Multiclass Classification with an Ensemble of Binary Classification Deep Networks

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Abstract:
Deep learning has been shown substantial research interest. Its power may lie in enhancing the parallel processing power of neural networks by forming deep neural networks. Deep neural network classifiers have been used frequently and are efficient. In multiclass deep network classifiers, the burden of classifying samples of different classes is put on a single classifier. As shown in this paper, the classification capability of deep networks can be further increased by using an ensemble of binary classification deep networks. In the proposed approach, a single (one-versus-all) deep network binary classifier is dedicated to each category classification. Subsequently, binary classification deep network ensembles have been investigated. Every network in an ensemble has been trained by a one-versus-all binary training technique using the Stochastic Gradient Descent with Momentum Algorithm. For classification of the test sample, the sample is presented to each network in the ensemble. After softmax-layer score voting, the network with the largest score is assumed to have classified the sample. Digit image recognition has been used for experimentation. Three datasets have been used for experimentation viz. the MATLAB Digit Image Dataset, the USPS+ Digit Image Dataset, and the MNIST Digit Image Dataset. The experiments demonstrate that given sufficient training, a Binary Classification Convolutional Neural Network (BCCNN) ensemble can outperform a conventional Multi-class Convolutional Neural Network (MCNN). In one of the experiments, it was noted that after training and testing of a BCCNN ensemble and an MCNN respectively on a subset of the MNIST Digit Image Dataset, the BCCNN ensemble gave a higher accuracy of 98.03% as compared to the MCNN which gave an accuracy of 97.90%. The architecture of the BCCNNs in an ensemble has also been modified in order to increase their recognition accuracy. On a large subset of the MNIST Digit Image Dataset, the modified BCCNN ensemble gave a higher accuracy of 98.50%, while as the MCNN gave an accuracy of 98.4875%.

Keywords: Binary Classification; Ensemble Learning; MNIST; Deep Neural Networks; Deep Learning;
1. Introduction

Two main approaches have been used to deal with multiclass problems using binary classification techniques [1]. First, adapting the internal operations of the training algorithm, and second, decomposing the multiclass problem into a set of binary classification problems. The first technique may be, sometimes, either impractical or not easy to implement [2]. Particularly for Support Vector Machines (SVMs), it was observed [3] that reformulating the first technique into its multiclass version led to high cost training techniques. Hence, the second technique [4-6,3,7-9] referred to as decomposition is commonly used. This involves reduction of classification among $K$ classes into $K$ binary problems, in which each one discriminates a certain class from rest of $K-1$ classes [10]. Rifkin and Klautau [10] state that this technique, in spite of its simplicity, gives performance which is comparable to other more complicated techniques when the binary classifier is well tuned. Decomposition also opens up new possibilities for using parallel processing, because the binary sub-problems are independent and may be solved in many processors [1]. All-together methods for multiclass classification have slow training speed [11].

While several algorithms have been proposed for solving binary problems, of which, some can be naturally extended to the multiclass case, and some need special formulation techniques to be able to solve multiclass problems. The first group of algorithms include decision-trees [12,13], neural networks [14], k-Nearest Neighbor [15], Naive Bayes classifier [16], and Support Vector Machine [17]. The second group includes techniques for conversion of the problem of multiclass classification into binary classification problem sets which are conveniently solved by binary classifiers e.g. SVM [17,18]. Multiclass Feedforward Neural Networks give a natural extension to multiclass classification [19,20]. Complementary Neural Network (CMTNN) [21] uses a pair of opposite Feedforward Backpropagation [22,23] neural networks for classification problems. These networks have been implemented for both binary as well as multi-class classification problems. However, due their complexity and difference from the conventional techniques they are not taken up here.

