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Recognising Handwritten Multi-digit Data using Convolutional Neural Networks

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ABSTRACT

Digitization is seen as an essential part these days. Many vendors at neighborhood markets still use paper bills, so this may be helpful there. In response to this urgent issue, this study introduces a fresh method for digitizing handwritten invoices. To replace handwritten invoices with digital ones, the proposed method employs image processing and neural networks. The proposed method is hassle-free for the vendor as all he has to do is snap a photo of the handwritten invoice.

INTRODUCTION

Due to the abundance of handwritten papers, there is a pressing need to digitise them so that they may be more easily accessed through digital systems like databases and online forms. Text recognition is a necessary and helpful tool for automatically converting integers converted from their analog to digital equivalents. This recognition method is carried out using neural networks. This model blew everyone away after training on the renowned MNIST dataset, achieving an error rate of less than 1%. Segmenting and pre-processing the input image was the primary effort before to the recognition stage. Resizing, normalising, denoising, thresholding, and segmentation are some of the pre-processing techniques employed. Before the recognition process could begin, the image had to be further modified into an input format that the neural network could understand.

2.LITERATURE SURVEY

1. In 1998, LeCun, Y., Bottou, L., Bengio, Y., and Haffner, P. published research.

Title: Learning Based on Gradients Implemented in TextRecognition

Summary: A fresh strategy is introduced in this work. to document recognition based on convolutional neural networks. The authors describe the architecture of the LeNet-5 network, which was developed for recognizing handwritten digits. By applying gradient-based learning, the model effectively extracts features from images and provides robust recognition performance. The study demonstrates that CNNs can achieve high accuracy in digit classification tasks, leading to widespread applications in character recognition.

2. Published in 2012 by Ciresan, D. C., Meier, U., and Schmidthuber, J.

Title: Multi-Column Deep Neural Networks for Handwritten Digit Recognition

Abstract: This paper introduces a multi-column deep Neural network design for recognizing handwritten numbers. The authors combine multiple neural network columns that independently classify digits and then merge the results for improved accuracy. The model was evaluated on the MNIST dataset, achieving state-of-the-art performance. This approach demonstrates the potential of deep learning architectures to outperform traditional methods in handwritten text recognition.

3. Graves, A., &Schmidhuber, J. (2009).

Title: Using Recurrent Neural Networks for Offline Handwriting Recognition

Abstract:

An innovative recurrent neural network (RNN) method for offline handwriting recognition is presented in this study. The model successfully recognizes handwritten writing by using long short-term memory (LSTM) networks to understand temporal connections in sequential input. The RNN model outperforms other state-of-the-art methods, suggesting it might be useful for reading lengthier handwritten character sequences, according to the findings.

4. Jaderberg, M., Simonyan, K., Zisserman, A., &Kavukcuoglu, K. (2014).

Title: Reading Text in the Wild with Convolutional Neural Networks

Abstract: This research explores the use of CNNs for recognizing text in natural images, focusing on challenging scenarios such as variable font sizes and orientations. The authors present an end-to-end system that utilizes a deep learning framework to achieve robust text recognition. The results demonstrate the system's effectiveness in real-world applications, highlighting the adaptability of CNNs to various text recognition tasks beyond isolated digit classification.

3.PROPOSED SYSTEM

Here are the main stages of the process:

A. Image Acquisition

The user may now choose an existing picture on their computer and upload it. The program supports a wide variety of picture formats and users may easily upload their own. As the file handler, this process makes use of the 'files' module from the google.colab library. In order to import the picture into the software, a file dialogue box will go up, letting the user pick the file from their computer. Once the image path is constructed, the 'imread' function from the OpenCV library is used to read the picture.

B. Image Pre-Processing

The program can do very little with the picture in its native format. Therefore, pre-processing the picture is necessary. Part of this procedure is:

1) Image Resizing:

It is possible that the input image is too big for the display. The first step in overcoming this is to decrease reduction of 50% in picture size with no change to aspect ratio intact. This is accomplished by utilisingthe'resize' technique that is part of the OpenCV package.

