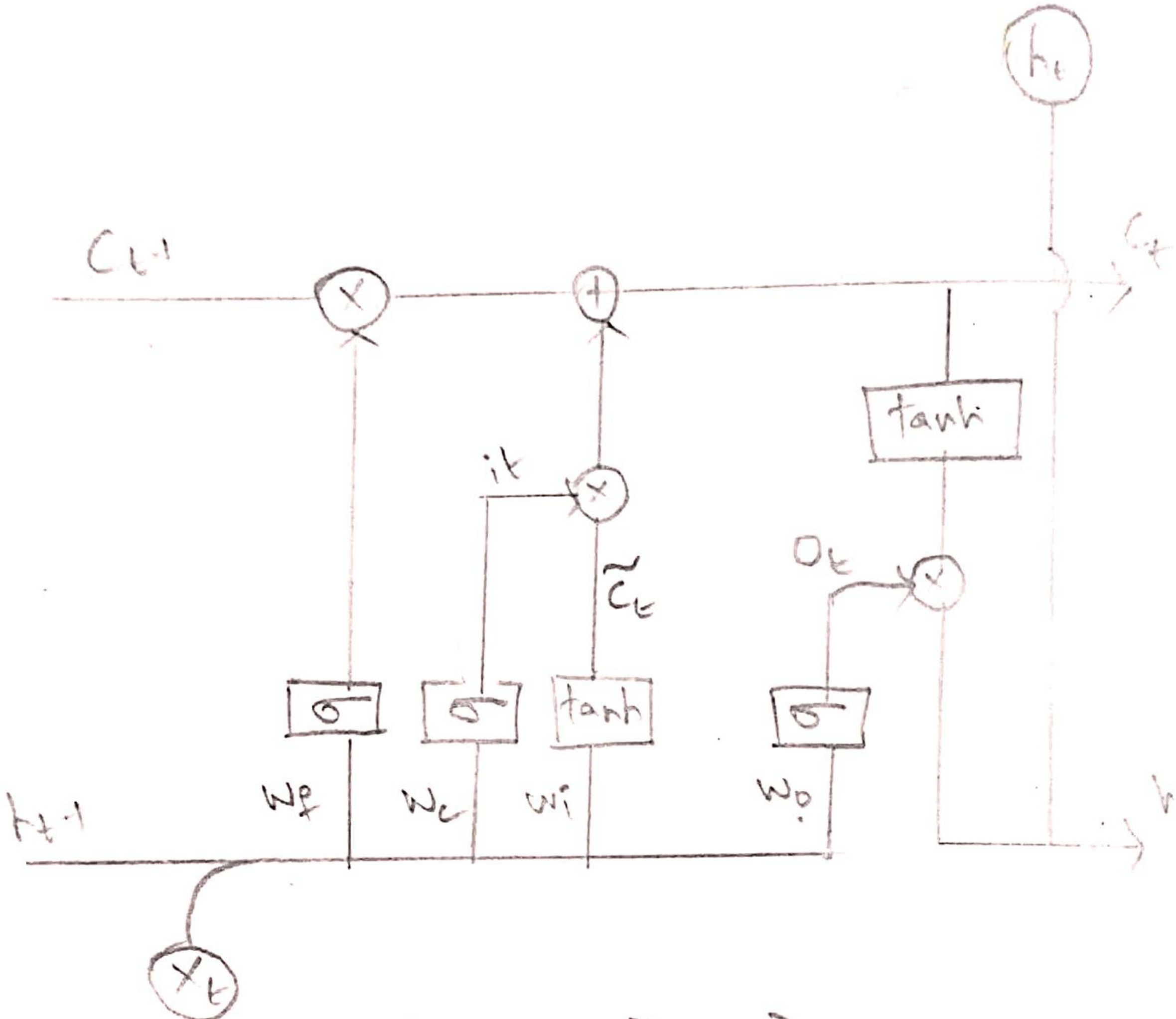


$$f_t = \sigma(W_f [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_c [h_{t-1}, x_t] + b_c)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

$$O_t = \sigma(W_o [h_{t-1}, x_t] + b_o)$$

$$h_t = O_t * \tanh(C_t)$$

Cell state Eq:

$$C_t = C_{t-1} \otimes f_t \oplus \tilde{C}_t \otimes i_t$$

Exp:9

EXPERIMENT USING LSTM

AIM

To implement and analyze a Long-Short-Term Memory (LSTM) network for sequential data modeling and prediction.

OBJECTIVES:

* To understand the architecture and working of LSTM
* Compare LSTM with simple RNNs in handling long-term dependencies.
* Implements an LSTM model for a real-world dataset.
* To evaluate model performance using traing and validation metrics.
* To observe how LSTMs mitigate vanishing/exploding gradient probleme.

PSEUDOCODE

↳ Import necessary libraries
↳ Load sequential dataset
↳ Preprocess data:
- Tokenize/normalize.
- Create input sequence and lables
- Pad/truncate to fixed length.

