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Handwritten Digit Recognition Using Deep Learning-Cnn

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Abstract: Handwritten digit recognition is an important application in computer vision, often utilized in banking, postal services, and educational tools. This paper presents a deep learning-based method that makes Convolutional neural network (CNN) use to appropriately classify the handwritten numbers. MNIST is one of the reference datasets used to train the model, which contain diverse samples of handwritten numerals. The CNN architecture includes multiple convolutional and pooling layers,Then come layers that are entirely connected and Regularization of dropouts to avoid overfitting. Techniques like data augmentation and transfer learning are applied to improve generalization and reduce computational load.

Performance was assessed by comparing and implementing several deep learning models and machine learning models. With precision, recall, and F1-score values of 0.99%, the CNN model also earned the maximum accuracy of 99.25%. These outcomes show how reliable and efficient CNNs are in recognizing handwritten digits. The system exhibits enormous potential for Empirical world uses that require precise and quick digit categorization.

KeyWords: ComputerVision,DeepLearning,MNISTDataset,Data Augmentation,Model Generalization,Digit Categorization, Precision ,Recall ,Classification Accuracy.

1. INTRODUCTION

Convolutional Neural Networks (CNNs) are a kind of deep learning models designed specifically to process and interpret visual data. The architecture of the human visual cortex served as inspiration., CNNs excel at recognizing spatial hierarchies and patterns within images. Their architecture primarily consists of three types of layers: pooling layers for feature extraction and convolutional layers for dimensionality reduction and categorization using fully connected layers.

CNNs are now the industry standard for handwritten digit recognition because they can automatically learn specific characteristics straight from raw pixel data, doing away with the requirement for manual feature engineering.CNNs maintain the spatial relationships between pixels, in contrast to standard neural networks,enabling them to detect edges,shapes and textures that are necessary to differentiate between numbers written in different styles and orientations.

The MNIST dataset has been used extensively to assess CNN performance. This has thousands of handwritten numbers with labels. Models trained on MNIST consistently achieve high accuracy often surpassing 99%, demonstrating their scalability and robustness. Additionally, techniques such as dropout regularization, data augmentation and batch normalization have further enhanced CNNs' generalization capabilities.

This study describes the deployment of a CNN-based handwritten digit recognition system, detailing its architecture, training methodology and performance metrics. Given the importance of accuracy and speed in practical applications, CNNs are demonstrated as powerful and efficient solutions for image classification tasks.

2. LITERATURE REVIEW

2.1 Perceptron:

The perceptron algorithm is a foundational technique for binary classification tasks. Initially, weights corresponding to each input feature are randomly initialized. In each iteration the algorithm calculates the inputs, weighted sum applies an activation function and generates an output. If the output is incorrect particularly when a positive input is misclassified the algorithm updates the weight vector by adding the input vector to it.The model is guided toward more accurate classification by this adjustment which is dependent on the input vector \mathbf{x} and weight vector \mathbf{w}'s present states.Until convergence, the iterative process keeps going. meaning no further misclassifications occur.

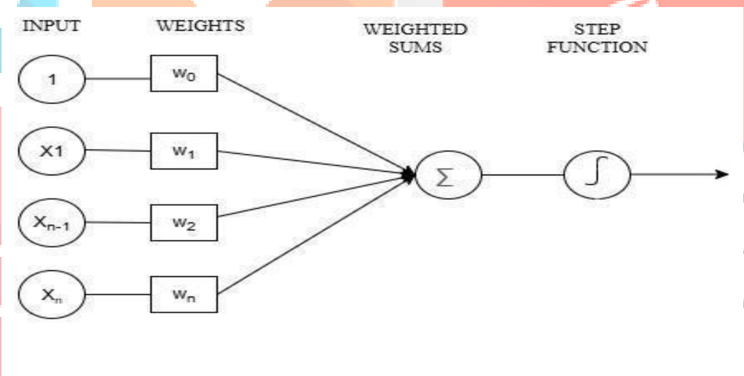


Figure 1- Perceptron

The primary objective of the perceptron learning find the optimal weights and thresholds that enable accurate data point separation using an algorithm..Once trained, The perceptron uses patterns and it has learnt to categorize new inputs. This approach is especially helpful for datasets that are structured such as those with multiple parameters and labels, where precise alignment between inputs and outputs is critical for performance.

