“ Inclusive Digit Recognition System”

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1. Introduction

Basic Information

Recently, machine learning (ML) has become very widespread in research and has been incorporated in a variety of applications, including text mining, spam detection, video recommendation, image classification, and multimedia concept retrieval .Among the different ML algorithms, deep learning (DL) is very commonly employed in these applications . Another name for DL is representation learning (RL).The continuing appearance of novel studies in the fields of deep and distributed learning is due to both the unpredictable growth in the ability to obtain data and the amazing progress made in the hardware technologies, e.g. High Performance Computing (HPC) .

DL is derived from the conventional neural network but considerably outperforms its predecessors. Moreover, DL employs transformations and graph technologies simultaneously in order to build up multi-layer learning models. The most recently developed DL techniques have obtained good outstanding performance across a variety of applications, including audio and speech processing, visual data processing, natural language processing (NLP), among others.

Overview

Recently Convolutional Neural Networks (CNN) becomes one of the most appealing approaches and has been an ultimate factor in a variety of recent success and challenging machine learning applications such as challenge ImageNet object detection image segmentation and face recognition. Therefore, we choose CNN for our challenging tasks of image classification. We can use it for handwriting digits recognition which is one of high academic and business transactions. There are many applications of handwriting digit recognition in our real life purposes. Precisely, we can use it in banks for reading checks, post offices for sorting letter, and many other related works.

Machine Learning (ML) is a subfield of artificial intelligence (AI). The goal of machine learning generally is to understand the structure of data and fit that data into models that can be understood and utilized by

people. Although machine learning is a field within computer science, it differs from traditional computational approaches. In traditional computing, algorithms are sets of explicitly programmed instructions used by computers to calculate or problem solve. Machine learning algorithms instead allow for computers to train on data inputs and use statistical analysis in order to output values that 2 fall within a specific range. Because of this,
machine learning facilitates computers in building models from sample data in order to automate decision-making processes based on data inputs.

Machine learning develops algorithms and builds models from data, and uses them to predict on new data. The main difference with traditional algorithm is that a model is built from inputs data rather than just execute a series of instructions. Supervised learning uses data with result labelled, while unsupervised learning using unlabelled data. There are a few common machine learning algorithms, such as regression, classification, neural network and deep learning. Reinforcement learning and representation learning are heavily used for deep learning.

In the current age of digitization, handwriting recognition plays an important role in information processing. A lot of information is available on paper, and processing of digital files is cheaper than processing traditional paper files. The aim of a handwriting recognition system is to convert handwritten characters into machine readable formats. The main applications are vehicle license-plate recognition, postal letter-sorting services, Cheque truncation system scanning and historical document preservation in archaeology departments, old documents automation in libraries and banks, etc. All these areas deal with large databases and hence demand high recognition accuracy, lesser computational complexity and consistent performance of the recognition system.

The deep learning field is ever evolving, and some of its variants are autoencoders, CNNs, recurrent neural networks (RNNs), recursive neural networks, deep belief networks and deep Boltzmann machines. Here, we introduce a convolutional neural network, which is a specific type of deep neural network having wide applications in image classification, object recognition, recommendation systems, signal processing, natural language processing, computer vision, and face recognition. The ability to automatically detect the important features of an object (here an object can be an image, a handwritten character, a face, etc.) without any human supervision or intervention makes them (CNNs) more efficient than their predecessors (Multilayer perceptron (MLP), etc.). The high capability of hierarchical feature learning results in a highly efficient CNN.

2. Motivation

Students with motor or learning challenges—such as dysgraphia, which affects handwriting, spelling, and the physical act of writing—often struggle to express their knowledge clearly on paper. This not only hurts their academic performance but also hurts their confidence and motivation in learning

1. Problem: Students with writing difficulties often struggle to communicate ideas, especially in subjects like math.

2. Importance of handwriting: Writing by hand reinforces learning, helps motor and cognitive development, and aids memory.

3. Solution potential: Using technology to interpret handwriting and provide immediate feedback can reduce barriers, promote independence, and support deeper learning.

4. It leverages the cognitive strength of handwriting—memory, motor skills, focus—to enhance learning.

5. It addresses accessibility challenges, enabling students with disabilities to engage authentically with arithmetic.

6. By combining handwriting-based input with real-time feedback, the system empowers students to learn more confidently and independently.

