Twitter Sentiment Analysis

Import necessary libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
import nltk
from sklearn.preprocessing import LabelEncoder
from keras.models import Sequential
from keras.layers import Dense, Dropout
from keras.utils import to_categorical
```

Load the dataset

```
training_data = pd.read_csv('twitter_training.csv')
validation_data = pd.read_csv('twitter_validation.csv')

training_data.shape

(74681, 4)

validation_data.shape

(999, 4)

training_data.dtypes

2401                                                          int64
Borderlands                                                  object
Positive                                                     object
im getting on borderlands and i will murder you all ,        object
dtype: object

training_data.describe()
```

```
                2401
count  74681.000000
mean    6432.640149
std     3740.423819
min        1.000000
25%     3195.000000
50%     6422.000000
75%     9601.000000
max    13200.000000
```

```
training_data.head()
```

```
   2401  Borderlands  Positive  \
0  2401  Borderlands  Positive
1  2401  Borderlands  Positive
2  2401  Borderlands  Positive
3  2401  Borderlands  Positive
4  2401  Borderlands  Positive

  im getting on borderlands and i will murder you all ,
0  I am coming to the borders and I will kill you...
1  im getting on borderlands and i will kill you ...
2  im coming on borderlands and i will murder you...
3  im getting on borderlands 2 and i will murder ...
4  im getting into borderlands and i can murder y...
```

```
validation_data.head()
```

```
   3364   Facebook Irrelevant  \
0   352     Amazon    Neutral
1  8312  Microsoft   Negative
2  4371      CS-GO   Negative
3  4433     Google    Neutral
4  6273       FIFA   Negative

  I mentioned on Facebook that I was struggling for motivation to go
for a run the other day, which has been translated by Tom’s great
auntie as ‘Hayley can’t get out of bed’ and told to his grandma, who
now thinks I’m a lazy, terrible person 🤣
0  BBC News - Amazon boss Jeff Bezos rejects clai...

1  @Microsoft Why do I pay for WORD when it funct...

2  CSGO matchmaking is so full of closet hacking,...

3  Now the President is slapping Americans in the...

4  Hi @EAHelp I’ve had Madeleine McCann in my cel...
```

Data Preprocessing

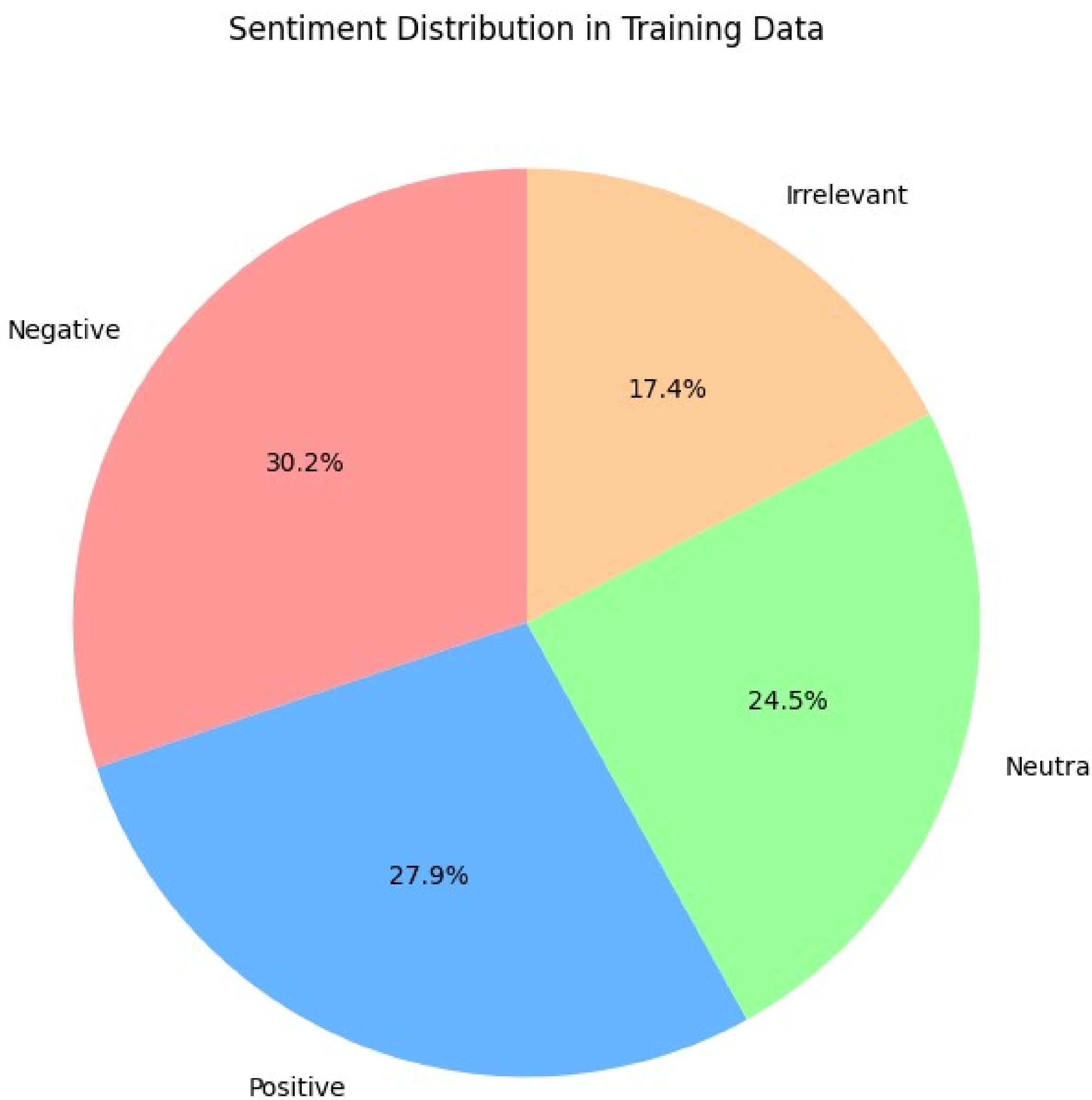
```
training_data.columns = ['ID', 'Entity', 'Sentiment', 'Message']
validation_data.columns = ['ID', 'Entity', 'Sentiment', 'Message']

