Importing Twitter Data

```
import pandas as pd
import os
from google.colab import drive
drive.mount('/content/drive')
extracted_dir_path = '/content/drive/MyDrive/TwitterData'
# Load train and test data
train_data_path = os.path.join(extracted_dir_path, 'train.csv')
test_data_path = os.path.join(extracted_dir_path, 'test.csv')
# Load train and test data with specified encoding
train_data = pd.read_csv(train_data_path, encoding='ISO-8859-1')
test_data = pd.read_csv(test_data_path, encoding='ISO-8859-1')
```

```
Mounted at /content/drive
```

Data Preprocessing

```
# Select necessary columns in train data
train_data = train_data[['text', 'sentiment']]

# Select necessary columns in test data
test_data = test_data[['text', 'sentiment']]

# Remove null values if any
train_data = train_data.dropna()
test_data = test_data.dropna()
```

```
# Lowercase the text
train_data['text'] = train_data['text'].str.lower()
test_data['text'] = test_data['text'].str.lower()

# Remove punctuation and special characters
train_data['text'] = train_data['text'].str.replace('[^\w\s]', '')
test_data['text'] = test_data['text'].str.replace('[^\w\s]', '')

# Remove stopwords
import nltk
from nltk.corpus import stopwords

nltk.download('stopwords')
stop_words = set(stopwords.words('english'))

train_data['text'] = train_data['text'].apply(lambda x: ' '.join([word for word i
test_data['text'] = test_data['text'].apply(lambda x: ' '.join([word for word in 

# Tokenize the text
from tensorflow.keras.preprocessing.text import Tokenizer

tokenizer = Tokenizer()
tokenizer.fit_on_texts(train_data['text'])

X_train = tokenizer.texts_to_sequences(train_data['text'])
X_test = tokenizer.texts_to_sequences(test_data['text'])

# Pad sequences
from tensorflow.keras.preprocessing.sequence import pad_sequences

max_len = max([len(x) for x in X_train + X_test])
X_train = pad_sequences(X_train, maxlen=max_len, padding='post')
X_test = pad_sequences(X_test, maxlen=max_len, padding='post')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()
train_data['sentiment'] = label_encoder.fit_transform(train_data['sentiment'])

# Convert sentiment labels to numeric labels for test data
test_data['sentiment'] = label_encoder.transform(test_data['sentiment'])

# Separate features (X) and target (y) for train and test data
X_train = tokenizer.texts_to_sequences(train_data['text'])
X_train = pad_sequences(X_train, maxlen=max_len, padding='post')
y_train = train_data['sentiment']

X_test = tokenizer.texts_to_sequences(test_data['text'])
X_test = pad_sequences(X_test, maxlen=max_len, padding='post')
y_test = test_data['sentiment']
```

LSTM Model

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense

# Define the model
lstm_model = Sequential([
    Embedding(input_dim=len(tokenizer.word_index) + 1, output_dim=100, input_leng
    LSTM(128),
    Dense(3, activation='softmax')
])

# Compile the model
lstm_model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metr

print(" ")
print("LSTM Model Architecture : ")
print(lstm_model.summary())
print(" ")

# Train the model
lstm_history = lstm_model.fit(X_train, y_train, epochs=20, batch_size=32, validat
```

```
LSTM Model Architecture :
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 31, 100)           2659400

 lstm (LSTM)                 (None, 128)               117248

 dense (Dense)               (None, 3)                 387

=================================================================
Total params: 2777035 (10.59 MB)
Trainable params: 2777035 (10.59 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None

Epoch 1/20
687/687 [==============================] - 36s 49ms/step - loss: 0.9443 - accu
Epoch 2/20
687/687 [==============================] - 6s 9ms/step - loss: 0.6443 - accura
Epoch 3/20
687/687 [==============================] - 5s 7ms/step - loss: 0.4456 - accura
Epoch 4/20
687/687 [==============================] - 4s 5ms/step - loss: 0.3134 - accura
Epoch 5/20
687/687 [==============================] - 5s 7ms/step - loss: 0.2313 - accura
Epoch 6/20
687/687 [==============================] - 4s 6ms/step - loss: 0.1754 - accura
Epoch 7/20
687/687 [==============================] - 4s 6ms/step - loss: 0.1407 - accura
Epoch 8/20
687/687 [==============================] - 5s 7ms/step - loss: 0.1208 - accura
Epoch 9/20
687/687 [==============================] - 5s 7ms/step - loss: 0.1060 - accura
Epoch 10/20
687/687 [==============================] - 7s 10ms/step - loss: 0.0866 - accu
Epoch 11/20
687/687 [==============================] - 8s 11ms/step - loss: 0.0748 - accu
Epoch 12/20
687/687 [==============================] - 7s 10ms/step - loss: 0.0705 - accu
Epoch 13/20
687/687 [==============================] - 7s 11ms/step - loss: 0.0599 - accu
Epoch 14/20
687/687 [==============================] - 7s 10ms/step - loss: 0.0521 - accu
Epoch 15/20
687/687 [==============================] - 6s 8ms/step - loss: 0.0486 - accura
Epoch 16/20
```

