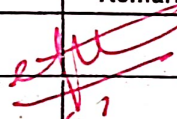
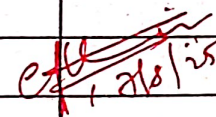
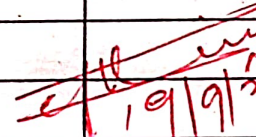
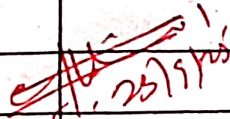
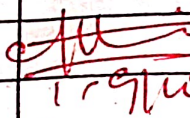


B.Tech - AI - 'A' section

3rd year

INDEX

NAME: TAMILSELVAN M STD: _____ SEC: _____ ROLL NO.: _____ SUB _____

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4	07/08/25	Build a Simple feed forward neural network to recognize handwritten character (MNIST Dataset)		
5	22/08/25	Study of Activation function & Their Role.		 19/9/25
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30/9/25
Exp: 8

BUILD A RECURRENT NEURAL NETWORK

AIM:

To implement a RNN model with

IMDB dataset.

OBJECTIVE:

- To understand the working of RNN in NLP.
- To Perform binary sentiment classification using the IMDB dataset.
- To utilize pre-trained word embeddings to improve model performance.

PSEUDOCODE:

1. Import libraries
↳ tensorflow
2. Load IMDB dataset
3. Split the data
4. Pad Sequences
5. Build a Simple RNN model
6. Compile the model
7. Train the model
8. Evaluate the model

IMDB - dataset (50,000)

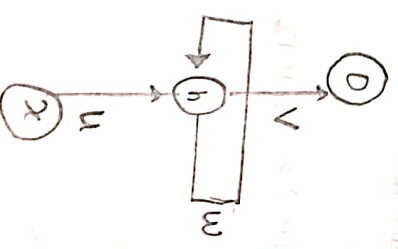
Label

→ 75,000 (Train)

Positive, Negative

→ 15,000 (Test)

ARCHITECTURE

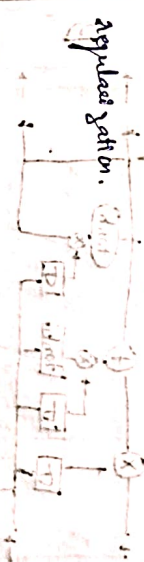


$$h_k^{(t)} = \sigma (w_h h^{(t-1)} + w_x e^{(t)} + b)$$

OBSERVATION

→ The RNN is able to learn temporal relationship in text, even though it is simpler than GRU.

→ Accuracy is decent for a basic model, especially without advanced things as application.



Justification

→ The use of Pre-trained

Embedding is a learned embedding layer allows the model to capture semantic meaning of words efficiently.

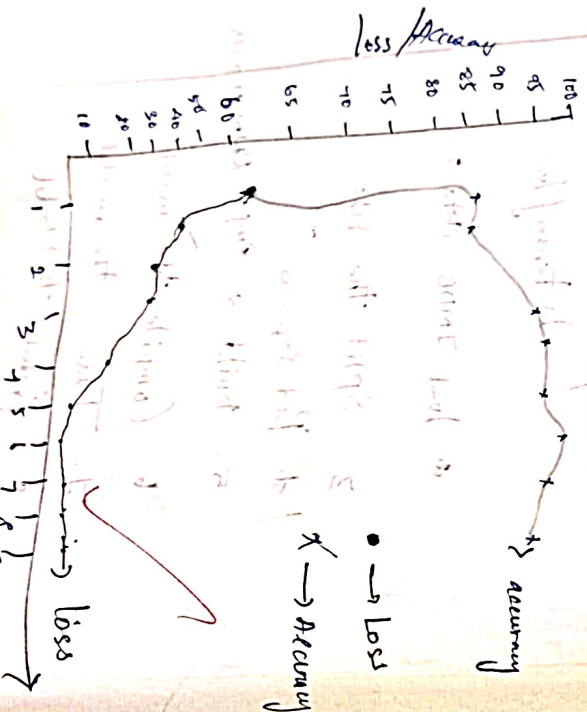
Train & Loss Accuracy
96.7 0.09

CONCLUSION:

