# Programming Test: Applying CNN and Autoencoders on MNIST Dataset

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Work Link: https://github.com/rudraneel18/MNIST-Dataset-Model

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***Abstract:-*** This paper presents an implementation using a Backpropagation Neural Network to achieve the classification of the MNIST handwritten digit database. Here, we utilize the classification accuracy and the training loss plot to assess the neural network's performance. According to the experimental findings, backpropagation neural networks can be used for real-world categorization problems. Additionally, we attempt to perform picture compression using Autoencoder and analyze its results. The performance is improved by increasing the speed of the neural network and decreasing the network size. The accuracy rate cannot be guaranteed, and various causes are covered. Then, we attempt to change the original neural network's structure into a convolutional neural network (CNN). The outcomes show that CNN can be used to enhance performance while tackling an image recognition challenge. Additionally, we create a Conv Autoencoder structure by combining CNN and Autoencoder, and we run specific tests. Finally, the output of our network system is compared to the output from a different study that used the same MNIST handwritten digit database.

**Keywords:** MNIST handwritten digit database; Neural Network; Back-propagation; Classification; Autoencoder; Convolutional Neural Network

## I. BACKGROUND

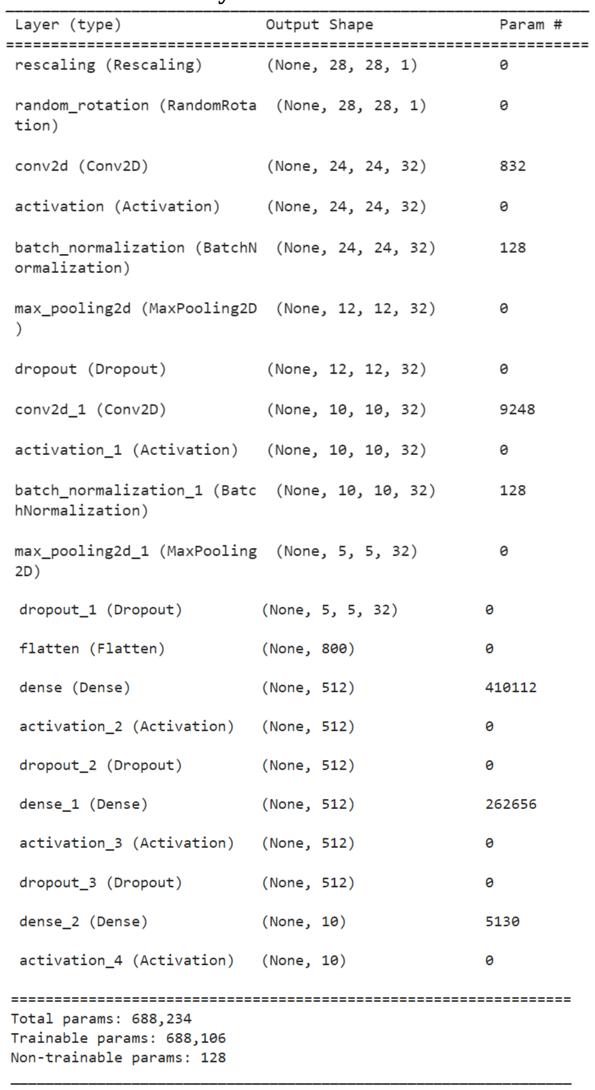
An important issue in optical character recognition is handwritten digit recognition, which can be utilized as a test case for pattern recognition theories and machine learning techniques. A number of common databases have arisen to support the study of machine learning and pattern recognition. The handwritten digits are preprocessed to evaluate the recognition outcomes of different algorithms and to lighten the burden, including segmentation and normalization.
This paper aims to define the application of neural networks to the MNIST handwritten digit classification problem. We must first create a neural network model to address the categorization issue and put it into practice. In addition, research has been conducted to examine various approaches that might affect how well our model performs.

## II. MATHEMATICAL FRAMEWORK

### 2.1 Method:-

As mentioned above, in this paper, we use MNIST handwritten digit database in which the handwritten digits have been preprocessed, including segmentation and normalization. There are 60,000 training images and 10,000 test images, and the dimensionality of each image sample vector is 28 * 28 = 784, where each element is binary.

