# Read Digits in Natural Scene Images using Convolutional Neural Networks

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## 1 Motivation

**How this project related to Computed Vision?**

- Since computer vision is about interpreting the images from the camera such as image processing, classifying images based on features, etcetera.
- In this project, we also use computer vision methods for pre-processing and post-processing such as image size reduction, image conversion, and many more, other than convolutional neural network.
- Digit recognition is a computer vision problem used in applications such as postal mail sorting, bank check processing, form data entry, etcetera.

**Why Convolutional Neural Network**

- Since fast processing, accuracy and speed for these applications is important therefore, convolutional neural network is useful in this case.
- Furthermore, according to state-of-the-art, it shows better performance as compare to other approaches[1]

## 2 Approach

The first part of this task consists of gathering data to train the network. We will use publicly available dataset; MNIST. Later on, we explain about this dataset in more details. Images from dataset will be preprocessed before feeding to the network. Later on, post-processing will be needed in cases where an image contains multiple digits to get a final result.

- Few possible approaches to solve this task are:
  - Multiple hand-crafted features
  - Template matching
  - Convolutional Neural Network(we use this)

### 2.1 Modified National Institute of Standards and Technology(MNIST) DataSet

This dataset we use for our project to train the convolution network and predict in real time. It was created by National Institute of Standards and Technology(NIST). It consists of 60,000 training examples; each digit has 6,000 images, and testing examples of 10,000 examples. Furthermore, this dataset is size-normalized and centered to a fixed-size image. This dataset is mostly used by people who are interested to learn about pattern recognition methods or machine learning by devoting minimum amount of time on pre-processing and formatting the images. Each image in dataset contains one digit, and all digits are handwritten. Sample images of data set is shown in figure.

### 2.2 Limitations

- Images contain only digits.
- Background is a solid color and does not change. (Black or white)
- Number should be distanced enough so that bounding boxes do not overlap with other number.

Figure 1: [3] Samples images of MNIST dataset

### 2.3 Graphic user interface (GUI)

We have designed a GUI to control the parameters for the binary threshold and the canny edge detector. The GUI can also show the images through different stages of the pre-processing steps. This is selected by a drop-down menu which contains the following options:

- Original: show the rgb image without any filter.
- Gray: show the image converted to gray-scale.
- Threshold: image after application of the binary threshold.
- Edge: shows the edge map.
- Median: shows threshold image after a median filter with 5x5 kernel.
- Contours: image with extracted contours.

- Bbox: shows original image with bounding boxes drawn around detected contours with the prediction.

