

# Handwritten digit recognition using CNN and Regression in Deep Learning

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**ABSTRACT**— Deep learning is majorly applied in the various areas due to its diversity of applications like medicine, sports, robotics, health, drones, surveillance etc. A significant aspect of pattern recognition is the handwritten recognition of numbers. In deep learning, CNN is a center of advancements that merge the Artificial Neural Network and the latest deep learning policies. CNN have been extensively utilized in the recognition of patterns, the categorization of texts, the handwritten recognition of numbers. CNN is firstly used in recognition of an object which is to take images as input, and then organize them into a certain category. The Handwritten digits recognition is a one of a kind. Linear regression algorithm to recognize numbers which belong to the categorization of nearest subspace in classification. Regression algorithm is broadly evaluated based on data from the numbers. The comparative analysis with various databases and technique, methods distinctly give back the efficacy of the linear regression viewpoint to number identification. The aim of the project is to study the performance accuracy of CNN, Regression and also to compare the accuracies. As part of this performance assessment of CNN and Regression, the standard dataset known as modified National Institute of Standards and Technology datasets(MNIST) is used.

**Keywords**—CNN, Linear regression, Image processing, MNIST, Deep learning.

#### I. INTRODUCTION

Handwritten digits identification is a kind of major issues in the implementations of pattern recognition. Number recognition implementations such as e-mail sorting, processing of bank checks, data entry, etc. In the mentioned applications of digit recognition, it is very important for the whole system in terms of performance that is speed and accuracy. Since from few years, several algorithms have been introduced in order to solve this problem. Number recognition is an important part of a handwritten character recognition system, due to the wide scope of its application.

In this paper, Algorithms of CNN and Linear regression are implemented in identification of digits and the performance of these algorithms are analyzed and compared. This is the major intention of the project. Further details of algorithms are explained in the sections below.

Usually, Handwriting Recognition of digit is classified into five phases and it is as follows. Acquisition of image, pre-processing, image segmentation, featuring extraction and the final step is classification.[1]

1.CNN

#### II. METHODOLOGY



Fig 1: A seven-layer CNN for digit recognition



CNN is the algorithm in which there are three major layers in CNN and they are convolution layer, next is pooling layer, and fully connected layer. Convolution layer is the core block of the CNN from which bunch of filters are be given to the input image. Primary function of convolution layer is to extract the image and edges, colour of the image. ReLU is a nonlinear activation layer. Convolution is linear, in order to add linearity ReLU will be added. It removes the overfitting and fit for the real-world case probability. Pooling layer is a nonlinear layer which is doing the function of down sample the image. Pooling the image by 2\*2 and the output is depending on the window size. Here down sampling is done because CNN is computing heavy and memory heavy and this down sampling reduces computational complexity and also memory complexity and size. And lastly fully connected layer which identify final output. Every input is connected to its coefficient and it is data heavy. CNN is of two phases first is training phase in which there will be lot of data in feedback pattern and second is inference or testing phase in order to do the real time applications The input layer or image is made up of 28\*28-pixel images, that means that it is a network that consist of 784 neurons that is used as the input. The input pixels are different shades of Gray, with a value of zero represents a white pixel and one as a black pixel. In this model, the CNN has 5 unseen layers. [2]

C (w, b) = 
$$1/2n \sum_{x} [y(x) - a^2]^2$$
 -----(1)

The input layer consists of images of 28\*28 pixels, which means that it's a network that contains 784 neurons that is used as the data to the input. Here input pixels of the image, with the value of zero as a white pixel and one as a black pixel. Here it is, the CNN model consists of five of the invisible layers.

The convolutional layer which is first layer that allows for the extraction of features in the image. Because of the pixels is connected to the neighbouring and close to the pixels of the convolution, it will help to maintain the relationship between the different elements of an image. The convolution filter to the image, using a smaller pixel of the filter in order to the file size in an image without any loss of the correlation between the pixels in size. In the CNN building, it is common to have a place in the pooling of the layers for each week of the layer to decrease the spatial size of the feature maps. The combination of layers will also help you diagnose problems with the installation process. We have selected for you are going to have a pool. In size, it lessens the number of parameters in the selection of the maximum, the average, or the sum of the values of the pixels. Max-Pooling is one of the very popular techniques of pooling, u

$$w^{new} = w^{old} - \eta \, \partial C / \partial w^{old}$$

$$b^{new} = b^{old} - \eta \partial C / \partial w^{old}$$
 -----(2)

#### 2. Linear Regression



Fig 2: Block Diagram of LRC for Digit Recognition

Figure 3.3 shows the functional scheme of the linear regression for classification. This is the term that is used to identify a class, categories of the particular testing image. There is a class in order to deal with the modeling of the input images from various input files. This is a prediction; it will be considered by the calculation of the estimated

response variable for every class of the model. The calculation of distance in between the original and also the estimated response variable. Finishing decision was made in approval of class within the smallest distance.



Information of input: for a Class of models for image Xi, I is equal to 1, 2....up to N, the testing image is a vector with y

Output: A Class, vector y

Firstly  $\beta i$ , is examined for every class of the model,  $\beta i = (XiXT (I) - 1XT (I, y), (I=1, 2...N)$ 

Then output y is calculated for each of the  $\beta i$ , y = Xi $\beta i$ , I=1, 2....N

The calculation of distance in between the initial and also the predicted responses of the variables where  $di(y) = ||y - yi||_2$ , I = 1, 2, ..., N.

