MULTI-LABEL CLASSIFICATION OF RETINAL DISEASES USING CONVOLUTIONAL NEURAL NETWORKS

Yuriy Bidochko
Penn-Trafford High School
MehtA+ Bootcamp

Grace Choi
Bloomington High School South
MehtA+ Bootcamp

William Wu
Monta Vista High School
MehtA+ Bootcamp

Mushfiquzzaman Mahim
Dhaka Residential Model College
MehtA+ Bootcamp

July 28, 2022

ABSTRACT

Globally over 25% of the world has vision problems, particularly in the developing world. To combat this issue, we present a multi-class classification machine learning model that recognizes 4 different eye retinal conditions, diabetic retinopathy, age-related macular degeneration, drusen, and retinal occlusion as well as healthy retinas. It is important to diagnose these diseases early on to reduce a patient's risk of losing their vision and becoming blind. But compounded with the fact that the need for ophthalmologists is increasing yet human diagnosis takes time, we present an alternative method for detection. We looked at two pretrained convolutional neural networks (CNNs) which were VGG-16 and ResNet-18. The model was trained on over 2,000 color retinal fundus images that came from a combination of four separate datasets. Through experimenting, our model eventually achieved a 94% validation accuracy. Thus, our model holds promise as an efficient way to identify retinal diseases.

1 Introduction

According to WHO's 2019 World Report on Vision, at least 2.2 billion people globally have a vision impairment but for half of those people, their condition hasn't been addressed yet or could have been prevented. [1] In regards to vision impairment, retinal diseases are the leading cause of blindness. Just in the United States alone, there are over 7.2 million cases of diabetic retinopathy, a condition where the retina swells after blood vessels break in association with diabetes, and over 2.1 million cases of age-related macular degeneration which occurs when the retina center deteriorates to a blind spot or blurred vision. [2, 3]. Another example is drusen, where lipid and protein deposits under the retina. [4]

Beyond their prevalence and causation of blindness, retinal diseases such as retinal occlusions where blood vessels to the retina are obstructed can double the chance for cardiovascular morbidity in diabetic patients. [5] Thus, combined with their pervasiveness and ability to damage a person's health, diagnosis and detection especially early is crucial for giving patients the treatment they need.

Unfortunately, in the US, there are about 32 ophthalmologists per 1,000,000 people, meaning that the need for more ophthalmologists is ever-increasing. [6] Currently, a large portion of retinal diseases can be detected using color retinal fundus imaging. However, if analyzed by a human being, each retinal image is time-consuming, often taking over 15 minutes for each diagnosis. [7] Therefore, this project aims to use machine learning to diagnose retinal diseases from color fundus imaging in a quick, efficient, and accurate manner.

2 Related Work

Machine learning has become well used to diagnose various diseases using image recognition such as for melanoma, a skin cancer, tumors and chest x-rays. Specifically for retinal diseases, previous groups have worked with machine learning and computer vision to diagnose single conditions like just diabetic retinopathy. [8] Other projects have worked on diagnosing a variety of eye conditions from different types of images.

However, some groups have conducted research similar to our model. Another research paper was published on detecting multiple diseases from a single database of retinal fundus images with convolution neural networks. [9] With a combination of data collected from a variety of sources and data augmentation, they were ultimately able to identify 19 diseases at the cost of having a slightly lower model accuracy. Our project is similar as we also use retinal fundus imaging and convolution neural networks, but instead, we used a different combined dataset.

3 Methodology

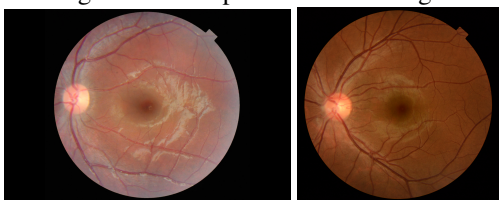
3.1 Dataset

To train the model, a dataset of color retinal fundus images was created from a combination of four existing databases:

- STARE - 400 images from Clemson University containing 14 disease classes [10]
- RIDB - 100 images of normal retinas from 20 subjects [11]
- JSIEC - 104 select images of normal, branch retinal vein occlusion, and central retinal vein occlusion retinas from Joint Shantou International Eye Center [12]
- RFMiD - 1920 images of 46 disease classes [13]

With the selected images in JSIEC, all of the images were not used, but for all other datasets, all images that were accessible were used. The total number of images was 2,524. Since this number was large enough, we felt it was adequate to not have to augment our data. All of these databases were publicly accessible.

Figure 1: Examples of Retina Images



The retina on the left is an unhealthy retina from the RFMiD dataset and the one on the right is a normal retina from the JSIEC dataset.

