Recognition of Handwritten Digit using Artificial Neural Network

ATANU DAS
Department Of Information Technology(Data Science),
Maulana Abdul Kalam Azad University Of Technology,Haringhata, Nadia 741249, West Bengal
atanu.das1729@gmail.com

Abstract

Handwritten character recognition is one of the practically important issues in pattern recognition applications. The applications of digit recognition includes in postal mail sorting, bank check processing, form data entry, etc. The heart of the problem lies within the ability to develop an efficient algorithm that can recognize hand written digits and which is submitted by users by the way of a scanner, tablet, and other digital devices. This paper presents an approach to off-line handwritten digit recognition based on different machine learning technique. The main objective of this paper is to ensure effective and reliable approaches for recognition of handwritten digits. Several machines learning algorithm namely, Multilayer Perceptron, Support Vector Machine, Naïve Bayes, Bayes Net, Random Forest, J48 and Random Tree has been used for the recognition of digits using WEKA.

Keywords pattern recognition, handwritten recognition, digit recognition, machine learning, WEKA, off-line handwritten recognition, machine learning algorithm, neural network, classification algorithm.

1.Introduction

Images of handwritten digits as 10 digits (0-9). Handwritten digits from the MNIST database are already famous among the community for many recent decades now, as decreasing the error rate with different classifiers and parameters. Digit recognition system is the working of a machine to train itself or recognizing the digits from different sources like emails, bank cheque, papers, images, etc. and in different real-world scenarios for online handwriting recognition on computer tablets or system, recognize number plates of vehicles, processing bank cheque amounts, numeric entries in forms filled up by hand (say tax forms) and so on. The handwritten digits are not always of the same size, width, orientation and justified to margins as they differ from writing of person to person, so the general problem would be while classifying the digits due to the similarity between digits such as 1 and 7, 5 and 6, 3 and 8, 2 and 5, 2 and 7, etc. This problem is faced more when many people write a single digit with a variety of different handwritings. Lastly, the uniqueness and variety in the handwriting of different individuals also influence the formation and appearance of the digits.

Handwritten digit recognition for banking system aims at ensuring effective and reliable approaches for recognition of handwritten digits and make banking operations easier and error free. In the current age of digitization, handwriting recognition plays an important role in information processing. A lot of information is available on paper, and processing of digital files is cheaper than processing traditional paper files. The aim of a handwriting recognition system is to convert handwritten characters into machine readable formats. Handwritten digit recognition has not only professional and commercial applications, but also has practical application in our daily life and can be of great help to the visually impaired. It also helps us to solve complex problems easily thus making our lives easier. Handwritten digit recognition has gained so much popularity from the aspiring beginner of machine learning and deep learning to an expert who has been practicing for years.

2. Modeling of an artificial neural network to recognize handwritten digits

We have implemented a Neural Network with 1 hidden layer having 100 activation units (excluding bias units). The data is loaded from a .mat file, features(X) and labels(y) were extracted. Then features are divided by 255 to rescale them into a range of [0,1] to avoid overflow during computation. Feedforward is performed with the training set for calculating the hypothesis and then backpropagation is done in order to reduce the error between the layers.