```
687/687 [==============================] - 4s 6ms/step - loss: 0.0441 - accura
Epoch 17/20
687/687 [==============================] - 7s 10ms/step - loss: 0.0414 - accur
Epoch 18/20
687/687 [==============================] - 5s 7ms/step - loss: 0.0386 - accura
Epoch 19/20
687/687 [==============================] - 6s 9ms/step - loss: 0.0331 - accura
Epoch 20/20
687/687 [==============================] - 5s 8ms/step - loss: 0.0338 - accura
```

```
# Evaluate the model
lstm_loss, lstm_accuracy = lstm_model.evaluate(X_test, y_test)
print("LSTM Test Accuracy:", lstm_accuracy)
```

```
111/111 [==============================] - 1s 5ms/step - loss: 2.1022 - accura
LSTM Test Accuracy: 0.6505376100540161
```

RNN Model

```
from keras.models import Sequential
from keras.layers import Embedding, SimpleRNN, Dense, Activation, Flatten
from keras.preprocessing.sequence import pad_sequences

# Pad sequences
X_train = pad_sequences(X_train, maxlen=max_len)
X_test = pad_sequences(X_test, maxlen=max_len)

# Build the RNN model
rnn_model = Sequential()

# Adjust the embedding input dimension based on your vocabulary size
vocab_size = len(tokenizer.word_index) + 1

rnn_model.add(Embedding(vocab_size, 32, input_length=max_len))
rnn_model.add(SimpleRNN(16, return_sequences=False, activation="relu"))
rnn_model.add(Dense(3))  # Three classes: negative, neutral, positive
rnn_model.add(Activation("softmax"))  # Softmax for multi-class classification

# Compile the model
rnn_model.compile(loss="sparse_categorical_crossentropy", optimizer="adam", metri

print(" ")
```

```
print("RNN Model Architecture : ")
print(rnn_model.summary())
print(" ")

# Train the model
rnn_history = rnn_model.fit(X_train, y_train, epochs=20, batch_size=32, validatio

# Evaluate the model
rnn_loss, rnn_accuracy = rnn_model.evaluate(X_test, y_test)
print("Test Accuracy:", rnn_accuracy)
```

```
RNN Model Architecture :
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_1 (Embedding)     (None, 31, 32)            851008

 simple_rnn (SimpleRNN)      (None, 16)                784

 dense_1 (Dense)             (None, 3)                 51

 activation (Activation)     (None, 3)                 0

=================================================================
Total params: 851843 (3.25 MB)
Trainable params: 851843 (3.25 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None

Epoch 1/20
687/687 [==============================] - 35s 48ms/step - loss: 1.0884 - accu
Epoch 2/20
687/687 [==============================] - 17s 25ms/step - loss: 1.0873 - accu
Epoch 3/20
687/687 [==============================] - 24s 35ms/step - loss: 1.0692 - accu
Epoch 4/20
687/687 [==============================] - 25s 36ms/step - loss: 1.0027 - accu
Epoch 5/20
687/687 [==============================] - 33s 48ms/step - loss: 0.9185 - accu
Epoch 6/20
687/687 [==============================] - 25s 37ms/step - loss: 0.8306 - accu
Epoch 7/20
687/687 [==============================] - 23s 34ms/step - loss: 0.7526 - accu
Epoch 8/20
687/687 [==============================] - 29s 42ms/step - loss: 0.6822 - accu
```

```
Epoch 9/20
687/687 [==============================] - 30s 43ms/step - loss: 0.6137 - accu
Epoch 10/20
687/687 [==============================] - 17s 25ms/step - loss: 0.5657 - accu
Epoch 11/20
687/687 [==============================] - 16s 23ms/step - loss: 0.5245 - accu
Epoch 12/20
687/687 [==============================] - 16s 24ms/step - loss: 0.4751 - accu
Epoch 13/20
687/687 [==============================] - 16s 23ms/step - loss: 0.4464 - accu
Epoch 14/20
687/687 [==============================] - 17s 25ms/step - loss: 0.4119 - accu
Epoch 15/20
687/687 [==============================] - 17s 25ms/step - loss: 0.3788 - accu
Epoch 16/20
687/687 [==============================] - 16s 23ms/step - loss: 0.3665 - accu
Epoch 17/20
687/687 [==============================] - 16s 23ms/step - loss: 0.3392 - accu
Epoch 18/20
687/687 [==============================] - 16s 24ms/step - loss: 0.3215 - accu
Epoch 19/20
687/687 [==============================] - 16s 24ms/step - loss: 0.2991 - accu
Epoch 20/20
```

Bi-Directional LSTM

```
from keras.layers import Bidirectional

# Build the Bidirectional LSTM model
bi_lstm_model = Sequential()
bi_lstm_model.add(Embedding(vocab_size, 32, input_length=max_len))
bi_lstm_model.add(Bidirectional(LSTM(64)))
bi_lstm_model.add(Dense(3, activation='softmax'))

bi_lstm_model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', me

print(" ")
print("Bi Directional LSTM Model Architecture : ")
print(bi_lstm_model.summary())
print(" ")