3.2 Data Processing

The procedure for data processing after obtaining the data is as follows:

Table 1: Data Processing

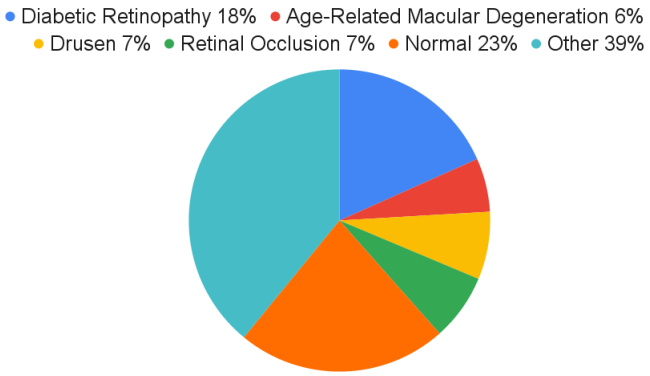
Step	Description
Fixing Typos	Extra capitalizations, characters such as quotes, and redundant entries were modified
Label	Each image was given its corresponding condition label vector
Drop Columns	Additional columns were dropped from the datasheet
Add File Path	Each image's file path was entered to its condition label

With the data obtained and ready to be processed, the first step involved fixing typos. Such errors fell under three main categories which were extra capitalizations like "Macroaneurysm" versus "MacroAneuroysm", additional characters like quotation marks at the end of disease condition entries, and redundant category names. For example, retinitis and retinitis pigmentosa were included separately. Other similar entries we combined were branch retinal vein occlusion

(BRVO), central retinal vein occlusion (CRVO), and retinal artery occlusions (RAO), simply into a single retinal occlusion category. Background diabetic retinopathy and background proliferative diabetic retinopathy were merged into a less specific category — diabetic retinopathy as well. Once the data was fixed, we moved onto to adding labels.

When we looked at the image totals for each category, we had very few images, so with the exception of four main disease conditions with normal, all of the images were combined under a "Other Disease" category. Thus, the classes are diabetic retinopathy, age-related macular degeneration, drusen, retinal occlusion, normal, and other diseases. From these categories, a label was created for each image following the class category in the previous sentence, in the order of diabetic retinopathy, age-related macular degeneration, drusen, retinal occlusion, and normal. A "1" denotes that the condition is present, and a "0" represents that the condition is absent. For example, a normal image can be represented as [0, 0, 0, 0, 1] while an other disease image would be written [0, 0, 0, 0, 0]. In total, the class distribution looks as the following image.

Figure 2: Data Distribution Between Classes



Next, all other columns in the datasheets that came with the datasets were dropped since we established labels for each image. Finally, all the information the model needs to diagnose is the image itself, so all other data feature columns were dropped. Then, the file paths for each image was mapped into the datasheet. There was no need to insert the actual image itself into the datasheet. Therefore, our datasheets end up with the image file path and label which we input into the model.

3.3 Model

The procedure for the model is as follows:

Table 2: Programming the Model

Step	Description
Intializing a Dataloader	Multiclass database class and dataloader function were created
Making a Convolutional Neural Network (CNN)	Pretrained models were created and had the last layer reset
Set Parameters	Loss function, scheduler/learning rate, optimizer were determined
Training Model	Function for training the model was created

With our datasheets prepared, we would input the images into the model to create a prediction and use the labels to confirm the accuracy for the model. The model was split into training and validation. We decided to use two different pretrained Convolution Neural Networks (CNN): VGG-16 and ResNet-18 to classify each retinal image.

To program the model, first a multiclass database class was called to create a dataloader function on. The dataloader was then fed the image file paths and labels on the datasheet. The dataloader also created the training and validation datasets as a dictionary. With the dataloader, the model ran over the data. A CNN function was created for the model which then had its parameters set. The loss function was BCEWithLogits and the optimizer was SGD, stochastic gradient descent. Additionally, as both models were pretrained on a different image dataset of a thousand classes, the final layer of the model had to be reset to the number of classes we had, which was 5 classes.

With all of the preparation complete, the model was trained on the data. Finally, a training function was initialized and run for several epochs to get the model with the highest accuracy. The tqdm library was used to display the process of the training model, and a calculation of accuracy was coded into the function itself. So when the model was run, the accuracy, epoch number, and progress was displayed for both the training and validation model.

Some variables for the model are:

Table 3: Model Variables

Variable	Value
Image Input Size	224 x 224
Learning Rate	0.01
Momentum	0.9
Step Size	7
Gamma	0.1

The model was trained on each subset database separately (STARE, RIDB, JSIEC, and RFMiD) and then another time on the combined total dataset. Ultimately, each model was ran five times. For each run, the model at the highest accuracy in the earliest epoch was retained.