Deep learning [24-27] involves training and use of deep networks. The power of deep networks lies in their ability to layerwise evolve patterns found in the presented data. The deep neural networks found today are larger than the neural networks used earlier. Not only has the number of layers used in neural networks increased, but also the number of neurons per layer and the variety of use of neurons has increased. Something like a Moore’s Law of Neurocomputing has evolved with respect to the number of neurons used in neural networks. As observed for classification purposes in deep networks, the increase of neurons has been done by increasing the number of layers while keeping the operating mode of the network as multiclass. In this paper, an effort has been made to increase the classification accuracy of deep neural networks by using them in an ensemble of binary-classification deep networks for the purpose of multi-class classification. The advantage of the proposed approach as demonstrated by the experiments is higher classification accuracy as compared to that of conventional deep network classifiers. Three digit image datasets namely the MATLAB Digit Image Dataset, the USPS+ Digit Image Dataset [28] and the MNIST Digit Image Dataset [29] were used. In one of the experiments which used a subset of the MNIST Digit Image Dataset, the accuracy of Binary Classification
Convolutional Neural Network (BCCNN) Ensemble was found to be 98.03% which was higher than that found after using a conventional Multi-class Convolutional Neural Network (MCNN) viz. 97.90%. After structural modifications to the ensemble, and subsequently testing it as well as a conventional deep network on a major subset of MNIST respectively, it was found that the proposed technique gave an accuracy of 98.50% which was higher than that of the conventional deep network viz. 98.4875%.

2. Proposed Approach

The proposed approach involves using deep neural networks as binary-classifiers in an ensemble which increases their classification accuracy. The proposed technique has also been used in multiclass classification using softmax aggregation of Binary SVM Classifiers [11]. However in the current work, we focus on multiclass classification using softmax aggregation of binary classification deep neural networks.

In the proposed technique, one-versus-all approach is used for training as well as for classification. Each BCCNN in the ensemble has the same number of and type of layers as a conventional MCNN, but only up to and excluding the fully connected layer. In each BCCNN used, the fully connected layer consists of two neurons, followed by a softmax layer, which in turn is followed by a binary classification layer. As per convention in a 10-digit image classifier MCNN, the fully connected layer consists of 10 neurons, followed by a softmax layer, which in turn is followed by a classification layer with ten neurons. The architectures of both the binary as well as the multiclass deep networks are shown in Figure 1.

The experimentation has been based on the task of digit-image recognition. $BCCNN_i$ ($i=1,2,3, \ldots 10$) is trained with the conventional deep network training algorithm of Stochastic Gradient Descent with Momentum. A 28-by-28 pixel array is used for each digit image. One-versus-all training is done end-to-end.

Once all BCCNNs have been trained, the ensemble is used for classification. A test sample to be classified is presented to all the 10 BCCNNs in a trained ensemble. Next, the softmax layer emission of each BCCNN in the ensemble is monitored. The BCCNN with maximum softmax score is assumed to have classified the sample. It should be noted that the MCNN is trained and used as per convention.
3. Experimentation

Experimentation was done on an Intel CORE i3 processor system with 6GB of RAM running Windows 7. Both the BCCNN ensemble, as well as the MCNN, were trained using the Stochastic Gradient Descent with Momentum Algorithm with Initial Learn Rate = 0.01, $L_2$
Regularization Factor = 0.0001, Momentum = 0.9, Validation Frequency = 50, and Validation Patience = 5. These were MATLAB defaults for training deep networks.

The digit-image datasets used were the MATLAB Digit Image Dataset (having 10000 instances), the USPS+ Digit Image Dataset (having 11000 instances) and the MNIST Digit Image Dataset (having 70000 instances).

The networks were usually trained with Mini-batch Size of 40 unless otherwise indicated in the tables below. First, a single MCNN was trained on a training set after which it was tested on the testing set. Next, an ensemble of BCCNNs was trained using same data after re-formatting the latter for one-versus-all binary classification. Afterwards the ensemble was tested on the corresponding testing dataset. For the same data, each BCCNN in the ensemble had almost the same training time to train as that of the MCNN.

The results of the experiments are given below.

