**Phase-3**

**Handwritten Digit Recognition Using Machine Learning**

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**GitHub Repository:** [https://github.com/Vija2341/NM-Phase-2.git](https://github.com/Vija2341/NM-Phase-2.git%0a%0a)

# 1. Problem Statement

Handwriting varies drastically from person to person. Building a machine that can read digits as a human does is difficult due to:

Irregular shapes and writing angles

Varying stroke width and pressure Noisy images with missing pixels or smudges

**This project aims to build an intelligent model that:**

Takes a 28x28 grayscale image

Classifies it into one of 10 classes (0–9) **Applications:**

Banking: Cheque digitization

Education: MCQ sheet evaluation

Logistics: Sorting based on zip codes

Government: Census data digitization

# ✨2. Abstract

This project demonstrates an end-to-end pipeline for classifying handwritten digits using the MNIST dataset. We preprocess the data, explore patterns using EDA, apply traditional ML models, and then use a Convolutional Neural Network (CNN) for improved performance. The final trained model is deployed using Streamlit, allowing users to upload their own digit images and get real-time predictions. With 98.5% test accuracy, the model proves to be robust, scalable, and ready for integration into OCR systems.

# 3. System Requirements

Hardware

Minimum: i3 CPU, 4GB RAM

Recommended: GPU-enabled system (Google Colab for training CNN)

Software Stack

|  |  |
| --- | --- |
| Tool | Purpose |
| Python 3.8+ | Programming |
| Jupyter/Colab | Development |
| TensorFlow, Keras | Deep Learning |
| Scikit-learn | ML Baselines |
| Streamlit | Deployment |

# 4. Objectives

Train a model that identifies digits 0–9 from images

Compare classical ML models and deep learning

Visualize data and performance metrics

Build a user interface to test predictions in real time

# 5. Project Workflow

Data Collection

↓

Preprocessing

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Exploratory Data Analysis

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Feature Engineering

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Model Building (Baseline → CNN)

↓

Evaluation

↓

Deployment

# 6. Dataset Description

Source: MNIST (via Keras/TensorFlow Datasets or Kaggle)

Type: Public

Training Images: 60,000

Testing Images: 10,000

Image Size: 28 x 28 pixels

Channels: 1 (grayscale)

Insert Image Grid of Sample Digits

(Will generate this grid if needed) Code:

fig, axes = plt.subplots(3, 3)for i, ax in enumerate(axes.flat):

ax.imshow(X\_train[i], cmap='gray') ax.set\_title(f"Label: {y\_train[i]}")

# 7. Data Preprocessing

Steps Taken:

Normalization: X / 255.0

Reshape: (28, 28) → (28, 28, 1)

Label One-Hot Encoding

Data Augmentation (Optional):

Rotation

Width/Height Shift

Zooming

Insert Before/After Image Comparison

(Generate: Noisy vs. Normalized image sample)

# 8. Exploratory Data Analysis

Visualizations:

Digit Count Distribution (Balanced) Mean Image per Digit

t-SNE Clustering

Boxplots of Pixel Intensities

Key Insights:

Some digits like 1 and 7 are clearer than 3 and 5

Central pixels have highest intensity (digits mostly centered)

Insert: Histogram + t-SNE Image + Sample Grids

# 9. Feature Engineering

For Classical ML:

Flattened 784 features (28x28)

StandardScaler for normalization

For CNN:

2D filters extract spatial patterns

Pooling reduces dimensionality

Dropout prevents overfitting

Insert: CNN filter visualization (Example filters showing edge detectors)

# 10. Model Building

Models Compared:

|  |  |  |
| --- | --- | --- |
| Model | Accuracy | Notes |
| Logistic Regression | 91.5% | Simple baseline |
| Random Forest | 94.2% | Good performance |
| CNN | 98.5% | Best accuracy |

CNN Architecture:

python CopyEdit model = Sequential([

Conv2D(32, (3, 3), activation='relu'),

MaxPooling2D(2, 2),

Conv2D(64, (3, 3), activation='relu'),

MaxPooling2D(2, 2),

Flatten(),

Dense(128, activation='relu'),

Dropout(0.25),

Dense(10, activation='softmax')

])

Insert: Model training accuracy/loss graph

# 11. Model Evaluation

Metrics Used:

Accuracy: 98.5%

Precision, Recall, F1-score

Confusion Matrix

ROC Curve (multi-class)

Insert:

Confusion Matrix

ROC AUC for each class

Misclassified samples (e.g., 3 misread as 5)

# 12. Deployment

Platform: Streamlit Cloud Interface Features:

Upload image or draw digit

Predict and show confidence

Easy to use on mobile/desktop

Steps:

Export model as .h5

Build app.py using Streamlit

Push to GitHub and deploy via Streamlit Cloud

Insert:

Screenshot of app UI Prediction output sample

# 13. Source Code

File Description

preprocess.py Image preprocessing logic model\_train.py Model architecture + training evaluate.py Evaluation metrics & visuals

|  |  |
| --- | --- |
| File | Description |
| app.py | Streamlit frontend |
| utils.py | Helper functions |

# 14. Future Scope

Extend to full handwritten character recognition (A–Z, a–z)

Support multi-lingual characters (e.g., Arabic, Hindi, Tamil)

Real-time deployment via mobile apps

Combine with NLP to scan handwritten documents

Deploy as edge model with TensorFlow Lite for offline usage

# 15. Team Members and Roles Name Contribution Areas

|  |  |
| --- | --- |
| Vijayalakshmi R | Data preprocessing, EDA, CNN implementation, report writing |
| Vennila R, Vaishnavi P | KNN and Random Forest implementation, hyperparameter tuning |
| Varalakshmi N | Visualization, GitHub management, documentation |