training_data['Message'] =
training_data['Message'].astype(str).fillna('')
validation_data['Message'] =
validation_data['Message'].astype(str).fillna('')
```

Exploratory Data Analysis

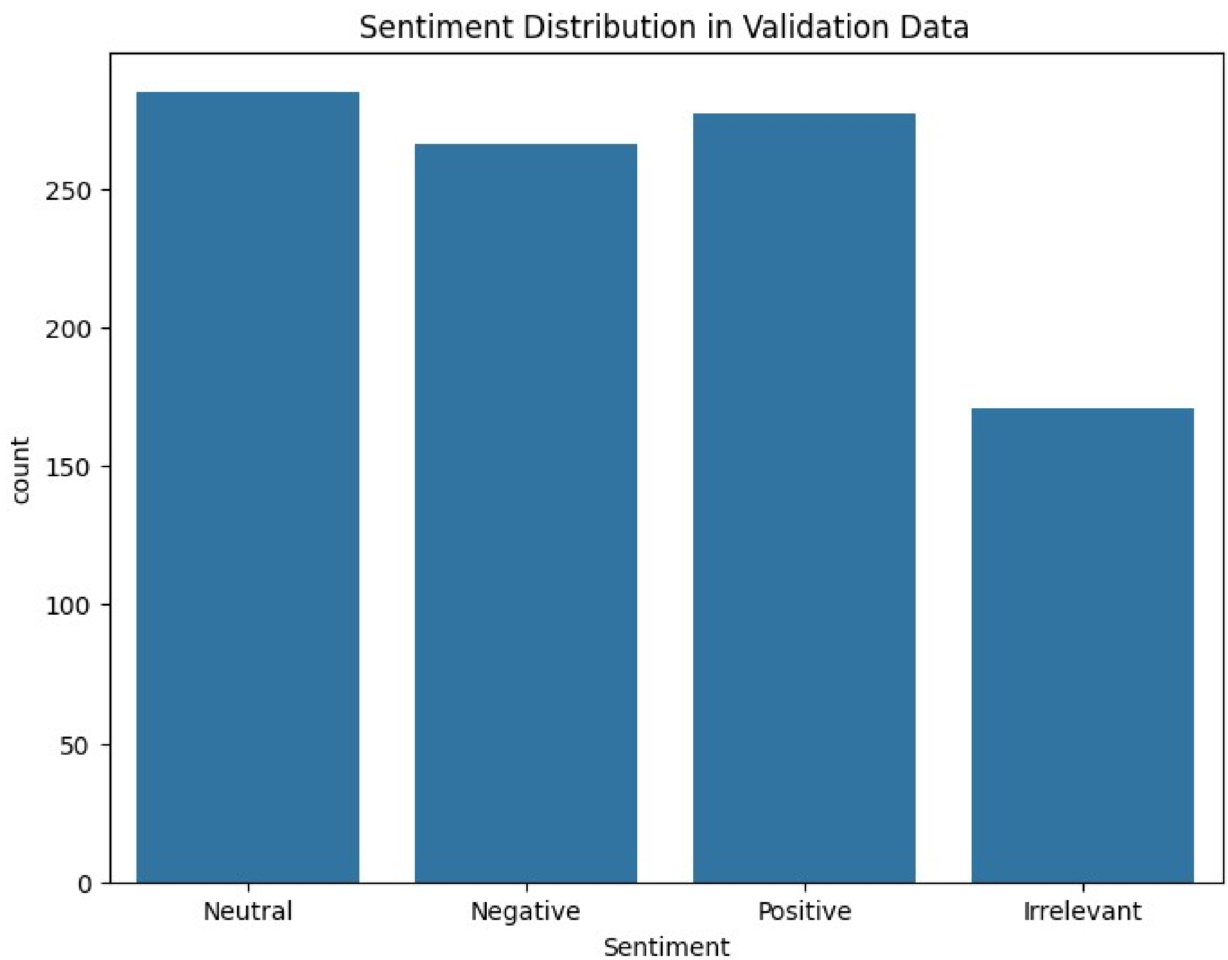
```
# EDA: Sentiment Distribution
plt.figure(figsize=(8, 6))
sns.countplot(x='Sentiment', data=training_data)
plt.title('Sentiment Distribution in Training Data')
plt.show()
```


```
sentiment_counts = training_data['Sentiment'].value_counts()