### 2.2 Model Summary


```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling (Rescaling)       (None, 28, 28, 1)         0

 random_rotation (RandomRota  (None, 28, 28, 1)        0
 tion)

 conv2d (Conv2D)             (None, 24, 24, 32)        832

 activation (Activation)     (None, 24, 24, 32)        0

 batch_normalization (BatchN  (None, 24, 24, 32)       128
 ormalization)

 max_pooling2d (MaxPooling2D  (None, 12, 12, 32)       0
 )

 dropout (Dropout)           (None, 12, 12, 32)        0

 conv2d_1 (Conv2D)           (None, 10, 10, 32)        9248

 activation_1 (Activation)   (None, 10, 10, 32)        0

 batch_normalization_1 (Batc  (None, 10, 10, 32)       128
 hNormalization)

 max_pooling2d_1 (MaxPooling  (None, 5, 5, 32)         0
 2D)

 dropout_1 (Dropout)         (None, 5, 5, 32)          0

 flatten (Flatten)           (None, 800)               0

 dense (Dense)               (None, 512)               410112

 activation_2 (Activation)   (None, 512)               0

 dropout_2 (Dropout)         (None, 512)               0

 dense_1 (Dense)             (None, 512)               262656

 activation_3 (Activation)   (None, 512)               0

 dropout_3 (Dropout)         (None, 512)               0

 dense_2 (Dense)             (None, 10)                5130

 activation_4 (Activation)   (None, 10)                0

=================================================================
Total params: 688,234
Trainable params: 688,106
Non-trainable params: 128
_________________________________________________________________
```

### 2.3 Preprocessing and Augmentation

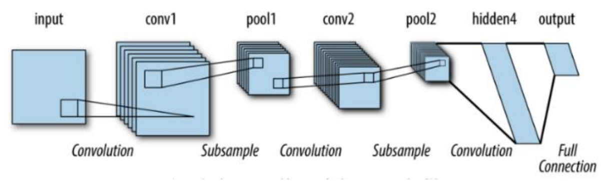
In order to prepare images for use in model training and inference, a method known as image preprocessing is used. This includes, but is not limited to, size, orientation, and color adjustments.

Since a model should have a specific type or sequence of inputs, we reshaped the input picture in this instance to be 28*28(width*height) for our model input. After which, we divided the RGB values of our input pixels by 255 to convert them to black and white.

Image augmentation refers to image alterations used to create alternative versions of comparable information to expose the model to a broader range of training instances. However, there is a crucial distinction between image augmentation and image preprocessing. Although image preprocessing techniques are applied to training and test sets, image augmentation is only used for the training data. As a result, in some circumstances, a transformation that would be an augmentation may be better as a pretreatment step. In this model, we chose to rotate the image by 10 degrees

### 2.4 Convolutional Neural Network (CNN):-

Convolutional Neural Networks are a special kind of multi-layer neural network. They are also trained with the backpropagation algorithm but with a different architecture from other neural networks. Convolutional Neural Networks are designed to recognize visual patterns directly from pixel images with minimal preprocessing, and they can recognize patterns with extreme variabilities, such as handwritten characters and even digits



### 2.5 Backpropagation neural network set up:-

As discussed in the section above, Back-propagation neural networks are supervised multi-layer feed-forward neural networks, commonly consisting of an input layer, an output layer, and one or several hidden layers. Here we build a neural network with only one hidden layer. The input layer contains 28 * 28 = 784 neurons, representing the features; the Hidden layer contains 300 neurons, using Sigmoid as activation function; And the output layer contains 10 neurons expressing the digits from 0 to 9.

Besides, we use the cross-entropy error function as the network loss function. The cross-entropy error function is more suitable for classification problems than the mean squared error (MSE) function. And it is convenient to use CrossEntropyLoss () to achieve it. As for the optimizer, here we tried Adam and RMSProp and chose to use the Adam optimizer implementing the Adam algorithm, which can be achieved by using Adam ().

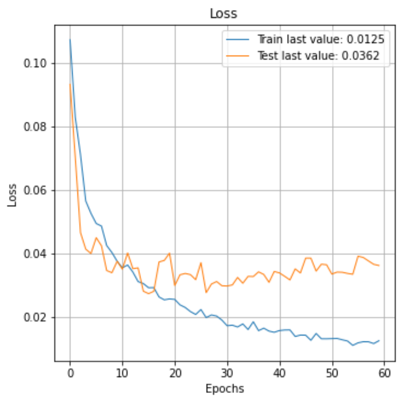
After defining the neural network, we train the model by batch. In order to set the appropriate parameters, such as batch_size, number_of_epochs, and learning rate, we conducted several tests to evaluate. There should be a balance among these parameters, contributing to the neural network's performance. Finally, the system parameters are given as number_of_epochs = 60, learning rate = 0.001, decay = 1e-4 and batch_size = 32.

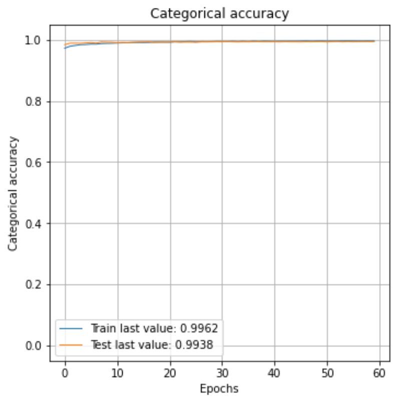
### 2.6 Evaluation:-

We decided to assess the training and testing accuracy to evaluate the neural network's effectiveness, make predictions, and present the outcomes generated by our neural network. Another visual depiction used during network learning is plotting historical loss from "all losses."

