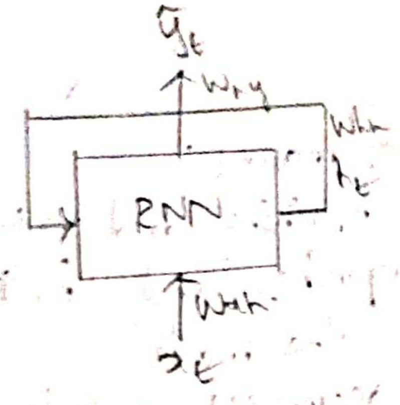


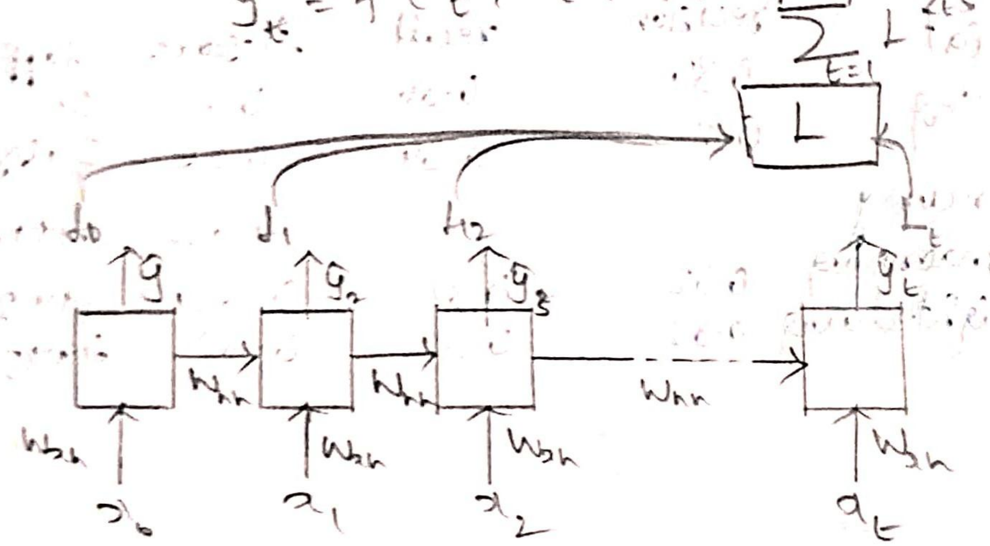
Output vector

$$\hat{y}_t = W_{hy}^T h_t$$

update Hidden State

$$h_t = \tanh(W_{hh}^T h_{t-1} + W_{xh}^T x_t)$$

$$\hat{y}_t = f(x_t, h_{t-1})$$



$$L = \sum_{t=1}^{T} L^{<t>}$$

$$\frac{\partial L}{\partial W_{hh}} = \frac{\partial L^{(t)}}{\partial y^{(t)}} \cdot \frac{\partial y^{(t)}}{\partial h^{(t)}} \cdot \left(\sum \frac{\partial h^{(t)}}{\partial h^{(k)}} \cdot \frac{\partial h^{(k)}}{\partial W_{hh}} \right)$$

$$\frac{\partial h^{(t)}}{\partial h^{(k)}} = \prod_{i=k+1} \frac{\partial h^{(i)}}{\partial h^{(i-1)}}$$

$$\frac{\partial h^{(1)}}{\partial h^{(0)}} \cdot \frac{\partial h^{(2)}}{\partial h^{(1)}}$$