3. Literature Review

1. Dmytro Zhelezniakov, Viktor Zaytsev & Olga Radyvonenko (2021)Title: Online Handwritten Mathematical Expression Recognition and Applications: A Survey, IEEE Access

2. AI-Powered Intelligent Tutoring Systems for Early Math Education .Published by A.Kumar, S. Pathak, R. Singh in arXiv preprint, 2022

3. Handwriting Fluency and Academic Success in Early Education Published by Claire Stevenson, Dr. Monica Daly in Frontiers in Psychology, 2022

4. AI Applications in Teaching and Rehabilitation of Handwriting Published by Karina Kalogeropoulou et al in Children (MDPI), 2023

5. Deep Learning-Based OCR and Dysgraphia Detection in Children Published by A. Vydeki, M. Narayanan, K. Rajasekar in arXiv preprint, 2024

6. A Review on Intelligent Educational Games for Mathematics Published by M. H. Huang, S. H. Teng, J. S. Lin in International Journal of AI in Education, 2022

7. Machine Learning for Early Numeracy in Game-Based Platforms Published by D. Lopez, J. Fang In Elsevier, Computers & Education, 2023

8. Neural Network Models for Recognizing Irregular Handwritten Digits Published by L. Green, P. Kapoor in Springer, 2023

9. Digit Recognition for Children's Handwriting in Educational Tools Published by N. Alvi, K. Sharma in IEEE Xplore, 2023

10. Gamified Learning Environments for Basic Arithmetic Skills Published by F. Mendes, S. Costa In ACM Transactions on Computing Education, 2024

4. Research Gaps

1. **Develop an Accurate Recognition Model**

Research Gap: Existing OCR and handwriting recognition technologies perform significantly worse on children's and atypically written input compared to adult or printed text. They fail to accommodate issues like poor letter formation, reversed characters, irregular spacing, and lack of structure.This gap highlights the need for specialized models trained on children's handwriting that factor in developmental writing patterns and deviations commonly seen in the target user group.

2. **Use ML Models to Recognize Hand-Drawn Digits from Children's Inputs**

Research Gap: Although some models show high recognition rates for children's digits (e.g., reaching 94–100% accuracy in person-dependent models), these results often rely on extremely limited subject pools and lack generalization validation. Broader pediatric handwriting variability remains underrepresented.

3. **Integrate Handwriting Input for Children (Touchscreen/Mouse)**

Research Gap: While handwriting interfaces are promising and preferred by young learners, most systems haven't been thoroughly tested with children or young children in informal educational settings. There's limited empirical evidence on their usability, error rates, or learning engagement in realistic interaction contexts (touch, mouse, stylus).

5. Problem Statements/ Research Problem

Following are the Identified Problems statements/ Research Problem of Project,

- Traditional arithmetic learning tools for are often rigid, non-interactive, and lack personalization.
- Most existing systems use fixed inputs like buttons or text, which are not natural or intuitive for very young learners.
- students commonly express answers through handwriting or drawing, but current educational games rarely support this input method.
- There is limited use of machine learning to recognize handwritten numbers specifically drawn by students.
- Learning tools also lack the ability to adapt the difficulty level based on a child’s performance or progress.

6.Objectives of Project/Research

The objectives of proposed work are as follows:

- Develop an Accurate Recognition Model Create a handwriting recognition system capable of interpreting handwritten arithmetic expressions—with symbols and operators—from diverse handwriting styles, including those typical of students with motor or learning disabilities.
- Support Personalized Adaptation Enable the system to learn and adapt to individual handwriting quirks (e.g., unique spacing or symbol placement), improving accuracy and user confidence through personalization.
- Implement Objective Usability and Performance Evaluation Evaluate the system’s performance using objective metrics—such as recognition accuracy, input duration, pen pressure variability, and handwriting stability—possibly combining them into a composite score for systematic comparison.
- Use machine learning models (e.g., CNN) to accurately recognize hand-drawn digits from children's inputs.
- Integrate handwriting recognition to allow students to write answers using touchscreens or mouse input instead of selecting predefined options.

7. Hypotheses/Research questions

Hypothesis 1: Personalized Adaptation Improves Accuracy

H_1: Allowing the system to adapt to an individual's handwriting (e.g., via a few calibration samples) will significantly increase recognition accuracy compared to a generic model.

Why this matters: Handwriting varies greatly between individuals, especially in learners with motor or learning disabilities. Co-adaptive systems—where both the user and AI adapt—can greatly boost recognition performance.

