Sequence Digit Recognitiontion using Deep Learning

on MNIST Dataset

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INTRODUCTION

What is Handwritten Digit Classification?

Handwritten digit classification is a crucial task in computer vision where a machine recognizes and categorizes handwritten numerical digits (0-9) from images. It is widely used in optical character recognition (OCR), banking, postal services, and automated form processing.

Problem Statement

- **Traditional machine learning techniques, such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN), require manual feature extraction, making them less efficient and less accurate. Handwriting varies among individuals, making it challenging for traditional methods to generalize well across different writing styles. The presence of noise, distortions, and overlapping strokes affects classification accuracy.**

Solution: Deep Learning-Based Approach

- Convolutional Neural Networks (CNNs) are used for automated feature extraction, reducing the need for manual intervention.
- CNNs are highly effective in handling image-based data, making them an ideal solution for digit classification.
- MNIST Dataset, a benchmark dataset of handwritten digits, is used to train and evaluate the model.

About the MNIST Dataset

- The MNIST (Modified National Institute of Standards and Technology) dataset is a benchmark dataset widely used for training and testing machine learning models in handwritten digit recognition.
- It consists of 70,000 grayscale images of handwritten digits (0-9), divided into:
  - 60,000 training images
  - 10,000 testing images
- Each image is 28×28 pixels in size and represents a single digit in grayscale.
- The dataset is widely used in research and deep learning projects due to its simlicity, size, and effectiveness in evaluating classification models.

Project Objective

- To develop an efficient CNN-based handwritten digit classification model that can recognize digits with high accuracy.
- To optimize model performance using hyperparameter tuning and data augmentation.
- To analyze model performance using accuracy metrics, confusion matrix, and classification reports.

LITERATURE REVIEW

Related Works & Research

1. **LeCun et al. (1998)**

   Overview: Introduced the LeNet-5 architecture, a pioneering CNN designed for handwritten digit recognition. Demonstrated CNNs' efficiency in processing and classifying visual data, laying the foundation for deep learning in image recognition.

2. **Hochuli et al. (2020)**

   Overview: Compared end-to-end approaches for digit string recognition, evaluating models like YOLO and CRNN. Highlighted the effectiveness of object-detection-based methods over traditional segmentation-based techniques.

3. **Gondere et al. (2021)**

   Overview: Investigated multi-script handwritten digit recognition using multi-task learning. Demonstrated that incorporating script classification as an auxiliary task enhances recognition performance across various writing systems.

MOTIVATION

- **Growing Need for Automation:** Handwritten digit recognition is essential in banking, postal services, and document processing, reducing manual efforts and errors.
- **Limitations of Traditional Methods:** Techniques like SVM and KNN require manual feature extraction, leading to lower accuracy and inefficiency.
- **Advancement in Deep Learning:** CNNs automate feature extraction, improving recognition accuracy and making models more robust against variations in handwriting.
- **Scalability and Real-World Application**: AI-driven digit classification enables fast, scalable solutions for OCR, financial transactions, and automated data entry.
- **Objective of the Project:** To develop a high-accuracy, deep learning-based handwritten digit recognition system that outperforms traditional methods in efficiency, accuracy, and scalability.

IMPLEMENTED METHODOLOGIES

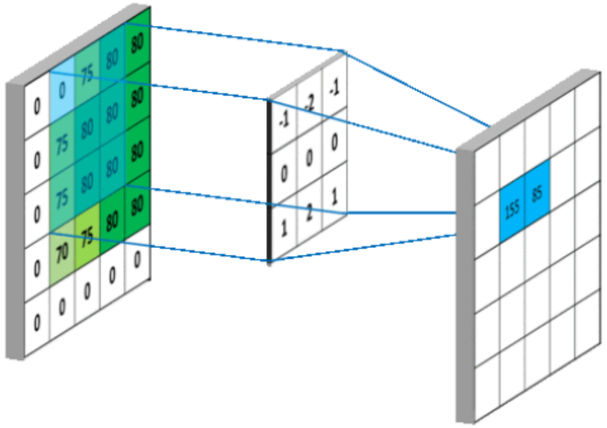
Step 1: Data Preprocessing

- **Grayscale Conversion:** Converted images to grayscale for consistency and reduced computational complexity.
- **Normalization:** Scaled pixel values to a range of 0-1 to improve model convergence.
- **Resizing:** Standardized all images to 28×28 pixels to match the input format of the CNN.
- **Data Augmentation:** Applied rotation, shifting, and zooming to enhance the model's ability to generalize across different handwriting styles.