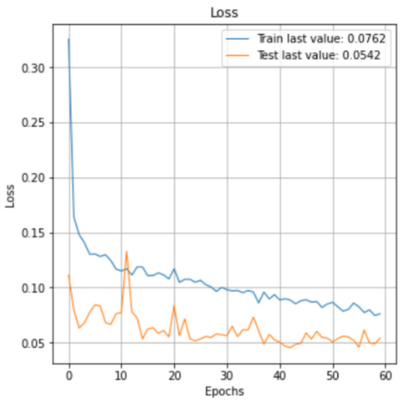
## III. Expected Results and Discussion

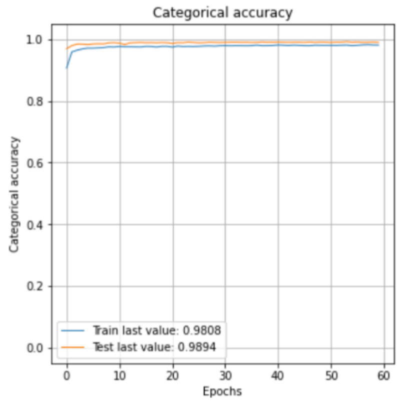
The result with Adam as optimizer has:
Loss = 0.0362 and model_accuracy=99.38%



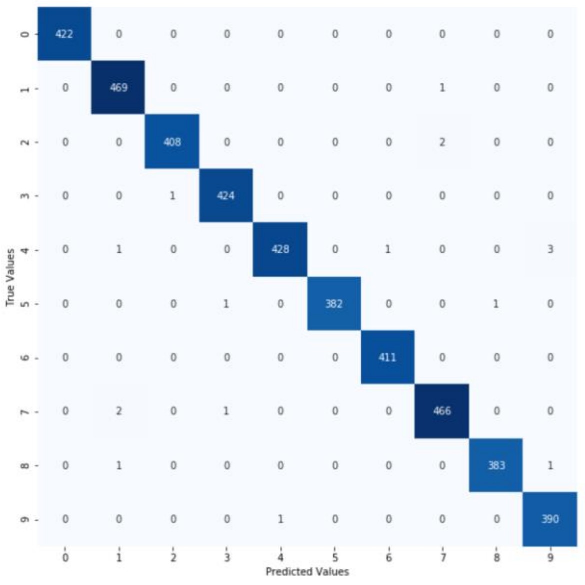


The result with Adam as optimizer has:
Loss=0.0542 and model_accuracy=98.94%



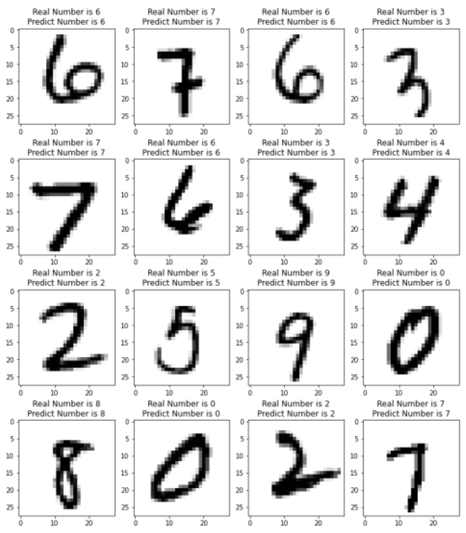


Confusion Matrix:



| True Values \ Predicted Values | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 422 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 469 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 2 | 0 | 0 | 408 | 0 | 0 | 0 | 0 | 2 | 0 | 0 |
| 3 | 0 | 0 | 1 | 424 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 1 | 0 | 0 | 428 | 0 | 1 | 0 | 0 | 3 |
| 5 | 0 | 0 | 0 | 1 | 0 | 382 | 0 | 0 | 1 | 0 |
| 6 | 0 | 0 | 0 | 0 | 0 | 0 | 411 | 0 | 0 | 0 |
| 7 | 0 | 2 | 0 | 1 | 0 | 0 | 0 | 466 | 0 | 0 |
| 8 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 383 | 1 |
| 9 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 390 |

Output:-



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- https://www.researchgate.net/publication/354999294_Knowledge_Extraction_in_Digit_Recognition_Using_MNIST_Dataset_Evolution_in_Handwriting_Analysis
- https://ieeexplore.ieee.org/document/6296535
- https://arxiv.org/pdf/1811.08278.pdf