Hypothesis 2: Prompt-Tuning Personalization Enhances Performance Efficiently

H_2: Using lightweight meta-learned personalization techniques (like prompt tuning) will further improve recognition accuracy with minimal computational cost and limited labeled data.

Why this matters: New methods such as "MetaWriter" allow personalization with very few modifications and without heavy re-training, making them practical for resource-constrained, assistive systems.

8. Research Methodology/Research Design/Block Diagram etc.

1. Data collection

The MNIST database contains 60,000 training images and 10,000 testing images. Half of the training set and half of the test set were taken from NIST's training dataset, while the other half of the training set and the other half of the test set were taken from NIST's testing dataset. The original creators of the database keep a list of some of the methods tested on it. In their original paper, they use a support-vector machine to get an error rate of 0.8%. An extended dataset similar to MNIST called EMNIST has been published in 2017, which contains 240,000 training images, and 40,000 testing images of handwritten digits and characters.

2. Dataset creation

The MNIST database was constructed from NIST's Special Database 3 and Special Database 1 which contain binary images of handwritten digits. NIST originally designated SD-3 as their training set and SD-1 as their test set. However, SD-3 is much cleaner and easier to recognize than SD-1. The reason for this can be found on the fact that SD-3 was collected among Census Bureau employees, while SD-1 was collected among high-school students. Drawing sensible conclusions from learning experiments requires that the result be independent of the choice of training set and test among the complete set of samples. Therefore it was necessary to build a new database by mixing NIST's datasets.

3. Data analysis

Before applying any model to our dataset, we need to find out characteristics of our dataset. Thus, we need to analyse our dataset and study the different parameters and relationship between these parameters. The datasets are shown in Fig below.

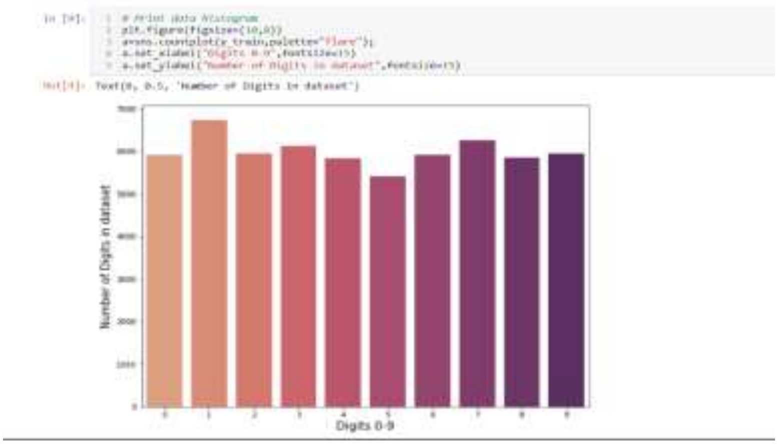

Figure No. 1: Graphical representation of MNIST- Dataset

4. Data pre-processing

The available data was divided into training set and test data. 63% of the data was used for the training set. The data is cleaned as all the NA are replaced by 0.0. Different graphs are plotted to study the distribution of data. The rating is important in order make the better classification. The study of the plots is done in order to choose better approach.

5. Dataflow Diagram

This flowchart illustrates a **character recognition workflow using a Convolutional Neural Network (CNN)**. Character images are first obtained and augmented to expand and diversify the dataset. The images are split into training and testing sets, both of which undergo pre-processing (e.g., resizing, normalization) to ensure consistency. The pre-processed training images are used for CNN modeling, where the network learns to identify patterns and features. The trained **Convolutional Neural Network Model** then classifies characters from testing images or **real-time input** (such as a live camera feed). Finally, the system outputs the recognized character, enabling accurate character recognition for applications like OCR or handwritten text analysis.

