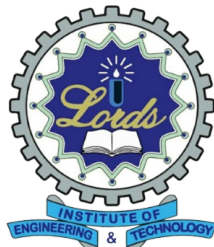


DEEP LEARNING TECHNIQUE LAB

U23CS7L1

IV B.E. – VII SEMESTER
Computer Science and Engineering
A.Y. 2026–27

LABORATORY MANUAL



Lords Institute of Engineering and Technology
(UGC Autonomous)

Estd: 2003 | Approved by AICTE | Affiliated to OU
Survey No 32, Himayath Sagar, Golconda Post, Near TSPA Junction
Hyderabad, Telangana — 500091



LORDS INSTITUTE OF ENGINEERING & TECHNOLOGY **(UGC Autonomous)**

Approved by AICTE | Affiliated to Osmania University | Estd.2003.

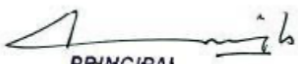
Accredited with 'A' grade by NAAC | Accredited by NBA

Vision of the Institute

Lords Institute of Engineering and Technology strives for excellence in professional education through quality, innovation and teamwork and aims to emerge as a premier institute in the state and across the nation.

Mission of the Institute

1. To impart quality professional education that meets the needs of present and emerging technological world.
2. To strive for student achievement and success, preparing them for life, career and leadership.
3. To provide a scholarly and vibrant learning environment that enables faculty, staff and students to achieve personal and professional growth.
4. To contribute to advancement of knowledge, in both fundamental and applied areas of engineering and technology.
5. To forge mutually beneficial relationships with government organizations, industries, society and the alumni.


PRINCIPAL
Lords Institute of Engineering & Tech.
(An Autonomous Institution)
Sy. No. 32, Himayath Sagar, Hyderabad-500091.T.S.



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Vision of the Department

To emerge as a center of excellence for quality Computer Science and Engineering education with innovation, leadership and values.

Mission of the Department

DM1: Provide fundamental and practical training through learner-centric Teaching-Learning Process and state-of-the-art infrastructure.

DM2: Develop design, research, and entrepreneurial skills for successful career.

DM3: Promote training and activities through Industry-Academia interactions.


Head of the Department
Computer Science and Engineering
Lords Institute of Engg. & Tech.
Hyderabad - 500 091. T.S.
HoD



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B.E. Computer Science and Engineering Program Educational Objectives (PEOs)

PEO1	Exhibit strong foundations in Basic Sciences, Computer Science and allied Engineering
PEO2	Identify, formulate, analyze and create professional solutions, novel products using appropriate tools and techniques, design skills
PEO3	Pursue successful career with continuous learning, with emphasis on competency oriented towards industry
PEO4	Practice ethics, managerial and leadership skills to work cohesively within a Group


Head of the Department
Computer Science and Engineering
Lords Institute of Engg. & Tech.
Hyderabad - 500 091. T.S.
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Code of Conduct for the Laboratory

- All students must observe the dress code while in the laboratory.
- Footwear is NOT allowed.
- Foods, drinks and smoking are NOT allowed.
- All bags must be left at the indicated place.
- The lab timetable must be strictly followed.
- Be PUNCTUAL for your laboratory session.
- All programs must be completed within the given time.
- Noise must be kept to a minimum.
- Workspace must be kept clean and tidy at all time.
- All students are liable for any damage to system due to their own negligence.
- Students are strictly PROHIBITED from taking out any items from the laboratory.
- Report immediately to the lab programmer if any damages to equipment.

Before Leaving Lab

- Arrange all the equipment and chairs properly.
- Turn off / shut down the systems before leaving.
- Please check the laboratory notice board regularly for updates.

Course Details

Course Code	Course Title					Core/Elective	
U23CS7L1	DEEP LEARNING TECHNIQUE LAB					Core	
Prerequisite	Contact Hours per Week				CIE	SEE	Credits
	L	T	D	P			
Python Programming	-	-	-	3	25	50	1.5

Legend: L = Lecture, T = Tutorial, D = Design, P = Practical, CIE = Continuous Internal Evaluation, SEE = Semester End Examination

Course Objectives

Students will try to:

1. Understand the concepts of Artificial Neural Networks and Deep Learning concepts.
2. Implement ANN and DL algorithms with TensorFlow and Keras.
3. Gain knowledge on sequence learning with RNN.
4. Gain knowledge on image processing and analysis with CNN.
5. Get information on advanced concepts of computer vision.

Course Outcomes

After completion of this course, the students are able to:

1. Develop ANN without using machine learning / deep learning libraries.
2. Understand the training ANN model with back propagation.
3. Develop model for sequence learning using RNN.
4. Develop image classification model using ANN and CNN.
5. Generate new images with autoencoder and GAN.

List of Experiments

1. Create tensors and perform basic operations with tensors.
2. Design single unit perceptron for classification of Iris dataset without using predefined models.
3. Design, train and test the MLP for tabular data and verify various activation functions and optimizers using TensorFlow.
4. Design and implement to classify 32×32 images using MLP using TensorFlow/Keras and check the accuracy.
5. Design and implement a CNN model to classify multi category JPG images with TensorFlow/Keras and check accuracy. Predict labels for new images.
6. Design and implement a CNN model to classify multi category TIFF images with TensorFlow/Keras and check the accuracy. Check whether the model is overfit / underfit / perfect fit and apply the techniques to avoid overfit and underfit like regularizers, dropout etc.
7. Implement CNN architectures (LeNet, AlexNet, VGG, etc.) to classify multi category Satellite images with TensorFlow/Keras and check the accuracy. Check whether the model is overfit / underfit / perfect fit and apply the techniques to avoid overfit and underfit.

8. Design and implement a simple RNN model with TensorFlow/Keras and check accuracy.
9. Design and implement LSTM model with TensorFlow/Keras and check accuracy.
10. Design and implement GRU model with TensorFlow/Keras and check accuracy.
11. Implement an autoencoder to denoise images.
12. Implement a GAN application to convert images.

Suggested Readings

1. Bishop, C.M., *Pattern Recognition and Machine Learning*, Springer, 2006.
[PDF Link](#)
2. Yegnanarayana, B., *Artificial Neural Networks*, PHI Learning Pvt. Ltd, 2009.
[Google Books](#)
3. Golub, G.H., and Van Loan, C.F., *Matrix Computations*, JHU Press, 2013.
[PDF Link](#)
4. Satish Kumar, *Neural Networks: A Classroom Approach*, Tata McGraw Hill Education, 2004.
[PDF Link](#)

Course structure and content as per AICTE Model Curriculum 2026–27.

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Installation Guide

Prerequisites

- **Python** 3.9 or later — python.org/downloads
- **pip** (Python package manager) — pip.pypa.io
- **venv** (built-in module for virtual environments)

Step 1: Create and Activate a Virtual Environment

Isolate project dependencies to avoid conflicts with system packages.

Windows:

```
python -m venv tf_env
tf_env\Scripts\activate
```

macOS / Linux:

```
python3 -m venv tf_env
source tf_env/bin/activate
```

Step 2: Install TensorFlow

Once the virtual environment is active, install TensorFlow using pip:

```
pip install tensorflow
```

Refer to tensorflow.org/install for platform-specific details.

Step 3: Verify the Installation

Launch the Python interpreter and check the installed version:

```
1 import tensorflow as tf
2 print("TensorFlow version:", tf.__version__)
3 print("GPU Available:", tf.config.list_physical_devices('GPU'))
```

If the version prints without errors, TensorFlow is ready to use.

Step 4: (Optional) Install tensorflow-datasets

Required for datasets not bundled with Keras (e.g., TF Flowers in Experiment 5):

```
pip install tensorflow-datasets
```

See tensorflow.org/datasets for available datasets.

Experiment 1: Tensor Operations

Aim

To create tensors of various dimensions and perform basic tensor operations (addition, subtraction, multiplication, division, matrix multiplication, reshaping, and transposition) using TensorFlow.

