```
pip install tensorflow
```

```
  Downloading libclang-18.1.1-py2.py3-none-manylinux2010_x86_64.whl.metadata (5.2 kB)
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.4.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-packages (from tensorflow) (24.2)
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.21.5,<6.0.0dev,>=3.20.3 in /usr/local/lib/pyt
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (2.32.3)
Requirement already satisfied: setuptools in /usr/local/lib/python3.11/dist-packages (from tensorflow) (75.2.0)
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.17.0)
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.0.1)
Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (4.13.1)
Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.17.2)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.71.0)
Collecting tensorboard~=2.19.0 (from tensorflow)
  Downloading tensorboard-2.19.0-py3-none-any.whl.metadata (1.8 kB)
Requirement already satisfied: keras>=3.5.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.8.0)
Requirement already satisfied: numpy<2.2.0,>=1.26.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (2.0.2)
Requirement already satisfied: h5py>=3.11.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.13.0)
Requirement already satisfied: ml-dtypes<1.0.0,>=0.5.1 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.5.1)
Collecting tensorflow-io-gcs-filesystem>=0.23.1 (from tensorflow)
  Downloading tensorflow_io_gcs_filesystem-0.37.1-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (14 kB)
Collecting wheel<1.0,>=0.23.0 (from astunparse>=1.6.0->tensorflow)
  Downloading wheel-0.45.1-py3-none-any.whl.metadata (2.3 kB)
Requirement already satisfied: rich in /usr/local/lib/python3.11/dist-packages (from keras>=3.5.0->tensorflow) (14.0.0)
Requirement already satisfied: namex in /usr/local/lib/python3.11/dist-packages (from keras>=3.5.0->tensorflow) (0.0.8)
Requirement already satisfied: optree in /usr/local/lib/python3.11/dist-packages (from keras>=3.5.0->tensorflow) (0.14.1)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorf
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow) (
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow) (
Requirement already satisfied: markdown>=2.6.8 in /usr/lib/python3/dist-packages (from tensorboard~=2.19.0->tensorflow) (3.3.6)
Collecting tensorboard-data-server<0.8.0,>=0.7.0 (from tensorboard~=2.19.0->tensorflow)
  Downloading tensorboard_data_server-0.7.2-py3-none-manylinux_2_31_x86_64.whl.metadata (1.1 kB)
Collecting werkzeug>=1.0.1 (from tensorboard~=2.19.0->tensorflow)
  Downloading werkzeug-3.1.3-py3-none-any.whl.metadata (3.7 kB)
Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.11/dist-packages (from werkzeug>=1.0.1->tensorboard~=2.19.
Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python3.11/dist-packages (from rich->keras>=3.5.0->tensorflow)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/python3.11/dist-packages (from rich->keras>=3.5.0->tensorflo
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.11/dist-packages (from markdown-it-py>=2.2.0->rich->keras>=3.5.0-
Downloading tensorflow-2.19.0-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (644.9 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 644.9/644.9 MB 1.1 MB/s eta 0:00:00
Downloading astunparse-1.6.3-py2.py3-none-any.whl (12 kB)
Downloading flatbuffers-25.2.10-py2.py3-none-any.whl (30 kB)
Downloading google_pasta-0.2.0-py3-none-any.whl (57 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 57.5/57.5 kB 17.9 kB/s eta 0:00:00
Downloading libclang-18.1.1-py2.py3-none-manylinux2010_x86_64.whl (24.5 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 24.5/24.5 MB 59.0 MB/s eta 0:00:00
Downloading tensorboard-2.19.0-py3-none-any.whl (5.5 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5.5/5.5 MB 95.9 MB/s eta 0:00:00
Downloading tensorflow_io_gcs_filesystem-0.37.1-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (5.1 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5.1/5.1 MB 83.9 MB/s eta 0:00:00
Downloading tensorboard_data_server-0.7.2-py3-none-manylinux_2_31_x86_64.whl (6.6 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 6.6/6.6 MB 106.7 MB/s eta 0:00:00
Downloading werkzeug-3.1.3-py3-none-any.whl (224 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 224.5/224.5 kB 15.5 MB/s eta 0:00:00
Downloading wheel-0.45.1-py3-none-any.whl (72 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 72.5/72.5 kB 5.6 MB/s eta 0:00:00
Installing collected packages: libclang, flatbuffers, wheel, werkzeug, tensorflow-io-gcs-filesystem, tensorboard-data-server, google-
Successfully installed astunparse-1.6.3 flatbuffers-25.2.10 google-pasta-0.2.0 libclang-18.1.1 tensorboard-2.19.0 tensorboard-data-se
```

