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Innovative CNN Strategies for Superior Handwritten Digit Recognition

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Abstract

Handwritten digit recognition is a fundamental problem in the field of computer vision and machine learning with numerous applications, such as postal code recognition, bank check processing, and digitizing historical documents. Convolutional Neural Networks have demonstrated remarkable success in various image recognition tasks, making them a popular choice for digit recognition. In this study, we present an enhanced approach to handwritten digit recognition using CNNs. Handwritten digit recognition plays a pivotal role in various applications, including optical character recognition, digit based and digitization of historical documents. Our method incorporates several novel techniques and optimizations to achieve superior accuracy and efficiency in digit recognition tasks. We begin by preprocessing the input images to enhance their quality and reduce noise. Subsequently, we employ a deep CNN architecture with multiple convolutional and pooling layers to extract hierarchical features from the digit images. Batch normalization and dropout layers are strategically applied to improve convergence and reduce over fitting. Additionally, we introduce data augmentation methods, such as rotation, scaling, and translation, to improve the model's generalization capabilities and reduce overfitting.

Keywords: Handwritten digit recognition, Convolutional Neural Network, Enhanced digit recognition, Image recognition, Epochs

INTRODUCTION

Handwritten Digit Recognition Using Convolutional Neural Networks" is an important and widely studied problem in the field of computer vision and machine learning. This task involves developing algorithms and models that can develop algorithms and models that can accurately recognize and classify handwritten digits, typically from 0 to 9. A basic issue in pattern recognition and machine learning, handwritten digit recognition has applications in financial document processing and postal automation. Because convolutional neural networks (CNNs) can capture local patterns and spatial hierarchies in data, they have become valuable tools for image classification tasks. In contrast to conventional techniques, this work investigates a more advanced way of handwritten digit recognition utilizing CNNs with the goal of achieving higher accuracy and efficiency.

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Recognizing handwritten digits is a fundamental component of various applications, including automated postal code recognition, check processing, and digitizing historical documents. In recent years, there has been significant progress in enhancing accuracy and efficiency of handwritten digit recognition systems, largely due to the advancements in deep learning and convolutional neural networks (CNNs). The suggested approach makes use of CNNs' hierarchical feature learning capabilities, which are ideal for picking up complex patterns in handwritten digits. This study

aims to improve recognition performance across various datasets by improving network design, training protocols, and data augmentation strategies. CNNs are used to simplify the preprocessing procedures that are usually involved in handwritten digit recognition and to enable reliable classification in a variety of scenarios [1-4]. Illustration of HDR is shown in Figure 1.

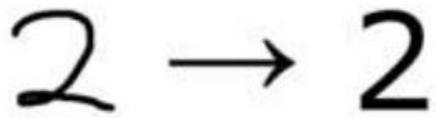

Figure 1. Illustration of HDR.

Dataset

Modified National Institute of Standards and Technology (MNIST) is a database which is freely available for handwritten digits and is standard for machine learning algorithms. It is like TIDigit which is a database of speech created by Texas Instruments, which tasks in speech recognition [9]. For our project, MNIST dataset is used. In this dataset, the images of digits were taken from a variety of scanned documents in which each image is Greyscaled and of 28*28 pixels. It uses 60,000 images to train the network and 10,000 images to evaluate how accurately the network learned to classify the images. Some of the sample images of the MNIST dataset are shown below in Figure 2.

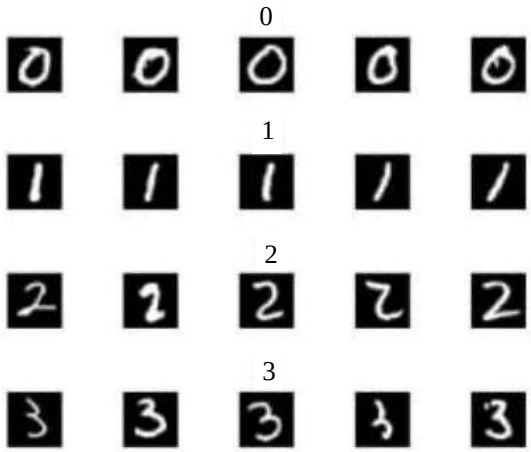

Figure 2. Sample of MNIST dataset.

To use the MNIST dataset in Keras, an API is provided to download and extract images, labels automatically. The task is to classify a given input image of a handwritten digit into one of the 10 classes representing the integer values from 0 to 9 inclusively.

