```python
import kagglehub

# Download latest version
path = kagglehub.dataset_download("lakshmi25npathi/imdb-dataset-of-50k-movie-reviews")

print("Path to dataset files:", path)
```

```
Using Colab cache for faster access to the 'imdb-dataset-of-50k-movie-reviews' dataset.
Path to dataset files: /kaggle/input/imdb-dataset-of-50k-movie-reviews
```

```python
!ls /kaggle/input/imdb-dataset-of-50k-movie-reviews
```

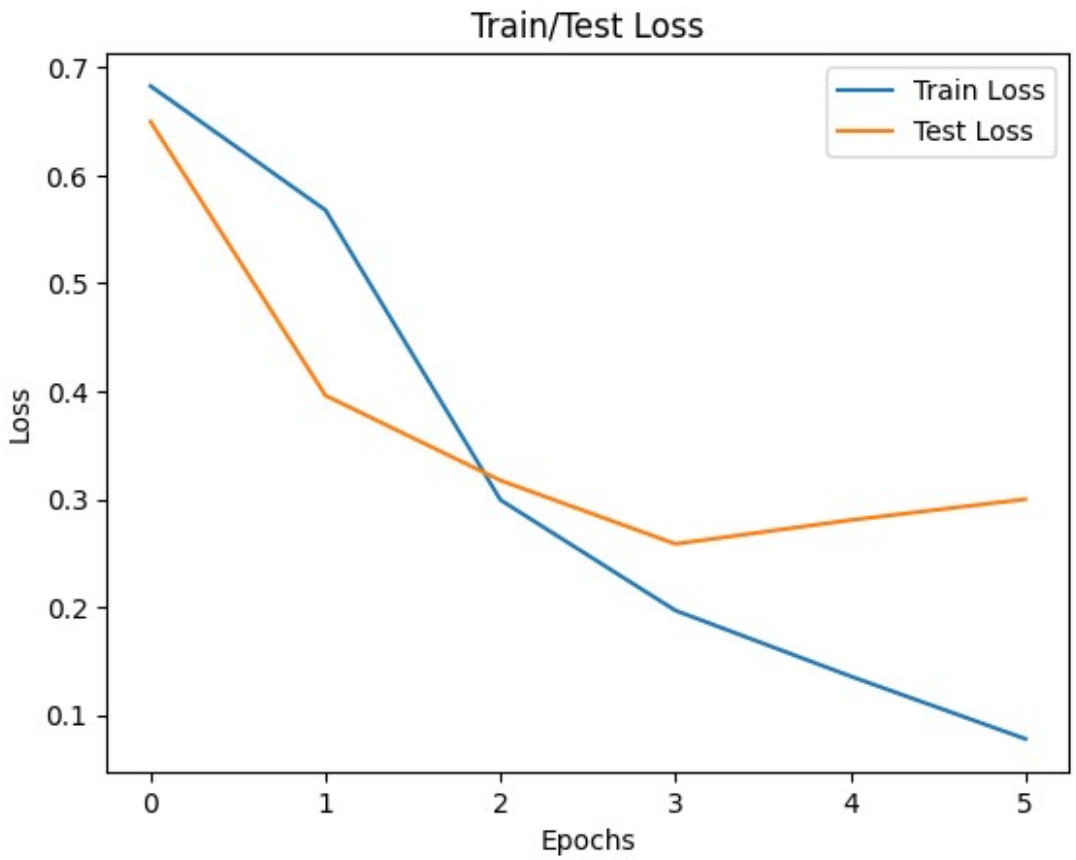
```
'IMDB Dataset.csv'
```

```python
import torch
import torch.nn as nn
import pandas as pd
import numpy as np
import re
from torch.utils.data import Dataset, DataLoader
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from collections import Counter
import matplotlib.pyplot as plt

# -------------------------
# 1 Device
# -------------------------
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

# -------------------------
# 2 Load IMDB dataset
# -------------------------
df = pd.read_csv('/kaggle/input/imdb-dataset-of-50k-movie-reviews/IMDB Dataset.csv')

# Encode labels
le = LabelEncoder()
df['sentiment'] = le.fit_transform(df['sentiment'])

# -------------------------
# 3 Tokenize and Vocabulary
# -------------------------
def tokenize(text):
    return re.findall(r'\b\w+\b', text.lower())

df['tokens'] = df['review'].apply(tokenize)
```

```
all_tokens = [token for tokens in df['tokens'] for token in tokens]
vocab = {word: idx + 2 for idx, (word, _) in
enumerate(Counter(all_tokens).items())}
vocab['<PAD>'] = 0
vocab['<UNK>'] = 1

def encode(tokens):
    return [vocab.get(token, 1) for token in tokens]

df['encoded'] = df['tokens'].apply(encode)

# -------------------------
# 4 Padding
# -------------------------
max_len = 300
def pad_sequence(seq):
    return seq[:max_len] + [0]*(max_len - len(seq)) if len(seq) <
max_len else seq[:max_len]

df['padded'] = df['encoded'].apply(pad_sequence)

# -------------------------
# 5 Train/Test split
# -------------------------
X = np.array(df['padded'].tolist())
y = np.array(df['sentiment'].tolist())

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

X_train = torch.tensor(X_train, dtype=torch.long).to(device)
X_test = torch.tensor(X_test, dtype=torch.long).to(device)
y_train = torch.tensor(y_train, dtype=torch.float32).to(device)
y_test = torch.tensor(y_test, dtype=torch.float32).to(device)

train_data = torch.utils.data.TensorDataset(X_train, y_train)
test_data = torch.utils.data.TensorDataset(X_test, y_test)

train_loader = DataLoader(train_data, batch_size=128, shuffle=True)
test_loader = DataLoader(test_data, batch_size=128)

# -------------------------
# 6 LSTM Model
# -------------------------
class LSTMClassifier(nn.Module):
    def __init__(self, vocab_size, embed_dim=200, hidden_dim=256,
output_dim=1, n_layers=2, bidirectional=True, dropout=0.3):
        super(LSTMClassifier, self).__init__()
        self.embedding = nn.Embedding(vocab_size, embed_dim,
padding_idx=0)
```

```
        self.lstm = nn.LSTM(embed_dim, hidden_dim,
num_layers=n_layers, batch_first=True,
                            bidirectional=bidirectional,
dropout=dropout)
        self.fc = nn.Linear(hidden_dim * 2 if bidirectional else
hidden_dim, output_dim)
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        x = self.embedding(x)
        _, (hidden, _) = self.lstm(x)
        if self.lstm.bidirectional:
            hidden = torch.cat((hidden[-2], hidden[-1]), dim=1)
        else:
            hidden = hidden[-1]
        out = self.fc(hidden)
        return self.sigmoid(out)

model = LSTMClassifier(vocab_size=len(vocab)).to(device)