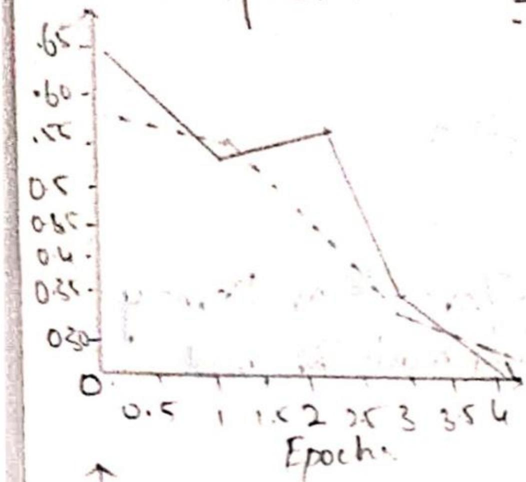
↳ Define LSTM model:
- Input layer
- ~~Embedding layer~~
- LSTM Layer
- Fully Connected Dense Output Layer

↳ Compile model:
- Loss function = CrossEntropy
- Optimizer = Adam.
- Materics = Accuracy.

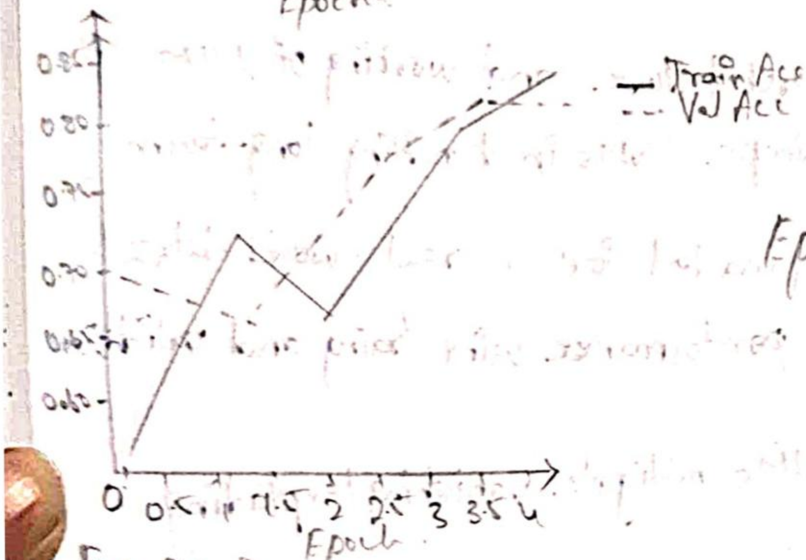
↳ Train model for fixed epoch:
Track traing loss and validation accuracy

Evaluate.

