

NAME:

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B TECH - A-I - "A"

STD:

3rd Year

DIV:

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SUBJECT:

DEEP LEARNING

INDEX

SR. NO.	DATE	TITLE	Marks	
			PAGE NO.	TEACHER'S SIGN
1	24/7/25	Exploring the Deep learning		
2	31/07/25	Implement a classifier using Open Source		
3	31/07/25	Study of the classifier with respect to statistical parameters.		
4	14/08/25	Build a simple feed forward neural network to recognize handwritten character. (MNIST DATASET)		
5	22/08/25	STUDY OF ACTIVATION FUNCTIONS AND THEIR ROLE		
6	9/09/25	Implement GRADIENT DESCENT AND BACK PROPAGATION IN DEEP NEURAL NETWORK		
7	16/09/25	Build a CNN model To classify Cat and Dog image.		
8	30/09/25	EXPERIMENT USING LSTM		
9	30/09/25	BUILD A RECURRENT NEURAL NETWORK		
10				

LAB-8 EXPERIMENT USING LSTM

AIM:- To build and implement a L-S-T-M (Long-short Memory) model for seq. prediction.

Pseudo Code:-

- Import req libraries
- Load & preprocess The Sequential dataset
- Normalize the data
- Create input-output pairs
- Reshape x into samples
- Define LSTM model;
- Initialize Seq. model
- Add Dense Output layer
- Compile the model with optimizer & loops
- Train the model using model.
- Evaluate model performance on test data
- Predict future or test samples
- Visualize predicted vs actual output

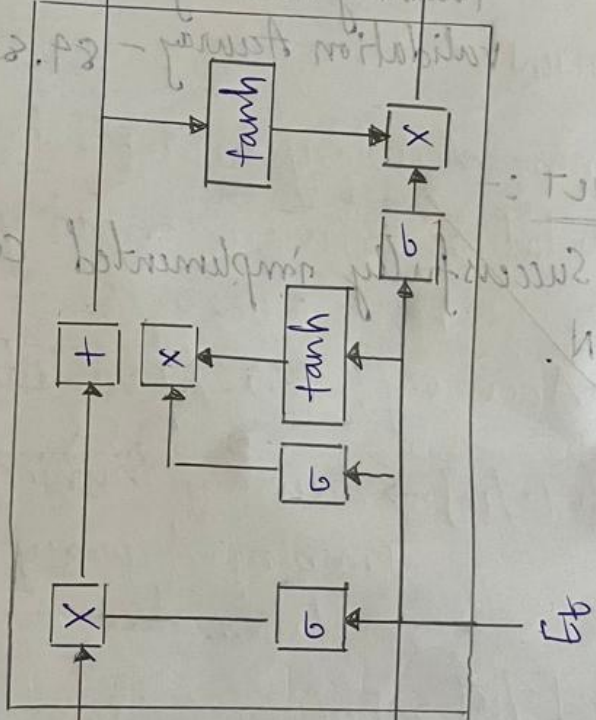
OBSERVATION :-

- The Training loss decreasing gradually with each epoch, indicating that the model is learning the sequence pattern
- LSTM perform better than Simple RNN's when dealing with long-term dependencies
- The predicted output closely follows the trend of actual data, demonstrating the model's ability to remember previous context

LSTM

L_{t-1}^{STM}

L_{t-1}^{STM}



Epoch [10] - Accuracy training loss - 0.0875
Validation Accuracy - 84.23%
Training Accuracy - 84.23%
Epoch [10] - Accuracy training loss - 0.1187
Validation Accuracy - 83.36%
Training Accuracy - 81.51%

Result: 100%
Successfully implemented LSTM

However, training time is higher compared to standard RNN due to more complex interactions