**Table 1. MATLAB Digit Image Dataset experimentation results**

| Network          | Training Set Size (N_R) | Validation Set Size / Testing Set Size (N_S) | Training Epochs | Mini Batch Size | Maximum Classification Accuracy On Testing Set (%) |
|------------------|-------------------------|---------------------------------------------|-----------------|-----------------|---------------------------------------------------|
| MCNN             | 1000                    | 500                                         | 8               | 128             | 94.00                                             |
| BCCNN Ensemble   | 1000                    | 500                                         | 7               | 40              | 93.60                                             |
| MCNN             | 5000                    | 1000                                        | 3               | 128             | 99.10                                             |
| BCCNN Ensemble   | 5000                    | 1000                                        | 3               | 40              | 99.20                                             |
| MCNN             | 7000                    | 1500                                        | 3               | 128             | 99.73                                             |
| BCCNN Ensemble   | 7000                    | 1500                                        | 3               | 40              | 99.80                                             |

**Table 2. USPS+ Digit Image Dataset experimentation results**

| Network          | Training Set Size (N_R) | Validation Set Size / Testing Set Size (N_S) | Training Epochs | Mini Batch Size | Maximum Classification Accuracy On Testing Set (%) |
|------------------|-------------------------|---------------------------------------------|-----------------|-----------------|---------------------------------------------------|
| MCNN             | 5000                    | 1000                                        | 4               | 128             | 98.60                                             |
| BCCNN Ensemble   | 5000                    | 1000                                        | 4               | 40              | 98.80                                             |
| MCNN             | 7000                    | 1750                                        | 4               | 40              | 99.14                                             |
| BCCNN Ensemble   | 7000                    | 1750                                        | 3               | 40              | 99.03                                             |

**Table 3. MNIST Digit Image Dataset experimentation results #1**
For the BCCNN Ensemble, it was observed that the classification accuracy increased with increase in amount of training data. As shown in Table 3, it was observed that after increasing the training set size from 7000 to 9000, the BCCNN ensemble was able to outperform the MCNN on grounds of classification accuracy. For an MNIST training subset with a size of 9000, a validation set size of 3000 and a testing set size of 3000, the accuracy of the trained BCCNN ensemble was 98.03% which was higher than that of the MCNN viz. 97.90%. One more observed characteristic of BCCNNs was faster training convergence than that of the MCNN. The training plots of both are shown in Figures 2(a) and 2(b).

More experimentation was done on the architecture of BCCNNs in order to improve their recognition accuracy. It was observed that if an eight-neuron fully-connected layer was inserted before the two-neuron fully-connected layer while retaining all other layers in the network, the recognition accuracy of the modified BCCNN ensemble was higher. For a randomly selected subset of the MNIST Digit Image Dataset, this observation was made as given in Table 4.

Table 4. *MNIST Digit Image Dataset* experimentation results #2
Figure 2 (a). Training accuracy and training loss plots for a single BCCNN

Figure 2(b). Training accuracy and training loss plots for an MCNN
As is observed from Table 4, the ensemble with the modified BCCNNs performed best on the given dataset. It must be noted that each BCCNN in the modified ensemble had two fully connected layers in succession. The first fully connected layer had eight neurons and the second fully connected layer had two neurons. These layers were followed by a softmax layer and a binary classification layer respectively in that order.

Further, as suggested by the fast training convergence of the BCCNNs (Figure 2.a), the learning rate was high which might have affected the training of the BCCNNs negatively. In order to investigate the effect of learning rate on training of the BCCNNs, the learning rate for training the ensemble was lowered from 0.01 to 0.005. The results of subsequent testing suggested an improvement in overall classification accuracy. The results of the experiments are shown in Table 5.