# -------------------------
# 7 Training
# -------------------------
criterion = nn.BCELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer,
'min', patience=2)

epochs = 6
train_losses, test_losses = [], []

for epoch in range(epochs):
    model.train()
    total_loss = 0
    for inputs, labels in train_loader:
        optimizer.zero_grad()
        outputs = model(inputs).squeeze()
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        total_loss += loss.item()
    train_loss = total_loss / len(train_loader)

    model.eval()
    total_loss = 0
    with torch.no_grad():
        for inputs, labels in test_loader:
            outputs = model(inputs).squeeze()
            loss = criterion(outputs, labels)
            total_loss += loss.item()
```

```
    test_loss = total_loss / len(test_loader)

    train_losses.append(train_loss)
    test_losses.append(test_loss)
    scheduler.step(test_loss)

    print(f"Epoch {epoch+1}/{epochs} | Train Loss: {train_loss:.4f} |
Test Loss: {test_loss:.4f}")

# -------------------------
# 8 Loss Curves
# -------------------------
plt.plot(train_losses, label='Train Loss')
plt.plot(test_losses, label='Test Loss')
plt.legend()
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Train/Test Loss')
plt.show()

# -------------------------
# 9 Evaluate Accuracy
# -------------------------
model.eval()
correct, total = 0, 0
with torch.no_grad():
    for inputs, labels in test_loader:
        outputs = model(inputs).squeeze()
        predicted = (outputs > 0.5).float()
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
accuracy = 100 * correct / total
print(f"Test Accuracy: {accuracy:.2f}%")

Using device: cuda
Epoch 1/6 | Train Loss: 0.6827 | Test Loss: 0.6498
Epoch 2/6 | Train Loss: 0.5677 | Test Loss: 0.3960
Epoch 3/6 | Train Loss: 0.2993 | Test Loss: 0.3174
Epoch 4/6 | Train Loss: 0.1969 | Test Loss: 0.2586
Epoch 5/6 | Train Loss: 0.1360 | Test Loss: 0.2807
Epoch 6/6 | Train Loss: 0.0780 | Test Loss: 0.3000
```




```
Test Accuracy: 89.77%

# 🔍 Prediction
def predict_sentiment(review, model, vocab, max_len, device):
    model.eval()
    tokens = tokenize(review)
    encoded = encode(tokens)
    padded = pad_sequence(encoded)
    input_tensor = torch.tensor(padded,
dtype=torch.long).unsqueeze(0).to(device)
    with torch.no_grad():
        output = model(input_tensor).squeeze()
        prediction = (output > 0.5).item()
    return "Positive" if prediction == 1 else "Negative",
output.item()

# Example prediction
sample_review = "This movie was absolutely amazing! I loved every part
of it."
sentiment, probability = predict_sentiment(sample_review, model,
vocab, max_len, device)
print(f"Review: \"{sample_review}\"")
print(f"Predicted Sentiment: {sentiment} (Probability:
```

```
{probability:.4f})")

sample_review_2 = "This movie was terrible. I hated it."
sentiment_2, probability_2 = predict_sentiment(sample_review_2, model,
vocab, max_len, device)
print(f"Review: \"{sample_review_2}\"")
print(f"Predicted Sentiment: {sentiment_2} (Probability:
{probability_2:.4f})")
```

```
Review: "This movie was absolutely amazing! I loved every part of it."
Predicted Sentiment: Positive (Probability: 0.9903)
Review: "This movie was terrible. I hated it."
Predicted Sentiment: Negative (Probability: 0.0013)
```

```
model.eval()
```

```
LSTMClassifier(
  (embedding): Embedding(101946, 200, padding_idx=0)
  (lstm): LSTM(200, 256, num_layers=2, batch_first=True, dropout=0.3,
bidirectional=True)
  (fc): Linear(in_features=512, out_features=1, bias=True)
  (sigmoid): Sigmoid()
)
```