Vanishing gradient

$$\left\| \frac{\partial h_i}{\partial h_{i-1}} \right\|_2 < 1$$

Exploding gradient

$$\left\| \frac{\partial h_{i}}{\partial h_{i-1}} \right\|_2 > 1$$

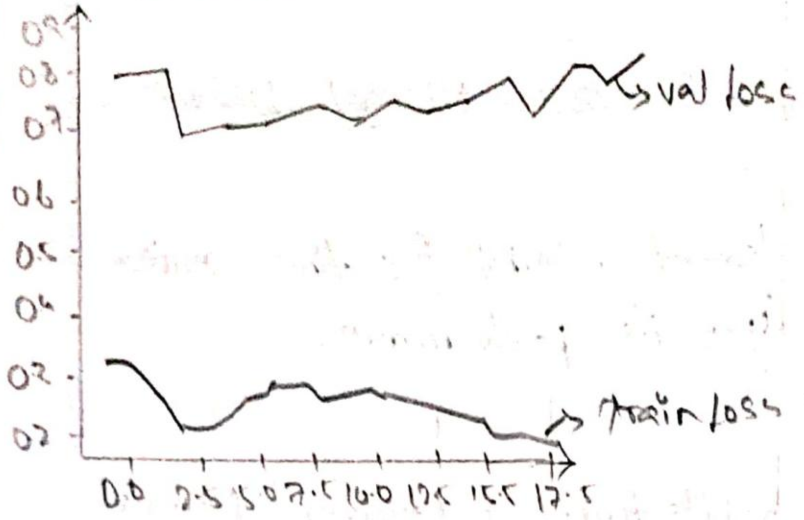
Exp8. BUILD A RECURRENT NEURAL NETWORK

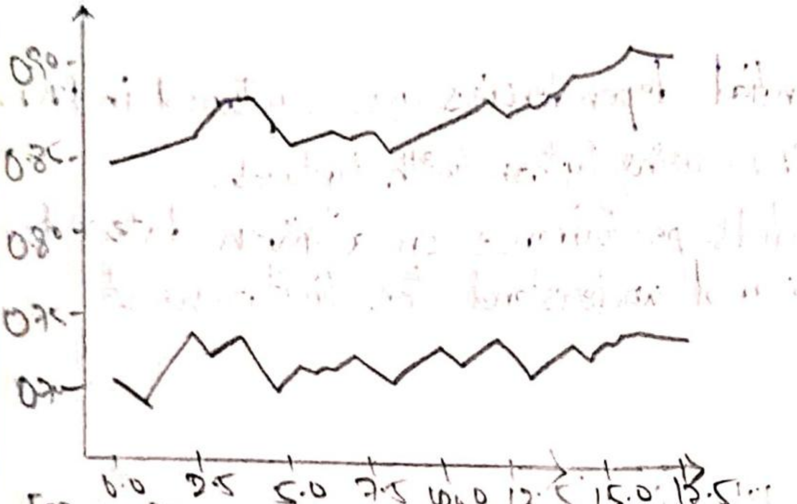
AIM:
To design and implement a RNN for time-series data and to analyze its performance.

OBJECTIVES:
* To understand the architecture of Reurrent Neural Networks.
* To learn how sequential dependencies are captured in RNN
* To implement an RNN using Python (with Pytorch).
* To evaluate the models performance on a given dataset.
* Intepet the results and understand the limitations of Vanilla RNN

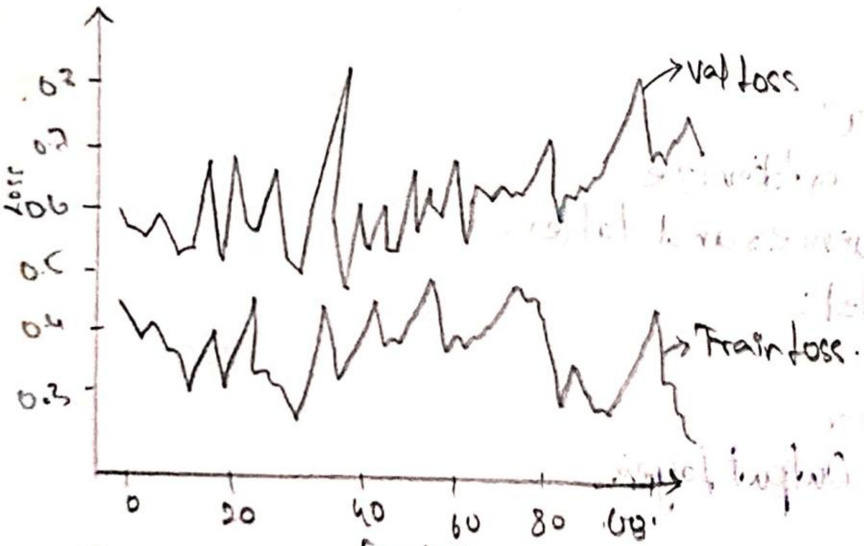
PSEUDOCODE
↳ Import required libraries
↳ Load dataset
↳ Preprocess data:
 - Normalize or tokenize
 - Create sequences and lables.
↳ Define RNN model:
 - Input Layer
 - Recurrent Layer
 - Fully Connected Output Layer
↳ Compile model:
 - Loss function = CrossEntropy
 - Optimizer = Adam
 - Metrics = Accuracy.
↳ Train Model:
 For each epoch:
 Forward pass
 Compute loss
 Backword pass

