Empirical Evaluation of Digit Recognition using Single layer and Multilayer Network

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Abstract

The Handwritten digit recognition is a significant area of research as there are many applications which are using handwritten recognition and it can also be applied to new application. There are various kinds of artificial neural networks have been used for Handwritten recognition. In this paper, we compare the single layer neural network with Principal Component Analysis (PCA) and Multilayer neural network, which follows the LeNet-5 architecture based on accuracy and loss using the dataset MNIST (Modified National Institute of Standards and Technology). As a research outcome, it is found that the Single layer neural network with PCA consumes less execution time and better training accuracy than Multilayer network. Multilayer network gives better testing and validation accuracy than Single layer neural network.

Keywords: Handwritten digit Recognition, MNIST, Artificial neural network.

1. Introduction

Handwriting recognition is a one of the most challenging and interesting field of computer vision tasks. This Handwriting recognition technique is used in various applications such as bank cheque analysis, US post mail sorting [8] and handwritten form processing [2]. There are different approaches that have been used with high accuracy [1, 2, 3, 4, 5, 6, 7].

Recognition is an umbrella term that holds many fields such as, image recognition, face recognition, finger print recognition, character recognition, numerals recognition, etc. [1]. Handwritten Digit Recognition is a clever scheme able to recognize handwritten digits as humanview. Handwritten digit recognition plays important role in various applications such as office automation, check verification, business, postal address reading and printed postal codes and data entry applications are few examples [2]. The handwritten digit recognition is a complex task because of the different handwriting styles.

Deep learning [9] is one of the hot research area that uses artificial neural networks to solve complex problems such as Handwritten digit recognition. Deep learning uses different types of neural networks such as Recurrent neural network, Convolution neural network(CNN)). Deep learning methods have reached state-of-the-art performance in computer vision [10,11], big data [12,13], automatic speech recognition [14,15] and in natural language processing [16]. Although, increase in computing power has contributed majorly to the growth of deep learning methods, deep learning methods try to develop better models from large-scale data.

CNN is used for Image recognition, Video recognition and etc. CNN is a multi-layer feed-forward neural network that extract features implicitly from the input data. CNN can solve complex, high-dimensional, non-linear mappings problems from huge amount of data. Additionally, CNN gives an outstanding recognition rates for characters and digits recognition [16]. The main advantage of CNN is that it implicitly extracts the important features [17].