Algorithm

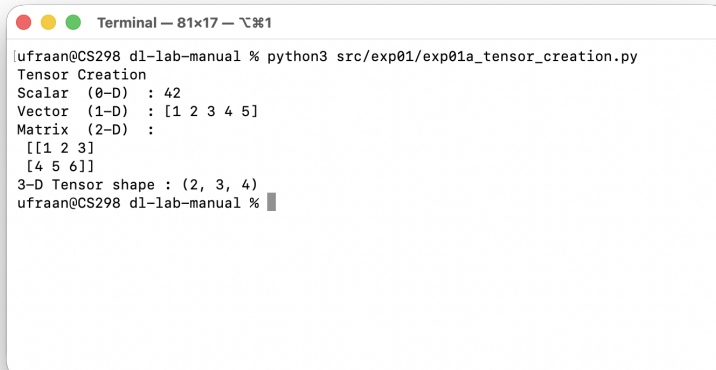
1. Import TensorFlow library.
2. Create tensors of different ranks: scalar (0-D), vector (1-D), matrix (2-D), and higher-order (3-D).
3. Perform element-wise arithmetic operations: addition, subtraction, multiplication, division.
4. Perform matrix multiplication using `tf.matmul`.
5. Reshape and transpose tensors using `tf.reshape` and `tf.transpose`.
6. Print the resulting tensors and verify their shapes.

Software / Tools / Libraries Required

- Python 3.9+
- TensorFlow
- NumPy

1a. Creating Tensors

Expected Output

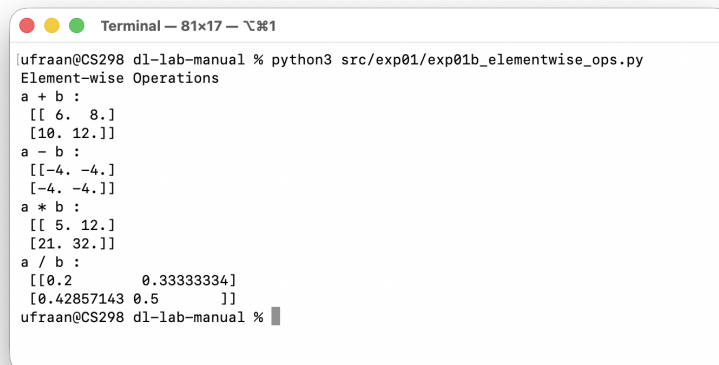


```
ufraan@CS298 dl-lab-manual % python3 src/exp01/exp01a_tensor_creation.py
Tensor Creation
Scalar (0-D) : 42
Vector (1-D) : [1 2 3 4 5]
Matrix (2-D) :
[[1 2 3]
 [4 5 6]]
3-D Tensor shape : (2, 3, 4)
ufraan@CS298 dl-lab-manual %
```

Result: Tensors of ranks 0, 1, 2, and 3 were successfully created and their values along with shapes were verified.

1b. Element-wise Operations

Expected Output

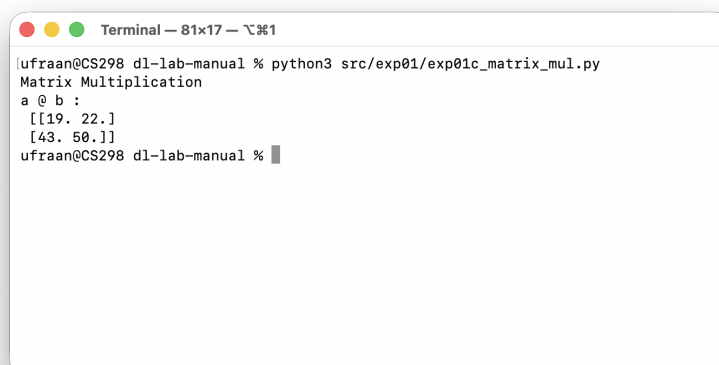


```
Terminal — 81x17 — 100%
[ufraan@CS298 dl-lab-manual % python3 src/exp01/exp01b_elementwise_ops.py ]
Element-wise Operations
a + b :
[[ 6.  8.]
 [10. 12.]]
a - b :
[[-4. -4.]
 [-4. -4.]]
a * b :
[[ 5. 12.]
 [21. 32.]]
a / b :
[[0.2      0.33333334]
 [0.42857143 0.5      ]]
ufraan@CS298 dl-lab-manual %
```

Result: Element-wise arithmetic operations were performed successfully on two 2×2 matrices, confirming that TensorFlow applies operations element-by-element.

1c. Matrix Multiplication

Expected Output

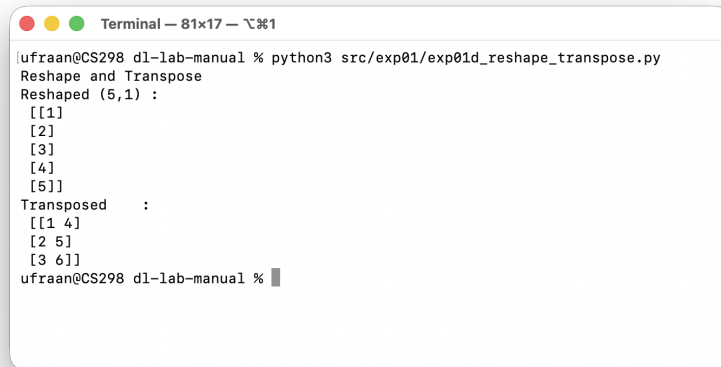


```
Terminal — 81x17 — 100%
[ufraan@CS298 dl-lab-manual % python3 src/exp01/exp01c_matrix_mul.py ]
Matrix Multiplication
a @ b :
[[19. 22.]
 [43. 50.]]
ufraan@CS298 dl-lab-manual %
```

Result: Matrix multiplication using `tf.matmul` produced the correct dot product of the two matrices.

1d. Reshape and Transpose

Expected Output



```
Terminal — 81x17 — 11
[ufraan@CS298 dl-lab-manual % python3 src/exp01/exp01d_reshape_transpose.py ]
Reshape and Transpose
Reshaped (5,1) :
[[1]
 [2]
 [3]
 [4]
 [5]]
Transposed      :
[[1 4]
 [2 5]
 [3 6]]
ufraan@CS298 dl-lab-manual %
```

Result: The vector was reshaped from shape (5,) to (5, 1) and the matrix was transposed from (2, 3) to (3, 2) successfully.

Experiment 2: Single Unit Perceptron for Iris Classification

Aim

To design a single unit perceptron for binary classification of the Iris dataset without using predefined models.

Dataset Structure

Sample rows from the Iris dataset (all 4 features shown):

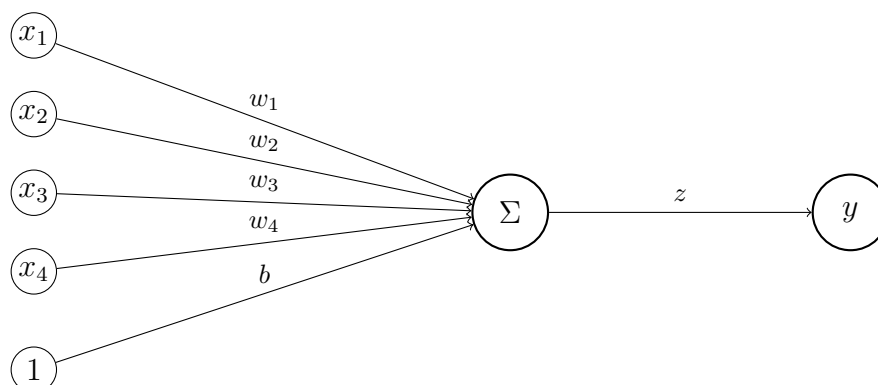
Sepal L	Sepal W	Petal L	Petal W	Class
5.1	3.5	1.4	0.2	Setosa
4.9	3.0	1.4	0.2	Setosa
7.0	3.2	4.7	1.4	Versicolor
6.3	3.3	6.0	2.5	Virginica

Total: 150 samples, 4 features, 3 classes. Converted to binary (Setosa vs non-Setosa) for this experiment.