For 5 Epochs

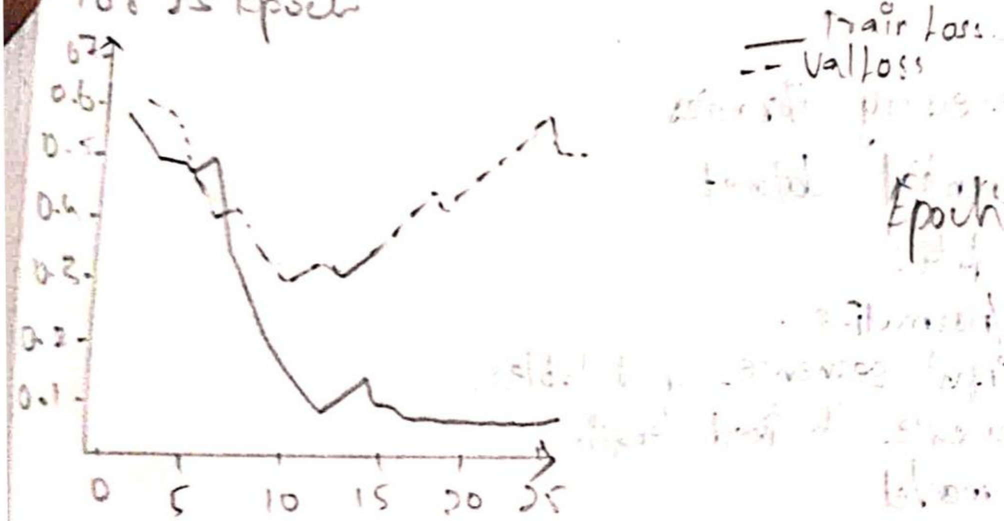


Epoch VS loss

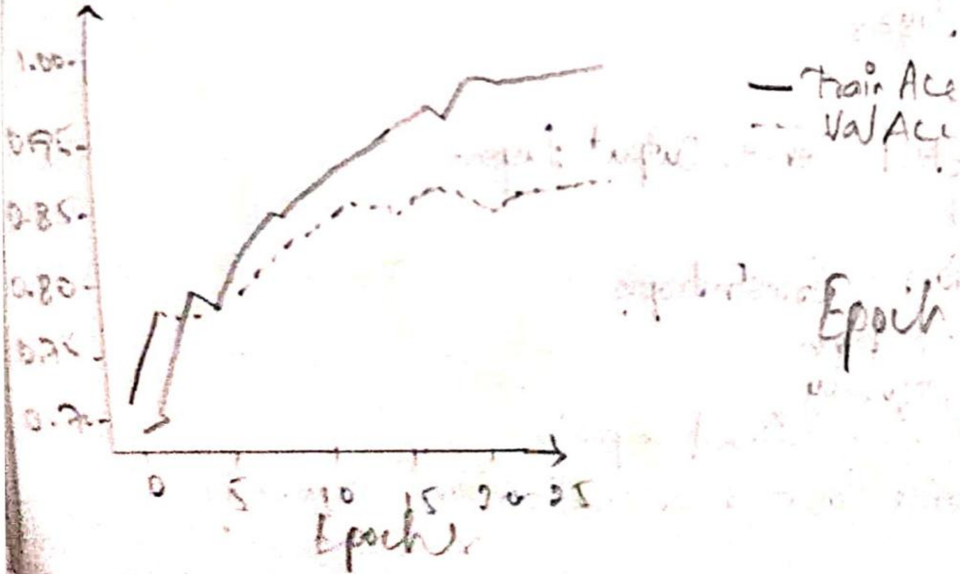


Epoch VS Accuracy

For 25 Epoch



Epoch VS loss



Epoch VS Accuracy

OBSERVATION

For 5 Epochs:

Epoch 1: Train loss = 0.6693, Train Acc = 0.5777, Val loss = 0.5873
Val Acc = 0.6964

Epoch 2: Train loss = .5622, Train Acc = 0.7189, Val loss = 0.5813, Val Acc = 0.6812

Epoch 3: Train loss = 0.5774, Train Acc = 0.7039, Val Loss = 0.4728, Val Acc = 0.7817

Epoch 4: Train loss = 0.3815, Train Acc = 0.8355, Val loss = 0.3546, Vall Acc = 0.8433

Epoch 5: Train Loss = 0.3002, Train Acc = 0.8761, Val loss = 0.3285, Val Acc = 0.8617

For 25 Epochs:

Epoch 1: Train loss: 0.5895, Train Acc, 0.6983, Val loss = 0.5814, Val Acc = 0.7028

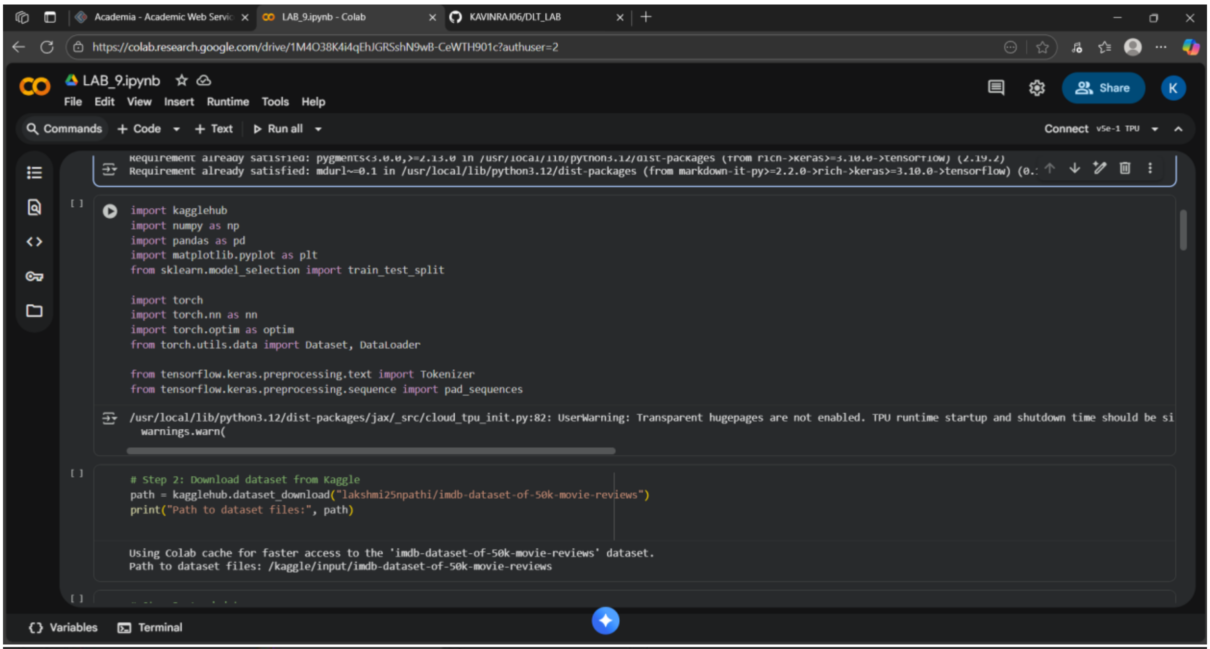
Epoch 2: Train loss: 0.5635, Train Acc, 0.7083, Val loss = 0.4816, Val Acc = 0.7789

Epoch 3: Train loss: 0.4690, Train Acc, 0.7856, Val loss = 0.725, Val Acc = 0.7808

Epoch 4: Train loss: 0.4813, Train Acc, 0.7792, Val loss 0.4496, Val Acc = 0.8039

Epoch 5: Train loss: 0.3717 Train Acc 0.8401, Val loss 0.3670, Val Acc 0.8314.