Step 2: CNN Model Architecture

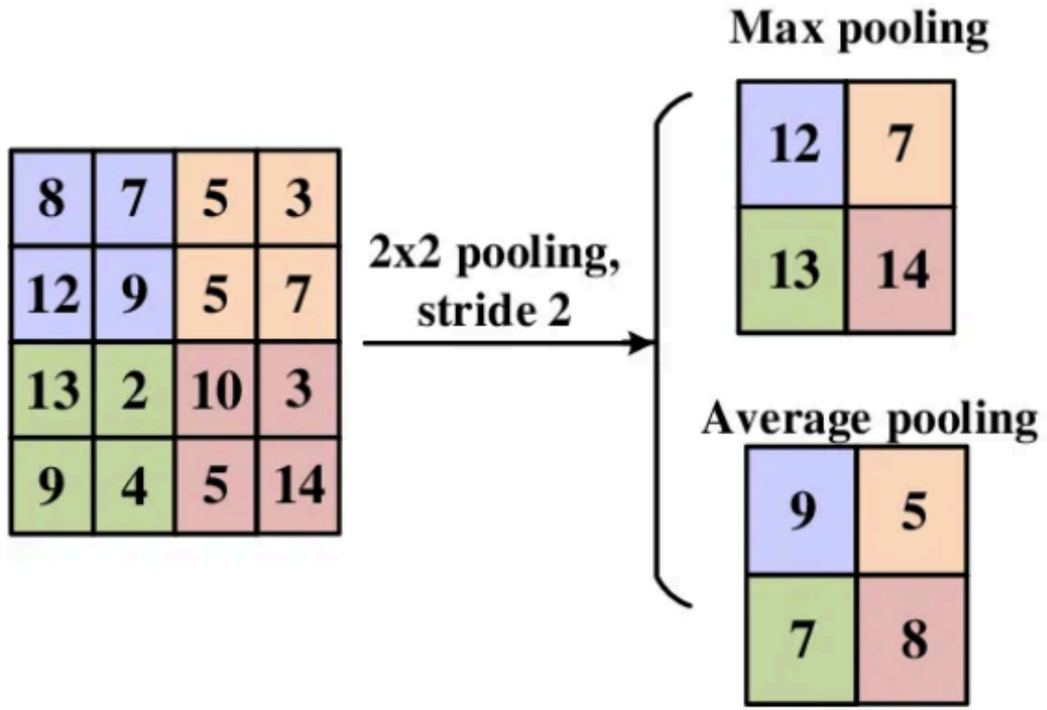
- **Convolutional Layers:** Extracted spatial features from digit images.

Image filtering (kernel) is process modifying image by changing its shades or colour of pixels. it is also used for brightness and contrast.