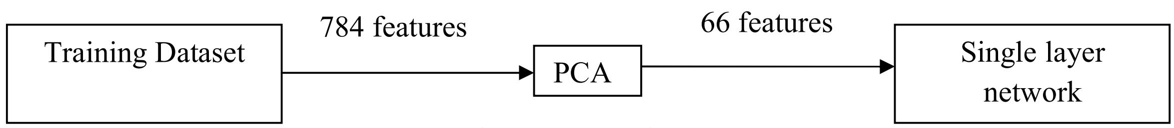

Figure 1:Overview

1.1.Outline of the Paper

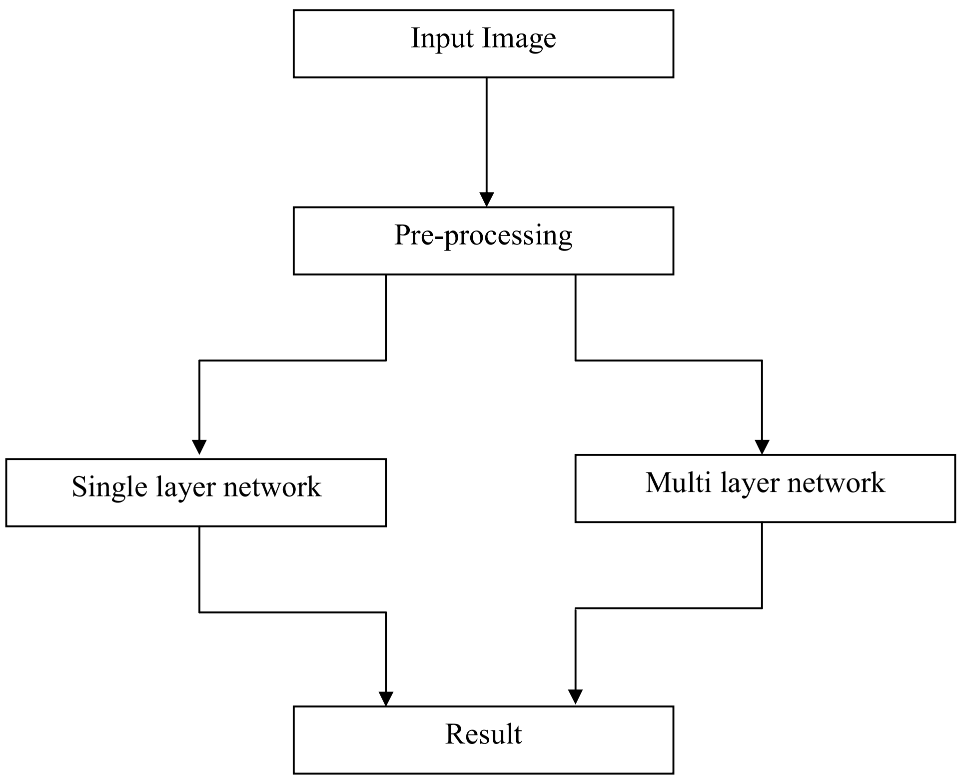

Figure 2: Outline of the Paper

2. Related Work

Many methods have been developed and best recognition rates are detailed for the recognition of English handwritten digits [13–15].

Niu and Suen [13] proposed a system to recognize handwritten digits using Convolutional Neural Network (CNN) and Support Vector Machine (SVM). There Experiments have been conducted on MNIST digit database. They achieve recognition rate of 94.40% with 5.60% with rejection. Tissera and McDonnell [14] introduced a supervised auto-encoder architecture based on extreme machine learning to classify Latin handwritten digits based on MNIST dataset. The proposed technique can correctly classify up to 99.19 %.

Ali and Ghani introduced Discrete Cosine Transform based on Hidden Markov models (HMM) to classify handwritten digits. They used MNIST as training and testing datasets. HMM have been applied as classifier to classify handwritten digits dataset. The algorithm provides promising recognition results on average 97.2 %.

Singh and S. P. Lal, have proposed a single layer neural network with principal component analysis[18].They used MNIST as training and testing datasets.

El-Sawy A., EL-Bakry H., Loey M have used the LeNet-5 architecture for Arabic Handwritten recognition[19].

Methodology

2.1.Architecture

2.1.1. Single layer network

The single hidden layer network have 3-layers (one input, one hidden and one output layer). Output from PCA is the input of the neural network which is 66 input neurons. There are 99 nodes in hidden layer. We select the neurons by the experiments with different hidden nodes and choosing the nodes which gave the highest cross validation (cv) accuracy. Forward propagation is used to classify the digit with respect to the output layer neurons. The output layer consist ten nodes, each corresponding to ten digits (0 to 9). The ten neuron's output is calculated and classified digit corresponds to neuron with highest output value (highestprobability).