The moldu was rund and executed sucssfully.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LAB_9.ipynb - Colab
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https://colab.research.google.com/drive/1M4O38K4i4qEhJGRSshN9wB-CeWTH901c?authuser=2
LAB_9.ipynb
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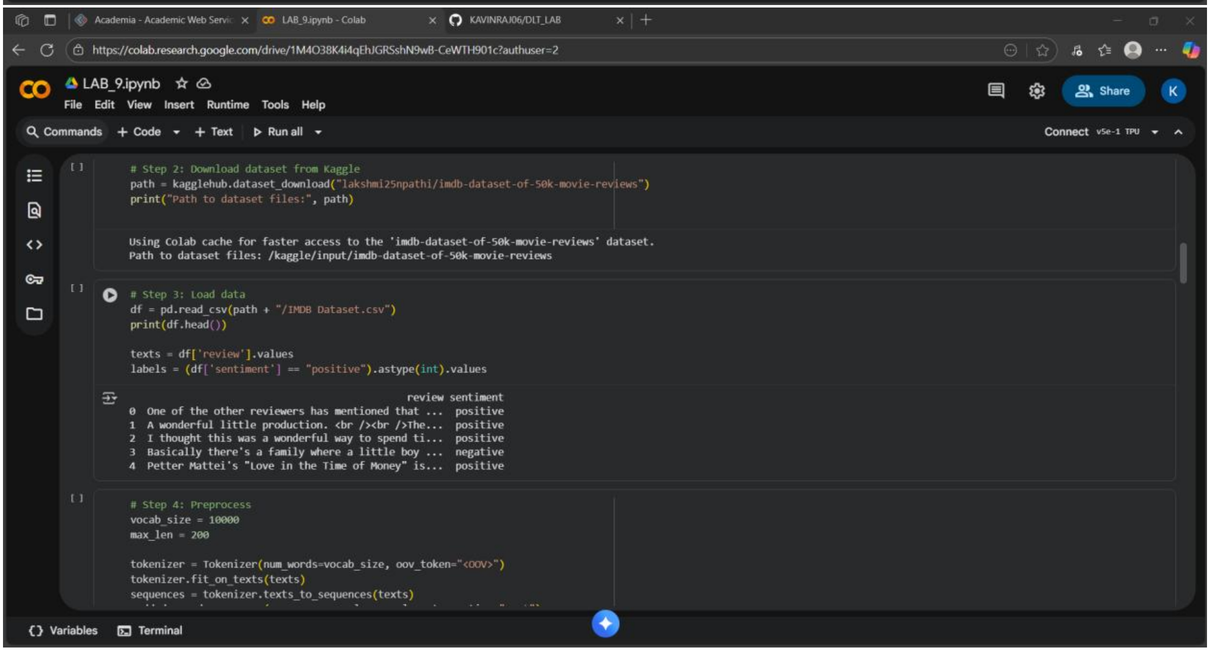
Commands + Code + Text Run all
Share
Connect v5e-1 TPU
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.12/dist-packages (from markdown-it-py>=2.2.0->rich->keras>=3.10.0->tensorflow) (0.:
import kagglehub
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
/usr/local/lib/python3.12/dist-packages/jax/_src/cloud_tpu_init.py:82: UserWarning: Transparent hugepages are not enabled. TPU runtime startup and shutdown time should be si
warnings.warn(
# Step 2: Download dataset from Kaggle
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
Variables
Terminal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KAVINRAJ06/DLT_LAB
https://colab.research.google.com/drive/1M4O38K4i4qEhJGRSshN9wB-CeWTH901c?authuser=2
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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
# Step 3: Load data
df = pd.read_csv(path + "/IMDB Dataset.csv")
print(df.head())
texts = df['review'].values
labels = (df['sentiment'] == "positive").astype(int).values
review sentiment
0 One of the other reviewers has mentioned that ... positive
1 A wonderful little production.

The... positive
2 I thought this was a wonderful way to spend ti... positive
3 Basically there's a family where a little boy ... negative
4 Petter Mattei's "Love in the Time of Money" is... positive
# Step 4: Preprocess
vocab_size = 10000
max_len = 200
tokenizer = Tokenizer(num_words=vocab_size, oov_token="<OOV>")
tokenizer.fit_on_texts(texts)
sequences = tokenizer.texts_to_sequences(texts)
Variables
Terminal