```
import os
import shutil
import pathlib
import random

import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

import matplotlib.pyplot as plt
```

```
# Fetch and prepare the IMDB dataset
!wget https://ai.stanford.edu/~amaas/data/sentiment/aclImdb_v1.tar.gz -O imdb_dataset.tar.gz
!tar -xzf imdb_dataset.tar.gz
!rm -rf aclImdb/train/unsup
```

```
--2025-04-08 17:14:02--  https://ai.stanford.edu/~amaas/data/sentiment/aclImdb_v1.tar.gz
Resolving ai.stanford.edu (ai.stanford.edu)... 171.64.68.10
Connecting to ai.stanford.edu (ai.stanford.edu)|171.64.68.10|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 84125825 (80M) [application/x-gzip]
Saving to: ‘imdb_dataset.tar.gz’

imdb_dataset.tar.gz 100%[===================>]  80.23M  21.2MB/s    in 4.3s

2025-04-08 17:14:07 (18.5 MB/s) - ‘imdb_dataset.tar.gz’ saved [84125825/84125825]
```

```
import os

def review_summary(directory="aclImdb", max_files=5):
    for dataset_type in ["train", "test"]:
        print(f"\nDataset Type: '{dataset_type}'")
        for label in ["pos", "neg"]:
            print(f"  Review Type: {label}")
            dir_path = os.path.join(directory, dataset_type, label)
            file_list = os.listdir(dir_path)[:max_files]
            for idx, review_file in enumerate(file_list):
                review_path = os.path.join(dir_path, review_file)
                with open(review_path, "r", encoding="utf-8") as review:
                    lines = review.readlines()
                print(f"\n  Review {idx + 1}: {review_file}")
                print(f"    Total Lines: {len(lines)}")
                print(f"    Preview (up to 5 lines):")
                print("    " + "\n    ".join(lines[:5]).strip())


review_summary(directory="aclImdb", max_files=5)
```

```
    This is a really really bad movie. However it's good to laugh at the horrible ideas and "special" effects. The plot centers aroun

Review 4: 10691_1.txt
  Total Lines: 1
  Preview (up to 5 lines):
  never before have i seen such a tale of such talentless hangers on been so ungrateful that their golden goose has failed to lay.

Review 5: 9839_3.txt
  Total Lines: 1
  Preview (up to 5 lines):
  It is a shame that a movie with such a good cinematography as this one had no plot to be supported by the work of Sarah Cawley (c
```

```
# Set up dataset folders
batch_sz = 32
root_path = pathlib.Path("aclImdb")
validation_path = root_path / "val"
training_path = root_path / "train"

for label in ("neg", "pos"):
    os.makedirs(validation_path / label, exist_ok=True)
    file_names = os.listdir(training_path / label)
    rnd = random.Random(1337)
    rnd.shuffle(file_names)
    val_count = int(0.2 * len(file_names))
    selected_for_val = file_names[-val_count:]

    for file in selected_for_val:
        src = training_path / label / file
        dest = validation_path / label / file
        if not os.path.exists(dest):
            shutil.move(src, dest)
```

```
# Load IMDB dataset splits
train_data = keras.utils.text_dataset_from_directory(
    "aclImdb/train", batch_size=batch_sz
)

validation_data = keras.utils.text_dataset_from_directory(
    "aclImdb/val", batch_size=batch_sz
)

test_data = keras.utils.text_dataset_from_directory(
    "aclImdb/test", batch_size=batch_sz
)

text_only_train = train_data.map(lambda text, label: text)
```

```
Found 20000 files belonging to 2 classes.
Found 5000 files belonging to 2 classes.
Found 25000 files belonging to 2 classes.
```

```
# Define tokenization settings
seq_len = 150
vocab_limit = 10000
tokenizer = layers.TextVectorization(
    max_tokens=vocab_limit,
    output_mode="int",
    output_sequence_length=seq_len,
)

tokenizer.adapt(text_only_train)
```

```
# Tokenize the datasets
encoded_train_ds = train_data.map(
    lambda text, label: (tokenizer(text), label),
    num_parallel_calls=4).take(100)  # Limit to 100 training samples

encoded_val_ds = validation_data.map(
    lambda text, label: (tokenizer(text), label),
    num_parallel_calls=4).take(10000)  # Limit to 10,000 validation samples

encoded_test_ds = test_data.map(
```

```
    lambda text, label: (tokenizer(text), label),
    num_parallel_calls=4)


# Model with embedding and LSTM layers
input_layer = tf.keras.Input(shape=(None,), dtype="int64")
embedded_layer = layers.Embedding(input_dim=vocab_limit, output_dim=128)(input_layer)
encoded_output = layers.Bidirectional(layers.LSTM(32))(embedded_layer)
dropout_layer = layers.Dropout(0.2)(encoded_output)
output_layer = layers.Dense(1, activation="sigmoid")(dropout_layer)

embedding_model = tf.keras.Model(input_layer, output_layer)

embedding_model.compile(optimizer="rmsprop",
                        loss="binary_crossentropy",
                        metrics=["accuracy"])

embedding_model.summary()
```