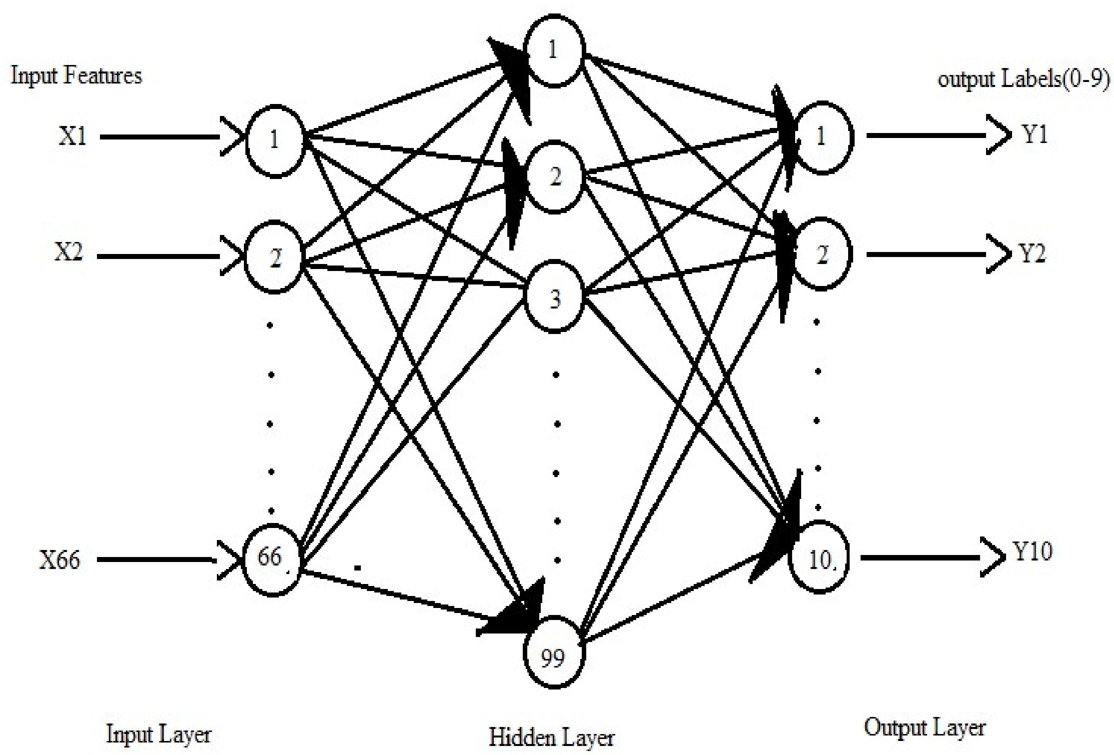

Figure 3: Single layer network

2.1.2. Multilayer network

The Multi layer neural network follows the architecture of LeNet-5 with some changes. The proposed network have 1-input layer, 1-output layer and 7-Hidden layers such as 2-convolution layer, 2-averge pooling layer and 3-fully connected layer.

MNIST is a common dataset used for both single layer and multilayer network. In which there are 60000-training data and 10000-testing data. Number of epochs in both the network are 30.

2.2.Pre processing

2.2.1. Normalization

To make the execution process fast we normalize the input value into 0-1. Each pixel value range is from 0-255. We divide each pixel's value by the value 255.

2.2.2. Feature Extraction by PCA for Single layer network

Principal component analysis (PCA) is a basic multivariate data analysis technique that is used in different area in machine learning and deep learning. It is used for dimensionality reduction of the dataset. PCA can be applied to the handwritten digit images by projecting the item onto smaller dimension.

The PCA algorithm can be implemented in the following steps [20]:

i. Calculate the mean for each dimension and subtract each training sample with the mean as shown in equations 1 and 2 respectively.

$$u[m] = \frac{1}{N}\sum_{i=1}^{N} X\,i \quad (1)$$

$$X = X - u[m] \quad (2)$$

ii. Find the covariance matrix and get the eigenvector (V) and eigenvalue (D) as in equation 3 and 4.

$$C = \frac{1}{N} \mathrm{X} * \mathrm{X}^{\mathrm{T}} \quad (3)$$

$$V^{-1} * CV = D \quad (4\_$$

iii. Sort the eigenvector and eigenvalue and select the Kth most significant eigenvectors. Project data X into K dimensional by multiplying X with top K eigenvectors.

$$Z = X * V(1{:}K) \quad (5)$$

where u[m] is the mean of training set, X is the sample oftraining set, N is number of sample acquired, C is the covariance matrix, V is the eigenvector of C and D is the eigenvalue of C, K is the value of principal component and Z is the eigenvector of X.

2.3.Training byBack propagation

Artificial Neural Network is a combination of simple artificial neurons that are linked to each other by their own connection strength This is used for various areas such as in health application for analyzing the heart disease in pattern recognition. [11] We trained the neural network by back propagation algorithm in which the learning is done by the changes of randomly initialized weights such that the classifier error is reduced. In back-propagation neural network, the learning is done by two parts. First, a input feature is presented to the input layer. The network propagates from layer to layer in a forward manner that is from input layer to output layer via hidden layers. The difference between actual output and desired output is calculated that is called as an error. The error is reduced as much as possible by adjusting the weights in back propagated manner.

2.4.Multilayer Network

CNN is a class of learning model based on human brain's information process. In the brain, each biological neuron has a receptive field observe data from some local neighborhood in visual space. They are particularly designed for the recognition of multi-dimensional data.

CNN architecture made up of with convolution layer, sub-sampling layer and fully connected layer. Convolution layer is responsible for feature extraction. Sub-sampling layers reduces the size of the image. Fully connected layer is an ordinary neural network.

