# Modifying Convolutional Neural Networks for Mathematical Equations

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**Abstract**

We propose a model that understands the equation written on a piece of paper. To enable the computer to understand the mathematical equation with numbers, operators and parentheses written by hand on a piece of paper with the help of computer vision and CNN. Multi-scale techniques are used in modern state-of-the-art methods to solve these issues. CNN.

## 1. Introduction

When you are pressed for time and must read an article, a textbook, or answer an equation, artificial intelligence can assist you. You wish there was a way to sum up the key points fast. It includes several methods for extracting equations from text files or PDFs and converting them to subsequent latex forms. These methods are utilized in deep learning. One of the common issues with optical character recognition is this (OCR). This task has been approached using a variety of strategies together. We'll examine a data-driven, neural network-based strategy today. Deep learning and machine learning have become increasingly important as a result of technological innovation. Now, handwriting recognition, robotics, artificial intelligence, and many more industries use machine learning and deep learning approaches. To create such a system, we must train our machines with data so they can learn and make the necessary predictions. Deep network learning techniques are progressively replacing older manual ways of extracting picture characteristics due to the recent rapid advancement of deep learning technologies in the field of image identification. Among them, CNN has garnered a lot of attention for its effective recognition algorithm. It is extensively utilized because the network can enter the original picture directly, avoiding the laborious pre-processing of the image, and has excellent accuracy.

## 2. Related Work

There is a thriving academic group that is researching handwriting digit recognition. Convolutional neural networks have been the subject of significant research for handwritten digit recognition [1,2,3,4]. The fields of online recognition, offline recognition, real-time handwriting recognition, signature verification, postage address interpretation, bank check processing, and writer recognition are just a few of the many that are now being researched.

## 3. Our Approach

Deep Learning has become a key tool for self-perception issues, such as interpreting visuals, human voices, and robots investigating the environment. For digit recognition, we want to use the Convolutional Neural Network idea. The suggested approach aims to comprehend CNN and apply it to the handwritten digit recognition system. From the 2D pictures, the convolutional neural network extracts the feature maps. The photos may then be classified using the feature maps. Instead of having a layer of neurons that are fully linked, the convolutional neural network examines the mapping of visual pixels with the neighborhood space. Convolutional neural networks are effective tools for processing signals and images. Even in computer vision disciplines like handwriting recognition, natural object categorization, and segmentation, CNN has shown to be a far superior tool than all other ones that have been used in the past. Creating a machine learning model that can detect people's handwriting may be the overarching goal.

### a) Preprocessing

The pre-processing step's function is to carry out different operations on the supplied picture. By making the picture suitable for segmentation, it essentially improves the image. Pre-processing is mostly done in order to pull an intriguing example out of the backdrop. The main tasks at this level are noise filtering, smoothing, and standardization. Pre-processing also contributes to a more condensed depiction of the case. A grayscale image is converted into a binary image using binarization. The first step in processing the training set photos is thresholding them into a binary image in order to decrease the amount of data. Data normalization is the first stage of the data preparation process. To apply distance calculations to it, this is done. This entails altering the data to fit inside a more constrained or typical range, such [0, 1]. The conventional 8-bit unsigned integer, with a high value range of [0, 255] at each pixel, serves as the foundation for the raw picture data.

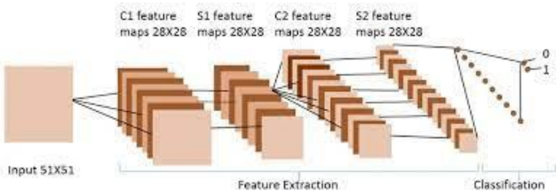
A smaller range for an attribute will result from its expression in smaller units, which tends to give such qualities more "weight" or impact.

### b) Segmentation

After the input photos have undergone pre-processing, a succession of images is used to create sub-images of individual digits. Pre-processed digit pictures are divided into a sub-image of distinct digits, each of which is given a number. The size of each digit is converted into pixels. Using an edge detection approach, the pictures from the dataset are segmented in this stage. An picture of a sequence of numbers is divided into smaller images of each individual number. An input picture that has been previously processed is divided into isolated digits by employing a labeling method to give each digit a number.

### c) Feature Extraction

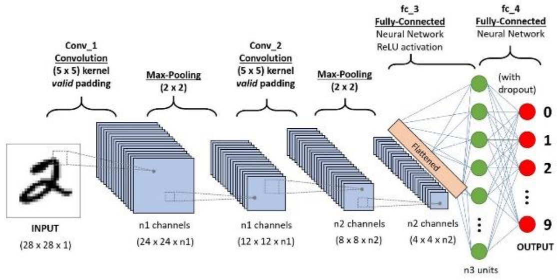
The photographs' distinctive elements may all be classified as attributes. Numerical data obtained from the separation of features from the image make up attribute information. At this stage, approaches like as histograms, projection-based techniques, Fourier and Wavelet transforms, or defining letters as a collection of fundamental shapes like curves and lines are used. The recognition stage is directly influenced by the data gathered from this stage, and the effectiveness of the recognition stage is directly influenced by the information's quality.




