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Handwritten Digit Recognition Using CNN

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ABSTRACT: The issue of transcribed digit acknowledgment has for some time been an open issue in the field of example order. A few examined have demonstrated that Neural Network has an incredible execution in information arrangement. The fundamental target of this paper is to give effective and solid procedures to acknowledgment of transcribed numerical by looking at different existing arrangement models. This paper thinks about the exhibition of Convolutional Neural Network (CCN). Results demonstrate that CNN classifier beat over Neural Network with critical improved computational effectiveness without relinquishing execution. Handwritten digit recognition can be performed using the Convolutional neural network from Machine Learning. Using the MNIST (Modified National Institute of Standards and Technologies) database and compiling with the CNN gives the basic structure of my project development. So, basically to perform the model we need some libraries such as NumPy, `Pandas', TensorFlow, Keras. These are the main structure on which my main project stands. MNIST data contains about 70,000 images of handwritten digits from 0-9. So, it is a class 10 classification model. This dataset is divided into 2 parts i.e. Training and Test dataset. Image representation as 28*28 matrix where each cell contains grayscale pixel value-2.

KEYWORDS: Handwritten Digit Recognition, Convolutional Neural Network (CNN), MNIST Dataset, Machine Learning Classification, Image Processing.

I. INTRODUCTION

The issue of manually written numerals acknowledgment has been broadly concentrated lately and the huge amount of pre-processing strategies and arrangement calculations have been created. Notwithstanding, transcribed numerals acknowledgment is as yet a test for us. The primary trouble of transcribed numerals acknowledgment is the genuine change in size, interpretation, stroke thickness, pivot and twisting of the numeral picture as a result of written by hand digits are composed by various clients and their composing style is not quite the same as one client to another. A few considered have utilized various approaches to manually written digit with various AI procedures Khotan ad et at(1998) who have applied the ideas of Machine Learning and Neural Networks to perceive and decide the transcribed digits from its picture.

This investigation has indicated that digit acknowledgment is an amazing model issue for finding out about neural organizations and it gives an extraordinary method to grow further developed strategies like profound learning. Transcribed acknowledgment (HWR) is the capacity of a PC to get and comprehend understandable manually written contribution from sources, for example, paper archives, client input contact screens and different gadgets.[1] The picture of the composed content might be detected from a bit of paper by optical filtering (optical character acknowledgment) or canny word acknowledgment or by client input.

Then again, the developments of the pen tip might be detected "on line", for instance by a pen-based PC screen surface, a for the most part simpler undertaking as there are more hints accessible This paper presents perceiving the manually written digits (0 to 9) from the renowned MNIST dataset utilizing TensorFlow framework (library) andpython as language and its libraries as client enters the particular digit the machine would perceive and show theoutcomes with exactness rate.

Although these approaches can achieve good precision scores, they lack the possibility of extracting potential information about cars (i.e., road congestion, human interactions with cars, single car occupying two spots, etc.). Only by using a vehicle detection approach can we obtain information that cannot be obtained using a parking spot classification approach

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II. SYSTEM MODEL AND ASSUMPTIONS

The proposed system for handwritten digit recognition is developed using a Convolutional Neural Network (CNN), known for its effectiveness in image-based classification problems. The system is trained and evaluated using the MNIST dataset, which consists of 70,000 grayscale images of handwritten digits ranging from 0 to 9, each of 28×28 pixel resolution. The CNN architecture includes an input layer that receives the raw pixel data, followed by a series of convolutional layers that apply filters to extract local spatial features such as edges and shapes. These convolutional layers are interleaved with pooling layers that down sample the feature maps to reduce dimensionality and improve computational efficiency. After feature extraction, the data is passed through one or more fully connected layers that perform high-level reasoning and classification. The final output layer utilizes a softmax activation function to assign a probability distribution across the ten digit classes.