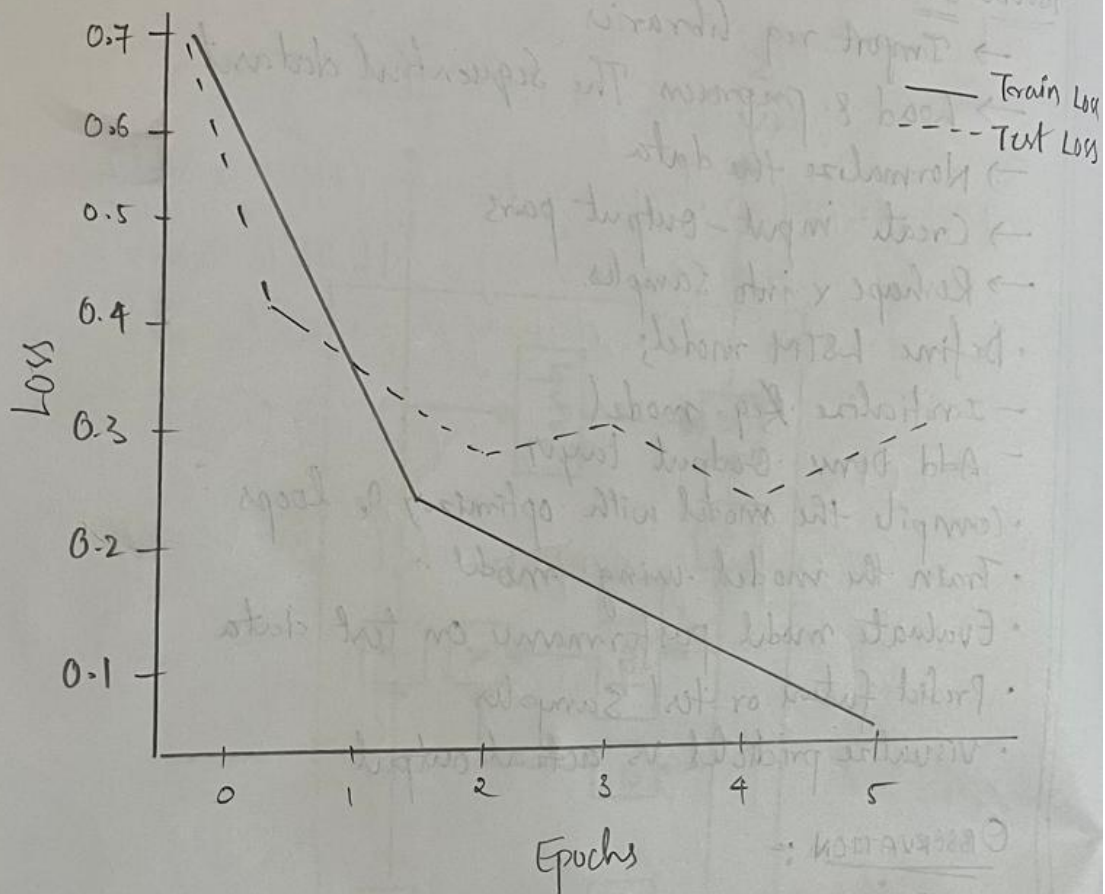
Result

The Experiment was successfully carried out and LSTM model was implemented to learn and predict seq pattern effectively

Using device : cuda

Epoch 1/6	Train Loss : 0.6747	Test Loss : 0.6733
Epoch 2/6	Train Loss : 0.4979	Test Loss : 0.3992
Epoch 3/6	Train Loss : 0.2916	Test Loss : 0.2746
Epoch 4/6	Train Loss : 0.2085	Test Loss : 0.2883
Epoch 5/6	Train Loss : 0.1415	Test Loss : 0.2725
Epoch 6/6	Train Loss : 0.0897	Test Loss : 0.3231

~~1/10~~



LSTM Test Accuracy :- 89.59%.

```
[ ] 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

[ ] !ls /kaggle/input/imdb-dataset-of-50k-movie-reviews

'IMDB Dataset.csv'

[ ] 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

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

```
[ ] # 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)

