# Developing the regression network generated from the classification network with deep learning

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**Abstract.** The field of image processing is very important in deep learning. One of the important applications in deep learning is the classification process after storing images in a data set, which requires training a deep neural network and a convolutional neural network (CNN) in MATLAB, because of the large amount of data carried by the color image, which leads to the need for deep learning technology, which leads to Discovering the number technology to create a matrix that includes the numbers from 0 to 9 in the 10 * 10 matrix, which leads to expanding the image store of the data set. In this work, a fast algorithm was created to create a large number matrix to store images, and the results that were achieved proved the efficiency of the algorithm.

**Keywords.** convolutional neural network (CNN), MATLAB, deep learning, regression convolutional neural network.

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## INTRODUCTION

Recently, convolutional neural networks (CNNs) have emerged as one of the most attractive approaches and have recently been instrumental in a variety of sophisticated and successful machine learning applications, such as the ImageNet challenge, object detection, image segmentation, and face recognition . Therefore, we choose CNN for our demanding image classification tasks. We can use it for handwritten digit recognition, which is one of the most important academic and business transactions. There are many applications of handwritten digit recognition in our real life. More specifically, we can use it in banks to read checks, in post offices to classify letters, and for many other related tasks. Convolutional neural networks are deep artificial neural networks. We can use it to classify images (e.g. naming what you see), group them by similarity ( photo search), and perform object detection within scenes. It can be used to identify faces, people, traffic signs, tumors, platypuses and many other aspects of visual data.The convolutional layer is the core component of a CNN. The layer parameters consist of a set of learnable filters (or kernels) that have a small receiving field but extend to the full depth of the input volume.

During the forward pass, each filter is folded across the width and height of the input volume , thereby calculating the dot product and creating a -dimensional activation map of that filter. This causes the network to learn when it sees a particular type of feature at a spatial location in the input. The activation maps are then fed into a down sampling layer, and like convolutions, this method is applied patch at a time. CNN also has a fully connected layer that classifies the output with one label per node. Over the years, various methods and algorithms have been used to improve the performance of FER. To overcome the problem of input with multiple well-known standard facial datasets , Ali [14] developed a deep neural network architecture that takes recorded facial images as input and classifies them. To recognize facial expressions in different facial views, Tong [10], proposed a new method based on the Deep Neural Network (DNN) in which the Scale Invariant Feature Transform (SIFT) corresponds to a set of reference points. were extracted from each facial image. Many studies have also been conducted using technical features (e.g.Scale Invariant Feature Transform (SIFT) [10] and Gabor [9], [6]), where the hyperparameters of the classifiers are tuned to provide better detection accuracies in a single database. Recently, several works on FER successfully used Convolutional Neural Networks (CNN) [2-4] for feature extraction and classification. CNNs are found in the literature and are referred to as a special type of multilayer perceptron (MLP) that focuses on the local relationship between pixels using receptive fields. They have been shown to achieve high recognition rates in various image recognition tasks; However, these methods use different CNN architectures to achieve the desired result.

## METHODOLOGY

In this work, we convert a trained classification network into a regression network. The pre-trained image classification networks have been trained on over a million images and can classify images into 10000 object categories such as keyboard, coffee cup, pencil, and many animals. The networks have learned large-scale feature representations for a variety of images. The network takes an image as input and then generates a label for the object in the image along with probabilities for each object class. In deep learning, transfer learning is used. You can use a pre-trained network as a starting point for learning a new task. In addition, the classification network that was trained was retrained to perform regression tasks. The example loads a pre-trained convolutional neural network architecture for classification, replaces the classification layers, and retrains the network to predict the angles of rotated handwritten digits. Corrects the rotation of the image by the expected values.

**A new convolutional neural network for regression in Deep Learning**

Unique Features of SCOMs

The application that was executed shows how to fit a regression model using convolutional neural networks to predict the rotation angles of handwritten digits. Convolutional Neural Networks (CNN or ConvNets) are essential tools for deep learning and are particularly suitable for analyzing image data. For example, you can use CNN to classify images.