Convolutional Neural Networks

Convolutional neural networks are deep artificial neural networks. We can use it to classify images (e.g., name what they see), cluster them by similarity (photo search) and perform object recognition within scenes. It can be used to identify faces, individuals, street signs, tumors, platypuses and many other aspects of visual data. The convolutional layer is the core building block of a CNN. The layer's parameters consist of a set of learnable filters (or kernels) which have a small receptive field but extend through the full depth of the input volume. During the forward pass, each filter is convolved across the width and height of the input volume, computing the dot product, and producing a 2-dimensional activation map of that filter. As a result, the network learns when they see some specific type of feature at some spatial position in the input. Then the activation maps are fed into a down sampling layer, and like convolutions, this method is applied one patch at a time. CNN has also fully connected layer that classifies output with one label per node.

RELATED WORK

Handwriting digit recognition has an active community of academics studying it. A lot of important work on convolutional neural networks happened for handwritten digit recognition [1,8,10]. There are many active areas of research such as Online Recognition, Offline recognition, Real-Time Handwriting Recognition, Signature Verification, Postal-Address Interpretation, Bank- Check Processing, Writer Recognition.

Savita Ahlawat et al. [5] explore advancements in the field of handwriting recognition, particularly leveraging deep learning techniques which have significantly enhanced performance in recent years. The study aims to enhance the accuracy of handwritten digit recognition by evaluating various convolutional neural network (CNN) architectures. This approach aims to eliminate the need for complex preprocessing, costly feature extraction, and the intricate ensemble methods typically employed in traditional recognition systems."

Dalia Mubarak Alsaffar et al. [6] delve into cryptography, which involves protecting data through the transformation of readable information into an unreadable format. This study undertakes a comparative analysis between the Advanced Encryption Standard (AES) and Rivest-Shamir-Adleman (RSA) encryption algorithms specifically for image encryption tasks using MATLAB. The research aims to assess and contrast the effectiveness, computational efficiency, and security characteristics of AES and RSA algorithms in the context of image encryption, providing insights into their practical applications and performance."

Matthew Y. W. Teow's [7] paper aims to bridge the gap in understanding the mathematical structure and computational implementation of convolutional neural networks (CNNs) through the introduction of a minimal model (Minimal CNN). This approach offers a clear and accessible explanation of the fundamental mathematical operations underlying CNNs.

METHODOLOGY

Deep Learning has emerged as a central tool for self-perception problems like understanding images, a voice from humans, robots exploring the world. We aim to implement the concept of Convolutional Neural Network for digit recognition. Understanding CNN and applying it to the handwritten digit recognition system is the target of the proposed model. Convolutional Neural Network extracts the features maps from the 2D images. Then it can classify the images using the features maps. The convolutional neural network considers the mapping of image pixels with the neighborhood space rather than having a fully connected layer of neurons. The convolutional neural network is a powerful tool in signal and image processing. Even in the fields of computer vision such as handwriting recognition, natural object classification, and segmentation, CNN has been a much better tool compared to all other previously implemented tools. The broader aim may be to develop a machine learning model that could recognize people’s handwriting.

Proposed System

System Architecture see in Figure 3.

The proposed model contains four stages to classify and detect the digits:

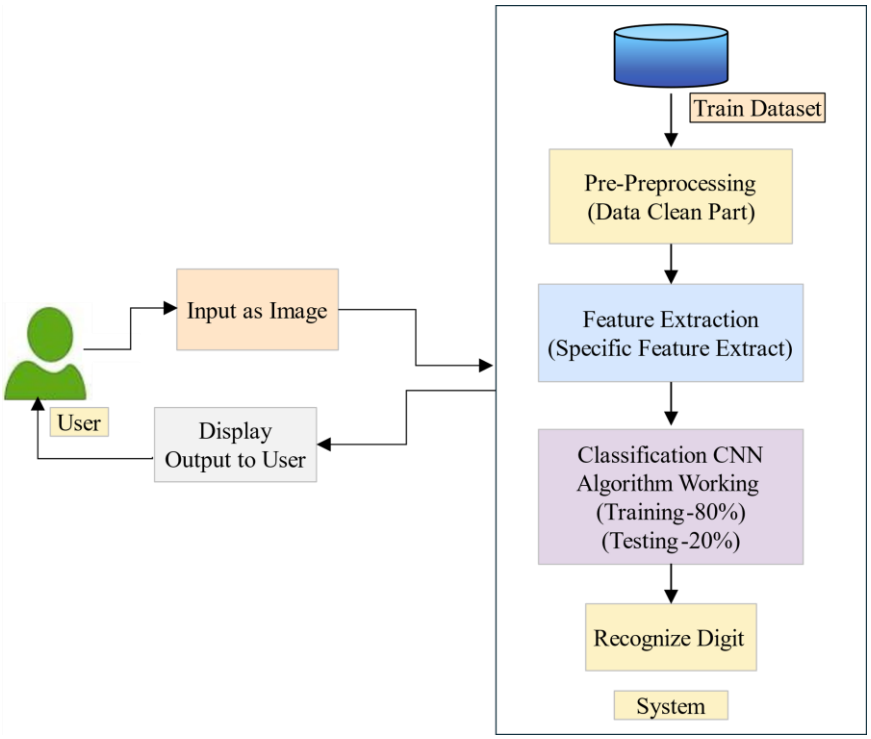

Figure 3. System Architecture.

Pre-Processing

Pre-processing is a part of HDR. If there are some rules like a box for each digit then, it will be much easier to detect the boundaries. The fundamental motivation behind pre-processing is to take off noise filtering, smoothing, and standardization. Binarization converts a Greyscaled image into a binary image.

Feature Extraction

Different types of algorithms used for feature extraction have different types of error rate. The errors made by each separate algorithm does not overlap, so combining all these methods lead to a perfect recognition rate and helps to reject the ambiguous digits recognition and improve the recognition rate of misclassified digits that can be recognized by humans.

Classification and Recognition

In the classification and recognition step, the extracted feature vectors are given as single input values to each classifier. CNN Convolution layer and the subsampling layer can have various layers. The down sampling layer is also known as pooling layer. The image is divided into small segments of small areas, and a value is calculated for each area. Then the calculated values are rearranged in sequence to form a new image. This process is like a fuzzy filter, which can increase the robustness of image feature withdrawal.

Training and Testing

Using the fit() method, a model can be trained. To see the skill of the trained model, test data is used as a validation dataset. Finally, to evaluate a model, the test dataset is used. Training is less complex because each module is designed to handle a specific subproblem. It is expected that each module can tackle the specific problem more efficiently and accurately because each module is trained independently which makes it easy to add and delete modules. Then, the model is trained using CNN and tested by giving new handwritten digit images that are not present in the dataset.

IMPLEMENTATION

The data which is already collected can be used for extracting the features of each digit. The availability of more powerful machine learning algorithms introduces an efficient and better approach to solve this problem. The project is divided into two modules as shown below Figure 4.

Pre-processing Module

Read the Image

OpenCV is a Machine Learning library that is used to read and manipulate images. The image is read and then stored in multiple copies for performing different operations. After reading the image is plotted in its shape to make sure it is read perfectly. Handwritten image is shown in Figure 5.

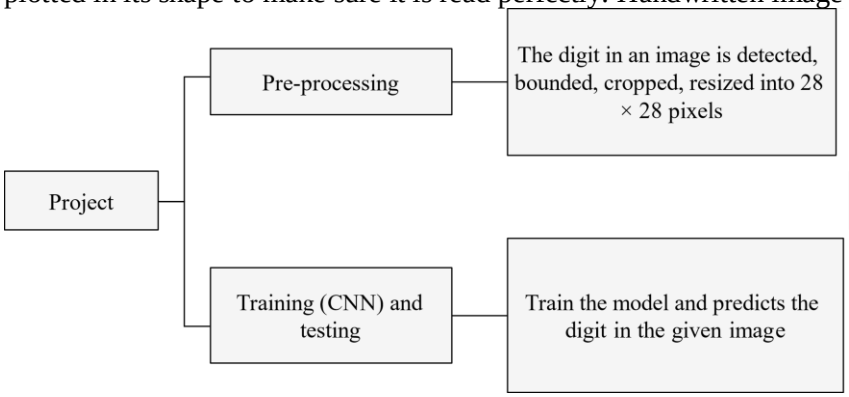

Figure 4. Modules of Handwritten digit Recognition.

