# DEEP LEARNING MODEL FOR RECOGNITION OF HANDWRITTEN NUMERALS WITH LOW COMPUTATIONAL COMPLEXITY AND SPACE

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## ABSTRACT

Traditional systems of handwritten Digit Recognition have depended on handcrafted functions and a massive amount of previous knowledge. Training a Optical character recognition (OCR) system primarily based totally on those stipulations is a hard task. Research in the handwriting recognition subject is centered on deep learning strategies and has accomplished breakthrough overall performance in the previous couple of years. Convolutional neural networks (CNNs) are very powerful in perceiving the structure of handwritten digits in ways that assist in automated extraction of features and make CNN the most appropriate technique for solving handwriting recognition problems. Here, our goal is to attain similar accuracy through the use of a pure CNN structure. CNN structure is proposed to be able to attain accuracy even higher than that of ensemble architectures, alongside decreased operational complexity and price. The proposed method gives 99.87 accuracy for real-world handwritten digit prediction with less than 0.1 % loss on training with 60000 digits while 10000 under validation

Keywords: Hand written, Optical, Character, Recognition, Constitutional, alongside

## 1.0 INTRODUCTION

Deep Learning is a supplementary part of machine learning algorithms and hence categorized in wider section of artificial intelligence. Digit Recognition is nothing but recognizing the digits in any document. Digit recognition framework is simply the working of a machine to prepare interpret the digits. Handwritten Digit Recognition is the capacity of a computer to interpret the manually written digits from different sources like messages, bank cheques, papers, pictures, and so forth and in various situations for web based handwriting recognition on PC tablets, handling bank cheques, digits entered in any forms etc.

Machine Learning provides several methods through which human efforts can be reduced in recognizing the manually written digits. Deep Learning is a supplementary part of machine learning method and hence categorized in wider section of artificial intelligence that trains computers to do what easily falls into place for people: learning through examples. With the utilization of deep learning methods, human attempts can be diminished in perceiving, learning, and recognizing. Using deep learning the computer learns to carry out classification works from pictures or contents from any document and many more. Deep Learning models can accomplish state of art accuracy, beyond the human level performance. The digit recognition model uses large datasets in order to recognize digits from distinctive sources an ensemble model has been designed using a combination of multiple CNN models. The recognition experiment was carried out for MNIST digits, and an accuracy of 99.87% was reported. Handwriting recognition of digit has been around since the 1980s. The task of handwritten digit recognition, using a classifier, has extraordinary significance and use such as online digit recognition on PC tablets, recognize zip codes on mail, processing bank check amounts, numeric sections in structures filled up by hand (for example - tax forms) and so on. There are various challenges faced while attempting to solve this problem. The handwritten digits are not always of the same thickness, size, or orientation and position relative to the margins. The main objective was to actualize a pattern characterization method to perceive the handwritten digits provided in the MNIST data set of images of handwritten digits (0-9). CNN (convolutional neural network)smaller than number of channels. Figure. 1 Shows a regular Neural Network of 3 layers. It is a simple neural network consisting of one input one hidden and one output layer. Figure. 2 shows ConvNet which is formed of 3D layers. Each layer transforms 3D input volume to 3D output volume with Differentiable functions. As observed, fig 2 has image input of 3D shape with height, width and length.