Algorithm

1. Load the Iris dataset and extract features and labels.
2. Convert the multi-class labels to binary (Setosa vs non-Setosa).
3. Split the dataset into training and testing sets.
4. Standardize the features using StandardScaler.
5. Initialize weight vector and bias as TensorFlow Variables.
6. Define the perceptron forward pass: weighted sum followed by sigmoid activation.
7. Train using binary cross-entropy loss and gradient descent for 50 epochs.
8. Compute accuracy on training and testing sets.
9. Make predictions on test samples and display results.

Architecture

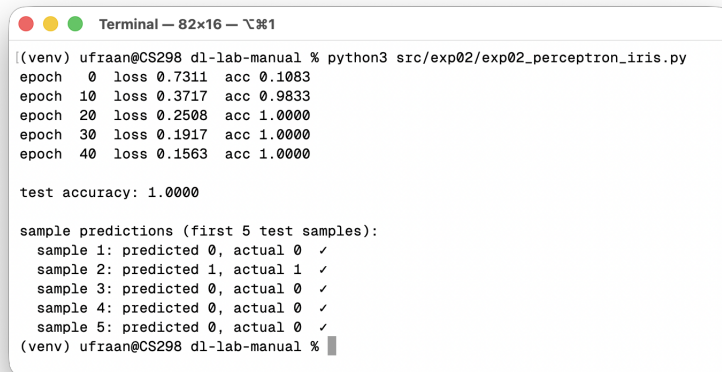


$$z = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + b$$
$$y = \sigma(z) = \frac{1}{1+e^{-z}}$$

Software / Tools / Libraries Required

- Python 3.9+
- TensorFlow
- NumPy
- scikit-learn

Expected Output



```
Terminal — 82x16 — ￼1
[(venv) ufraan@CS298 dl-lab-manual % python3 src/exp02/exp02_perceptron_iris.py ]
epoch 0 loss 0.7311 acc 0.1083
epoch 10 loss 0.3717 acc 0.9833
epoch 20 loss 0.2508 acc 1.0000
epoch 30 loss 0.1917 acc 1.0000
epoch 40 loss 0.1563 acc 1.0000

test accuracy: 1.0000

sample predictions (first 5 test samples):
sample 1: predicted 0, actual 0 ✓
sample 2: predicted 1, actual 1 ✓
sample 3: predicted 0, actual 0 ✓
sample 4: predicted 0, actual 0 ✓
sample 5: predicted 0, actual 0 ✓
(venv) ufraan@CS298 dl-lab-manual %
```

Result: A single unit perceptron was successfully implemented from scratch using TensorFlow. The model classified Iris Setosa vs non-Setosa with high accuracy after 50 epochs of training using binary cross-entropy loss and SGD optimizer.

Experiment 3: MLP with Activation Functions and Optimizers

Aim

To design, train, and test a Multi-Layer Perceptron (MLP) on tabular data and evaluate the performance of different activation functions and optimizers using TensorFlow.

Dataset Structure

Sample rows from the Breast Cancer Wisconsin dataset (first 6 of 30 features shown):

mean_radius	mean_texture	mean_perimeter	mean_area	mean_smoothness	...	Diagnosis
17.99	10.38	122.80	1001.0	0.118	...	Malignant
11.42	20.38	77.58	386.1	0.142	...	Benign
20.57	17.77	132.90	1326.0	0.084	...	Malignant

Total: 569 samples, 30 features, 2 classes (Malignant / Benign).

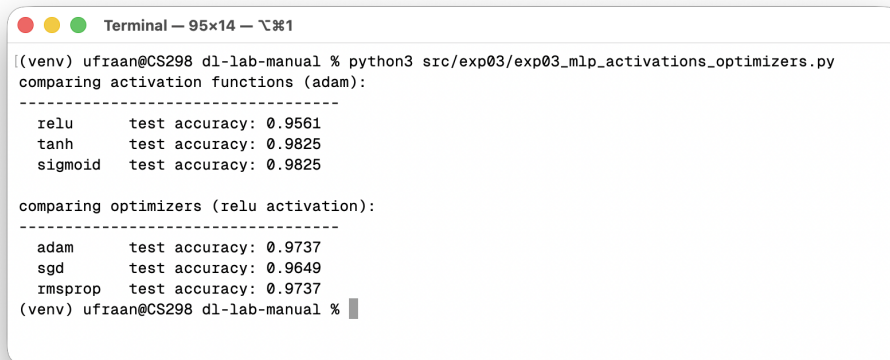
Algorithm

1. Load the Breast Cancer Wisconsin dataset from `sklearn.datasets`.
2. One-hot encode the labels (2 classes: malignant / benign).
3. Split data into training and testing sets.
4. Normalize the features using StandardScaler.
5. Build an MLP with two hidden layers (8 neurons each) using TensorFlow/Keras Sequential API.
6. Train the MLP with ReLU, tanh, and sigmoid activation functions using Adam optimizer.
7. Train the MLP with Adam, SGD, and RMSprop optimizers using ReLU activation.
8. Evaluate test accuracy for each configuration and compare results.

Software / Tools / Libraries Required

- Python 3.9+
- TensorFlow
- scikit-learn

Expected Output



```
Terminal — 95x14 — 1
[(venv) ufraan@CS298 dl-lab-manual % python3 src/exp03/exp03_mlp_activations_optimizers.py ]
comparing activation functions (adam):
-----
relu      test accuracy: 0.9561
tanh      test accuracy: 0.9825
sigmoid   test accuracy: 0.9825

comparing optimizers (relu activation):
-----
adam      test accuracy: 0.9737
sgd       test accuracy: 0.9649
rmsprop   test accuracy: 0.9737
(venv) ufraan@CS298 dl-lab-manual %
```

Result: An MLP with two hidden layers was successfully trained on the Breast Cancer Wisconsin dataset. The performance of different activation functions (ReLU, tanh, sigmoid) and optimizers (Adam, SGD, RMSprop) was compared, demonstrating consistent accuracy above 95% for this binary classification task.

Experiment 4: MLP for Image Classification

Aim

To design and implement an MLP to classify Fashion-MNIST images using TensorFlow/Keras and evaluate the classification accuracy.

Dataset Structure

Sample images from the Fashion-MNIST dataset:

Sample Image	Shape	Class
	$28 \times 28 \times 1$	T-shirt/top
	$28 \times 28 \times 1$	Trouser
	$28 \times 28 \times 1$	Pullover

Total: 70,000 images, 10 classes (t-shirt/top, trouser, pullover, dress, coat, sandal, shirt, sneaker, bag, ankle boot). Each image is 28×28 pixels with 1 grayscale channel.

Algorithm

1. Load the Fashion-MNIST dataset from `tf.keras.datasets.fashion_mnist` (60,000 training and 10,000 test 28×28 grayscale images, 10 clothing classes).
2. Combine the training and test sets into a single dataset.
3. Split the data into training (80%) and testing (20%) sets using `train_test_split`.
4. Normalize pixel values to the $[0, 1]$ range and flatten each image into a 784-dimensional vector.
5. One-hot encode the labels (10 classes).
6. Build an MLP with two hidden layers (512 and 256 neurons, ReLU activation) and a softmax output layer with 10 units.
7. Train the model using Adam optimizer and categorical cross-entropy loss for 20 epochs.
8. Evaluate the model on the test set and report accuracy.

