```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
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,\ SimpleRNN,\ LSTM,\ Dense,\ Dropout
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report
# Set random seed
np.random.seed(42)
tf.random.set_seed(42)
# Create sample dataset (replace with your own dataset)
def load data():
    # Sample data - in real application, load your dataset
    texts = [
        "I absolutely loved this movie, it was fantastic!",
        "This product is amazing, best purchase ever",
        "The service was terrible and the staff was rude",
        "I really hated the experience, would not recommend",
        "The movie was okay, nothing special but not bad either",
        "This restaurant is great, I'll definitely come back",
        "The quality of the product is poor",
        "I'm quite satisfied with my purchase",
        "The customer service was outstanding",
        "This is the worst experience I've ever had"
    1
    # Labels: 0=negative, 1=neutral, 2=positive
    labels = [2, 2, 0, 0, 1, 2, 0, 1, 2, 0]
    # Generate more data by adding variations
    expanded texts = texts.copy()
    expanded_labels = labels.copy()
    modifiers = ["really", "very", "extremely", "somewhat", "kind of"]
    for _ in range(90): # Add 90 more samples
        idx = np.random.randint(0, len(texts))
        text = texts[idx]
        label = labels[idx]
        # Add random modifier
        if np.random.random() > 0.5:
            words = text.split()
            insert_pos = np.random.randint(1, len(words))
            words.insert(insert_pos, np.random.choice(modifiers))
            text = " ".join(words)
        expanded_texts.append(text)
        expanded_labels.append(label)
    return np.array(expanded_texts), np.array(expanded_labels)
# Load and prepare data
texts, labels = load_data()
X_train, X_test, y_train, y_test = train_test_split(texts, labels, test_size=0.2)
# Tokenize text
max words = 5000
max\_len = 100
tokenizer = Tokenizer(num_words=max_words)
tokenizer.fit_on_texts(X_train)
X_train_seq = tokenizer.texts_to_sequences(X_train)
X_test_seq = tokenizer.texts_to_sequences(X_test)
# Pad sequences
X_train_pad = pad_sequences(X_train_seq, maxlen=max_len)
X test pad = pad sequences(X test seq, maxlen=max len)
# Build RNN model
model = Sequential([
    Embedding(max_words, 128, input_length=max_len),
    LSTM(64, return_sequences=True), # Use LSTM instead of SimpleRNN for better performance
    Dropout(0.3),
    LSTM(32), # Second LSTM layer
    Dropout(0.3),
    Dense(3, activation='softmax') # 3 classes: negative, neutral, positive
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    model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
    # Train model
    history = model.fit(
        X_train_pad, y_train,
        epochs=10,
        batch_size=32,
        validation_split=0.2,
        verbose=1
    )
    # Evaluate model
    loss, accuracy = model.evaluate(X_test_pad, y_test)
    print(f"Test accuracy: {accuracy:.4f}")
    # Make predictions
    y_pred = model.predict(X_test_pad)
    y_pred_classes = np.argmax(y_pred, axis=1)
    # Generate confusion matrix
    cm = confusion_matrix(y_test, y_pred_classes)
    plt.figure(figsize=(8, 6))
    plt.imshow(cm, interpolation='nearest', cmap='Blues')
    plt.title('Confusion Matrix')
    plt.colorbar()
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.xticks([0, 1, 2], ['Negative', 'Neutral', 'Positive'])
plt.yticks([0, 1, 2], ['Negative', 'Neutral', 'Positive'])
    # Add labels in each cell
    for i in range(3):
        for j in range(3):
            plt.text(j, i, str(cm[i, j]), ha='center', va='center')
    plt.tight_layout()
    plt.savefig('confusion matrix.png')
    plt.close()
    # Print classification report
    print("\nClassification Report:")
    print(classification_report(y_test, y_pred_classes,
                                target_names=['Negative', 'Neutral', 'Positive']))
    # Plot training history
    plt.figure(figsize=(12, 5))
    plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'], label='Training')
    plt.plot(history.history['val_accuracy'], label='Validation')
    plt.title('Model Accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()
    plt.subplot(1, 2, 2)
    plt.plot(history.history['loss'], label='Training')
    plt.plot(history.history['val_loss'], label='Validation')
    plt.title('Model Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()
    plt.tight_layout()
    plt.savefig('training_history.png')
    plt.close()
    # Test with new examples
    def predict sentiment(text):
        sequence = tokenizer.texts_to_sequences([text])
        padded = pad_sequences(sequence, maxlen=max_len)
        prediction = model.predict(padded)[0]
        class_idx = np.argmax(prediction)
        sentiment = ['Negative', 'Neutral', 'Positive'][class_idx]
        return sentiment, prediction[class_idx]
    # Test examples
    test_examples = [
        "The food was delicious and the service was excellent",
        "This was a complete waste of money",
        "The product works as expected, nothing extraordinary"
```

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print("\nPredictions on new examples:")
for text in test examples:
    sentiment, confidence = predict_sentiment(text)
    print(f"Text: '{text}'")
    print(f"Sentiment: {sentiment} (confidence: {confidence:.4f})")
print("Analysis complete.")