# Train the model
bi_lstm_history = bi_lstm_model.fit(X_train, y_train, epochs=20, batch_size=32, va

# Evaluate the model
```

```
bi_lstm_loss, bi_lstm_accuracy = bi_lstm_model.evaluate(X_test, y_test)
print("Test Accuracy:", bi_lstm_accuracy)
```

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_2 (Embedding)     (None, 31, 32)            851008    
                                                                 
 bidirectional (Bidirection  (None, 128)               49664     
 al)                                                             
                                                                 
 dense_2 (Dense)             (None, 3)                 387       
                                                                 
=================================================================
Total params: 901059 (3.44 MB)
Trainable params: 901059 (3.44 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None

Epoch 1/20
687/687 [==============================] - 19s 23ms/step - loss: 0.8323 - accu
Epoch 2/20
687/687 [==============================] - 7s 10ms/step - loss: 0.5654 - accu
Epoch 3/20
687/687 [==============================] - 5s 8ms/step - loss: 0.4013 - accura
Epoch 4/20
687/687 [==============================] - 6s 9ms/step - loss: 0.2981 - accura
Epoch 5/20
687/687 [==============================] - 5s 8ms/step - loss: 0.2361 - accura
Epoch 6/20
687/687 [==============================] - 6s 9ms/step - loss: 0.1918 - accura
Epoch 7/20
687/687 [==============================] - 7s 10ms/step - loss: 0.1541 - accu
Epoch 8/20
687/687 [==============================] - 5s 8ms/step - loss: 0.1277 - accura
Epoch 9/20
687/687 [==============================] - 6s 9ms/step - loss: 0.1104 - accura
Epoch 10/20
687/687 [==============================] - 5s 7ms/step - loss: 0.0888 - accura
Epoch 11/20
687/687 [==============================] - 6s 9ms/step - loss: 0.0798 - accura
Epoch 12/20
687/687 [==============================] - 5s 7ms/step - loss: 0.0675 - accura
Epoch 13/20
687/687 [==============================] - 6s 9ms/step - loss: 0.0612 - accura
Epoch 14/20
687/687 [==============================] - 5s 8ms/step - loss: 0.0531 - accura
Epoch 15/20
```

```
687/687 [==============================] - 5s 7ms/step - loss: 0.0449 - accura
Epoch 16/20
687/687 [==============================] - 6s 9ms/step - loss: 0.0431 - accura
Epoch 17/20
687/687 [==============================] - 5s 7ms/step - loss: 0.0436 - accura
Epoch 18/20
687/687 [==============================] - 6s 9ms/step - loss: 0.0330 - accura
Epoch 19/20
687/687 [==============================] - 5s 7ms/step - loss: 0.0315 - accura
Epoch 20/20
687/687 [==============================] - 6s 8ms/step - loss: 0.0270 - accura
111/111 [==============================] - 0s 4ms/step - loss: 2.6877 - accura
Test Accuracy: 0.6448783278465271
```

GRU Model

```
from keras.layers import GRU

# Build the GRU model
gru_model = Sequential()
gru_model.add(Embedding(vocab_size, 32, input_length=max_len))
gru_model.add(GRU(64))
gru_model.add(Dense(3, activation='softmax'))

gru_model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metri

print(" ")
print("Gated Recurrent Unit (GRU) Model Architecture : ")
print(gru_model.summary())
print(" ")

# Train the model
gru_history = gru_model.fit(X_train, y_train, epochs=20, batch_size=32, validatio

# Evaluate the model
gru_loss, gru_accuracy = gru_model.evaluate(X_test, y_test)
print("Test Accuracy:", gru_accuracy)
```

```
Gated Recurrent Unit (GRU) Model Architecture :
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
```

```
 embedding_3 (Embedding)     (None, 31, 32)            851008

 gru (GRU)                   (None, 64)                18816

 dense_3 (Dense)             (None, 3)                 195

=================================================================
Total params: 870019 (3.32 MB)
Trainable params: 870019 (3.32 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None

Epoch 1/20
687/687 [==============================] - 16s 21ms/step - loss: 1.0882 - accu
Epoch 2/20
687/687 [==============================] - 5s 7ms/step - loss: 1.0879 - accura
Epoch 3/20
687/687 [==============================] - 4s 6ms/step - loss: 0.8354 - accura
Epoch 4/20
687/687 [==============================] - 4s 5ms/step - loss: 0.5846 - accura
Epoch 5/20
687/687 [==============================] - 4s 6ms/step - loss: 0.4039 - accura
Epoch 6/20
687/687 [==============================] - 4s 6ms/step - loss: 0.2804 - accura
Epoch 7/20
687/687 [==============================] - 4s 6ms/step - loss: 0.2043 - accura
Epoch 8/20
687/687 [==============================] - 4s 5ms/step - loss: 0.1616 - accura
Epoch 9/20
687/687 [==============================] - 5s 7ms/step - loss: 0.1301 - accura
Epoch 10/20
687/687 [==============================] - 3s 5ms/step - loss: 0.1103 - accura
Epoch 11/20
687/687 [==============================] - 3s 5ms/step - loss: 0.0942 - accura
Epoch 12/20
687/687 [==============================] - 4s 6ms/step - loss: 0.0793 - accura
Epoch 13/20
687/687 [==============================] - 4s 6ms/step - loss: 0.0715 - accura
Epoch 14/20
687/687 [==============================] - 3s 5ms/step - loss: 0.0617 - accura
Epoch 15/20
687/687 [==============================] - 4s 5ms/step - loss: 0.0543 - accura
Epoch 16/20
687/687 [==============================] - 4s 6ms/step - loss: 0.0548 - accura
Epoch 17/20
687/687 [==============================] - 4s 5ms/step - loss: 0.0487 - accura
Epoch 18/20
687/687 [==============================] - 4s 5ms/step - loss: 0.0399 - accura
Epoch 19/20
```

```
687/687 [==============================] - 4s 6ms/step - loss: 0.0380 - accura
Epoch 20/20
687/687 [==============================] - 4s 6ms/step - loss: 0.0319 - accura
```