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

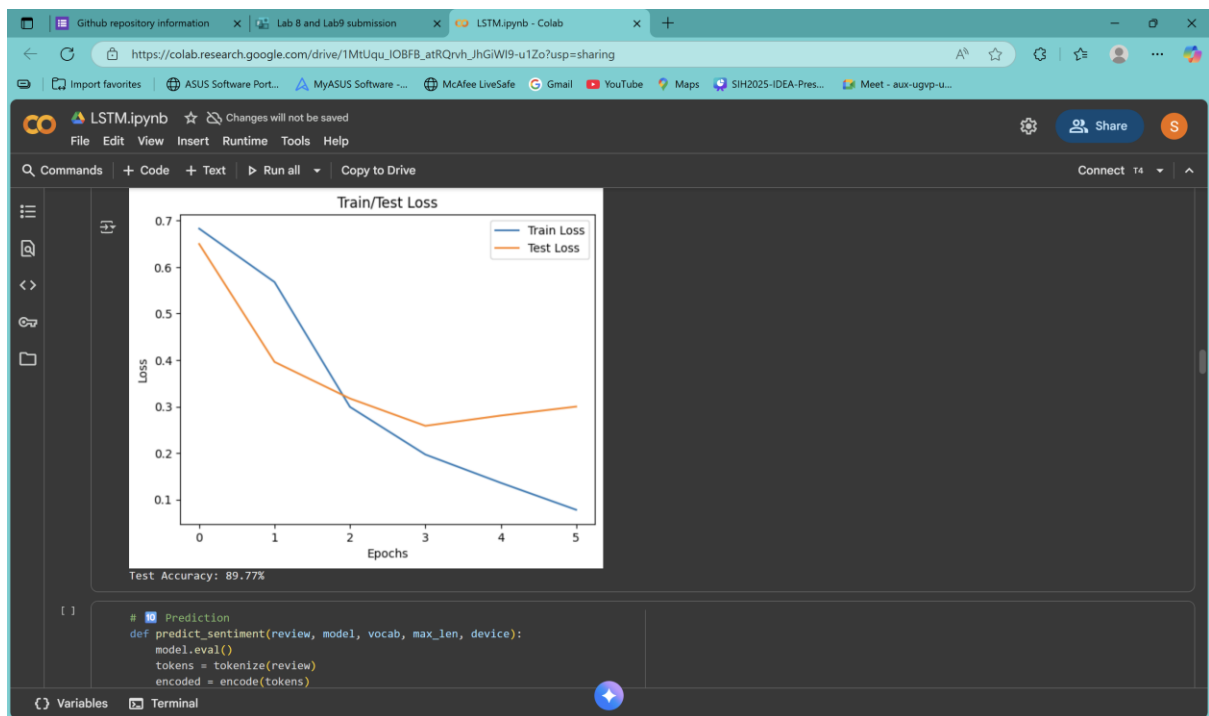
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

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)

# -----
# LSTM Model
# -----
class LSTMClassifier(nn.Module):
```

Github repository information | Lab 8 and Lab9 submission | LSTM.ipynb - Colab

https://colab.research.google.com/drive/1MtUqu_I0BF8_atRQrvh_JhGIW9-u1Zo?usp=sharing

Import favorites | ASUS Software Port... | MyASUS Software ... | McAfee LiveSafe | Gmail | YouTube | Maps | SIH2025-IDEA-Pres... | Meet - aux-ugvp-u...

LSTM.ipynb | Changes will not be saved | File Edit View Insert Runtime Tools Help | Share | S

Commands | + Code | + Text | ▶ Run all | Copy to Drive | Connect T4

