\Programs\Python\Python3
```

```
WARNING: pip is being invoked by an old script wrapper. This will fail in a future v
ersion of pip.
Please see https://github.com/pypa/pip/issues/5599 for advice on fixing the underlyi
ng issue.
To avoid this problem you can invoke Python with '-m pip' instead of running pip dir
ectly.
```

```
Requirement already satisfied: scikit-learn in c:\users\nasru\appdata\local\p

Requirement already satisfied: numpy>=1.17.3 in c:\users\nasru\appdata\local\

Requirement already satisfied: scipy>=1.3.2 in c:\users\nasru\appdata\roaming

Requirement already satisfied: joblib>=1.1.1 in c:\users\nasru\appdata\local\

Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\nasru\appdata

[notice] A new release of pip is available: 23.1.2 -> 24.0
[notice] To update, run: C:\Users\nasru\AppData\Local\Programs\Python\Python3
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\nasru\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\nasru\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

```
Out[30]:  True
```

2. Import ncessary libraries

In [13]:

```
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from wordcloud import WordCloud
import matplotlib.pyplot as plt
```

3. Prepare text for word cloud

In [14]:

```
positive_text = " ".join(data_cleaned.loc[data_cleaned['Sentiment'] == 'Positive',
neutral_text = " ".join(data_cleaned.loc[data_cleaned['Sentiment'] == 'Neutral', 'T
negative_text = " ".join(data_cleaned.loc[data_cleaned['Sentiment'] == 'Negative',
```

4. Function to Tokenize and Remove Stopwords

In [15]:

```
def clean_text(text):
    stop_words = set(stopwords.words('english'))
    word_tokens = word_tokenize(text)
    filtered_text = " ".join([word for word in word_tokens if word.lower() not in s
    return filtered_text
```

5. Apply Cleaning Function to Each Sentiment Category

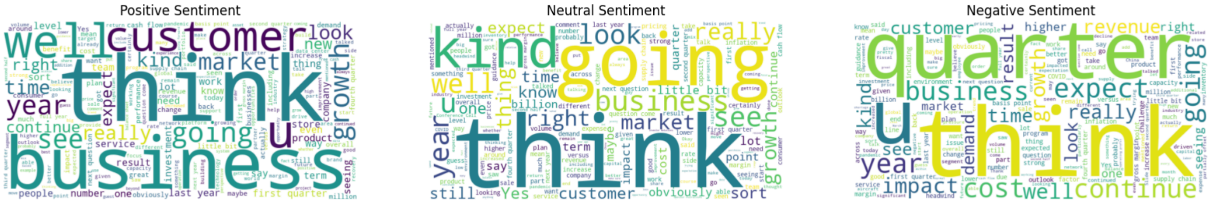
In [16]:

```
positive_cleaned = clean_text(positive_text)
neutral_cleaned = clean_text(neutral_text)
negative_cleaned = clean_text(negative_text)
```

6. Generate and Display Word Clouds

In [17]:

```
# Generating word clouds
wordcloud_pos = WordCloud(width = 800, height = 400, background_color ='white').gen
wordcloud_neu = WordCloud(width = 800, height = 400, background_color ='white').gen
wordcloud_neg = WordCloud(width = 800, height = 400, background_color ='white').gen

# Displaying the word clouds for each sentiment
plt.figure(figsize=(20, 10))

plt.subplot(1, 3, 1)
plt.imshow(wordcloud_pos, interpolation='bilinear')
plt.title('Positive Sentiment')
plt.axis('off')

plt.subplot(1, 3, 2)
plt.imshow(wordcloud_neu, interpolation='bilinear')
plt.title('Neutral Sentiment')
plt.axis('off')
plt.subplot(1, 3, 3)
plt.imshow(wordcloud_neg, interpolation='bilinear')
plt.title('Negative Sentiment')
plt.axis('off')

plt.show()
```


