Google Colab Lab Assignment 5.3 - Sequence Text Classification using LSTM

Course Name: MDM Deep Learning

Lab Title: To forecast future values of a univariate time series using LSTM-based models.

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Objective

To classify text sequences using LSTM-based models. The task involves sentiment classification using the Twitter Sentiment Analysis dataset.

1. Import Required Libraries

In [ ]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, precision_score, f1_score, confusion_matrix, classification_report

from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
```

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
```

2. Load and Inspect Dataset

In [ ]:

```
# Load training and validation datasets
train_df = pd.read_csv('/content/twitter_training.csv', header=None)
valid_df = pd.read_csv('/content/twitter_validation.csv', header=None)

# Assign column names
train_df.columns = ['ID', 'Entity', 'Sentiment', 'Tweet']
valid_df.columns = ['ID', 'Entity', 'Sentiment', 'Tweet']

# Combine both datasets
df = pd.concat([train_df, valid_df], ignore_index=True)

# Show dataset info and sample
print(df.info())
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 75682 entries, 0 to 75681
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
```

--- ------ -------------- -----

0 ID 75682 non-null int64

1 Entity 75682 non-null object

2 Sentiment 75682 non-null object

3 Tweet 74996 non-null object

dtypes: int64(1), object(3)

memory usage: 2.3+ MB

None

Out[ ]:

	ID	Entity	Sentiment	Tweet
0	2401	Borderlands	Positive	im getting on borderlands and i will murder yo...
1	2401	Borderlands	Positive	I am coming to the borders and I will kill you...
2	2401	Borderlands	Positive	im getting on borderlands and i will kill you ...
3	2401	Borderlands	Positive	im coming on borderlands and i will murder you...
4	2401	Borderlands	Positive	im getting on borderlands 2 and i will murder ...

3. Preprocess the Dataset

In [ ]:

```
# Drop rows with missing values
df.dropna(subset=['Tweet', 'Sentiment'], inplace=True)

# Filter only valid sentiments
df = df[df['Sentiment'].isin(['Positive', 'Negative', 'Neutral'])]
```

 # Encode sentiment labels into integers

label_encoder = LabelEncoder()

df['Sentiment'] = label_encoder.fit_transform(df['Sentiment'])

 # Extract features and labels

texts = df['Tweet'].values

labels = df['Sentiment'].values

4. Tokenization and Padding

In [ ]:

 # Tokenization parameters

vocab_size = 10000

max_length = 100

oov_token = ""

padding_type = 'post'

trunc_type = 'post'

 # Tokenize tweets

tokenizer = Tokenizer(num_words=vocab_size, oov_token=oov_token)

tokenizer.fit_on_texts(texts)

sequences = tokenizer.texts_to_sequences(texts)

padded_sequences = pad_sequences(sequences, maxlen=max_length, padding=padding_type, truncating=trunc_type)

5. Split the Data

In [ ]:

```
X_train, X_test, y_train, y_test = train_test_split(padded_sequences, labels,
test_size=0.2, random_state=42)


print("Training samples:", len(X_train))

print("Testing samples:", len(X_test))
```

Training samples: 49559

Testing samples: 12390

6. Build the LSTM Model

In [ ]:

```
model = Sequential()

model.add(Embedding(input_dim=vocab_size, output_dim=128,
input_length=max_length))

model.add(LSTM(64, return_sequences=False))

model.add(Dropout(0.3))

model.add(Dense(32, activation='relu'))

model.add(Dropout(0.2))

model.add(Dense(3, activation='softmax'))  # 3 classes: Positive, Negative, Neutral


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

model.summary()
```

/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/embedding.py:90: UserWarning: Argument `input_length` is deprecated. Just remove it.

warnings.warn(

Model: "sequential"

Layer (type)	Output Shape	Param #
embedding (Embedding)	?	0 (unbuilt)
lstm (LSTM)	?	0 (unbuilt)
dropout (Dropout)	?	0
dense (Dense)	?	0 (unbuilt)
dropout_1 (Dropout)	?	0
dense_1 (Dense)	?	0 (unbuilt)

