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# Handwritten English Digit Recognition

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***Abstract*—Understanding handwritten digits through automated systems is a fundamental requirement in many intelligent applications. This work introduces a deep learning–based solution for recognizing handwritten English digits using the Convolutional Network (CNN) architecture. The model which we are using is trained and validated using the MNIST dataset, which consists of grayscale digit images covering numbers from zero through nine. In contrast to traditional approaches that rely on manually crafted features, the system which we have proposed learns meaningful representations directly from image pixels. Experimental results describe consistent accuracy of results across diverse handwriting styles. The developed model can be effectively applied in automated document processing, form digitization, and financial data entry, while also providing a scalable base for future handwritten text recognition systems.**

***Index Terms*—Handwritten Digit Recognition, Convolutional Neural Network, MNIST Dataset, Deep Learning, Image Classification**

## I. Introduction

Recognizing handwritten digits automatically is difficult because no two people write numbers in exactly the same way. Differences in stroke shape, writing speed, orientation, and spacing introduce significant complexity when attempting to classify handwritten numerals. Despite these challenges, reliable digit recognition systems are essential in applications such as cheque verification, postal sorting, examination evaluation, and digital record management.

Early handwritten digit recognition systems relied on handcrafted manually designed feature extraction techniques together with traditional classification methods. Although they delivered acceptable accuracy, these systems were limited by their sensitivity to variations in handwriting and required significant manual effort to design effective features, their performance was often limited by feature quality and poor adaptability to unseen handwriting styles. The growth of the deep learning, led by Convolutional Neural Networks, allowed models to learn directly from raw images and achieve much higher handwritten digit recognition accuracy. By capturing spatial patterns efficiently, Convolutional Neural Networks are highly effective for digit classification tasks, and MNIST serves as the commonly used benchmark dataset.

## II. Literature Survey

Over time, many different methods have been proposed or developed for handwritten digit recognition. Bernard et al. [1] explored Random Forest classifiers and demonstrated improved robustness through ensemble learning. Sharma et al. [2] introduced a Graph Neural Network–based framework that models handwritten digit trajectories, achieving improved convergence characteristics. Support Vector Machine–based classification using shape-oriented features was investigated by Reddy et al. [3].

Peng et al. [4] proposed a dimensionality reduction approach combined with logistic regression to reduce computational complexity for rotated digits. Bernard et al. [5] examined an edit-distance-based KNN classifier using symbolic digit representations. Comparative evaluations by Chen et al. [6] confirmed that the effectiveness and dominance of CNN–based deep learning models. Other studies [7]–[10] explored probabilistic and regression-based techniques. But deep learning neural networks consistently achieved higher accuracy and scalability.

## III. System Design and Implementation

The handwritten digit recognition system is designed as a modular processing pipeline that converts raw handwritten digit images into accurate numerical predictions. The system integrates preprocessing, CNN-based feature learning, classification, and evaluation components to ensure accuracy, robustness, and computational efficiency.

### A. Overall System Architecture

The overall system architecture consists of multiple stages: dataset input, preprocessing, CNN-based feature learning, classification, and performance evaluation. The MNIST dataset is used as the primary source of input, consisting of grayscale hand-written digit images.

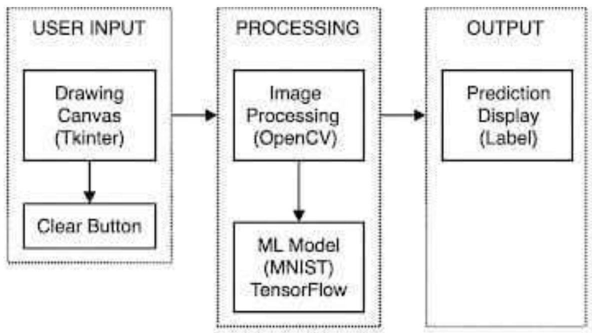


Fig. 1. Overall architecture of the handwritten digit recognition system

The modular structure allows individual components to be enhanced or replaced independently, making the system adaptable for future extensions such as handwritten character or word recognition.