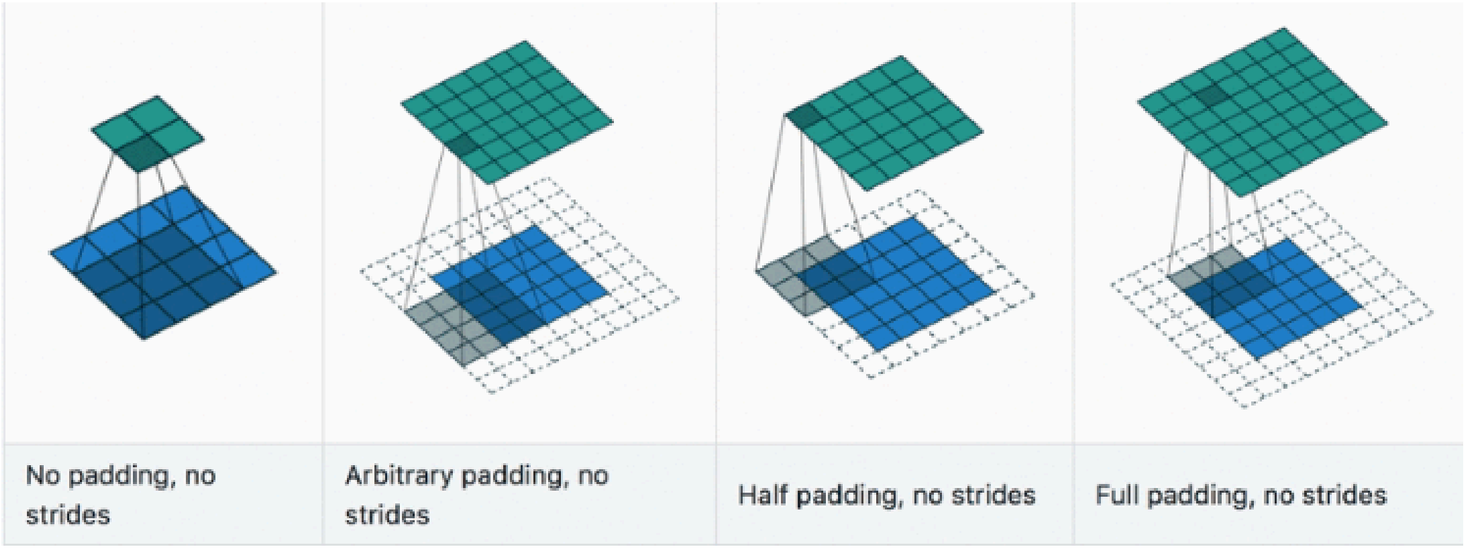
- **Pooling layer**

Pooling layer used to reduce feature map dimension's. Thus it reduces no. of parameters to learn and amount of computation performed in network. pooling layer summarises features present in a region of feature map generated by convolutional layer.