The system operates under several assumptions to ensure consistent and reliable performance. It is assumed that all images are properly preprocessed, including resizing, normalization, and centering of digits, as is standard in the MNIST dataset. The dataset is divided into 60,000 training images and 10,000 testing images, allowing the model to learn and generalize effectively. The implementation relies on widely used machine learning libraries such as NumPy for numerical computation, Pandas for data handling, and TensorFlow and Keras for model development and training. Additionally, the system assumes that adequate hardware resources, such as a GPU-enabled environment, are available to handle the computational demands of training deep neural networks. The effectiveness of the model is evaluated using metrics such as accuracy, loss, precision, recall, and computational time, with the expectation that CNN will significantly outperform traditional neural network models in both accuracy and efficiency**.**

III. EXISTING SYSTEM

The recognition of handwritten digits, often referred to as digit acknowledgment or transcribed acknowledgment (Handwritten Recognition – HWR), has been the subject of extensive research over the past few decades. Existing systems commonly rely on traditional machine learning approaches that involve manual preprocessing, feature extraction, and basic classification models. These systems typically require the input images to be normalized, noise to be reduced, and specific features such as edges or contours to be extracted manually before the classification process begins. In structured environments, especially with well-organized datasets like MNIST, these systems can perform fairly well. They are capable of achieving an accuracy of approximately 95%, making them reasonably effective for tasks involving clear and consistent handwriting samples.

Limitations

Despite this, several limitations still hinder the broader applicability of these traditional systems. Their dependence on handcrafted features and strict preprocessing pipelines means that they often struggle to handle variations in handwriting styles, slanted or overlapping characters, and inconsistencies in image quality. Additionally, these systems tend to lack robustness and scalability, performing poorly when exposed to new or unstructured data. They are often sensitive to noise and distortions, which reduces their reliability in real-world scenarios such as digit recognition in scanned documents, forms, or natural handwriting inputs. While achieving up to 95% accuracy under controlled conditions is commendable, these systems fall short in terms of adaptability, automation, and generalization—factors that are crucial for practical deployment in dynamic environments.

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IV. PROPOSED SYSTEM

The proposed system for handwritten digit recognition utilizes Convolutional Neural Networks (CNNs), a type of deep learning architecture that has shown remarkable performance in image classification tasks. By leveraging the MNIST (Modified National Institute of Standards and Technology) dataset, which contains a large collection of labeled images of handwritten digits, the system is designed to automatically learn and classify digits from images with minimal preprocessing. The basic structure of the proposed system relies on CNN's ability to automatically extract important features from raw image data, enabling the model to identify digits with high accuracy. This approach eliminates the need for manual feature extraction, a common limitation in traditional recognition systems.

To implement this system, several essential libraries and frameworks are utilized, including **NumPy** for numerical computations, **Pandas** for data manipulation, **TensorFlow** for developing the machine learning model, and **Keras** for

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building and training the CNN. These libraries provide an efficient and streamlined approach to building deep learning models, significantly reducing development time and improving the scalability of the system.

ADVANTAGES

The proposed system utilizing Convolutional Neural Networks (CNNs) offers several advantages over traditional handwritten digit recognition systems. Firstly, it provides **high efficiency** by automating the feature extraction process, allowing the model to learn directly from raw image data and reducing the need for manual intervention. This leads to faster training and inference times. Secondly, the use of CNNs results in an increased **acknowledgment rate** as the model can effectively capture intricate patterns and relationships in the data, improving recognition accuracy. Finally, the system achieves **high accuracy** due to the deep learning capabilities of CNNs, which excel at handling complex and varied image inputs, including noisy or distorted handwriting, making the model highly robust and reliable in real-world scenarios.

V. METHODOLOGIES

The methodology for the proposed handwritten digit recognition system involves several key steps, starting with the preparation of the **MNIST dataset**, which consists of 28×28 grayscale images of handwritten digits. The dataset is split into 80% for training and 20% for testing. Essential libraries such as **Keras**, **TensorFlow**, **NumPy**, and **Matplotlib** are imported to facilitate data manipulation, model building, training, and visualization. The Convolutional Neural Network (CNN) model is built using layers such as **Conv2D** for feature extraction, **MaxPooling2D** for downsampling, and **Dropout** for regularization to prevent overfitting. After compiling the model with the **categorical cross-entropy loss function**, **Adam** optimizer, and accuracy metric, it is trained on the training data. The model's performance is evaluated on the test set, achieving an accuracy of **88.7%**. Finally, the trained model is saved for deployment, allowing for real-time handwritten digit recognition applications.