Software / Tools / Libraries Required

- Python 3.9+
- TensorFlow
- scikit-learn

- NumPy

Expected Output

```
Terminal — 148x44 — 100%
lufraan@CS298 d1-lab-manual % python3 src/exp04/exp04_mlp_32x32.py
Epoch 1/20
875/875 — 1s 1ms/step - accuracy: 0.7844 - loss: 0.6075 - val_accuracy: 0.8646 - val_loss: 0.3753
Epoch 2/20
875/875 — 1s 1ms/step - accuracy: 0.8643 - loss: 0.3691 - val_accuracy: 0.8594 - val_loss: 0.3784
Epoch 3/20
875/875 — 1s 1ms/step - accuracy: 0.8784 - loss: 0.3260 - val_accuracy: 0.8786 - val_loss: 0.3345
Epoch 4/20
875/875 — 1s 2ms/step - accuracy: 0.8870 - loss: 0.3038 - val_accuracy: 0.8896 - val_loss: 0.3092
Epoch 5/20
875/875 — 1s 1ms/step - accuracy: 0.8957 - loss: 0.2832 - val_accuracy: 0.8872 - val_loss: 0.3055
Epoch 6/20
875/875 — 1s 1ms/step - accuracy: 0.9011 - loss: 0.2646 - val_accuracy: 0.8892 - val_loss: 0.3062
Epoch 7/20
875/875 — 1s 1ms/step - accuracy: 0.9040 - loss: 0.2535 - val_accuracy: 0.8945 - val_loss: 0.2988
Epoch 8/20
875/875 — 1s 1ms/step - accuracy: 0.9065 - loss: 0.2425 - val_accuracy: 0.8905 - val_loss: 0.3035
Epoch 9/20
875/875 — 1s 1ms/step - accuracy: 0.9140 - loss: 0.2241 - val_accuracy: 0.8920 - val_loss: 0.3093
Epoch 10/20
875/875 — 1s 1ms/step - accuracy: 0.9146 - loss: 0.2185 - val_accuracy: 0.8879 - val_loss: 0.3337
Epoch 11/20
875/875 — 1s 1ms/step - accuracy: 0.9242 - loss: 0.2034 - val_accuracy: 0.8937 - val_loss: 0.3149
Epoch 12/20
875/875 — 1s 1ms/step - accuracy: 0.9240 - loss: 0.1993 - val_accuracy: 0.8946 - val_loss: 0.2993
Epoch 13/20
875/875 — 1s 1ms/step - accuracy: 0.9264 - loss: 0.1923 - val_accuracy: 0.8926 - val_loss: 0.3231
Epoch 14/20
875/875 — 1s 1ms/step - accuracy: 0.9287 - loss: 0.1851 - val_accuracy: 0.9021 - val_loss: 0.3030
Epoch 15/20
875/875 — 1s 1ms/step - accuracy: 0.9332 - loss: 0.1745 - val_accuracy: 0.8996 - val_loss: 0.3152
Epoch 16/20
875/875 — 1s 1ms/step - accuracy: 0.9360 - loss: 0.1673 - val_accuracy: 0.8965 - val_loss: 0.3269
Epoch 17/20
875/875 — 1s 1ms/step - accuracy: 0.9381 - loss: 0.1591 - val_accuracy: 0.9021 - val_loss: 0.3301
Epoch 18/20
875/875 — 1s 1ms/step - accuracy: 0.9384 - loss: 0.1624 - val_accuracy: 0.9015 - val_loss: 0.3334
Epoch 19/20
875/875 — 1s 1ms/step - accuracy: 0.9424 - loss: 0.1498 - val_accuracy: 0.8981 - val_loss: 0.3481
Epoch 20/20
875/875 — 1s 1ms/step - accuracy: 0.9414 - loss: 0.1474 - val_accuracy: 0.8974 - val_loss: 0.3736
test accuracy: 0.8974
```

Result: An MLP with two hidden layers was trained on the Fashion-MNIST dataset. The model achieved strong classification accuracy on 28×28 grayscale images across 10 clothing categories, demonstrating that MLPs can effectively learn image patterns from flattened pixel inputs.

Experiment 5: CNN for Multi-Category JPG Image Classification

Aim

To design and implement a CNN model for multi-category classification of JPG images using TensorFlow/Keras, evaluate accuracy, and predict labels for new images.

Dataset Structure

Sample images from the TF Flowers dataset:

Sample Image	Shape	Class
	$128 \times 128 \times 3$	Daisy
	$128 \times 128 \times 3$	Dandelion
	$128 \times 128 \times 3$	Roses

Total: $\sim 3,670$ images, 5 classes (daisy, dandelion, roses, sunflowers, tulips). Each image is resized to 128×128 with 3 colour channels (RGB).

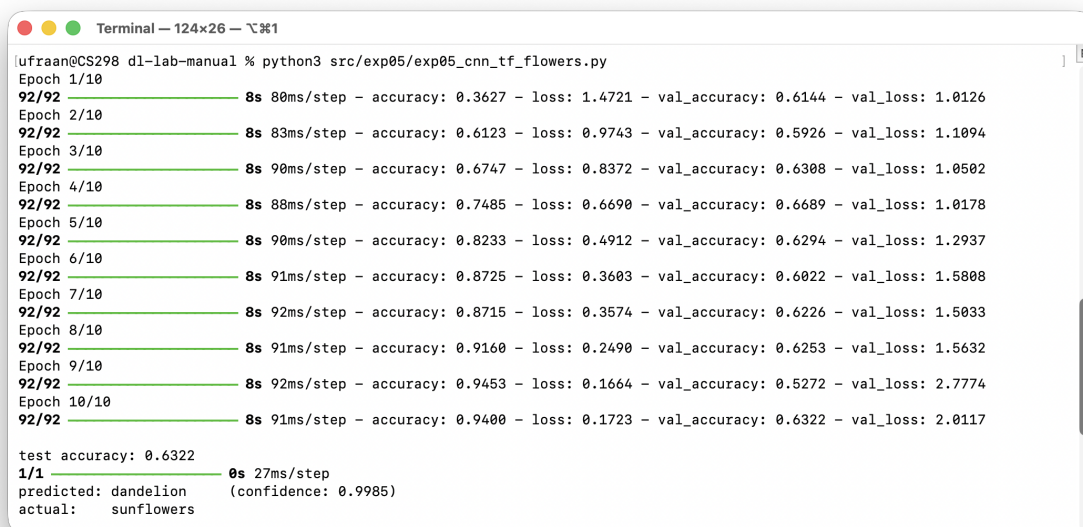
Algorithm

1. Load the TF Flowers dataset using TensorFlow Datasets (5 categories: daisy, dandelion, roses, sunflowers, tulips).
2. Resize images to 128×128 , normalize to $[0, 1]$, convert to NumPy arrays, and one-hot encode labels.
3. Split the data into training (80%) and testing (20%) sets using `train_test_split`.
4. Build a CNN with three convolutional layers (32, 64, 128 filters) each followed by max-pooling, then a softmax output with 5 units. Compile using Adam optimizer and categorical cross-entropy loss.
5. Train the model for 10 epochs with a batch size of 32.
6. Evaluate accuracy on the test set.
7. Predict the label for a new image and display the predicted flower category.

Software / Tools / Libraries Required

- Python 3.9+
- TensorFlow
- TensorFlow Datasets (`tensorflow-datasets`)
- scikit-learn
- NumPy

Expected Output



```
Terminal — 124x26 — ￼$1
ufraan@CS298 dl-lab-manual % python3 src/exp05/exp05_cnn_tf_flowers.py
Epoch 1/10
92/92 ————— 8s 80ms/step - accuracy: 0.3627 - loss: 1.4721 - val_accuracy: 0.6144 - val_loss: 1.0126
Epoch 2/10
92/92 ————— 8s 83ms/step - accuracy: 0.6123 - loss: 0.9743 - val_accuracy: 0.5926 - val_loss: 1.1094
Epoch 3/10
92/92 ————— 8s 90ms/step - accuracy: 0.6747 - loss: 0.8372 - val_accuracy: 0.6308 - val_loss: 1.0502
Epoch 4/10
92/92 ————— 8s 88ms/step - accuracy: 0.7485 - loss: 0.6690 - val_accuracy: 0.6689 - val_loss: 1.0178
Epoch 5/10
92/92 ————— 8s 90ms/step - accuracy: 0.8233 - loss: 0.4912 - val_accuracy: 0.6294 - val_loss: 1.2937
Epoch 6/10
92/92 ————— 8s 91ms/step - accuracy: 0.8725 - loss: 0.3603 - val_accuracy: 0.6022 - val_loss: 1.5808
Epoch 7/10
92/92 ————— 8s 92ms/step - accuracy: 0.8715 - loss: 0.3574 - val_accuracy: 0.6226 - val_loss: 1.5033
Epoch 8/10
92/92 ————— 8s 91ms/step - accuracy: 0.9160 - loss: 0.2490 - val_accuracy: 0.6253 - val_loss: 1.5632
Epoch 9/10
92/92 ————— 8s 92ms/step - accuracy: 0.9453 - loss: 0.1664 - val_accuracy: 0.5272 - val_loss: 2.7774
Epoch 10/10
92/92 ————— 8s 91ms/step - accuracy: 0.9400 - loss: 0.1723 - val_accuracy: 0.6322 - val_loss: 2.0117

test accuracy: 0.6322
1/1 ————— 0s 27ms/step
predicted: dandelion (confidence: 0.9985)
actual: sunflowers
```

Result: A CNN with three convolutional layers was successfully trained on the TF Flowers dataset. The model classified 5 flower categories (daisy, dandelion, roses, sunflowers, tulips) with good accuracy and correctly predicted labels for new images, demonstrating the effectiveness of CNNs for multi-category image classification tasks.