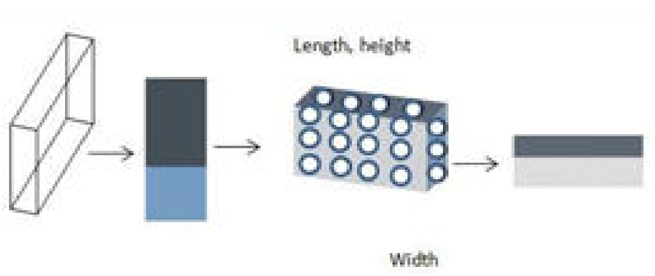



**Figure 1.** Architecture of Neural network

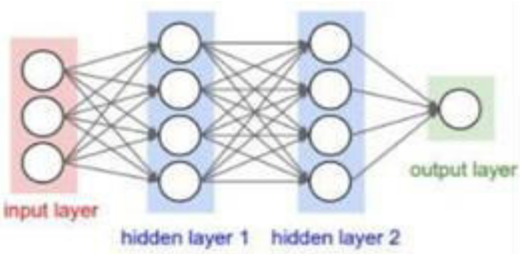



**Figure 2.** Architecture of Convolution neural network

## 2.0 LITERATURE REVIEW

Convolution means complex and hence a simple neural network is complex when it consists of many layers performing operations. Each layer performs dot product of input pixel and then passed to the next layer. These convolution layers are followed by soft max function (loss function) and then a fully connected layer. There are 3 important types of layer named: Convolution Layer, pooling layer, fully connected layer. The input is image of d x d x n size, where d is width and height and n stands for number of channels (for RGB its 3). Convolution layers has x filters having size f x f x g here f is smaller than the dimension of image and g can either be same or Digit Recognition is a noteworthy and vital issue. As the manually written digits aren't of a comparable size, thickness, position and direction, numerous difficulties need to be taken into consideration to decide the problem of handwritten digit recognition. The distinctiveness and collection in the composition styles of numerous people additionally affect the instance and presence of the digits.An early attempt in the area of character recognition Research was done by Grimsdale in 1959.The foundation of a high-quality deal of research work in Bhagyashree P M et al Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol, July-August-2021, 7 (4) : 153-158 the early sixties was primarily based on an method called analysis-by-synthesis technique recommended by Eden in 1968.The great significance of Eden's work was that he formally proved that all handwritten characters are shaped through a finite quantity of schematic features, a factor that became implicitly included in preceding works. This perception was later utilized in all methods in syntactic (structural) strategies of character recognition. It is the approach for perceiving and arranging transcribed digits. It has a huge variety of applications, for example, programmed bank checks, postal locations and tax files and so on.The intention of this project is to put in force a classification algorithm to apprehend the handwritten digits with the use of Deep Learning.Deep Learning is a part of machine learning algorithms and therefore classified in wider segment of artificial intelligence. Deep learning numerous architecture offers with deep neural network, recurrent neural network, deep belief networks and these were applied to variety of fields of computer like speech recognition, machine translation, natural language processing, social network filtering, bioinformatics and drug designs. It is one of the most crucial types of deep learning. It offers with multi layers of neural network and as a result is most crucial set of rules to categorize pictures or handwritten symbols. Deep neural networks is a growing area which is efficient with GPUs as it takes large amount of information to process and consumes much less computation time.The final result of this work confirmed that the highest accuracy rate was 99.87% was obtained in MNIST dataset using deep learning approach and the best learning rate at 15000 iterations. It is determined that the accuracy slowly starts reducing or remains consistent after 15000 iterations. The overall performance ratio of GPU: CPU is observed to be 30:1.It is concluded that computation time in GPU exponentially decreases compared to CPU. Future works is targeted on further elevating the accuracy of recognition by improving pre-processing of information that is fed into deep convolution neural network. Moreover computation of overall performance can be raised by including more than one GPUs for execution. The after consequences of probably the most broadly utilized Machine Learning Algorithms like SVM, KNN and RFC and with Deep Learning calculation like multilayer CNN utilising Keras with Tensorflow. Using these, the accuracy of 99.87% is acquired whilst contrasted with 97.91% utilizing SVM, 96.67% utilising KNN, 96.89% utilising RFC was acquired. Handwritten Digit Recognition Using Deep Learning confirmed that using Deep Learning systems, provides the capacity to get a very high measure of accuracy. In addition, execution of CNN utilising Tensorflow offers a stunningly better result of 99.87%. Despite the fact that the hardship of the procedure and codes seems to be extra whilst contrasted with standard Machine Learning algorithms yet the accuracy is increasingly obvious. Different researchers have worked on different methods during the seven decades and have proposed different methods for pre-processing, segmentation, recognition and post processing. Different methods like labelling schema for syntactic description of the pictures, syntax directed interpretation of different classes of pictures, description and generation based, synthesis method have been used during the decade of sixties. Rules modification on the basis of experience, split and merge algorithm, syntactic pattern recognition by boundary approximation using polygons on the basis of concavity and adaptive threshold methods have been applied during seventies. Work on writing slant, structured segment matching, fuzzy set, statistical, time delay and sliding window have been carried out during eighties. Works on vast areas in this field have been carried out in nineties. During this period the works that have been carried out are based on principal component analysis, modular concept, thinning method, segmentation by analyzing stroke shapes, pre-processing, back propagation, morphological filtering, OCR, HMM, binarization, chain coding, recognition methods using Eigen values, post processing, weighted least squares to correct baseline skew, multiple directional feature extraction and cascade neural First decade of the 21st century has evidenced different works on the methods based on multi expert framework for character recognition, neuro heuristic approach, HMM, OCR, feature extraction, genetic processing,MLP etc. The work that has been carried out during the current decade is based on diagonal based feature extraction, SVM classifier, fuzzy, probabilistic neural network, zone based method, and distribution based method, sliding window and Eigen value.

