HAND WRITTEN DIGIT RECOGNITION USING CONVOLUTIONAL NEURAL NETWORK

[1]K.Suma,[2]V.Sindhuja,[3]B.Dharma Rah,[4]V.Soma jaya raju

[1]Assistant Professor, [234]Students

Department of Computer Science and Engineering

Siddhartha institute of technology & sciences,narapally

sumakadari_cse@siddhartha.co.in,23TQ1A0528@siddhartha.co.in, 23TQ1A0539@siddhartha.co.in, 23TQ1A0547@siddhartha.co.in,

ABSTRACT

Handwritten digit recognition is an important application in the field of computer vision and pattern recognition. This research proposes a deep learning–based framework for accurate handwritten digit classification using edge-enhanced preprocessing and convolutional neural networks. The MNIST dataset is used for training and testing the model.

Images are first preprocessed using edge enhancement techniques to improve structural feature visibility. A convolutional neural network architecture incorporating Inception modules and global average pooling is used for feature extraction and classification.

The proposed model achieves high classification accuracy while maintaining computational efficiency. Experimental evaluation demonstrates reliable performance in recognizing handwritten digits, making the approach suitable for applications such as document digitization, automated data entry, and intelligent recognition systems. Handwritten Digit Recognition is an important application of image processing and deep learning that focuses on identifying numerical digits (0–9) from handwritten images.

This project proposes a system based on Convolutional Neural Networks (CNN) to accurately classify handwritten digits. The system takes digit images as input, performs preprocessing techniques such as normalization and resizing, and feeds them into a CNN model for feature extraction and classification. Unlike traditional methods that rely on manual feature engineering, CNN automatically learns relevant features, improving accuracy and efficiency.

The model is trained using standard datasets such as MNIST, which contains a large collection of labeled handwritten digit images. Through multiple layers including convolution, pooling, and fully connected layers, the system learns patterns and variations in handwriting styles. The proposed system achieves high accuracy and demonstrates robustness against noise and distortions in input images. This approach reduces human effort, speeds up the recognition process, and can be effectively used in real-world applications like postal automation, bank cheque processing, and document digitization.

I INTRODUCTION

Handwritten digit recognition is an important research area in the field of pattern recognition and computer vision, with applications in postal mail sorting, bank check processing, form digitization, and intelligent document analysis. Automatic recognition of handwritten digits remains a challenging task due to variations in writing styles, noise, distortions, and differences in stroke thickness. Traditional machine learning techniques such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Random Forest classifiers have been widely used for handwritten digit classification; however, these approaches rely heavily on manual feature extraction and often struggle to generalize across diverse handwriting patterns. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have significantly improved recognition performance by automatically learning hierarchical feature representations from raw image data. Studies have shown that CNN-based architectures outperform conventional machine learning methods on benchmark datasets such as MNIST, achieving high classification accuracy and improved robustness in handwritten digit recognition tasks . Several recent works have explored different deep learning architectures and hybrid models to further enhance recognition accuracy. For example, CNN-based approaches combined with data augmentation and optimized training strategies have demonstrated recognition accuracies above 98% on the MNIST dataset. Hybrid architectures such as CNN–BiLSTM and CNN–SVM models have also been proposed to improve feature learning and classification performance. Additionally, lightweight CNN models have been developed for real-time digit recognition systems deployed on embedded devices such as Raspberry Pi and FPGA-based platforms. Research has also investigated ensemble learning techniques, neuromorphic computing models, and optimized CNN architectures to improve recognition efficiency and scalability. Despite these advancements, challenges remain in effectively capturing multi-scale 7 handwriting features and maintaining high performance across varying handwriting styles and real-world conditions . To address these challenges, this study proposes a CNN–Inception based handwritten digit recognition model that integrates convolutional feature extraction with a GoogLeNet-inspired Inception module for multi-scale feature learning. The model is trained and evaluated using the MNIST dataset, which contains 70,000 grayscale images of handwritten digits. By combining convolution layers, multi-scale feature extraction, and efficient classification mechanisms, the proposed architecture aims to improve feature representation and achieve reliable digit classification performance. The effectiveness of the proposed system is evaluated using training and validation accuracy curves, loss analysis, and confusion matrix evaluation to demonstrate its capability for accurate handwritten digit recognition. Handwritten digit recognition (HDR) is a fundamental problem in the fields of pattern recognition, computer vision, and artificial intelligence. The ability of machines to automatically recognize handwritten characters has significant applications in document processing, postal mail sorting, bank cheque verification, automatic form processing, and intelligent data entry systems. Despite decades of research, handwritten digit recognition continues to present challenges due to variations in individual writing styles, distortions in handwritten characters, differences in stroke thickness, and noise introduced during image acquisition or scanning. These challenges make it difficult for traditional rule-based systems to accurately interpret handwritten digits across diverse datasets.