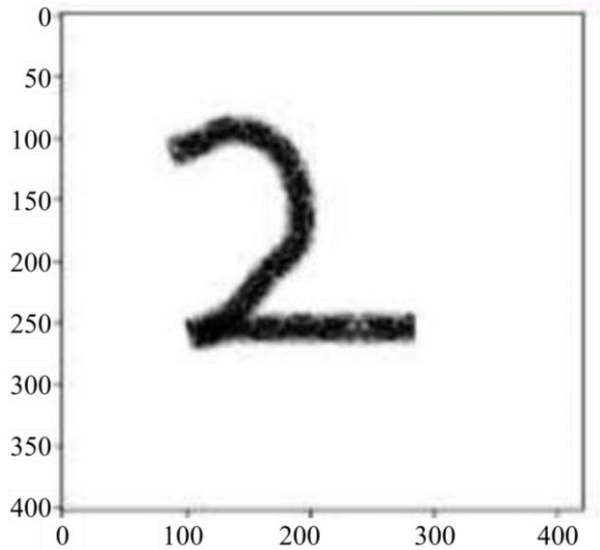

Figure 5. Handwritten image.

Converting an RGB Image to a Greyscale Image

An RGB image that is three-dimensional is converted to a Greyscale image as shown in Figure 6. that is one dimensional. A BGR image is a three-dimensional image (w, h, c)

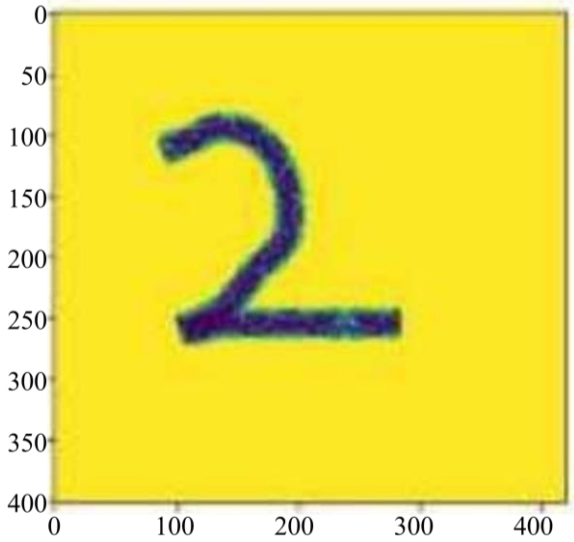

Figure 6. Greyscale image.

Remove Noise

Gaussian blur is applied to the greyscale image to remove noise in the image as shown in Figure 7.

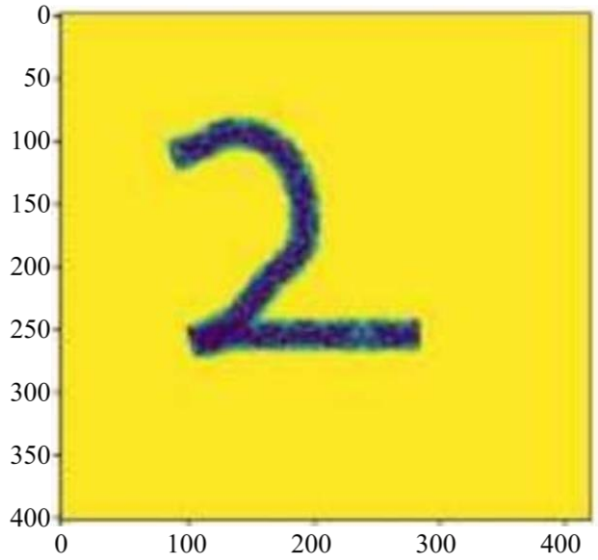

Figure 7. Image after applying Gaussian blur.

Object Detection

The standard step for object detection is Otsu thresholding is shown in Figure 8.

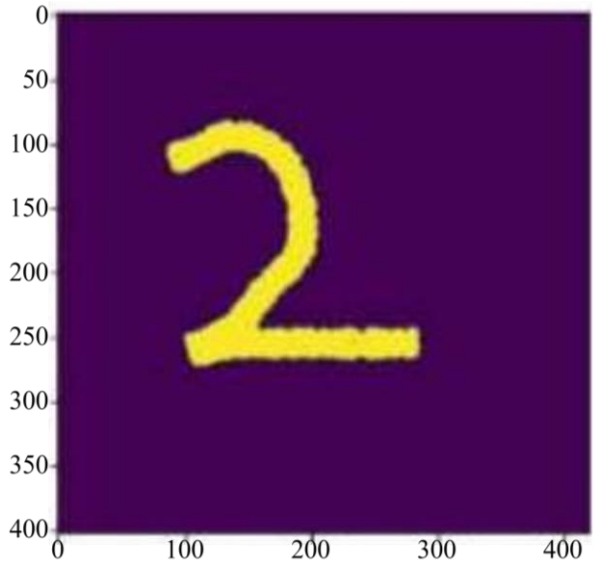

Figure 8. Image after applying Otsu thresholding.