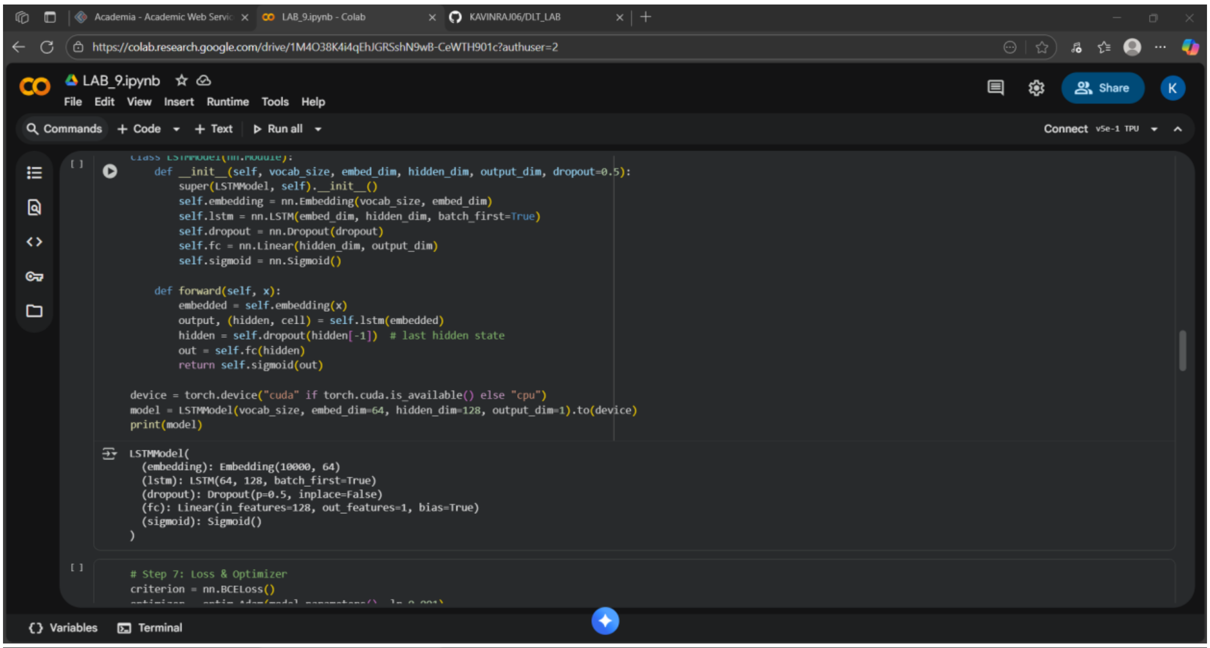
```python
# Step 4: Preprocess
vocab_size = 10000
max_len = 200

tokenizer = Tokenizer(num_words=vocab_size, oov_token="<OOV>")
tokenizer.fit_on_texts(texts)
sequences = tokenizer.texts_to_sequences(texts)
padded = pad_sequences(sequences, maxlen=max_len, truncating="post")

X_train, X_test, y_train, y_test = train_test_split(padded, labels, test_size=0.2, random_state=42)
```

```python
# Convert to PyTorch tensors
X_train = torch.tensor(X_train, dtype=torch.long)
y_train = torch.tensor(y_train, dtype=torch.float32)
X_test = torch.tensor(X_test, dtype=torch.long)
y_test = torch.tensor(y_test, dtype=torch.float32)
```

```python
# Step 5: Create Dataset & DataLoader
class IMDBDataset(Dataset):
    def __init__(self, X, y):
        self.X = X
        self.y = y

    def __len__(self):
        return len(self.y)
```

```python
    def __len__(self):
        return len(self.y)

    def __getitem__(self, idx):
        return self.X[idx], self.y[idx]

train_dataset = IMDBDataset(X_train, y_train)
test_dataset = IMDBDataset(X_test, y_test)

train_loader = DataLoader(train_dataset, batch_size=64, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=64, shuffle=False)
```

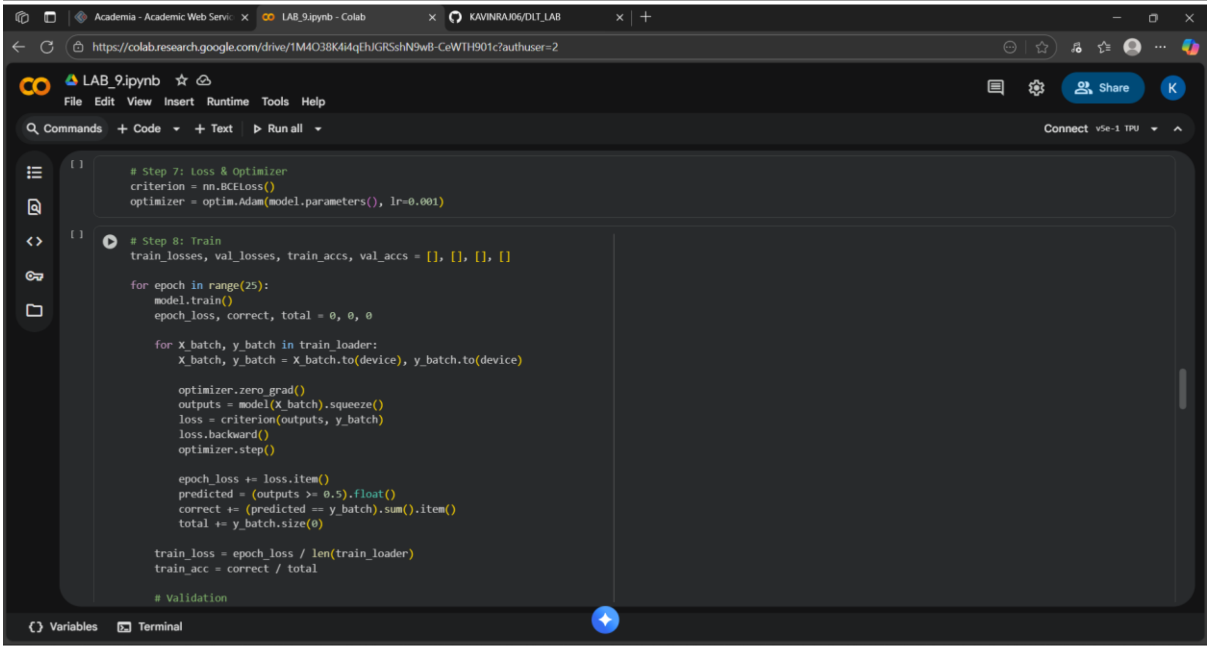
```python
# Step 6: Build LSTM Model
class LSTMModel(nn.Module):
    def __init__(self, vocab_size, embed_dim, hidden_dim, output_dim, dropout=0.5):
        super(LSTMModel, self).__init__()
        self.embedding = nn.Embedding(vocab_size, embed_dim)
        self.lstm = nn.LSTM(embed_dim, hidden_dim, batch_first=True)
        self.dropout = nn.Dropout(dropout)
        self.fc = nn.Linear(hidden_dim, output_dim)
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        embedded = self.embedding(x)
        output, (hidden, cell) = self.lstm(embedded)
        hidden = self.dropout(hidden[-1])  # last hidden state
        out = self.fc(hidden)
        return self.sigmoid(out)
```



```python
class LSTMModel(nn.Module):
    def __init__(self, vocab_size, embed_dim, hidden_dim, output_dim, dropout=0.5):
        super(LSTMModel, self).__init__()
        self.embedding = nn.Embedding(vocab_size, embed_dim)
        self.lstm = nn.LSTM(embed_dim, hidden_dim, batch_first=True)
        self.dropout = nn.Dropout(dropout)
        self.fc = nn.Linear(hidden_dim, output_dim)
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        embedded = self.embedding(x)
        output, (hidden, cell) = self.lstm(embedded)
        hidden = self.dropout(hidden[-1])  # last hidden state
        out = self.fc(hidden)
        return self.sigmoid(out)

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = LSTMModel(vocab_size, embed_dim=64, hidden_dim=128, output_dim=1).to(device)
print(model)
```

```
LSTMModel(
  (embedding): Embedding(10000, 64)
  (lstm): LSTM(64, 128, batch_first=True)
  (dropout): Dropout(p=0.5, inplace=False)
  (fc): Linear(in_features=128, out_features=1, bias=True)
  (sigmoid): Sigmoid()
)
```

```python
# Step 7: Loss & Optimizer
criterion = nn.BCELoss()
```