```
[ ] 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()
)
```

Variables | Terminal

LAB-9 BUILD A RECURRENT NEURAL NETWORK

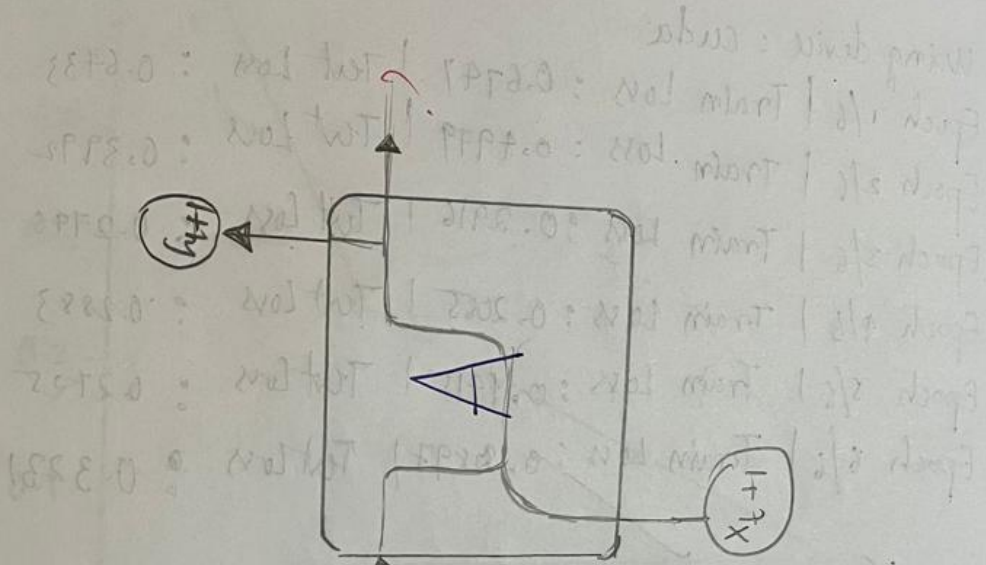
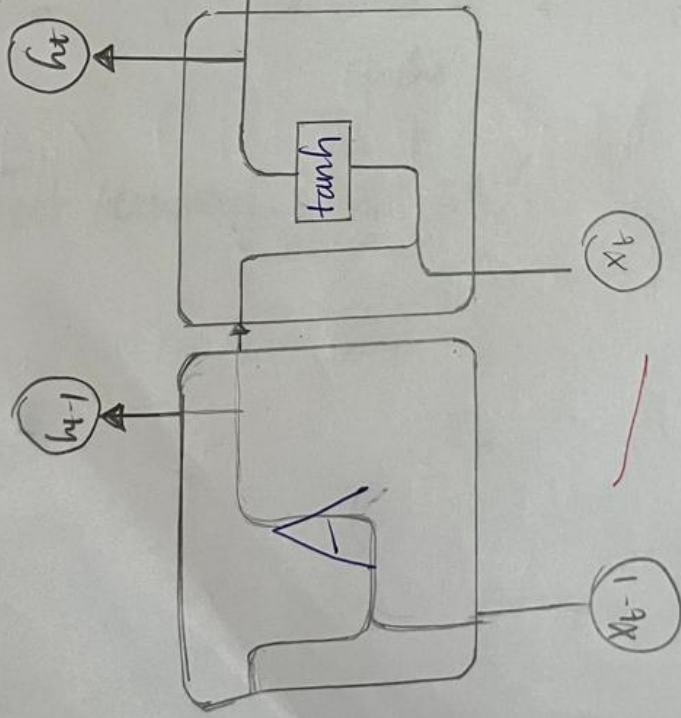
AIM :- To design, implement and evaluate a RNN model for sequential data, such as text, and analysis its performance.

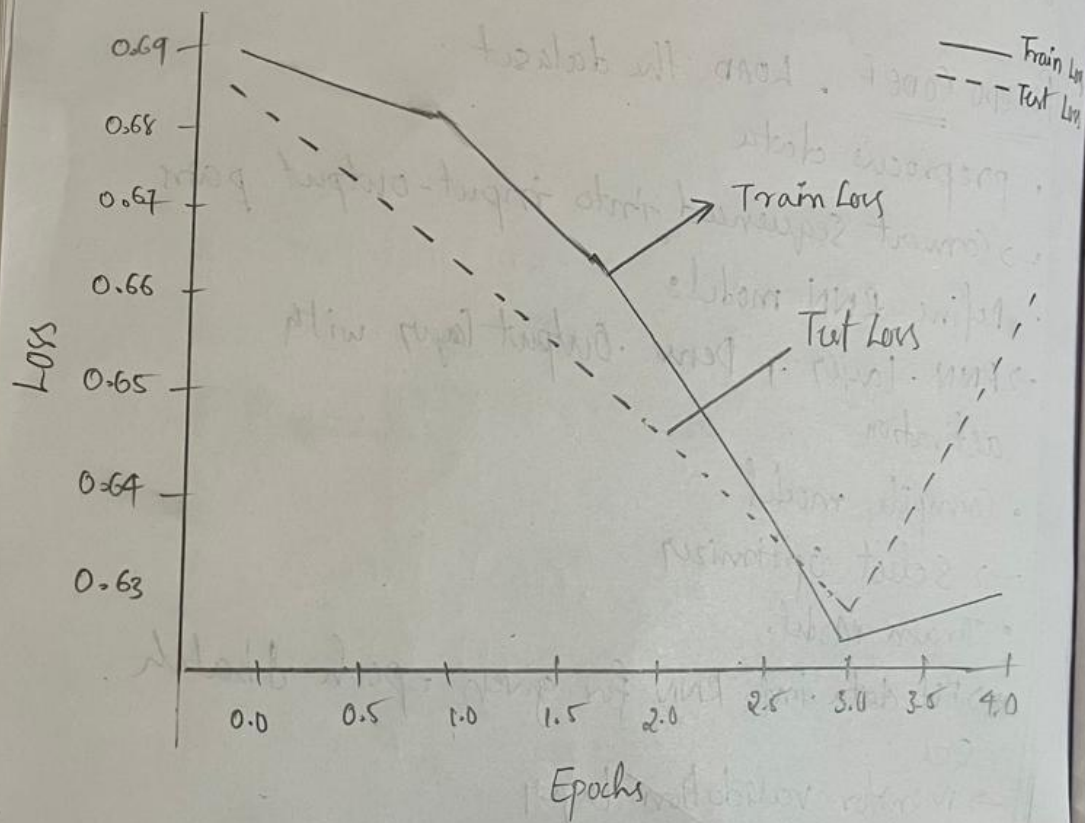
PSEUDO CODE :-

- LOAD the dataset.

- preprocess data
 - Convert sequenced into input-output pairs
- Define RNN model:
 - RNN layer + Dense Output layer with activation
- Compile model
 - Select Optimizer
- Train Model:
 - Fit data into RNN for given epoch & batch size
 - Monitor validation layer
- Evaluate ~~model~~:
 - Test data
- Visualize results:
 - Plot accuracy & Loss Curves
- Conducts observation & Results