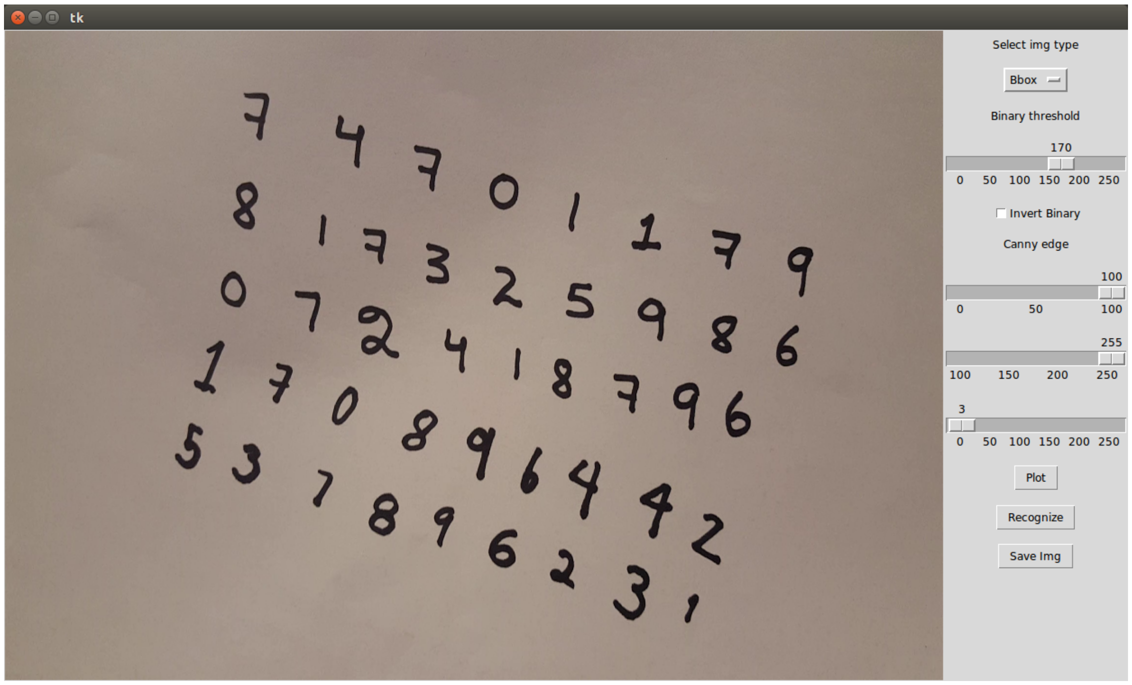


Figure 2: Graphic user interface.

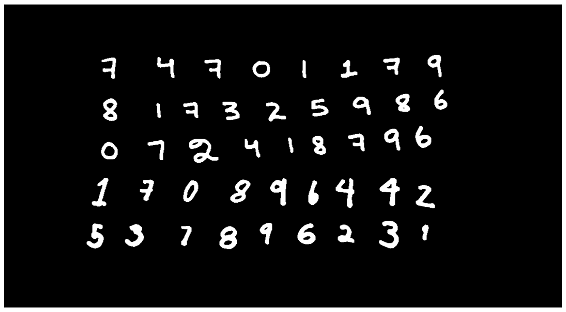
## 2.4 Pre-Processing

### 2.4.1 Pre-Processing of DataSet

Since each image contain single digit with their label, therefore, we just do little pre-processing. First, we convert every image to the fixed size of (28,28,1) for faster computations. Then, we normalize all the images to make sure all pixels lies within one range. To make things easier for network, each image along with its label is converted from 1-dimensional class array to 10-dimensional class matrices by using Keras utility function.

### 2.4.2 Pre-Processing of Live Images

For image pre-processing, we apply a series of filters to the image and detect contours that will represent the numbers. The first step is to resize the image to 1040x720 since we are using a cell phone camera to record and the original resolution exceeds the screen resolution. We pre-process first by converting the image into gray-scale and apply a Gaussian filter with a 5x5 kernel to smooth the image. The next step is to apply a binary threshold and since the background is constant (solid color), we can adjust the threshold to highlight the numbers. We then use the threshold image to compute an edge map via the Canny edge detector.


(a) Binary threshold image

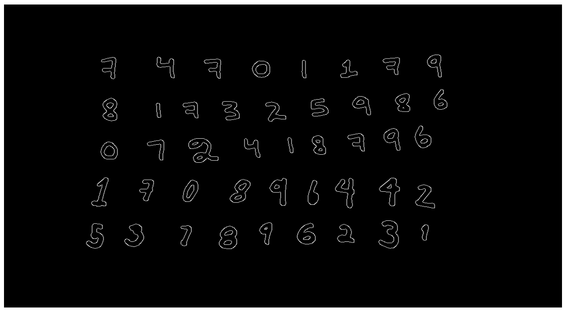
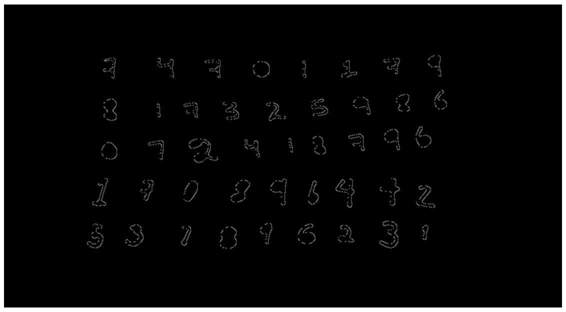

(b) Edge map with Canny edge detector

Figure 3: Images from first pre-processing steps.

The next step is to localize and extract the numbers from the image. For this we extract the contours from the edge map and only take the contours with an area bigger than 20 pixels. After obtaining the contours, we draw a bounding box surrounding each contour and crop each rectangle. Each rectangle is resized to a 28x28 and feed to the CNN classifier.