Total params: 0 (0.00 B)

Trainable params: 0 (0.00 B)

Non-trainable params: 0 (0.00 B)

7. Train the Model with Callbacks

In [ ]:

```
es = EarlyStopping(monitor='val_loss', patience=3, verbose=1,
restore_best_weights=True)

mc = ModelCheckpoint('best_twitter_lstm.h5', save_best_only=True, monitor='val_loss',
verbose=1)


history = model.fit(X_train, y_train,
                    validation_split=0.1,
                    epochs=10,
                    batch_size=32,
                    callbacks=[es, mc],
                    verbose=1)
```

Epoch 1/10

1394/1394 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 91ms/step - accuracy: 0.3555 - loss: 1.0969

Epoch 1: val_loss improved from inf to 1.09421, saving model to best_twitter_lstm.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

1394/1394 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **139s** 96ms/step - accuracy: 0.3555 - loss: 1.0969 - val_accuracy: 0.3785 - val_loss: 1.0942

Epoch 2/10

1394/1394 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 90ms/step - accuracy: 0.3662 - loss: 1.0953

Epoch 2: val_loss improved from 1.09421 to 1.09376, saving model to best_twitter_lstm.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

1394/1394 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **138s** 93ms/step - accuracy: 0.3662 - loss: 1.0953 - val_accuracy: 0.3785 - val_loss: 1.0938

Epoch 3/10

1394/1394 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 92ms/step - accuracy: 0.3611 - loss: 1.0959

Epoch 3: val_loss improved from 1.09376 to 1.09328, saving model to best_twitter_lstm.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

1394/1394 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **133s** 95ms/step - accuracy: 0.3611 - loss: 1.0959 - val_accuracy: 0.3785 - val_loss: 1.0933

Epoch 4/10

1394/1394 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 92ms/step - accuracy: 0.3607 - loss: 1.0961

Epoch 4: val_loss improved from 1.09328 to 1.09312, saving model to best_twitter_lstm.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

1394/1394 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **142s** 96ms/step - accuracy: 0.3607 - loss: 1.0961 - val_accuracy: 0.3785 - val_loss: 1.0931

Epoch 5/10

1394/1394 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 89ms/step - accuracy: 0.3608 - loss: 1.0957

Epoch 5: val_loss did not improve from 1.09312

1394/1394 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **130s** 93ms/step - accuracy: 0.3608 - loss: 1.0957 - val_accuracy: 0.3785 - val_loss: 1.0933

Epoch 6/10

1394/1394 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 91ms/step - accuracy: 0.3639 - loss: 1.0950

Epoch 6: val_loss did not improve from 1.09312

1394/1394 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **145s** 95ms/step - accuracy: 0.3639 - loss: 1.0950 - val_accuracy: 0.3785 - val_loss: 1.0937

Epoch 7/10

1394/1394 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 91ms/step - accuracy: 0.3611 - loss: 1.0961

Epoch 7: val_loss did not improve from 1.09312

1394/1394 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **139s** 93ms/step - accuracy: 0.3611 - loss: 1.0961 - val_accuracy: 0.3785 - val_loss: 1.0935

Epoch 7: early stopping

Restoring model weights from the end of the best epoch: 4.

8. Evaluate the Model

In [ ]:

```
# Predictions
y_pred_probs = model.predict(X_test)
y_pred = np.argmax(y_pred_probs, axis=1)

# Evaluation Metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')
```

```
print(f"Accuracy: {accuracy:.4f}")

print(f"Precision: {precision:.4f}")

print(f"F1-score: {f1:.4f}")
```

388/388 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **16s** 37ms/step

Accuracy: 0.3646

Precision: 0.1330

F1-score: 0.1949

/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))