RNN





RNN Test Accuracy: 58.64%

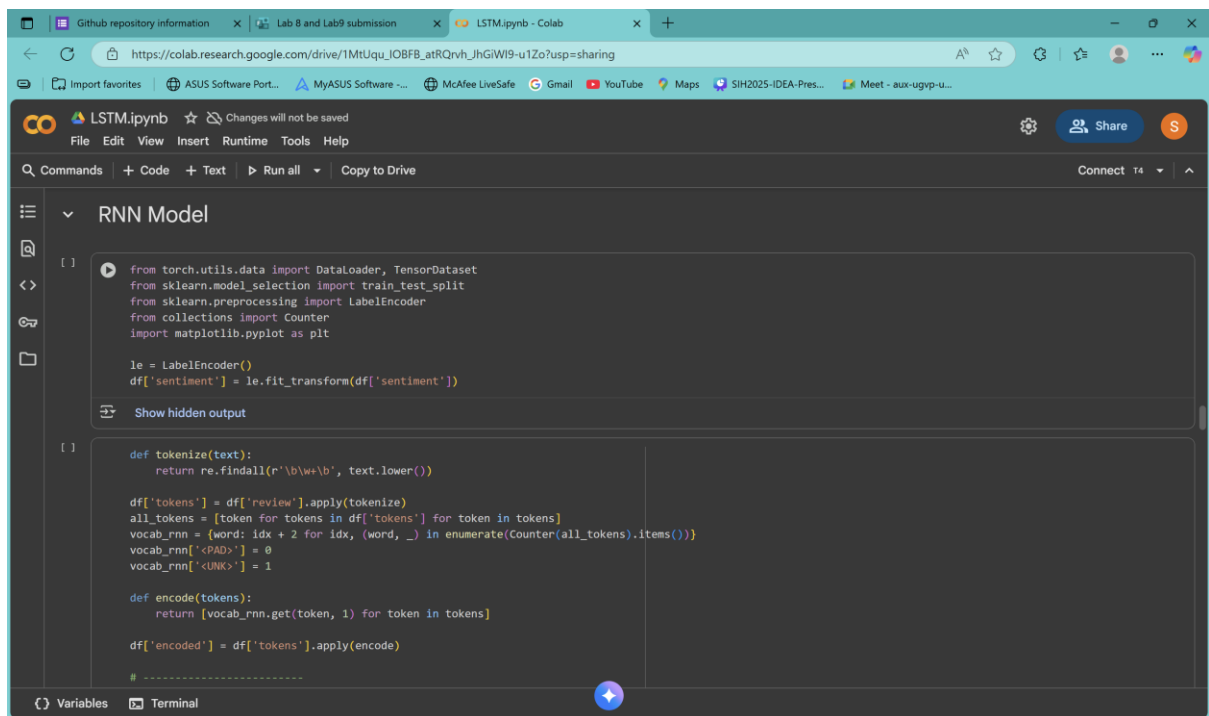
OBSERVATION 1-

- The training accuracy increases with epochs, while the loss decreased
- overfitting can occur if too many epochs are used without regularisation (dropout)
- LSTM variants perform more efficiently on long sequences due to vanishing gradient mitigation
- validation performance depends on dataset complexity & preprocessing quality

Result - A R.N.N as Successfully and trained a Sequential data. "Successfully Implemented".

Epoch 1/5 | Train Loss: 0.6893 | Test Loss: 0.6854
Epoch 2/5 | Train Loss: 0.6832 | Test Loss: 0.6708
Epoch 3/5 | Train Loss: 0.6645 | Test Loss: 0.6527
Epoch 4/5 | Train Loss: 0.6277 | Test Loss: 0.6308
Epoch 5/5 | Train Loss: 0.6296 | Test Loss: 0.6724

~~1/10~~



LSTM.ipynb

