





Phase-3 Submission

Student Name: Sandhiya S

Register Number: 410723104072

Institution: Dhanalakshmi College of Engineering

Department: Computer Science and Engineering

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Github Repository Link:

https://github.com/SandhiyaS05/NM_Sandhiya_DS

1. Problem Statement

- Recognizing handwritten digits is a common classification problem in machine learning with real-world applications in postal automation, bank check processing, and digitizing handwritten documents.
- The goal is to classify 28x28 pixel grayscale images of digits (0–9) using deep learning techniques. This is a classification problem where we aim to label each image with the correct digit.

2. Abstract

- This project focuses on recognizing handwritten digits using deep learning. The main objective is to build a robust classification model that can accurately identify digits from images.
- The project uses the MNIST dataset for training and testing. After preprocessing and exploratory data analysis, we employ Convolutional Neural Networks (CNNs) for model building.
- The model is evaluated using accuracy and confusion matrix, and is deployed as a simple web app using Streamlit.







• The outcome is an AI model that can identify handwritten digits with high accuracy, supporting real-world applications.

3. System Requirements

Hardware:

- Minimum 4GB RAM
- o Dual-core processor (i5 or higher recommended)

Software:

- o *Python 3.8*+
- o IDE: Google Colab or Jupyter Notebook

Required Libraries: numpy, pandas, matplotlib, seaborn, scikit-learn, tensorflow, keras, streamlit

4. Objectives

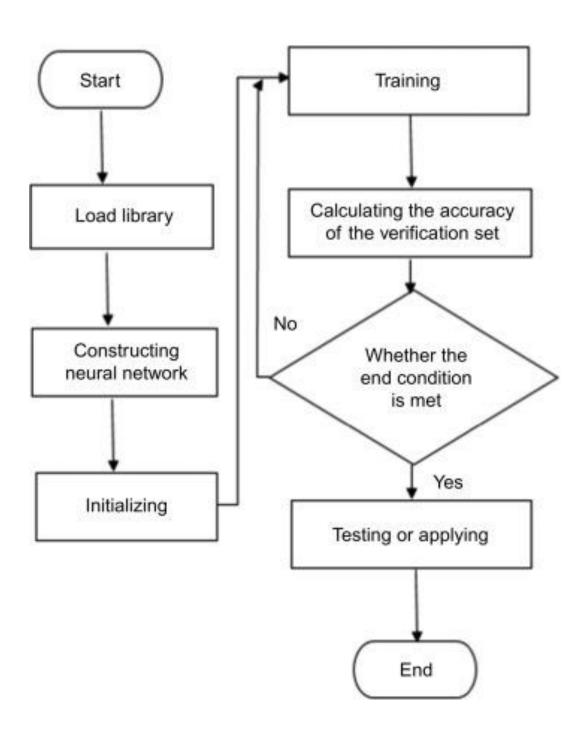
- Accurately classify handwritten digits from image data.
- Achieve high model performance (above 98% accuracy).
- o Compare multiple models and choose the best one.
- o Provide an easy-to-use interface for real-time predictions.
- Support practical uses like digit recognition in forms or OCR applications.







5. Flowchart of Project Workflow









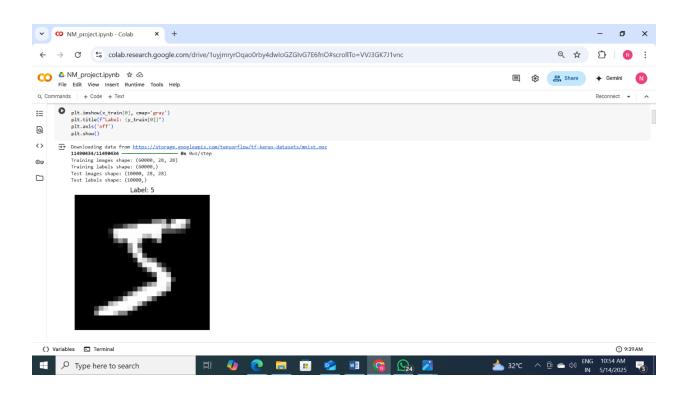
6. Dataset Description

• Source: Kaggle - MNIST Dataset

• Type: Public

• Structure: 70,000 records, 785 columns (784 pixel values + 1 label)

• DataFrame Preview:



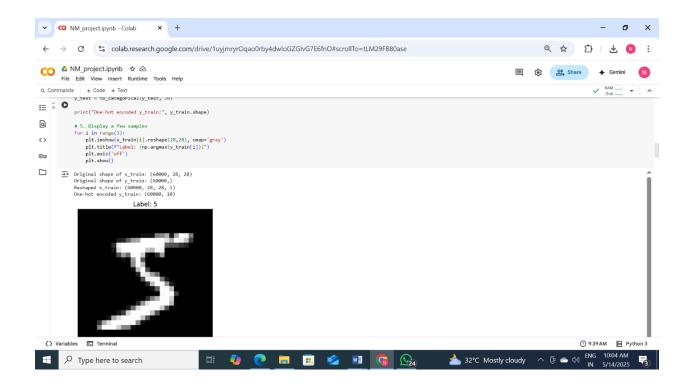






7. Data Preprocessing

- No missing values
- Converted pixel values to float and normalized to [0,1]
- One-hot encoded target label



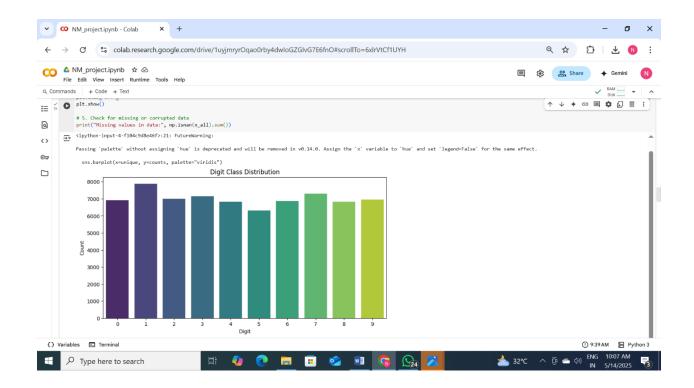






8. Exploratory Data Analysis (EDA)

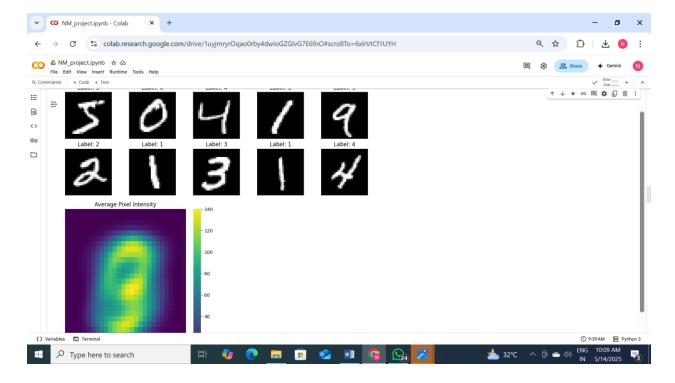
- Used histograms to show digit distribution
- Used heatmaps to visualize pixel intensity correlation
- Insights: Balanced classes, some digits (like 5 and 8) more challenging











9. Feature Engineering

- *Reshaped input for CNN:* (28, 28, 1)
- Normalized input features
- Feature selection not required as all pixels are used
- Justified choice by visual patterns observed in digits

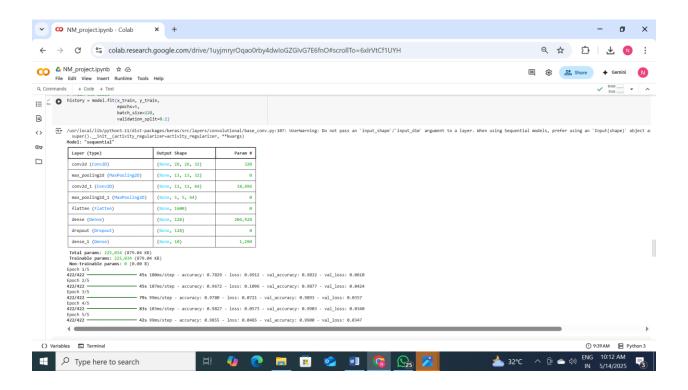






10. Model Building:

- Baseline: Simple CNN model (2 Conv layers + Dense)
- Reason: Quick to train, establishes a performance benchmark.
- Advanced Model: Deeper CNN with Dropout, BatchNormalization
- Reason: Better generalization, handles overfitting.