**PROBLEM STATEMENT**

The goal of this project is to create a model that will be able to detect and identify the handwritten digits from its image by using the concepts of Convolution Neural Network. Though the task is to create a model which can recognize the digits, it can be extended to letters and an individual's handwriting. The major goal of the proposed system is understanding Convolutional Neural Network, and applying it to the handwritten recognition system. shown in Figure 4, pre-processing, Data Encoding, Model Construction, Training & Validation, Model Evaluation & Prediction. Since the loading dataset is necessary for any process, all the steps come after it.

**Figure 3.** Sample MNIST data

**3.1 DigitModel ():** This function loads a pre-trained deep learning model for recognizing handwritten digits from files (digits_cnn_model.json and digits_cnn_weights.h5) and prints its summary.

**3.2 SentimentModel():** This function loads pre-trained deep learning models for text and image-based sentiment detection from files (sentimentModel.pkl and _mini_XCEPTION.106-0.65.hdf5) and prints the summary of the image-based sentiment model.

**3.3 DigitRecognize():** This function allows the user to upload a test image, preprocesses it, feeds it into the loaded digit recognition model, and displays the predicted digit along with the input image.

**3.4 A. Pre-Processing**

After loading the data, the data is separated into X and y where X is the image, and y is the label corresponding to X. As shown in figure 5, the first layer or input layer for our model is convolution. Convolution takes each pixel as a neuron, and so we need to reshape the images such that each pixel value is in its own space, thus converting a 28x28 matrix of greyscale values into 28x28x1 tensor. With the right dimensions for all the images, it split the images into train and test for further steps.

**4. Methodology**

In this paper, we used MNIST as a primary dataset to train the model, and it consists of 70,000 handwritten raster images from 250 different sources out of which 60,000 are used for training, and the rest are used for training validation. MNIST data is represented in the IDX file format and are look like in figure 3. Our proposed method mainly separated into stages, as

**A. Data Encoding**

This is an optional step since we are using the cross-categorical entropy as loss function; we have to specify the network that the given labels are categorical in nature.

**B. Model Construction**

After data encoding, the images and labels are ready to be fitted into the model. The model is composed of feature extraction with convolution and binary classification. Convolution and max-pooling are carried out to extract the features in the image, and a 32 3x3 convolution filters are applied to a 28x28 image followed by a max-pooling layer of 2x2 pooling size followed by another convolution layer with 64 3x3 filters. In the end, we obtain 7x7 images to flatten. Flatten layer will flatten the 7x7 images into a series of 128 values that will be mapped to a dense layer of 128 neurons that are connected to the categorical output layer of 10 neurons.

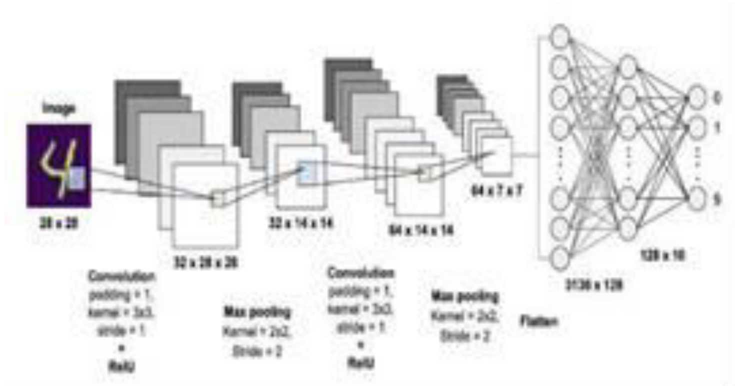


**Figure 5.** Proposed model

**C. Training & Validation**

After building the model, we compiled a model with adam optimizer and particular cross-entropy loss function, which are standard in making a CNN. Once the model is successfully assembled, then we can train the model with training data for 100 iterations, but as the numbers of iteration increases, there is a chance for overfitting.