- **Paddind Layer**

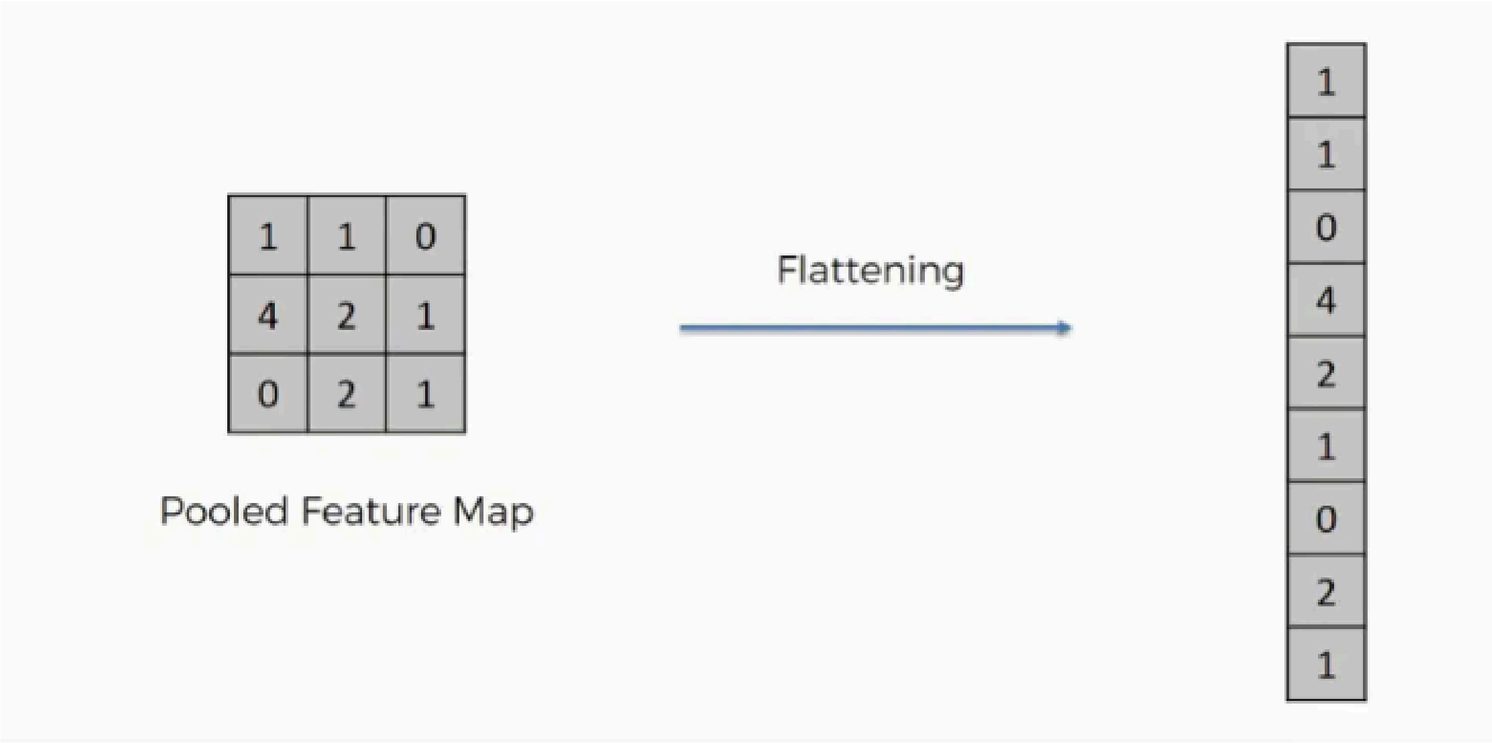
Its similar like convolutional layer as it refers amount of pixels added to an image when it is being processed by kernel or filter. when don’t use stride then by default is 1. Half padding mean half of filter size and full padding mean padding equal to size of filter/kernel. Padding is done to reduce the loss of data among the sides/boundary of the image.



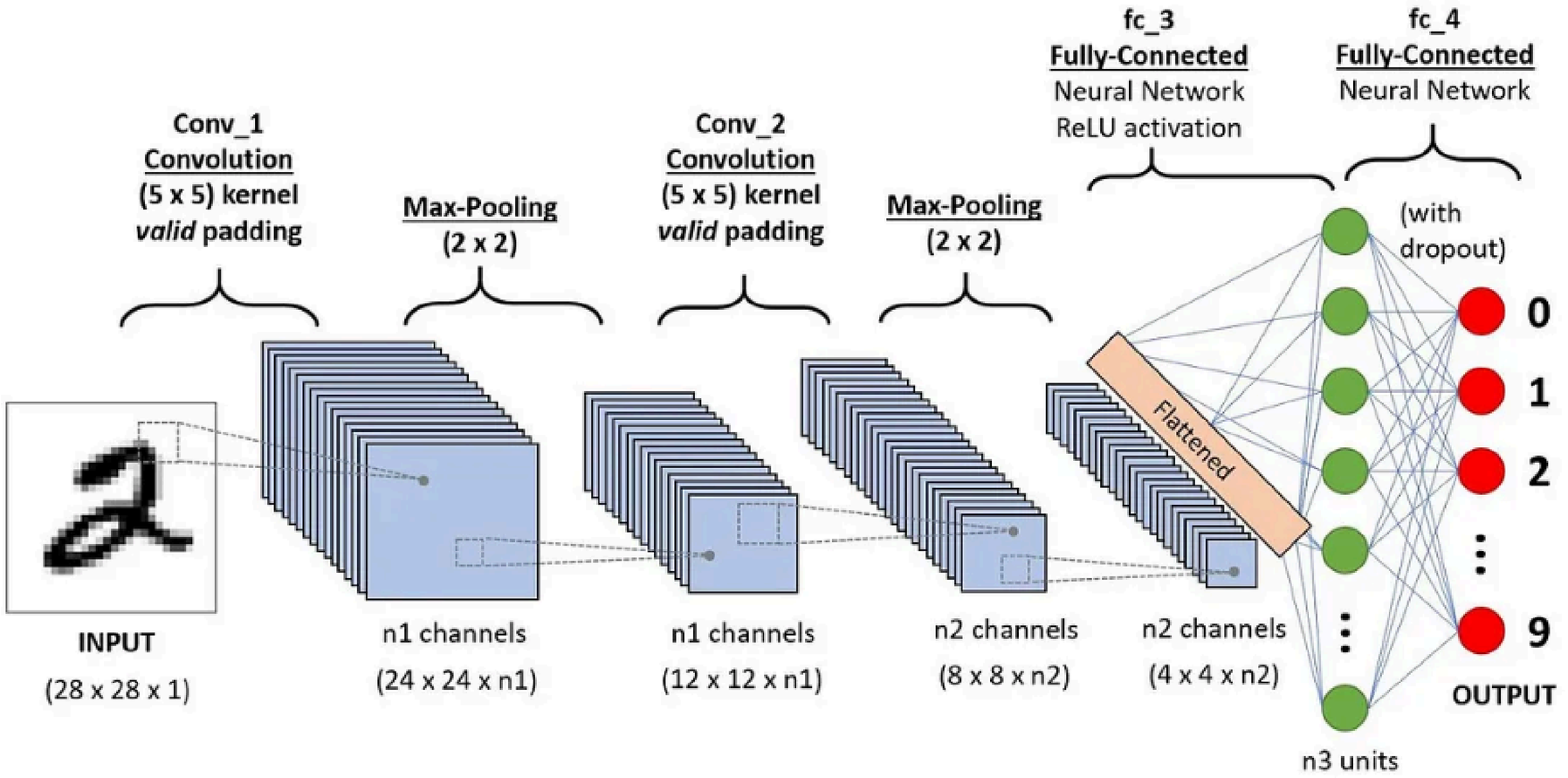
Padding effects output image size while filtering in Conv/padding layer