*Feature Extraction*

### d) Classification and Recognition

The qualities of the data in the image are compared to the database classes during the classification step to identify which class the image belongs to. Template matching, neural networks, classification algorithms, statistical learning, and structural learning are just a few of the numerous methods used at this stage. The used data sets are essential to the high performance and accuracy of this stage, and they should be produced to include as many samples and kinds as is practical.




*Simple Structure of CNN*

## 4. Results and Discussions

This section contains the findings and comments for the CNN-based handwritten digit recognition system. A functioning sample of the A recognition method for Handwritten Digits Using CNN is also provided.

### Creating and training the model

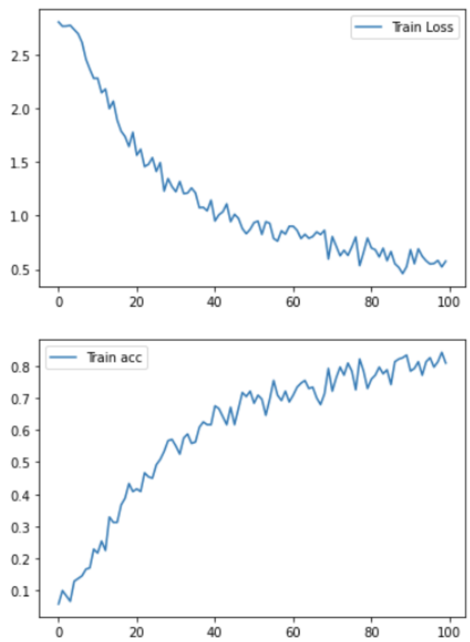
In this paragraph, we give an illustration of the process flow for a CNN-based recognition system for handwritten digits:

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 40, 40, 32)        320

 max_pooling2d (MaxPooling2D  (None, 20, 20, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 20, 20, 64)        18496

 max_pooling2d_1 (MaxPooling  (None, 10, 10, 64)       0
 2D)

 conv2d_2 (Conv2D)           (None, 10, 10, 128)       73856

 max_pooling2d_2 (MaxPooling  (None, 5, 5, 128)        0
 2D)

 flatten (Flatten)           (None, 3200)              0

 dense (Dense)               (None, 128)               409728

 dense_1 (Dense)             (None, 16)                2064

=================================================================
Total params: 504,464
Trainable params: 504,464
Non-trainable params: 0
_________________________________________________________________
```

*Creating Model*

```
# fit the model
hist = model.fit_generator(train,validation_data=valid,epochs=100 ,verbose=1,validation_steps = 10)
24/24 [==============================] - 0s 19ms/step - loss: 0.6839 - accuracy: 0.7833
Epoch 92/100
24/24 [==============================] - 1s 20ms/step - loss: 0.5528 - accuracy: 0.7917
Epoch 93/100
24/24 [==============================] - 0s 20ms/step - loss: 0.6918 - accuracy: 0.8125
Epoch 94/100
24/24 [==============================] - 0s 19ms/step - loss: 0.6227 - accuracy: 0.7708
Epoch 95/100
24/24 [==============================] - 0s 19ms/step - loss: 0.5799 - accuracy: 0.8125
Epoch 96/100
24/24 [==============================] - 0s 19ms/step - loss: 0.5501 - accuracy: 0.8250
Epoch 97/100
24/24 [==============================] - 0s 18ms/step - loss: 0.5548 - accuracy: 0.7958
Epoch 98/100
24/24 [==============================] - 0s 19ms/step - loss: 0.5832 - accuracy: 0.8125
Epoch 99/100
24/24 [==============================] - 0s 19ms/step - loss: 0.5231 - accuracy: 0.8417
Epoch 100/100
24/24 [==============================] - 0s 19ms/step - loss: 0.5766 - accuracy: 0.8083
```

*Training Model*




*Training Loss - Accuracy*

## 5. Conclusion

The release of a sizable dataset has sparked considerable interest in the scientific community in a system for handwritten digit recognition. In this study, handwritten digit identification using the dataset is studied using the well-known random forest (RF) and convolutional neural network (CNN) techniques. We have conducted some tests with various preprocessing processes, feature types, and baselines using the dataset as a typical testbed. The performance of RFs and CNNs on this dataset is then demonstrated to be competitive with state-of-the-art algorithms, with CNNs being the quickest with the right hardware. This study shows that there are several approaches to developing adaptive digit recognition systems. The technique described in this study can also be used to future online handwritten digit recognition systems. One portion of the data set will be used for training and the other portion for testing. It is possible to improve the output accuracy by properly training the models. The suggested paper aids in deciphering the scribbled numbers. This research may be expanded to recognize characters written by hand.

## 6. References

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