CNN Model

```
from keras.layers import Conv1D, GlobalMaxPooling1D

# Build the CNN model
cnn_model = Sequential()
cnn_model.add(Embedding(vocab_size, 32, input_length=max_len))
cnn_model.add(Conv1D(128, 5, activation='relu'))
cnn_model.add(GlobalMaxPooling1D())
cnn_model.add(Dense(3, activation='softmax'))

cnn_model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metri

print(" ")
print(" Convolutional Neural Network (CNN) Model Architecture : ")
print(cnn_model.summary())
print(" ")

# Train the model
cnn_history = cnn_model.fit(X_train, y_train, epochs=20, batch_size=32, validatio

# Evaluate the model
cnn_loss, cnn_accuracy = cnn_model.evaluate(X_test, y_test)
print("Test Accuracy:", cnn_accuracy)
```

```
 Convolutional Neural Network (CNN) Model Architecture :
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_4 (Embedding)     (None, 31, 32)            851008

 conv1d (Conv1D)             (None, 27, 128)           20608

 global_max_pooling1d (Glob  (None, 128)               0
 alMaxPooling1D)

 dense_4 (Dense)             (None, 3)                 387
```

```
=================================================================
Total params: 872003 (3.33 MB)
Trainable params: 872003 (3.33 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None

Epoch 1/20
687/687 [==============================] - 16s 19ms/step - loss: 0.8165 - accu
Epoch 2/20
687/687 [==============================] - 5s 7ms/step - loss: 0.5454 - accura
Epoch 3/20
687/687 [==============================] - 3s 5ms/step - loss: 0.3268 - accura
Epoch 4/20
687/687 [==============================] - 3s 4ms/step - loss: 0.1856 - accura
Epoch 5/20
687/687 [==============================] - 4s 6ms/step - loss: 0.1115 - accura
Epoch 6/20
687/687 [==============================] - 3s 4ms/step - loss: 0.0713 - accura
Epoch 7/20
687/687 [==============================] - 4s 5ms/step - loss: 0.0482 - accura
Epoch 8/20
687/687 [==============================] - 3s 4ms/step - loss: 0.0341 - accura
Epoch 9/20
687/687 [==============================] - 4s 5ms/step - loss: 0.0248 - accura
Epoch 10/20
687/687 [==============================] - 2s 4ms/step - loss: 0.0189 - accura
Epoch 11/20
687/687 [==============================] - 3s 4ms/step - loss: 0.0170 - accura
Epoch 12/20
687/687 [==============================] - 3s 4ms/step - loss: 0.0136 - accura
Epoch 13/20
687/687 [==============================] - 3s 5ms/step - loss: 0.0130 - accura
Epoch 14/20
687/687 [==============================] - 3s 4ms/step - loss: 0.0119 - accura
Epoch 15/20
687/687 [==============================] - 3s 4ms/step - loss: 0.0118 - accura
Epoch 16/20
687/687 [==============================] - 2s 4ms/step - loss: 0.0102 - accura
Epoch 17/20
687/687 [==============================] - 2s 4ms/step - loss: 0.0095 - accura
Epoch 18/20
687/687 [==============================] - 3s 5ms/step - loss: 0.0088 - accura
Epoch 19/20
```

BERT Model

```
from transformers import BertTokenizer, TFBertForSequenceClassification
from keras.callbacks import EarlyStopping

# Load BERT tokenizer
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')

# Tokenize inputs
X_train_tokens = tokenizer(list(train_data['text']), padding=True, truncation=Tru
X_test_tokens = tokenizer(list(test_data['text']), padding=True, truncation=True,

# Load pre-trained BERT model
bert_model = TFBertForSequenceClassification.from_pretrained('bert-base-uncased')

# Freeze BERT layers
for layer in bert_model.layers:
    layer.trainable = False

# Compile the model
bert_model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metr

print(" ")
print(" Bidirectional Encoder Representations from Transformers (BERT) Model Arch
print(bert_model.summary())
print(" ")


# Early stopping
early_stopping = EarlyStopping(monitor='val_accuracy', patience=2, restore_best_w

# Train the model
bert_history = bert_model.fit(X_train_tokens, y_train, epochs=10, batch_size=32,
                              validation_split=0.2, callbacks=[early_stopping])

# Evaluate the model
bert_loss, bert_accuracy = bert_model.evaluate(X_test_tokens, y_test)
print("Test Accuracy:", bert_accuracy)
```

```
/usr/local/lib/python3.10/dist-packages/huggingface_hub/utils/_token.py:88: Us
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tak
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access pu
  warnings.warn(
```

tokenizer_config.json: 100% 48.0/48.0 [00:00<00:00, 2.43kB/s] vocab.txt: 100% 232k/232k [00:00<00:00, 5.07MB/s]

tokenizer.json: 100% 466k/466k [00:00<00:00, 3.68MB/s]

config.json: 100% 570/570 [00:00<00:00, 42.1kB/s]