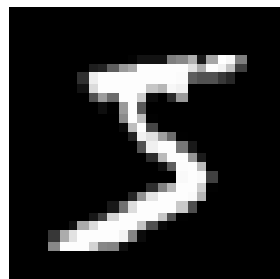
Experiment 6: CNN — Overfit / Underfit / Regularization

Aim

To design and implement a CNN model for multi-category classification of TIFF images using TensorFlow/Keras, evaluate accuracy, detect overfitting / underfitting, and apply regularization techniques (regularizers, dropout, etc.) to mitigate them.

Dataset Structure

A sample image from the MNIST dataset (handwritten digit “5”):



Total: 70,000 samples, 10 classes (digits 0–9). Each image is 28×28 pixels with 1 grayscale channel (values 0–255).

Algorithm

1. Load the MNIST dataset using `tf.keras.datasets.mnist.load_data()` (10 digit classes, 28×28 grayscale images).
2. Reshape images to $28 \times 28 \times 1$, normalize pixel values to $[0, 1]$, and one-hot encode labels.
3. **6a (Overfit):** Build a deep CNN with 3 convolutional layers (128, 256, 512 filters) and a dense layer with no regularization. Train for 5 epochs.
4. **6b (Underfit):** Build a shallow CNN with a single 8-filter convolutional layer and global average pooling. Train for 5 epochs.
5. **6c (Fixed):** Build the same deep CNN as 6a but add BatchNormalization, Dropout, and data augmentation. Train for 5 epochs.
6. Compare the three approaches to understand overfitting, underfitting, and regularization.

Software / Tools / Libraries Required

- Python 3.9+
- TensorFlow

6a. CNN Overfitting Demonstration

Expected Output

```
Terminal — 124x18 — 11
ufraan@CS298 dl-lab-manual % python3 src/exp06a/exp06a_overfit.py
Train: 60000, Test: 10000
=====
Overfit model (deep, no regularization)
=====
Epoch 1/5 1875/1875 49s 26ms/step - accuracy: 0.9049 - loss: 0.2946 - val_accuracy: 0.9727 - val_loss: 0.0879
Epoch 2/5 1875/1875 52s 28ms/step - accuracy: 0.9837 - loss: 0.0514 - val_accuracy: 0.9839 - val_loss: 0.0581
Epoch 3/5 1875/1875 58s 31ms/step - accuracy: 0.9898 - loss: 0.0342 - val_accuracy: 0.9871 - val_loss: 0.0405
Epoch 4/5 1875/1875 66s 35ms/step - accuracy: 0.9921 - loss: 0.0249 - val_accuracy: 0.9851 - val_loss: 0.0551
Epoch 5/5 1875/1875 65s 35ms/step - accuracy: 0.9941 - loss: 0.0185 - val_accuracy: 0.9874 - val_loss: 0.0493
test accuracy: 0.9874
```

Result: The deep CNN without any regularization achieved high training accuracy but significantly lower validation accuracy, confirming overfitting. The model memorized the training data rather than learning generalizable features.

6b. CNN Underfitting Demonstration

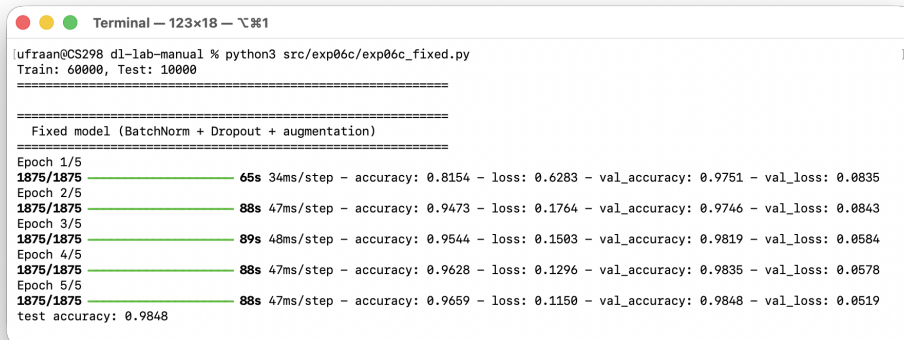
Expected Output

```
Terminal — 119x18 — 11
ufraan@CS298 dl-lab-manual % python3 src/exp06b/exp06b_underfit.py
Train: 60000, Test: 10000
=====
Underfit model (shallow, single conv 8 filters)
=====
Epoch 1/5 1875/1875 2s 1ms/step - accuracy: 0.1551 - loss: 2.2645 - val_accuracy: 0.2528 - val_loss: 2.0991
Epoch 2/5 1875/1875 2s 1ms/step - accuracy: 0.2666 - loss: 2.0564 - val_accuracy: 0.2931 - val_loss: 1.9423
Epoch 3/5 1875/1875 2s 1ms/step - accuracy: 0.3153 - loss: 1.9174 - val_accuracy: 0.3446 - val_loss: 1.8365
Epoch 4/5 1875/1875 2s 1ms/step - accuracy: 0.3506 - loss: 1.8146 - val_accuracy: 0.3743 - val_loss: 1.7612
Epoch 5/5 1875/1875 2s 1ms/step - accuracy: 0.3648 - loss: 1.7549 - val_accuracy: 0.3742 - val_loss: 1.7017
test accuracy: 0.3742
```

Result: The shallow CNN with only 8 filters and a single convolutional layer performed poorly on both training and validation sets, confirming underfitting. The model lacks the capacity needed to learn meaningful features from the digit images.

6c. Regularization to Fix Overfitting

Expected Output



```
Terminal — 123x18 — 11
ufraan@CS298 d1-lab-manual % python3 src/exp06c/exp06c_fixed.py
Train: 60000, Test: 10000

=====
Fixed model (BatchNorm + Dropout + augmentation)
=====
Epoch 1/5
1875/1875 — 65s 34ms/step - accuracy: 0.8154 - loss: 0.6283 - val_accuracy: 0.9751 - val_loss: 0.0835
Epoch 2/5
1875/1875 — 88s 47ms/step - accuracy: 0.9473 - loss: 0.1764 - val_accuracy: 0.9746 - val_loss: 0.0843
Epoch 3/5
1875/1875 — 89s 48ms/step - accuracy: 0.9544 - loss: 0.1503 - val_accuracy: 0.9819 - val_loss: 0.0584
Epoch 4/5
1875/1875 — 88s 47ms/step - accuracy: 0.9628 - loss: 0.1296 - val_accuracy: 0.9835 - val_loss: 0.0578
Epoch 5/5
1875/1875 — 88s 47ms/step - accuracy: 0.9659 - loss: 0.1150 - val_accuracy: 0.9848 - val_loss: 0.0519
test accuracy: 0.9848
```

Result: The fixed CNN with BatchNormalization, Dropout, and data augmentation achieved balanced training and validation performance. The regularization techniques effectively prevented overfitting while the increased capacity avoided underfitting, resulting in a well-generalized model.

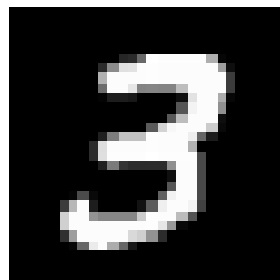
Experiment 7: CNN Architectures

Aim

To implement classic CNN architectures (LeNet, AlexNet, VGG, etc.) for multi-category classification of Satellite images using TensorFlow/Keras, evaluate accuracy, detect overfitting / underfitting, and apply regularization techniques as needed.