**D. Model Evaluation & Prediction**

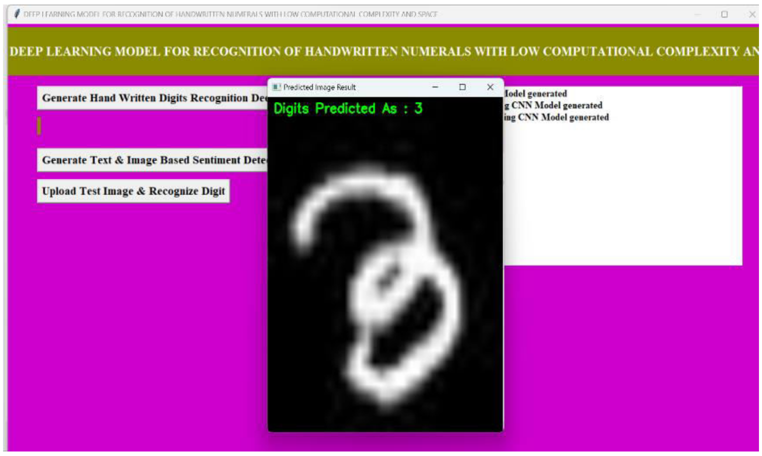
For real-world image classification prediction, we need to do an image pre-processing on the real-world images as model training was done with greyscale raster images. The steps of image pre-processing are

- Loading image
- Convert the image to greyscale
- Resize the image to 28x28
- Converting the image into a matrix form
- Reshape the matrix into 28x28x1

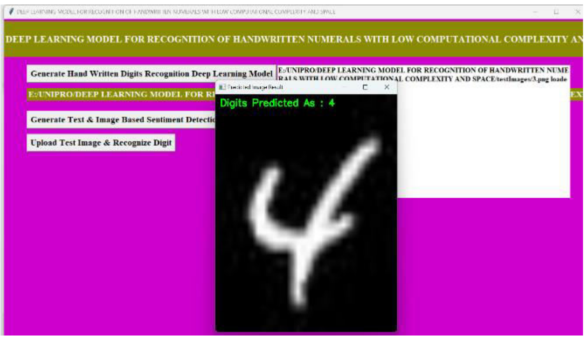
After pre-processing, we predict the label of the image by passing the pre-processed image through the neural network. The output we get is a list of 10 activation values 0 to 9, respectively. The position having the highest value is the predicted label for the image.

## 5. RESULT

The experiment was conducted on handwritten digits of the standard kaggle dataset using the CNN classifier for training the machine. For this, the MNIST database of handwritten digits was used. This dataset has a training set of 60,000 examples, and a test set of 10,000 examples. The model will get trained from 60,000 inputs and then it will check for accuracy of the model on 10,000 test set examples. Keras library is used with a Tensorflow backend for building the model and will download the dataset from Keras itself. Trained the model in 12 epoches and got accuracy of 99.87% and test loss of 0.043464561576.




In above screen Deep learning CNN model recognige the digit 3

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## 6. CONCLUSION

This paper attempts to use deep learning tools to train a classifier to recognize handwritten digits. Also, the use of techniques in Computer Vision was explored to investigate the effect of selection image preprocessing, feature extraction and classifiers on the overall accuracy. The dataset used for the experiment is MNIST dataset originally constituted of 60,000 training, and 10,000 testing images which are x 28 grayscale (0-255) labeled and bitmap format. It is a brilliant database for machine learning and characters recognition methods while taking minimal efforts in preprocessing and formatting. It can be seen from the experimental results that CNN is much better than other classifiers.

## 7. FUTURE SCOPE

In this paper, the complex recognition problem associated with handwriting is an interesting topic for future research areas. Handwritten digit recognition system can be extended to a recognition system that can also able to recognize handwritten character and handwritten symbols. Future studies might consider on hardware implementation of recognition system For instance, when some anonymous pieces of handwritten digit are found at a crime site, and it is possible to automatically identify **that the writer may be a "left-handed man," that** would reduce the set of suspects to be investigated. In general, these classification problems are extremely complex, since it is quite hard to detect which handwriting features correctly characterize each involved class. One clear example of this happens in the classification of gender. Even though the feminine writing is more circular and uniform than the masculine one, there are some examples which ma**sculine writing may exist with a "feminine"** appearance. This could be another exact topic in the field of handwritten digit recognition for future work.

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