model.safetensors: 100% 440M/440M [00:01<00:00, 227MB/s]

```
All PyTorch model weights were used when initializing TFBertForSequenceClassif

Some weights or buffers of the TF 2.0 model TFBertForSequenceClassification we
You should probably TRAIN this model on a down-stream task to be able to use i

 Bidirectional Encoder Representations from Transformers (BERT) Model Architec
Model: "tf_bert_for_sequence_classification"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 bert (TFBertMainLayer)      multiple                  109482240

 dropout_37 (Dropout)        multiple                  0 (unused)

 classifier (Dense)          multiple                  1538

=================================================================
Total params: 109483778 (417.65 MB)
Trainable params: 0 (0.00 Byte)
Non-trainable params: 109483778 (417.65 MB)
_________________________________________________________________
None

Epoch 1/10
WARNING:tensorflow:AutoGraph could not transform <function infer_framework at
Cause: for/else statement not yet supported
To silence this warning, decorate the function with @tf.autograph.experimental
WARNING: AutoGraph could not transform <function infer_framework at 0x7ee5e473
Cause: for/else statement not yet supported
To silence this warning, decorate the function with @tf.autograph.experimental
687/687 [==============================] - 260s 316ms/step - loss: nan - accur
Epoch 2/10
687/687 [==============================] - 202s 294ms/step - loss: nan - accur
Epoch 3/10
687/687 [==============================] - 202s 295ms/step - loss: nan - accur
111/111 [==============================] - 28s 154ms/step - loss: nan - accura
Test Accuracy: 0.4012450575828552
```

Model Comparison

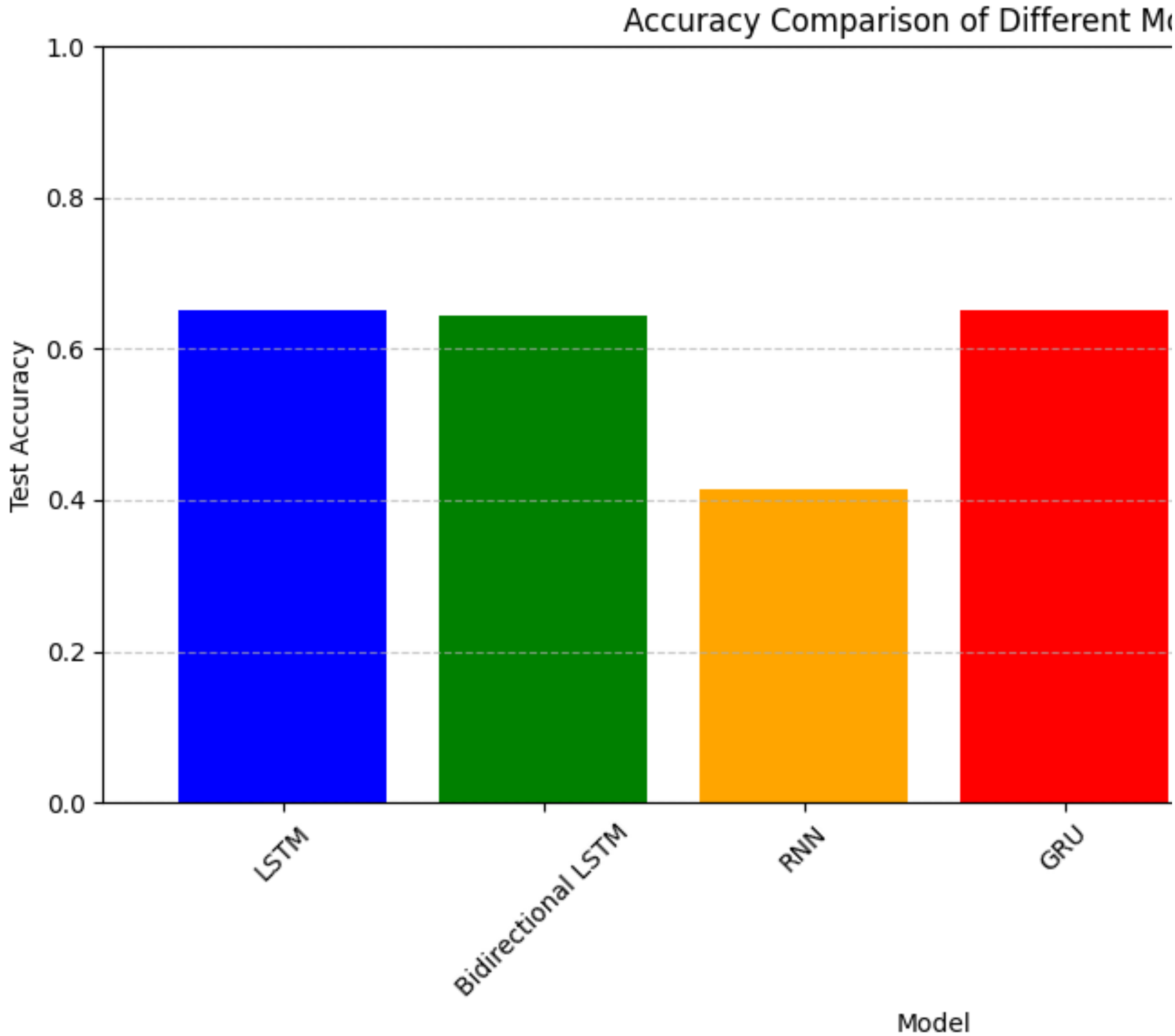
```
# Evaluate LSTM model
lstm_loss, lstm_accuracy = lstm_model.evaluate(X_test, y_test)
print("LSTM Test Accuracy:", lstm_accuracy)

# Evaluate Bidirectional LSTM model
bi_lstm_loss, bi_lstm_accuracy = bi_lstm_model.evaluate(X_test, y_test)
print("Bidirectional LSTM Test Accuracy:", bi_lstm_accuracy)

# Evaluate RNN model
rnn_loss, rnn_accuracy = rnn_model.evaluate(X_test, y_test)
print("RNN Test Accuracy:", rnn_accuracy)

# Evaluate GRU model
gru_loss, gru_accuracy = gru_model.evaluate(X_test, y_test)
print("GRU Test Accuracy:", gru_accuracy)

# Evaluate CNN model
cnn_loss, cnn_accuracy = cnn_model.evaluate(X_test, y_test)
print("CNN Test Accuracy:", cnn_accuracy)

# Evaluate BERT model
bert_loss, bert_accuracy = bert_model.evaluate(X_test_tokens, y_test)
print("BERT Test Accuracy:", bert_accuracy)
```

```
111/111 [==============================] - 0s 3ms/step - loss: 2.1022 - accura
LSTM Test Accuracy: 0.6505376100540161
111/111 [==============================] - 0s 4ms/step - loss: 2.6877 - accura
Bidirectional LSTM Test Accuracy: 0.6448783278465271
111/111 [==============================] - 1s 5ms/step - loss: 1.7674 - accura
RNN Test Accuracy: 0.4136955440044403
111/111 [==============================] - 0s 3ms/step - loss: 2.4522 - accura
GRU Test Accuracy: 0.6511035561561584
111/111 [==============================] - 0s 2ms/step - loss: 2.5631 - accura
CNN Test Accuracy: 0.6290322542190552
111/111 [==============================] - 17s 157ms/step - loss: nan - accura
BERT Test Accuracy: 0.4012450575828552
```

```
import pandas as pd

# Create a dictionary to store accuracy results
accuracy_results = {
    "Model": ["LSTM", "Bidirectional LSTM", "RNN", "GRU", "CNN", "BERT"],
    "Test Accuracy": [lstm_accuracy, bi_lstm_accuracy, rnn_accuracy, gru_accuracy
}

# Convert the dictionary to a DataFrame
df_accuracy = pd.DataFrame(accuracy_results)

# Print the DataFrame
display(df_accuracy)
```

