1. Download and Extract the Dataset

```
!wget https://ai.stanford.edu/~amaas/data/sentiment/aclImdb_v1.tar.gz # Download the IMDB movie reviews dataset
!tar -xzf aclImdb_v1.tar.gz # Extract the contents of the compressed file
```

Show hidden output

2. Load and Preprocess the Data

```
import os
from sklearn.utils import shuffle  # used to shuffle the data randomly

# Function to load text and labels from a given directory
def load_imdb_data(data_dir):
    texts, labels = [], []
    for label_type in ['pos', 'neg']:  # loop through positive and negative folders
        dir_name = os.path.join(data_dir, label_type)
        for fname in os.listdir(dir_name):  # loop through each file in the folder
            if fname.endswith('.txt'):
                with open(os.path.join(dir_name, fname), encoding='utf-8') as f:
                    texts.append(f.read())
                labels.append(1 if label_type == 'pos' else 0)  # label: 1 for pos, 0 for neg
    return texts, labels

# Load training and test data
train_texts, train_labels = load_imdb_data('aclImdb/train')
test_texts, test_labels = load_imdb_data('aclImdb/test')

# Shuffle the data to avoid any order bias
train_texts, train_labels = shuffle(train_texts, train_labels, random_state=42)
test_texts, test_labels = shuffle(test_texts, test_labels, random_state=42)
```

3. Text Preprocessing

```
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
import numpy as np

# Parameters
max_words = 10000 # maximum number of words to keep based on frequency.
maxlen = 500 # ensures that all input sequences are of the same fixed length (500 tokens).

# Tokenize
tokenizer = Tokenizer(num_words=max_words)
tokenizer.fit_on_texts(train_texts)

# Convert texts to sequences of integers (word indices)
x_train = tokenizer.texts_to_sequences(train_texts)
x_test = tokenizer.texts_to_sequences(test_texts)

# Pad sequences to ensure uniform input length for the model
x_train = pad_sequences(x_train, maxlen=maxlen)
x_test = pad_sequences(x_test, maxlen=maxlen)

# Convert labels to NumPy arrays for training
y_train = np.array(train_labels)
y_test = np.array(test_labels)
```

4. Build the CNN Model

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, Conv1D, MaxPooling1D, GlobalMaxPooling1D, Dense, Dropout

model = Sequential([
    Embedding(max_words, 128, input_length=maxlen),# Converts word indices into dense vectors of size 128

    Conv1D(128, 5, activation='relu'), # Applies 128 filters of size 5 to extract local features
```

```
    MaxPooling1D(pool_size=2),  # Downsamples the output of the convolution to reduce dimensionality

    Dropout(0.5),#  Randomly drops 50% of the units to reduce overfitting

    GlobalMaxPooling1D(),  # Flattens the feature maps into a single vector

    Dense(10, activation='relu'),  # Fully connected layer with 10 units and ReLU activation

    Dense(1, activation='sigmoid')  # Single neuron with sigmoid activation for binary classification

])
model.build(input_shape=(None, maxlen))  # explicitly build the model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])# Compile the model with binary cross-entropy loss and Adam

# Display the model architecture
model.summary()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/embedding.py:90: UserWarning: Argument `input_length` is deprecated. Just
  warnings.warn(
Model: "sequential"
```

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 500, 128)	1,280,000
conv1d (Conv1D)	(None, 496, 128)	82,048
max_pooling1d (MaxPooling1D)	(None, 248, 128)	0
dropout (Dropout)	(None, 248, 128)	0
global_max_pooling1d (GlobalMaxPooling1D)	(None, 128)	0
dense (Dense)	(None, 10)	1,290
dense_1 (Dense)	(None, 1)	11

Total params: 1,363,349 (5.20 MB)

5. Train and Evaluate

```
from tensorflow.keras.callbacks import EarlyStopping

history = model.fit(
    x_train, y_train,
    validation_split=0.2,
    epochs=2,
    batch_size=64,
    # callbacks=[EarlyStopping(monitor='val_loss', patience=2)]  # EarlyStopping was TESTED and It was removed because overfitting started a
    # so training was manually limited to 2 epochs for better generalization.
)
# Evaluate on test set
loss, accuracy = model.evaluate(x_test, y_test)
print("Test Accuracy:", accuracy)
model.save("sentiment_cnn_model.h5")
```

```
Epoch 1/2
313/313 ━━━━━━━━━━━━━━━━━━━━ 146s 457ms/step - accuracy: 0.6751 - loss: 0.5822 - val_accuracy: 0.8690 - val_loss: 0.3448
Epoch 2/2
313/313 ━━━━━━━━━━━━━━━━━━━━ 202s 459ms/step - accuracy: 0.9102 - loss: 0.2264 - val_accuracy: 0.8922 - val_loss: 0.2920
782/782 ━━━━━━━━━━━━━━━━━━━━ 45s 57ms/step - accuracy: 0.8831 - loss: 0.3036
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is consi
Test Accuracy: 0.8853999972343445
```

6. Print Some Predictions with Actual Text

