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Tuning Convolution Neural networks for Hand Written Digit Recognition

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***Abstract*—** Complex neural networks will take much time for training; we can achieve better accuracy with simpler models by tuning hyper-parameters of the model. Hyper parameter tuning is required for neural networks to improve the accuracy and to reduce the training time of neural networks. In this paper we used simple CNN model with four convolution layers, two pooling layers and two fully connected layers with hyper parameter tuning, batch normalization, learning rate decay, and normalization techniques to recognize hand written digit recognition. This model is giving 99.54% on test set.

Keywords— Convolution Neural Networks, CNN, Deep Learning, Parameter Tuning, Batch Normalization.

I. INTRODUCTION

Recently, Deep Neural Networks gained the much popularity because of its ability to solve complex problems. Deep Neural Networks are inspired by human brain, they are widely used in computer vision especially Convolution Neural Networks (CNN) [8] are playing vital role in computer vision applications.

In computer vision human hand writing recognition accurately is challenging task. Deep Neural Networks are used in this kind of complex problems it is difficult to solve complex problems by using shallow networks.

But all these Deep Neural Networks suffer from over fitting problem because of high variance; over fitting can be avoided by regularization techniques.

A. Convolution Neural Networks

In 1989 the new technique CNN was introduced by Yann LeCun for solving computer vision problems, Convolution Neural Network is multi layered feed forward neural network each layer consists of multiple neurons. When input is unstructured and very large then conventional neural networks can't perform well on that data, first we have to reduce dimensions of data without losing important information. In CNN convolution layers are used for extracting required features by applying convolution filters. Pooling layers are used for reducing the number of trainable parameters, pooling layers introduced between convolution layers. Flattening layer serialize the input features to feed Neural Network. Fully connected layer is the neural network that will take the final decision this layer will return the probability for each decision variable.

B. Regularization of Neural Networks

There are various regularization techniques are there, most commonly used techniques are L2 Regularization, Dropout, Early Stopping, Data Augmentation. In L2 regularization cost function will be modified by adding regularization term.

$$J(w, b) = 1/m \sum^{n}_{i=1} (\text{target} - \text{predicted})^2 + \lambda/2m \sum ||w||^2$$

by adding regularization term to cost function it will restrict coefficients to fit perfectly to avoid over fitting. In Dropout technique randomly drop some nodes from neural network that will make network sparse, over fitted network so sensitive to small functions by dropping some nodes from network can be generalized then there will be no problem of over fitting. Early stopping is another technique that stops the training of neural network at point where more training increasing the error. Data Augmentation is another widely used technique to regularize neural network if more training data provided networks will perform better on unseen data, Data Augmentation generates data by image transformation techniques like rotating, horizontal flipping, vertical flipping etc.

C. Hyper parameter tuning

Hyper parameters tuning process finds best hyper parameters that are involved in building the Neural Network, if the network is deep we have to deal with number of hyper parameters like number of hidden layers, number of nodes in

each hidden layers, mini batch size, learning rate decay, optimization algorithms and momentum. By selecting appropriate hyper parameters we can get better performance.

D. Batch Normalization

Batch Normalization makes Neural Network robust; it makes training of deep neural networks much easier by converting activation values at hidden layers into specific range according to variance. If inputs of one hidden layers are in certain range training algorithms like gradient descent training will be much simpler and algorithm converge at faster rate

Rest of the paper is organized as follows, Section II contain the related work of Convolution Neural Networks tuning, Section III contain the methodology, which contains different techniques we used to tune CNN, Section IV describes results and discussion, Section V contains conclusion and future scope.

II. RELATED WORK

In There are numerous models proposed for image classification like handwritten digit recognition, deep learning models are performing better when compared with other models. Deep learning models accuracy further can be improved by tuning hyper parameters, batch normalization and regularization techniques.

In [1] James Bergstra and Yoshua Bengio proposed random search for hyper-parameter optimization. Y. Hou and H. Zhao [2] proposed depth neural networks to improve the hand written digit recognition. In [3] U. Meier, D. C. Ciresan, L. M. Gambardella and J. Schmidhuber proposed new technique Committee of Simple Neural Nets.

