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An Improved Handwritten Digits Recognition Using Histogram & ML Techniques

Logasree R B[1], Shashank T V[2], Rajani M[3]
[1,2] PG Scholar, Dept. of CSE, Vijaya vittala Institute of Tech., Bengaluru, Karnataka, India
[3]Professor, Dept. of CSE, Vijaya vittala Institute of Tech., Bengaluru, Karnataka, India
***Emails:** logashreerb@gmail.com[1], shashanktv8@gmail.com[2], mrajaniratnakumar@gmail.com [3]*

Abstract
This project presents an improved technique called Handwritten Digit Recognition System (HDRS) based on supervised pattern recognition. The proposed system aims to identify and recognize digits within handwritten numbers in grayscale images. The architecture consists of two principal phases: Training (Phase-I) and Digit Recognition/Testing (Phase-II). Phase-I contains three stages: pre-processing (improving quality using standard arithmetic operations), feature extraction (histogram technique over image blocks), and classification into 10 distinct classes. Phase-II introduces additional stages including segmentation (splitting images into non-overlapping blocks containing individual digits), mapping using a threshold method, pattern matching, and probability-based validation. Experimental results show that the proposed system achieves high accuracy, making it highly suitable for practical handwritten digit recognition tasks.

***Keywords:** Handwritten Digit Recognition System (HDRS), Supervised Learning, Feature Extraction, Image Segmentation, Histogram Technique.*

1. Introduction
Handwritten digit recognition (HDR) is a primary branch of Optical Character Recognition (OCR) that enables computer systems to interpret human handwritten numerical inputs. HDR systems are broadly categorized into online mode (capturing real-time pen stroke trajectories on digital surfaces) and offline mode (processing static digital representations from scanners or cameras). While online recognition benefits from mature structural data, offline recognition deals purely with visual pixel densities, posing major operational challenges due to variations in individual writing styles and cross-class ambiguities (e.g., distinguishing 1 from 7, or 0 from 8). Modern applications of robust recognition loops include banking infrastructure (automating cheque leaf parsing), post offices (sorting parcels via postal PIN codes), medical facilities (interpreting handwritten prescriptions), and electronic commerce workflows. Because these applications involve sensitive financial or logistical parameters, minimizing error metrics is paramount.

2. Literature Survey
The field of handwritten digit recognition is characterized by extensive scholarly experimentation. Xiao Feng Han et al. integrated LeNet-5 Convolutional Neural Network (CNN) architectures to construct robust deep learning pipelines for image semantics [1-6]. Yoshihiro Shim et al. improved classification boundaries by merging a pre-trained Alex-Net feature extractor with a Support Vector Machine (SVM) classifier, achieving a test error rate of 0.93% on the MNIST database after utilizing pattern distortions like cosine translations. Similarly, Xiao-Xiao Niu et al. documented a hybrid CNN-SVM framework that automatically extracts raw image geometries, achieving a 99.81% recognition rate. Hong Zhang et al. introduced specific multi-feature extraction methods spanning structural, distribution, and projection attributes passed into deep networks to filter background distortions. Matthew Y.W. Teow contributed to the structural accessibility of these deep frameworks by designing a layered Minimal CNN model targeting learners. Furthermore, Luca Maria Gambardella et al. evaluated plain multi-layer perceptrons with online back- propagation, proving that deep, massive architectures accelerated by graphics processing hardware can reduce error rates to 0.35%.

3. Methodology and System Architecture
The proposed framework systematically handles

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incoming handwritten image arrays across two distinct phases, breaking down processing blocks from raw data entry to probabilistic validation shown in Figure 1.

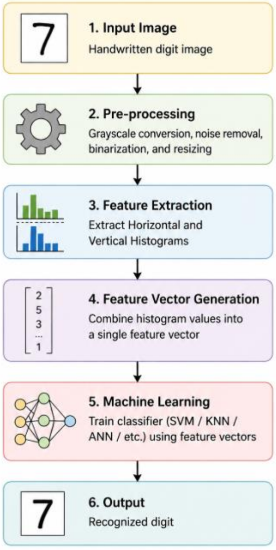


Figure 1 **Methodology and System Architecture**

3.1. Input Sample Array Configuration

The system parses individually constructed grayscale image inputs normalized across standard spatial dimensions including 50×50, 100×100, and 150×150 pixels. The input matrix configuration is mathematically represented as $X = \{x_i\}$ for $i = 0, 1, ..., n$, where x_i represents individual matrix blocks parsed along horizontal row counters and vertical column paths.

3.2. Pre-Processing Block

To suppress unwilling background noise and artifacts, standard arithmetic threshold operations are deployed. The pipeline converts inconsistent gray variations into binary pixel content, mapping foreground text explicitly to black values ($b_i = 0$) and isolating the high-frequency boundaries of the target digit.

3.3. Feature Extraction and Segmentation

The feature extraction block targets the structural black frequency F(b) across sub-divided image spaces using a block-based histogram technique. In Phase II, a dedicated segmentation layer splits composite numbers into finite, non-overlapping block matrices, allowing localized mapping via thresholding parameters.

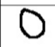
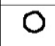
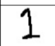
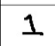
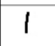
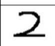
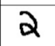
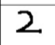
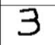
4. Results and Discussion

For system validation, an experimental dataset consisting of 30 distinct grayscale digit samples (3 Variations for each class from 0 to 9) was evaluated. All samples were normalized to standard 50×50 pixel boundaries to evaluate recognition performance shown in Table 1 and 2.

Table 1 **Normalized resolution**

Sl. No.	Sample Name / Class Identifier	Normalized Resolution (H × W)
1	0.1, 0.2, 0.3 (Class 0)	50 × 50 pixels
2	1.1, 1.2, 1.3 (Class 1)	50 × 50 pixels
3	2.1, 2.2, 2.3 (Class 2)	50 × 50 pixels
4	3.1, 3.2, 3.3 (Class 3)	50 × 50 pixels
5	4.1, 4.2, 4.3 (Class 4)	50 × 50 pixels
6	5.1, 5.2, 5.3 (Class 5)	50 × 50 pixels
7	6.1, 6.2, 6.3 (Class 6)	50 × 50 pixels
9	8.1, 8.2, 8.3 (Class 8)	50 × 50 pixels
10	9.1, 9.2, 9.3 (Class 9)	50 × 50 pixels

Table 2 **Training Stage with Samples (3 different classes)**

Classes	Image Name	Image
0	0.1	
	0.2	
	0.3	
1	1.1	
	1.2	
	1.3	
2	2.1	
	2.2	
	2.3	
	3.1	

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Conclusion

This work presents a structured and robust approach to Handwritten Digit Recognition using supervised learning frameworks. By dividing the architecture into specialized pipelines for preprocessing, block-based histogram feature extraction, sub-digit segmentation, and probabilistic validation, the model effectively counters individual handwriting variations and cross-class classification noise. The structural suitability verified across uniform pixel test samples highlights its capabilities for automated real-world workflows, cutting labor overhead and maximizing classification throughput.

References (12 Pt)

The References section must include all relevant published works, and all listed references must be cited in the text. References should be written in the order of them appearing in the text. Within the text, cite listed references use APA style, by their author's last name and year (e.g., husnussalam (2010). The author(s) must check the accuracy of all cite listed references, as the irjaeh Journal will not be responsible for incorrect in-text reference citations. International Research Journal on Advanced Engineering Hub (IRJAEH) adopts APA (American Psychological Association) for reference and citation in text. Authors can use various software to make it easier. All submitted papers in irjaeh Journal are suggested using Reference management applications such as Mendeley, Zotero or EndNote

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