The conclusion is made in approval of class which is having a minimum distance of di(x).[7]

#### III. RESULTS AND ANALYSIS Data Set

The data set used in this project is the MNIST dataset, which actually consists of sixty thousand training and ten thousand test images of grayscale, and in bitmap format. Figure 4.1 shows a set of digits from the MNIST dataset. The missing values has been examined prior to the application. The information does not contain any missing values. It is one of the good databases for deep learning and also pattern identification methods, in mean time it will take a minimum of effort, in the pre-processing and also in formatting.



Fig 4.1: The digits from the MNIST dataset

In this section, the result obtained from the project are displayed, here recognition of handwritten digits is done with two algorithms one is CNN and REGRESSION. The performance of both the algorithms are observed here. In MATLAB the design format is created in order to recognize the digits in one platform. Buttons are created in the design and they are first button for Training the MNIST datasets which takes around 5 minutes to train into the designed model. A button for Regression identification and one button for CNN identification. As shown in the below snapshot. After that Inputs are browsed from the test data sets file. And Regression button gives the output with the run time percentage, and CNN button gives the output with the runtime percentage. After testing all the 15 datasets the Accuracy percentage will be calculated for each algorithm.

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Fig4.3.1: This shows the design for digit recognition in MATLAB, with Browse button to insert the image as input image, and datasets are trained in the Training dataset button and the Run time percentage will be displayed. And the Accuracy will be calculated for 15 testing datasets.

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Fig 4.3.2: Training datasets which are trained to model.



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Fig 4.3.3: This is the MATLAB Design which have a button called as Training Datasets to Train the MNIST datasets to the project.

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Fig 4.3.3.1: The training of databases with 30 iterations in case of initialization.

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Fig 4.3.3.2: The training of databases with 30 iterations in case of training error.

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Fig 4.3.4: The training of MNIST datasets finished and its graphical representation.

As shown in the above graph blue line represents the trained accuracy and red line represents the loss or error of accuracy.



Fig 4.3.5: These are the test datasets which are given as the input to the Designed system one by one.



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Fig 4.3.6: Test datasets are given as the input as shown above.

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Fig 4.3.7: Clicking on the Run Regression button shows the output of the REGRESSION algorithm with Noise image.



Fig 4.3.8: Clicking the Run CNN button will display the CNN algorithm output in the notebook.

 Table 1: Here the performance of Digit 5 is shown and the Run time performance is good in

 REGRESSION compared to CNN and Accuracy performance is good in CNN compared to

 PECPESSION

Testin g datas ets	REGRESS ION Identificati on	CNN Identifica tion	Run time of REGRES SION in s	Run time of CNN in s
1	Incorrect	Correct	0.084887 s	0.147262 s
2	Correct	Correct	0.010523 s	0.01127 0 s
3	Incorrect	Correct	0.003899 s	0.00286 1 s
4	Incorrect	Correct	0.002099 s	0.00331 1 s
5	Correct	Correct	0.027055 s	0.02827 9 s
6	Correct	Correct	0.002260 s	0.02827 9 s
7	Correct	Correct	0.002848 s	0.00296 0 s



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8	Correct	Correct	0.04613 s	0.04757
				S
9	Correct	Correct	0.002917	0.00343
			S	4 s
10	Correct	Correct	0.003379	0.00448
			S	5 s
11	Incorrect	Incorrect	0.001417	0.00154
			S	0 s
12	Correct	Correct	0.001336	0.00154
			S	0 s
13	Correct	Correct	0.004111	0.02506
			S	S
14	Correct	Correct	0.002568	0.00286
			S	3 s
15	Correct	Correct	0.004150	0.00416
			s	3 s
ACC	80%(Regre	93.33%(	Take less	Takes
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By comparing with all the 15 datasets for this digit, the conclusion is performance of the CNN is better when compared to Regression on the basis of Accuracy percentage, but when compared to run time there is a small difference between them and regression takes less time compared to CNN. The overall performance of each digit that is 0-9 is tested and the accuracy for each digit is calculated for both the algorithms, and the results are shown in the below table.

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Handwritten Digits	Accuracy of CNN	Accuracy of Regression	
0	86.66	80	
1	100	93.33	
2	93.33	86.66	
3	100	93.33	
4	93.33	86.66	
5	93.33	80	
6	93.33	86.66	
7	100	93.33	
8	86.33	80	
9	93.33	86.66	
Total	93.99	86.66	

## Table2: By giving the test datasets as input for each digit the Accuracy is calculated for both the Algorithms.

### IV. CONCLUSION

In this project, Handwritten digit recognition is done by the usage of deep learning algorithm CNN and one more algorithm that is Linear regression. And, the implementation of such methods in computer vision has been studied and explored the effect of sample, image processing, extraction of features, and also classification. Datasets used in this project is MNIST dataset, these are initially created from sixty thousand training and ten thousand test images in 28\*28 grayscale and labeled, bitmap format. This is an excellent database for digit recognition method. Accuracy and also runtime performance of both algorithms are shown in the results section. As a result, the CNN, REGRESSION models, were applied and compared in this project in order to find which algorithm performs better. As a result, the Performance of CNN is better compared to REGRESSION.

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