Dataset Structure

A sample image from the MNIST dataset (handwritten digit “3”):



Total: 70,000 samples, 10 classes (digits 0–9). Each image is 28×28 pixels with 1 grayscale channel (values 0–255).

Algorithm

1. Load the MNIST dataset using `tf.keras.datasets.mnist.load_data()` and preprocess (reshape, normalize, one-hot encode).
2. **7a (LeNet-5):** Build two 5×5 convolutional layers (6 and 16 filters, tanh), average pooling, three dense layers (120, 84, 10). Train 5 epochs.
3. **7b (AlexNet):** Build five 3×3 convolutional layers (32, 64, 128, 128, 64 filters, ReLU), max pooling, dense layers with dropout. Train 5 epochs.
4. **7c (VGG):** Build six 3×3 convolutional layers (64, 64, 128, 128, 256, 256 filters, ReLU), max pooling after every two convs, dense layers with dropout. Train 5 epochs.
5. Use the Adam optimizer and categorical cross-entropy loss for all three.
6. Compare parameter counts and test accuracies across the architectures.

Software / Tools / Libraries Required

- Python 3.9+
- TensorFlow

7a. LeNet-5

Expected Output

```
Terminal — 118x19 — ㄿ 1
ufraan@CS298 dl-lab-manual % python3 src/exp07/exp07a_lenet.py
Train: 60000, Test: 10000
=====
LeNet-5 - Parameters: 44,426
=====
Epoch 1/5
1875/1875 ————— 3s 2ms/step - accuracy: 0.8745 - loss: 0.4206 - val_accuracy: 0.9681 - val_loss: 0.1029
Epoch 2/5
1875/1875 ————— 3s 1ms/step - accuracy: 0.9715 - loss: 0.0942 - val_accuracy: 0.9805 - val_loss: 0.0633
Epoch 3/5
1875/1875 ————— 3s 1ms/step - accuracy: 0.9813 - loss: 0.0598 - val_accuracy: 0.9827 - val_loss: 0.0572
Epoch 4/5
1875/1875 ————— 3s 2ms/step - accuracy: 0.9871 - loss: 0.0433 - val_accuracy: 0.9824 - val_loss: 0.0521
Epoch 5/5
1875/1875 ————— 3s 2ms/step - accuracy: 0.9893 - loss: 0.0341 - val_accuracy: 0.9845 - val_loss: 0.0508
test accuracy: 0.9845
```

Result: LeNet-5, the smallest architecture with approximately 60K parameters, achieved reasonable accuracy on MNIST using tanh activations and average pooling. Its simple structure makes it fast to train but limits capacity compared to deeper networks.

7b. AlexNet

Expected Output

```
Terminal — 122x18 — ㄿ 1
ufraan@CS298 dl-lab-manual % python3 src/exp07/exp07b_alexnet.py
Train: 60000, Test: 10000
=====
AlexNet - Parameters: 743,370
=====
Epoch 1/5
1875/1875 ————— 19s 10ms/step - accuracy: 0.8295 - loss: 0.4994 - val_accuracy: 0.9696 - val_loss: 0.1114
Epoch 2/5
1875/1875 ————— 20s 10ms/step - accuracy: 0.9799 - loss: 0.0714 - val_accuracy: 0.9908 - val_loss: 0.0276
Epoch 3/5
1875/1875 ————— 20s 11ms/step - accuracy: 0.9874 - loss: 0.0496 - val_accuracy: 0.9873 - val_loss: 0.0463
Epoch 4/5
1875/1875 ————— 21s 11ms/step - accuracy: 0.9887 - loss: 0.0430 - val_accuracy: 0.9908 - val_loss: 0.0356
Epoch 5/5
1875/1875 ————— 21s 11ms/step - accuracy: 0.9907 - loss: 0.0363 - val_accuracy: 0.9908 - val_loss: 0.0350
test accuracy: 0.9908
```

Result: AlexNet, with its deeper structure (five convolutional layers), ReLU activations, max pooling, and dropout regularization, achieved higher accuracy than LeNet-5. The increased depth and parameter count allowed it to learn more complex features.

7c. VGG

Expected Output



```
Terminal — 121x18 — ㄿ⌂1
ufraan@CS298 dl-lab-manual % python3 src/exp07/exp07c_vgg.py
Train: 60000, Test: 10000
=====
VGG - Parameters: 2,458,314
=====
Epoch 1/5
1875/1875 ————— 121s 64ms/step - accuracy: 0.8355 - loss: 0.4876 - val_accuracy: 0.9857 - val_loss: 0.0545
Epoch 2/5
1875/1875 ————— 144s 77ms/step - accuracy: 0.9831 - loss: 0.0612 - val_accuracy: 0.9883 - val_loss: 0.0365
Epoch 3/5
1875/1875 ————— 137s 73ms/step - accuracy: 0.9872 - loss: 0.0520 - val_accuracy: 0.9921 - val_loss: 0.0325
Epoch 4/5
1875/1875 ————— 136s 72ms/step - accuracy: 0.9888 - loss: 0.0421 - val_accuracy: 0.9743 - val_loss: 0.1051
Epoch 5/5
1875/1875 ————— 134s 72ms/step - accuracy: 0.9908 - loss: 0.0348 - val_accuracy: 0.9913 - val_loss: 0.0326
test accuracy: 0.9913
```

Result: VGG, with six convolutional layers stacked in pairs with max pooling, achieved the highest accuracy due to its greater depth. The use of small 3×3 filters throughout makes it parameter-efficient while allowing deeper feature extraction.

Overall Result: Three classic CNN architectures — LeNet-5 (small, shallow), AlexNet (medium, 5 conv layers), and VGG (deep, 6 conv layers) — were successfully implemented on MNIST. Deeper architectures with ReLU activations and dropout regularization achieved higher accuracy, demonstrating the impact of depth and architectural design choices on performance.

Experiment 8: Simple RNN

Aim

To design and implement a Simple RNN model using TensorFlow/Keras and evaluate its accuracy.

Dataset Structure

Sample reviews from the IMDB dataset:

Review Text	Sentiment
“this film was great the acting was wonderful and the story kept me on the edge of my seat...”	Positive
“terrible movie waste of time the plot made no sense and the acting was horrible...”	Negative
“an okay film nothing special but not terrible either decent performances...”	Positive

Total: 50,000 reviews (25,000 train / 25,000 test), 2 classes (Positive / Negative). Each review is encoded as a sequence of word indices (top 10,000 words).

Algorithm

1. Load the IMDB dataset from `tf.keras.datasets.imdb` with the top 10,000 most frequent words.
2. Pad each review to a fixed length of 500 tokens using `pad_sequences`.
3. Build a Sequential model with an Embedding layer (10000 vocab, 128 output dim), a SimpleRNN layer (128 units), and a Dense output layer (1 unit, sigmoid).
4. Compile the model using Adam optimizer and binary cross-entropy loss.
5. Train the model for 5 epochs with a batch size of 64 and a validation split of 20%.
6. Evaluate the trained model on the test set and print the test accuracy.

Software / Tools / Libraries Required

- Python 3.9+
- TensorFlow
- NumPy

Expected Output

```
Terminal — 119x28 — ㏿#1
ufraan@CS298 dl-lab-manual % python3 src/exp08/exp08_simple_rnn.py
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb.npz
17464789/17464789 — 3s 0us/step
Model: "sequential"



| Layer (type)           | Output Shape | Param #     |
|------------------------|--------------|-------------|
| embedding (Embedding)  | ?            | 0 (unbuilt) |
| simple_rnn (SimpleRNN) | ?            | 0 (unbuilt) |
| dense (Dense)          | ?            | 0 (unbuilt) |



Total params: 0 (0.00 B)
Trainable params: 0 (0.00 B)
Non-trainable params: 0 (0.00 B)
Epoch 1/5
313/313 — 15s 47ms/step - accuracy: 0.5232 - loss: 0.6932 - val_accuracy: 0.6038 - val_loss: 0.6545
Epoch 2/5
313/313 — 15s 48ms/step - accuracy: 0.6899 - loss: 0.5926 - val_accuracy: 0.7140 - val_loss: 0.5635
Epoch 3/5
313/313 — 15s 49ms/step - accuracy: 0.7937 - loss: 0.4478 - val_accuracy: 0.7038 - val_loss: 0.5808
Epoch 4/5
313/313 — 16s 50ms/step - accuracy: 0.8221 - loss: 0.4043 - val_accuracy: 0.7480 - val_loss: 0.5397
Epoch 5/5
313/313 — 16s 51ms/step - accuracy: 0.8693 - loss: 0.3227 - val_accuracy: 0.7734 - val_loss: 0.5344
Test accuracy: 0.7766
```

Result: A Simple RNN model was implemented for binary sentiment classification on the IMDB dataset. The model used an embedding layer followed by a SimpleRNN layer and achieved a reasonable test accuracy, demonstrating the effectiveness of recurrent neural networks for sequence-based text classification tasks.