9. Confusion Matrix

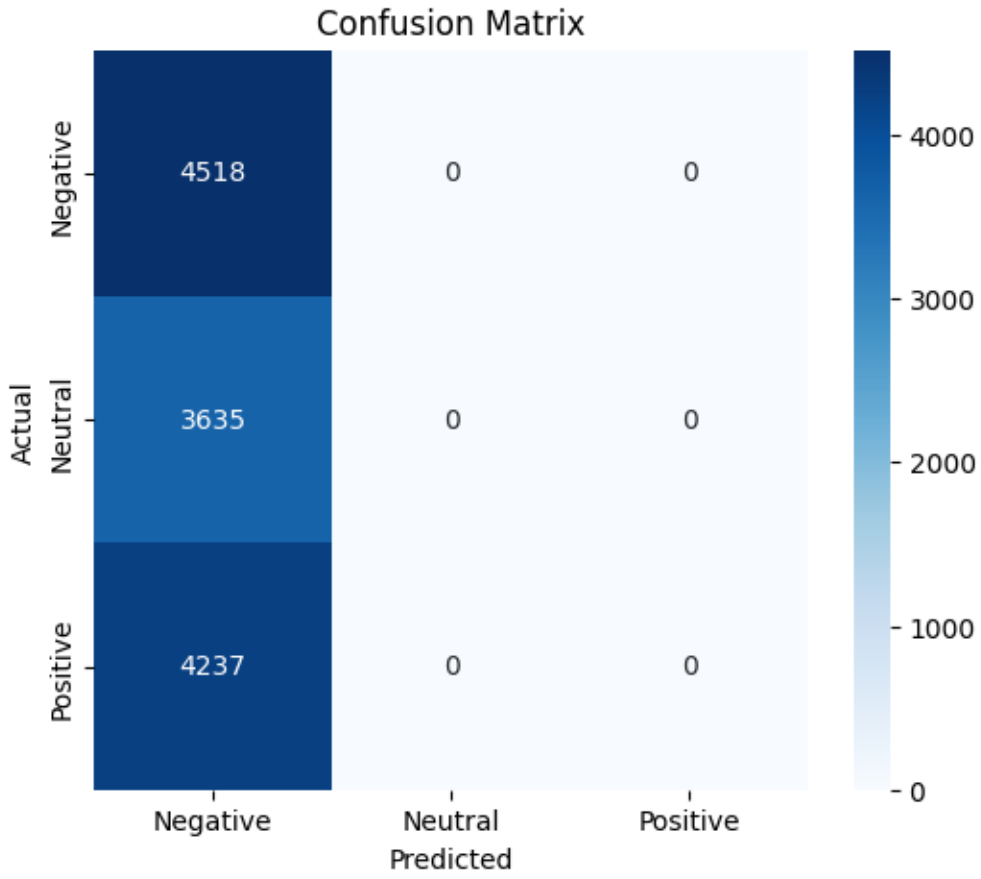
In [ ]:

```
cm = confusion_matrix(y_test, y_pred)


plt.figure(figsize=(6,5))

sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",

        xticklabels=label_encoder.classes_,

        yticklabels=label_encoder.classes_)

plt.xlabel("Predicted")

plt.ylabel("Actual")

plt.title("Confusion Matrix")

plt.show()
```

 # Classification Report

print("\nClassification Report:\n")

print(classification_report(y_test, y_pred, target_names=label_encoder.classes_))



Classification Report:

	precision	recall	f1-score	support
Negative	0.36	1.00	0.53	4518
Neutral	0.00	0.00	0.00	3635
Positive	0.00	0.00	0.00	4237
accuracy			0.36	12390

macro avg 0.12 0.33 0.18 12390

weighted avg 0.13 0.36 0.19 12390

/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))

/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))

/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))

10. Accuracy & Loss Curves (Training vs Validation)

In [ ]:

```
# Plot Accuracy and Loss over epochs
plt.figure(figsize=(14, 5))

# Accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy', marker='o')
plt.plot(history.history['val_accuracy'], label='Val Accuracy', marker='o')
plt.title('Model Accuracy Over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)
```