**Table 5. MNIST Digit Image Dataset experimentation results #3**

| Network              | Learning Rate | Training Set Size (N_r) | Validation Set Size / Testing Set Size (N_s) | Training Epochs | Mini Batch Size | Maximum Classification Accuracy On Testing Set (%) |
|----------------------|---------------|-------------------------|---------------------------------------------|-----------------|----------------|--------------------------------------------------|
| MCNN                 | 0.01          | 3000                    | 1250                                        | 6               | 40             | 96.48                                            |
| BCCNN Ensemble       | 0.01          | 3000                    | 1250                                        | 5               | 40             | 96.80                                            |
| BCCNN Ensemble       | 0.005         | 3000                    | 1250                                        | 5               | 40             | 97.52                                            |
| Modified BCCNN       | 0.005         | 3000                    | 1250                                        | 6               | 40             | 97.84                                            |

As is observed from Table 5, the modified BCCNN ensemble having been trained using a learning rate of 0.005 performed best. Each BCCNN in this modified ensemble had two fully connected layers (as detailed previously).

In the context of this work, first, the MATLAB Digit Image Dataset as well as the USPS+ Digit Image Dataset were used exhaustively. The MNIST Digit Image Dataset was also used to some extent. Next, for comprehensive testing of the MNIST Digit Image Dataset, it was also used extensively. From MNIST a randomly selected subset with 40000 training instances, 8000 validation instances and 8000 testing instances respectively, was used. Table 6 gives a comparison of the experimental results for this large subset, after using it on an MCNN and on a modified BCCNN ensemble trained using a low learning rate of 0.005.

**Table 6. MNIST Digit Image Dataset experimentation results #4**

| Network              | Learning Rate | Training Set Size (N_r) | Validation Set Size / Testing Set Size (N_s) | Training Epochs | Mini Batch Size | Maximum Classification Accuracy On Testing Set (%) |
|----------------------|---------------|-------------------------|---------------------------------------------|-----------------|----------------|--------------------------------------------------|
| MCNN                 | 0.01          | 40000                   | 8000                                        | 2               | 40             | 98.4875                                          |
| Modified BCCNN       | 0.005         | 40000                   | 8000                                        | 2               | 40             | 98.5000                                          |
As is observed from Table 6, the modified BCCNN ensemble trained using a low learning rate had higher classification accuracy as compared to that of the MCNN.

4. Conclusion

Using ensembles of binary classification deep networks for multiclass classification is a promising area of research. Each network in the ensemble is trained end-to-end using the one-versus-all approach. For testing the trained ensemble, a sample is presented to each network in the ensemble. Softmax layer score voting of all deep network in the ensemble is done. After voting, the ensemble member with the largest score is assumed to have classified the sample. For experimentation, the task of digit-image recognition was used. Three digit image datasets namely the MATLAB Digit Image Dataset, the USPS+ Digit Image Dataset, and the MNIST Digit Image Dataset were used. The experimental results demonstrated that a Binary Classification Convolutional Neural Network (BCCNN) Ensemble can outperform a conventional Multi-class Convolutional Neural Network (MCNN). For example, using a subset of the MNIST Digit Image Dataset, the BCCNN ensemble gave an accuracy of 98.03% while as an MCNN gave an accuracy of 97.90%. Architectural modification of the BCCNN ensembles was also done in order to increase their recognition accuracy. On a subset of the MNIST Digit Image Dataset, a structurally modified ensemble was used which had two fully connected layers in succession having eight neurons and two neurons respectively, in addition to the layers used previously. The modified BCCNN ensemble outperformed the normal BCCNN ensemble as well as the conventional MCNN for the same subset of MNIST. The modified BCCNN ensemble gave a classification accuracy of 98.50% while as the MCNN gave a classification accuracy of 98.4875%. Continuing in this line of research, future work would involve making more modifications to the architecture of BCCNNs in order to increase their efficiency. Also, work would be done on extending the applications of the proposed approach to different areas of deep learning with the help of larger and more powerful deep networks.