Block Diagram

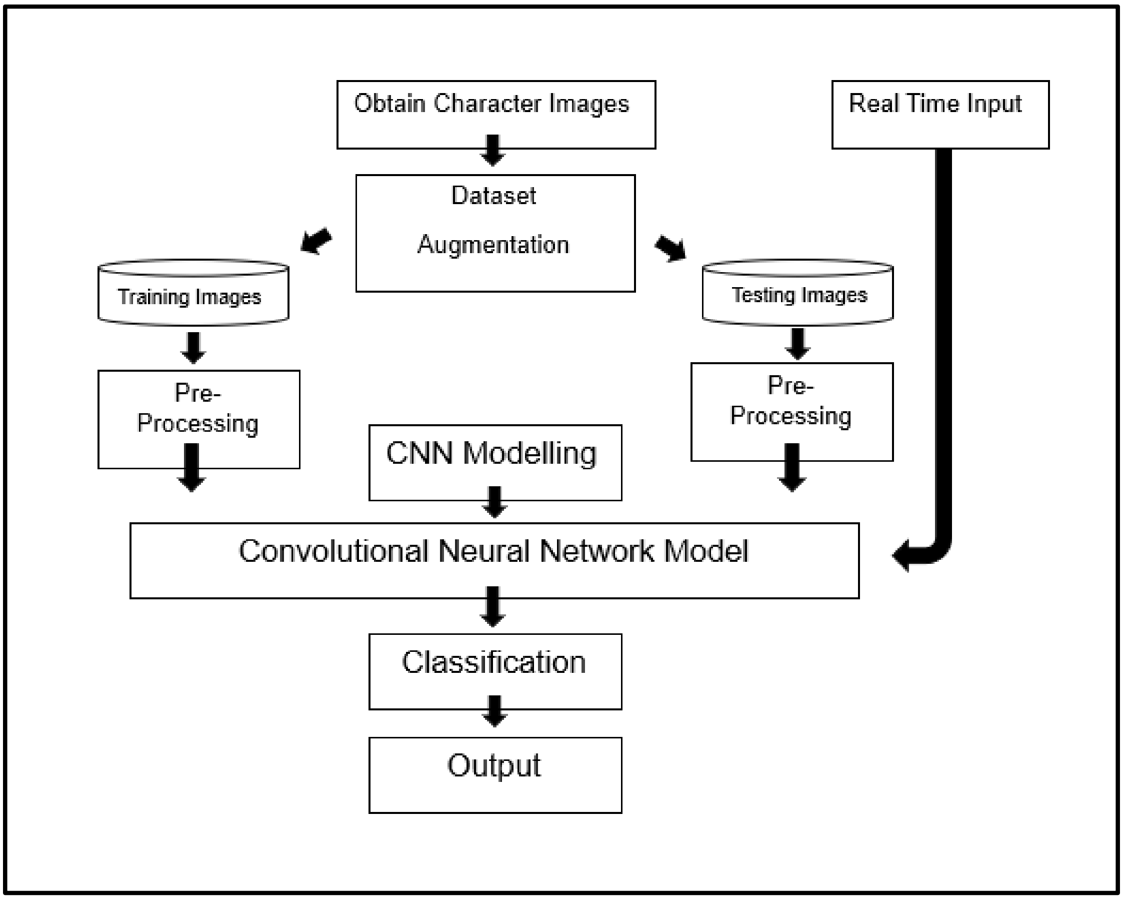

Figure No. 2: Dataflow Diagram of Inclusive Digit Recognition System

6. Convolutional Neural Networks (CNN)

➢ Applications of CNN

Simple applications of CNNs which we can see in everyday life are obvious choices, like facial recognition software, image classification, speech recognition programs, etc. These are terms which we, as laymen, are familiar with, and comprise a major part of our everyday life, especially with image-savvy social media networks like Instagram. Some of the key applications of CNN are listed here -

1. Decoding Facial Recognition

Facial recognition is broken down by a convolutional neural network into the following major components -

- Identifying every face in the picture
- Focusing on each face despite external factors, such as light, angle, pose, etc.
- Identifying unique features
- Comparing all the collected data with already existing data in the database to match a face with a name.

A similar process is followed for scene labeling as well.

2. Analyzing Documents

Convolutional neural networks can also be used for document analysis. This is not just useful for handwriting analysis, but also has a major stake in recognizers. For a machine to be able to scan an individual's writing, and then compare that to the wide database it has, it must execute almost a million commands a minute. It is said with the use of CNNs and newer models and algorithms, the error rate has been brought down to a minimum of 0.4% at a character level, though it's complete testing is yet to be widely seen.

3. Historic and Environmental Collections

CNNs are also used for more complex purposes such as natural history collections. These collections act as key players in documenting major parts of history such as biodiversity, evolution, habitat loss, biological invasion, and climate change.

4. Understanding Climate

CNNs can be used to play a major role in the fight against climate change, especially in understanding the reasons why we see such drastic changes and how we could experiment in curbing the effect. It is said that the data in such natural history collections can also provide greater social and scientific insights, but this would require skilled human resources such as researchers who can physically visit these types of repositories. There is a need for more manpower to carry out deeper experiments in this field.