Positive Sentiment
Neutral Sentiment
Negative Sentiment

5. Display First Row Text Before and After Tokenization:

In [18]:

```
from sklearn.feature_extraction.text import TfidfVectorizer

# Clean the first row's text
cleaned_text = clean_text(data_cleaned['Text'].iloc[0])

# Initialize TF-IDF Vectorizer
tfidf_vectorizer = TfidfVectorizer()

# Fit and transform the cleaned text using TF-IDF
# Note: We need to pass a list even if it's just one document
tfidf_result = tfidf_vectorizer.fit_transform([cleaned_text])

# Display the original and cleaned text
print("Original Text:\n", data_cleaned['Text'].iloc[0])
print("\nCleaned Text:\n", cleaned_text)

# Display the TF-IDF vectorized form
# Convert the sparse matrix to a dense array and display the TF-IDF values
print("\nTF-IDF Vectorized Form (first few values):")
print(tfidf_result.toarray()[0][:10])  # Displaying only the first 10 values for br

# Also, to give more context, let's display some of the feature names (words) corre
print("\nCorresponding Feature Names (words) for the first few TF-IDF values:")
print(tfidf_vectorizer.get_feature_names_out()[:10])  # Displaying only the first 1
```

```
Original Text:
 Good morning, and thank you for standing by Welcome to Abbott's First Quarter 2022
Earnings Conference Call [Operator Instructions] This call is being recorded by Abbo
tt With the exception of any participant's questions asked during the question-and-a
nswer session, the entire call, including the question-and-answer session, is materi
al copyrighted by Abbott It cannot be recorded or rebroadcast without Abbot's expres
sed written permission
I would now like to introduce Mr Scott Leinenweber, Vice President, Investor Relatio
ns, Licensing and Acquisitions Good morning, and thank you for joining us With me to
day are Robert Ford, Chairman and Chief Executive Officer; and Bob Funck, Executive 
Vice President, Finance and Chief Financial Officer Robert and Bob will provide open
ing remarks Following their comments, we will take your questions
Before we get started, some statements made today may be forward-looking for purpose
s of the Private Securities Litigation Reform Act of 1995, including the expected fi
nancial results for 2022 Abbott cautions that these forward-looking statements are s
ubject to risks and uncertainties that may cause actual results to differ materially
from those indicated in the forward-looking statements Economic, competitive, govern
mental, technological and other factors that may affect Abbott's operations are disc
ussed in Item 1A Risk Factors to our annual report on Form 10-K for the year ended D
ecember 31, 2021 Abbott undertakes no obligation to release publicly any revisions t
o forward-looking statements as a result of subsequent events or developments, excep
t as required by law
On today's conference call, as in the past, non-GAAP financial measures will be used
to help investors understand Abbott's ongoing business performance These non-GAAP fi
nancial measures are reconciled with the comparable GAAP financial measures in our e
arnings news release and regulatory filings from today, which are available on our w
ebsite at abbott

Cleaned Text:
 Good morning thank standing Welcome Abbott First Quarter Earnings Conference Call O
perator Instructions call recorded Abbott exception participant questions asked sess
ion entire call including session material copyrighted Abbott recorded rebroadcast w
ithout Abbot expressed written permission would like introduce Mr Scott Leinenweber 
Vice President Investor Relations Licensing Acquisitions Good morning thank joining 
us today Robert Ford Chairman Chief Executive Officer Bob Funck Executive Vice Presi
dent Finance Chief Financial Officer Robert Bob provide opening remarks Following co
mments take questions get started statements made today may purposes Private Securit
ies Litigation Reform Act including expected financial results Abbott cautions state
ments subject risks uncertainties may cause actual results differ materially indicat
ed statements Economic competitive governmental technological factors may affect Abb
ott operations discussed Item Risk Factors annual report Form year ended December Ab
bott undertakes obligation release publicly revisions statements result subsequent e
vents developments except required law today conference call past financial measures
used help investors understand Abbott ongoing business performance financial measure
s reconciled comparable GAAP financial measures earnings news release regulatory fil
ings today available website abbott

TF-IDF Vectorized Form (first few values):
[0.05488213 0.43905704 0.05488213 0.05488213 0.05488213 0.05488213
 0.05488213 0.05488213 0.05488213 0.10976426]

Corresponding Feature Names (words) for the first few TF-IDF values:
['abbot' 'abbott' 'acquisitions' 'act' 'actual' 'affect' 'annual' 'asked'
 'available' 'bob']
```

6. Model Building (Ensemble Learning)

1. Feature Extraction

In [21]:

```
from sklearn.feature_extraction.text import TfidfVectorizer

# Clean the dataset's text and prepare for TF-IDF
X_cleaned = data_cleaned['Text'].apply(clean_text)
y = data_cleaned['Sentiment']

tfidf_vectorizer = TfidfVectorizer(max_features=5000)
X_tfidf = tfidf_vectorizer.fit_transform(X_cleaned)
```

Step 2 & 3: Model Training and Evaluation (5mins-10mins)

In [22]:

```
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
import numpy as np

# Initialize the models
models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Random Forest": RandomForestClassifier(n_estimators=100),
    "Gradient Boosting": GradientBoostingClassifier(n_estimators=100)
}

# Dictionary to hold model names and their scores
model_scores = {}

# Evaluate each model using cross-validation and store the scores
for model_name, model in models.items():
    scores = cross_val_score(model, X_tfidf, y, cv=5, scoring='accuracy')
    model_scores[model_name] = scores

# Convert the scores to a DataFrame for easy comparison
import pandas as pd
```

In [23]:

```
df_scores = pd.DataFrame(model_scores).melt(var_name='Model', value_name='Accuracy'
comparison_df = df_scores.groupby('Model')['Accuracy'].agg(['mean', 'std']).reset_i
```