10/9/25

Exp-8 Long Short-Term Memory (LSTM) Model

Aim:

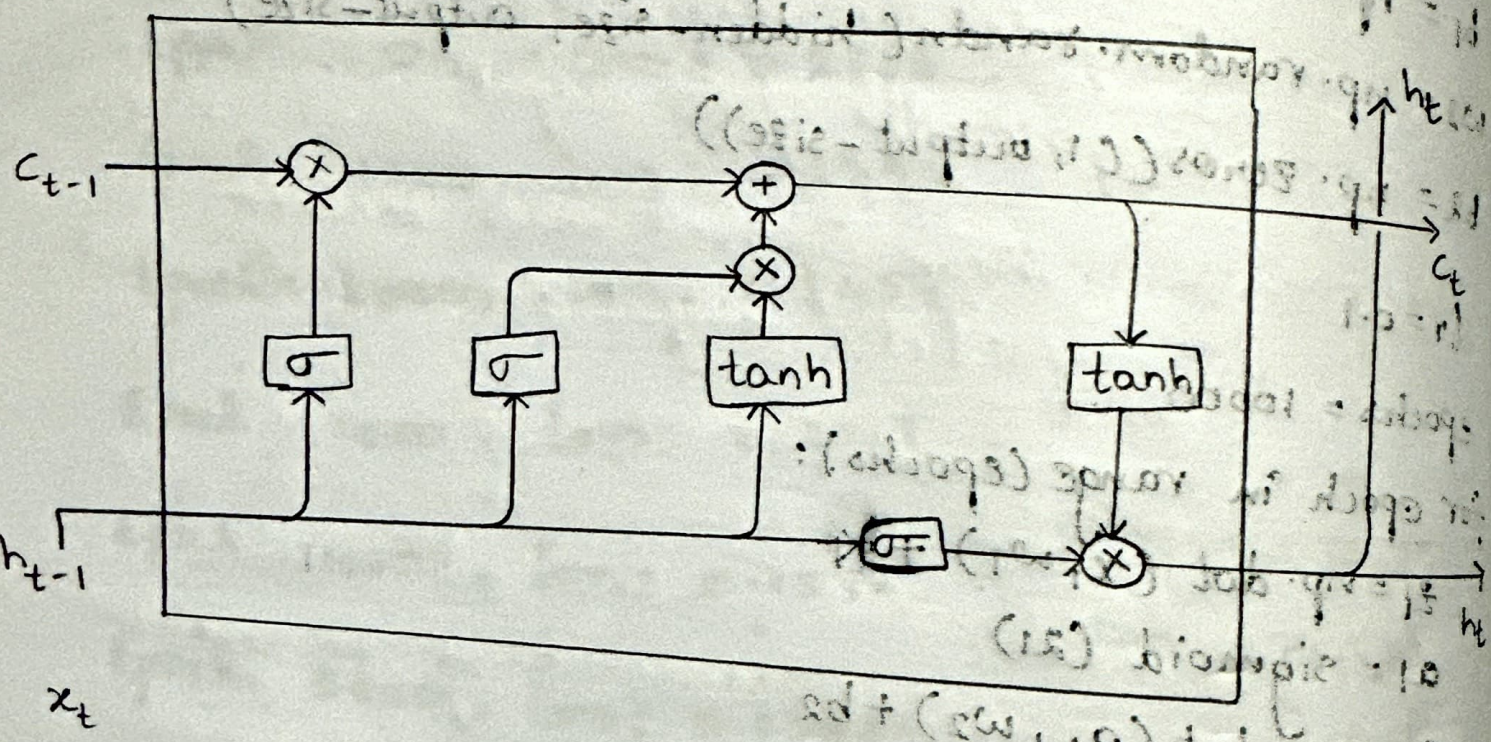
To implement an LSTM model for sequence prediction and observe how it learns temporal dependencies in data.