### B. Data Preprocessing

Preprocessing ensures uniformity and improves learning efficiency. All MNIST images are normalized by scaling pixel intensity values to the range [0,1]. This normalization stabilizes gradient updates and accelerates model convergence. The images are reshaped to match CNN input requirements, enabling consistent feature extraction.

### C. CNN Model Design

The CNN architecture is responsible for automatic feature extraction and classification. Convolutional layers learn essential visual patterns such as edges and curves, while pooling layers reduce spatial dimensions. Dropout layers are used to improve the model's ability to generalize, and the final digit classification is carried out by fully connected layers with a SoftMax activation function.

### D. Model Training and Optimization

The implementation of the model is carried out in Python with the help of TensorFlow and Keras. The data is split into training and testing sets. T h e t raining of model is performed using the Adam optimizer and categorical cross-entropy loss. Mini-batch training over multiple epochs improves generalization and computational efficiency.

### E. Testing and Performance Evaluation

Model performance is evaluated on unseen test data using classification accuracy as the primary metric. The trained CNN demonstrates strong generalization capability, confirming its effectiveness for handwritten digit recognition tasks.

## IV. Results and Discussion

The proposed CNN mode demonstrates strong recognition accuracy on the MNIST dataset. Training and validation loss curves show stable convergence, indicating effective learning of discriminative features. Misclassifications are primarily observed for visually similar digits due to ambiguous handwriting styles.

### A. GUI-Based Application Results

The model is deployed within a graphical user interface through which users can draw digits or upload handwritten images for prediction. The system preprocesses input in real time and produce immediate predictions, demonstrating suitability for interactive applications.

### B. Obtained Output Visualization

The system presents the handwritten digit entered by the user together with the predicted digit produced by the CNN model.

### C. Discussion

By combining a deep learning model with a user-friendly interface, the system becomes more practical and easy to use. The system into a deployable solution rather than a purely experimental model. Compared to traditional classifiers such as SVM and KNN, the CNN- based approach offers superior accuracy and adaptability. The system is scalable and can be extended to support broader handwritten recognition tasks.

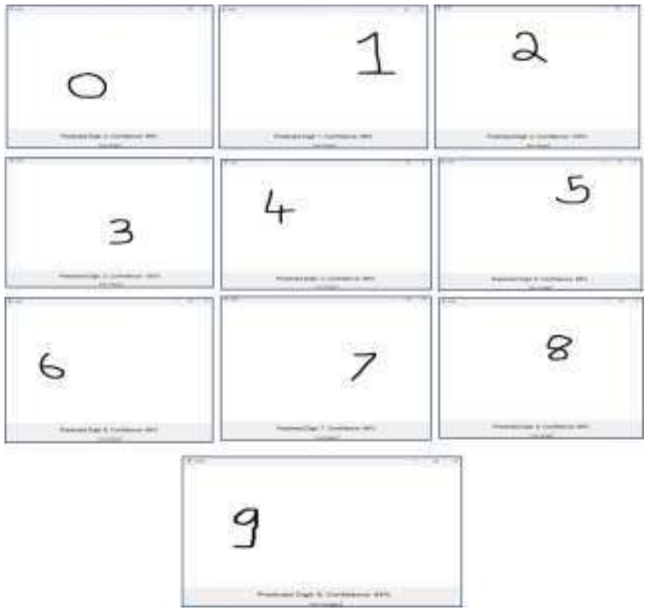

Fig. 2. Output of the live handwritten digit recognition system

## V. Conclusion

This paper presents a convolutional neural network–based handwritten English digit recognition system that achieves reliable performance across varied handwriting styles. By eliminating reliance on handcrafted features, The method which we have proposed demonstrates that the enhanced robustness along with higher accuracy. The system works well for practical, real-world applications such as document digitization and automated data entry. Future work may focus on exploring deeper network architectures, applying data augmentation techniques, and deploying the system in real-time environments.

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