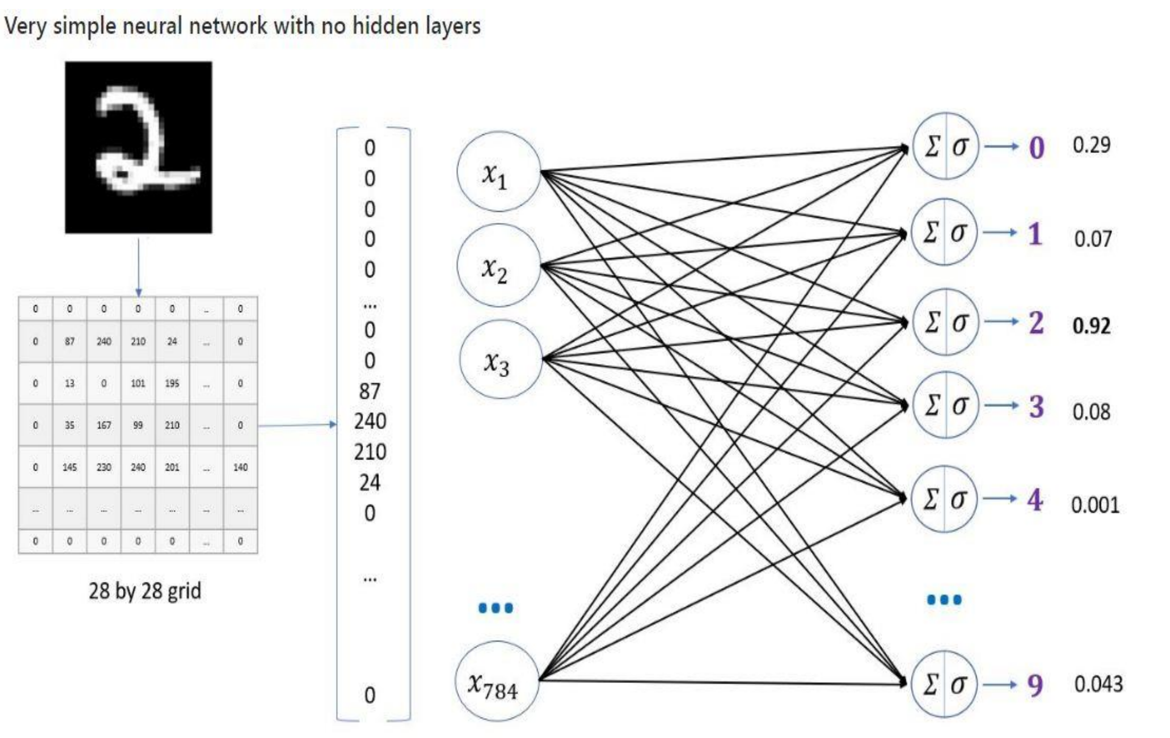

Figure 1.The function performs feed-forward and backpropagation.

- Forward propagation: Input data is fed in the forward direction through the network. Each hidden layer accepts the input data, processes it as per the activation function and passes it to the successive layer. We will use the sigmoid function as our "activation function".

- Backward propagation: It is the practice of fine-tuning the weights of a neural net based on the error rate obtained in the previous iteration.

It also calculates cross-entropy costs for checking the errors between the prediction and original values. In the end, the gradient is calculated for the optimization objective.

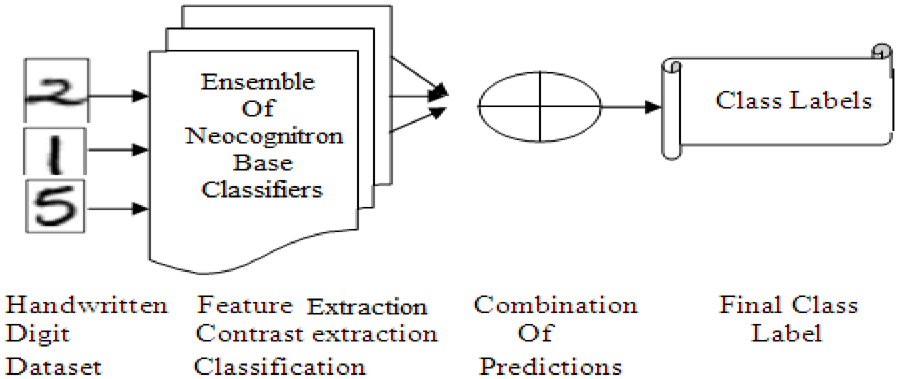

Figure 2. Model for recognition of handwritten digits using ANN

The input layer consists of 28 by 28 pixel images whichmean that the network contains 784 neurons as input data.The input pixels are grayscale with a value 0 for a white pixel and 1 for a black pixel. A Flatten layer is used which converts the 2D featured map matrix to a 1D feature vector and allows the output to get handled by the fully connected layers. The MNIST handwritten digits database is used for the experiment. Out of 70,000 scanned images of handwritten digits from the MNIST database, 60,000 scanned images of digits are used for training the network and 10,000 scanned images of digits are used to test the network. The images that are used for training and testing the network all are the grayscale image with a size of 28×28 pixels. Character x is used to represent a training input where x is a 784-dimensional vector as the input of x is regarded as 28×28 pixels. The equivalent desired output is expressed by y(x). The network aims is to find the convenient weights and biases so that the output of the network approximates y(x) for all training inputs x as it completely depends on weight values and bias values known as the dense layer.The output layer of the network consists of ten neurons and determines the digits numbered from 0 to 9.

3.MNIST DATASET

Modified National Institute of Standards and Technology (MNIST) is a large set of computer vision dataset which is extensively used for training and testing different systems. It was created from the two special datasets of National Institute of Standards and Technology (NIST) which holds binary images of handwritten digits. The training set contains handwritten digits from 250 people, among them 50% training dataset was employees from the Census

Bureau and the rest of it was from high school students .However, it is often attributed as the first datasets amongother datasets to prove the effectiveness of the neural networks.