- **Flatten operation**

Intuition behind flattening layer is to converts data into 1-dimentional array for feeding next layer. we flatted output of convolutional layer into single long feature vector. which is connected to final classification model, called fully connected layer. let's suppose we've [5,5,5] pooled feature map are flattened into 1x125 single vector. So, flatten layers converts multidimensional array to single dimensional vector.



CNN Model Structure Visualization



Step 3: Training & Hyperparameter Tuning

To enhance the model's accuracy and efficiency, **Keras Tuner** was used to optimize key hyperparameters:

1. **Filter Size (Number of Filters in Convolutional Layers)**
   - Explored filter sizes **(32, 64, 128)** to determine the best feature extraction capacity.
   - **Larger filters** captured more complex patterns but increased computational cost.
   - **Smaller filters** focused on finer details but risked missing global features.
   - **Optimal Choice:** A balance between **filter size and computational efficiency** was achieved.
2. **Number of Dense Layer Units**
   - Tuned between **32, 64, and 128 neurons** in the fully connected layer.
   - **Fewer neurons** led to underfitting, while **too many neurons** caused unnecessary complexity.
   - **Optimal Choice:** A moderate number of units improved classification performance without overfitting.
3. **Learning Rate (Optimizer Tuning - Adam Optimizer)**
   - Explored **learning rates of 0.01, 0.001, and 0.0001** to control weight updates.
   - **High learning rates** caused unstable training and poor convergence.
   - **Low learning rates** resulted in slow training progress.
   - **Optimal Choice: 0.001** provided stable and efficient convergence.

Step 4: Model Evaluation

- **Confusion Matrix:** Visualized model predictions vs. actual labels to identify misclassifications.
- **Accuracy & Loss Graphs:** Monitored training progress and ensured the model did not overfit.

