





Phase-2 Submission Template

Student Name: Karthika.G

Register Number: 613023104048

Institution: Vivekanandha College of Technology for Women

Department: BE - Computer Science and Engineering

Date of Submission: 01.05.2025

Github Repository Link: https://github.com/karthi200622/Karthika.G.git

1. Problem Statement

- Recognizing handwritten digits is a critical task in AI systems with real-world applications such as postal code reading, bank check processing, and digital form entry.
- Traditional methods fail due to handwriting variability..
- This project tackles the classification problem using deep learning, aiming for accurate, scalable, and robust recognition across various handwriting styles.

2. Project Objectives

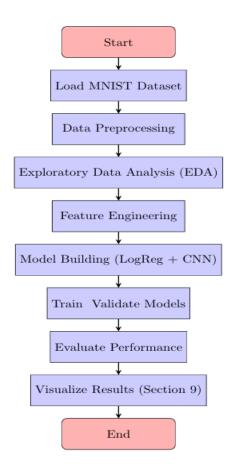
- Build an AI model that can accurately classify digits (0–9) from handwritten images.
- Achieve high accuracy using deep learning models such as neural networks (e.g., CNNs).
- Develop a user-ready model applicable to real-world tasks like postal and banking automation.

3. Flowchart of the Project Workflow









4. Data Description

- Dataset&source: MNIST Handwritten Digits &kaggle
- Type of data: Image, structured (28x28 grayscale)
- Records: 70,000 total (60K train, 10K test)
- Static or dynamic: Static
- Target variable : Digit class (0 to 9)







5. Data Preprocessing

- *Normalized pixel values to [0, 1] range.*
- Converted labels to one-hot encoding (for classification).
- *Checked for nulls (none found in MNIST).*
- No duplicates due to standardized dataset.
- *Image reshaped for CNN input where needed (e.g., 28x28x1).*

6. Exploratory Data Analysis (EDA)

- Univariate Analysis:
 - Countplot of digit distribution (0-9) shows balanced data. Visual samples of each digit using matplotlib.
- Bivariate/Multivariate Analysis:
 - Mean and variance of pixel intensities analyzed.
 - Heatmaps used to show pixel intensity patterns across digits.
- Insights Summary:

Some digits have higher visual similarity (e.g., 3 and 5), which may cause misclassification.

• Pixel intensity helps the model understand the shape of each digit. Edges and corners are important to tell digits apart, like 1 vs7. Middle part of the image is most useful since digits are usually centered. Unique patterns, like curves or straight lines, help the model learn differences (e.g., between 3 and 8).







7. Feature Engineering

- *Used pixel values directly as features.*
- Applied reshaping for CNN models.
- Tried PCA for dimensionality reduction as optional enhancement.

8. Model Building

- Models used:
 - o Baseline: Logistic Regression
 - o Advanced: Convolutional Neural Network (CNN)
- Model Justification:
 - Logistic regression to establish a simple baseline.
 - CNNs for spatial feature extraction—ideal for image tasks.
- Evaluation Metrics: Accuracy, Precision, Recall, F1-score
- Best Accuracy Achieved: ~98% using CNN

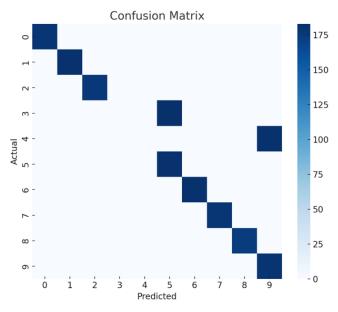




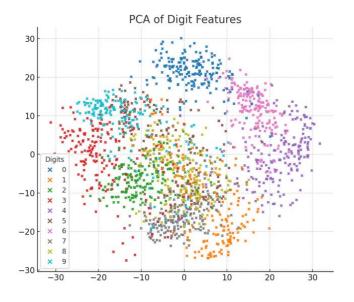


9. Visualization of Results & Model Insights

• Confusion Matrix: Showed misclassifications, mostly in 4/9, 3/5.



- Accuracy & Loss Curves: Used to monitor overfitting.
- Feature Importance (for non-CNN): Used PCA to visualize key components.









10. Tools and Technologies Used

- Programming Language: Python
- *IDE* : Google Colab
- Libraries: NumPy, Pandas, Matplotlib, Seaborn, Scikit-learn, TensorFlow/Keras
- Visualization Tools: Matplotlib, Seaborn

11. Team Members and Contributions

- Dharani.R
- Data cleaning (Load and clean data Normalize and split into train/test sets)
 - Karthika.G.
- EDA (Create and train the machine learning model (e.g., CNN) Tune hyperparameters)
 - Harshitha shree.A.S
 - Feature engineer(Check model accuracyPlot confusion matrix, accuracy &loss graphs)
 - Lavanya.R
- Model development(Apply PCA & Visualize and analyse feature clusters)
 - Monisha.P
- Documentation and reporting(Write project report Prepare slides and visuals