Finding and Drawing Contours

The findContours() and drawContours methods() are used for finding and drawing boundaries of the detected object in an image as shown in Figure 9.

Training & Testing Module

Any model learns by using past data and Machine Learning algorithms. It learns from the past data by feature extractions. For training the model, a sequence of hidden layers is created with some nodes in each layer. Then, we compile the model by 'categorical_crossentropy'as loss function, 'adam' as an optimizer , and 'accuracy' as metrics.

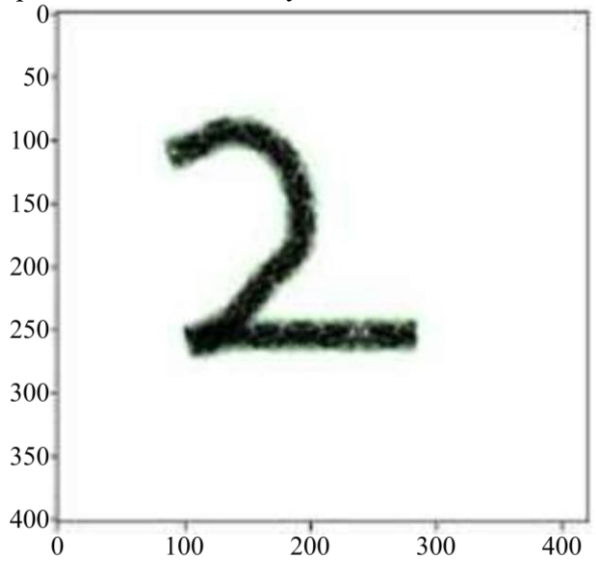

Figure 9. Image with Contours.

RESULT ANALYSIS

As CNN got high accuracy, it is used for training the model. The accuracies of the training and the testing dataset are plotted below Figure 10. If we increase the Epoch value the accuracy of model increases

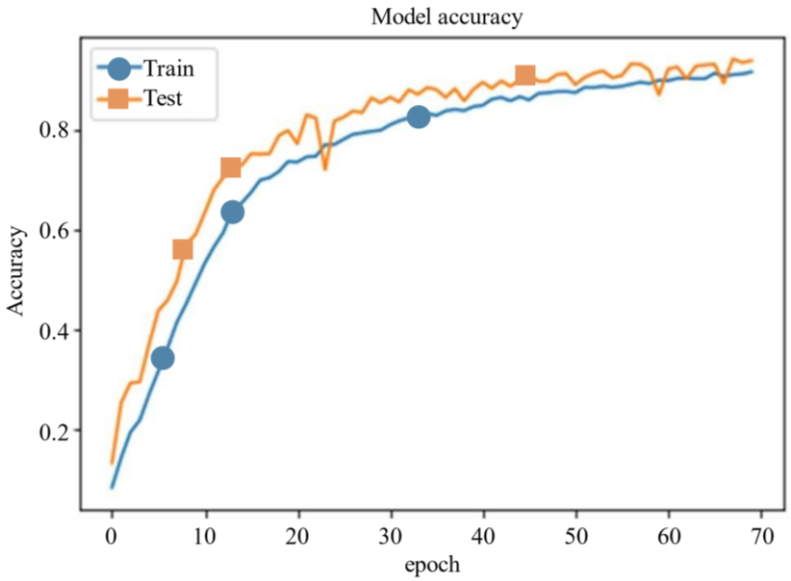

Figure 10. Model Accuracy w.r.t epoch.

So, the training accuracy of CNN is 99.23% and test accuracy is 99.53%.

Table.1 Model Accuracy

Model	Loss	Accuracy
CNN	2.67	99.63

CONCLUSION

In conclusion, the research on "Innovative CNN Strategies for Superior Handwritten Digit Recognition" underscores the significance of applying deep learning techniques like CNNs to solve complex image recognition tasks. The results of this study can have substantial implications in the development of automated systems for digit recognition and other related applications. As technology continues to advance, further improvements and adaptations of these models are likely to contribute to even greater accuracy and efficiency in the recognition of handwritten digits.

Future Scope

Research and develop more efficient CNN architectures specifically tailored for handwritten digit recognition. Investigate advanced data augmentation techniques to further enhance model generalization and reduce overfitting. Develop techniques to estimate uncertainty in model predictions, especially important for scenarios where confident predictions are crucial Develop techniques to improve model robustness against adversarial attacks, especially in security-critical applications. Explore fusion techniques for combining information from multiple modalities in a synergistic manner.

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