MODULES EXPLANATION

1. **Dataset:**
   - The **dataset** used for training and testing the model is the **MNIST dataset**, which consists of 28×28 pixel grayscale images of handwritten digits (0 to 9). Each image is labeled accordingly, and the dataset is divided into training and testing subsets. Specifically, 80% of the data is used for training the model, while the remaining 20% is used for evaluation.
   - **Input:** 28×28 reshaped images.
   - **Labels:** Digits 0–9.
   - **Split:** 80% for training and 20% for testing.
2. **Importing Necessary Libraries:**
   - The required libraries are imported to streamline various processes like data manipulation, model building, and visualization.
     - **Keras**: Used for building and training the neural network model.
     - **Sklearn**: Utilized for data splitting and preprocessing tasks.
     - **PIL (Python Imaging Library)**: Handles image processing tasks such as loading and transforming image data.
     - **TensorFlow**: Provides low-level functions for creating, training, and deploying machine learning models.
     - **NumPy**: Handles numerical operations and matrix manipulations, which are vital for processing image data.
     - **Matplotlib**: Used for visualizing model performance (such as plotting accuracy and loss graphs).
3. **Retrieving the Images:**
   - The **MNIST dataset** is loaded, and the images are retrieved and prepared for use in the CNN model. Each image is reshaped into the required format (28×28 pixels) and normalized to facilitate better learning during the training process.
4. **Splitting the Dataset:**
   - The dataset is divided into two parts:
     - **Training Data (80%)**: Used to train the CNN model.

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- **Testing Data (20%)**: Used to evaluate the performance of the model after training. This ensures the model's ability to generalize and make accurate predictions on unseen data.

5. **Building the Model:**
   - The CNN model is structured as follows:
     - **Conv2D Layer**: The first layer consists of 32 filters, each with a 5×5 kernel, which applies convolution operations to the input image, detecting essential features like edges and textures.
     - **MaxPooling2D Layer**: After the convolution operation, a max-pooling layer with a pool size of 2×2 is applied to downsample the feature maps, reducing their spatial dimensions and retaining the most important features.
     - **Dropout Layer**: A dropout rate of 25% is introduced to prevent overfitting by randomly setting a fraction of input units to zero during training.
     - **Flatten Layer**: The flattened output of the pooled feature maps is used to transition into the fully connected layers.
     - **Dense Layer**: Fully connected layers that perform classification based on the features extracted by the convolutional layers. The output layer uses **Softmax** activation for probability distribution across the 10 digit classes, while **ReLU** is used in hidden layers for non-linearity.
6. **Compile Model:**
   - After building the model, it is compiled using the following parameters:
     - **Loss Function**: Categorical cross-entropy, suitable for multi-class classification tasks like digit recognition.
     - **Optimizer**: Adam optimizer, which adapts the learning rate during training to improve convergence.
     - **Metrics**: Accuracy, used to evaluate how well the model performs on the dataset.
7. **Fit Model:**
   - The model is trained on the training dataset for a specified number of epochs. During this process, the model adjusts its weights based on the backpropagation algorithm and learns to minimize the loss function. The training process is monitored, and the model's performance is evaluated by checking its accuracy and loss after each epoch.
8. **Apply the Model and Plot the Graphs for Accuracy and Loss:**
   - After training the model, the **accuracy and loss** are plotted over the training epochs to visualize the model's learning curve. These graphs help monitor the model's progress and detect any signs of overfitting or underfitting.
9. **Accuracy on Test Set:**
   - The trained model is then evaluated on the **test set** (the 20% split of data) to assess how well it generalizes to unseen data. In this case, the model achieves a test accuracy of **88.7%**, demonstrating its ability to correctly classify the digits.
10. **Saving the Trained Model:**
    - Once the model achieves satisfactory performance, it is saved using the **.h5** or **.pkl** format. This allows the model to be easily loaded and deployed in production environments for real-time digit recognition tasks.