Experiment 9: LSTM

Aim

To design and implement an LSTM model using TensorFlow/Keras and evaluate its accuracy.

Dataset Structure

Sample reviews from the IMDB dataset:

Review Text	Sentiment
“this film was great the acting was wonderful and the story kept me on the edge of my seat...”	Positive
“terrible movie waste of time the plot made no sense and the acting was horrible...”	Negative
“an okay film nothing special but not terrible either decent performances...”	Positive

Total: 50,000 reviews (25,000 train / 25,000 test), 2 classes (Positive / Negative). Each review is encoded as a sequence of word indices (top 10,000 words).

Algorithm

1. Load the IMDB dataset from `tf.keras.datasets.imdb` with the top 10,000 most frequent words.
2. Pad each review to a fixed length of 500 tokens using `pad_sequences`.
3. Build a Sequential model with an Embedding layer (10000 vocab, 128 output dim), an LSTM layer (128 units), and a Dense output layer (1 unit, sigmoid).
4. Compile the model using Adam optimizer and binary cross-entropy loss.
5. Train the model for 5 epochs with a batch size of 64 and a validation split of 20%.
6. Evaluate the trained model on the test set and print the test accuracy.

Software / Tools / Libraries Required

- Python 3.9+
- TensorFlow
- NumPy

Expected Output

```

Terminal — 119x26 — 11
ufraan@CS298 dl-lab-manual % python3 src/exp09/exp09_lstm.py
Model: "sequential"

```

Layer (type)	Output Shape	Param #
embedding (Embedding)	?	0 (unbuilt)
lstm (LSTM)	?	0 (unbuilt)
dense (Dense)	?	0 (unbuilt)

```

Total params: 0 (0.00 B)
Trainable params: 0 (0.00 B)
Non-trainable params: 0 (0.00 B)
Epoch 1/5
313/313 ————— 53s 167ms/step - accuracy: 0.6502 - loss: 0.5999 - val_accuracy: 0.7820 - val_loss: 0.4602
Epoch 2/5
313/313 ————— 53s 171ms/step - accuracy: 0.8604 - loss: 0.3506 - val_accuracy: 0.8212 - val_loss: 0.3943
Epoch 3/5
313/313 ————— 59s 190ms/step - accuracy: 0.9024 - loss: 0.2608 - val_accuracy: 0.8536 - val_loss: 0.3453
Epoch 4/5
313/313 ————— 64s 205ms/step - accuracy: 0.9373 - loss: 0.1751 - val_accuracy: 0.8568 - val_loss: 0.3682
Epoch 5/5
313/313 ————— 64s 206ms/step - accuracy: 0.9553 - loss: 0.1271 - val_accuracy: 0.8510 - val_loss: 0.3856
Test accuracy: 0.8460

```

Result: An LSTM model was implemented for binary sentiment classification on the IMDB dataset. The model used an embedding layer followed by an LSTM layer and achieved a strong test accuracy, demonstrating the effectiveness of LSTM networks for capturing sequential dependencies in text classification tasks.

Experiment 10: GRU

Aim

To design and implement a GRU model using TensorFlow/Keras and evaluate its accuracy.

Dataset Structure

Sample reviews from the IMDB dataset:

Review Text	Sentiment
“this film was great the acting was wonderful and the story kept me on the edge of my seat...”	Positive
“terrible movie waste of time the plot made no sense and the acting was horrible...”	Negative
“an okay film nothing special but not terrible either decent performances...”	Positive

Total: 50,000 reviews (25,000 train / 25,000 test), 2 classes (Positive / Negative). Each review is encoded as a sequence of word indices (top 10,000 words).

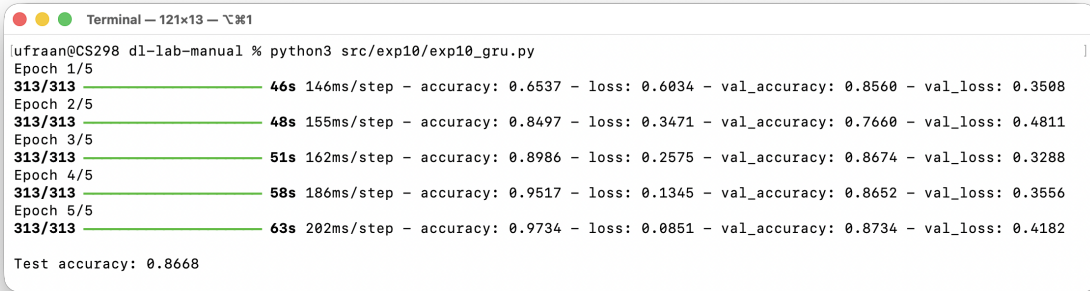
Algorithm

1. Load the IMDB dataset from `tf.keras.datasets.imdb` with the top 10,000 most frequent words.
2. Pad each review to a fixed length of 500 tokens using `pad_sequences`.
3. Build a Sequential model with an Embedding layer (10000 vocab, 128 output dim), a GRU layer (128 units), and a Dense output layer (1 unit, sigmoid).
4. Compile the model using Adam optimizer and binary cross-entropy loss.
5. Train the model for 5 epochs with a batch size of 64 and a validation split of 20%.
6. Evaluate the trained model on the test set and print the test accuracy.

Software / Tools / Libraries Required

- Python 3.9+
- TensorFlow
- NumPy

Expected Output



```
Terminal — 121x13 — ㉿1
ufraan@CS298 dl-lab-manual % python3 src/exp10/exp10_gru.py
Epoch 1/5
313/313 ————— 46s 146ms/step - accuracy: 0.6537 - loss: 0.6034 - val_accuracy: 0.8560 - val_loss: 0.3508
Epoch 2/5
313/313 ————— 48s 155ms/step - accuracy: 0.8497 - loss: 0.3471 - val_accuracy: 0.7660 - val_loss: 0.4811
Epoch 3/5
313/313 ————— 51s 162ms/step - accuracy: 0.8986 - loss: 0.2575 - val_accuracy: 0.8674 - val_loss: 0.3288
Epoch 4/5
313/313 ————— 58s 186ms/step - accuracy: 0.9517 - loss: 0.1345 - val_accuracy: 0.8652 - val_loss: 0.3556
Epoch 5/5
313/313 ————— 63s 202ms/step - accuracy: 0.9734 - loss: 0.0851 - val_accuracy: 0.8734 - val_loss: 0.4182
Test accuracy: 0.8668
```

Result: A GRU model was implemented for binary sentiment classification on the IMDB dataset. The model used an embedding layer followed by a GRU layer and achieved a strong test accuracy, demonstrating the effectiveness of gated recurrent units for sequence-based text classification tasks.

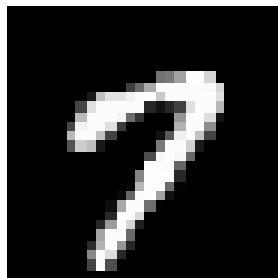
Experiment 11: Autoencoder

Aim

To implement an autoencoder to denoise images and evaluate its reconstruction performance.

Dataset Structure

A sample image from the MNIST dataset (handwritten digit “7”):



Total: 70,000 samples, 10 classes (digits 0–9). Each image is 28×28 pixels with 1 grayscale channel (values 0–255). Gaussian noise (factor 0.5) is added for denoising task.