Description:

LSTMs are a type of RNN designed to capture long-term dependencies in sequential data. They use memory cells and gates (input, forget and output gates) to regulate information flow, making them effective in tasks like time series prediction, language modeling, and speech

Procedure:

1.) Import required libraries and generate a sequence dataset (sine wave).
2.) Preprocess the data into input-output pairs for training.
3.) Define a LSTM model using keras/TensorFlow.
4.) Train the model on the dataset.
5.) Evaluate the model and predict future sequence values.


c_{t-1}
h_{t-1}
x_t
σ
σ
tanh
σ
tanh
c_t
h_t

code:

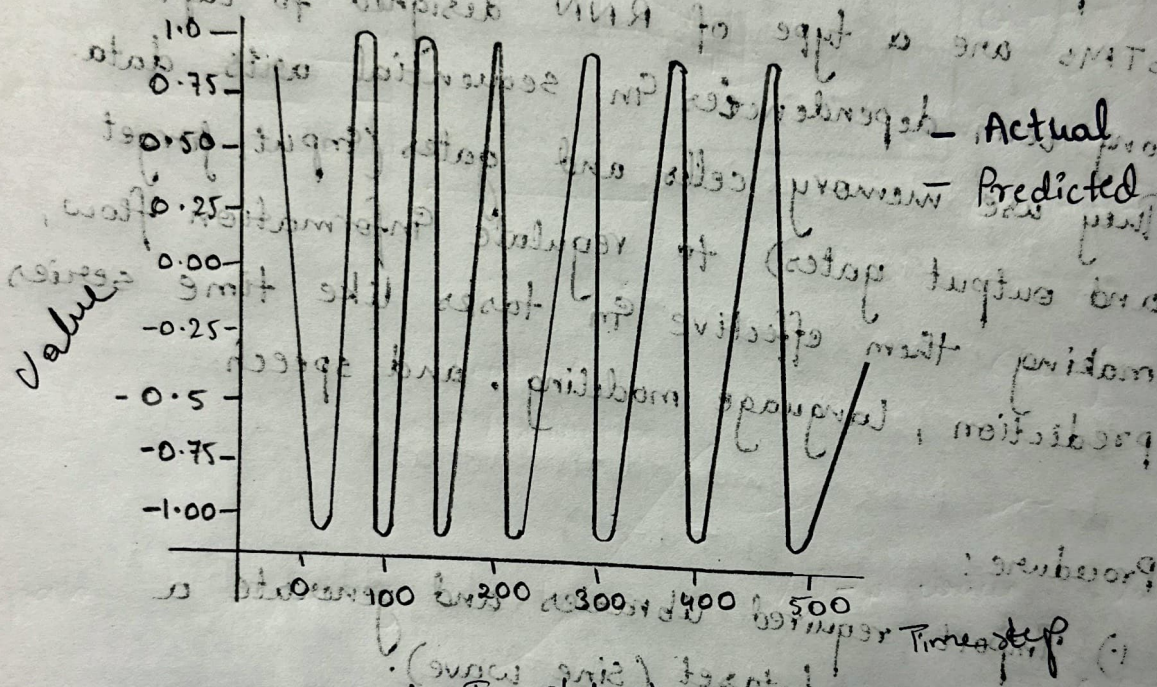
```
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense

x = np.linespace(0, 50, 500)
y = np.sin(x)

seq_length = 20
X, Y = [], []
  for i in range(len(y) - seq_length):
      X.append(y[i:i+seq_length])
      Y.append(y[i+seq_length])
  X = np.array(X)
  Y = np.array(Y)

X = X.reshape(X.shape[0], X.shape[1], 1)

  model = Sequential()
  model.add(LSTM(50, activation = 'tanh', input_shape =
        (seq_length, 1)))
  model.add(Dense(1))
  model.compile(optimizer = 'adam', loss = 'mse')

history = model.fit(X, Y, epochs = 20, verbose = 0)

  pred = model.predict(X, verbose = 0)

plt.plot(y, label = "Actual")
  plt.plot(pred, label = "Predicted")
  plt.legend()
  plt.show()
```

Output:

1.) Training loss (MSE) decreases during epochs

Epoch 1/20 - Loss: ~0.05

Epoch 20/20 - Loss: ~0.0012



2.) Graph output - The plot shows

→ The black curve (Actual sine wave)

→ The grey curve (predicted sine wave by LSTM) which closely follows the actual one after training

Result:

1.) The LSTM model successfully learned the sine wave patterns with a final loss close to zero.

2.) The predicted curve overlapped with the actual curve, proving the model's ability to capture sequential dependencies