Image Preprocessing & GUI

Preprocessing Steps

- Convert image to grayscale
- Apply thresholding to isolate digits
- Use contour detection to locate each digit
- Segment and resize each digit to 28×28 pixels

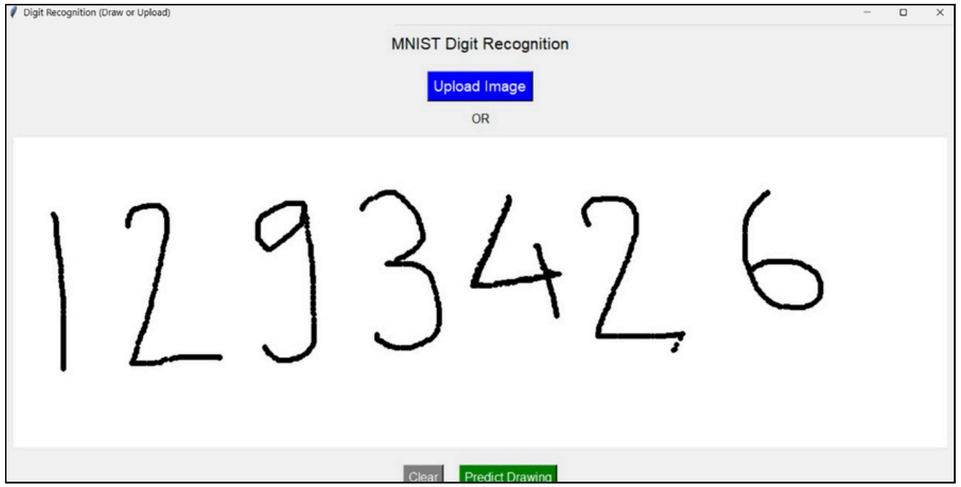
Prediction

- Each digit is passed into the CNN model
- CNN outputs a predicted digit
- Final sequence is reconstructed and displayed

GUI Overview

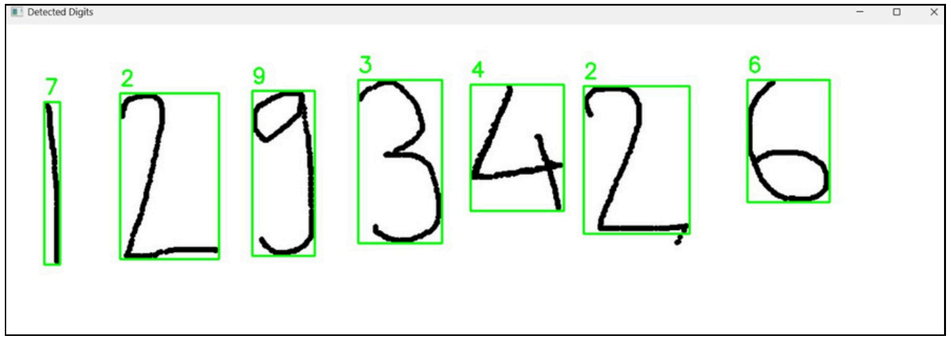
Tkinter-Based Interface

- Upload image or draw digits on canvas
- Drawing supported using mouse strokes



Output Display

- Detected digits highlighted with bounding boxes
- Predicted digits shown using OpenCV annotations
- Final result shown in a popup message



ANALYSIS OF RESULT

The implemented system for handwritten sequence digit recognition was evaluated based on training metrics, model performance, and practical usage through the GUI. The analysis covers how well the model generalized to new data, its ability to segment and recognize multiple digits from complex inputs, and its performance in different usage scenarios.

Model Accuracy and Loss Trends

The CNN model achieved a training accuracy of 98.78% and a test accuracy of 99.45%, indicating strong generalization.

The validation loss (0.0202) and training loss (0.0426) remained low, showing no signs of overfitting.