2.2 Single-Layer Neural Network:

The STEPNET method effectively decomposes complex classification tasks into simpler subproblems using linear decision boundaries, making it well-suited for training single-layer neural networks. The quality of the input data representation has a significant impact on how well these networks perform techniques such as normalization and feature encoding significantly improve classification accuracy. With optimized learning rules and carefully prepared inputs, single-layer networks have demonstrated results comparable to more advanced models like multilayer perceptrons (MLPs) and convolutional neural networks (CNNs), particularly on structured datasets such as European postal digits and U.S. zip codes.

Single-layer networks are perfect for hardware implementation because of their straightforward architecture, offering fast and resource-efficient solutions for real-time handwritten digit recognition.These networks are inevitably restricted to linearly separable data and frequently find it difficult to convey the complicated, nonlinear patterns typical in diverse handwriting styles. Consequently, deeper models like CNNs are generally preferred in modern applications that require higher accuracy and adaptability.

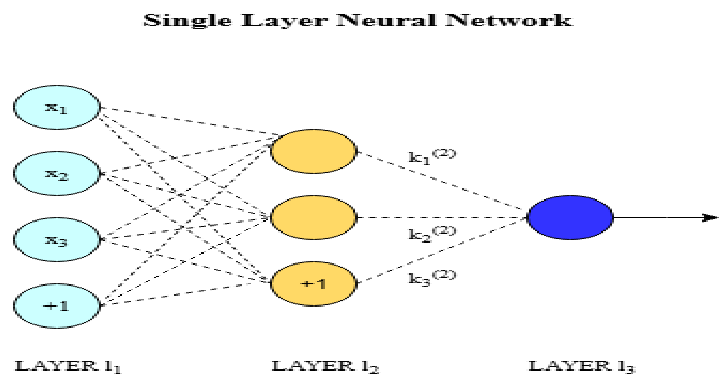


Figure 2- Single Layer Neural Network

2.3 Multilayer Perceptron:

A feedforward neural network with one or more input layers, one or more hidden layers, and an output layer is called a multilayer perceptron. Unlike single-layer networks, MLPs can learn complex, non-linear patterns, making them well-suited for recognizing handwritten digits.In the buried layers, every neuron uses an activation function, such sigmoid or ReLU, to change inputs and record abstract information.The output layer typically classifies digits 0 through 9 using a SoftMax activation function.

Studies have shown that MLPs trained on datasets like MNIST achieve high accuracy, especially when combined with techniques such as dropout regularization and proper data normalization.The ability of convolutional neural networks (CNNs) to capture spatial hierarchies allows them to outperform MLPs in image-related tasks. MLPs remain a strong baseline model for digit classification, particularly in low-resource environments.