plt.figure(figsize=(8, 8))
```

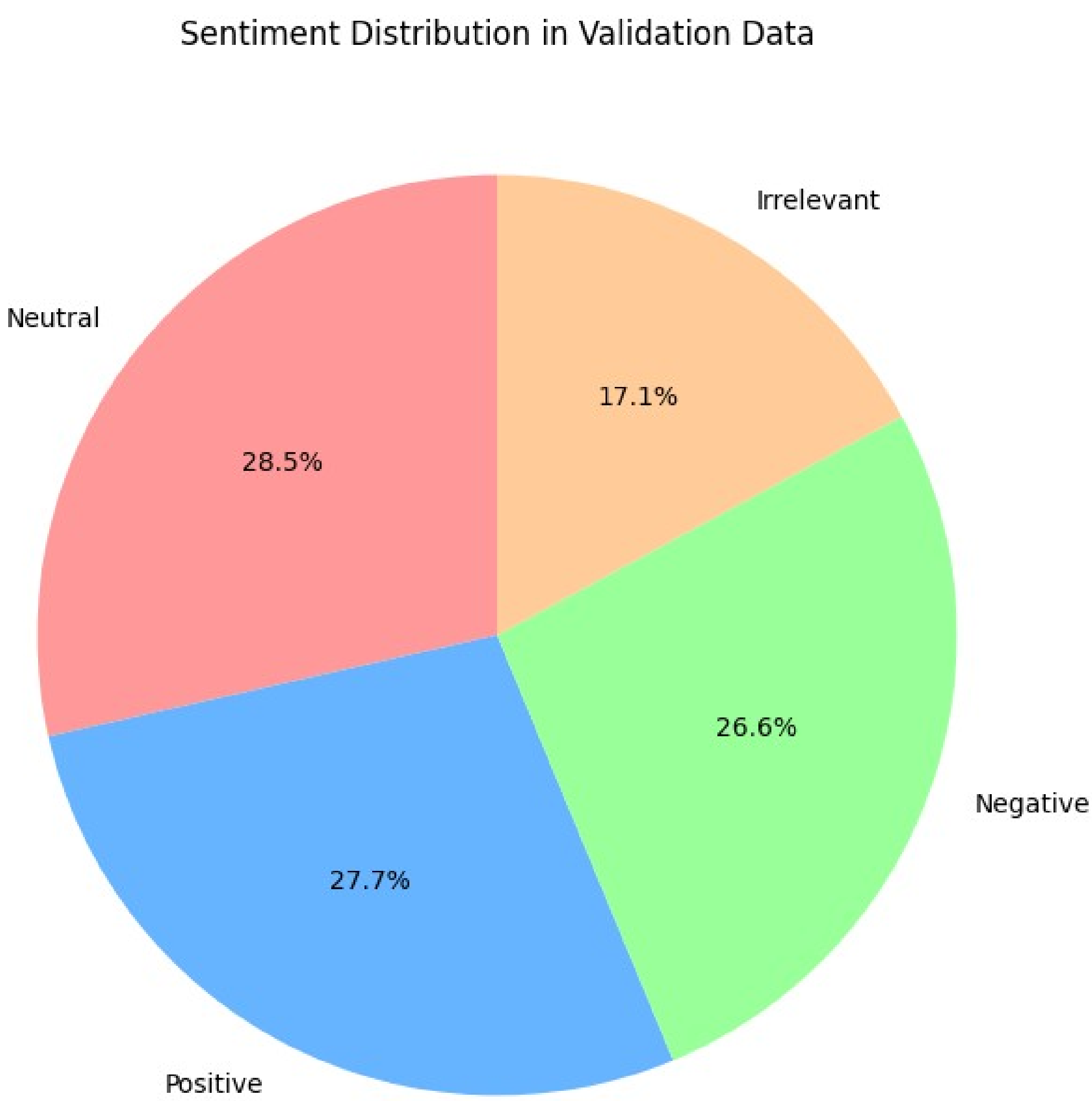
```
plt.pie(sentiment_counts, labels=sentiment_counts.index,
autopct='%1.1f%%', startangle=90,
colors=['#ff9999','#66b3ff','#99ff99','#ffcc99'])
plt.title('Sentiment Distribution in Training Data')
plt.show()
```



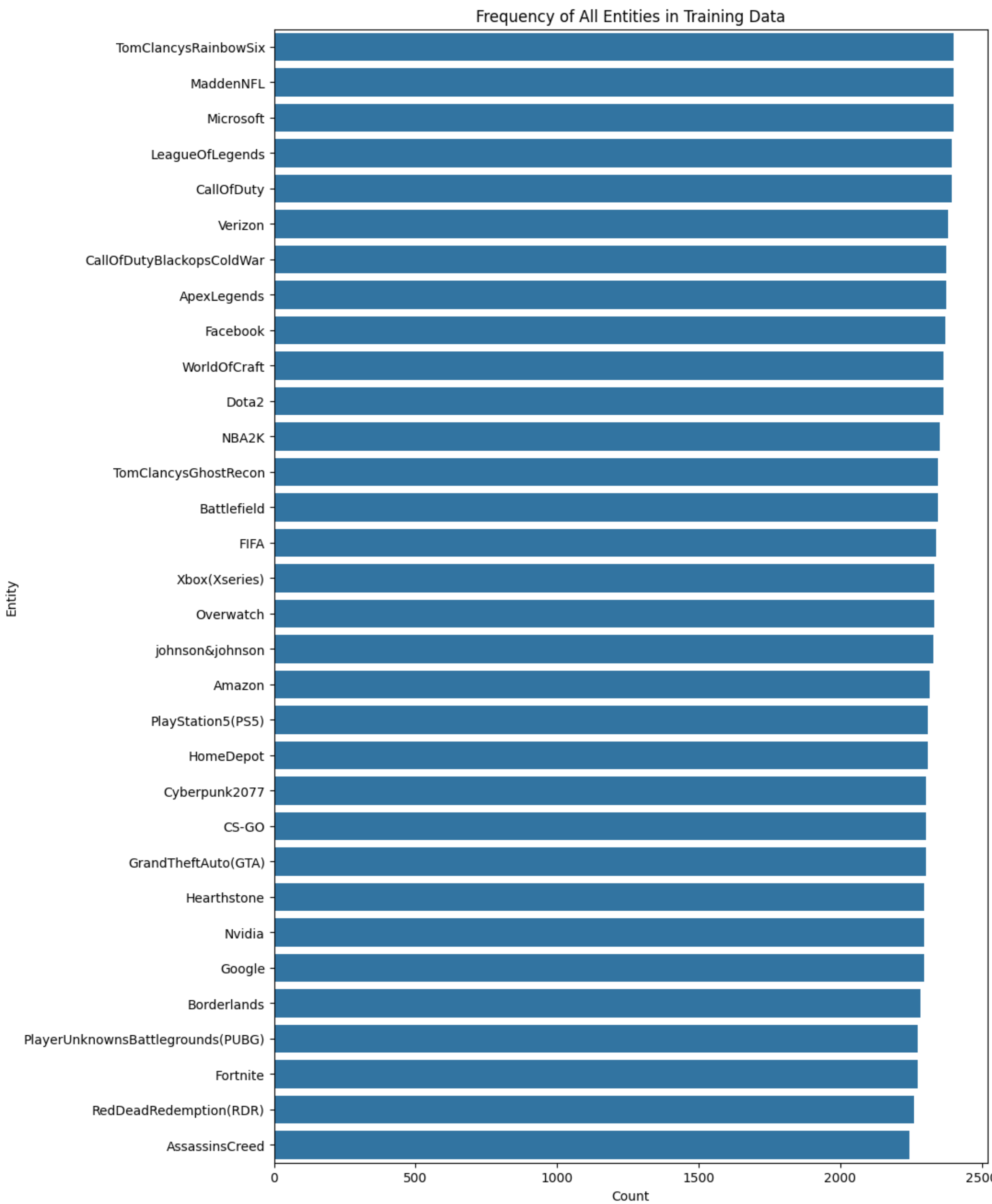

```
plt.figure(figsize=(8, 6))
sns.countplot(x='Sentiment', data=validation_data)
plt.title('Sentiment Distribution in Validation Data')
plt.show()
```