II LITERATURE SURVEY

Pal, L. M. (2026). [1]. A Comparative Study of Image Processing Methods for Handwritten Digit Classification. Explanation: Reviews image processing techniques for handwritten digit recognition. Dataset: MNIST and similar datasets. Methods: Image preprocessing, feature extraction, CNN classifiers. Results: CNN-based models achieved higher accuracy than traditional ML methods. Relation: Supports use of CNN architectures for digit recognition. Ogundipe, A., Oloye, T. I., & Zubair,

A. R. (2026). [2]. TinyML-Powered Handwritten Digit Recognition Device for the Visually Impaired. Explanation: Real-time recognition device for visually impaired users. Dataset: Curated handwritten digit dataset similar to MNIST. Methods: CNN optimized using TinyML deployed on Raspberry Pi. Results: Accurate and low-latency recognition on embedded hardware. Relation: Relevant for lightweight edge-based recognition systems. Prakash, S., Bansal, S., Gupta, K., & Veerlapati,

H. N. (2026). [3]. Handwritten Digit Recognition Using Deep Learning. Explanation: CNN-based approach for digit recognition. Dataset: MNIST. Methods: Convolutional, pooling, dropout layers with categorical cross-entropy. Results: Over 98% accuracy. Relation: Shows effectiveness of CNN over traditional algorithms. Camargo Rojas, M. A., Sánchez Pérez, G., Portillo-Portillo, J., Toscano Medina, L. K., Hernández Suárez, A., Olivares Mercado, J., & García Villalba,

L. J. (2026). [4]. Towards Electoral Digitization: Automatic Classification of Handwritten Numbers in 12 PREP System Records. Explanation: Digit recognition in electoral records. Dataset: PREP dataset. Methods: CNN architectures including ResNet-18, MobileNetV3, EfficientNet with augmentation. Results: ResNet-18 achieved best performance. Relation: Demonstrates real-world deployment of CNN recognition systems. Che, L., Huang, Z., & Jiang,

L. (2026). [5]. Lightweight Network-Based Real-Time Radar Recognition of In-Air Handwritten Digit Trajectories. Explanation: Radar-based recognition of digits written in air. Dataset: Custom dataset from volunteers. Methods: FMCW radar sensing, Kalman filtering, lightweight CNN. Results: 99.09% accuracy with small model size. Relation: Shows efficient real-time recognition models. Jiang, B., Xiong, Y., Liu, X., Shi, Y., Zhao,

W., Ma, G., & Wang, H. (2026). [6]. Hybrid Intelligence for Handwritten Digit Recognition by Fusing Deep Spatial Features and High-Performance Classification. Explanation: Combines deep learning and SVM classification. Dataset: MNIST. Methods: ResNet18 feature extraction + ThunderSVM classification. Results: Faster training and better generalization. Relation: Demonstrates hybrid deep learning approaches.

Jiang, B., Xiong, Y., Liu, X., Shi, Y., Zhao, W., Ma, G., & Wang, H. (2025). [7]. Dual Mode α-FA-Based Perovskite Memristors for Neuromorphic Computing and Handwritten Digit Recognition. Explanation: Neuromorphic hardware for digit recognition. Dataset: MNIST. Methods: Spiking Neural Network implemented with memristor hardware. Results: 93% accuracy. Relation: Shows hardware-based AI recognition.

III SYSTEM ANALYSIS

Handwritten Digit Recognition is a machine learning-based system designed to identify and classify handwritten digits (0–9) from images. The system uses deep learning techniques, specifically Convolutional Neural Networks (CNN), to automatically extract features from digit images and perform classification. The need for such a system arises in applications like postal code recognition, bank cheque processing, and digitizing handwritten documents. The system processes input images through multiple layers such as convolution, pooling, and fully connected layers to achieve high accuracy. It improves efficiency, reduces human effort, and minimizes errors in digit recognition tasks.

Existing system

The existing system for handwritten digit recognition mainly relies on traditional machine learning algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and manual feature extraction techniques. These systems require handcrafted features like edge detection, pixel density, and shape analysis. The performance of such systems depends heavily on the quality of feature engineering and may not generalize well to different handwriting styles.