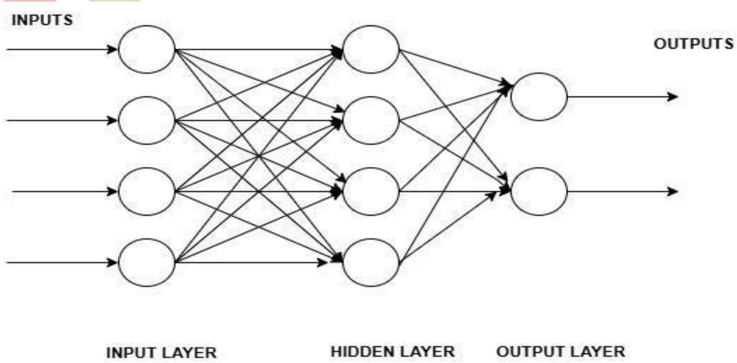


Figure 3—Multi-Layer Network

3. CONVOLUTION NEURAL NETWORK:

The most widely used deep learning models for applications using images, such as handwritten digit recognition, are Convolutional Neural Networks (CNNs). These networks automatically learn spatial hierarchies of features through layers of convolution, pooling, and nonlinear activation functions. In digit recognition CNNs directly process raw pixel data, extracting patterns such as edges, curves, and textures that uniquely identify each digit.

Convolutional layers for extracting features, pooling layers for reducing dimensionality, and fully linked layers for classification make up the standard CNN design. Studies consistently show that CNNs outperform traditional models like single-layer neural networks and multilayer perceptrons, often achieving accuracy exceeding 99% on standard datasets such as MNIST.

CNNs maintain an efficiency appropriate for real-time applications and are excellent at generalizing across a variety of handwriting styles, making them highly practical for deployment in Empirical world systems. Moreover their scalability and adaptability allow for deeper architectures that further improve recognition performance without requiring manual feature engineering.

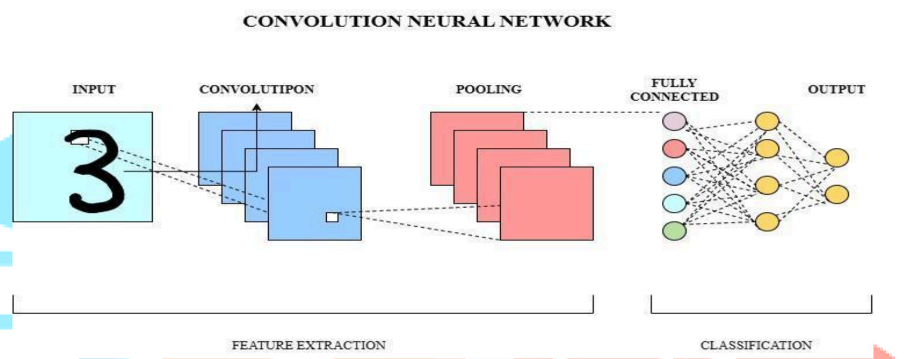


Figure 4- Convolution Neural Network

[1] A. Shrivastava et al

Reviews machine learning approaches including perceptrons.Discusses limitations of single-layer perceptrons in complex tasks.
Highlights the transition to multi-layer perceptrons (MLPs).MLPs show better performance on digit recognition.Compares traditional ML with deep learning methods.Perceptrons struggle with non linear decision boundaries.CNNs are shown to outperform MLPs in image tasks.The review includes accuracy standards.Emphasizes the evolution from perceptron to deep networks.Suggests CNNs as the current best practice.

[2] M. Y. W. Teow

This paper introduces a minimal single-layer CNN model for digit recognition.It emphasizes simplicity in architecture to aid understanding of CNNs. The model uses basic convolution and pooling operations.Achieves reasonable accuracy on MNIST with minimal layers. Focuses on interpretability rather than performance.Useful for educational purposes and foundational learning. Highlights the role of feature maps and filters. Demonstrates how even shallow networks can learn digit patterns. Includes visualizations of learned features. Serves as a stepping stone to deeper architectures.

[3] S. Jain, R. Chauhan

Compares DNN, CNN and RNN for handwritten digit recognition.Multi-layer DNNs are evaluated for their depth and learning capacity. CNNs outperform DNNs in spatial feature extraction. RNNs are less effective for static image data.The study uses standard datasets like MNIST. Accuracy and training time are compared across models. emphasizes the significance of architectural selection. Multi-layer networks show improved generalization. CNNs are favored for image jobs because of their local connectedness. For further research, the author proposes hybrid models.

