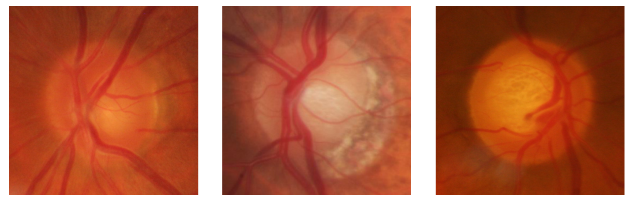
Transfer Learning for Early and Advanced Glaucoma Detection with Convolutional Neural Networks

Ali Serener
Electrical and Electronic Engineering
Near East University
Nicosia, Cyprus
ali.serener@neu.edu.tr

Sertan Serte
Electrical and Electronic Engineering
Near East University
Nicosia, Cyprus
sertan.serte@neu.edu.tr

***Abstract*—Glaucoma affects millions of people worldwide and is an eye disease that can lead to vision loss if left untreated. Open-angle glaucoma is the most common type and gradually leads to vision deterioration without many early warning signs or painful symptoms. Clinical diagnosis of glaucoma by specialists is possible but the methods used are either expensive or takes a lot of time. This paper presents automatic detection of early and advanced glaucoma using fundus images. ResNet-50 and GoogLeNet deep convolutional neural network algorithms are trained and fine-tuned using transfer learning for classification. It is shown that GoogLeNet model outperforms ResNet-50 for the detection of early as well as advanced glaucoma detection.**

Keywords—deep learning, fundus images, glaucoma, histogram equalization, transfer learning.



(a) No glaucoma (b) Early glaucoma (c) Advanced glaucoma

Fig. 1: Sample normal, early and advanced glaucoma images

I. INTRODUCTION

Glaucoma is a chronic eye disease that occurs as a result of optic nerve damage due to intraocular pressure inside the eye. It is estimated that by 2020 glaucoma will affect around 80 million people around the world [1]. In the early stages of glaucoma, there are no vision loss symptoms but as it gradually progresses it can lead to irreversible blindness. Besides vision loss, high intraocular pressure and optic nerve damage, a large cup-to-disc ratio is also another indication of glaucoma. Even though there is no cure, vision deterioration may be controlled with early treatment.

Glaucoma diagnosis in the clinical environment involves intraocular pressure measurement, visual-field testing or optic disk examination on fundus images. Even though intraocular pressure is an indication of glaucoma, its measurement is not an effective way of glaucoma diagnoses as some patients with glaucoma may have normal eye pressure. Visual-field testing, on the other hand, requires special equipment that some clinics may not have. The last method, optic disk examination, is more convenient than the other two and is more widely used by specialists for early glaucoma detection. Still, it bears the disadvantages that it is costly and time-consuming.

The fact that there are millions of people around the world diagnosed with glaucoma led researchers to investigate the automatic detection of glaucoma. With the introduction of deep convolutional neural networks such as AlexNet [2], GoogLeNet [3], [4], VGG [5], ResNet [6] and DenseNet [7], researchers have attempted to use them for glaucoma diagnosis. Their research focused mainly on two areas. The first included using deep learning for feature extraction and the second involved the use of domain knowledge and medical features for detection.

Inspired by this, this paper uses deep learning techniques to classify early and advanced glaucoma on fundus images with the help of transfer learning. The datasets used contains normal as well as early and advanced glaucoma images. A sample image for each category is shown in Figure 1. A fifty layer ResNet as well as a GoogLeNet deep learning architecture are used for the classifications. To overcome the disadvantage of having a small number of images in the testing dataset, training is first performed on a different dataset and transfer learning is used to detect the glaucomatous fundus images.

The organization of this paper is as follows. First, recent advances in glaucoma classification using convolutional neural networks are given. Then, ResNet and GoogLeNet deep learning model and dataset details are explained. Finally, the performance of these models are evaluated for two different classifications and the results are analyzed and discussed.