In [5] C. Laurent, G. Pereyra, P. Brakel, Y. Zhang and Y. Bengio, [6] Y. Xie, H. Jin and E. C. C. Tsang and in [7] D. Ito, T. Okamoto and S. Koakutsu, improved the performance of deep networks by batch using normalization. L. Chen, S. Wang, W. Fan, J. Sun and S. Naoi used new method [9] Cascading Training for Relaxation CNN on Handwritten Character Recognition, in [10] Tai-cong Chen, Da-jian Han, F. T. K. Au and L. G. Tham improved the neural networks performance by using learning rate decay and in [12] K. T. Islam, G. Mujtaba, R. G. Raj and H. F. Nweke improved the performance of handwritten digit recognition.

III. METHODOLOGY

A. Tuning of Convolution Neural Networks

To improve the accuracy of convolution neural network on MNIST handwritten digit dataset we applied parameter tuning, regularization and batch normalization. We created Convolution Neural Network (CNN) with four convolution layers with filter size 32 and kernel size 3 between each convolution layer we applied Batch normalization, in fully connected layer we have used 2 hidden layers with activation function relu, to avoid over fitting we introduced dropout between hidden layers with dropout rate 0.2, in the output layer we used softmax as activation function with ten nodes. We tried with two optimization algorithms RMSprop and Adam we are getting better results when adam optimizer used and we used categorical cross entropy as loss function and applied learning rate decay for better convergence of algorithm.

1) Parameter Tuning

Hyper parameter tuning is used to find the best hyper parameters; in this hyper parameter tuning we tested several combinations of hyper parameters. Grid Search is one hyper parameter tuning technique. GridSearchCV will train Artificial Neural Networks using k-fold cross validation to get relevant accuracy with different combination of the dictionary of hyper parameters and returns the best accuracy with best selection of these values.
In this paper we used random search instead of Grid Search because grid search will take much time in deep Neural Networks.

2) Normalization

Normalization will be used in neural networks to reduce over fitting. We applied dropout normalization between every hidden layer, we added dropout layer with rate 0.25 after each hidden layer.

We applied data augmentation by using keras library function. Data augmentation creates more training data by image transformation techniques, so neural networks trained with more data there will be no problem of over fitting.

3) Batch Normalization

Batch Normalization makes Neural Network training faster and also helpful in covariance shifting. We applied Batch normalization at every hidden layer of our model.

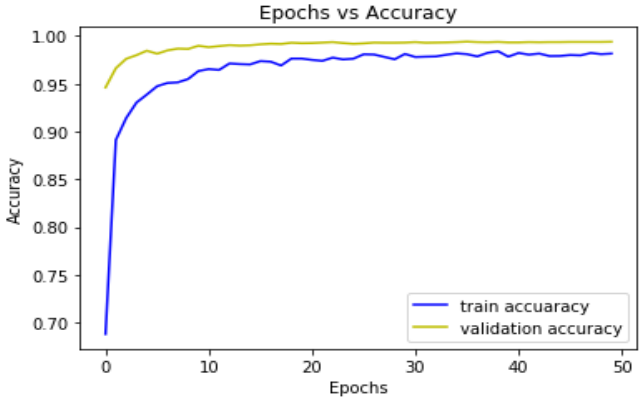

Figure 1. Accuracy train set vs test set

IV. Results and Discussion

After applying all the above tuning techniques we got accuracy 98.04% for training set, on test set we got 99.54% accuracy. We have plotted the graph for accuracies of train, test for different number of epochs.