[4] P. Anand et al

Implements CNN using TensorFlow for digit recognition. Uses Python and MNIST dataset for experimentation.Architecture includes convolution, pooling, and dense layers.Achieves high accuracy with minimal preprocessing.Highlights ease of implementation with TensorFlow.Discusses training time and model optimization.Visualizes feature maps and layer outputs. Demonstrates robustness across digit classes.Suggests future work on colored and multi-digit images.Validates CNN as a reliable approach for digit classification.

[5] A. Gupta et al

Provides a comprehensive review of CNNs for digit recognition. Summarizes various architectures and their performance.

Discusses LeNet, AlexNet, and custom CNNs.Highlights CNN's ability to extract spatial features.Reviews training techniques and hyperparameter tuning.Includes comparative accuracy across models. Mentions challenges like overfitting and data imbalance.Suggests CNNs for real-time applications.Recommends hybrid models for improved results.Positions CNN as the dominant method in the field.

4. RESEARCH METHODOLOGY

Handwritten digit recognition typically begins with the collection and preparation of image data, most commonly sourced from the MNIST dataset. This dataset contains thousands of labeled grayscale images representing digits from 0 to 9. The images undergo preprocessing where pixel values are normalized usually scaled between 0 and 1 and reshaped to match the input requirements of different models. For example, multilayer perceptrons (MLPs) require flattened vectors, whereas convolutional neural networks (CNNs) preserve the two-dimensional structure to leverage spatial features.

Following preprocessing various models are trained to classify the labeled digits. Single-layer perceptrons serve as a baseline but are limited to handling linearly separable data. MLPs introduce hidden layers and nonlinear activation functions, enabling them to learn more complex patterns. CNNs particularly effective for image-related tasks, utilize convolutional layers to extract localized features,layer pooling to lower dimensionality and fully connected layers to make final classification decisions. Usually backpropagation is used to train these models and algorithms like Adam or stochastic gradient descent are used for optimization.

Metrics such as confusion matrices and precision are used to evaluate the performance of the model. Because CNNs can directly learn hierarchical and spatially invariant features from raw pixel data, they routinely outperform other models. This robustness allows them to handle variations in handwriting style, stroke thickness, and orientation, making CNNs the preferred choice for empirical world applications including automated form processing, postal sorting, and bank check verification.

4..1 **Pre-processing** : Pre-processing involves taking the input image to carry out cleaning tasks. It effectively improves the image through noise removal. Additionally, Images may require conversion to binary or grayscale formats. which is accomplished during this stage.

4..2 **Segmentation:** After preprocessing the input images, a segmentation technique is used to separate individual characters. These characters are then stored in a series of images. The borders in each character image are then removed, if they exist. Finally, each character is resized to a specific dimension.

4.3 **Feature Extraction**: Feature extraction is performed on the segmented characters. In this instance, the features are obtained through a CNN utilizing the ReLU activation function. The CNN processes each character image to create a smaller matrix through convolution and pooling. Ultimately, the smaller matrix is transformed into a vector format using the ReLU function.

4.4 **Classification and Recognition**: The generated feature vector serves as a distinct input to establish the relevant class. Throughout the training phase, the parameters, biases and weights are computed. These computed parameters, biases and weights are then utilized during the testing phase for classification and recognition objectives