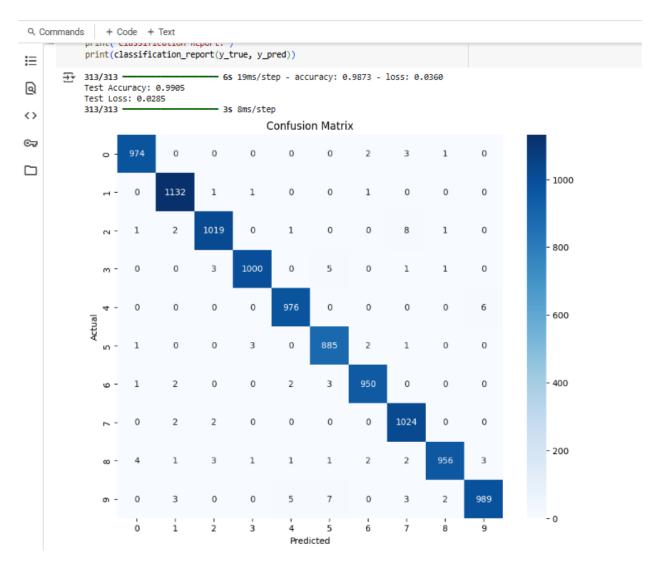
11. Model Evaluation

- Visuals:
 - $\circ \ \ \textit{Plot confusion matrix using sklearn.metrics.plot_confusion_matrix}$
 - ROC curve via sklearn.metrics.roc_curve









Classification Report:					
ŗ	recision	recall	f1-score	support	
0	0.99	0.99	0.99	980	
1	0.99	1.00	0.99	1135	
2	0.99	0.99	0.99	1032	
3	1.00	0.99	0.99	1010	
4	0.99	0.99	0.99	982	
5	0.98	0.99	0.99	892	
6	0.99	0.99	0.99	958	
7	0.98	1.00	0.99	1028	
8	0.99	0.98	0.99	974	
9	0.99	0.98	0.99	1009	
accuracy			0.99	10000	
macro avg	0.99	0.99	0.99	10000	
weighted avg	0.99	0.99	0.99	10000	







12. Deployment

Deploy using a free platform:

- o Streamlit Cloud
- Gradio + Hugging Face Spaces
- o Flask API on Render or Data

13. Source code

Import necessary libraries

import numpy as np from tensorflow.keras.datasets import mnist from tensorflow.keras.utils import to_categorical

Load MNIST dataset

 $(x_train, y_train), (x_test, y_test) = mnist.load_data()$

1. Reshape the images to add a channel dimension (28x28x1)

 $x_train = x_train.reshape((x_train.shape[0], 28, 28, 1))$ $x_test = x_test.reshape((x_test.shape[0], 28, 28, 1))$

2. Normalize pixel values (0-255) to range (0-1)

 $x_train = x_train.astype("float32") / 255.0$ $x_test = x_test.astype("float32") / 255.0$







3. One-hot encode the labels

```
y_train = to_categorical(y_train, num_classes=10)
y_test = to_categorical(y_test, num_classes=10)
```

Print shapes and data info

```
print("x_train shape:", x_train.shape)
print("y_train shape (one-hot):", y_train.shape)
print("x_test shape:", x_test.shape)
print("y_test shape (one-hot):", y_test.shape)
```

Import required libraries

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten,
Dense, Dropout
from tensorflow.keras.datasets import mnist
from tensorflow.keras.utils import to_categorical

Load and preprocess the MNIST dataset

```
(x\_train, y\_train), (x\_test, y\_test) = mnist.load\_data()

x\_train = x\_train.reshape(-1, 28, 28, 1).astype('float32') / 255.0

x\_test = x\_test.reshape(-1, 28, 28, 1).astype('float32') / 255.0

y\_train = to\_categorical(y\_train, 10)

y\_test = to\_categorical(y\_test, 10)
```

Build the CNN model

```
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
```







14. Future scope

- Model Optimization: Use techniques like pruning, quantization for lighter deployment.
- Real-time Handwriting Input: Extend from static image input to real-time webcam/touch input.
- Cross-Platform App: Develop a mobile-friendly version using TFLite.







15. Team Members and Roles

Team Members	Roles	Responsibility
Sandhiya S	Team Leader	Data cleaning,EDA
Nithiyasree K	Member 1	Feature Engineering, Data Modeling
Pachaiyammal P	Member 2	Model Evaluation, Visualization
Nivetha D	Member 3	Documentation, Reporting