Model: "functional"

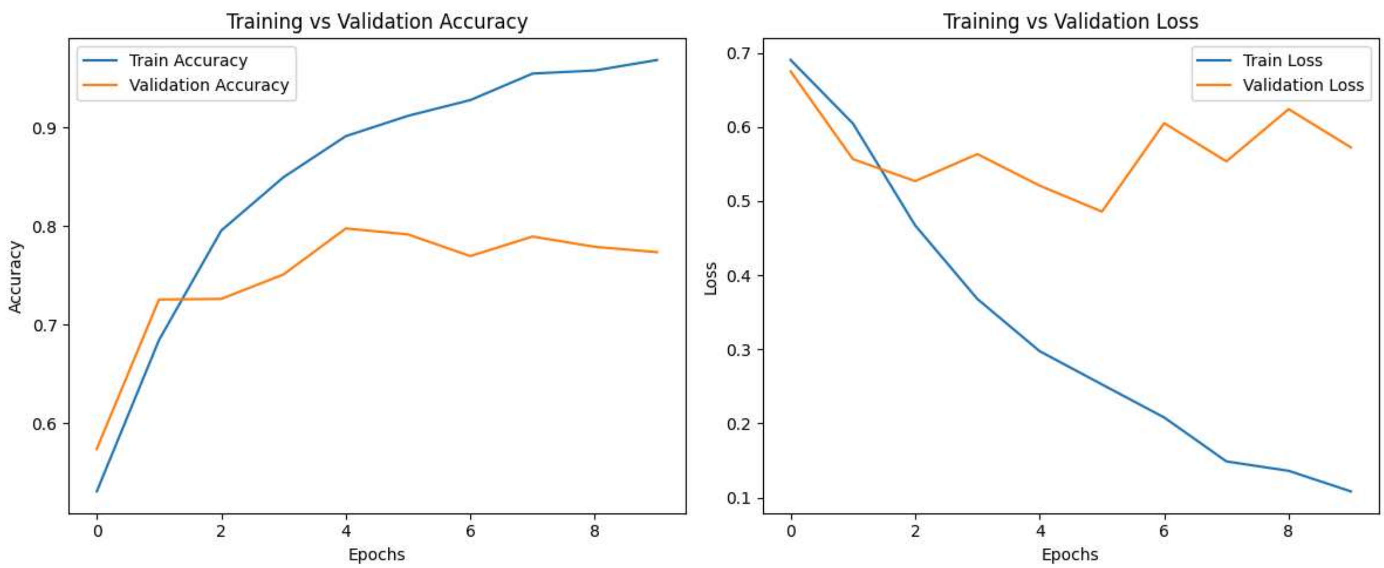
Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, None)	0
embedding (Embedding)	(None, None, 128)	1,280,000
bidirectional (Bidirectional)	(None, 64)	41,216
dropout (Dropout)	(None, 64)	0
dense (Dense)	(None, 1)	65