```
sentiment_counts = validation_data['Sentiment'].value_counts()

plt.figure(figsize=(8, 8))
plt.pie(sentiment_counts, labels=sentiment_counts.index,
autopct='%1.1f%%', startangle=90,
colors=['#ff9999','#66b3ff','#99ff99','#ffcc99'])
plt.title('Sentiment Distribution in Validation Data')
plt.show()
```



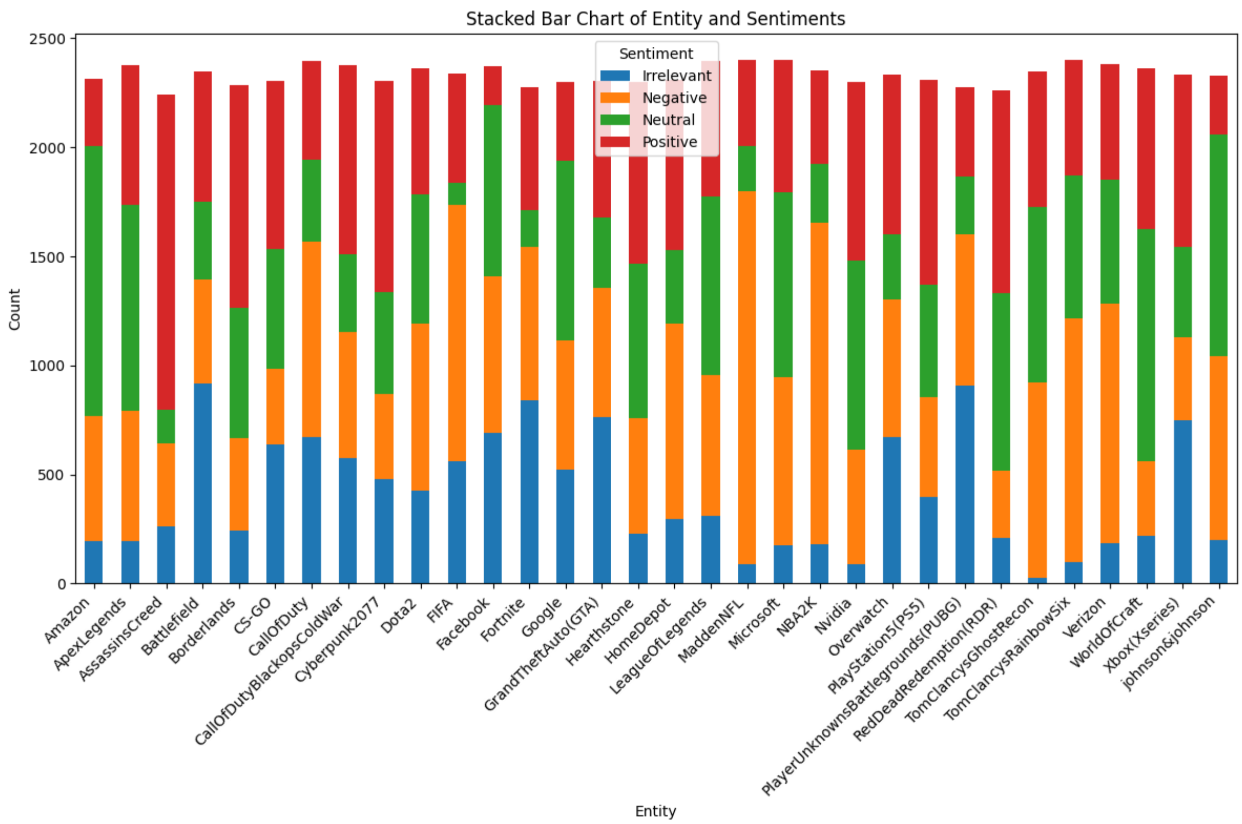

```python
# Count the occurrences of each entity in the training dataset
entity_counts = training_data['Entity'].value_counts()

plt.figure(figsize=(10, len(entity_counts) / 2))
sns.barplot(y=entity_counts.index, x=entity_counts.values, orient='h')
plt.title('Frequency of All Entities in Training Data')
plt.xlabel('Count')
plt.ylabel('Entity')
plt.show()
```



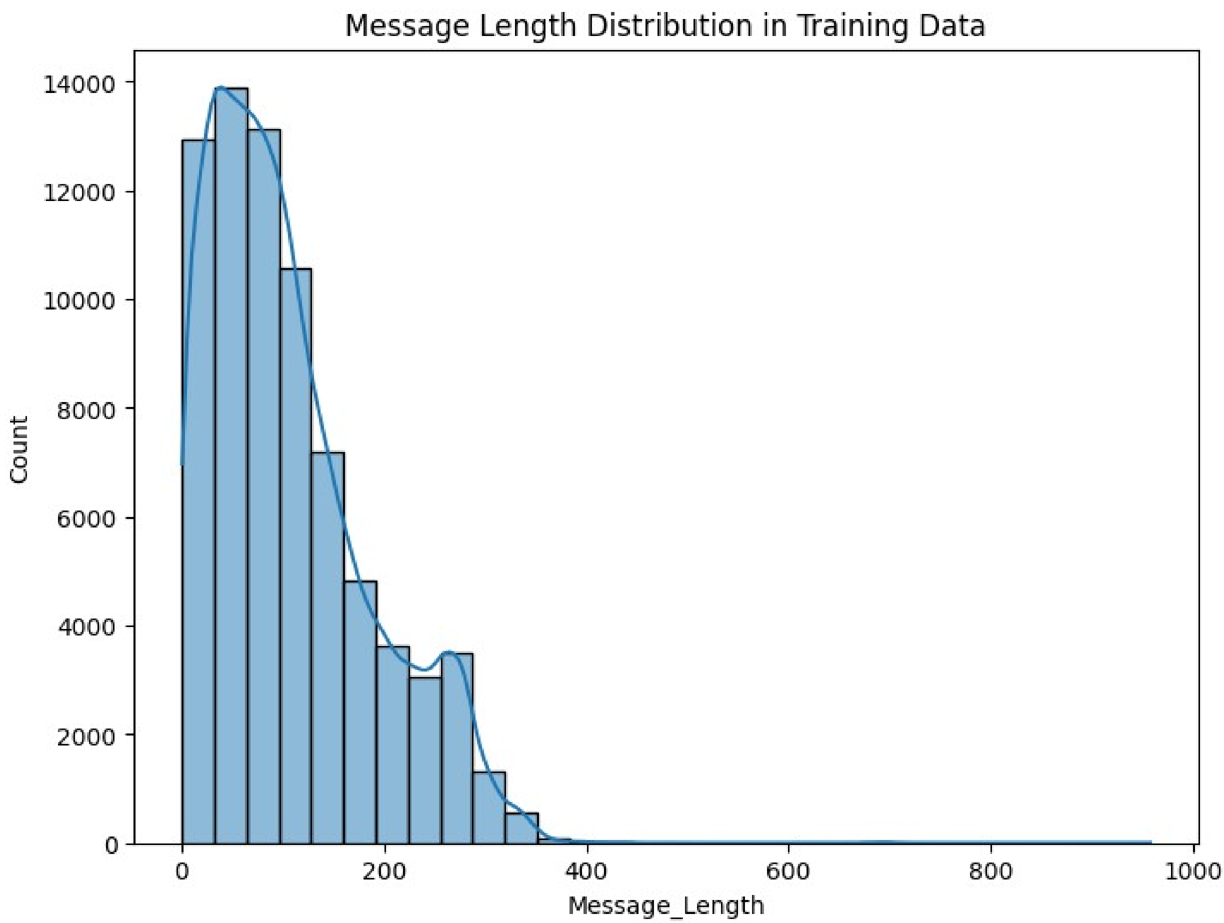