Step 4. Model Comparison

In [28]:

```
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
```

```
import numpy as np
import pandas as pd

# Initialize the models
models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Random Forest": RandomForestClassifier(n_estimators=100, class_weight='balance
    "Gradient Boosting": GradientBoostingClassifier(n_estimators=100)
}

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X_tfidf, y, test_size=0.2, rand

# Initialize a list to store results
results = []

# Train and evaluate each model
for model_name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    report = classification_report(y_test, y_pred, output_dict=True, zero_division=

    results.append({
        'Model': model_name,
        'Accuracy': accuracy,
        'Precision': report['macro avg']['precision'],
        'Recall': report['macro avg']['recall'],
        'F1-Score': report['macro avg']['f1-score']
    })

results_df = pd.DataFrame(results)

model_scores = {}
for model_name, model in models.items():
    scores = cross_val_score(model, X_tfidf, y, cv=5, scoring='accuracy')
    model_scores[model_name] = scores

df_scores = pd.DataFrame(model_scores).melt(var_name='Model', value_name='Accuracy'
comparison_df = df_scores.groupby('Model')['Accuracy'].agg(['mean', 'std']).reset_i

for result in results:
    row_index = comparison_df.index[comparison_df['Model'] == result['Model']].toli
    comparison_df.at[row_index, 'Single Split Accuracy'] = result['Accuracy']
    comparison_df.at[row_index, 'Precision'] = result['Precision']
    comparison_df.at[row_index, 'Recall'] = result['Recall']
    comparison_df.at[row_index, 'F1-Score'] = result['F1-Score']
```

In [29]:

```
comparison_df_sorted = comparison_df.sort_values(by='Single Split Accuracy', ascend
comparison_df_sorted
```

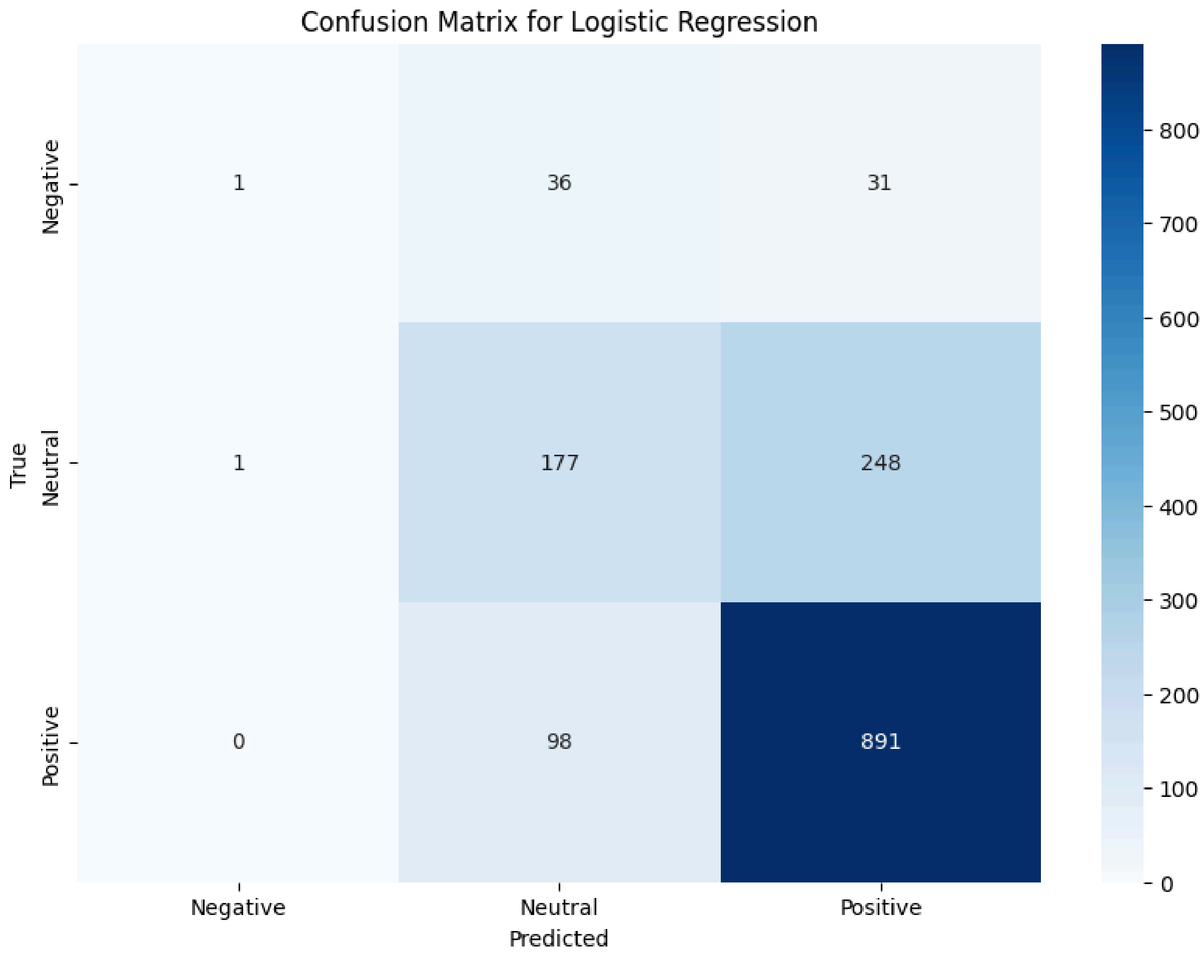
Out[29]:

	Model	mean	std	Single Split Accuracy	Precision	Recall	F1-Score
0	Logistic Regression	0.712588	0.013057	0.720836	0.610223	0.443703	0.444760
1	Gradient Boosting	0.691675	0.008638	0.697910	0.524253	0.410083	0.411446
2	Random Forest	0.695586	0.010364	0.684423	0.428244	0.370604	0.348203