Total params: 1,321,281 (5.04 MB)
Trainable params: 1,321,281 (5.04 MB)

```
callbacks_list = [
    tf.keras.callbacks.ModelCheckpoint("embedding_model.keras", save_best_only=True)
]



checkpoint_callbacks = [
    tf.keras.callbacks.ModelCheckpoint("best_embedding_model.keras", save_best_only=True)
]



import matplotlib.pyplot as plt

# Fit the model and store the training history
history_embedded = embedding_model.fit(
    encoded_train_ds,
    validation_data=encoded_val_ds,
    epochs=10,  # Adjust the number of epochs as needed
    callbacks=checkpoint_callbacks  # Or callbacks_list, if preferred
)

# Extract the training history
train_history = history_embedded.history

# Plot training and validation performance
plt.figure(figsize=(12, 5))

# Subplot for accuracy
plt.subplot(1, 2, 1)
plt.plot(train_history['accuracy'], label='Train Accuracy')
plt.plot(train_history['val_accuracy'], label='Validation Accuracy')
plt.title('Training vs Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

# Subplot for loss
plt.subplot(1, 2, 2)
plt.plot(train_history['loss'], label='Train Loss')
```

```
plt.plot(train_history['val_loss'], label='Validation Loss')
plt.title('Training vs Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Adjust layout and display the plot
plt.tight_layout()
plt.show()
```

```
Epoch 1/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 12s 93ms/step - accuracy: 0.5151 - loss: 0.6929 - val_accuracy: 0.5740 - val_loss: 0.6749
Epoch 2/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 8s 84ms/step - accuracy: 0.6526 - loss: 0.6353 - val_accuracy: 0.7254 - val_loss: 0.5565
Epoch 3/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 8s 84ms/step - accuracy: 0.7788 - loss: 0.4909 - val_accuracy: 0.7260 - val_loss: 0.5269
Epoch 4/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 8s 84ms/step - accuracy: 0.8528 - loss: 0.3682 - val_accuracy: 0.7508 - val_loss: 0.5634
Epoch 5/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 8s 83ms/step - accuracy: 0.8872 - loss: 0.3113 - val_accuracy: 0.7974 - val_loss: 0.5209
Epoch 6/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 8s 84ms/step - accuracy: 0.9194 - loss: 0.2387 - val_accuracy: 0.7914 - val_loss: 0.4858
Epoch 7/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 8s 82ms/step - accuracy: 0.9236 - loss: 0.2171 - val_accuracy: 0.7694 - val_loss: 0.6052
Epoch 8/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 8s 83ms/step - accuracy: 0.9505 - loss: 0.1587 - val_accuracy: 0.7892 - val_loss: 0.5536
Epoch 9/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 8s 84ms/step - accuracy: 0.9623 - loss: 0.1158 - val_accuracy: 0.7788 - val_loss: 0.6240
Epoch 10/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 8s 85ms/step - accuracy: 0.9768 - loss: 0.0860 - val_accuracy: 0.7734 - val_loss: 0.5724
```




```
# Download and extract GloVe word embeddings
!wget http://nlp.stanford.edu/data/glove.6B.zip -O glove_embeddings.zip
!unzip -q glove_embeddings.zip
```

```
--2025-04-08 17:15:47--  http://nlp.stanford.edu/data/glove.6B.zip
Resolving nlp.stanford.edu (nlp.stanford.edu)... 171.64.67.140
Connecting to nlp.stanford.edu (nlp.stanford.edu)|171.64.67.140|:80... connected.
HTTP request sent, awaiting response... 302 Found
Location: https://nlp.stanford.edu/data/glove.6B.zip [following]
--2025-04-08 17:15:47--  https://nlp.stanford.edu/data/glove.6B.zip
Connecting to nlp.stanford.edu (nlp.stanford.edu)|171.64.67.140|:443... connected.
HTTP request sent, awaiting response... 301 Moved Permanently
Location: https://downloads.cs.stanford.edu/nlp/data/glove.6B.zip [following]
--2025-04-08 17:15:48--  https://downloads.cs.stanford.edu/nlp/data/glove.6B.zip
Resolving downloads.cs.stanford.edu (downloads.cs.stanford.edu)... 171.64.64.22
Connecting to downloads.cs.stanford.edu (downloads.cs.stanford.edu)|171.64.64.22|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 862182613 (822M) [application/zip]
Saving to: ‘glove_embeddings.zip’

glove_embeddings.zi 100%[===================>] 822.24M  5.01MB/s    in 2m 39s
```

```
2025-04-08 17:18:27 (5.17 MB/s) - ‘glove_embeddings.zip’ saved [862182613/862182613]
```

```
# Prepare the GloVe embedding matrix
embedding_dim = 100
glove_file_path = "glove.6B.100d.txt"

embeddings_dict = {}
with open(glove_file_path) as f:
    for line in f:
        word, coefficients = line.split(maxsplit=1)
        coefficients = np.fromstring(coefficients, "f", sep=" ")
        embeddings_dict[word] = coefficients

vocab_list = tokenizer.get_vocabulary()
word_to_idx = dict(zip(vocab_list, range(len(vocab_list))))

embedding_matrix = np.zeros((vocab_limit, embedding_dim))
for word, index in word_to_idx.items():
    if index < vocab_limit:
        vector = embeddings_dict.get(word)
        if vector is not None:
            embedding_matrix[index] = vector
```

```
# Pretrained embedding layer model
embedding_layer = layers.Embedding(
    vocab_limit,
    embedding_dim,
    embeddings_initializer=tf.keras.initializers.Constant(embedding_matrix),
    trainable=False,
    mask_zero=True,
)

input_layer = tf.keras.Input(shape=(None,), dtype="int64")
embedded_output = embedding_layer(input_layer)
encoded_output = layers.Bidirectional(layers.LSTM(32))(embedded_output)
dropout_layer = layers.Dropout(0.2)(encoded_output)
output_layer = layers.Dense(1, activation="sigmoid")(dropout_layer)

pretrained_embedding_model = tf.keras.Model(input_layer, output_layer)
```

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers as l # Import layers and assign alias 'l'

input_layer = tf.keras.Input(shape=(None,), dtype="int64")
embedded_output = embedding_layer(input_layer)
encoded_output = l.Bidirectional(l.LSTM(32))(embedded_output)
dropout_layer = l.Dropout(0.2)(encoded_output)
output_layer = l.Dense(1, activation="sigmoid")(dropout_layer)

pretrained_model = tf.keras.Model(input_layer, output_layer)

pretrained_model.compile(optimizer="rmsprop",
                         loss="binary_crossentropy",
                         metrics=["accuracy"])