In this study LeNet-5 CCN architecture is used. LeNet-5. The network have 9 layers including oneinput layer, one output layer, two convolutional layers and two sub-sampling, three fully connected layers as multi-layer perceptron hidden layers for nonlinear classification.

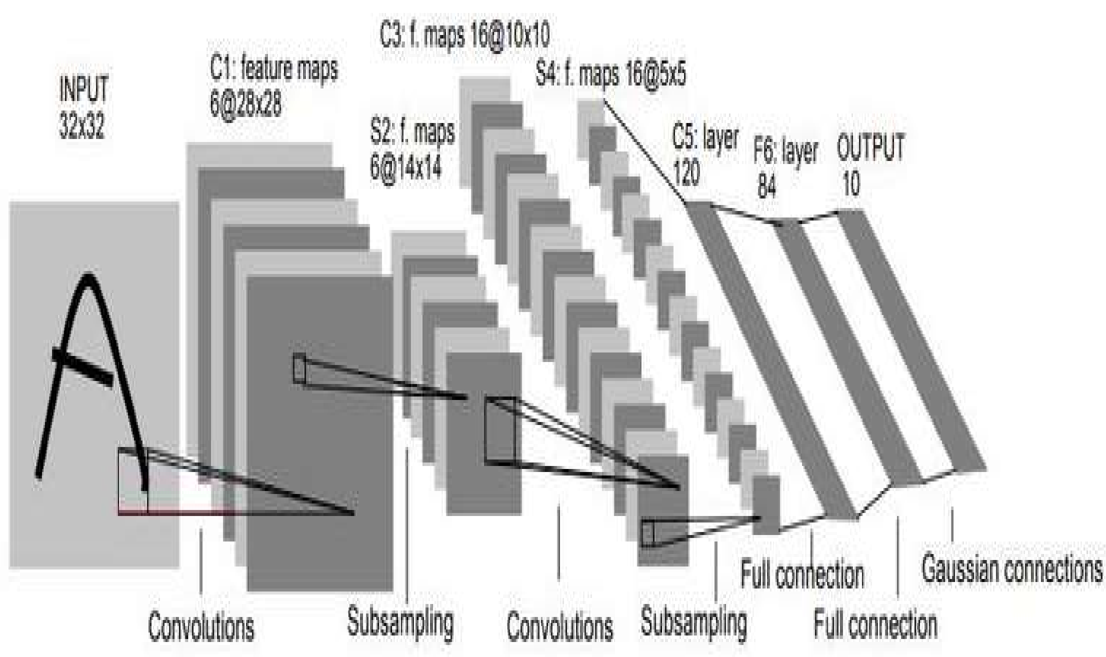

Figure 4: LeNet-5 Architecture

3. EXPERIMENTAL RESULTS

3.1.Performance Metrics & Evaluation:

The performance metrics such as Training accuracy, Training loss, Validation accuracy, Validation loss, Testing accuracy, Testing loss and execution time are calculated to analyze the performance of the networks