```
# Stacked Bar Chart of Sentiment Distribution by Entity
entity_sentiment_counts = pd.crosstab(training_data['Entity'],
training_data['Sentiment'])

plt.figure(figsize=(12, 8))
```

```python
entity_sentiment_counts.plot(kind='bar', stacked=True, figsize=(12,
8))
plt.title('Stacked Bar Chart of Entity and Sentiments')
plt.xlabel('Entity')
plt.ylabel('Count')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

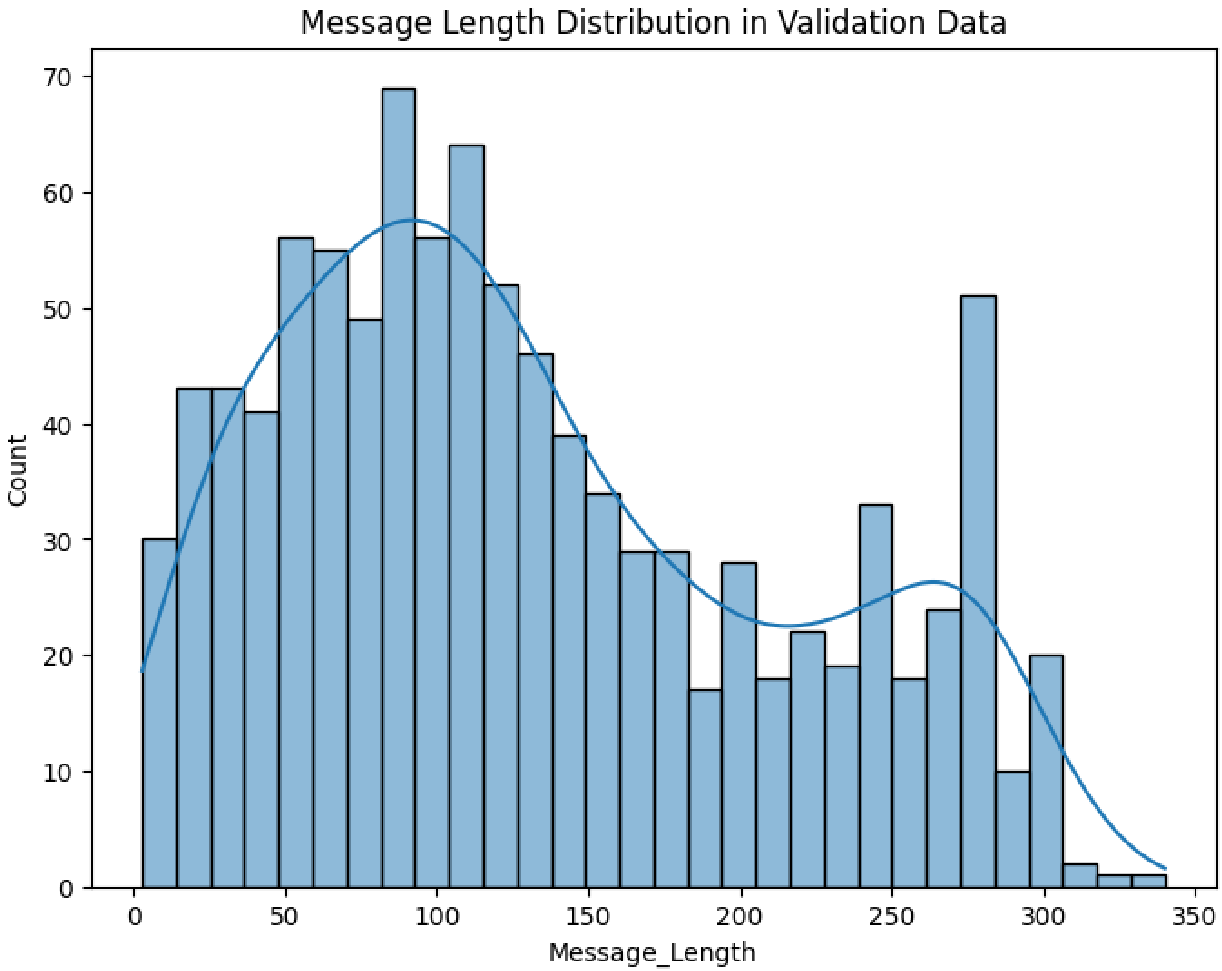
```
<Figure size 1200x800 with 0 Axes>
```




```python
# EDA: Message Length Distribution
training_data['Message_Length'] = training_data['Message'].apply(len)
validation_data['Message_Length'] =
validation_data['Message'].apply(len)

plt.figure(figsize=(8, 6))
sns.histplot(training_data['Message_Length'], kde=True, bins=30)
plt.title('Message Length Distribution in Training Data')
plt.show()
```




```
plt.figure(figsize=(8, 6))
sns.histplot(validation_data['Message_Length'], kde=True, bins=30)
plt.title('Message Length Distribution in Validation Data')
plt.show()
```




```
# Filter messages based on sentiment categories
positive_messages = ' '.join(training_data[training_data['Sentiment']
== 'Positive']['Message'])
negative_messages = ' '.join(training_data[training_data['Sentiment']
== 'Negative']['Message'])
neutral_messages = ' '.join(training_data[training_data['Sentiment']
== 'Neutral']['Message'])
irrelevant_messages = '
'.join(training_data[training_data['Sentiment'] == 'Irrelevant']
['Message'])

# Create word clouds for each sentiment category
wordcloud_positive = WordCloud(width=800, height=400,
background_color='white').generate(positive_messages)
wordcloud_negative = WordCloud(width=800, height=400,
background_color='white').generate(negative_messages)
wordcloud_neutral = WordCloud(width=800, height=400,
background_color='white').generate(neutral_messages)
wordcloud_irrelevant = WordCloud(width=800, height=400,
background_color='white').generate(irrelevant_messages)
```

```python
# Set up subplots to show all word clouds
plt.figure(figsize=(16, 12))

# Plot Positive WordCloud
plt.subplot(2, 2, 1)
plt.imshow(wordcloud_positive, interpolation='bilinear')
plt.title('Word Cloud for Positive Sentiment')
plt.axis('off')

# Plot Negative WordCloud
plt.subplot(2, 2, 2)
plt.imshow(wordcloud_negative, interpolation='bilinear')
plt.title('Word Cloud for Negative Sentiment')
plt.axis('off')

# Plot Neutral WordCloud
plt.subplot(2, 2, 3)
plt.imshow(wordcloud_neutral, interpolation='bilinear')
plt.title('Word Cloud for Neutral Sentiment')
plt.axis('off')

# Plot Irrelevant WordCloud
plt.subplot(2, 2, 4)
plt.imshow(wordcloud_irrelevant, interpolation='bilinear')
plt.title('Word Cloud for Irrelevant Sentiment')
plt.axis('off')

# Display the plots
plt.tight_layout()
plt.show()
```