(a) Extracted contours.

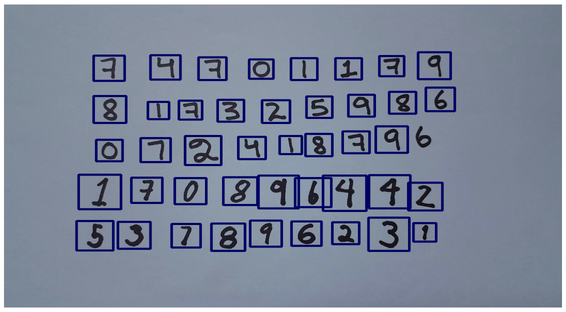

(b) Bounding box drawn over original image.

Figure 4: Images from second pre-processing steps.

## 2.5 Keras Library

In order to construct Convolutional Neural Network(CNN) model, we use Keras library. It is python deep learning library running on top of TensorFlow and Theano. We use Keras because it supports CNN and recurrent networks, and it is easier to use. It also runs on central processing unit(CPU) and graphics processing unit(GPU)[4].

## 2.6 Convolutional Neural Network(CNN)

Convolutional neural networks are made up of neurons that have adjustable weights and biases. Each neuron receives input, perform a dot product with weights and apply activation function to it; usually we use Rectified Linear Unit (ReLU). These networks assume that inputs are always images. Features are extracted to determine information about the image.

Furthermore, layers in CNN are arranged in 3 dimensions: width, height, depth. These networks have ability to reduce the amount of parameters; such as weights and biases, without loosing any valuable information. This also helps for faster computations[5][6].

### 2.6.1 Architecture

CNN architecture is mainly consists of three main layers arranged in sequential order:

- Convolutional layer: This is first layer of network. It performs convolution operation with each pixel based on filter size. Filter contains random values initially(which can be considered as weights), each number in filter is multiplied with its corresponding pixel in image. After that, all values inside filter are added, we get only single number. Figure 5 gives clear idea how this works. Here size of our filter is 5 by 5, after multiplication and addition, we get one number which we can see in right side of image. This process is performed on every location of image. So, we get important features of image, and these important features are fed to next layer for further processing. Furthermore, we can also use more than one convolution layer, it depends upon complexity of image. Lastly, weights inside filters are adjusted according to back-propagation algorithm; where first we computed error between current output and desired output, and based on error we adjust our weights to get more closer to our desired output.

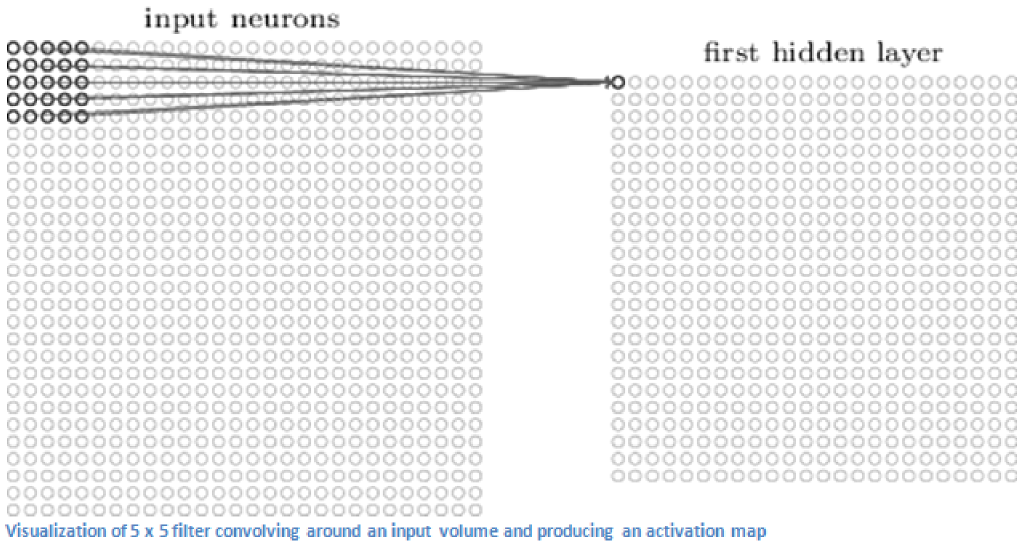

input neurons
first hidden layer
Visualization of 5 x 5 filter convolving around an input volume and producing an activation map

Figure 5: [5] Visualization of 5 by 5 filter

- Pooling layer: The main purpose of this layer is to reduce the size of image. This helps in reducing amount of parameters, which requires less computation and also reduction in variance in image. Furthermore, pooling is achieved into two different ways; max and average pooling. Max pooling considers element with maximum value inside filter. While, average pooling computes average of all elements inside filter and replace average value in image.