```

warnings.warn(

Model: "sequential"

Layer (type)	Output Shape	Param #
embedding (Embedding)	?	0 (unbuilt)
lstm (LSTM)	?	0 (unbuilt)
dropout (Dropout)	?	0
lstm_1 (LSTM)	?	0 (unbuilt)
dropout_1 (Dropout)	?	0
dense (Dense)	?	0 (unbuilt)

```
Total params: 0 (0.00 B)
 Trainable params: 0 (0.00 B)
 Non-trainable params: 0 (0.00 B)
Epoch 1/10
2/2 -
                       - 18s 2s/step - accuracy: 0.3333 - loss: 1.0985 - val_accuracy: 0.3750 - val_loss: 1.0777
Epoch 2/10
2/2
                        3s 176ms/step - accuracy: 0.4375 - loss: 1.0705 - val_accuracy: 0.3750 - val_loss: 1.0532
Epoch 3/10
                        - 0s 268ms/step - accuracy: 0.4375 - loss: 1.0397 - val_accuracy: 0.3750 - val_loss: 1.0282
2/2
Epoch 4/10
2/2
                       - 1s 256ms/step - accuracy: 0.4375 - loss: 1.0052 - val accuracy: 0.3750 - val loss: 1.0061
Epoch 5/10
2/2
                        - 1s 264ms/step - accuracy: 0.4375 - loss: 0.9772 - val_accuracy: 0.3750 - val_loss: 0.9730
Epoch 6/10
2/2
                        - 1s 164ms/step - accuracy: 0.4375 - loss: 0.9723 - val_accuracy: 0.3750 - val_loss: 0.9185
Epoch 7/10
                         0s 186ms/step - accuracy: 0.4583 - loss: 0.9290 - val_accuracy: 0.5000 - val_loss: 0.8658
2/2
Epoch 8/10
                        - 0s 158ms/step - accuracy: 0.6562 - loss: 0.8393 - val accuracy: 0.6250 - val loss: 0.8111
2/2
Epoch 9/10
2/2 -
                        0s 157ms/step - accuracy: 0.6875 - loss: 0.8011 - val_accuracy: 0.6250 - val_loss: 0.7494
Epoch 10/10
                         0s 160ms/step - accuracy: 0.6771 - loss: 0.7376 - val_accuracy: 0.6250 - val_loss: 0.6919
2/2
1/1
                        - 0s 59ms/step - accuracy: 0.8000 - loss: 0.6997
Test accuracy: 0.8000
                        - 0s 360ms/step
Classification Report:
                           recall f1-score
              precision
                                              support
                   0.90
                             1.00
                                       0.95
                                                     9
   Negative
    Neutral
                   0.00
                             0.00
                                       0.00
                                                     4
    Positive
                   9.79
                             1.00
                                       0.82
                                                    7
    accuracy
                                       0.80
                                                   20
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0.53
                               0.67
                                          0.59
                                                       20
   macro avg
weighted avg
                    0.65
                               0.80
                                          0.71
```

/usr/local/lib/python3.11/dist-packages/sklearn/metrics/\_classification.py:1565: UndefinedMetricWarning: Precision is ill-define \_warn\_prf(average, modifier, f"{metric.capitalize()} is", len(result))

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Predictions on new examples:
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0s 345ms/step
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Text: 'The food was delicious and the service was excellent'

Sentiment: Positive (confidence: 0.5338)

## 0s 44ms/step

Text: 'This was a complete waste of money' Sentiment: Positive (confidence: 0.8031)

**- 0s** 44ms/step

Text: 'The product works as expected, nothing extraordinary'

Sentiment: Positive (confidence: 0.7214)

Analysis complete.

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