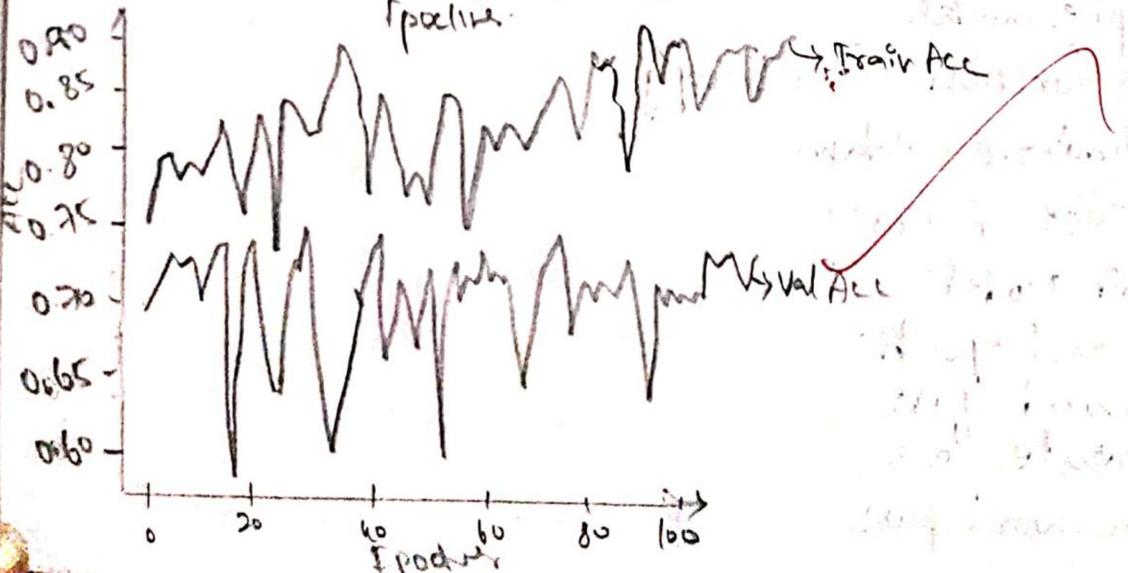
For 20 Epochs





For 100 Epochs





Store loss & accurracy.

Evaluate model on test/validation set.

Visualize results [loss vs epoch, accuracy vs epoch]

OBSERVATION

For 100 epochs

	presion	recall	f1-score	support
0.0	0.71	0.73	0.72	4961
1.0	0.72	0.71	0.71	5039
accuracy			$\boxed{0.72}$	10000.
macro avg	0.72	0.72	0.72	10000
weighted avg.	0.72	0.72	0.72	10000.

For 20 Epochs.

	presion	recall	f1-score	support
	0.71	0.74	0.74	4961
	0.75	0.75	0.75	5039
acerracy			$\boxed{0.75}$	10000
maro avg	0.71	0.75	0.75	10000
weighted avg	0.75	0.75	0.75.	10000

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RESULT:

The experimnt was Implemented and executed succesfully with 72% acerracy for 100 epochs and 75 for 20 epochs.

```python
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
```

```python
# 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
```

```python
# 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
```