A classification layer calculates cross-entropy loss for classification and weighted classification tasks with mutually exclusive classes. In typical classification networks, the classification layer usually follows a softmax layer. In the classification layer, trainNetwork takes the values of the softmax function and assigns each entry to with the entropy function for k classes of intersection in a system in equation (1) for N the number of samples K is the number of classes $w_i$ is the weight for class i, $t_{ni}$ is the indicator that the nth sample belongs to the $ith$ class, and $y_{ni}$

$$loss = -\frac{1}{N}\sum_{n=1}^{N}\sum_{i=1}^{K} w_i t_{ni} ln y_{ni} \qquad (1)$$

**Fast algorithm for creating a new regression convolutional neural network**

The algorithm to predict continuous data such as angles and distances, you can insert a regression layer at the end of the network. The example creates a convolutional neural network architecture, trains the network, and uses the trained network to predict the angles of rotated handwritten numbers.

**Download trainers**

The classification network in the digits Net.mat file is responsible for classifying handwritten numbers

**Step 1:** Entering information: The image information contains the form of numbers with a certain angle, which is responsible for rotating the images, which are in the form of a four-dimensional matrix, which is obtained with the following instructions: digitTrain4DArrayData and digitTest4DArrayData, so that the outputs are in rotation angles with degrees YTrain and YValidation, in figure 1 contain 20,000 images of the trained data, so that 100 images are displayed randomly.

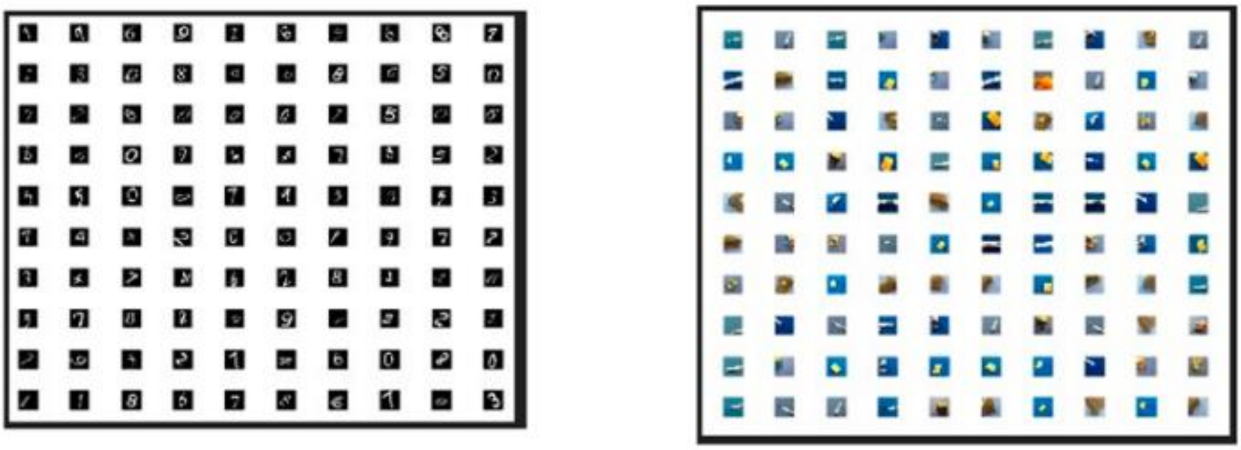

**Fig. 1**. Contain 20,000 images of the trained data, so that 100 images are displayed randomly

**Step2: The last layers and replace them:** The convolutional layers of the network extract features from the image, which are used by the final learning layer and the final classification layer to classify the input image.

**Step3: Frozen primary layers**

The network is now ready to retrain with the new data. You can optionally "freeze" the weights of previous layers in the network by setting the learning rates on those layers to zero. During training, trainNetwork does not update the parameters of frozen layers. Use the supporting function freezeWeights to set the learning rates to zero in the first 12 layers.

