



## HIGH ACCURACY HANDWRITTEN DIGIT RECOGNITION USING DEEP CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE

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**ABSTRACT:** Handwritten digit recognition has become a great interest of research with the improvement of computer vision technology due to its wide application in different fields including, ZIP code recognition, postal system automation and automatic processing of bank checks. Deep Convolutional Neural Network has recently gained popularity because of its improved performance over the typical machine learning algorithms. This paper presents, High accuracy Handwritten Digit Recognition using Deep Convolutional Neural Network architecture. Handwritten digit recognition can be performed using the DCNN from Machine Learning Using the MNIST (Modified National Institute of Standards and Technologies) database. MNIST data contains about 70,000 images of handwritten digits from 0-9. The experimental results show that the enhanced CNN model outperforms other recognition techniques with high algorithm convergence and an accuracy of 98.66% when trained on the MNIST dataset.

**KEYWORDS:** Handwritten digit, MNIST data, Deep Convolutional Neural Network.

### I. INTRODUCTION

With the rapid development of science and technology in the last decade, the era of artificial intelligence has arrived, and machine learning disciplines and techniques are widely used in various fields of our lives. Handwritten digit recognition has become a great interest of research with the improvement of computer vision technology due to its wide application in different fields including, ZIP code recognition postal system automation, automatic processing of bank checks, reading ID card, license plate

The issue of manually written numerals acknowledgment has been broadly concentrated lately and the huge amount of pre-processing strategies and arrangement calculations has 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.

In text recognition printed or handwritten text is digitally encoded for its recognition by means of optical scanners or special software's [2]. Several researchers are already working in the field of text recognition and research is already going on for the recognition of various scripts like Devanagari, Bangla, English and etc. But the recognition of text which is handwritten is a difficult task due to the different handwriting of the people, handwriting styles are also different based on the different age groups, different dialect and different regions. Document Analysis and Recognition (DAR) systems help to transfer the data between humans and computers. The main task of DAR is to automatically extract the information which is written on the paper and to generate the suitable



symbolic representation of the information which can be processed by the computers [3].

Character recognition is a process that interacts a predefined code to the object's letters, numerals and symbols which are drawn on the paper or an electronic surface. In this, recognition of each character is carried out. For the recognition of text, systems first segment each word into individual characters and then assign one class to each of the characters [4]. While working with printed text this approach is generally known as Optical Character Recognition (OCR). OCR is used exigently in number plate recognition, data digitizing, automatic key information extraction, smart education, helping visually disabled people, computer vision and many other sectors.

Deep learning belongs to a method in machine learning based on learning about digital representations. Deep learning is precisely a neural network that analyzes and learns by establishing and simulating the human brain. It imitates the operating mechanism of the human brain to interpret data, such as text, images, sounds, and so on. The emergence of deep learning has solved low recognition efficiency and poor recognition effect in previous handwritten digital recognition technology. It has also accelerated the training speed of recognition models, which makes learning technology a good choice in handwritten digital recognition. The main reason for this performance gain is that with increased data, the state of art machine learning algorithms does not improve its performance whereas the deep learning model gets better and better with increased data. Deep Convolutional Neural Network (D-CNN) is a certain type of deep learning network that is proven to work well on image data. The main objective of

this paper is to classify handwritten digits using a seven layer D-CNN.

## II. LITERATURE SURVEY

O. Paul [5] works on NumtaDB dataset, the author has applied some pre-processing like resize, grayscale conversion, thresholding, cropping etc and best accuracy has found by using CNN which is 91%. T. I. Aziz, A. S. Rubel, M. S. Salekin, and R. Kushol, et al. [6] introduced a method where they used local gradient direction pattern based feature descriptor. For classification they used KNN (K-Nearest Neighbor) and SVM (Support Vector Machine). On CMATERdb3.1.1 dataset 95.62% accuracy was obtained.

Anca Ignat, Bogdan Aciobanitei, et. al. [7] we propose a new feature extraction method for offline handwritten digit recognition. The method combines basic image processing techniques such as rotations and edge filtering in order to extract digit characteristics. As classifiers, we use k-NN (k Nearest Neighbor) and Support Vector Machines (SVM). The methods are tested on a commonly employed database of handwritten digits' images, MNIST (Mixed National Institute of Standards and Technology) on which the classification rate is over 99%.

Tasnuva Hassan, Haider Adnan Khan, et. al. [8] exploit LBP for handwritten Bangla numeral recognition. Local Binary Pattern (LBP) is a simple yet robust texture descriptor that has been widely used in many computer vision applications including face recognition. We classify Bangla digits from their LBP histograms using K Nearest Neighbors (KNN) classifier. The performance of three different variations of LBP - the basic LBP, the uniform LBP and the simplified LBP was investigated. The proposed OCR system was evaluated on the off-line handwritten Bangla numeral

database CMATERdb 3.1.1, and achieved an excellent accuracy of 96:7% character recognition rate.

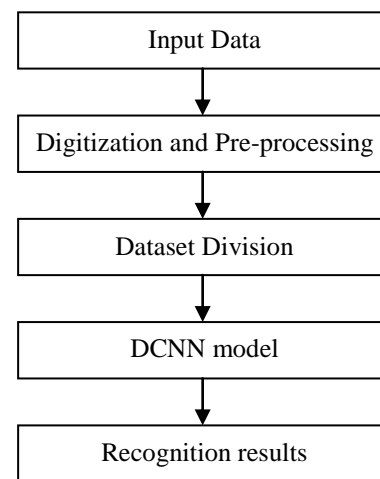
H. A. Khan, A. Al Helal, and K. I. Ahmed, et al. [9] proposed a scheme for Bangla handwritten character recognition that uses a sparse representation classifier based method. They obtained 94% accuracy on CMATERdb3.1.1 dataset. They used zone density as feature extraction method.

S. España-Boquera, M.J. Castro-Bleda, J. Gorbe-Moya, F. Zamora-Martinez, et. al. [10] proposes the use of hybrid Hidden Markov Model (HMM)/Artificial Neural Network (ANN) models for recognizing unconstrained offline handwritten texts. The structural part of the optical models has been modeled with Markov chains, and a Multilayer Perceptron is used to estimate the emission probabilities. This paper also presents new techniques to remove slope and slant from handwritten text and to normalize the size of text images with supervised learning methods. Slope correction and size normalization are achieved by classifying local extrema of text contours with Multilayer Perceptrons. Slant is also removed in a nonuniform way by using Artificial Neural Networks. Experiments have been conducted on offline handwritten text lines from the IAM database, and the recognition rates achieved, in comparison to the ones reported in the literature, are among the best for the same task.

### III. HANDWRITTEN DIGIT RECOGNITION USING DCNN

The architecture of High accuracy Handwritten Digit Recognition using Deep Convolutional Neural Network is represented in below Fig. 1.

The dataset used for the experiment is the MNIST dataset of handwritten digits, containing grayscale images of hand- drawn digits. Our digit dataset contains about 70,000 images of digits 0-9. Each digit has a resolution of 32 X 32. The image is reshaped into 784 X 1 and stored in a csv file. This is further divided into two parts i.e., Training set data and Testing set data. The training dataset contains about 60,000 handwritten digits and the test dataset contains about 10,000 handwritten digits.



**Fig. 1: HANDWRITTEN DIGIT RECOGNITION ARCHITECTURE**

When we are required to build a predictive model, we have to look and manipulate the data before we start modelling which includes multiple pre-processing steps such as importing the images, changing the size of the images, changing the colour of the images, visualizing the image dataset and converting them from categorical to vector form.

The basic architecture of Deep Convolutional Neural Network (D-CNN) consists of some steps which may appear many times in an orderly way in a particular network. The main three layers of a D-CNN are convolution layer, pooling layer and fully connected layer. The D-CNN



architecture used for this paper is inspired by LeNet-5 architecture. This architecture consists of 7 layers. The input images are feed to the network taking 50 images as a batch at a time. All images are re sized to have 32 x 32 dimensions and all these images are true color or RGB images. Each layer of DCNN is described in the following.

**Convolution Layer 1:** this layer takes as input the 32 x 32 x 3 RGB images (where 3 is the number of color channels) and convolves it with 32 different randomly initialized filters.

**Max Pool Layer 1:** This layer takes as input the 32 x 32 x 32 output from the previous layer and performs max pooling. For max pooling 2 x 2 filters and a stride of 2 is used. After applying max pooling, the shape of output becomes 16 x 16 x 32.

**Convolution Layer 2:** This layer takes as input the previous layers output and run convolution operation with 64 filters. Same convolution is used in this layer. The output shape is 16 x 16 x 64.

**Max Pool Layer 2:** This layer takes as input the output from previous layer and applies a 2 x 2 max pool with stride of 2. So, the output shape is 8 x 8 x 64.

**Convolution Layer 3:** This layer takes as input the previous layers output and run convolution operation with 128 filters. The output shape is 8 x 8 x 128.

**Max Pool Layer 3:** This layer takes as input the output from previous layer and applies a 2 x 2 max pool with stride of 2. So, the output shape is 4x4x 128.

**Fully Connected Layer:** The output from previous layer is flattened to be a linear array of 2048 values and feed to the fully connected layer. This fully connected layer consists of 512 nodes.

After the fully connected layer a softmax output unit predicts the categories. All 10 output classes are assigned a probability value that sums up to 1. The class containing highest probability is the chosen prediction. All these steps are combined in total under one thing that is known as Exploratory Data Analysis. We are performing these steps to ease our computing speed and reduce the complexity of the model.

#### IV. RESULT ANALYSIS

The test after effects of the MNIST transcribed digit dataset utilizing various boundaries of DCNN models. This is the final part of my project where we will check if our model is predicting the digits accurately and with what percentage it is correctly predicting it. We have split the datasets into two parts, i.e. training set and test set in the ration of 80:20. In order to validate the performance of the model, 20% of the training images were used. So, what I have done here is I have extracted some of the images from the test dataset and kept it into a folder. Now my prediction code with take all the images from that folder and starting pre-processing the images and then will start to predict the images.

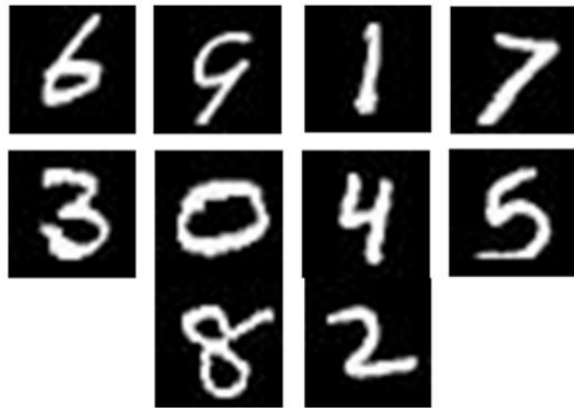


Fig. 2: IMAGES FROM TEST DATASET

From the figure it can be seen that, the training and validation accuracy keeps increasing with each epoch as the model is trained and during last 8 epochs it is above 99% for dataset.

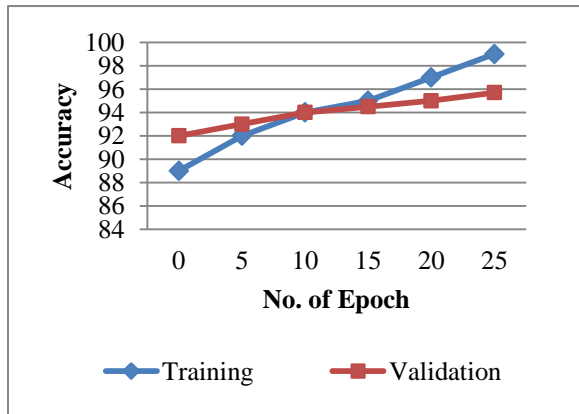


Fig. 3: TRAINING AND VALIDATION ACCURACY

The generalization of the proposed model was also evaluated in this work. In order to evaluate the generalization capability of the DCNN model, the performance of the model has been tested by a completely unseen prepared test dataset. The DCNN model trained with MNIST dataset has been achieved a score of 98.66% test accuracy on the prepared test dataset.

Table 1: COMPARATIVE ACCURACY ANALYSIS

Model	Accuracy (%)
DCNN	98.66
CNN	90.2

SVM	89.7
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Table I shows a comparison of accuracy parameters for Handwritten Digit Recognition using described DCNN and other models as CNN and SVM. The proposed model achieved state-of-art performance than other models.

## V. CONCLUSION

In this paper, High accuracy Handwritten Digit Recognition using Deep Convolutional Neural Network is described. Various methods are available for the recognition of text like Machine learning where it is required to manually extract the various features and then a classifier is imposed for the purpose of classification, but with the help of deep learning (DCNN) it is not required to manually extract the features for the purpose of classification. The D-CNN architecture used for this paper consists of 7 layers. The input images are feed to the network taking 50 images as a batch at a time. We have split the datasets into two parts, i.e. training set and test set in the ration of 80:20. The handwritten digit recognition accuracy is as high as 98.66%, reflecting its more superior recognition accuracy when compared with other methods.

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