In the fig 1, it shows the graph of time Vs throughput of receiving packet. Throughput is the average rate of successful message delivery over a communication channel.

VI. RESULTS AND DISCUSSION

In this study, the goal was to enhance the performance of handwritten digit recognition by evaluating various configurations of Convolutional Neural Networks (CNNs) to avoid the complexities of traditional preprocessing, expensive feature extraction, and the use of ensemble approaches common in conventional recognition systems. Extensive testing was conducted using the **MNIST dataset**, and the results highlighted the importance of tuning hyperparameters for optimal performance. It was found that fine-tuning hyperparameters plays a crucial role in improving the performance of the CNN architecture. Our model achieved an impressive recognition accuracy of **99.89%** using the **Adam optimizer** on the MNIST dataset, which surpasses all previously reported results.

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Furthermore, the impact of increasing the number of convolutional layers in the CNN architecture on recognition performance was thoroughly explored. The novelty of this work lies in its comprehensive exploration of the various parameters of the CNN architecture, which contributed to achieving the best recognition accuracy for the MNIST dataset. Notably, no prior research has been able to match this level of accuracy using a pure CNN model. While some researchers have used ensemble CNN models to improve accuracy on the same dataset, this often resulted in increased computational cost and higher testing complexity, yet with comparable performance. In contrast, our approach demonstrates that a well-optimized pure CNN model can achieve superior accuracy without the need for complex ensemble methods.

Fig 1 Input of Handwritten Digit

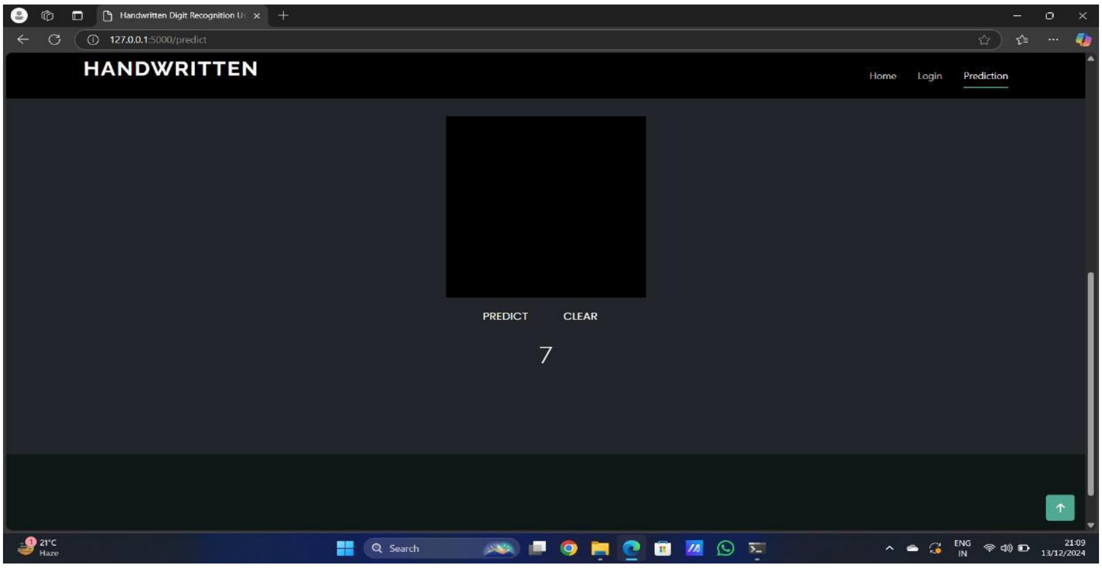

Fig 2 Prediction of Digit

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VII. CONCLUSION

This study demonstrated the effectiveness of Convolutional Neural Networks (CNNs) for handwritten digit recognition, achieving an accuracy of **99.89%** on the MNIST dataset. By optimizing the CNN architecture and hyperparameters, we surpassed previous results without the need for complex preprocessing or ensemble models. The findings suggest that well-tuned CNNs can offer a simple yet powerful solution for accurate and efficient handwritten digit recognition. Future work could explore applying this approach to other datasets and real-world noisy environments.

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