```
from torch.utils.data import DataLoader, TensorDataset
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from collections import Counter
import matplotlib.pyplot as plt

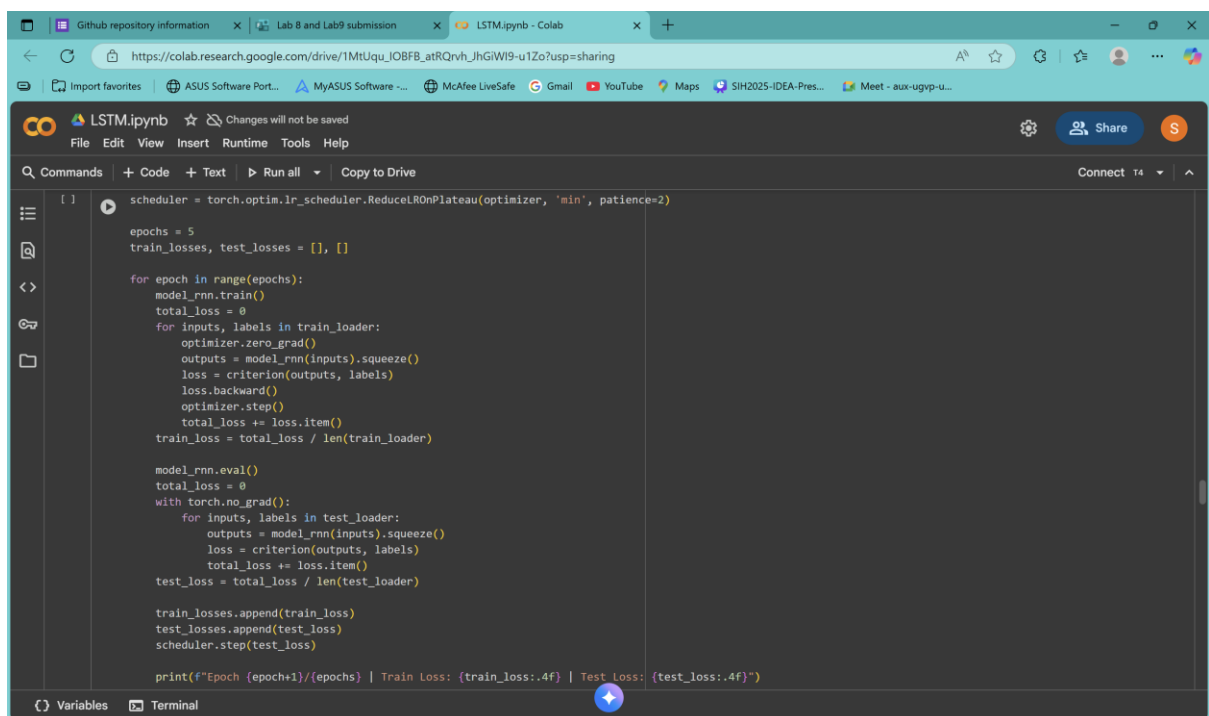
le = LabelEncoder()
df['sentiment'] = le.fit_transform(df['sentiment'])