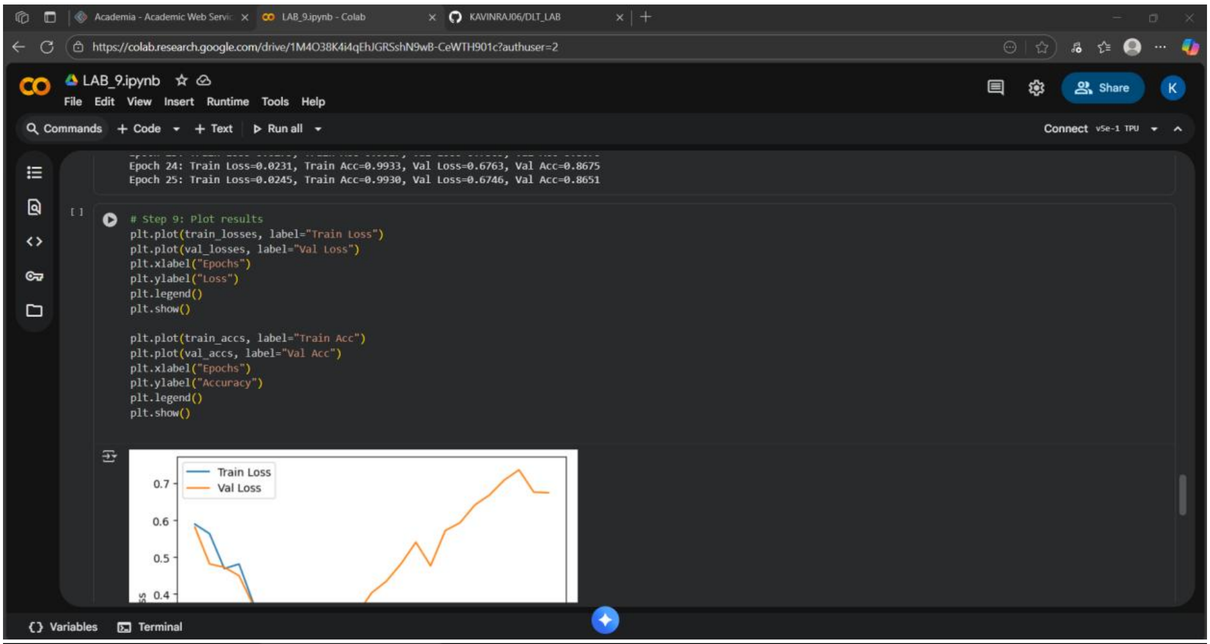
```python
# Step 7: Loss & Optimizer
criterion = nn.BCELoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)
```

```python
# Step 8: Train
train_losses, val_losses, train_accs, val_accs = [], [], [], []

for epoch in range(25):
    model.train()
    epoch_loss, correct, total = 0, 0, 0

    for X_batch, y_batch in train_loader:
        X_batch, y_batch = X_batch.to(device), y_batch.to(device)

        optimizer.zero_grad()
        outputs = model(X_batch).squeeze()
        loss = criterion(outputs, y_batch)
        loss.backward()
        optimizer.step()

        epoch_loss += loss.item()
        predicted = (outputs >= 0.5).float()
        correct += (predicted == y_batch).sum().item()
        total += y_batch.size(0)

    train_loss = epoch_loss / len(train_loader)
    train_acc = correct / total

    # Validation
```

```python
    train_loss = epoch_loss / len(train_loader)
    train_acc = correct / total

    # Validation
    model.eval()
    val_loss, correct, total = 0, 0, 0
    with torch.no_grad():
        for X_batch, y_batch in test_loader:
            X_batch, y_batch = X_batch.to(device), y_batch.to(device)
            outputs = model(X_batch).squeeze()
            loss = criterion(outputs, y_batch)
            val_loss += loss.item()
            predicted = (outputs >= 0.5).float()
            correct += (predicted == y_batch).sum().item()
            total += y_batch.size(0)

    val_loss /= len(test_loader)
    val_acc = correct / total

    train_losses.append(train_loss)
    val_losses.append(val_loss)
    train_accs.append(train_acc)
    val_accs.append(val_acc)

    print(f"Epoch {epoch+1}: Train Loss={train_loss:.4f}, Train Acc={train_acc:.4f}, "
          f"Val Loss={val_loss:.4f}, Val Acc={val_acc:.4f}")
```

