International Journal of Scientific Research and Engineering Development-– Volume 3 - Issue 4, July - Aug 2020

Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Improvization of Diabetic Retinopathy classification Using Hyperparameter Tuning

Dr.R.Thangarajan*, S.Sriram**, B.Yashwanth***, V.Yashwanth****

*(Information Technology, Kongu Engineering College, Perundurai
Email: rt.cse@kongu.edu)

**(Computer Science and Engineering, Kongu Engineering College, and Perundurai
Email: tingu.2399@gmail.com)

***(Computer Science and Engineering, Kongu Engineering College, and Perundurai
Email: yashwabalaji@gmail.com)

****(Computer Science and Engineering, Kongu Engineering College, and Perundurai
Email: veyashwanth99@gmail.com)

--************************----------------------------------

Abstract:

Diabetic Retinopathy (DR) classification and improvement of the result by hyper-parameter tuning is done for the evaluation of the retinopathy detection. Diabetic retinopathy is caused by the increase in the level of glucose in the blood and it causes damage to the blood vessels in the eye which results in the loss of sight of the individuals because of the deposits of micro-anuerysms, hard exudates, and neo vascularization in the area of retina. Convolution Neural Network (CNN) which is based on deep learning provides a promising approach for the classification of the retinal images based on the level of severity as suggested by the medical professionals. Inception V3 model is employed to train the images for efficient classification of the retinal images with maximum accuracy.

***Keywords* — diabetic retinopathy, deep learning, convolution neural networks, hyper parameter tuning**

--************************----------------------------------

I. INTRODUCTION

Diabetic mellitus is a serious health issue among many individuals and it results in the increase of the blood glucose level for a long period of time and it is going to affect a lot more people in the upcoming decade. Diabetic mellitus can slowly affect the retinal area and can cause Diabetic Retinopathy (DR) due to the increase in the level of glucose in the blood vessels. So it is important to classify the severity of the Diabetic Retinopathy based on the scales plotted before by the International Clinical Diabetic Retinopathy and Diabetic Macular Edma Disease Severity Scales, categorized by Wilkinson in 2003 for the classification of the retinopathy into five stages, which are 1.No Diabetic Retinopathy (Stage 1) 2.Mild Non-proliferate Diabetic Retinopathy (NPDR)(Stage2) 3. Moderate level of NPDR (Stage 3) 4. High level of NPDR (Stage 4) and 5. Proliferative DR (Stage 5). This is how the stages of the Diabetic Retinopathy are being classified.

Diabetic Retinopathy(DR) is an important classification technique to identify Diabetic Mellitus and other stages of Retinopathy. The efficient classification of the Diabetic Retinopathy involves the image analysis based technique to classify the images from the dataset effectively and the main goal of the paper is to classify the images accurately when compared to the other previous classification techniques and this can be done only by tuning the Hyper-parameters. Since the classification has attained an ample amount of accuracy its performance can be stepped up by tuning hyper-parameters. Initially, the classification of the image is done with the deep learning Convolution Neural Networks(CNN). It is the most effective and predominant image classification technique and it has been employed in various image classifications like lung failure detection, pattern identification classification, breast cancer identification and to identify the proteins from the skin lesions, etc. Various experiments have been made in the past for the classifiers and their development. There has been various Deep Learning Convolution Neural Network architecture for the classification of the DR stages and after analyzing various architectures we found out that the best outcome comes from the Inception V3 architecture and we have used almost around 4000 images from the Kaggle dataset which is open-sourced and it almost contains around 31,000 image dataset which is of high resolution and the pre-processing steps can be reduced since the quality of the images is of Higher standards which are of greater advantage and we have chosen some hyper-parameters like bandwidth, dropout to improve its efficiency and we have also applied various optimizers to check for the classification accuracy changes. The result is the improved classification of the images based on the severity scales by tuning the chosen and the identified hyper-parameters.

II. METHOD

The Neural networks are the efficient method for image classification and it has proven to be the best technique. With the name convolution it has to be clearly understood that it extract features from the input images by separating or cropping the images into a particular sized matrix and it extracts various features and analysis are to be done in it. Some examples are detection of edges, Sharpening and blurring are to be identified. Followed by convolution it also introduces non-linearity and sub-sampling in which non-linearity is achieved through the ReLU which is nothing but Rectified Linear Unit which makes the negative pixels in the matrixed images to Zero and this way it introduces Non-linearity. The next step is the pooling or the sub sampling which is to reduce the dimensionality of the extracted feature which is nothing but to retain the necessary information and neglecting all the other information which are unnecessary then with the neural networks a lot more layers are added in between to improve the efficiency to perform classification of the images.

In this paper we are going to see the architecture of VGG16 and Inception V3 models on its classification of the images and the hyper-paramter tuning of the selected parameters and their changes in classification after tuning.

A. VGG16

VGG16 is an architecture of CNN and it contains 16 layers and hence the name VGG16. The main advantage of the VGG16 architecture is its ability to construct the hidden layers effectively.Here there are 13 convolution layers, 5 max pooling layers and 3 dense layers which totally comes up with 21 layers but it has only 16 weighted layers to gain the output. The main drawback of the VGG16 is its own weightage of the layers which are completely connected and thus increases the training duration of the dataset and similar to VGG16 there is also another architecture called VGG19 which consists of 19 weighted layers.