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

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

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



```
scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer, 'min', patience=2)

epochs = 5
train_losses, test_losses = [], []

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

    model_rnn.eval()
    total_loss = 0
    with torch.no_grad():
        for inputs, labels in test_loader:
            outputs = model_rnn(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}")
```

Colab interface showing the execution of an LSTM model. The top bar indicates the file is not saved. The left sidebar shows the file explorer. The main area displays the code and its output.

```

correct += (predicted == labels).sum().item()
accuracy_rnn = 100 * correct / total
print(f" RNN Test Accuracy: {accuracy_rnn:.2f}%")

Epoch 1/5 | Train Loss: 0.6851 | Test Loss: 0.6567
Epoch 2/5 | Train Loss: 0.6454 | Test Loss: 0.6347
Epoch 3/5 | Train Loss: 0.6036 | Test Loss: 0.6925
Epoch 4/5 | Train Loss: 0.6691 | Test Loss: 0.6940
Epoch 5/5 | Train Loss: 0.6884 | Test Loss: 0.6734
RNN Test Accuracy: 61.15%

```

```

import torch
import re

# Function to preprocess and tokenize a new review
def preprocess_review(review, vocab, max_len=200):
    tokens = re.findall(r'\b\w+\b', review.lower())
    encoded = [vocab.get(token, 1) for token in tokens] # 1 = <UNK>
    if len(encoded) < max_len:
        encoded += [0] * (max_len - len(encoded)) # pad
    else:
        encoded = encoded[:max_len]
    return torch.tensor(encoded, dtype=torch.long).unsqueeze(0).to(device) # shape: [1, max_len]

# Prediction function
def predict_sentiment(model, review, vocab):
    model.eval()
    with torch.no_grad():
        input_tensor = preprocess_review(review, vocab)
        output = model(input_tensor).squeeze()
        prediction = 1 if output.item() > 0.5 else 0
    return prediction

```

Variables and Terminal tabs are visible at the bottom.