3.1.1. Output

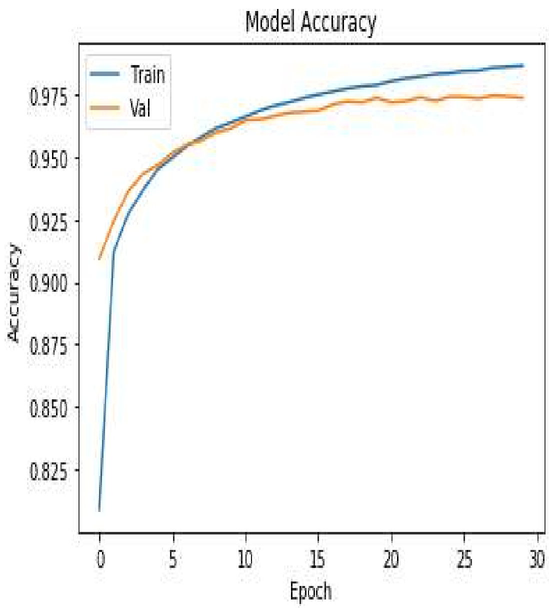

Figure 5: Accuracy of Single layer network with PCA

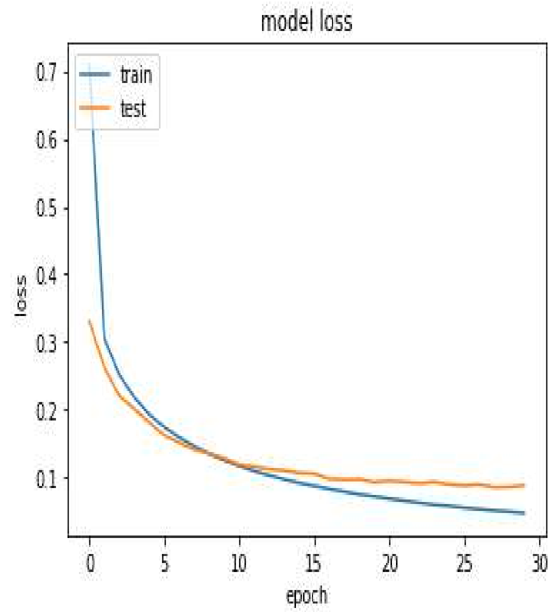

Figure 6:Loss of Single layer network with PCA

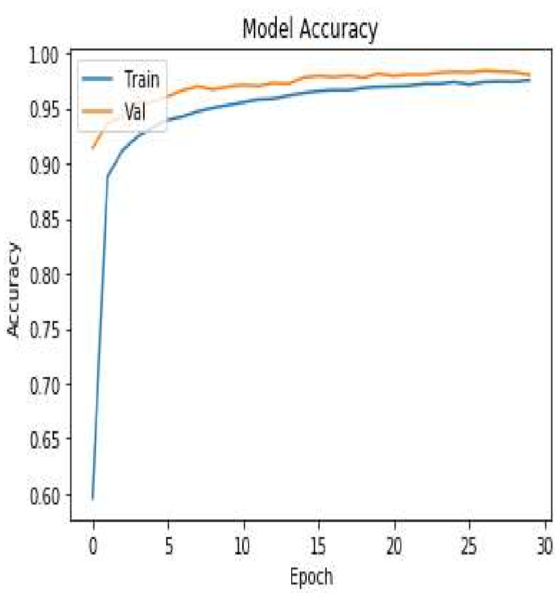

Figure 7: Accuracy of Multilayer Network

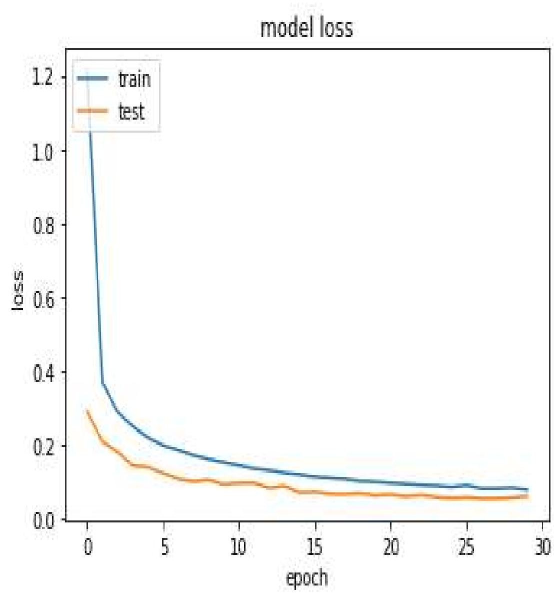

Figure 8: Loss of Multilayer Network

3.1.2. Results

Metrics / Network	Training Accuracy	Validation Accuracy	Testing Accuracy
Single layer Network with PCA	98.66	97.36	97.36
Multilayer Network	97.54	98.02	98.02

Table 2: Accuracy

Metrics / Network	Training Loss	Validation Loss	Testing Loss
Single layer Network with PCA	4.75	8.78	8.78
Multilayer Network	8	6.3	6.2

Table 3: Loss

Network / Metrics	Execution Time (30-Epochs)
Single layer Network with PCA	103 seconds
Multilayer Network	744 seconds

Table 4: Execution Time

4. Conclusion

From the results we observe that single layer neural network with PCA consumes less execution time but at the time of validation and testing the accuracy of the network has been reduced and the loss of the network has been increased which leads to the problem overfitting. Whereas, Multilayer network produces better result in all the stages such as training, testing and validating. Hence, it is observed that the multilayer network is a better option than single layer network for the real time problems like Handwritten Recognition.

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