	Model	Test Accuracy
0	LSTM	0.650538
1	Bidirectional LSTM	0.644878
2	RNN	0.413696
3	GRU	0.651104
4	CNN	0.629032
5	BERT	0.401245

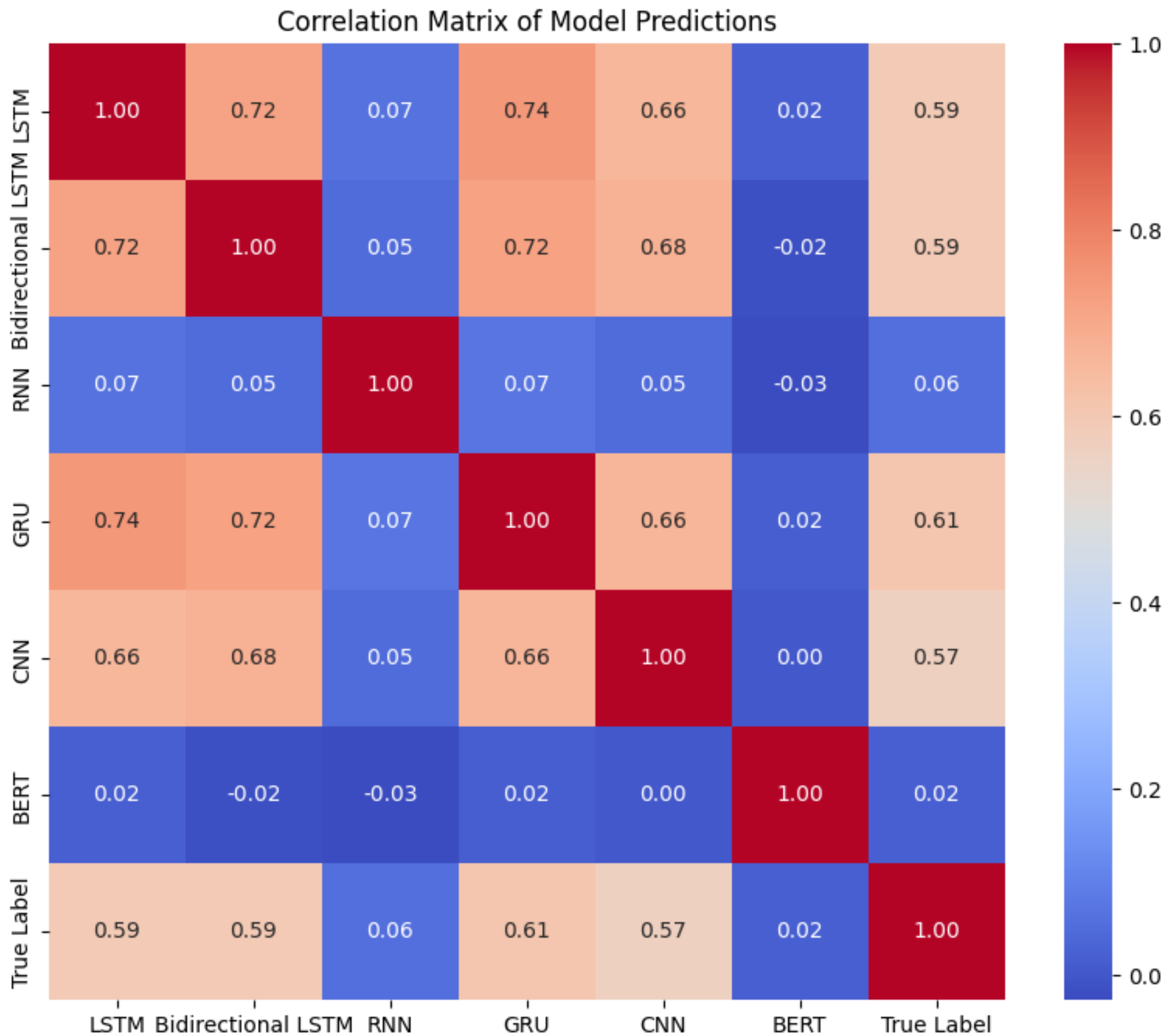
```
import matplotlib.pyplot as plt

# Plot accuracy results
plt.figure(figsize=(10, 6))
plt.bar(df_accuracy["Model"], df_accuracy["Test Accuracy"], color=['blue', 'green',
plt.xlabel('Model')
plt.ylabel('Test Accuracy')
plt.title('Accuracy Comparison of Different Models')
plt.ylim(0, 1)  # Set y-axis limit from 0 to 1
plt.xticks(rotation=45)  # Rotate x-axis labels for better visibility
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```