II. RELATED WORK

Several recent studies have used convolutional neural networks to classify glaucoma. Among them, Ahn et al. [8] investigated the performance of early and advanced glaucoma detection of fundus images with the help of a GoogleNet Inception model and a newly created convolutional neural network model. Chen et al. [9] used deep learning, along with dropout and data augmentation techniques, to detect glaucoma on two fundus datasets. In [10], feature extractions of fundus images were done using convolutional neural networks and images were classified into normal and glaucomatous types using an SVM classifier. Fu et al. [11] proposed a disc-aware ensemble network for automatic glaucoma screening by combining fundus image's deep hierarchical context and the local optic disc region. Li et al. [12] presented the performance of a deep learning algorithm to detect referable glaucomatous optic neuropathy on fundus images. In [13], fundus images of racially and ethnically diverse people and a few deep learning architectures were used to detect glaucomatous optic neuropathy. Shibata et al. [14] developed a deep learning algorithm to look for glaucoma on fundus images and compared the results to three ophthalmologists. Orlando et al. [15] pre-trained convolutional neural networks on non-medical data to detect glaucoma on a fundus dataset. Sevastopolsky [16] utilized deep learning for automatic optic disc and cup segmentation of eye fundus images to classify glaucoma. A glaucoma detection system was developed in [17] to first extract the necessary features using convolutional networks and then most discriminative features were selected to be fed to softmax linear classifier to detect glaucoma on retinal fundus images. Asaoka et al. [18] used a deep feed-forward neural network classifier to distinguish between preperimetric glaucoma visual fields and healthy visual fields. Chakravarty [19] segmented optic disc-optic cup using a multi-task convolutional neural network to predict the existence of glaucoma in fundus images. In [20], domain knowledge and retinal fundus images were combined using a deep learning model to automatically diagnose glaucoma. Chen et al. [21] captured the discriminative features using a deep learning architecture to characterize patterns related to glaucoma. A curriculum learning method and a multi-stage deep learning model were used in [22] to diagnose glaucoma. In [23], glaucoma was detected using a multi-model deep learning framework that included a deep convolutional autoencoder and a traditional convolutional neural network classifier.

The aim of this paper is to use deep convolutional neural networks to detect early and advanced stages of glaucoma on fundus images. It is vital especially to catch the eye disease at its early stages for timely treatment. If gone undetected at the early stages, an advanced stage treatment is also crucial to prevent further vision loss that may lead to blindness.

III. METHOD

A. Preprocessing

All fundus images are histogram equalized, as shown in Figure 2. Each image is decomposed into blue, red and green channels. After that histogram equalization is applied to each of the channels. Finally, histogram equalized channels are merged in order to obtain 256×256×3 images.

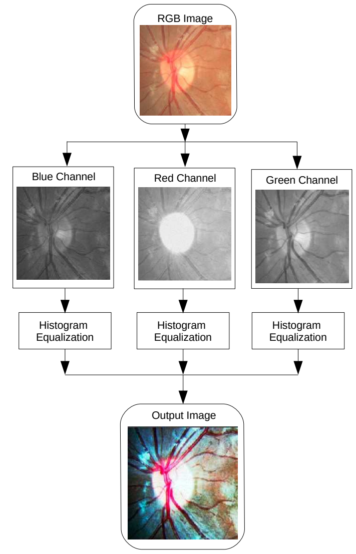


Fig. 2: Preprocessing for glaucoma detection.

B. Classification

The classifications of early and advanced glaucoma stages are done using fifty layer ResNet and GoogLeNet convolutional networks. Approximately one million images of ImageNet dataset are used to pre-train these models. With such a high number of images, the network parameters will be well established.

The fundus images used in this work have the three categories of no glaucoma (healthy), early glaucoma and advanced glaucoma. In order to adjust their parameters, a total of 5430 augmented images are used for training the pre-trained deep learning models. Then, transfer learning is performed to fine-tune these models to detect two classes of glaucoma.

The testing is done using 144 images and a probabilistic estimate of each class is calculated when each image is inputted to already tuned models. Finally, the images are classified using the class with the highest probability.

IV. IMPLEMENTATION

For training, ResNet-50 and GoogLeNet architectures are used. The training for these models are done using a single NVIDIA GeForce GTX 1080Ti GPU running a Caffe deep learning framework.

V. DATASET

We used the public image dataset of [8] to train the deep learning systems. There are 1544 fundus images in this dataset, 788 of which in no glaucoma (healthy) category, 289 in early glaucoma category and 467 in advanced glaucoma category (see Table I). As the number of images in the training dataset is small, data augmentation is carried out to obtain another set of images. Table II lists the number of images in each category after augmentation.

For performance evaluation, public RIM-ONE dataset version one [24] was used. This dataset contains 158 images which are categorized as no glaucoma (healthy), early glaucoma, moderate glaucoma and advanced glaucoma (deep glaucoma in [24]). Each category has 118, 12, 14 and 14 images, respectively. Note that moderate glaucoma category of [24] was not used here and is not included in this table (see Table III). All images have been resized to 256×256×3.

VI. PERFORMANCE EVALUATION

To evaluate the performance of the deep learning methods, two classifications are performed for each. The first classification is the detection of early glaucoma and for this, both

(a) Early Glaucoma

(b) Advanced Glaucoma

Fig. 3: ROC curve comparison of early and advanced glaucoma detection.

Table I: Details of dataset given in [8].

Glaucoma Type	No. of Images
No Glaucoma	788
Early Glaucoma	289
Advanced Glaucoma	467
Total	1544

Table II: Dataset given in [8] after augmentation.

Glaucoma Type	No. of Images
No Glaucoma	1656
Early Glaucoma	1818
Advanced Glaucoma	1956
Total	5430

Table III: RIM-ONE dataset details.