**Step 4: Train Network Creates:** the network training options. Set the initial learning rate to 0.001. Monitor network accuracy during training by providing validation data. Enable the training progress graph and disable the command window output. Create a network TrainNetwork. This command uses a supported GPU if available.

**Step 5: Test Network:** Test Network Test network performance by evaluating the accuracy of validation data. Use predict to predict the rotation angles of the validation images.

## DISCUSSION

Evaluate model performance by calculating: The percentage of predictions within an acceptable margin of error. The root mean square error (RMSE) of the predicted and actual rotation angles. Calculate the prediction error between the predicted and actual rotation angle. Calculate the number of predictions within an acceptable margin of error from the actual angles. Set the threshold to 10 degrees. Predictions for calculating threshold percentage for accuracy = 0.7532 Use root mean square error (RMSE= 8.9696) in Fig. 2, measure the differences between predicted and actual rotation angles in Fig. 3.

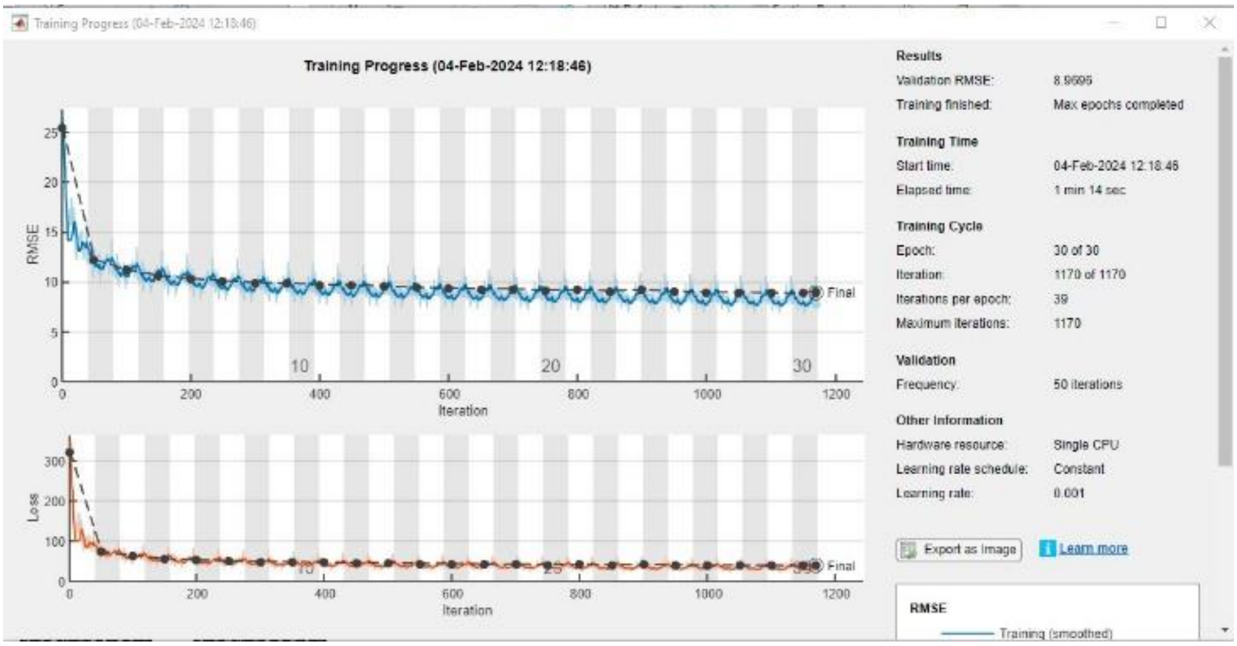


**Fig. 2.** Predictions for calculating threshold percentage for accuracy = 0.7532 Use root mean square error (RMSE= 8.9696)