2) Image Denoising:

Unwanted contours may be detected or detection accuracy may be negatively affected if the supplied image has intrinsic noise. Filtering the image is the first step in preventing this. Some examples of filters are the median filter, the averaging filter, and the Gaussian filter. However, after extensive testing, it was determined that non-local means denoising was the most effective method for this particular application. Therefore, the best filter was determined to be an half the original size while maintaining the same aspect ratio

Grayscale Conversion:

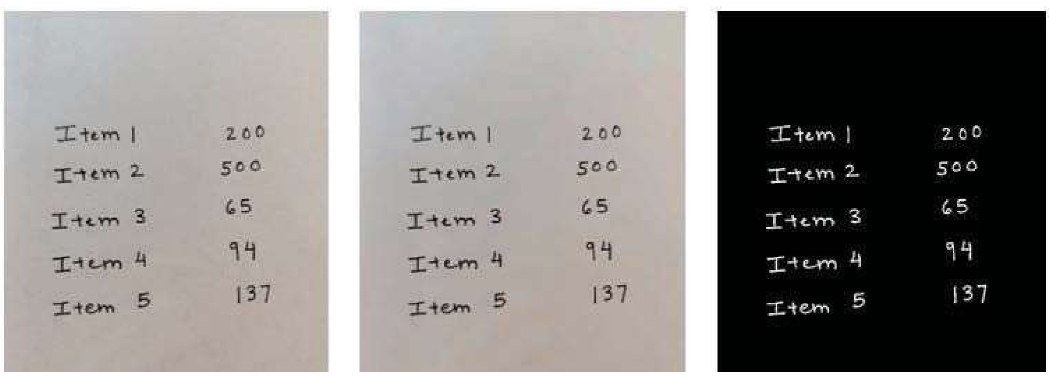
Using the OpenCV library, we can see that the picture is in BGR. We need to transform this picture into a greyscale one where every pixel has an intensity value between 0 and 255, with 0 being a totally the range from 255 (completely white) to 255 (black), and any shade in between. With the help of an in-built OpenCV library method, the image was converted to greyscale.

3) Image Segmentation:

When it comes to pre-processing methods, segmentation is king. The dimensionality of the picture is fundamentally diminished in this way. One such method is binary thresholding. A binary image, in which each pixel can only take on one of two possible values, is created using this method. The user can specify a threshold to determine which pixel will have a given value. This program makes advantage of adaptive Gaussian thresholding. With this method. A kernel applies the Gaussian filter before performing the thresholding operation locally on the picture. This comes in handy especially if there are details in the image that must be kept. In this case, the optimal kernel size for the Gaussian filter was determined to be 11.

4) ContourDetection

The most basic definition of a contour is an image with continuous strokes. Letters, numbers, etc., could be depicted by these strokes. To isolate the numbers from the background, we must first be able to recognise these features. Consequently, the detecting function receives the binary thresholded picture and uses it to perform contour detection. The x- and y-coordinates of the origin and destination points of these contours are returned by this function. To further emphasise these features, a rectangle is drawn around them. To feed this specific contour—or digit—into the neural network for recognition, the last step is to transform it into an individual image. We anticipated that the pricing would be written on the right half of the image, so we only looked at that half.



(a) (b)(c)

Figure 1: (a) Base picture, (b) Denoised image, and (c) Binary thresholded file.