References

1. Lorena AC, Carvalho ACP, Gama JMP (2008) A review on the combination of binary classifiers in multiclass problems. Artif Intell Rev 30:19-37. doi:10.1007/s10462-009-9114-9
2. Passerini A, Pontil M, Frasconi P (2004) New results on error correcting output codes of kernel machines. IEEE Trans Neural Netw, 15:45-54
3. Hsu C-W, Lin C-J (2002) A comparison of methods for multi-class support vector machines. IEEE Trans Neural Netw, 13 (2):415-425
4. Diettreich TG, Bakiri G (1995) Solving multiclass learning problems via error correcting output codes. journal of Artificial Intelligence Research 39:1-38
5. Friedman J (1996) Another approach to polychotomous classification. Stanford University,
6. Allwein E, Shapire R, Singer Y (2000) Reducing multiclass to binary: A unifying approach for margin classifiers. Journal of Machine Learning Research:113-141
7. Zhang M-L, Zhou Z-H (2014) A review on multi-label learning algorithms. IEEE Transactions on Knowledge and Data Engineering 26 (8):1819-1837
8. Zhou Z-H, Zhang M-L (2016) Multi-label learning. In: Sammut C, Webb GI (eds) Encyclopedia of Machine Learning and Data Mining. Berlin:Springer, pp 1-8
9. Zhang M-L, Li Y-K, Liu X-Y, Geng X (2018) Binary relevance for multi-label learning: an overview. Front Comput Sci 12 (2):191-202. doi:https://doi.org/10.1007/s11704-017-7031-7
10. Rifkin R, Klautau A (2004) Parallel networks that learn to pronounce english text. Journal of Machine Learning Research:101-141
11. Duan K, Keerthi SS, Chu W, Shevade SK, Poo AN Multi-category Classification by Soft-Max Combination of Binary Classifiers. In: Fourth International Workshop on Multiple Classifier Systems, 2003.
12. Breiman L, Friedman J, Olshen RA, Stone CJ (1984) Classification and Regression Trees. Chapman and Hall,
13. Quinlan JR (1993) C4.5: Programs for Machine Learning. Morgan Kaufmann,
14. Bishop CM (1995) Neural Networks for Pattern Recognition. Oxford University Press,
15. Bay SD Combining nearest neighbor classifiers through multiple feature subsets. In: ICML, 1998. pp 37-45
16. Rish I An empirical study of the naive bayes classifier. In: IJCAI Workshop on Empirical Methods in Artificial Intelligence, 2001.
17. Cortes C, Vapnik V (1995) Support-vector networks. Machine Learning:273-292
18. Burges CJ (1998) A tutorial on support vector machines for pattern recognition. Data Mining and Knowledge Discovery:1-47
19. Aly M (2005) Survey on Multiclass Classification Methods.
20. Omar L, Ivrisimtzis I (21 Sep 2019) Using theoretical ROC curves for analysing machine learning binary classifiers. arXiv: 190909816v1
21. Kraipeerapun P, Fung CC, Nakkrasae S (2009) Porosity prediction using bagging of complementary neural networks. Advances in Neural Networks:175-184
22. Rumelhart DE, Hinton GE, Williams RJ (1986) Learning representations by back-propagating errors. Nature 323 (6088):533
23. Rumelhart DE, Hinton GE, McClelland JL (1986) A general framework for parallel distributed processing. Parallel distributed processing: Explorations in the microstructure of cognition 1:45-76
24. LeCun Y, Bengio Y, Hinton G (2015) Deep learning. nature 521 (7553):436
25. Schmidhuber J (2015) Deep learning in neural networks: An overview. Neural networks 61:85-117
26. Goodfellow I, Bengio Y, Courville A (2016) Deep learning. MIT press,
27. Shin H-C, Roth HR, Gao M, Lu L, Xu Z, Nogues I, Yao J, Mollura D, Summers RM (2016) Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. IEEE transactions on medical imaging 35 (5):1285-1298
28. USPS Handwritten Digit Dataset http://www.cs.nyu.edu/~roweis/data.html.
29. LeCun Y, Bottou L, Bengio Y, Haffner P (1998) Gradient-based learning applied to document recognition. Proceedings of the IEEE 86 (11):2278-2324