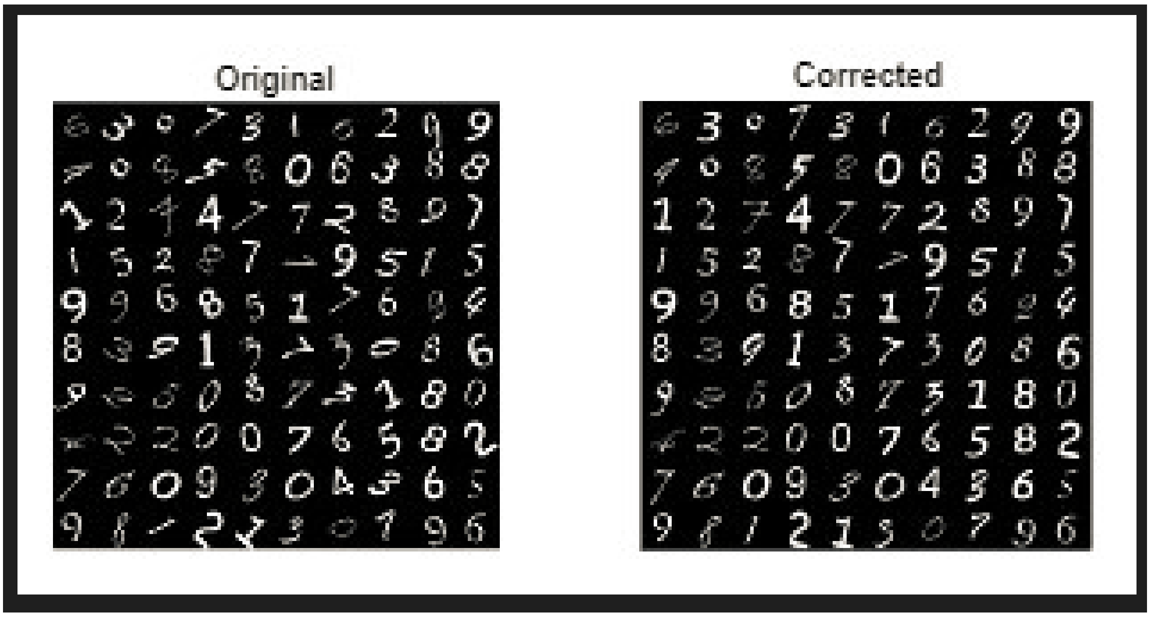


**Fig. 3.** Measure the differences between predicted and actual rotation angles

## CONCLUSION

The area of image processing is very important in deep learning. One of the important applications of deep learning is the classification process after storing images in a data set, which requires training a deep neural network and a convolutional neural network (CNN) in MATLAB due to the large amount of data carried by the image. This led to the need for deep learning technology, which led to the discovery of numerical technology to create a matrix containing the numbers 0. to 9 in the 10*10 matrix, which led to an expansion of the image storage of the data set. In this work, a fast algorithm was developed to create an array of large numbers for storing images, and the results obtained showed the efficiency of the algorithm.

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## Розробка регресійної мережі створеної з класифікаційної мережі з використанням глибокого навчання


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**Анотація.** Обробка зображень є дуже важливою в галузі глибокого навчання. Однією з важливих застосувань глибокого навчання є процес класифікації після зберігання зображень у наборі даних, що вимагає тренування глибокої нейронної мережі та згорткової нейронної мережі (CNN) у MATLAB через велику кількість даних, які містить кольорове зображення, що призводить до необхідності використання технології глибокого навчання, яка дозволяє виявити технологію чисел для створення матриці, яка включає числа від 0 до 9 у матриці розміром 10 * 10, що призводить до розширення сховища зображень у наборі даних. У цій роботі було створено швидкий алгоритм для створення великої числової матриці для зберігання зображень, а результати, яких було досягнуто, довели ефективність алгоритму.



**Ключові слова.** згорткова нейронна мережа (CNN), MATLAB, глибоке навчання, регресійна згорткова нейронна мережа.