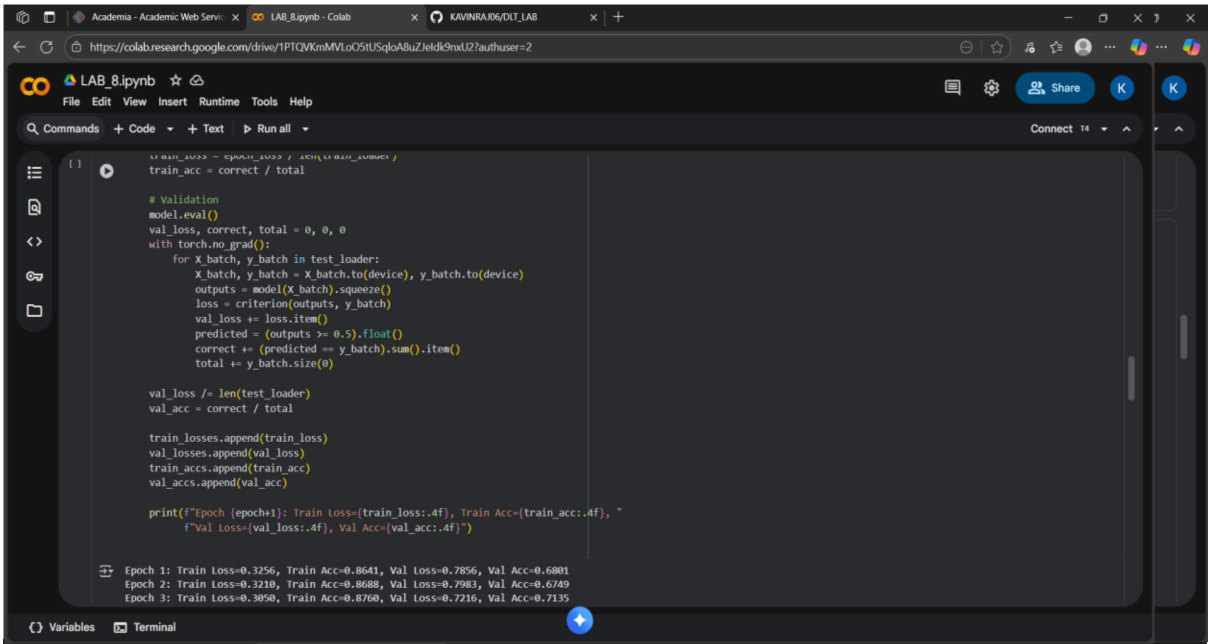
```
                                              review sentiment
0  One of the other reviewers has mentioned that ...  positive
1  A wonderful little production. <br /><br />The...  positive
2  I thought this was a wonderful way to spend ti...  positive
3  Basically there's a family where a little boy ...  negative
4  Petter Mattei's "Love in the Time of Money" is...  positive
```

```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)
```

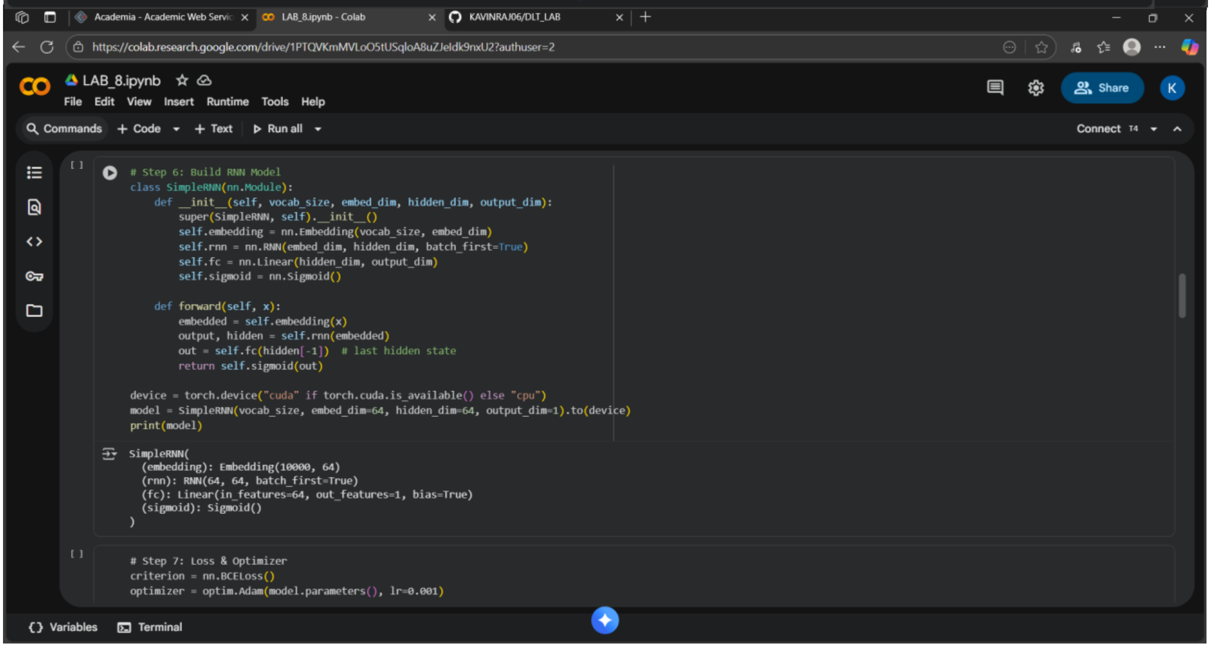
```python
# Step 5: Create Dataset & DataLoader
class IMDBDataset(Dataset):
    def __init__(self, X, y):
        self.X = X
        self.y = y

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

    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 RNN Model
class SimpleRNN(nn.Module):
    def __init__(self, vocab_size, embed_dim, hidden_dim, output_dim):
```



```
    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}")
```