```
y_pred_prob = model.predict(x_test)# Predict probabilities for test set

y_pred = (y_pred_prob > 0.5).astype("int32") # Convert probabilities to binary class predictions (threshold = 0.5)

index_word = {v: k for k, v in tokenizer.word_index.items()}# Create a reverse dictionary to map word indices back to words
```

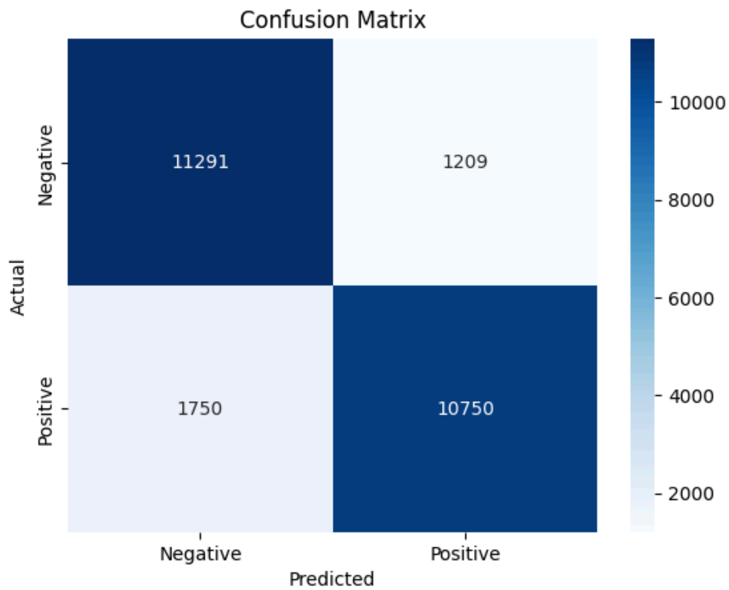
```
def decode_review(seq): # Function to decode a sequence of word indices back to a readable review
    return ' '.join([index_word.get(i, '?') for i in seq if i != 0])

# Print a few sample reviews with their actual and predicted labels
for i in range(5):
    print(f"\n--- Review #{i+1} ---")
    print("Review Text:")
    print(decode_review(x_test[i]))
    print("Actual:", "Positive" if y_test[i] == 1 else "Negative")
    print("Predicted:", "Positive" if y_pred[i] == 1 else "Negative")
    print("="*80)
```

```
782/782 ━━━━━━━━━━━━━━━━━━━━ 43s 55ms/step

--- Review #1 ---
Review Text:
i can't comment on the accuracy of this production historical or literary but i can say that i enjoyed it if there is a god the sound tr
Actual: Positive
Predicted: Positive
================================================================================

--- Review #2 ---
Review Text:
this is possibly the worst of the cockney gangster genre that has the british film industry since guy ritchie unleashed lock stock and t
Actual: Negative
Predicted: Negative
================================================================================

--- Review #3 ---
Review Text:
this was a very faithful presentation of life in the mid 50's the dialogue on and the banter with his follow colleagues was exceptionall
Actual: Positive
Predicted: Positive
================================================================================

--- Review #4 ---
Review Text:
a movie theater with a bad history of past gruesome murders of course the bloody killings start written directed shot scored and edited
Actual: Negative
Predicted: Negative
================================================================================

--- Review #5 ---
Review Text:
a man kicks a dog in the air br br a woman kicks a cow out of her bed br br a man kicks a down the sidewalk br br a woman sucks on a toe
Actual: Negative
Predicted: Negative
================================================================================
```

7. Evaluation metrics

```
# Import necessary libraries for evaluation and visualization
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# Print detailed classification metrics: precision, recall, f1-score for each class
print(classification_report(y_test, y_pred, target_names=["Negative", "Positive"]))

# Compute the confusion matrix to see counts of true positives, true negatives, false positives, and false negatives
cm = confusion_matrix(y_test, y_pred)

# Visualize the confusion matrix as a heatmap with annotations
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=["Negative", "Positive"], yticklabels=["Negative", "Positive"])

# Label axes and add title to the plot
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```

```
              precision    recall  f1-score   support

    Negative       0.87      0.90      0.88     12500
    Positive       0.90      0.86      0.88     12500

    accuracy                           0.88     25000
   macro avg       0.88      0.88      0.88     25000
weighted avg       0.88      0.88      0.88     25000
```



Interpretation of Evaluation:

The model achieved approximately 88% accuracy on the test set, indicating good overall performance in classifying positive and negative reviews.

Precision and recall scores are balanced for both classes (Positive and Negative), with slight variations:

- Negative class: Higher recall (0.90), the model correctly identifies most negative reviews.
- Positive class: Higher precision (0.90), positive predictions are usually correct

F1-Scores (both 0.88) reflect a good balance between precision and recall for both classes.

The confusion matrix confirms most predictions are correct, with few misclassifications.

Overall, the model performs well on unseen data. There is still room for improvement through further tuning, more data, or additional regularization.