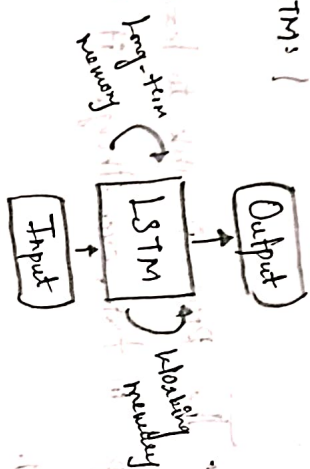
Successfully implemented a Simple

Rank

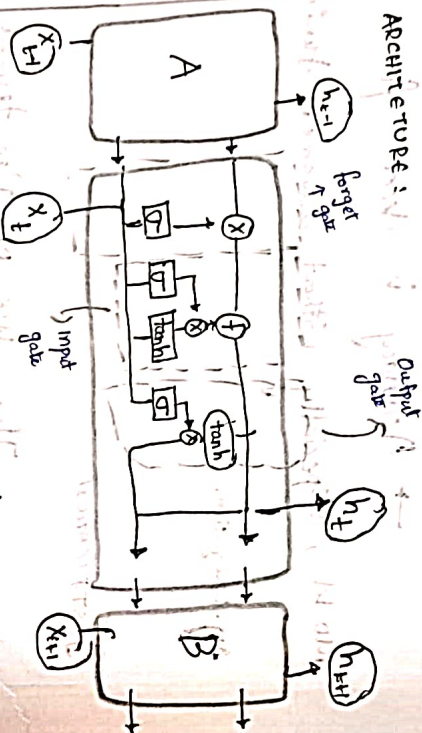
Epoch	Accuracy	Loss
1/9	62%	62%
2/9	87%	37%
3/9	86%	31%
4/9	93%	17%
5/9	98%	6%
6/9	98%	4%
7/9	99%	1%
8/9	97%	7%
9/9	96%	9%



LSTM:



ARCHITECTURE:



APPLICATION: Image Captioning, Machine Translation

Music Generation, Auto Handwriting Generation

Ex 9
30/9/25

EXPERIMENT Using LSTM

AIM:

Long Short Term Memory (LSTM) is an enhanced version of the RNN. Designed by Hochreiter and Schmidhuber. Build a LSTM to predict the next value.

Objective

To implement a simple LSTM network using Keras and Tensorflow in python.

Pseudocode:

1. Installing required libraries
2. Data preparation
3. Build the LSTM model
4. Train model
5. Make a Prediction

OBSERVATION:

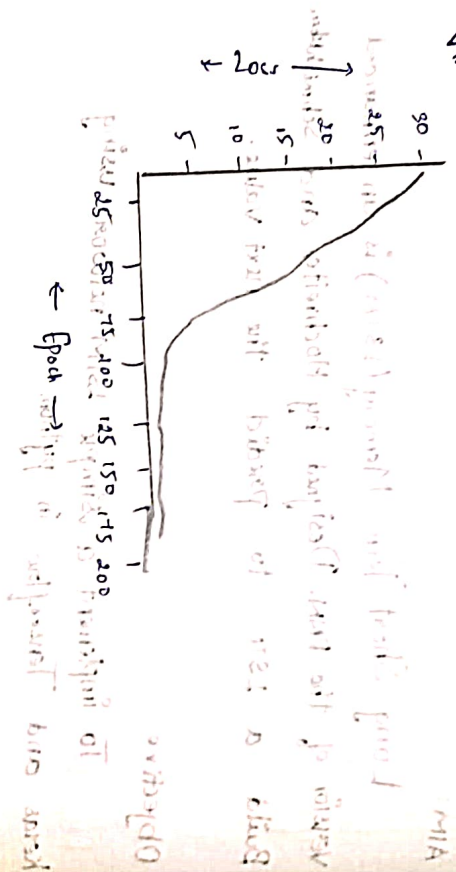
Data Preparation:

$X = [[1, 2, 3], [2, 3, 4], [3, 4, 5], [4, 5, 6]]$

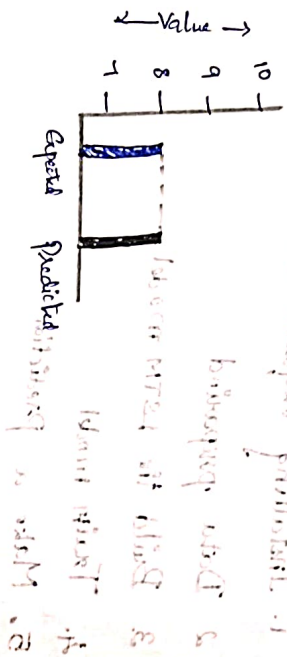
$Y = [A, B, C, D]$ In sequence and

features is the number of features at each time stamp

Visual Representation



Expected Vs Predicted



Expected, Predicted, Difference, Loss

Frequency

Loss

Loss function

to calculate the loss

of the model

with the

data

Model Building

- 50 LSTM units \rightarrow 'ReLU' activation function
- A dense (fully connected) layer with one unit is added (1)
- Optimizer \rightarrow Adam
- Loss function \rightarrow (MSE) "Mean Square Error"
- Training Epoch \rightarrow 200 with Suppress Verbose
- Make Prediction

Output

Predicted next value for [5, 16, 7]: 8.01

Result:

Implemented a simple LSTM

model. Predicted next value from trained sequence.