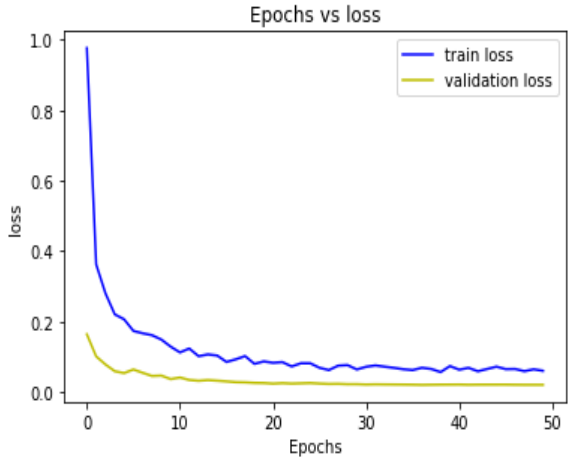

Figure 2. Loss train set vs test set

Table 1. Accuracy before tuning vs After Tuning

	Train	Test
CNN	97.42%	98.94%
CNN after Tuning	98.04%	99.54%

We are getting better Result after tuning process. Before tuning for the same model we got 98.94% accuracy on test set after tuning we got 99.54% accuracy.

V. Conclusion and Future Scope

From the above results we can conclude that we improved the CNN accuracy by applying parameter tuning, Batch normalization, Regularization and Normalization techniques without increasing model complexity. In future we have to try with bigger dadasets like ImageNet and little modification to architecure.

References

[1] James Bergstra and Yoshua Bengio. 2012. Random search for hyper-parameter optimization. *J. Mach. Learn. Res.* 13 (February 2012), 281-305.

[2] Y. Hou and H. Zhao, "Handwritten digit recognition based on depth neural network," *2017 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS)*, Okinawa, 2017, pp. 35-38

[3] U. Meier, D. C. Ciresan, L. M. Gambardella and J. Schmidhuber, "Better Digit Recognition with a Committee of Simple Neural

[4] Nets," *2011 International Conference on Document Analysis and Recognition*, Beijing, 2011, pp. 1250-1254.

[5] L. Deng, "The MNIST Database of Handwritten Digit Images for Machine Learning Research [Best of the Web]," in *IEEE Signal Processing Magazine*, vol. 29, no. 6, pp. 141-142, Nov. 2012.

[6] C. Laurent, G. Pereyra, P. Brakel, Y. Zhang and Y. Bengio, "Batch normalized recurrent neural networks," *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Shanghai, 2016, pp. 2657-2661.

[7] Y. Xie, H. Jin and E. C. C. Tsang, "Improving the lenet with batch normalization and online hard example mining for digits recognition," *2017 International Conference on Wavelet Analysis and Pattern Recognition (ICWAPR)*, Ningbo, 2017, pp. 149-153.

[8] D. Ito, T. Okamoto and S. Koakutsu, "A learning algorithm with a gradient normalization and a learning rate adaptation for the mini-batch type learning," *2017 56th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE)*, Kanazawa, 2017, pp. 811-816.

[9] L. Lv, X. Cai, Y. Zeng and C. Chen, "Facial feature extraction method based on fast and effective convolutional neural network," *2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, Chongqing, 2017, pp. 2011-2015.

[10] L. Chen, S. Wang, W. Fan, J. Sun and S. Naoi, "Cascading Training for Relaxation CNN on Handwritten Character Recognition," *2016 15th International Conference on Frontiers in Handwriting Recognition (ICFHR)*, Shenzhen, 2016, pp. 162-167.

[11] Tai-cong Chen, Da-jian Han, F. T. K. Au and L. G. Tham, "Acceleration of Levenberg-Marquardt training of neural networks with variable decay rate," *Proceedings of the International Joint Conference on Neural Networks, 2003.*, Portland, OR, 2003, pp. 1873-1878 vol.3.

[12] T. Tanprasert and T. Kripruksawan, "An approach to control aging rate of neural networks under adaptation to gradually changing context," *Proceedings of the 9th International Conference on Neural Information Processing, 2002. ICONIP '02.*, Singapore, 2002, pp. 174-178 vol.1.

[13] K. T. Islam, G. Mujtaba, R. G. Raj and H. F. Nweke, "Handwritten digits recognition with artificial neural network," *2017 International Conference on Engineering Technology and Technopreneurship (ICE2T)*, Kuala Lumpur, 2017, pp. 1-4.

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