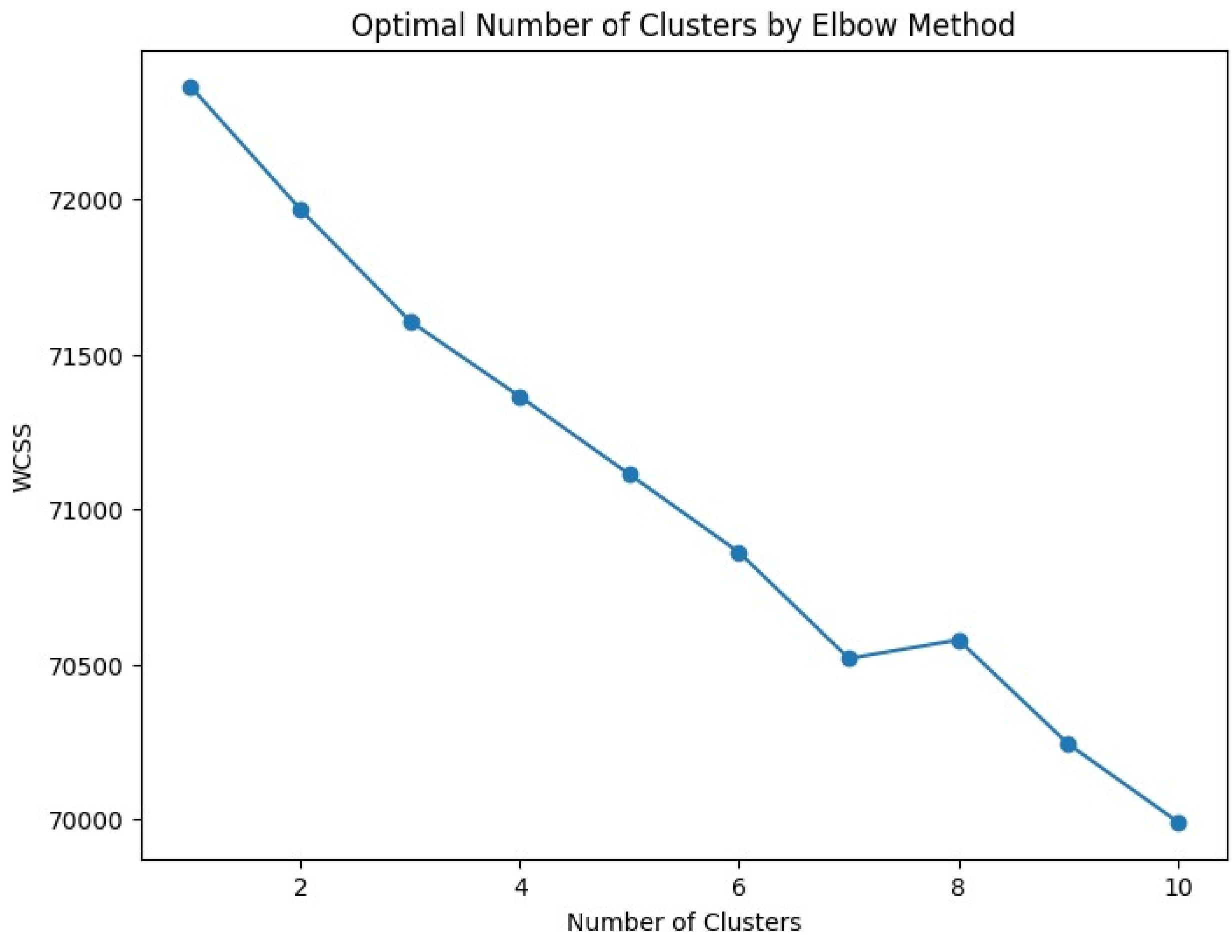
TF-IDF Vectorization

```
# Preprocess the text using TF-IDF
tfidf_vectorizer = TfidfVectorizer(max_features=5000)

# Transform the training and validation messages
X_train_tfidf =
tfidf_vectorizer.fit_transform(training_data['Message'])
X_validation_tfidf =
tfidf_vectorizer.transform(validation_data['Message'])

# Target labels
y_train = training_data['Sentiment']
y_validation = validation_data['Sentiment']
```