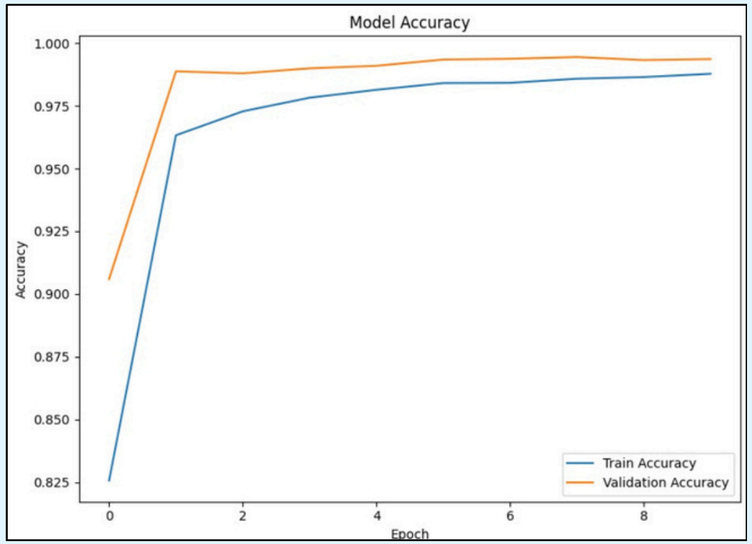


Fig Training Vs Validation accuracy graph

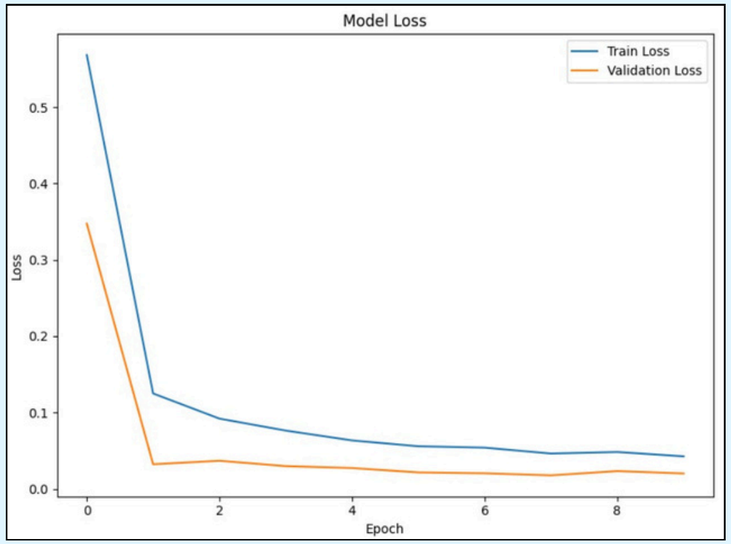
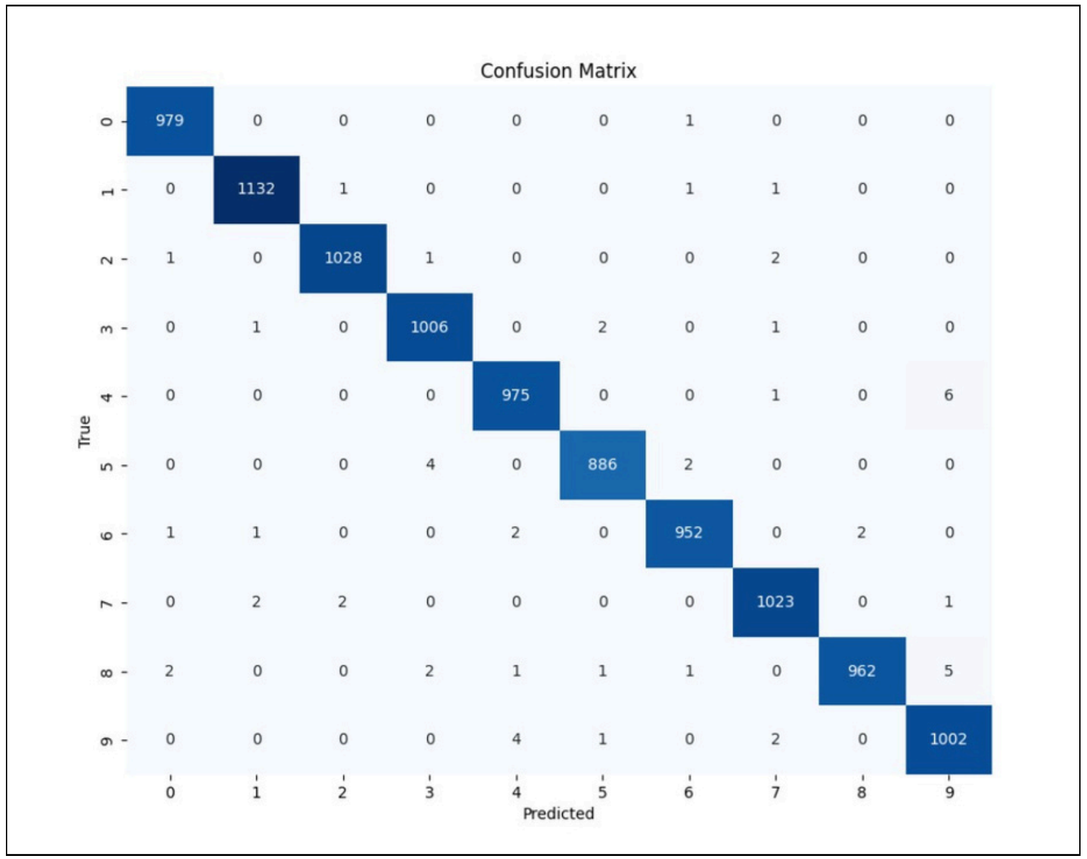