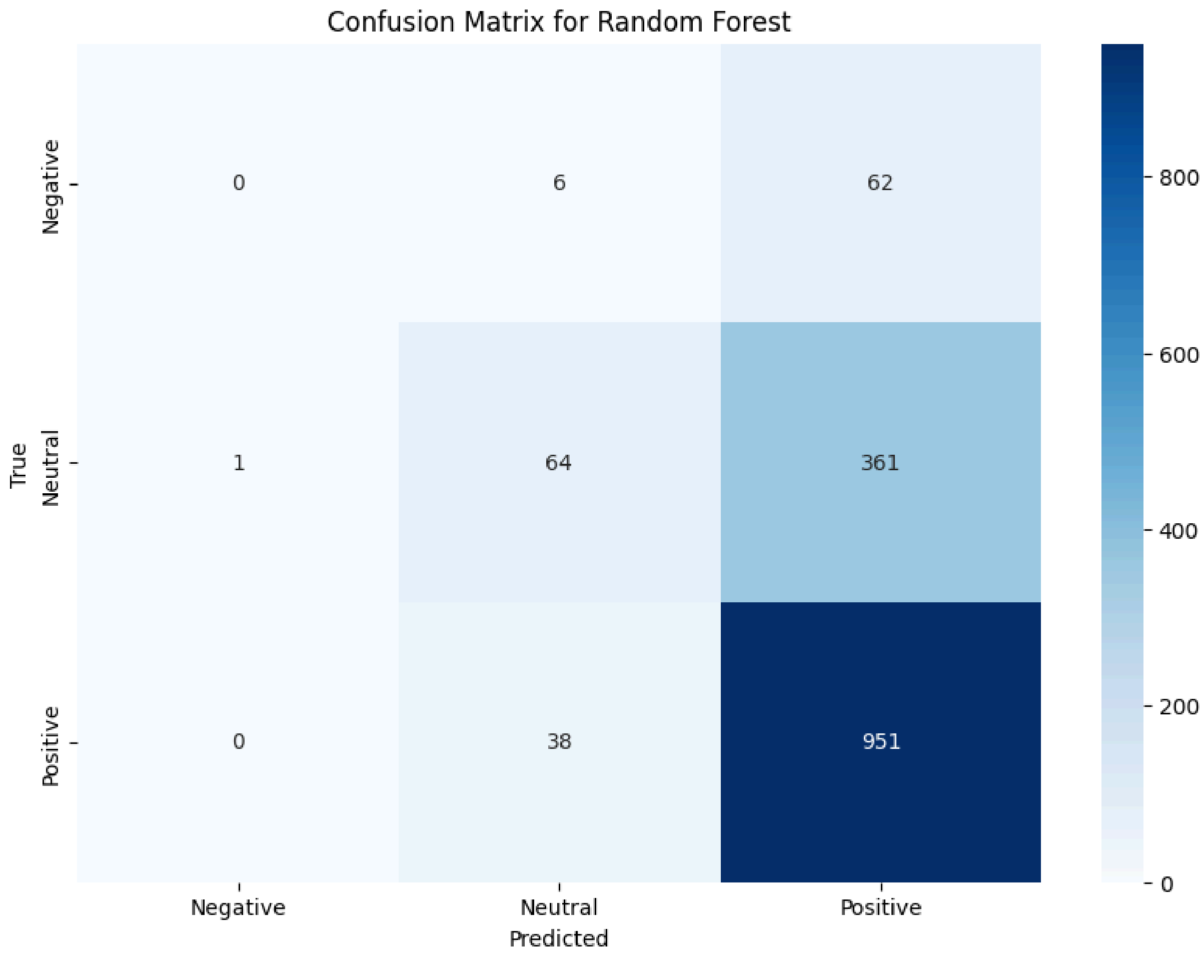
Classification Report

In [30]:

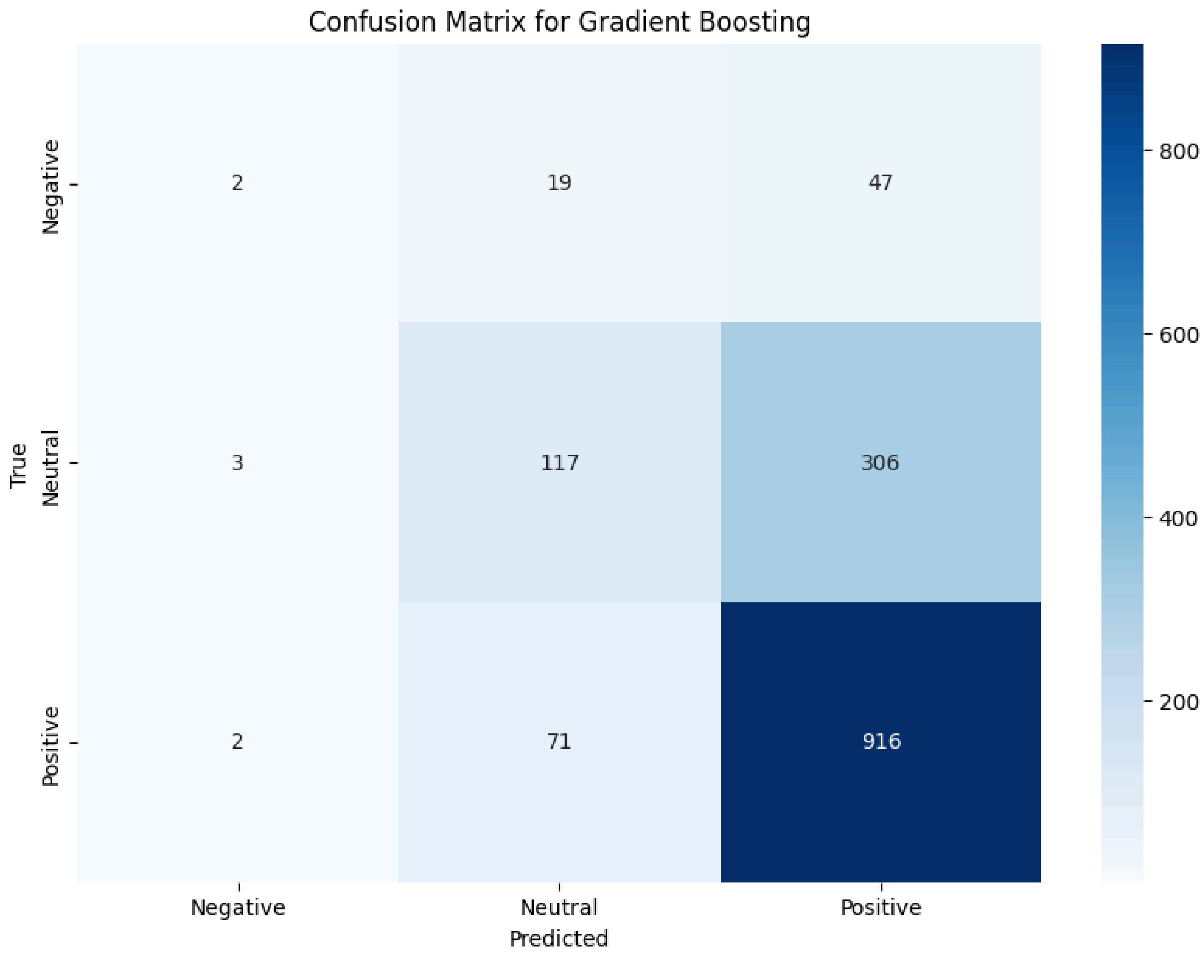
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

for model_name, model in models.items():
    # Assuming model has been fitted as per your previous code and predictions have
    y_pred = model.predict(X_test)

    # Confusion Matrix
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(10, 7))
    sns.heatmap(cm, annot=True, fmt="d", cmap='Blues', xticklabels=np.unique(y), yt
    plt.title(f'Confusion Matrix for {model_name}')
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.show()

    # Classification Report
    report = classification_report(y_test, y_pred, zero_division=0)
    print(f'Classification Report for {model_name}:\n{report}\n')
```



```
Classification Report for Logistic Regression:
              precision    recall  f1-score   support

    Negative       0.50      0.01      0.03        68
     Neutral       0.57      0.42      0.48       426
    Positive       0.76      0.90      0.83       989

    accuracy                           0.72      1483
   macro avg       0.61      0.44      0.44      1483
weighted avg       0.69      0.72      0.69      1483
```



```
Classification Report for Random Forest:
              precision    recall  f1-score   support

    Negative       0.00      0.00      0.00        68
     Neutral       0.59      0.15      0.24       426
    Positive       0.69      0.96      0.80       989