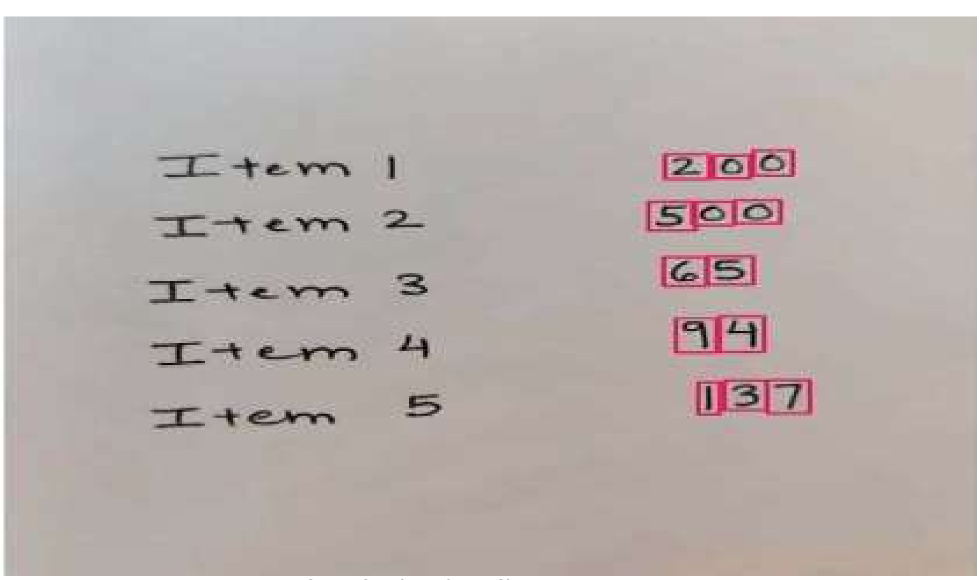


FIGURE 2: Identifying Shapes (Digits)

4.PROPOSED ARCHITECTURE

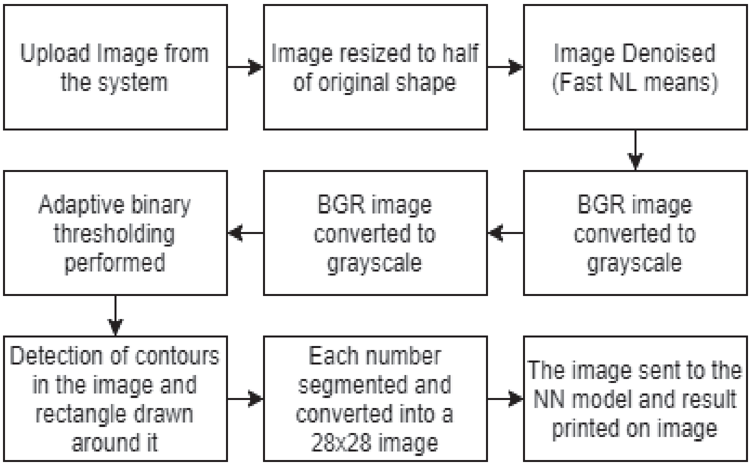
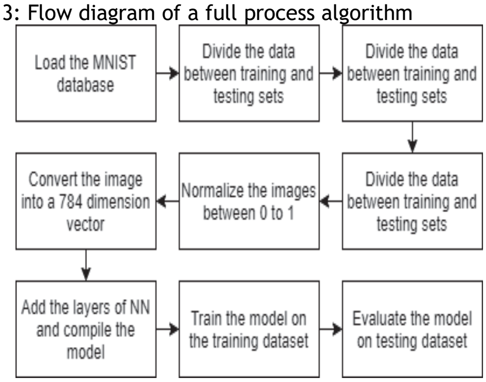


Figure 3: Flow diagram of a full process algorithm



Development of a neural network model flowchart (Fig. 4).

5.RESULTS AND DISCUSSION

After extracting 28x28 images from the source image, we sent them into the neural network, and the output met our expectations. Out of the thirteen numbers provided, the model accurately identified twelve. However, with the help of newly built state-of-the-art neural networks, such as CNNs or RNNs, nearly perfect prediction accuracy is within reach.

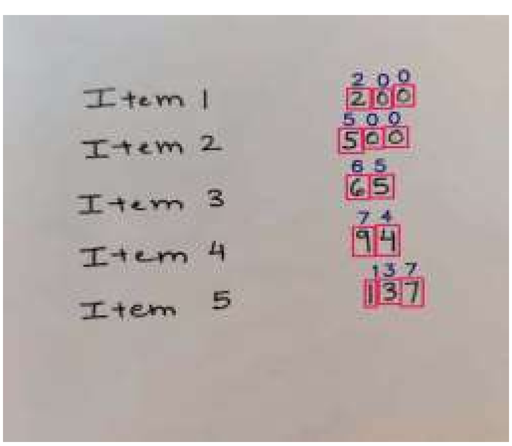


Fig.5. Outcomes from the CNN model

CONCLUSION

The proposal comprised image processing and ml methods. The suggested neural networks model recognised handwritten numbers 99.06% accurately. The planned work has provided the framework, but it can be improved and developed. Recognition of handwritten letters and digits is a future possibility.

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