Fig Training Vs Validation Loss graph

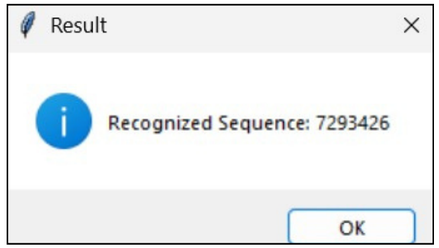
Confusion Matrix Insights

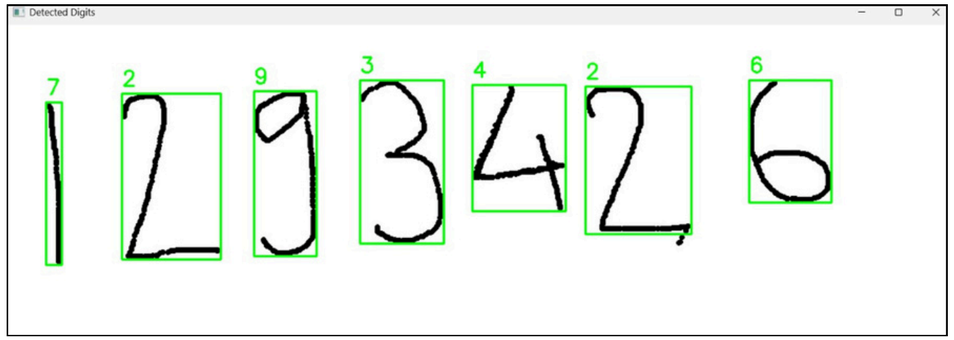
The confusion matrix revealed that digits like 4 vs 9 and 5 vs 6 had minimal but expected misclassifications due to visual similarity.



GUI-Based Predictions

- **The system performed well with both drawn digits and uploaded images.**
- **Contour detection effectively segmented individual digits even when spacing was irregular or digits were drawn in quick strokes.**
- **Prediction accuracy remained high when digits were clear and properly separated. In rare cases where digits overlapped heavily, minor segmentation errors could occur.**





CONCLUSION

- Successfully implemented a system to recognize handwritten digit sequences using a Convolutional Neural Network (CNN) trained on the MNIST dataset.
- Integrated image preprocessing (grayscale, thresholding, contour detection) for accurate digit segmentation.
- Developed a Tkinter-based GUI for interactive use: users can upload images or draw digits.
- Achieved high performance with 99.45% test accuracy and strong generalization.
- Visual output with OpenCV annotations ensures easy result interpretation.

Future Scope

- Support for Alphanumeric Recognition
- Implement deeper architectures like ResNet or use RNNs for better sequence context.
- Multilingual Handwriting Support
- Expand to recognize scripts from different languages (e.g., Hindi, Arabic).

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Thank You!

CONTRIBUTERS

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