```
import numpy as np
import seaborn as sns

# Make predictions for each model
lstm_preds = np.argmax(lstm_model.predict(X_test), axis=1)
bi_lstm_preds = np.argmax(bi_lstm_model.predict(X_test), axis=1)
rnn_preds = np.argmax(rnn_model.predict(X_test), axis=1)
gru_preds = np.argmax(gru_model.predict(X_test), axis=1)
cnn_preds = np.argmax(cnn_model.predict(X_test), axis=1)
bert_preds = np.argmax(bert_model.predict(X_test_tokens)[0], axis=1)

# Create a DataFrame to store the predictions
```

```
df_preds = pd.DataFrame({
    "LSTM": lstm_preds,
    "Bidirectional LSTM": bi_lstm_preds,
    "RNN": rnn_preds,
    "GRU": gru_preds,
    "CNN": cnn_preds,
    "BERT": bert_preds,
    "True Label": y_test
})

# Calculate the correlation matrix
correlation_matrix = df_preds.corr()

# Plot the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm", fmt=".2f", square=Tr
plt.title('Correlation Matrix of Model Predictions')
plt.show()
```

```
111/111 [==============================] - 0s 3ms/step
111/111 [==============================] - 0s 4ms/step
111/111 [==============================] - 1s 6ms/step
111/111 [==============================] - 0s 3ms/step
111/111 [==============================] - 0s 3ms/step
111/111 [==============================] - 17s 153ms/step
```

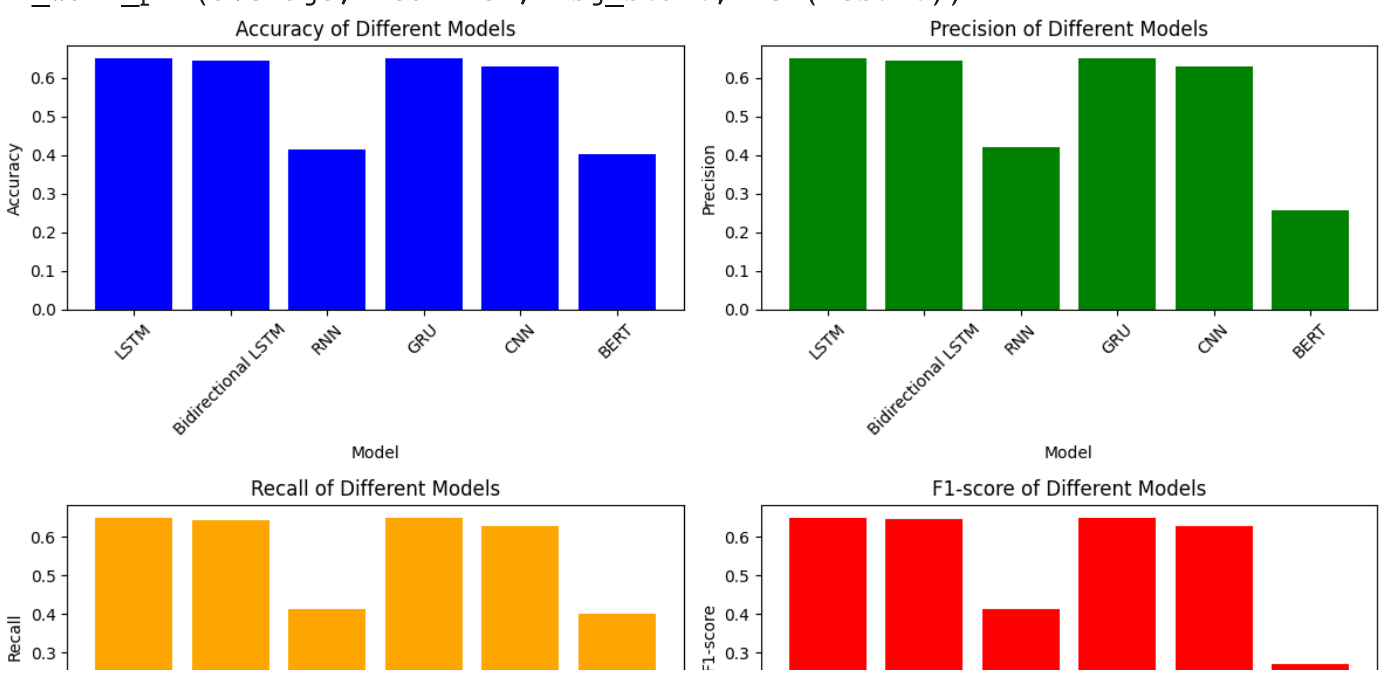


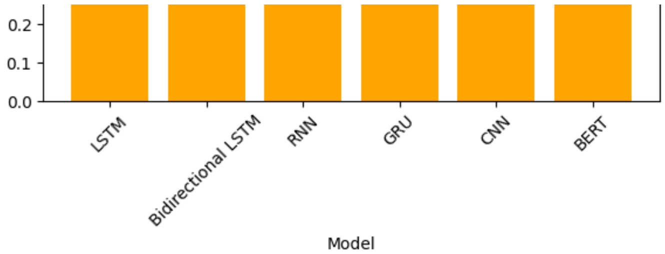

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_sco
```