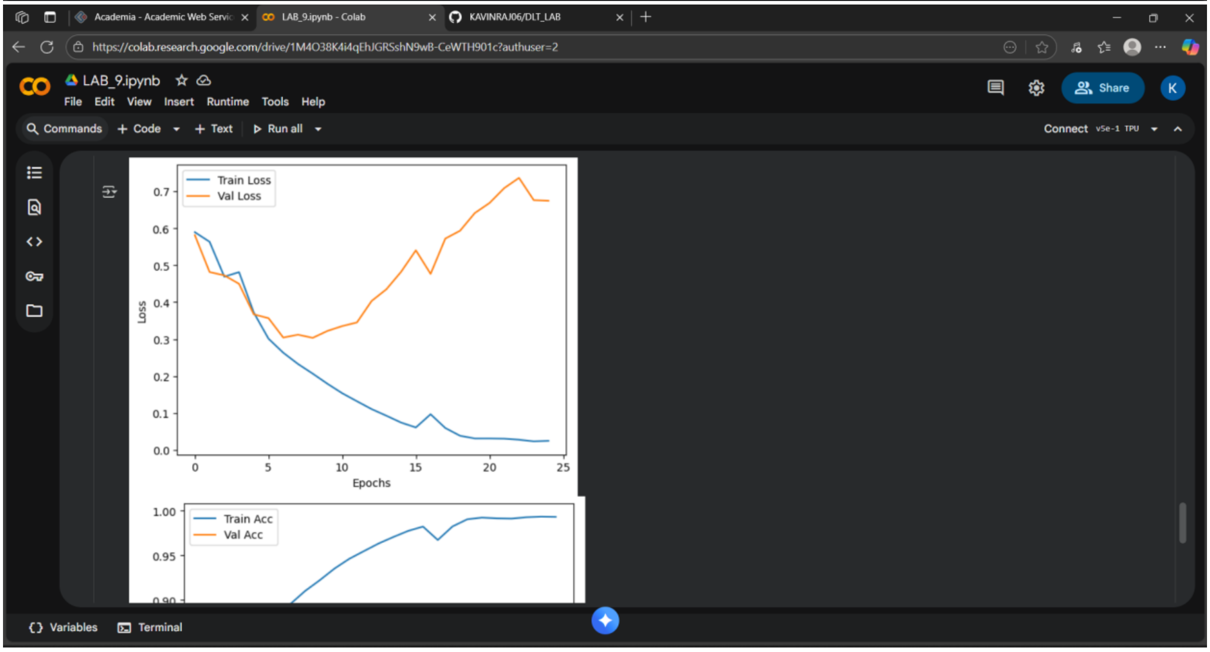
```
Epoch 1: Train Loss=0.5895, Train Acc=0.6983, Val Loss=0.5814, Val Acc=0.7023
Epoch 2: Train Loss=0.5635, Train Acc=0.7083, Val Loss=0.4816, Val Acc=0.7789
Epoch 3: Train Loss=0.4690, Train Acc=0.7856, Val Loss=0.4725, Val Acc=0.7808
Epoch 4: Train Loss=0.4813, Train Acc=0.7792, Val Loss=0.4496, Val Acc=0.8039
Epoch 5: Train Loss=0.3717, Train Acc=0.8401, Val Loss=0.3670, Val Acc=0.8314
Epoch 6: Train Loss=0.3010, Train Acc=0.8773, Val Loss=0.3566, Val Acc=0.8413
Epoch 7: Train Loss=0.2631, Train Acc=0.8954, Val Loss=0.3042, Val Acc=0.8685
Epoch 8: Train Loss=0.2326, Train Acc=0.9100, Val Loss=0.3120, Val Acc=0.8745
Epoch 9: Train Loss=0.2065, Train Acc=0.9222, Val Loss=0.3034, Val Acc=0.8756
Epoch 10: Train Loss=0.1790, Train Acc=0.9352, Val Loss=0.3221, Val Acc=0.8784
Epoch 11: Train Loss=0.1535, Train Acc=0.9461, Val Loss=0.3352, Val Acc=0.8730
Epoch 12: Train Loss=0.1317, Train Acc=0.9548, Val Loss=0.3451, Val Acc=0.8732
Epoch 13: Train Loss=0.1104, Train Acc=0.9634, Val Loss=0.4033, Val Acc=0.8737
Epoch 14: Train Loss=0.0925, Train Acc=0.9706, Val Loss=0.4349, Val Acc=0.8727
Epoch 15: Train Loss=0.0740, Train Acc=0.9774, Val Loss=0.4823, Val Acc=0.8691
Epoch 16: Train Loss=0.0607, Train Acc=0.9822, Val Loss=0.5404, Val Acc=0.8688
Epoch 17: Train Loss=0.0965, Train Acc=0.9672, Val Loss=0.4767, Val Acc=0.8693
Epoch 18: Train Loss=0.0592, Train Acc=0.9823, Val Loss=0.5722, Val Acc=0.8672
Epoch 19: Train Loss=0.0382, Train Acc=0.9904, Val Loss=0.5934, Val Acc=0.8687
Epoch 20: Train Loss=0.0309, Train Acc=0.9923, Val Loss=0.6413, Val Acc=0.8622
Epoch 21: Train Loss=0.0310, Train Acc=0.9914, Val Loss=0.6685, Val Acc=0.8689
Epoch 22: Train Loss=0.0304, Train Acc=0.9911, Val Loss=0.7089, Val Acc=0.8681
Epoch 23: Train Loss=0.0275, Train Acc=0.9927, Val Loss=0.7365, Val Acc=0.8670
Epoch 24: Train Loss=0.0231, Train Acc=0.9933, Val Loss=0.6763, Val Acc=0.8675
Epoch 25: Train Loss=0.0245, Train Acc=0.9930, Val Loss=0.6746, Val Acc=0.8651
```