B. INCEPTIONV3

Inception Net architecture comes out with extracting multiple feature from the same networks like 1x1, 3x3, 5x5 convolutions and the output from the convolutions are stacked up before it is fed up to the next upcoming layers. Inception layers are originally obtained from the GoogleNet and it is to be called as Inception vN where N is the number given officially after further improvement in the architecture. The main advantage of the architecture is its low weightage of the layers when compared with other architectures like VGG16 and ResNet and hence it is best to be used for the classification of the images.

C. DATASET

The dataset consists of almost 31,000 images which are taken from the Kaggle dataset. All the images consists of all the possibilities of the severity scales. The images are open sourced and can be easily accessed. The images are taken from various sources with different pixel density and with various lightning conditions. Hence with such larger dataset, requires larger computational power so we have taken 4000 images with mixed possibilities of the scenario and performed the classification procedures.

D. HYPERPARAMETER TUNING

The CNN is trained and it can be able to classify the images based on the severity scales. Hence in order to increase the performance of the classification task, we have choosen the two hyper parameters namely bandwidth and dropout and fine tuned the parameters to increase the efficiency. Then we have varied the batch size in between the trainings and also we tried changing the number of epochs to get the changes in the accuracy of classification.

E. PERFORMANCE

From classifying the images with respect to the five classifiers by using different architectures like VGG16 and Inception V3 we get the accuracy of the classification. We got an accuracy of 71.44 % on using both the architectures. But since the computational and the efficiency is more in Inception V3 we made the final classification on InceptionNet and obtained this accuracy which is much more better results when compared with the previous classification of the images.

III. DISCUSSIONS

The Accuracy thus obtained after the classification is better than the other classifications and this improvement may be because of various factors that has been implemented starting from varying the hyperparameter values and thus tuning it in a better way for their improvement and more efforts are also done in changing the optimizers like adagrad, adamax and SGD are used respectively for the betterment of the classification and by changing these optimizers the changes in the results are minimum and there is no much difference between the results. Several more layers are added additionally along with the InceptionNet layers and this process is done to enhance the learning process and improving its efficiency and these changes consecutively added up together to show up with the good classification results. Even the experts find it difficult to find out the retinopathy and this would definitely bring up with the good results and would be helpful for the medical society.

FUTURE WORK

Here for the classification of the images Convolution Neural Networks (CNN) are used and may be we can improve it with some other image classification techniques if it is needed and to identify some other hyper parameters that adversely affect the performance of the classification.

ACKNOWLEDGMENT

I would like to thank Dr.R.Thangarajan, who has guided us throughout the project and helped us in solving various issues related in choosing the best architecture for classification and other performance metrics and I would also thank the institution in giving us the great opportunity to take up the project and made us to give our contribution towards the machine learning society.

REFERENCES

[1] G. Danaei, M. M. Finucane, Y. Lu, G. M. Singh, M. J. Cowan, C. J. Paciorek, J. K. Lin, F. Farzadfar, Y.-H. Khang, G. A. Stevens, M. Rao, M. K. Ali, L. M. Riley, C. A. Robinson, and M. Ezzati, "National, regional, and global trends in fasting plasma glucose and diabetes prevalence since 1980: systematic analysis of health examination surveys and epidemiological studies with 370 country-years and 2·7 million participants," The Lancet, vol. 378, issue 9785, 2011, pp. 31-40.

[2] L. Wu, P. Fernandez-Loaiza, J. Sauma, E. Hernandez-Bogantes, and M. Masis, "Classification of diabetic retinopathy and diabetic macular edema," World Journal of Diabetes, vol. 4, issue 6, Dec. 2013, pp. 290-294.

[3] C. P. Wilkinson, F. L. Ferris, R. E. Klein, P. P. Lee, C. D. Agardh, M.

Davis, D. Dills, A. Kampik, R. Pararajasegaram, J. T. Verdaguer, and G. D. R. P. Group, "Proposed international clinical diabetic retinopathy and diabetic macular edema disease severity scales," Ophthalmology, vol. 110, issue 9, Sep. 2003, pp. 1677-1682.

[4] T. Y. Wong, C. M. G. Cheung, M. Larsen, S. Sharma, and R. Simó, "Diabetic retinopathy," Nature Reviews Disease Primers, vol. 2, Mar. 2016, pp. 1-16.

[5] H. Zhong, W.-B. Chen, and C. Zhang, "Classifying fruit fly early embryonic developmental stage based on embryo in situ hybridization images," in Proceedings of IEEE International Conference on Semantic Computing (ICSC 2009), IEEE, Sep. 2009, pp. 145-152.

[6] J. D. Osborne, S. Gao, W.-B. Chen, A. Andea, and C. Zhang, "Machine classification of melanoma and nevi from skin lesions," in Proceedings of the 2011 ACM Symposium on Applied Computing (SAC 2011), ACM, Mar. 2011, pp. 100-105.

[7] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. W. M. van der Laak, B. van Ginneken, and C. I. Sánchez, "A survey on deep learning in medical image analysis," Medical image analysis, vol. 42, Dec. 2017, pp. 60-88.

[8] M. Anthimopoulos, S. Christodoulidis, L. Ebner, A. Christe, S. Mougiakakou, "Lung pattern classification for interstitial lung diseases using a deep convolutional neural network," IEEE transactions on medical imaging, vol. 35, issue 5, May 2016, pp. 1207-1216.

[9] A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, and S. Thrun, "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, issue 7639, Feb. 2017, pp.115-118.