A Self-Supervised approach for Glaucoma Screening

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Glaucoma is one of the leading causes of blindness in the world today. Early diagnosis and treatment of the same can prevent blindness. The Artificial Intelligence for RObust Glaucoma Screening(AIRGOS) challenge is organised to develop a solution for glaucoma screening from Colour Fundus Photography(CFP). As part of the challenge, we present two algorithms for 1). Ungardability prediction, 2). Referable glaucoma(RG) and No referable glaucoma(NRG) classification. The proposed method includes an unsupervised learning technique for grading the retinal fundus images and a supervised approach for classifying fundus images as RG or NRG with class imbalance problems considered. From the preliminary test phase result, the approach gives comparable results for the glaucoma screening performance and robustness.

AIROGS, Glaucoma, Fundus Images, One Class Classification, Supervised Learning, ResNet18

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Introduction

Glaucoma is one of the most significant causes of permanent vision loss worldwide. It has no clear symptoms at the early stage of the disease. It is characterised by worsening of the optical nerve head as well as ganglion cells in the retina. This is developed due to the blockage of the flow of aqueous humor through the eye canal resulting in increased pressure inside the eye chamber which in turn increases the size of the optic cup and damages the fibers on the optic head. This gradually reduces the vision of the patient. The only remedy to prevent vision loss is early detection and timely treatment. Once the patient lost his vision it cannot be recovered. The diagnosis of glaucoma is mainly done on the basis of three methods.

1. Intraocular Pressure Meaurement(IPM)
2. Function based Visual Field Test.
3. Optic Nerve Head(ONH).

Among these methods, ONH examination is the most efficient method for detecting glaucoma in the early stages. This technique uses various morphological parameters such as vertical cup to disc ratio(CDR), Edge to disc ratio(EDR), Neuro retinal Border Ratio(NBR), and disc diameter to detect glaucoma on retinal fundus images. [1]
The AIROGS Challenge is hosted as a part of the International Symposium on Biomedical Imaging (ISBI) 2022. The main aim of the challenge is to develop a robust algorithm for screening glaucoma from Colour Fundus Photography(CFP). In our algorithm, we present a one class classification model with ResNet-18 architecture inspired by the idea of [2] and [3] for grading the retinal fundus images. For classification modified ResNet-18 architecture is taken as a backbone network and class imbalance of the dataset is also taken into account using focal loss.

Material and Methods

In the following section, we detail the dataset we used and the methodology of our algorithm.

Dataset. The Rotterdam EyePACS AIROGS dataset [4] contains 113,893 CFP images from 60,357 subjects and 500 different sites with a heterogeneous ethnicity. All image are labelled as referable glaucoma, no referable glaucoma or ungradable.
The training subset consists of 102,000 gradable images. The test subset consists of 11,000 gradable and ungradable images.
In order to increase the robustness of the algorithm, the training set is provided only with gradable images and ungradable images are excluded. In the test phase all image types acquired during screening will be included, simulating a real-world scenario. The participants are not allowed to download the test dataset. The preliminary test phase contains only 10% of the final test dataset.

Quality assessment of Fundus images using Self supervised learning method. For classifying the fundus image as gradable and ungradable, inspired by the work of [2] where a one class classification method was presented for unsupervised anomaly detection. The one class classifier builds a feature space by extracting the features of the training sample which contain only the positive samples(gradable images). The challenge training set includes only gradable images. Classifying the test samples as gradable and ungradable images is done based on their feature space position. For our network, we used a ResNet-18 backbone trained on Fundus image datasets from the Rotterdam EyePACS AIROGS dataset. Fig. 1 schematically visualizes the proposed model architecture.

Glaucoma screening. Glaucoma screening is achieved by classifying the dataset as referable glaucoma and no referable

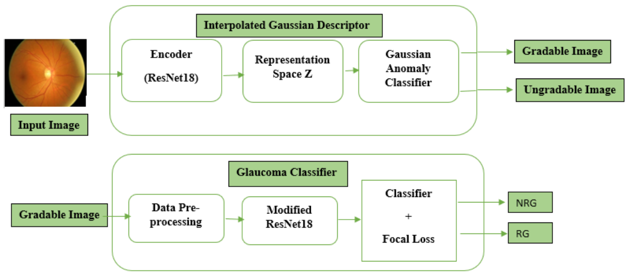

Fig. 1. Proposed Model Architecture.

glaucoma. The training dataset consists of 98172 non referable glaucoma images and 3270 referable glaucoma images. Dataset suffers class imbalance problem. To eliminate the barrier between classes, we have added a Focal Loss function [5]to the model to resolve the class imbalance problem. For our binary classifier, we use ResNet-50 as a backbone network. For the network, we initialised our network with the weights from the ImageNet dataset and train the whole network with the Rotterdam EyePACS AIROGS train dataset. Fig. 1 schematically visualizes the proposed model architecture.

Network Training. For the Glaucoma screening process, we split our train data set into training and validation sets. The training set consists of 97172 non referable images and 3070 referable images and the validation set consist of 1000 non-referable images and 200 referable images. For network training, we used an image size of 512 $\times$ 512 pixels and a batch size of 256. In our algorithm, the focal loss has been used as a classification loss in the Glaucoma screening process to overcome the class imbalance problem inspired by the work of [5]. We trained the network for 300 epochs until convergence. For grading fundus images self-supervised learning technique is used. Training dataset consists of 95442 images including both NRG and RG images(gradable) and 6000 for testing(gradable). The network was trained for 50 epochs with batch size 32,image size of 256 $\times$ 256 pixels and learning rate 1e-4.

Evaluation and Results

The AIROGS challenge evaluation is based on two aspects Glaucoma screening performance and robustness. Glaucoma classification performance is evaluated using the partial area under the receiver operator characteristic curve (90 - 100% specificity) for referable glaucoma(α) and sensitivity at 95% specificity (β). The screening performance metrics are based on these specificity ranges. The agreement between the reference and the decisions on image gradability is measured using Cohen's Kappa Score.The area under receiver operator characteristic curve is determined using the human reference for ungradability as the true label and ungradability scalar value by prediction as target score.
The results of the preliminary test phase 2 of our model were the screening sensitivity was 0.75625, screening partial AUC was 0.8380, the ungradability Kappa score was 0.3295, and the ungradability AUC was 0.7801.

Discussion and Conclusion

In this work, we presented our baseline algorithm for the AIROGS challenge, based on the Supervised and self-supervised training methods. The preliminary test phase result of the algorithm is included in the Evaluation and Result Section. The final test phase result will be available in "https://airogs.grand-challenge.org/evaluation/final-test-phase/leaderboard/" after the deadline of the challenge.

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