DisAdavantages of Existing system

- Requires manual feature extraction
- Less accuracy compared to deep learning models
- Poor performance on complex handwriting styles
- Time-consuming preprocessing
- Limited scalability for large datasets

Proposed system

The proposed system uses Convolutional Neural Networks (CNN), which automatically learn features from raw image data without manual intervention. The system takes handwritten digit images as input (e.g., MNIST dataset), preprocesses them (normalization and resizing), and feeds them into a CNN model. The model consists of convolution layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. The trained model predicts the digit with high accuracy. This approach improves performance, reduces human effort, and adapts well to different handwriting styles.

Advantages of Proposed System

- High accuracy in digit recognition
- Automatic feature extraction
- Robust to variations in handwriting
- Faster processing after training
- Scalable and efficient

IV METHODOLOGY

1. Data Collection

The dataset used for this project is the **MNIST dataset**, which contains 70,000 grayscale images of handwritten digits (0–9).

- 60,000 images for training
- 10,000 images for testing

🔷 2. Data Preprocessing

Before feeding data into the model, preprocessing is performed:

- Convert images into grayscale (if not already)
- Normalize pixel values (0–255 → 0–1)
- Resize images to a fixed dimension (28×28 pixels)

3. Model Design (CNN Architecture)

- Convolution Layer: Extracts features using filters
- Activation Function (ReLU): Introduces non-linearity
- Pooling Layer (Max Pooling): Reduces spatial dimensions
- Flatten Layer: Converts 2D data to 1D

4. Model Training

- The dataset is split into training and validation sets
- The model is trained using optimization algorithms like Adam
- Loss function used: Categorical Cross-Entropy
- Training is performed over multiple epochs to improve accuracy

5. Model Evaluation

- The trained model is tested using test data
- Performance metrics:

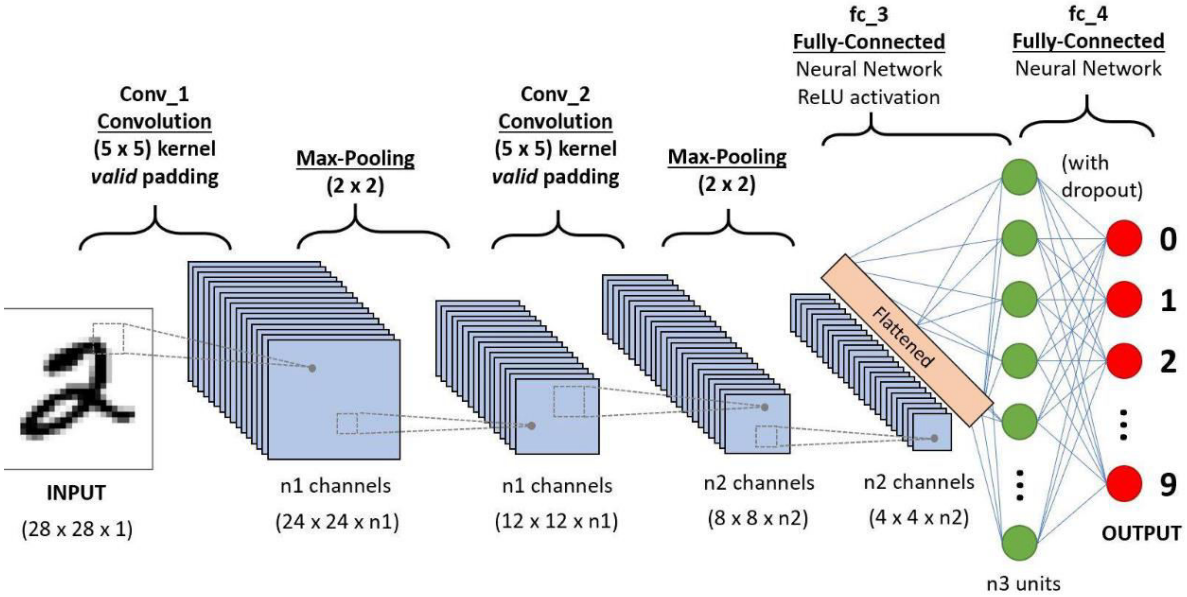
  Accuracy

  Loss

  Confusion Matrix

System Architecture

A Convolutional Neural Network (CNN) is a type of deep learning model specially designed for image processing. It automatically detects important features like edges, shapes, and textures from images.