 # Loss

plt.subplot(1, 2, 2)

plt.plot(history.history['loss'], label='Train Loss', marker='o')

plt.plot(history.history['val_loss'], label='Val Loss', marker='o')

plt.title('Model Loss Over Epochs')

plt.xlabel('Epochs')

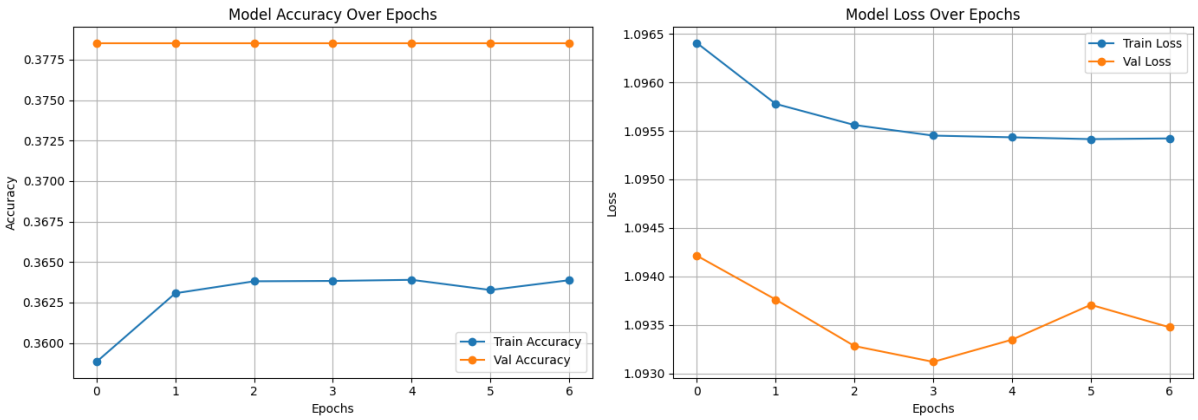
plt.ylabel('Loss')

plt.legend()

plt.grid(True)

plt.tight_layout()

plt.show()



11. Classification Report as a DataFrame (Pretty Table)

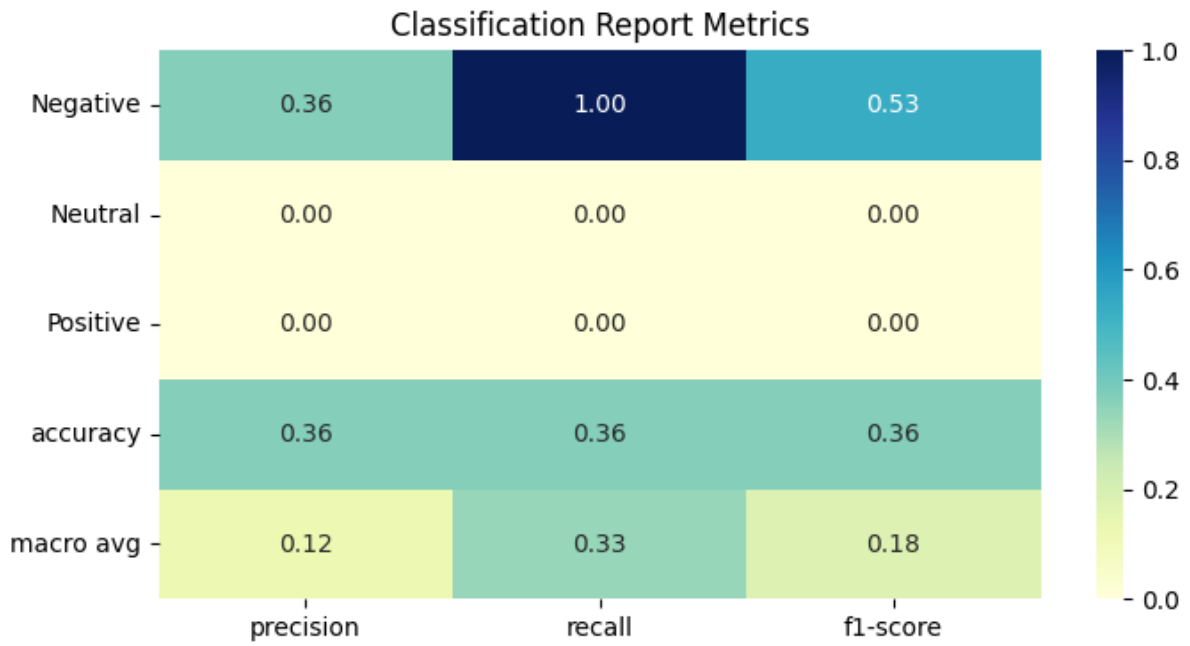
In [ ]:

from sklearn.metrics import classification_report

 # Get unique labels used in y_test

```python
unique_labels = np.unique(y_test)

# Inverse transform numeric labels to their original string names
class_names = label_encoder.inverse_transform(unique_labels)

# Generate classification report
report_dict = classification_report(y_test, y_pred, target_names=class_names,
output_dict=True)
report_df = pd.DataFrame(report_dict).transpose()

# Plot as heatmap
plt.figure(figsize=(8, 4))
sns.heatmap(report_df.iloc[:-1, :-1], annot=True, fmt='.2f', cmap='YlGnBu')
plt.title("Classification Report Metrics")
plt.show()
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```



4. Bar Plot of Sentiment Distribution in Dataset

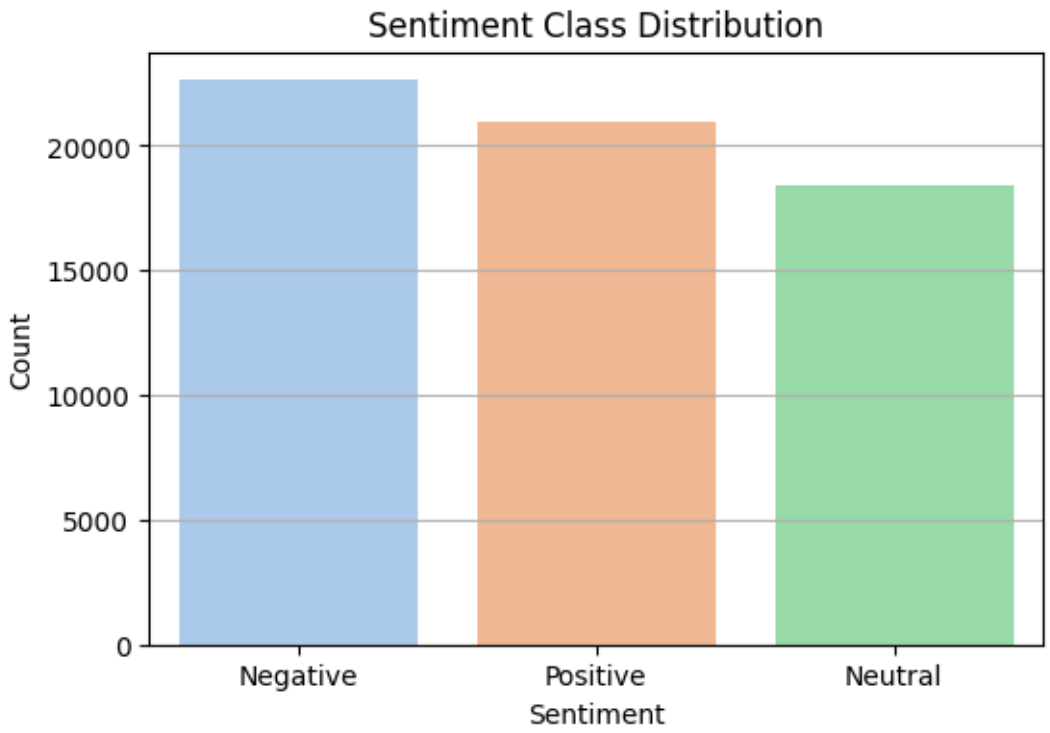
In [ ]:

```
sentiment_counts = df['Sentiment'].value_counts()
sentiment_labels = label_encoder.inverse_transform(sentiment_counts.index)

plt.figure(figsize=(6,4))
sns.barplot(x=sentiment_labels, y=sentiment_counts.values, palette='pastel')
plt.title("Sentiment Class Distribution")
plt.xlabel("Sentiment")
plt.ylabel("Count")
plt.grid(True, axis='y')
plt.show()
```

```
<ipython-input-16-22d8d52787cb>:5: FutureWarning:
```

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

sns.barplot(x=sentiment_labels, y=sentiment_counts.values, palette='pastel')



5. Word Cloud (Optional but Fancy)

In [ ]:

from wordcloud import WordCloud

 # Combine all tweets into one string

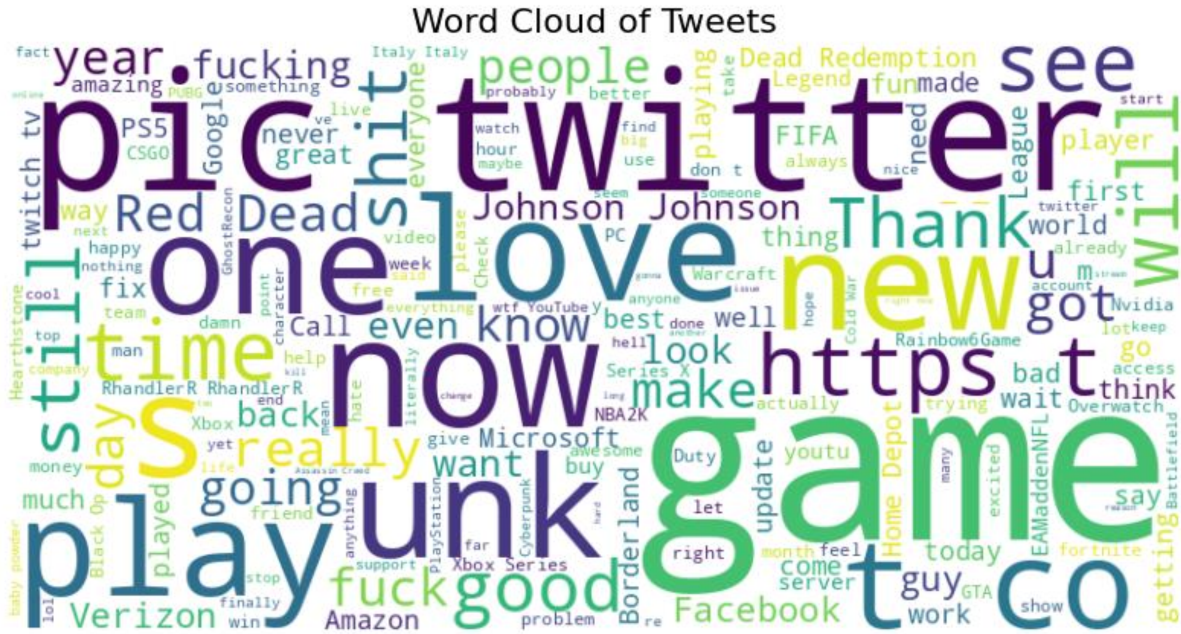
all_text = ' '.join(df['Tweet'])

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

plt.figure(figsize=(10,5))

plt.imshow(wordcloud, interpolation='bilinear')

```
plt.axis('off')

plt.title("Word Cloud of Tweets", fontsize=16)

plt.show()
```



Declaration

I, Yashas Nepalia, confirm that the work submitted in this assignment is my own and has been completed following academic integrity guidelines. The code is uploaded on my GitHub repository account, and the repository link is provided below:

GitHub Repository Link: https://github.com/YashasNepalia/Deep-Learning.git

Signature: Yashas Nepalia