Our model can be viewed here: https://mehta-ai-aimlresearchbootcamp22.github.io/final-project/

4 Results

Our results were fairly accurate; each dataset yielded a minimum validation accuracy of 93% for both VGG-16 and ResNet-18 pretrained models. The accuracy for STARE dataset consists of all disease classifications with a majority of them being "other disease". The RIDB and JSIEC databases had 100% accuracies which was very surprising. But these databases had fewer images and two or less classes, so they were expected to be pretty good. RFMiD, the largest dataset out of the ones used, had a slightly lower accuracy possibly due to more variation. ResNet-18 performed slightly better than VGG-16 in our combined dataset. This could be due to the fact that ResNet-18 is deeper because of more layers.

Table 4: Validation Accuracies

Database	VGG-16	ResNet-18
STARE	95%	95%
RIDB	100%	100%
JSIEC	100%	100%
RFMiD	94%	94%
Combined	93%	94%

5 Conclusion and Future Work

In this paper, we present a model that can successfully distinguish and classify diabetic retinopathy, age-related macular degeneration, drusen, retinal occlusion, healthy eyes, and images that fit in the "other diseases" category.

In terms of future work, we hope to be able to obtain more data across all of our datasets so our model can train on more data to become more accurate. Obtaining more data could also allow us to expand the number of classes/labels, allowing us to identify a larger range of diseases. Some other major eye diseases that we did not classify include glaucoma, cataracts, and myopia. We also would like to fix our class imbalance problem by having a similar amount of each retinal disease. In addition, we would want to augment our data, so that our model can detect slightly dissimilar retinal images. Ultimately, this project can be considered a success, and our model holds promise to aiding the fight towards treating retinal diseases.

6 Division of Labor

We divided the work as follows:

- Data Collection = Yuriy Bidochko, Grace Choi, William Wu, Mushfiquzzaman Mahim
- Data Processing = Yuriy Bidochko, Grace Choi, William Wu
- Model Creation = Yuriy Bidochko, Grace Choi
- Poster = Grace Choi, William Wu
- Paper = Grace Choi, William Wu, Yuriy Bidochko

7 Acknowledgements

The researchers would like to acknowledge the MehtA+ team for their guidance and assistance throughout the project. Specifically, thank you to Ms. Haripriya Mehta, Mr. Bhagirath Mehta, Ms. Andrea Jaba, and Ms. Anna Muyan Li.

References

[1] World Health Organization. World Report on Vision. 2019.

[2] National Eye Institute. Eye Disease Statistics Fact Sheet. 2014.

[3] Mayo Clinic Staff. Retinal Diseases. 2022.

[4] Daniel Porter. What are drusen? 2022.

[5] Cleveland Clinic. Retinal Vein Occlusion (RVO). 2019.

[6] Serge Resnikoff, Van Charles Lansingh, Lindsey Washburn, William Felch, Tina-Marie Gauthier, Hugh R Taylor, Kristen Eckert, David Parke, and Peter Wiedemann. Estimated number of ophthalmologists worldwide (international council of ophthalmology update): will we meet the needs? *British Journal of Ophthalmology*, 104(4):588–592, 2020.

[7] eyesolutions. Fundus photography eye test. 2021.

[8] krispective. Multi-class image classification using transfer learning with deep convolutional neural networks. 2021.

[9] M. A. Rodriguez, H. AlMarzouqi, and P. Liatsis. Multi-label retinal disease classification using transformers, 2022.

[10] Clemson University. Structured analysis of the retina, 2004. data retrieved from The STARE Project,`https://cecas.clemson.edu/~ahoover/stare/`.

[11] M. Usman Akram, Anum Abdul Salam, Sajid Gul Khawaja, Syed Gul Hassan Naqvi, and Shoab Ahmed Khan. Ridb: A dataset of fundus images for retina based person identification, 2020.

[12] Ling Ping Cen, Jie Ji, Jian Wei Lin, Si Tong Ju, Hong Jie Lin, Tai Ping Li, Yun Wang, Jian Feng Yang, Yu Fen Liu, Shaoying Tan, Li Tan, Dongjie Li, Yifan Wang, Dezhi Zheng, Yongqun Xiong, Hanfu Wu, Jingjing Jiang, Zhenggen Wu, Dingguo Huang, Tingkun Shi, Binyao Chen, Jianling Yang, Xiaoling Zhang, Li Luo, Chukai Huang, Guihua Zhang, Yuqiang Huang, Tsz Kin Ng, Haoyu Chen, Weiqi Chen, Chi Pui Pang, and Mingzhi Zhang. Automatic detection of 39 fundus diseases and conditions in retinal photographs using deep neural networks, August 2021.

[13] Samiksha Pachade. Retinal-image analysis for multi-disease detection, 2021. data retrieved from RIADD Grand Challenge, `https://riadd.grand-challenge.org/`.