pretrained_model.summary()
```

```
Model: "functional_2"
```

Layer (type)	Output Shape	Param #	Connected to
input_layer_2 (InputLayer)	(None, None)	0	-
embedding_1 (Embedding)	(None, None, 100)	1,000,000	input_layer_2[0][0]
not_equal_1 (NotEqual)	(None, None)	0	input_layer_2[0][0]
bidirectional_2 (Bidirectional)	(None, 64)	34,048	embedding_1[1][0], not_equal_1[0][0]
dropout_2 (Dropout)	(None, 64)	0	bidirectional_2[0][0]
dense_2 (Dense)	(None, 1)	65	dropout_2[0][0]

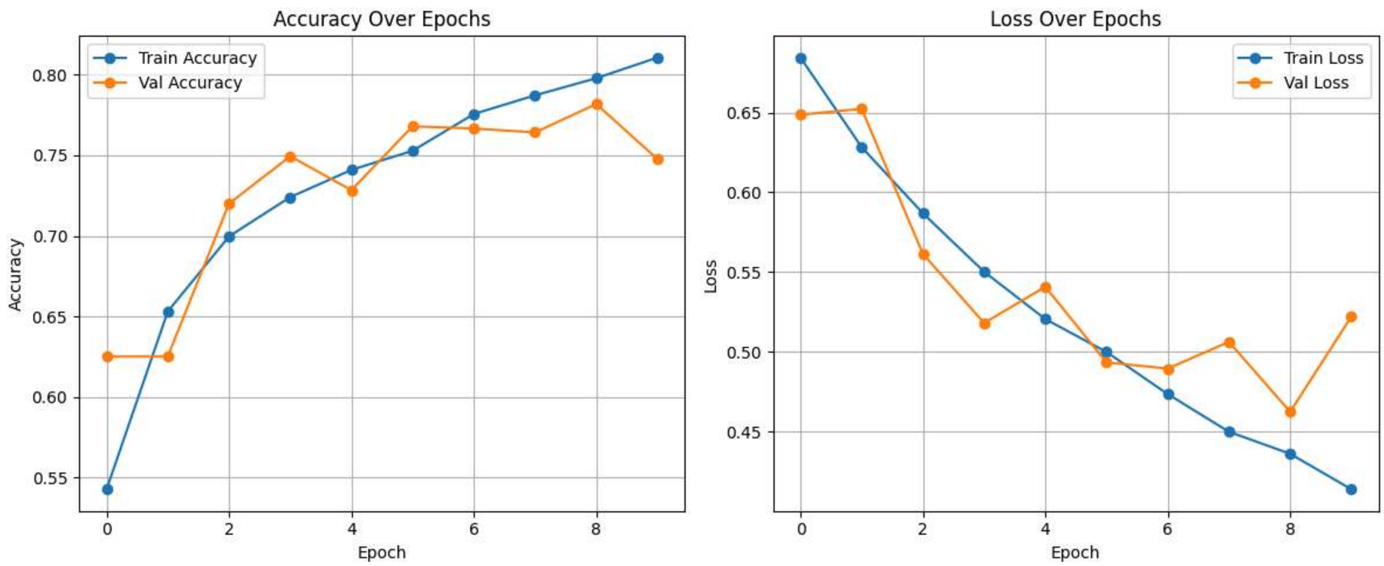
```
Total params: 1,034,113 (3.94 MB)
Trainable params: 34,113 (133.25 KB)
```

```
training_callbacks = [
    keras.callbacks.ModelCheckpoint("pretrained_lstm_model.keras", save_best_only=True)
]

training_history = pretrained_model.fit(
    encoded_train_ds,
    validation_data=encoded_val_ds,
    epochs=10,
    callbacks=training_callbacks
)
```

```
Epoch 1/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 24s 212ms/step - accuracy: 0.5133 - loss: 0.6977 - val_accuracy: 0.6252 - val_loss: 0.6486
Epoch 2/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 11s 108ms/step - accuracy: 0.6407 - loss: 0.6368 - val_accuracy: 0.6252 - val_loss: 0.6523
Epoch 3/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 12s 124ms/step - accuracy: 0.6992 - loss: 0.5907 - val_accuracy: 0.7200 - val_loss: 0.5614
Epoch 4/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 11s 109ms/step - accuracy: 0.7193 - loss: 0.5519 - val_accuracy: 0.7494 - val_loss: 0.5181
Epoch 5/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 10s 97ms/step - accuracy: 0.7336 - loss: 0.5269 - val_accuracy: 0.7284 - val_loss: 0.5408
Epoch 6/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 12s 122ms/step - accuracy: 0.7370 - loss: 0.5066 - val_accuracy: 0.7680 - val_loss: 0.4934
Epoch 7/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 12s 124ms/step - accuracy: 0.7846 - loss: 0.4611 - val_accuracy: 0.7666 - val_loss: 0.4895
Epoch 8/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 10s 102ms/step - accuracy: 0.7897 - loss: 0.4503 - val_accuracy: 0.7642 - val_loss: 0.5063
Epoch 9/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 12s 119ms/step - accuracy: 0.8000 - loss: 0.4327 - val_accuracy: 0.7818 - val_loss: 0.4624
Epoch 10/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 11s 110ms/step - accuracy: 0.8049 - loss: 0.4118 - val_accuracy: 0.7476 - val_loss: 0.5222
```