Glaucoma Type	No. of Images
No Glaucoma	118
Early Glaucoma	12
Advanced Glaucoma	14
Total	144

ResNet and GoogLeNet models have been used. The second classification is advanced glaucoma detection and again the same two deep learning models are used. Each model has been trained using the dataset given in [8] and then tested on RIM-ONE dataset.

The performance of early glaucoma detection is evaluated by calculating the area under the receiver operating characteristic (ROC) curve (E-AUC), accuracy (E-ACC), sensitivity (E-SE), and specificity (E-SP) parameters. Similarly, the area under the ROC curve (A-AUC), accuracy (A-ACC), sensitivity (A-SE), and specificity (A-SP) parameters are calculated for advanced glaucoma detection. The average area under the ROC curve (AVG-AUC) is also calculated for early and advanced glaucoma detection.

A. *Early Glaucoma Classification*

The detection of early glaucoma is performed using ResNet and GoogLeNet models. These models are trained with 289 early glaucoma fundus images of [8]. Testing is carried out on 12 early glaucoma fundus images of RIM-ONE dataset.

For this classification, the accuracy of the ResNet-50 model is 0.90, the sensitivity is 0.42, the specificity is 0.94 and the area under the ROC curve is 0.84. For the GoogLeNet model, the accuracy is 0.91, the sensitivity is 0.17, the specificity is 0.98 and the area under the ROC curve is 0.91. These results are tabulated in Table IV.

Figure 3a shows the ROC curves of early glaucoma classifications. It is observed here that GoogLeNet has a higher AUC than ResNet-50.

B. *Advanced Glaucoma Classification*

Besides early glaucoma classification, the two deep learning models are used to analyze the classification performance of advanced glaucoma on fundus images. For this, 467 advanced glaucoma images of [8] are used to train the models and 14 advanced glaucoma images of RIM-ONE dataset are used to test them.

The accuracy performance of this classification for ResNet-50 is 0.86, the sensitivity is 0.21, the specificity is 0.93 and the area under the ROC curve is 0.74. On the other hand, the performance accuracy of this classification for the GoogLeNet model is 0.85, the sensitivity is 0.29, the specificity is 0.91 and the area under the ROC curve is 0.75. Table IV lists these results.

Figure 3b shows the ROC curves of advanced glaucoma classifications. It can be seen here that the AUC is almost the same for both deep learning models.

VII. DISCUSSIONS

Fundus images are used for automated detection of early and advanced glaucoma. The images are first trained using the dataset of [8], Then, two deep learning models, namely

Table IV: Performance comparison of the deep learning methods.

Network	AVG-AUG	E-AUC	E-ACC	E-SE	E-SP	A-AUC	A-ACC	A-SE	A-SP
ResNet-50	0.79	0.84	0.90	0.42	0.94	0.74	0.86	0.21	0.93
GoogLeNet	0.83	0.91	0.91	0.17	0.98	0.75	0.85	0.29	0.91

ResNet-50 and GoogLeNet, are utilized to test the performance of these models on RIM-ONE dataset. As the number of images in the RIM-ONE dataset is small, transfer learning is used. Performance results show that for early glaucoma classification, accuracy, specificity and the area under the ROC curve results of GoogLeNet model are better than ResNet-50 model results. However, for advanced glaucoma classification, only sensitivity and the area under the ROC curve results of GoogLeNet architecture are better. If we consider the overall performance of these two models and thus take into account the average area under the ROC curve results, we see that GoogLeNet model has performed better than ResNet-50 model for early as well as advanced glaucoma detection. Notice that there is a performance trade-off between sensitivity and specificity values [25].

VIII. CONCLUSIONS

Early and advanced glaucoma classifications are performed on fundus images using two deep learning methods, ResNet-50 and GoogLeNet. The performances of the two models are evaluated in terms of accuracy, sensitivity, specificity and the area under the ROC curve. The results show that for early, advanced as well as overall glaucoma detection GoogLeNet outperforms ResNet-50.

REFERENCES

[1] H. A. Quigley and A. T. Broman, "The number of people with glaucoma worldwide in 2010 and 2020," *British journal of ophthalmology*, vol. 90, no. 3, pp. 262–267, 2006.

[2] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in neural information processing systems*, pp. 1097–1105, 2012.

[3] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1–9, 2015.

[4] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2818–2826, 2016.

[5] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.

[6] S. Targ, D. Almeida, and K. Lyman, "Resnet in resnet: Generalizing residual architectures," *arXiv preprint arXiv:1603.08029*, 2016.

[7] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4700–4708, 2017.

[8] J. M. Ahn, S. Kim, K.-S. Ahn, S.-H. Cho, K. B. Lee, and U. S. Kim, "A deep learning model for the detection of both advanced and early glaucoma using fundus photography," *PloS one*, vol. 13, no. 11, p. e0207982, 2018.