K-Means++ Clustering

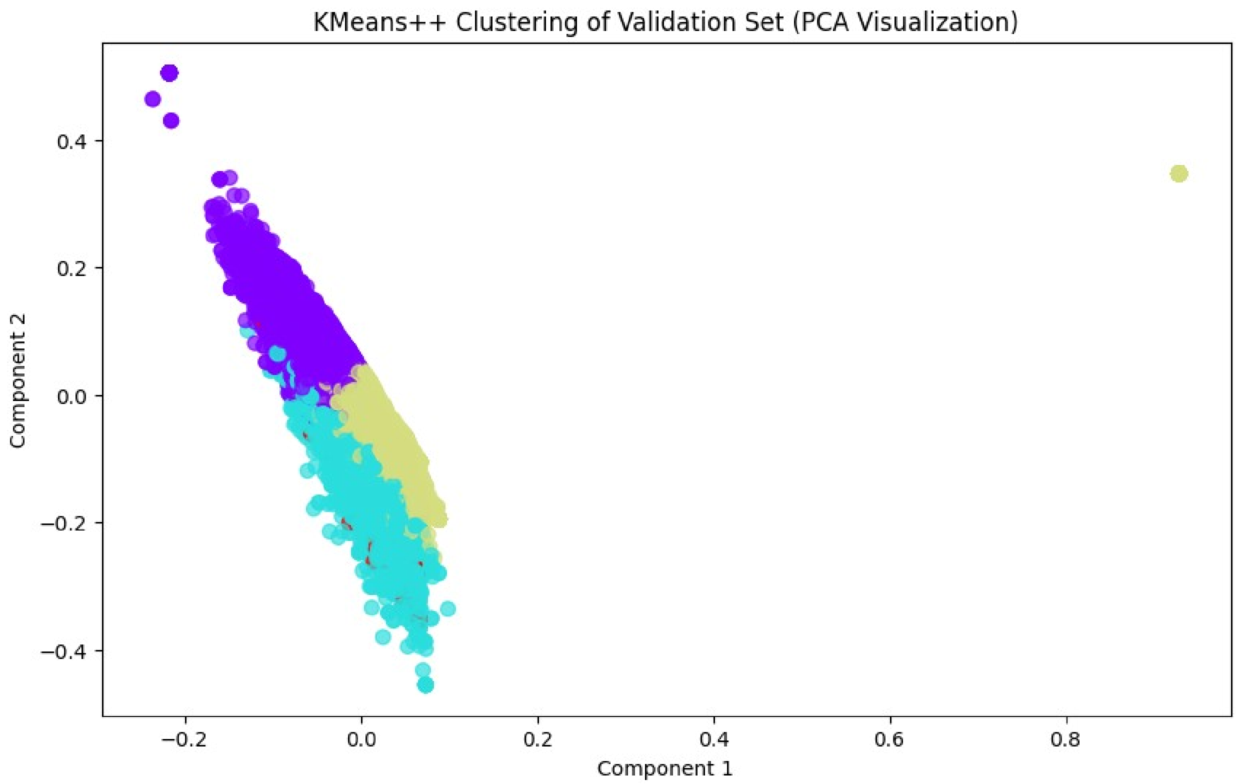
```
# Calculate WCSS
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
    kmeans.fit(X_train_tfidf)
    wcss.append(kmeans.inertia_)

# Plot the WCSS
plt.figure(figsize=(8, 6))
plt.plot(range(1, 11), wcss, marker='o')
plt.title('Optimal Number of Clusters by Elbow Method')
```

```
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()
```




```
# Initialize the KMeans model
kmeans_model = KMeans(n_clusters=4, init='k-means++', random_state=42)

# Train the model
kmeans_model.fit(X_train_tfidf)

KMeans(n_clusters=4, random_state=42)

# 3. Predict cluster labels for the validation set
cluster_labels = kmeans_model.predict(X_train_tfidf)

# Dimensionality Reduction using PCA
pca = PCA(n_components=2)
X_train_pca = pca.fit_transform(X_train_tfidf.toarray())

# Plot the PCA result with cluster labels
plt.figure(figsize=(10, 6))
```

```
plt.scatter(X_train_pca[:, 0], X_train_pca[:, 1], c=cluster_labels,
cmap='rainbow', s=50, alpha=0.7)
plt.title('KMeans++ Clustering of Validation Set (PCA Visualization)')
plt.xlabel('Component 1')
plt.ylabel('Component 2')
plt.show()
```




```
import numpy as np
np.unique(cluster_labels, return_counts=True)
```

```
(array([0, 1, 2, 3]), array([29233,  3810, 40090,  1548],
dtype=int64))
```

```
from sklearn.metrics import silhouette_score
score = silhouette_score(X_train_tfidf, cluster_labels)
print(f'Silhouette Score: {score}')
```

```
Silhouette Score: 0.007898007860315403
```

Naive Bayes Classifier

```
nb_model = MultinomialNB()
nb_model.fit(X_train_tfidf, y_train)
y_pred_nb = nb_model.predict(X_validation_tfidf)
```

```
accuracy_nb = accuracy_score(y_validation, y_pred_nb)
report_nb = classification_report(y_validation, y_pred_nb)
print("Naive Bayes Accuracy:", accuracy_nb)
print("Naive Bayes Classification Report:\n", report_nb)
```

```
Naive Bayes Accuracy: 0.7137137137137137
Naive Bayes Classification Report:
               precision    recall  f1-score   support

  Irrelevant       0.83      0.51      0.63       171
    Negative       0.66      0.83      0.74       266
     Neutral       0.78      0.62      0.69       285
    Positive       0.68      0.82      0.75       277

    accuracy                           0.71       999
   macro avg       0.74      0.70      0.70       999
weighted avg       0.73      0.71      0.71       999
```

Logistic Regression

```
lr_model = LogisticRegression(max_iter=1000)
lr_model.fit(X_train_tfidf, y_train)
y_pred_lr = lr_model.predict(X_validation_tfidf)

accuracy_lr = accuracy_score(y_validation, y_pred_lr)
report_lr = classification_report(y_validation, y_pred_lr)
print("Logistic Regression Accuracy:", accuracy_lr)
print("Logistic Regression Classification Report:\n", report_lr)
```

```
Logistic Regression Accuracy: 0.8188188188188188
Logistic Regression Classification Report:
               precision    recall  f1-score   support

  Irrelevant       0.83      0.73      0.77       171
    Negative       0.80      0.88      0.84       266
     Neutral       0.86      0.78      0.82       285
    Positive       0.80      0.86      0.83       277

    accuracy                           0.82       999
   macro avg       0.82      0.81      0.81       999
weighted avg       0.82      0.82      0.82       999
```