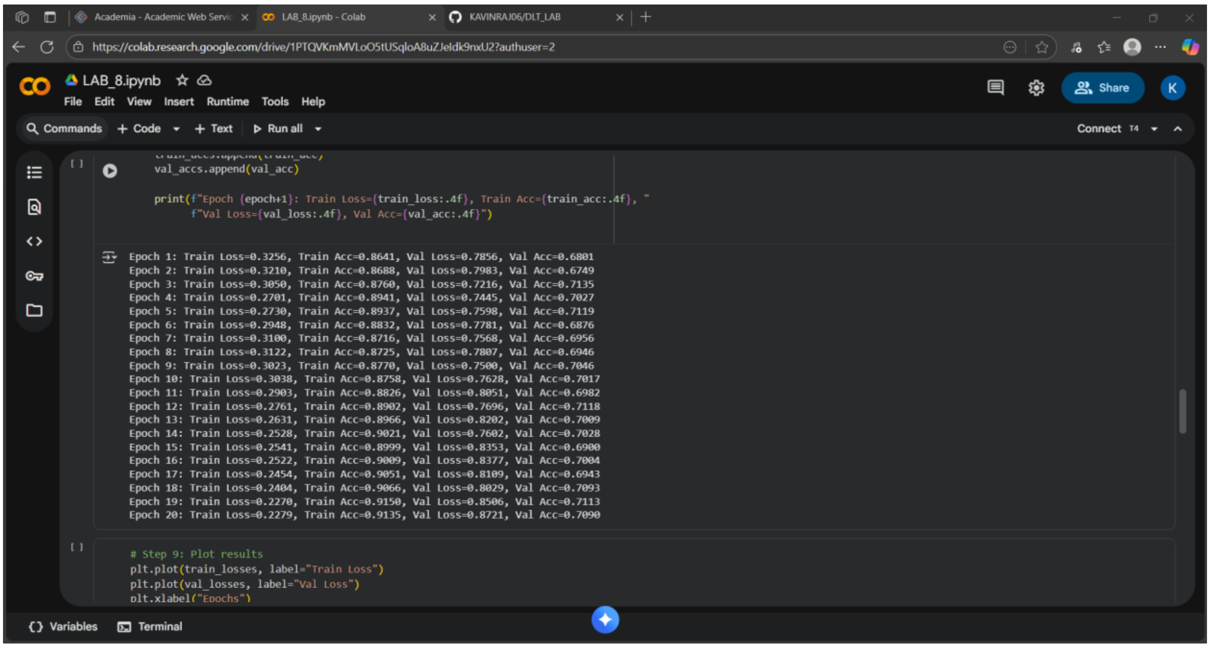
```
Epoch 1: Train Loss=0.3256, Train Acc=0.8641, Val Loss=0.7856, Val Acc=0.6801
Epoch 2: Train Loss=0.3210, Train Acc=0.8688, Val Loss=0.7983, Val Acc=0.6749
Epoch 3: Train Loss=0.3050, Train Acc=0.8760, Val Loss=0.7216, Val Acc=0.7135
```



```
# Step 6: Build RNN Model
class SimpleRNN(nn.Module):
    def __init__(self, vocab_size, embed_dim, hidden_dim, output_dim):
        super(SimpleRNN, self).__init__()
        self.embedding = nn.Embedding(vocab_size, embed_dim)
        self.rnn = nn.RNN(embed_dim, hidden_dim, batch_first=True)
        self.fc = nn.Linear(hidden_dim, output_dim)
        self.sigmoid = nn.Sigmoid()

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

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