[9] X. Chen, Y. Xu, D. W. K. Wong, T. Y. Wong, and J. Liu, "Glaucoma detection based on deep convolutional neural network," in *2015 37th annual international conference of the IEEE engineering in medicine and biology society (EMBC)*, pp. 715–718, IEEE, 2015.

[10] B. Al-Bander, W. Al-Nuaimy, M. A. Al-Taee, and Y. Zheng, "Automated glaucoma diagnosis using deep learning approach," in *2017 14th International Multi-Conference on Systems, Signals & Devices (SSD)*, pp. 207–210, IEEE, 2017.

[11] H. Fu, J. Cheng, Y. Xu, C. Zhang, D. W. K. Wong, J. Liu, and X. Cao, "Disc-aware ensemble network for glaucoma screening from fundus image," *IEEE transactions on medical imaging*, vol. 37, no. 11, pp. 2493–2501, 2018.

[12] Z. Li, Y. He, S. Keel, W. Meng, R. T. Chang, and M. He, "Efficacy of a deep learning system for detecting glaucomatous optic neuropathy based on color fundus photographs," *Ophthalmology*, vol. 125, no. 8, pp. 1199–1206, 2018.

[13] M. Christopher, A. Belghith, C. Bowd, J. A. Proudfoot, M. H. Goldbaum, R. N. Weinreb, C. A. Girkin, J. M. Liebmann, and L. M. Zangwill, "Performance of deep learning architectures and transfer learning for detecting glaucomatous optic neuropathy in fundus photographs," *Scientific reports*, vol. 8, no. 1, p. 16685, 2018.

[14] N. Shibata, M. Tanito, K. Mitsuhashi, Y. Fujino, M. Matsuura, H. Murata, and R. Asaoka, "Development of a deep residual learning algorithm to screen for glaucoma from fundus photography," *Scientific reports*, vol. 8, no. 1, p. 14665, 2018.

[15] J. I. Orlando, E. Prokofyeva, M. del Fresno, and M. B. Blaschko, "Convolutional neural network transfer for automated glaucoma identification," in *12th International Symposium on Medical Information Processing and Analysis*, vol. 10160, p. 101600U, International Society for Optics and Photonics, 2017.

[16] A. Sevastopolsky, "Optic disc and cup segmentation methods for glaucoma detection with modification of u-net convolutional neural network," *Pattern Recognition and Image Analysis*, vol. 27, no. 3, pp. 618–624, 2017.

[17] Q. Abbas, "Glaucoma-deep: detection of glaucoma eye disease on retinal fundus images using deep learning," *Int J Adv Comput Sci Appl*, vol. 8, no. 6, pp. 41–5, 2017.

[18] R. Asaoka, H. Murata, A. Iwase, and M. Araie, "Detecting preperimetric glaucoma with standard automated perimetry using a deep learning classifier," *Ophthalmology*, vol. 123, no. 9, pp. 1974–1980, 2016.

[19] A. Chakravarty and J. Sivswamy, "A deep learning based joint segmentation and classification framework for glaucoma assesment in retinal color fundus images," *arXiv preprint arXiv:1808.01355*, 2018.

[20] Y. Chai, H. Liu, and J. Xu, "Glaucoma diagnosis based on both hidden features and domain knowledge through deep learning models," *Knowledge-Based Systems*, vol. 161, pp. 147–156, 2018.

[21] X. Chen, Y. Xu, S. Yan, D. W. K. Wong, T. Y. Wong, and J. Liu, "Automatic feature learning for glaucoma detection based on deep learning," in *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pp. 669–677, Springer, 2015.

[22] O. Perdomo, V. Andrearczyk, F. Meriaudeau, H. Müller, and F. A. González, "Glaucoma diagnosis from eye fundus images based on deep morphometric feature estimation," in *Computational pathology and ophthalmic medical image analysis*, pp. 319–327, Springer, 2018.

[23] A. Pal, M. R. Moorthy, and A. Shahina, "G-eyenet: A convolutional autoencoding classifier framework for the detection of glaucoma from retinal fundus images," in *2018 25th IEEE International Conference on Image Processing (ICIP)*, pp. 2775–2779, IEEE, 2018.

[24] F. Fumero, S. Alayón, J. L. Sanchez, J. Sigut, and M. Gonzalez-Hernandez, "Rim-one: An open retinal image database for optic nerve evaluation," in *2011 24th international symposium on computer-based medical systems (CBMS)*, pp. 1–6, IEEE, 2011.

[25] A. D Fleming, S. Philip, K. A Goatman, G. J Prescott, P. F Sharp, and J. A Olson, "The evidence for automated grading in diabetic retinopathy screening," *Current Diabetes Reviews*, vol. 7, no. 4, pp. 246–252, 2011.