Random Forest

```
rf_model = RandomForestClassifier(n_estimators=100, max_depth= 100,
random_state=42)
rf_model.fit(X_train_tfidf, y_train)
y_pred_rf = rf_model.predict(X_validation_tfidf)
```

```python
accuracy_rf = accuracy_score(y_validation, y_pred_rf)
report_rf = classification_report(y_validation, y_pred_rf)
print("Random Forest Accuracy:", accuracy_rf)
print("Random Forest Classification Report:\n", report_rf)
```

```
Random Forest Accuracy: 0.938938938938939
Random Forest Classification Report:
               precision    recall  f1-score   support

  Irrelevant       1.00      0.88      0.94       171
    Negative       0.95      0.96      0.95       266
     Neutral       0.91      0.94      0.93       285
    Positive       0.92      0.95      0.94       277

    accuracy                           0.94       999
   macro avg       0.95      0.93      0.94       999
weighted avg       0.94      0.94      0.94       999
```

Decision Tree

```python
# Initialize the Decision Tree model
dt_model = DecisionTreeClassifier(random_state=42)

# Train the model
dt_model.fit(X_train_tfidf, y_train)
```

```
DecisionTreeClassifier(random_state=42)
```

```python
# Make predictions on the validation set
y_pred_dt = dt_model.predict(X_validation_tfidf)

# Evaluate the model
accuracy_dt = accuracy_score(y_validation, y_pred_dt)
report_dt = classification_report(y_validation, y_pred_dt)

# Classification Report
print("Decision Tree Model Accuracy:", accuracy_dt)
print("Decision Tree Model Classification Report:\n", report_dt)
```

```
Decision Tree Model Accuracy: 0.8868868868868869
Decision Tree Model Classification Report:
               precision    recall  f1-score   support

  Irrelevant       0.91      0.82      0.87       171
    Negative       0.90      0.95      0.92       266
     Neutral       0.87      0.86      0.86       285
    Positive       0.88      0.90      0.89       277

    accuracy                           0.89       999
   macro avg       0.89      0.88      0.88       999
```

```
weighted avg       0.89      0.89      0.89       999
```

Artificial Neural Network

```
# Encode Sentiments into numerical values
encoder = LabelEncoder()
y_train_encoded = encoder.fit_transform(y_train)
y_validation_encoded = encoder.transform(y_validation)

# One-hot encoding
y_train_categorical = to_categorical(y_train_encoded)
y_validation_categorical = to_categorical(y_validation_encoded)

# Build the neural network model
model = Sequential()

model.add(Dense(512, input_dim=X_train_tfidf.shape[1],
activation='relu'))

model.add(Dropout(0.5))

model.add(Dense(256, activation='relu'))

model.add(Dropout(0.5))

model.add(Dense(4, activation='softmax'))

model.compile(loss='categorical_crossentropy', optimizer='adam',
metrics=['accuracy'])
```

```
c:\Users\mades\AppData\Local\Programs\Python\Python310\lib\site-
packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass
an `input_shape`/`input_dim` argument to a layer. When using
Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer,
**kwargs)
```

```
# Train the model
history = model.fit(X_train_tfidf.toarray(), y_train_categorical,
epochs=10, batch_size=64,
validation_data=(X_validation_tfidf.toarray(),
y_validation_categorical))
```

```
Epoch 1/10
1167/1167 ━━━━━━━━━━━━━━━━━━━━ 16s 13ms/step - accuracy: 0.5624 -
loss: 1.0160 - val_accuracy: 0.9349 - val_loss: 0.2506
Epoch 2/10
1167/1167 ━━━━━━━━━━━━━━━━━━━━ 15s 13ms/step - accuracy: 0.8621 -
loss: 0.3801 - val_accuracy: 0.9610 - val_loss: 0.1315
```

```
Epoch 3/10
1167/1167 ━━━━━━━━━━━━━━━━━━━━ 14s 12ms/step - accuracy: 0.9238 -
loss: 0.2085 - val_accuracy: 0.9720 - val_loss: 0.1233
Epoch 4/10
1167/1167 ━━━━━━━━━━━━━━━━━━━━ 15s 12ms/step - accuracy: 0.9391 -
loss: 0.1570 - val_accuracy: 0.9690 - val_loss: 0.1177
Epoch 5/10
1167/1167 ━━━━━━━━━━━━━━━━━━━━ 15s 13ms/step - accuracy: 0.9432 -
loss: 0.1350 - val_accuracy: 0.9720 - val_loss: 0.1159
Epoch 6/10
1167/1167 ━━━━━━━━━━━━━━━━━━━━ 14s 12ms/step - accuracy: 0.9507 -
loss: 0.1200 - val_accuracy: 0.9690 - val_loss: 0.1214
Epoch 7/10
1167/1167 ━━━━━━━━━━━━━━━━━━━━ 14s 12ms/step - accuracy: 0.9514 -
loss: 0.1138 - val_accuracy: 0.9680 - val_loss: 0.1251
Epoch 8/10
1167/1167 ━━━━━━━━━━━━━━━━━━━━ 15s 13ms/step - accuracy: 0.9519 -
loss: 0.1128 - val_accuracy: 0.9720 - val_loss: 0.1306
Epoch 9/10
1167/1167 ━━━━━━━━━━━━━━━━━━━━ 15s 12ms/step - accuracy: 0.9556 -
loss: 0.1050 - val_accuracy: 0.9690 - val_loss: 0.1472
Epoch 10/10
1167/1167 ━━━━━━━━━━━━━━━━━━━━ 15s 13ms/step - accuracy: 0.9560 -
loss: 0.1031 - val_accuracy: 0.9690 - val_loss: 0.1369

# Make predictions on the validation set
y_pred_ann = model.predict(X_validation_tfidf.toarray())
y_pred_ann_labels = np.argmax(y_pred_ann, axis=1)

32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

# Decode the predicted labels
y_pred_labels = encoder.inverse_transform(y_pred_ann_labels)

# Evaluate the model
accuracy_ann = accuracy_score(y_validation, y_pred_labels)
report_ann = classification_report(y_validation, y_pred_labels)

# Classification Report
print("ANN Model Accuracy:", accuracy_ann)
print("ANN Model Classification Report:\n", report_ann)

ANN Model Accuracy: 0.968968968968969
ANN Model Classification Report:
               precision    recall  f1-score   support

  Irrelevant       0.96      0.96      0.96       171
    Negative       0.98      0.97      0.98       266
     Neutral       0.98      0.97      0.97       285
    Positive       0.95      0.97      0.96       277
```

```
    accuracy                           0.97       999
   macro avg       0.97      0.97      0.97       999
weighted avg       0.97      0.97      0.97       999


#Plot the loss over epochs
plt.figure(figsize=(8, 6))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Epoch vs Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```