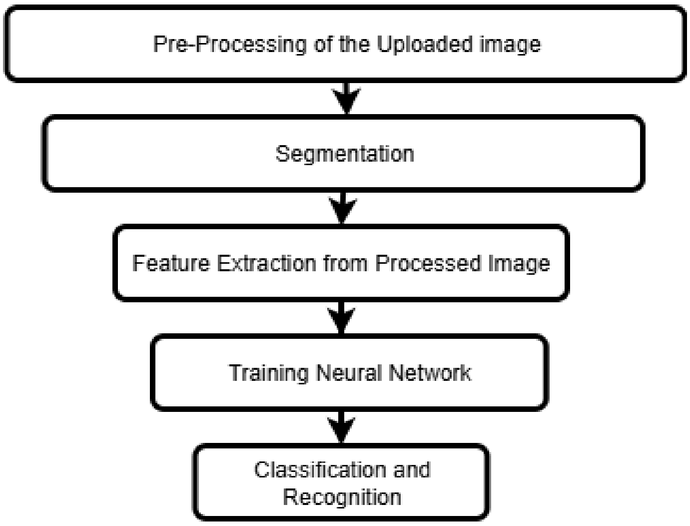


Figure 5- Processed System

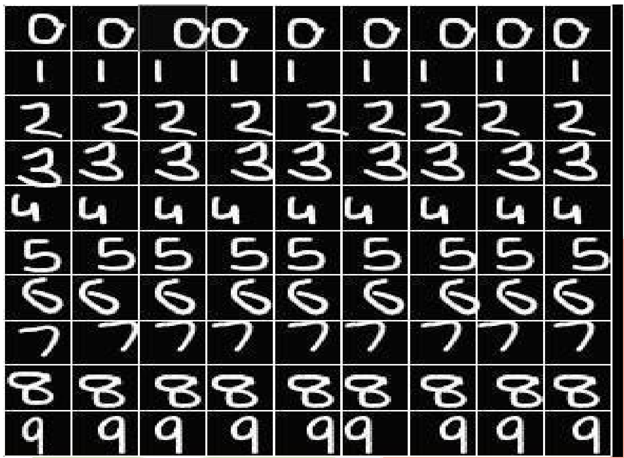


Figure 6- MINST Dataset

5. RESULT

Several models have been assessed using standard datasets such as MNIST to test classification accuracy and generalization to new data, based on reviewed research on handwritten digit recognition. Single-layer perceptron models typically achieve accuracies below 95% offering fast computation with simple calculations. However, these basic models struggle with complex digit patterns and have limited performance, although they remain straightforward to implement.

Multilayer perceptrons (MLPs) improved on this by introducing hidden layers and nonlinear activation functions, achieving accuracy between 97% and 98.5%. While MLPs performed well, they lacked the ability to effectively capture spatial patterns inherent in image data. Support Vector Machines (SVMs), when combined with robust feature extraction techniques, also reached approximately 98% accuracy. However, SVMs require more extensive preprocessing and are less scalable compared to other approaches.

Convolutional Neural Networks (CNNs) consistently demonstrated superior results, achieving accuracies ranging from 99.2% to 99.87%. CNNs excel by directly utilizing raw pixel data to learn hierarchical feature representations, enabling them to automatically understand different levels of features. This capability allows CNNs to handle significant variations in handwriting styles, stroke thickness and orientations.

Moreover, CNNs have demonstrated a high degree of suitability for Empirical world applications such as mail sorting and bank check processing. Their scalability and adaptability make them effective across diverse deployment environments, solidifying their position as the most powerful solution for handwritten digit recognition across varied writing styles.

Create GUI to predict digits:

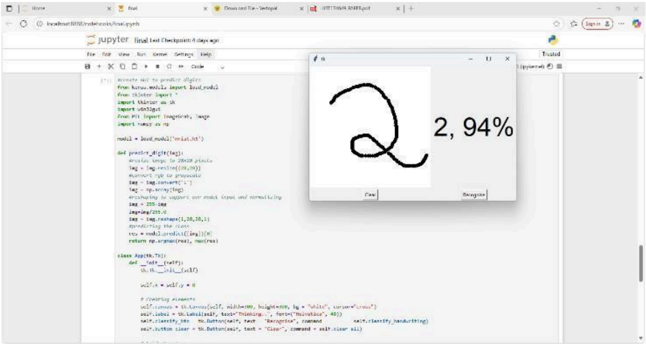


Figure 6- Prediction of digit 2

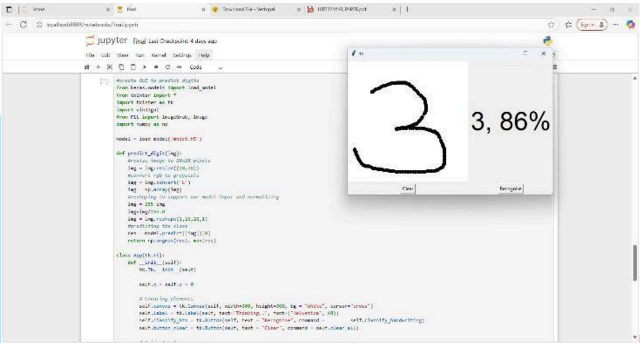


Figure 7- Prediction of digit 3

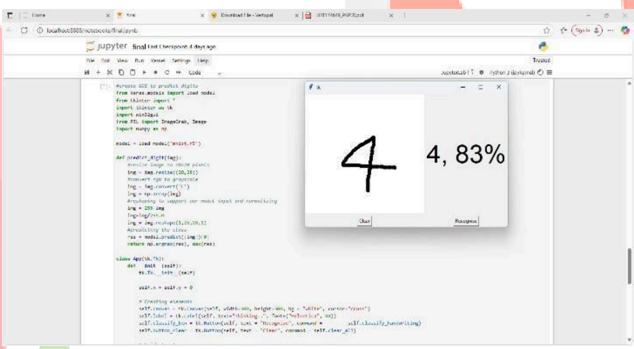
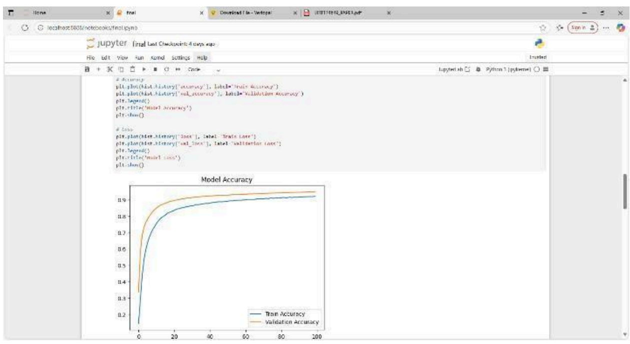


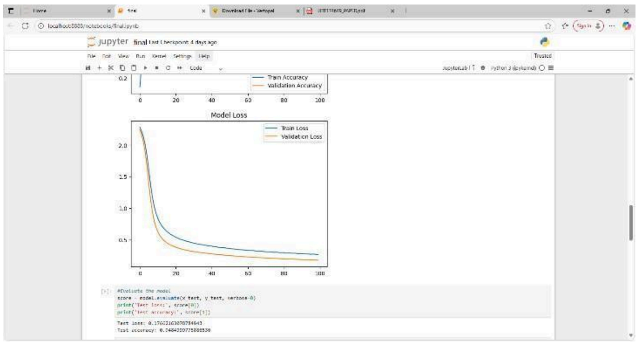
Figure 8- Prediction of digit 4

Model Evaluation:

Plot curve for accuracy in training and validation:



Plot curve of losses for training and verification:



CONCLUSION

The study previously discussed the division of the training dataset and testing subsets. In this experiment 80% of the information was set aside for training and 20% for testing. The dataset comprised 800 training images and 200 testing images each representing handwritten digits ranging from 0 to 9. Using TensorFlow, a convolutional neural network (CNN) model was developed and trained on the training dataset. The trained model achieved an overall accuracy of 94% when tested on the validation set. All digit classes from 0 to 9 were successfully predicted.

For future work, plans include analyzing how variations in training parameters affect overall classification accuracy. Additionally, extending the model to recognize letters and double digit numbers is underway with the aim of improving accuracy, particularly on colored images. Efforts are also being made to expand predictions to include double digit and triple digit inputs broadening the model's applicability.

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