    accuracy                           0.68      1483
   macro avg       0.43      0.37      0.35      1483
weighted avg       0.63      0.68      0.61      1483
```

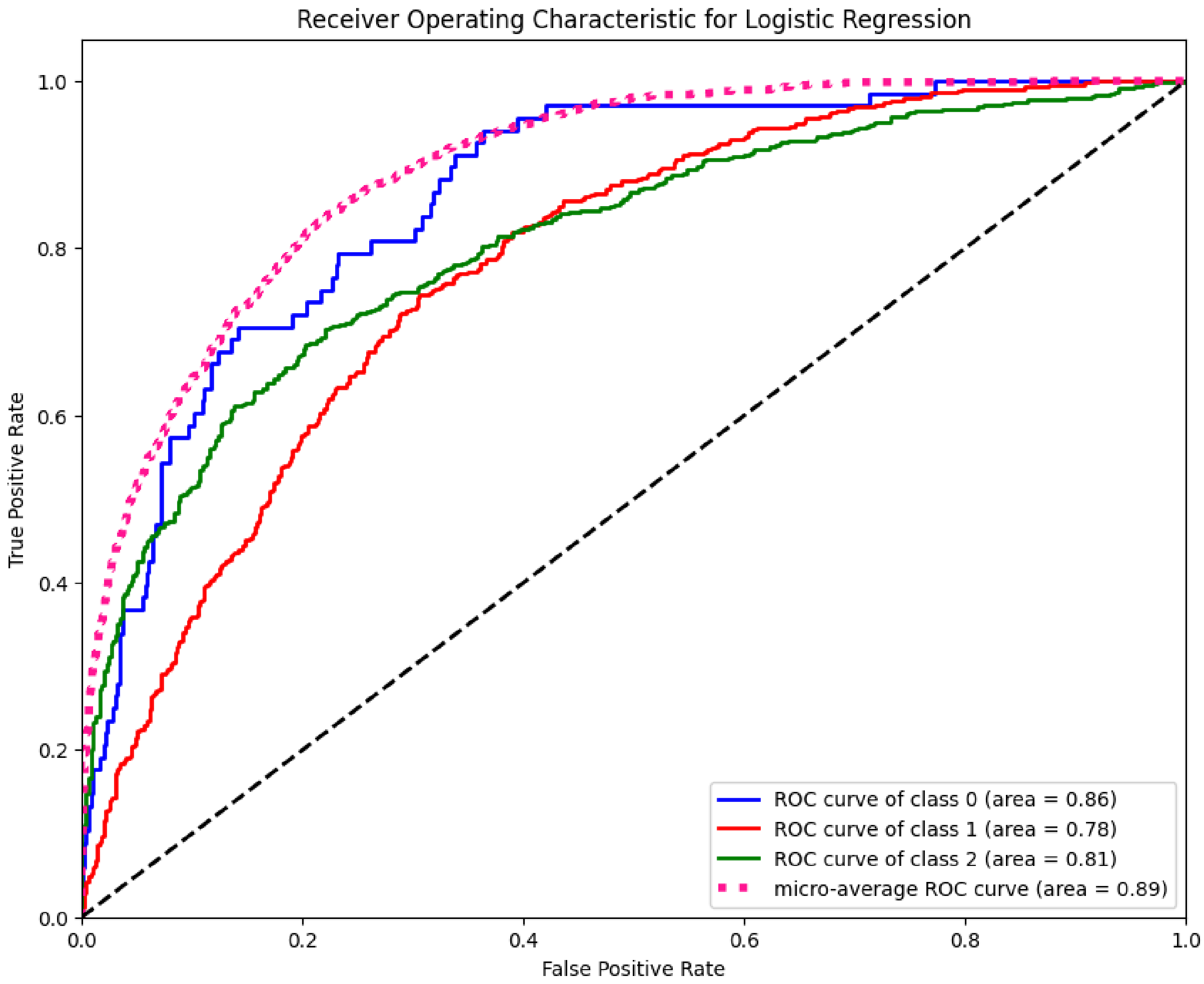


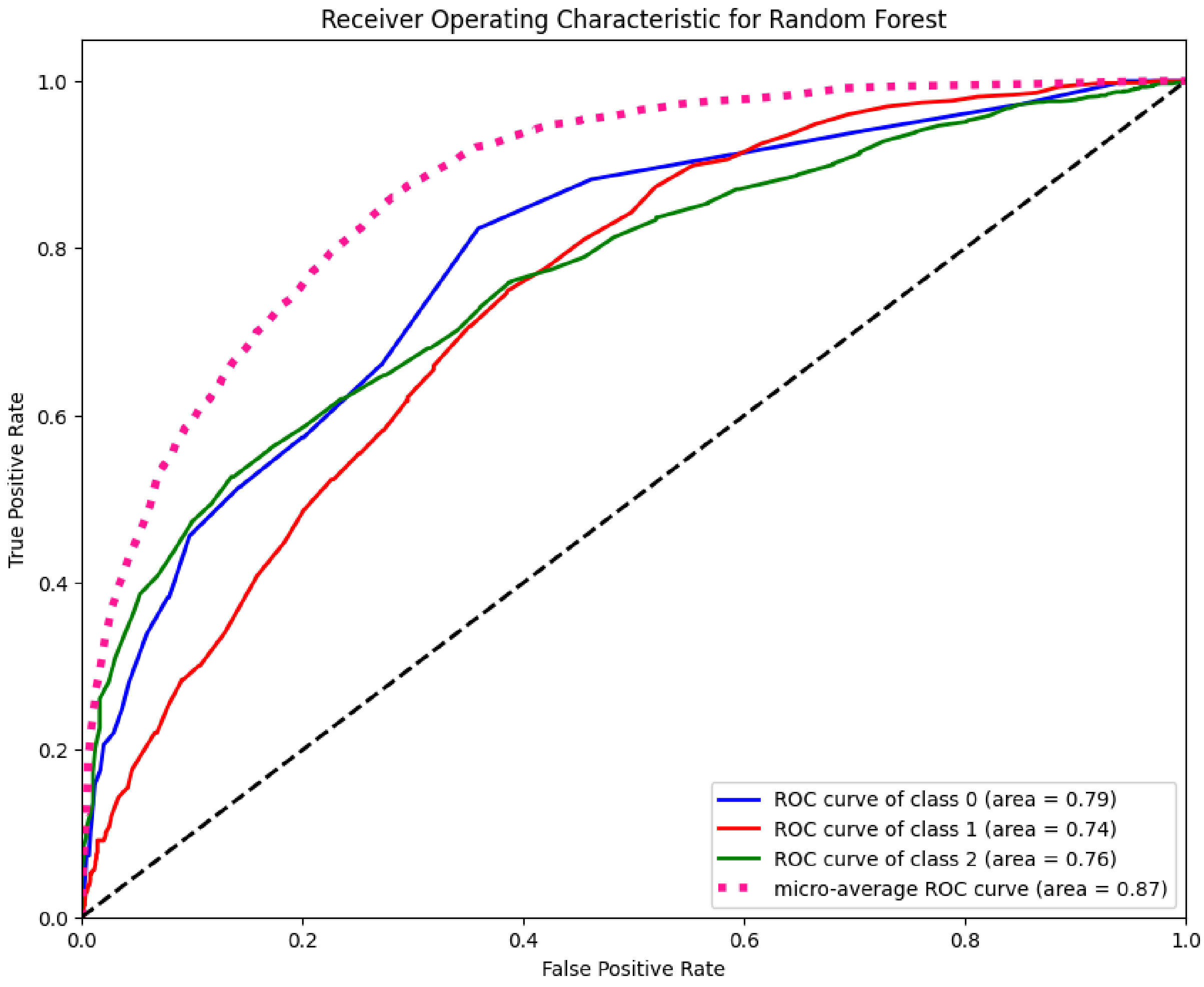
```
Classification Report for Gradient Boosting:
              precision    recall  f1-score   support