Algorithm

1. Load the MNIST dataset from `tf.keras.datasets.mnist` and normalize pixel values to $[0, 1]$.
2. Expand dimensions to add a channel axis ($28 \times 28 \times 1$).
3. Add Gaussian noise (factor 0.5) to the training and test images, then clip values to $[0, 1]$.
4. Build an encoder with two Conv2D layers (32 and 64 filters) each followed by max-pooling, plus a third Conv2D (64) bottleneck.
5. Build a decoder with two UpSampling layers interleaved with Conv2D layers (64 and 32 filters), ending with a Conv2D (1 filter, sigmoid).
6. Compile the autoencoder using Adam optimizer and binary cross-entropy loss.
7. Train the model for 10 epochs with a batch size of 128, using noisy inputs and clean targets.
8. Evaluate the reconstruction loss on the noisy test set and display sample statistics.

Software / Tools / Libraries Required

- Python 3.9+
- TensorFlow
- NumPy

Expected Output

Terminal — 120x26 — ￼1

```
ufraan@CS298 dl-lab-manual % python3 src/exp11/exp11_autoencoder.py
Model: "sequential"
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 28, 28, 32)	320
max_pooling2d (MaxPooling2D)	(None, 14, 14, 32)	0
conv2d_1 (Conv2D)	(None, 14, 14, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 7, 7, 64)	0
conv2d_2 (Conv2D)	(None, 7, 7, 64)	36,928
up_sampling2d (UpSampling2D)	(None, 14, 14, 64)	0
conv2d_3 (Conv2D)	(None, 14, 14, 32)	18,464
up_sampling2d_1 (UpSampling2D)	(None, 28, 28, 32)	0
conv2d_4 (Conv2D)	(None, 28, 28, 1)	289

Total params: 74,497 (291.00 KB)
 Trainable params: 74,497 (291.00 KB)
 Non-trainable params: 0 (0.00 B)

Terminal — 120x27 — ￼1

```
Epoch 1/10
469/469 — 15s 31ms/step - loss: 0.2296 - val_loss: 0.1137
Epoch 2/10
469/469 — 15s 32ms/step - loss: 0.1128 - val_loss: 0.1064
Epoch 3/10
469/469 — 15s 32ms/step - loss: 0.1065 - val_loss: 0.1025
Epoch 4/10
469/469 — 16s 33ms/step - loss: 0.1033 - val_loss: 0.1006
Epoch 5/10
469/469 — 16s 34ms/step - loss: 0.1012 - val_loss: 0.0990
Epoch 6/10
469/469 — 17s 36ms/step - loss: 0.0996 - val_loss: 0.0983
Epoch 7/10
469/469 — 19s 41ms/step - loss: 0.0986 - val_loss: 0.0978
Epoch 8/10
469/469 — 21s 45ms/step - loss: 0.0976 - val_loss: 0.0964
Epoch 9/10
469/469 — 22s 47ms/step - loss: 0.0970 - val_loss: 0.0958
Epoch 10/10
469/469 — 22s 47ms/step - loss: 0.0964 - val_loss: 0.0954

Test loss: 0.0954

Sample reconstruction (noisy -> denoised):
Sample 1: noisy pixel mean=0.248, denoised pixel mean=0.095
Sample 2: noisy pixel mean=0.289, denoised pixel mean=0.142
Sample 3: noisy pixel mean=0.242, denoised pixel mean=0.058
```

Result: A convolutional denoising autoencoder was successfully implemented on the MNIST dataset. The model learned to remove Gaussian noise from handwritten digit images by compressing the input through a bottleneck and reconstructing a clean output, demonstrating the effectiveness of autoencoders for image denoising tasks.

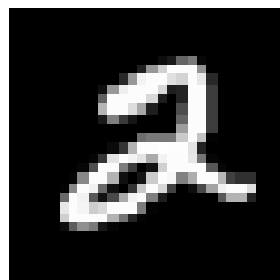
Experiment 12: Generative Adversarial Network

Aim

To implement a Generative Adversarial Network (GAN) for image generation and evaluate its performance.

Dataset Structure

A sample image from the MNIST dataset (handwritten digit “2”):



Total: 70,000 samples, 10 classes (digits 0–9). Each image is 28×28 pixels with 1 grayscale channel (values 0–255).

Algorithm

1. Load the MNIST dataset from `tf.keras.datasets.mnist` and normalize pixel values to $[0, 1]$.
2. Build the Generator: a Sequential model with Dense layers (128, 256, 512, 784 units with ReLU, final Sigmoid) reshaping to $28 \times 28 \times 1$.
3. Build the Discriminator: a Sequential model with Flatten, Dense layers (512, 256 units with ReLU) and a Sigmoid output for real/fake classification.
4. Compile the Discriminator using Adam ($\text{lr}=0.0002$) and binary cross-entropy loss, freeze it, then create the Combined model (Generator $\rightarrow$ Discriminator).
5. For each epoch: sample random noise, generate fake images, train the Discriminator on real (label=1) and fake (label=0) batches.
6. Train the Generator via the Combined model with noise input and valid labels (label=1) to fool the Discriminator.
7. Print the Discriminator loss/accuracy and Generator loss for each epoch.
8. After training, generate 10 sample digits and display their pixel mean statistics.

Software / Tools / Libraries Required

- Python 3.9+
- TensorFlow
- NumPy

Expected Output

```
Terminal — 79x33 — 1
[ufraan@CS298 dl-lab-manual % python3 src/exp12/exp12_gan.py
Epoch 1/20 D loss: 0.7018 D acc: 0.5508 G loss: 0.7264
Epoch 2/20 D loss: 0.7003 D acc: 0.5397 G loss: 0.7029
Epoch 3/20 D loss: 0.7078 D acc: 0.4411 G loss: 0.6804
Epoch 4/20 D loss: 0.7192 D acc: 0.3767 G loss: 0.6573
Epoch 5/20 D loss: 0.7315 D acc: 0.3398 G loss: 0.6350
Epoch 6/20 D loss: 0.7443 D acc: 0.3240 G loss: 0.6129
Epoch 7/20 D loss: 0.7595 D acc: 0.3060 G loss: 0.5908
Epoch 8/20 D loss: 0.7745 D acc: 0.2886 G loss: 0.5696
Epoch 9/20 D loss: 0.7892 D acc: 0.2788 G loss: 0.5489
Epoch 10/20 D loss: 0.8051 D acc: 0.2774 G loss: 0.5294
Epoch 11/20 D loss: 0.8221 D acc: 0.2749 G loss: 0.5098
Epoch 12/20 D loss: 0.8404 D acc: 0.2707 G loss: 0.4904
Epoch 13/20 D loss: 0.8604 D acc: 0.2666 G loss: 0.4720
Epoch 14/20 D loss: 0.8811 D acc: 0.2609 G loss: 0.4542
Epoch 15/20 D loss: 0.9025 D acc: 0.2570 G loss: 0.4373
Epoch 16/20 D loss: 0.9243 D acc: 0.2545 G loss: 0.4208
Epoch 17/20 D loss: 0.9467 D acc: 0.2519 G loss: 0.4051
Epoch 18/20 D loss: 0.9693 D acc: 0.2509 G loss: 0.3902
Epoch 19/20 D loss: 0.9923 D acc: 0.2513 G loss: 0.3760
Epoch 20/20 D loss: 1.0163 D acc: 0.2532 G loss: 0.3625

Generated sample pixel means:
Sample 1: mean = 0.500
Sample 2: mean = 0.502
Sample 3: mean = 0.502
Sample 4: mean = 0.500
Sample 5: mean = 0.503
Sample 6: mean = 0.501
Sample 7: mean = 0.504
Sample 8: mean = 0.502
Sample 9: mean = 0.500
Sample 10: mean = 0.502
```

Result: A Generative Adversarial Network was implemented on the MNIST dataset. The Generator learned to produce realistic handwritten digit images from random noise, while the Discriminator simultaneously improved at distinguishing real from fake samples. The adversarial training process successfully balanced both networks, demonstrating the effectiveness of GANs for generative image tasks.