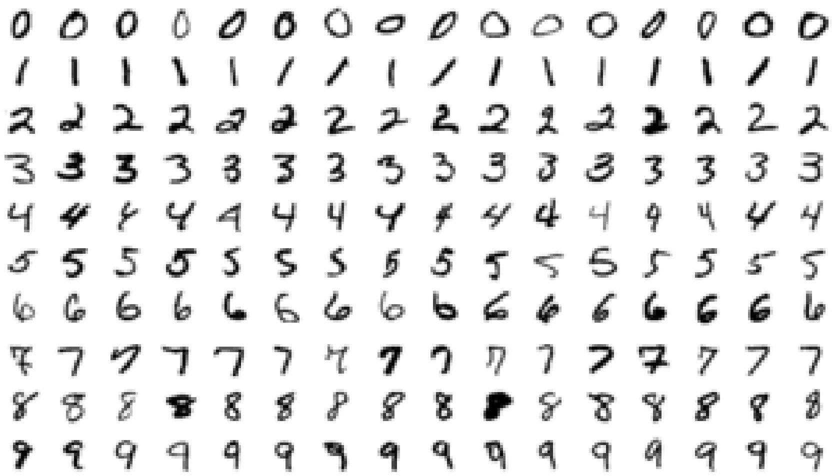

Figure 3. Example of the MNIST dataset

The database contains 60,000 images used for training as well as few of them can be used for cross-validation purposes and 10,000 images used for testing . All the digits are grayscale and positioned in a fixed size where the intensity lies at the center of the image with 28×28 pixels . Since all the images are 28×28 pixels, it forms an array which can be flattened into 28*28=784 dimensional vector. Each component of the vector is a binary value which describes the intensity of the pixel.

RESULT

```
Out[34]: Text(69.0, 0.5, 'Truth')
```

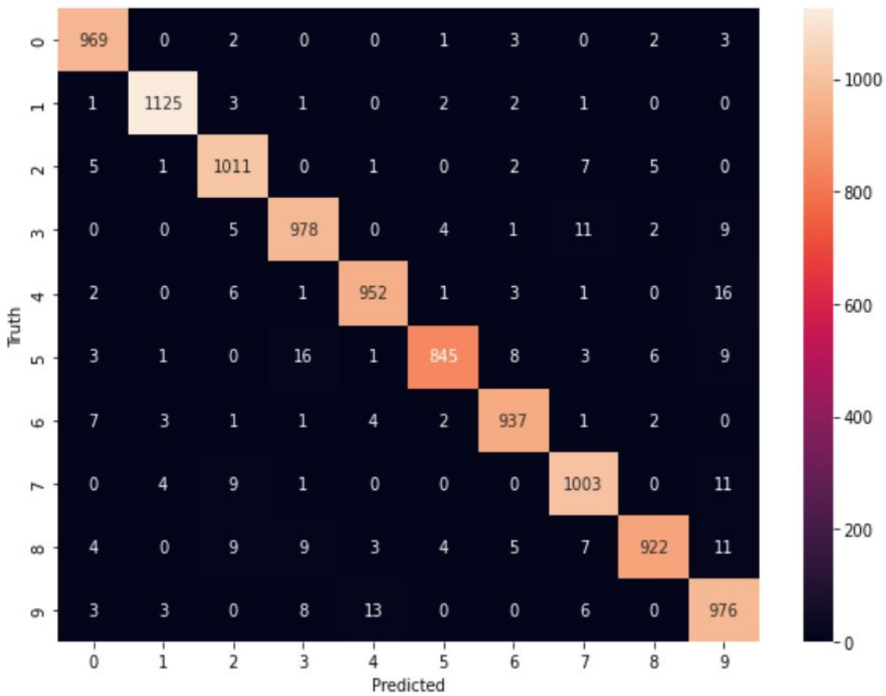

Figure 4. Confusion matrix for actual and predicted value and error

An epoch means training the neural network with all the training data for one cycle. In an epoch, we use all of the data exactly once.

```
Epoch 1/10
1875/1875 [==============================] - 2s 756us/step - loss: 0.2703 - accuracy: 0.9236
Epoch 2/10
1875/1875 [==============================] - 2s 912us/step - loss: 0.1223 - accuracy: 0.9643
Epoch 3/10
1875/1875 [==============================] - 2s 889us/step - loss: 0.0873 - accuracy: 0.9734
Epoch 4/10
1875/1875 [==============================] - 2s 818us/step - loss: 0.0668 - accuracy: 0.9798
Epoch 5/10
1875/1875 [==============================] - 2s 872us/step - loss: 0.0531 - accuracy: 0.9833
Epoch 6/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.0424 - accuracy: 0.9870
Epoch 7/10
1875/1875 [==============================] - 2s 912us/step - loss: 0.0344 - accuracy: 0.9895
Epoch 8/10
1875/1875 [==============================] - 2s 860us/step - loss: 0.0280 - accuracy: 0.9914
Epoch 9/10
1875/1875 [==============================] - 2s 861us/step - loss: 0.0234 - accuracy: 0.9927
Epoch 10/10
1875/1875 [==============================] - 2s 839us/step - loss: 0.0203 - accuracy: 0.9936
Out[35]: <keras.callbacks.History at 0x26a5515afa0>
```