Key Components:

- Convolution Layer: Extracts features using filters
- ReLU Activation: Introduces non-linearity
- Pooling Layer: Reduces image size and computation
- Fully Connected Layer: Makes final predictions

🔷 Working Principle:

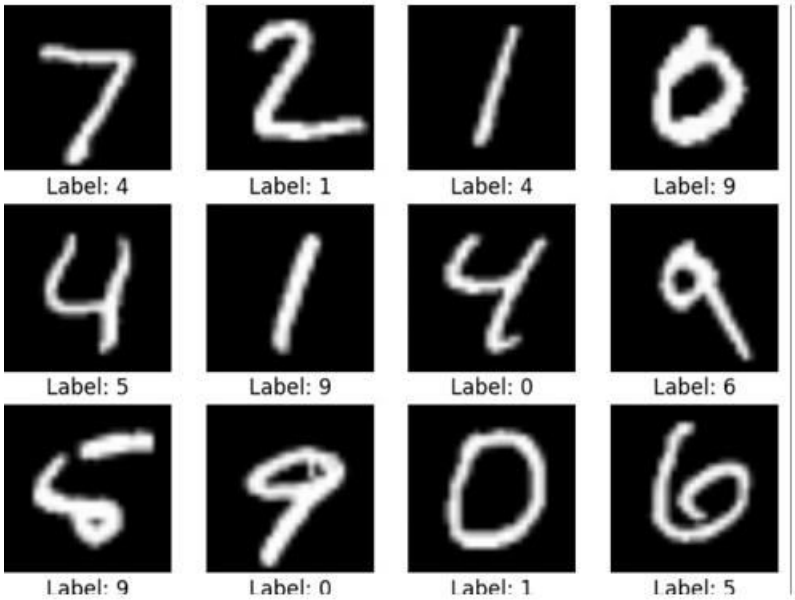
- The input image is passed through multiple convolution layers
- Features are extracted and refined
- The model learns patterns of digits during training
- Finally, it predicts the digit class (0–9)

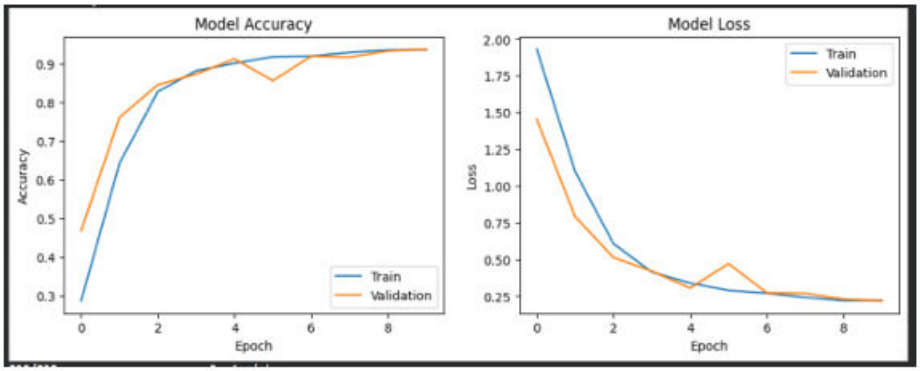
🔷 Dataset Example:

- MNIST dataset (60,000 training images + 10,000 testing images)

IV RESULTS &OUTPUT

The figure shows sample handwritten digit images from the test dataset along with their corresponding labels. These examples illustrate the variability in handwriting styles used for evaluating the proposed CNN–Inception model. The model learns distinctive features from such images to accurately classify digits from 0 to 9.





VI CONCLUSION

In this study, a CNN–Inception based handwritten digit recognition model was proposed to improve the accuracy and reliability of digit classification tasks. The system was developed and evaluated using the MNIST dataset, which contains 70,000 grayscale images of handwritten digits ranging from 0 to 9. The proposed architecture integrates Convolutional Neural Networks (CNNs) for feature extraction with a GoogLeNet-inspired Inception module to capture multi-scale spatial features from handwritten images. The preprocessing stage included normalization and reshaping of the images to ensure efficient model training and stable convergence. During training, the model learned hierarchical features from the handwritten digit images through convolution, activation, pooling, and feature concatenation operations. The use of the Inception module allowed the network to analyze the input image at different filter sizes, thereby improving the representation of complex handwriting patterns. Experimental results demonstrated that the proposed model achieved approximately 94% classification accuracy on the MNIST test dataset. The training and validation accuracy curves showed stable convergence, while the loss values gradually decreased during the training process. The confusion matrix analysis indicated that most digits were correctly classified, with only minor misclassifications occurring between 28 visually similar digits. Overall, the results confirm that the proposed CNN–Inception

architecture provides an effective solution for handwritten digit recognition and can be applied to various document processing and automation applications.

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