    Negative       0.29      0.03      0.05        68
     Neutral       0.57      0.27      0.37       426
    Positive       0.72      0.93      0.81       989

    accuracy                           0.70      1483
   macro avg       0.52      0.41      0.41      1483
weighted avg       0.66      0.70      0.65      1483
```

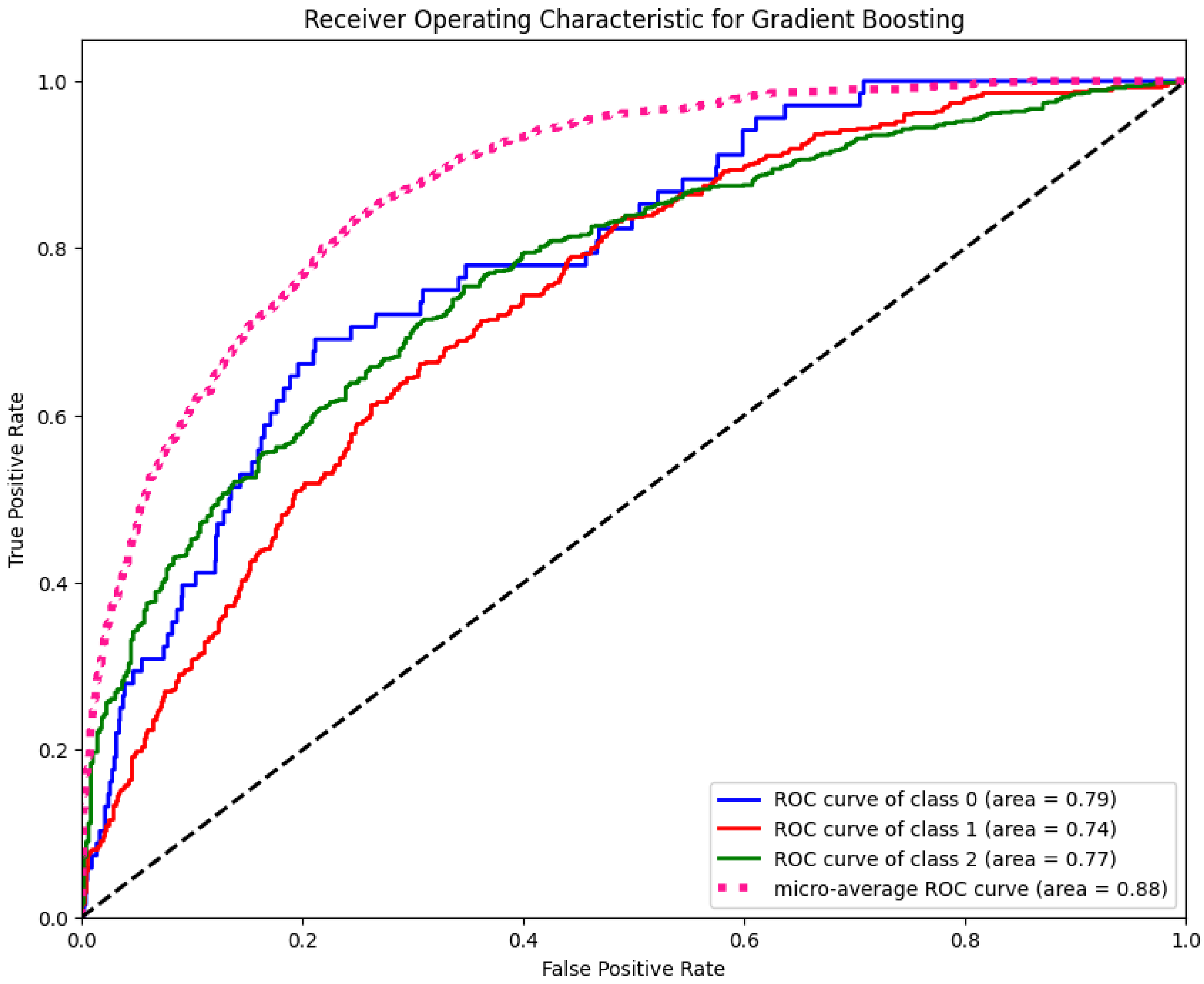
ROC and AUC Curve

In [31]:

```python
from sklearn.preprocessing import label_binarize
from sklearn.metrics import roc_auc_score, roc_curve, auc
from itertools import cycle

# Binarize the labels for multiclass
y_binarized = label_binarize(y, classes=np.unique(y))
n_classes = y_binarized.shape[1]

# Splitting the data with the binarized labels
X_train, X_test, y_train_bin, y_test_bin = train_test_split(X_tfidf, y_binarized, t
for model_name, model in models.items():
    # Fit model
    model.fit(X_train, y_train)

    # Predict probabilities
    y_proba = model.predict_proba(X_test)

    # Compute ROC curve and ROC area for each class
    fpr = dict()
    tpr = dict()
    roc_auc = dict()
    for i in range(n_classes):
        fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_proba[:, i])
        roc_auc[i] = auc(fpr[i], tpr[i])

    # Compute micro-average ROC curve and ROC area
    fpr["micro"], tpr["micro"], _ = roc_curve(y_test_bin.ravel(), y_proba.ravel())
    roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

    # Plot ROC curve for each class and the micro-average
    plt.figure(figsize=(10, 8))
    colors = cycle(['blue', 'red', 'green'])
    for i, color in zip(range(n_classes), colors):
        plt.plot(fpr[i], tpr[i], color=color, lw=2,
                 label=f'ROC curve of class {i} (area = {roc_auc[i]:.2f})')

    plt.plot(fpr["micro"], tpr["micro"], color='deeppink', linestyle=':', linewidth
             label=f'micro-average ROC curve (area = {roc_auc["micro"]:.2f})')

    plt.plot([0, 1], [0, 1], 'k--', lw=2)
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'Receiver Operating Characteristic for {model_name}')
    plt.legend(loc="lower right")
    plt.show()
```


Receiver Operating Characteristic for Logistic Regression
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve of class 0 (area = 0.86)
ROC curve of class 1 (area = 0.78)
ROC curve of class 2 (area = 0.81)
micro-average ROC curve (area = 0.89)


Receiver Operating Characteristic for Random Forest
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve of class 0 (area = 0.79)
ROC curve of class 1 (area = 0.74)
ROC curve of class 2 (area = 0.76)
micro-average ROC curve (area = 0.87)



7. Model Prediction

Step 1: Determine the Best-Performing Model

In [32]:

```
best_model_name = comparison_df_sorted.iloc[0]['Model']
```

Step 2: Save the Best-Performing Model

In [33]:

```
import pickle

# Example: Assuming the best model is the Gradient Boosting Classifier
best_model = models[best_model_name]

# Retrain on the entire dataset if necessary
best_model.fit(X_tfidf, y)

# Save the model to a pickle file
model_filename = 'best_model.pkl'
pickle.dump(best_model, open(model_filename, 'wb'))
```

```python
# Save the TF-IDF vectorizer as well
vectorizer_filename = 'tfidf_vectorizer.pkl'
pickle.dump(tfidf_vectorizer, open(vectorizer_filename, 'wb'))
```

Step 3: Create a Function for Predictions

In [34]:

```python
def predict_text(text):
    # Load the saved model and vectorizer
    loaded_model = pickle.load(open('best_model.pkl', 'rb'))
    loaded_vectorizer = pickle.load(open('tfidf_vectorizer.pkl', 'rb'))

    # Clean and vectorize the text
    cleaned_text = clean_text(text)
    vectorized_text = loaded_vectorizer.transform([cleaned_text])

    # Make a prediction
    prediction = loaded_model.predict(vectorized_text)

    return prediction
```

Step 4: Predict New Inputs

In [35]:

```python
import pickle

user_input = input("Enter your text for sentiment analysis: ")
prediction = predict_text(user_input)
print(f"The predicted sentiment is: {prediction[0]}")
```

```
The predicted sentiment is: Positive
```

Predict Text Function

In [2]:

```python
import pickle
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
import nltk

# Ensure NLTK resources are available
nltk.download('punkt', quiet=True)
nltk.download('stopwords', quiet=True)

def clean_text(text):
    """Clean and preprocess text."""
    stop_words = set(stopwords.words('english'))
    word_tokens = word_tokenize(text)
    filtered_text = " ".join([word for word in word_tokens if word.lower() not in s
    return filtered_text

def predict_text(text, model_filename='best_model.pkl', vectorizer_filename='tfidf_
    """Predict sentiment of the given text using the saved model and vectorizer."""
    # Load the saved model and vectorizer
    loaded_model = pickle.load(open(model_filename, 'rb'))
    loaded_vectorizer = pickle.load(open(vectorizer_filename, 'rb'))

    # Clean and vectorize the text
    cleaned_text = clean_text(text)
    vectorized_text = loaded_vectorizer.transform([cleaned_text])

    # Make a prediction
    prediction = loaded_model.predict(vectorized_text)

    return prediction[0]

# Example of using the predict_text function with user input
user_input = input("Enter your text for sentiment analysis: ")
predicted_sentiment = predict_text(user_input)
print(f"The predicted sentiment is: {predicted_sentiment}")
```

```
The predicted sentiment is: Positive
```

In [ ]: