

# Hand written Digit Recognition Using CNN

Trupti R. Dilhiwala <sup>1</sup> Trupti R. Dilhiwala, <sup>2</sup>Purvi Patel, <sup>3</sup>Bhavini Patel, <sup>4</sup>Hemangini Mehta, <sup>5</sup>Nensi Panchal,

Bhagwan Mahavir College of Engineering and Technology, Vesu, Surat Corresponding Author: <sup>1</sup>Purvi Patel, <sup>2</sup>Bhavini Patel, <sup>3</sup>Hemangini Mehta, <sup>4</sup>Nensi Panchal

Date of Submission: 20-06-2023

Date of Acceptance: 29-06-2023

ABSTRACT: This research paper is on the verge of Handwritten digit recognition is the capability of a computer to recognize the human handwritten digits from different sources like images, papers, touch screens, etc., and classify them into 10 predefined classes (0-9).Recognition of handwritten numbers is the process that enables machines to recognize human handwritten numbers. This is not an easy task for the machine because the figures written by hand are not perfect, vary from person to person, and can be manufactured with many different flavours. The images of the manuscript numbers are shown as a 28\*28 matrix where each cell is composed of a gray-scale pixel value. We have performed handwritten digit recognition with the help of

handwritten digit recognition with the help of MNIST datasets using Convolution Neural Network (CNN) model. Our main objective is to get the accuracy of the model along with their execution time to get the best possible model for digit recognition. We are getting 99% accuracy with CNN.

**KEYWORDS:** Handwritten Digit Recognition, MNIST Dataset

#### I. INTRODUCTION

In this paper, recognition of handwritten numerals is the abilityof a computer to recognize handwritten human numerals from variou s sources such as images, papers, touch screens, etc., and classify them into 10 predefined classes (0-9). Digit recognition has many applications like number plate recognition, postal mail sorting, bank check processing, etc. [2].

Recognition of handwritten numbers is the process that enables machines to recognize human handwritten numbers. It is not an easy task for the machine because handwritten digits are not perfect, vary from person-to-person, and can be made with many different flavours. Among thousands of datasets available in the market, MNIST is the most popular dataset for enthusiasts of machine learning learning.So, there and deep are 10 different categories in the MNIST dataset. The images of manuscript numbers are shown as a matrix of 28\*28 where each cell consists of agrayscale pixel value.

In Handwritten digit recognition, we face many challenges because of different styles of writing of different peoples as it is not an Optical character recognition. For this, we have used Convolutional Neural Network. These algorithms are carried out on the basis of their accuracy.

E.g. For an automated cheque processing system where the system recognizes the amount and date of the cheque, high accuracy is critical. If the system recognizes an incorrect number, it may cause significant damage that is not desirable. That's why an algorithm with high accuracy is required in these real world applications [1].

So that the most accurate algorithm with the least chances of errors can be employed in various applications of handwritten digit recognition [3].





**II. PROPOSED WORK** 

Working of CNN (Convolution Neural Network)

CNN, also known as ConvNets, are made up of several layers and are mostly used for image processing and object detection.Yann LeCun developed the original CNN in 1988 under the name LeNet.It was used to recognise characters such as ZIP codes and numbers. The CNN is widely used to identify satellite images, process medical images, forecast time series, and detect anomalies.

# How Do CNNs Work?

CNN's have multiple layers that process and extract features from data:

# **Convolution Layer**

- CNN has a convolution layer that has several filters to perform the convolution operation. **Rectified Linear Unit (ReLU)**
- CNN's have a ReLU layer to perform operations

on elements. The output is a rectified feature map.

# **Pooling Layer**

- The rectified feature map next feeds into a pooling layer. Pooling is a down- sampling operation that reduces the dimensions of the feature map.
- The pooling layer then converts the resulting two-dimensional arrays from the pooled feature map into a single, long, continuous, linear vector by flattening it.

#### **Fully Connected Layer**

• A fully connected layer forms when the flattened matrix from the pooling layer is fed as an input, which classifies and identifies the images.

Below is an example of an image processed via CNN.





Figure 2.1: Convolution Neural Network

# **III. IMPLEMENTATION**

The implementation of handwritten digit recognition by Convolutional Neural Network [11] is done using Keras. It is an open-source neural network library that is used to design and implement deep learning models. Based on working accuracy and the number of epochs (in deep learning algorithms) we have used Convolutional Neural Network Classifier.

**Step:1** First we have handwritten images with labels of images taken as input images that is shown below also taken from MNIST dataset which is already in database of Keras library.



Figure 3.1: Handwritten Input data images from

#### **MNIST** dataset

**Step: 2** Pre-processing is an initial step in the deep learning which focuses on improving the input data by normalizing the input data we reshaped all the images present in the dataset in 2-dimensional images i.e. (28, 28, 1)



Figure 3.2: Normalized image-1

**Step: 3** Each pixel value of the images lies between 0 to 255 so, we Normalized these pixel values by converting the dataset into 'float32' and then dividing by 255.0 so that the input features will range between 0.0 to 1.0. The dimension of the input image is set to 28(Height), 28(Width), 1(Number of channels).

10																									14	14		
- 2									- 18										. 4									. ed
- 1							- e					. a									- e					. 6		- 60)
- 1		- 44		1.6			- a		- 10			- i i i							1.0		- 4					- 64		- 80
- 7												1.4		÷. 6		1.0	14	1.0	- 4		1.0			. 4		10		- 80
- 8													1.4	28	18	1.14	128	1.00	1.11	1.00	180	212	147	10.0				- m)
- ř									100	18	144	the	178	mr	2114	201	210	inter	175	172	27.8	201	1.75	-				1 erî
÷			÷.					1.08	238	303	203	28.5	183	201	213	2018	280	250	1.66	80	87	14						1.00
÷								1.1	276	365	253	1915	254	20	110	183	340	340			. 0	1.4				. 61		100
- 1				14	- 6	- 4	1.0	1	60	714	107	265	150	244.	10		140	114	- 6	1.2	- ñ	- ÷		- 4	- 61	- 61		- 26
- 1		- 21		14		- 2		1.4		10		-	110	100	1.4	- 2	1.6		1.4	1.4	1.4	- 6				14		- 24
- 2	- 21			1.00	- 6		- E			1	1.6	275	110	1.000	1										÷.	- 20		- 22
÷	- 2	- W.		1.00	- ii	- 2	1.1			- ÷		14	116	28.8	.28			1.2					- 2		- 61	14		100
- 1			1.2	1.2		- 2			1.1		- i i i	1.1	14	244	105	144	-	- 5	1.4		1.10	- 5	- 2	- 2	÷.	12		- 22
- 8	÷.			12	- 2	- 2	- 5		- 2		- 2	- 5	1.1	121	1.00		112	110	1.6		- 5	- 1	- 2			-		- 23
- 2	12.1	- 64	÷.	- 2	- 2	- 2	1		- 5		- 2		- 2	- 14		100	31.1	10.1	100		- 6			- 2	÷.	- 61		- 23
- 2	- 21	- 22		- 2	- 2	- 2	- 2				12	<u> </u>		- 5	1.1		100	-10	-	100	- E	- 5		- 2	- 21	- 22	- 21	- 23
- 2	-	12	- 21	12	1.2	- 2	1.2	- 5	- 2	- 2	- 2	- 5	- 2	- 2	- 2	- 72	1.0	144	100	144	- 22	- 5	- 2	- 2	- 2	- 20	- 2	- 26
- 2	- 2	- 22	- 21	12	- 2	- 1	1.2		- 2		1.2	- 2	- 2	- 1		- 24	-	100	141	100	12		- 2	- 2	- 1	- 21		122
- 0	- 2	- 21		- 2	- 2	- 2	- 5		- 2	- 2	- 2	02			-		-	11.1	223		- 2	- 2	· 2		- 21	- 2-	- 2	- 23
- 2	÷.	-21	- 21	12	- 2	- 2	- 2	- 1	- 2	- 2	- 6	1.2	10		100		-	100		~	12	- 2	- 2	- 2	12	- 2-	- 2	- 22
- 51	- 21		- 21	- 2	- 2	- 2	12			- 22	- 22		100		-	100	12	- 12	- 12			- 2	- 2	- 2	- 21	- 22	- 2	- 22
- 1	-	- 2	- 21	- 5	- 2	- 2	1	1.5		-67	-22	52	-122	-	100	22	- 72	- 2	- 2	- 2	- 1	- 2	- 2	- 1	- 2-	- 2-	- 21	- 23
- 2	- 2	100	- 21	- 2		1.75	1014	343	500	21.1	55	144	110		- 72	12	- 5	- 2	1.2	. 9	- 5	- 5	- 2	- 5	12	-21	÷.	123
- 2	12	122	- 21	- 2	110	161	36.5	100	56	14	32	140	12	- 12	- 2	- 2	- 2	- 2	- 2	- 2	- C	- 2	- 2	- 2	12	-2-	- 2	122
- 10	- 2	- 22		-2	10		- 1		110	102	212	12	- 2	- 2	- 2	- 2	- 2	- 2	- 2	- 2	- 2	- 2	- 2	- 2	× 0.	- 2	- 2	- 03
- 11	-	- 21		- 2	- 2	- 2	- 2	12	- 2	- 2	- 2	- 2	- 2	- 2		- 2	- 5	- 2	- 2	- 2	- 2	- 2	- 2	- 2	-2-	- 21		6.6.2.2.2.2.5.6
- 51	- 2	12	- 5	- 2	- 2	- 5	- 2	- 1		- 2	12	- 2	- 2	- 2	- 2	- 2	- 2	- 2	- 2	- 5	- 2	- 2	- 2	- 2	12	- 21	- 5	12.
						. *						. *																- 11

Figure 3.3: Normalized image-2

**Step: 4** Then we divide data in two parts training data and testing data. For training data we are using 60000 data and for testing we are using 10000 data with dimension 28(width)\*28(height).

**Step: 5** Then we create a neural network and we train data into neural network shown in below figure like,

Epich 1/38	
	195 96/htep - 2005; 0.2013 - accuracy; 0.9400
	17a 9ms/step - Ioas: 0.0790 - aituraty: 0.9757
1875/1875 [] - Epech 4/30	178 9#5/620p' - Loss: 0,8525 - accura(y) 0.3825
1875/1875 [] - Spech 5/32	18x 9m/step - Loss: 0.0752 - accoracy: 0.9889
1863/1875 [	
18/5/18/5 []	385 965/step - Less: 6.6285 - accuracy: 0.3964

Figure 3.4: created CNN model

**Step:6** now from that first image is flatten and then relu activation function is applied at hidden layer and at output layer 10 neurons apply with softmax activation function by running the CNN model we



compile model with adam optimizer and generate accuracy in matrics then increasing by epoch we get accuracy that shows in tabular format. Which is describe as a result of model. Summary of model shown below.

Model: "sequential 2"

Layer (type)	Output Shape	Param #
flatten_2 (Flatten)	(None, 784)	0
dense_4 (Dense)	(None, 512)	481928
dense_5 (Dense)	(None, 10)	5130

Total params: 407,850 Trainable params: 407,050

Non-trainable params: 0

#### Figure 3.5: Summary of CNN model

# **IV. RESULT**

After executing the models, we found that CNN has the highest accuracy on training data. We have trained our deep learning model up to 5 epochs.

Epoch	Loss Rate	Accuracy
1	0.20	0.94
2	0.07	0.97
3	0.05	0.98
4	0.03	0.98
5	0.02	0.99

Table 4.1: Loss and accuracy of CNN with

#### increasing number of epochs

At last testing result shown which is almost nearer

to training result as shown in below figure

111/113 [+= -----] - 3% dam/step - Ioss: 8.6015 - accuracy: 8.9097 [0.07146408/5417/08447, 0.0707000208961118]

**Figure 4.1 Testing evaluation result** 

# **V.CONCLUSION**

We have implemented models for handwritten digit recognition using MNIST datasets, based on deep learning algorithms CNN. We have found that CNN gave the most accurate results for handwritten digit recognition. So, this makes us conclude that CNN is best suitable for any type of prediction problem including image data as an input.

#### REFERENCES

Dixit, Ritik, et al. "Handwritten Digit [1]. Recognition Using Machine and Deep Learning Algorithms." International Journal of Computer Applications, vol. 176, no. 42, July 2020, pp. 27-33.

DOI.org (Crossref), https://doi.org/10.5120/ijca2020920550

- [2]. Phiphiphatphaisit, Sirawan, and OlarikSurinta. "Food Image Classification with Improved MobileNet Architecture and Data Augmentation." Proceedings of the 2020 The 3rd International Conference on Information Science and System, ACM, 2020, pp. 51-56. DOI.org (Crossref), https://doi.org/10.1145/3388176.33881 79.
- [3]. Ali Nur, Mukerem, et al. "Handwritten Geez Digit Recognition Using Deep Learning." Applied Computational Intelligence and Soft Computing, edited by AbidhanBardhan, vol. 2022, Nov. 2022, pp. 1-12. DOI.org (Crossref), https://doi.org/10.1155/2022/8515810.