```
SimpleRNN(
  (embedding): Embedding(10000, 64)
  (rnn): RNN(64, 64, batch_first=True)
  (fc): Linear(in_features=64, out_features=1, bias=True)
  (sigmoid): Sigmoid()
)
```

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



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KAVINRAJ06/DLT_LAB
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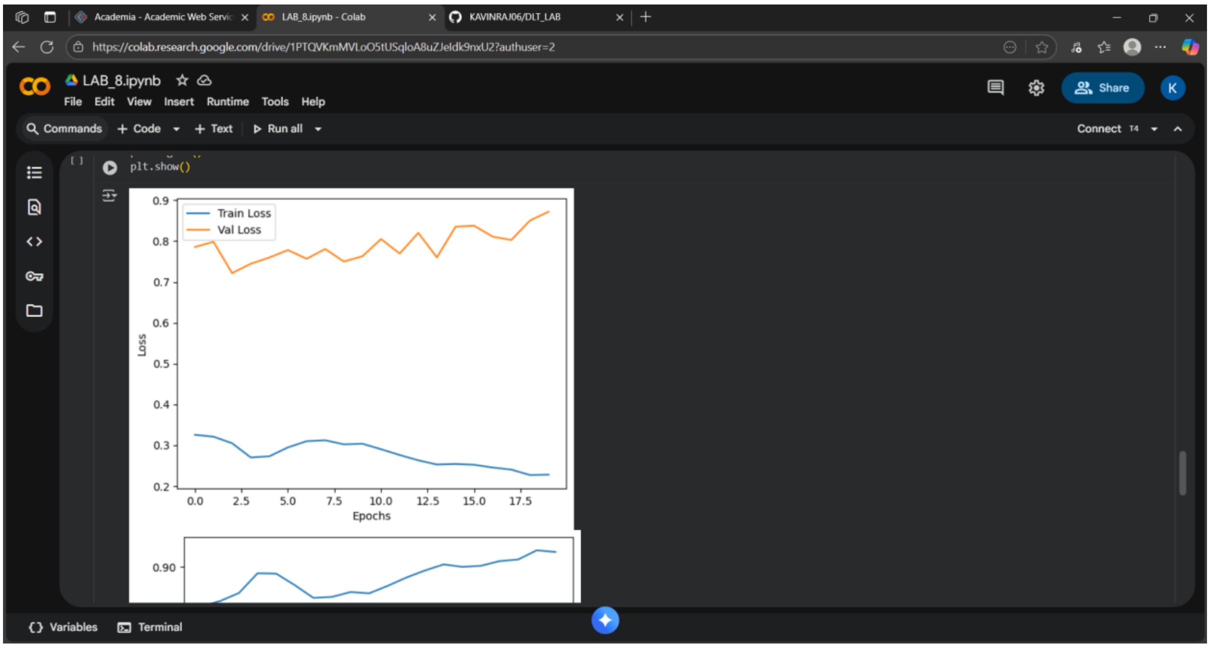
LAB_8.ipynb
File Edit View Insert Runtime Tools Help
Commands + Code + Text Run all
Share
Connect T4
val_accs.append(val_acc)
print(f"Epoch {epoch+1}: Train Loss={train_loss:.4f}, Train Acc={train_acc:.4f}, "
f"Val Loss={val_loss:.4f}, Val Acc={val_acc:.4f}")
Epoch 1: Train Loss=0.3256, Train Acc=0.8641, Val Loss=0.7856, Val Acc=0.6801
Epoch 2: Train Loss=0.3210, Train Acc=0.8688, Val Loss=0.7983, Val Acc=0.6749
Epoch 3: Train Loss=0.3050, Train Acc=0.8760, Val Loss=0.7216, Val Acc=0.7135
Epoch 4: Train Loss=0.2701, Train Acc=0.8941, Val Loss=0.7445, Val Acc=0.7027
Epoch 5: Train Loss=0.2730, Train Acc=0.8937, Val Loss=0.7598, Val Acc=0.7119
Epoch 6: Train Loss=0.2948, Train Acc=0.8832, Val Loss=0.7781, Val Acc=0.6876
Epoch 7: Train Loss=0.3100, Train Acc=0.8716, Val Loss=0.7568, Val Acc=0.6956
Epoch 8: Train Loss=0.3122, Train Acc=0.8725, Val Loss=0.7807, Val Acc=0.6946
Epoch 9: Train Loss=0.3023, Train Acc=0.8770, Val Loss=0.7500, Val Acc=0.7046
Epoch 10: Train Loss=0.3038, Train Acc=0.8758, Val Loss=0.7628, Val Acc=0.7017
Epoch 11: Train Loss=0.2903, Train Acc=0.8826, Val Loss=0.8051, Val Acc=0.6982
Epoch 12: Train Loss=0.2761, Train Acc=0.8902, Val Loss=0.7696, Val Acc=0.7118
Epoch 13: Train Loss=0.2631, Train Acc=0.8966, Val Loss=0.8202, Val Acc=0.7009
Epoch 14: Train Loss=0.2528, Train Acc=0.9021, Val Loss=0.7602, Val Acc=0.7028