```
import matplotlib.pyplot as plt

# Extract training history
metrics = training_history.history # Changed from history_pretrained to training_history

# Create a figure with two subplots
plt.figure(figsize=(12, 5))

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

# Loss plot
plt.subplot(1, 2, 2)
plt.plot(metrics['loss'], label='Train Loss', marker='o')
plt.plot(metrics['val_loss'], label='Val Loss', marker='o')
plt.title('Loss Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Loss')
```

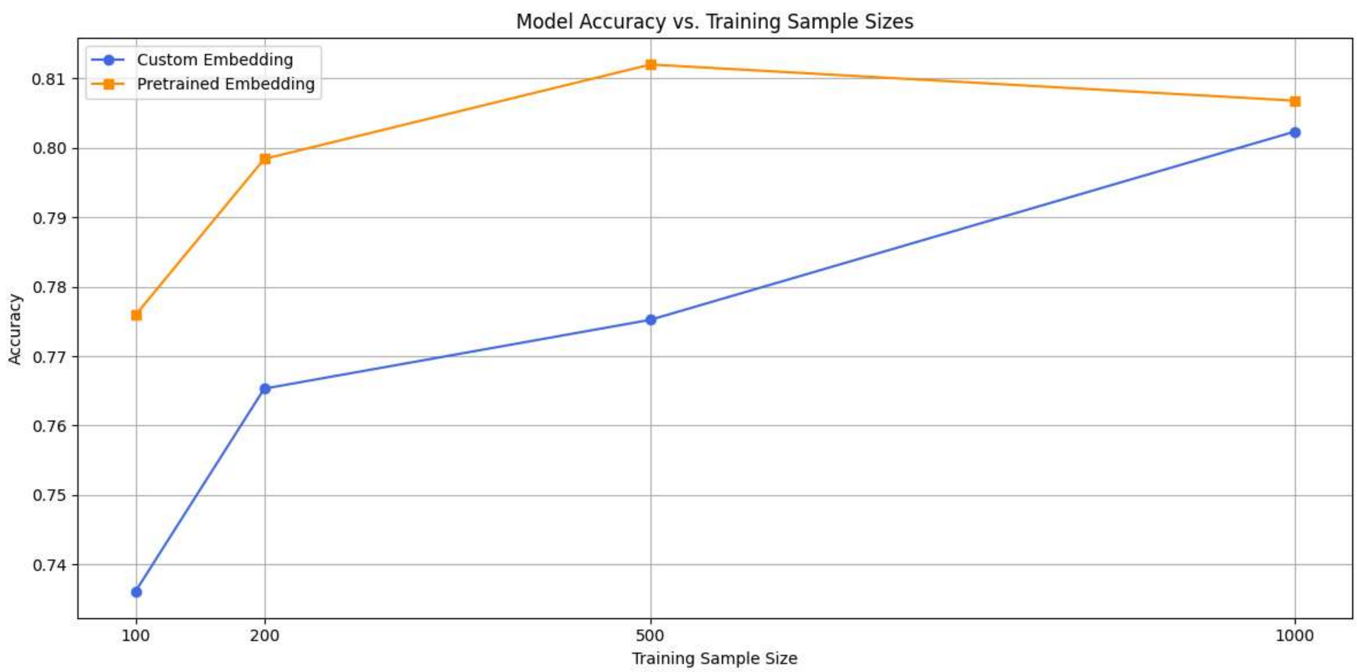
```
plt.legend()
plt.grid(True)

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




```
import numpy as np
import matplotlib.pyplot as plt
import time

# Define training sizes
sample_sizes = [100, 200, 500, 1000]
embed_accs = []
pretrained_accs = []

# Setup plot
plt.figure(figsize=(12, 6))
plt.title('Model Accuracy vs. Training Sample Sizes')
plt.xlabel('Training Sample Size')
plt.ylabel('Accuracy')
plt.grid(True)

# Iterate through each sample size
for size in sample_sizes:
    print(f"\n### Training with {size} samples ###")

    # Prepare dataset of current sample size
    limited_train_ds = train_data.take(size)
    # Tokenize the limited dataset
    limited_encoded_train_ds = limited_train_ds.map(lambda text, label: (tokenizer(text), label))


    # Train custom embedding model
    print("→ Training Custom Embedding Model")
    embedding_model.fit(limited_encoded_train_ds, validation_data=encoded_val_ds, epochs=10, verbose=0)
    acc_embed = embedding_model.evaluate(encoded_test_ds, verbose=0)[1]
    embed_accs.append(acc_embed)
    print(f"Custom Embedding Accuracy: {acc_embed:.4f}")

    # Train pretrained embedding model
    print("→ Training Pretrained Embedding Model")
    pretrained_model.fit(limited_encoded_train_ds, validation_data=encoded_val_ds, epochs=10, verbose=0)
    acc_pretrained = pretrained_model.evaluate(encoded_test_ds, verbose=0)[1]
    pretrained_accs.append(acc_pretrained)
    print(f"Pretrained Embedding Accuracy: {acc_pretrained:.4f}")

# Plot final results
plt.plot(sample_sizes, embed_accs, marker='o', label='Custom Embedding', color='royalblue')
plt.plot(sample_sizes, pretrained_accs, marker='s', label='Pretrained Embedding', color='darkorange')
```

```
plt.xticks(sample_sizes)
plt.legend()
plt.tight_layout()
plt.show()
```

```
### Training with 100 samples ###
→ Training Custom Embedding Model
Custom Embedding Accuracy: 0.7361
→ Training Pretrained Embedding Model
Pretrained Embedding Accuracy: 0.7759

### Training with 200 samples ###
→ Training Custom Embedding Model
Custom Embedding Accuracy: 0.7653
→ Training Pretrained Embedding Model
Pretrained Embedding Accuracy: 0.7984

### Training with 500 samples ###
→ Training Custom Embedding Model
Custom Embedding Accuracy: 0.7752
→ Training Pretrained Embedding Model
Pretrained Embedding Accuracy: 0.8120

### Training with 1000 samples ###
→ Training Custom Embedding Model
Custom Embedding Accuracy: 0.8023
→ Training Pretrained Embedding Model
Pretrained Embedding Accuracy: 0.8068
```