5. Grey Areas

Introduction of the grey area into CNNs is posed to provide a much more realistic picture of the real world. Currently, CNNs largely function exactly like a machine, seeing a true and false value for every question. However, as humans, we understand that the real world plays out in a thousand shades of grey. Allowing the machine to understand and process fuzzier logic will help it understand the grey area us humans live in and strive to work against. This will help CNNs get a more holistic view of what human sees.

6. Advertising

CNNs have already brought in a world of difference to advertising with the introduction of programmatic buying and data-driven personalized advertising

7. Other Interesting Fields

CNNs are poised to be the future with their introduction into driverless cars, robots that can mimic human behaviour, aides to human genome mapping projects, predicting earthquakes and natural disasters, and maybe even self-diagnoses of medical problems. So, you wouldn't even have to drive down to a clinic or schedule an appointment with a doctor to ensure your sneezing attack or high fever is just the simple flu and not symptoms of some rare disease. One problem that researchers are working on with CNNs is brain cancer detection. The earlier detection of brain cancer can prove to be a big step in saving more lives affected by this illness.

5.7 External Interface Requirements

The external interface requirements are classified into two categories such as

5.8.1 Hardware Requirements

1. Pentium-IV (Processor).
2. 256 MB Ram
3. 512 KB Cache Memory
4. Hard disk 10 GB
5. Microsoft Compatible 101 or more Key Board

5.8.2 Software Requirements

1. Operating System : Windows

9. Expected Results & Discussion

1. Accurate Handwritten Digit Recognition

   The system is expected to accurately recognize handwritten numbers drawn by children using a touchscreen or mouse, with a recognition accuracy of above 90% on clean inputs.

2. Engaging and Intuitive User Interface

   The UI will be child-friendly, with large buttons, colorful visuals, and minimal text to support intuitive interaction.

3. Successful Integration of ML Model with Frontend

   A trained CNN model will be successfully integrated into the web application , ensuring smooth interaction between input, recognition, and response.

4. Dataset Creation or Adaptation (if applicable)

A custom dataset or a modified version of MNIST (or similar) tailored for children's handwriting may be developed or utilized for better model accuracy on -style writing.

10. Chapters Plan

1. Literature Review (June – Aug2025):
   Comprehensive review of existing research on handwriting recognition, MNIST dataset applications, and CNN models was carried out in the first four months.
2. Component Identification & Selection (July – Sept 2025):
   Tools, datasets (MNIST), and frameworks (Jupyter Notebook, Python, CNN models) were identified and finalized.
3. Designing (July– Oct 2025):
   System architecture, block diagram, and workflow design were developed and refined to meet project objectives.
4. Coding (Aug – Dec 2025):
   Practical implementation of the project, including model coding, preprocessing techniques, and dataset handling, was done progressively.
5. Experimental Analysis (Sept 2025 – Jan 2026):
   CNN models were trained and tested on MNIST, with experimental analysis to evaluate performance and accuracy.
6. Testing & Debugging (Oct 2025 – Feb 2026):
   Errors and inconsistencies in model training and evaluation were identified and fixed to optimize performance.
7. Preparation of Project Report (Nov 2025 – Feb 2026):
   Documentation of methodology, results, and findings was prepared for project submission.
8. Thesis/Poster Draft Submission (Jan – Mar 2026):
   Final draft of the thesis and poster was compiled and submitted for evaluation.

11. Month wise Work Plan

Months Activities	JUN '25	JUL '25	AUG' 25	SEPT '25	OCT' 25	NOV' 25	DEC' 25	JAN' 26	FEB' 26	MAR' 26
Literature Reviews	√	√	√							
Component Identification & Selection		√	√	√	√					
Designing		√	√	√	√					
Coding			√	√	√	√	√	√		
Experimental Analysis				√	√	√	√	√		
Testing and Debugging					√	√	√	√	√	
Preparation of Project Report						√	√	√	√	
Thesis/Poster Draft Submission									√	√

References

[1] Dmytro Zhelezniakov, Viktor Zaytsev & Olga Radyvonenko (2021)Title: Online Handwritten Mathematical Expression Recognition and Applications: A Survey, IEEE Access

[2] AI-Powered Intelligent Tutoring Systems for Early Math Education .Published by A.Kumar, S. Pathak, R. Singh in arXiv preprint, 2022

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