Epoch 15: Train Loss=0.2541, Train Acc=0.8999, Val Loss=0.8353, Val Acc=0.6900
Epoch 16: Train Loss=0.2522, Train Acc=0.9009, Val Loss=0.8377, Val Acc=0.7004
Epoch 17: Train Loss=0.2454, Train Acc=0.9051, Val Loss=0.8109, Val Acc=0.6943
Epoch 18: Train Loss=0.2404, Train Acc=0.9066, Val Loss=0.8029, Val Acc=0.7093
Epoch 19: Train Loss=0.2270, Train Acc=0.9150, Val Loss=0.8506, Val Acc=0.7113
Epoch 20: Train Loss=0.2279, Train Acc=0.9135, Val Loss=0.8721, Val Acc=0.7090
# Step 9: Plot results
plt.plot(train_losses, label="Train Loss")
plt.plot(val_losses, label="Val Loss")
plt.xlabel("Epochs")
Variables
Terminal



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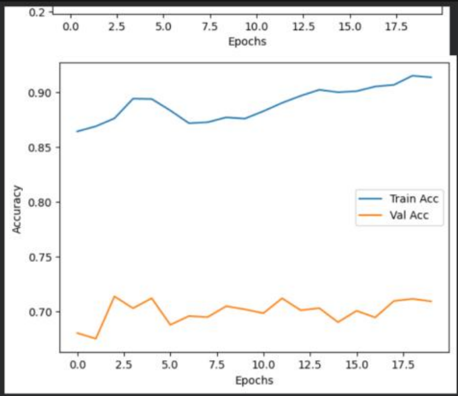
https://colab.research.google.com/drive/1PTQVKmMVLoO5tUSqloA8uZJeldk9nxU2?authuser=2
LAB_8.ipynb
File Edit View Insert Runtime Tools Help
Commands + Code + Text Run all
Share
Connect T4
plt.show()
Train Loss
Val Loss
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
Loss
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Epochs
0.90
Variables
Terminal




```python
from sklearn.metrics import classification_report

model.eval()
y_pred = []
y_true = []
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()
        predicted = (outputs >= 0.5).float()
        y_pred.extend(predicted.cpu().numpy())
        y_true.extend(y_batch.cpu().numpy())

print(classification_report(y_true, y_pred))
```

```
              precision    recall  f1-score   support

         0.0       0.71      0.70      0.70      4961
         1.0       0.71      0.72      0.71      5039

    accuracy                           0.71     10000
   macro avg       0.71      0.71      0.71     10000
weighted avg       0.71      0.71      0.71     10000
```