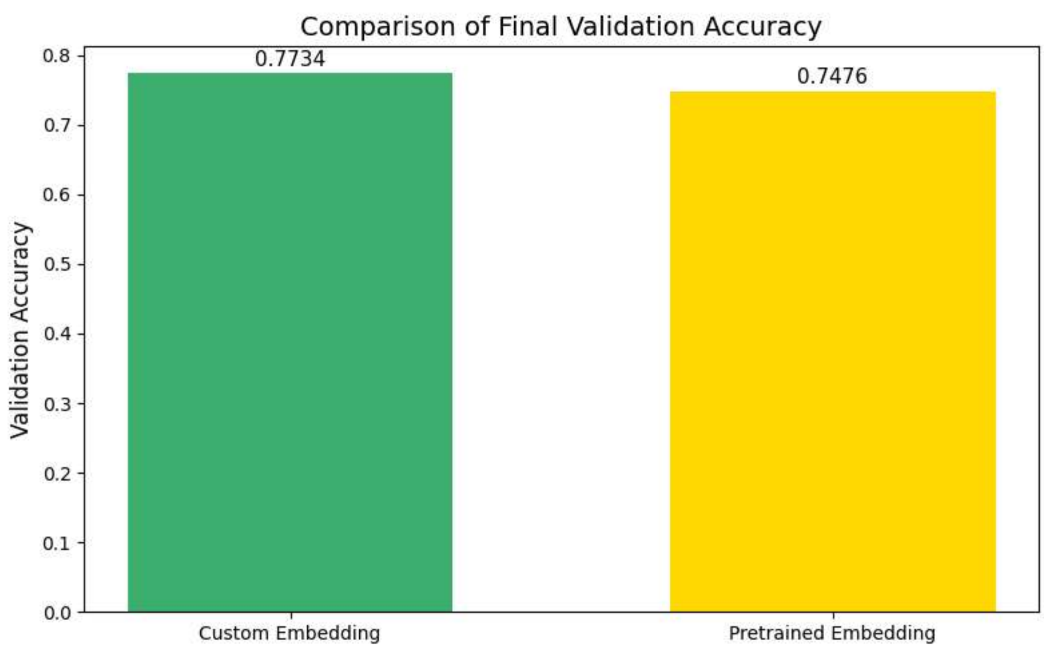



```
import pandas as pd

# Combine results into a single DataFrame
summary_df = pd.DataFrame({
    "Sample Size": sample_sizes,
    "Custom Embedding Accuracy": embed_accs,  # Use embed_accs instead of embedding_accuracies
    "Pretrained Embedding Accuracy": pretrained_accs  # Use pretrained_accs instead of pretrained_accuracies
})

# Display summary table
print("\n=== Model Accuracy Summary ===")
print(summary_df.to_string(index=False))
```

```
=== Model Accuracy Summary ===
 Sample Size  Custom Embedding Accuracy  Pretrained Embedding Accuracy
         100                    0.73612                        0.77592
         200                    0.76532                        0.79840
```