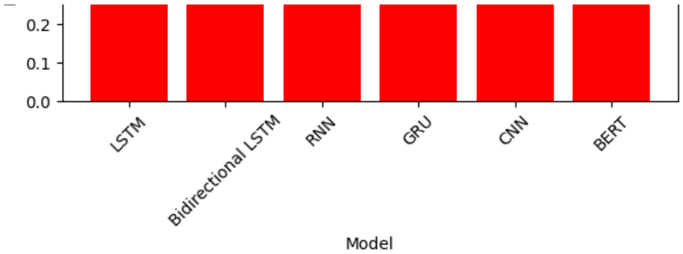
```
# Compute performance metrics for each model
metrics_dict = {
    "Model": ["LSTM", "Bidirectional LSTM", "RNN", "GRU", "CNN", "BERT"],
    "Accuracy": [accuracy_score(y_test, lstm_preds),
                 accuracy_score(y_test, bi_lstm_preds),
                 accuracy_score(y_test, rnn_preds),
                 accuracy_score(y_test, gru_preds),
                 accuracy_score(y_test, cnn_preds),
                 accuracy_score(y_test, bert_preds)],
    "Precision": [precision_score(y_test, lstm_preds, average='weighted'),
                  precision_score(y_test, bi_lstm_preds, average='weighted'),
                  precision_score(y_test, rnn_preds, average='weighted'),
                  precision_score(y_test, gru_preds, average='weighted'),
                  precision_score(y_test, cnn_preds, average='weighted'),
                  precision_score(y_test, bert_preds, average='weighted')],
    "Recall": [recall_score(y_test, lstm_preds, average='weighted'),
               recall_score(y_test, bi_lstm_preds, average='weighted'),
               recall_score(y_test, rnn_preds, average='weighted'),
               recall_score(y_test, gru_preds, average='weighted'),
               recall_score(y_test, cnn_preds, average='weighted'),
               recall_score(y_test, bert_preds, average='weighted')],
    "F1-score": [f1_score(y_test, lstm_preds, average='weighted'),
                 f1_score(y_test, bi_lstm_preds, average='weighted'),
                 f1_score(y_test, rnn_preds, average='weighted'),
                 f1_score(y_test, gru_preds, average='weighted'),
                 f1_score(y_test, cnn_preds, average='weighted'),
                 f1_score(y_test, bert_preds, average='weighted')]
}

# Create a DataFrame for the metrics
df_metrics = pd.DataFrame(metrics_dict)

# Plot the performance metrics
plt.figure(figsize=(12, 8))

# Accuracy
plt.subplot(2, 2, 1)
plt.bar(df_metrics["Model"], df_metrics["Accuracy"], color='blue')
plt.title('Accuracy of Different Models')
plt.xlabel('Model')
plt.ylabel('Accuracy')
plt.xticks(rotation=45)

# Precision
```

```
plt.subplot(2, 2, 2)
plt.bar(df_metrics["Model"], df_metrics["Precision"], color='green')
plt.title('Precision of Different Models')
plt.xlabel('Model')
plt.ylabel('Precision')
plt.xticks(rotation=45)

# Recall
plt.subplot(2, 2, 3)
plt.bar(df_metrics["Model"], df_metrics["Recall"], color='orange')
plt.title('Recall of Different Models')
plt.xlabel('Model')
plt.ylabel('Recall')
plt.xticks(rotation=45)

# F1-score
plt.subplot(2, 2, 4)
plt.bar(df_metrics["Model"], df_metrics["F1-score"], color='red')
plt.title('F1-score of Different Models')
plt.xlabel('Model')
plt.ylabel('F1-score')
plt.xticks(rotation=45)

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

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:134
  _warn_prf(average, modifier, msg_start, len(result))
```




0.2
0.1
0.0
LSTM
Bidirectional LSTM
RNN
GRU
CNN
BERT
Model


0.2
0.1
0.0
LSTM
Bidirectional LSTM
RNN
GRU
CNN
BERT
Model