Figure 5. Accuracy and loss using Epoch

```
In [37]: model.evaluate(X_test,y_test)

313/313 [==============================] - 0s 825us/step - loss: 0.0853 - accuracy: 0.9784

Out[37]: [0.08525817841291428, 0.9783999919891357]
```

Figure 6. Final model Accuracy and loss using test dataset

CONCLUSION

Machines will power our future. We hope that this has given us a glimpse into how they learn. In this study, we have used digit images pixels as features vector and ANN as classifiers for handwritten digits recognition. We have used publicly available MNIST database for evaluating our experiments. From the results, it can see that our experiment result achieved 97.84% recognition accuracy. In future work, we plan to work on more datasets and we will further optimize the parameters of ANN to obtain higher accuracies with low implementation time. Finally, we are interested in using a combination hybrid method of feature extraction with ensemble classifier.

REFERENCES

[1] M. Nagu, N. V. Shankar, and K. Annapurna, "A novel method for Handwritten Digit Recognition with Neural Networks," 2011.

[2] Y. LeCun, B. E. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. E. Hubbard, et al., "Handwritten digit recognition with a back-propagation network," in Advances in neural information processing systems, 1990, pp. 396-404.

[3] A. Ashworth, Q. Vuong, B. Rossion, M. Tarr, Q. Vuong, M. Tarr, et al., "Object Recognition in Man, Monkey, and Machine," Visual Cognition, vol. 5, pp. 365-366, 2017.

[4] J. Janai, F. Güney, A. Behl, and A. Geiger, "Computer Vision for Autonomous Vehicles: Problems, Datasets and State-of-the-Art," arXiv preprint arXiv:1704.05519, 2017.

[5] K. Islam and R. Raj, "Real-Time (Vision-Based) Road Sign Recognition Using an Artificial Neural Network," Sensors, vol. 17, p. 853, 2017.

[6] D. Arpit, Y. Zhou, B. Kota, and V. Govindaraju, "Normalization propagation: A parametric technique for removing internal covariate shift in deep networks," in International Conference on Machine Learning, 2016, pp. 1168-1176.

[7] I. Patel, V. Jagtap, and O. Kale, "A Survey on Feature Extraction Methods for Handwritten Digits Recognition," International Journal of Computer Applications, vol. 107, 2014.

[8] I. H. Witten, E. Frank, M. A. Hall, and C. J. Pal, Data Mining: Practical machine learning tools and techniques: Morgan Kaufmann, 2016.

[9] Y. LeCun, C. Cortes, and C. Burges, "MNIST handwritten digit database, 1998," URL http://www. research. att. com/~ yann/ocr/mnist, 2016.

[10] K. T. Islam, R. G. Raj, and G. Mujtaba, "Recognition of Traffic Sign Based on Bag-of-Words and Artificial Neural Network," Symmetry, vol. 9, p. 138, 2017.

[11] R. Hecht-Nielsen, "Kolmogorov's mapping neural network existence theorem," in Proceedings of the international conference on Neural Networks, 1987, pp. 11-13.

[12] P. M. Kamble and R. S. Hegadi, "Handwritten Marathi character recognition using R-HOG Feature," Procedia Computer Science, vol. 45, pp. 266-274, 2015.

[13] B. Su, S. Lu, S. Tian, J.-H. Lim, and C. L. Tan, "Character Recognition in Natural Scenes Using Convolutional Co-occurrence HOG," in ICPR, 2014, pp. 2926-2931.

[14] S. Tian, S. Lu, B. Su, and C. L. Tan, "Scene text recognition using co-occurrence of histogram of oriented gradients," in 2013 12th International Conference on Document Analysis and Recognition, 2013, pp. 912-916.

[15] J. Varagul and T. Ito, "Simulation of Detecting Function object for AGV Using Computer Vision with Neural Network," Procedia Computer Science, vol. 96, pp. 159-168, 2016.

[16] A. Boukharouba and A. Bennia, "Novel feature extraction technique for the recognition of handwritten digits," Applied Computing and