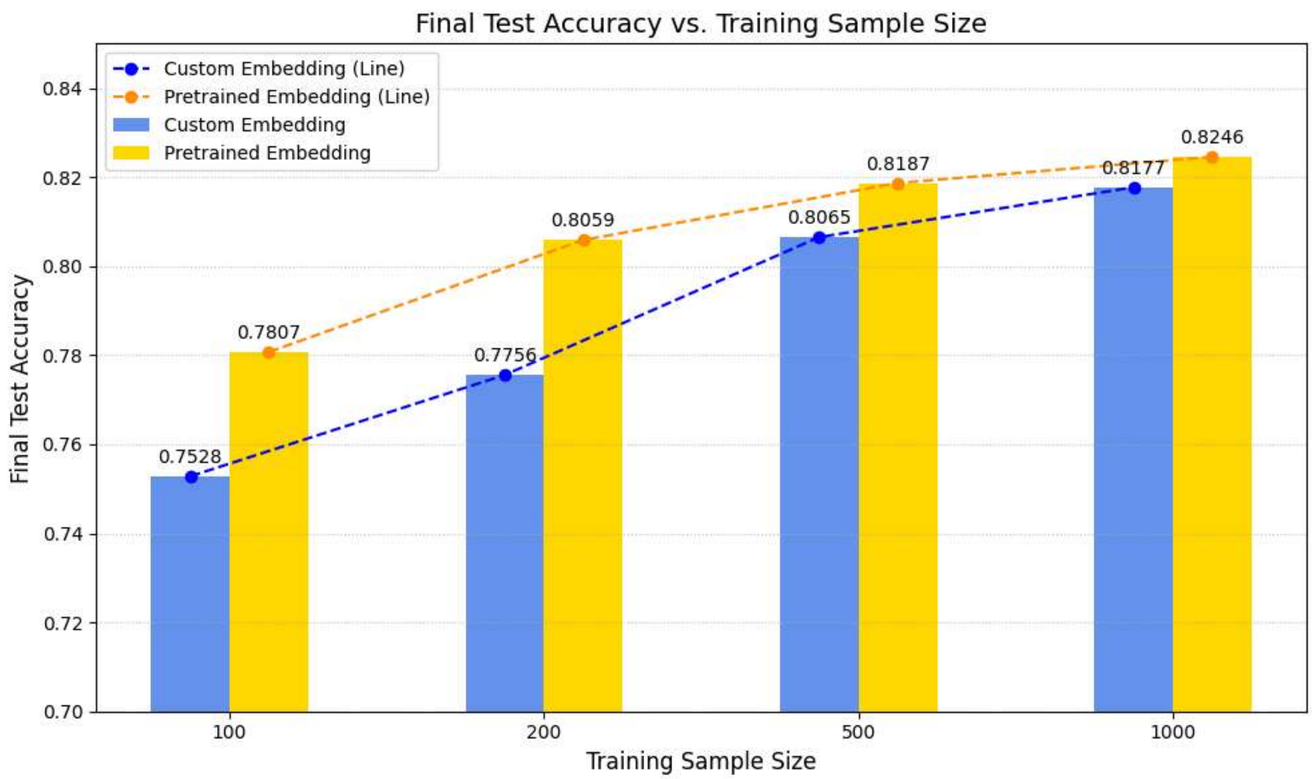
```
 500                   0.77524                         0.81200
1000                   0.80232                         0.80680
```

```
import numpy as np
import matplotlib.pyplot as plt

# Define model names and final validation accuracies
models = ['Custom Embedding', 'Pretrained Embedding']
final_val_accuracies = [
    history_embedded.history['val_accuracy'][-1],
    training_history.history['val_accuracy'][-1]  # Use training_history instead of history_pretrained
]

# Create bar plot
plt.figure(figsize=(8, 5))
bars = plt.bar(models, final_val_accuracies, color=['mediumseagreen', 'gold'], width=0.6)

# Add labels and title
plt.ylabel('Validation Accuracy', fontsize=12)
plt.title('Comparison of Final Validation Accuracy', fontsize=14)

# Annotate bars with accuracy values
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, height + 0.005,
             f'{height:.4f}', ha='center', va='bottom', fontsize=11)

# Show the plot
plt.tight_layout()
plt.show()
```




```
import numpy as np
import matplotlib.pyplot as plt

# Data
sample_sizes = [100, 200, 500, 1000]
embedding_accuracies = [0.75280, 0.77556, 0.80652, 0.81772]
pretrained_accuracies = [0.78072, 0.80588, 0.81868, 0.82456]

# Setup
bar_width = 0.25
x = np.arange(len(sample_sizes))

# Plot
plt.figure(figsize=(10, 6))

# Bars
bars1 = plt.bar(x - bar_width/2, embedding_accuracies, width=bar_width,
                color='cornflowerblue', label='Custom Embedding')
```

```
bars2 = plt.bar(x + bar_width/2, pretrained_accuracies, width=bar_width,
                color='gold', label='Pretrained Embedding')

# Lines
plt.plot(x - bar_width/2, embedding_accuracies, marker='o',
         color='blue', linestyle='--', label='Custom Embedding (Line)')
plt.plot(x + bar_width/2, pretrained_accuracies, marker='o',
         color='darkorange', linestyle='--', label='Pretrained Embedding (Line)')

# Labels & title
plt.xlabel('Training Sample Size', fontsize=12)
plt.ylabel('Final Test Accuracy', fontsize=12)
plt.title('Final Test Accuracy vs. Training Sample Size', fontsize=14)
plt.xticks(x, sample_sizes)
plt.ylim(0.7, 0.85)
plt.legend()

# Annotate values
for i in range(len(sample_sizes)):
    plt.text(x[i] - bar_width/2, embedding_accuracies[i] + 0.003,
             f'{embedding_accuracies[i]:.4f}', ha='center', fontsize=10)
    plt.text(x[i] + bar_width/2, pretrained_accuracies[i] + 0.003,
             f'{pretrained_accuracies[i]:.4f}', ha='center', fontsize=10)

# Final touches
plt.grid(axis='y', linestyle=':', alpha=0.7)
plt.tight_layout()
plt.show()
```



Start coding or generate with AI.