- Fully-Connected layer: This layer takes input from previous layer; can be convolution or pooling layer and convert output of network according to number of classes. In our case, we have 10 classes; 0 to 9. so it outputs 10 values along with the probability of each digit. This is done by using soft-max activation function, which returns probabilities. [5][6]

Figure 6 below shows block diagram that we used to train the model.

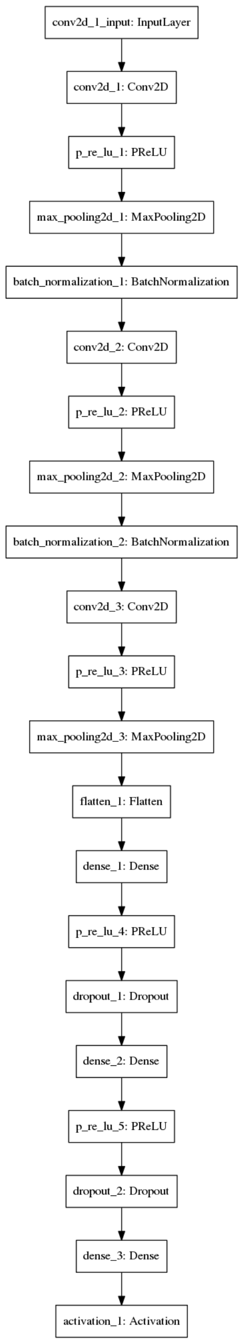


Figure 6: CNN Model used to train MNIST dataset

### 2.7 Post-Processing

The post-processing consists of handling the predicted number for each cropped image sent to the CNN classifier. Once we have the predicted number, we draw the predicted number over the corresponding bounding box. An example image is shown in Figure 7.

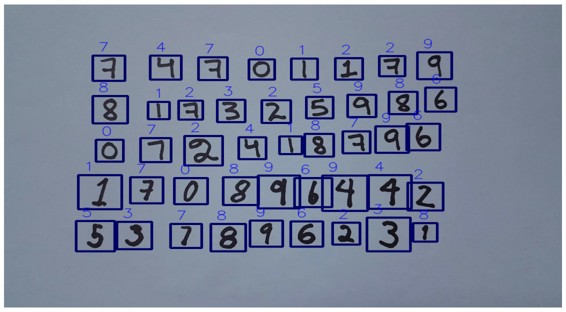


Figure 7: Image with number prediction.

### 2.8 Challenges

- Different Lighting conditions
- Shadows
- Distance between multi-digits(If digits are too close, then contour detection becomes incorrect, which also affects classification by CNN)
- Different perspective view
- Occluded and blurred digits

### 2.9 Results

After training on 60,000 samples images and testing on 10,000 images, we got accuracy of 99.13%.
Furthermore, we also tested on real time, and classification results are satisfy. (attach figure of classification using real time here)

## References

[1] Pierre Sermanet, Soumith Chintala and Yann LeCun, "Convolutional Neural Networks Applied to House Numbers Digit Classification", The Courant Institute of Mathematical Sciences - New York University

[2] Yuval Netzer , Tao Wang , Adam Coates , Alessandro Bissacco1 , Bo Wu , Andrew Y. Ng, "Reading Digits in Natural Images with Unsupervised Feature Learning", In NIPS Workshop on Deep Learning and Unsupervised Feature Learning, 2011.

[3] http://theanets.readthedocs.io/en/stable/examples/mnist-classifier.html

[4] https://keras.io/

[5] https://adeshpande3.github.io/adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/

[6] http://cs231n.github.io/convolutional-networks/