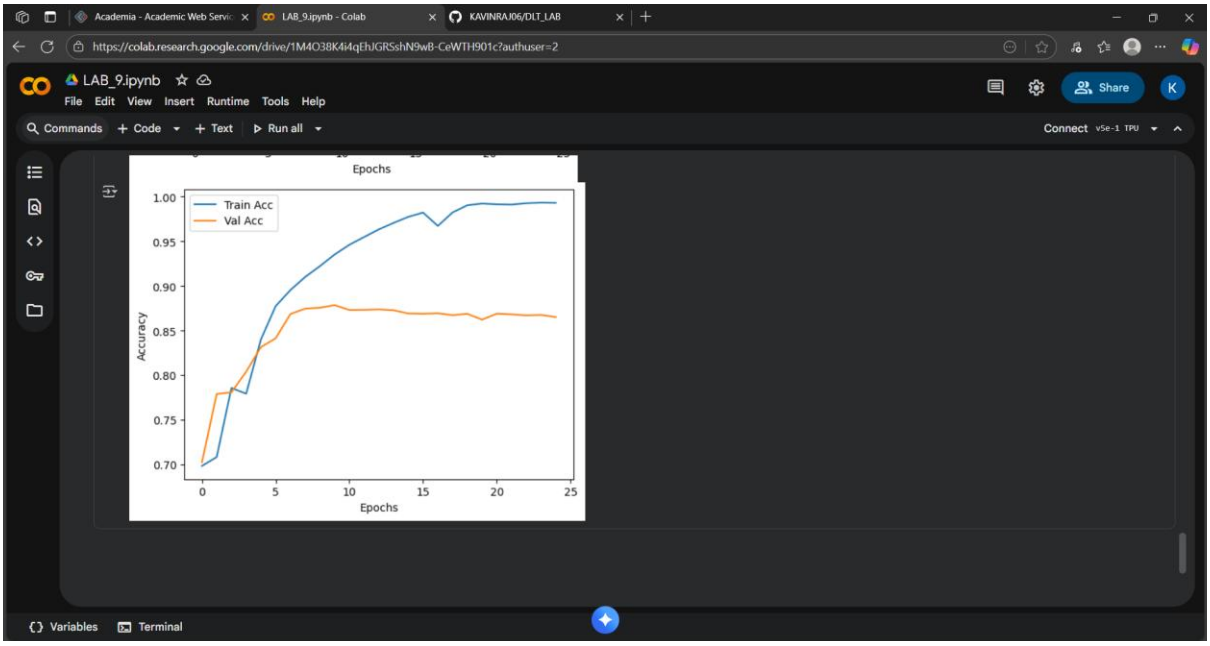
```python
# Step 9: Plot results
plt.plot(train_losses, label="Train Loss")
plt.plot(val_losses, label="Val Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
```



```
Epoch 24: Train Loss=0.0231, Train Acc=0.9933, Val Loss=0.6763, Val Acc=0.8675
Epoch 25: Train Loss=0.0245, Train Acc=0.9930, Val Loss=0.6746, Val Acc=0.8651
```

```python
# Step 9: Plot results
plt.plot(train_losses, label="Train Loss")
plt.plot(val_losses, label="Val Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()

plt.plot(train_accs, label="Train Acc")
plt.plot(val_accs, label="Val Acc")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```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+ Code
+ Text
Run all
Connect
Epochs
Train Acc
Val Acc
Accuracy
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0
5
10
15
20
25
Epochs
Variables
Terminal