Detecting Glaucoma in Retinal Images

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Introduction

Ophthalmology heavily relies on image classification for the detection of certain eye diseases, making it the perfect area for computer systems to automate the diagnosis process to some degree. Researchers have begun using artificial intelligence techniques for the detection of eye diseases. An IEEE Spectrum article explains how researchers have used machine learning to detect an eye disease called leukocoria. This app scans portraits for leukocoria by looking for the appearance of a white reflection in the pupil of the eye. The researchers used convolutional neural networks. They were successful in that the app can catch leukocoria, on average, almost nine months before diagnosis. This is significant because this time frame can make the difference between losing and saving the eye through proper treatment. NIH also released an article about the applications of artificial intelligence in diagnosing general eye diseases based on multimodal data. This article demonstrates that there is significant promise in detecting certain eye diseases using computer systems.

This computer program aims to detect glaucoma. According to the National Eye Institute, glaucoma is a group of eye diseases that can cause permanent vision loss. Glaucoma is an eye disease that can cause permanent vision loss. According to the Center for Disease Control and Prevention, about three million Americans have glaucoma and it is the second leading cause of blindness worldwide. If the disease goes untreated, it may result in permanent blindness. However, this can be prevented through early diagnosis as opthamologists can offer steps to protect vision. Since early detection of glaucoma is critical to save eyesight, it is worthwhile to create a computational system that detects this disease. A research study done by Topcon Corporation, RIKEN, and Tohoku University details how a machine learning algorithm was developed by observing the thickness and deviation maps of the macula and optic disk. Although this algorithm mainly relies on data derived from optical coherence tomography, the research paper also provides a baseline for how algorithms can use retinal fundus images to detect glaucoma. Another article explains that there is great promise in using deep-learning applications in glaucoma diagnosis. It describes how convolutional neural networks can be used to train deep-learning algorithms on retinal fundus images. These articles provide a framework for developing a system that can accurately detect glaucoma in retinal fundus images. This computer program expands on those projects to detect glaucoma with a more sophisticated, comprehensive, and accurate design.

Methods

This computer program mainly relies on image processing and machine learning. First, the computer program inputs retinal fundus images. Then, it extracts numerical features from this data, such as kurtosis, using image processing techniques. Once the computer program has processed the inputted images, it then conducts classification analysis with supervised machine learning techniques. The accuracy and performance of these classification models is tested with a confusion matrix.

The data consists of 4000 retinal fundus images. This specific type of image was chosen because these images are obtained through fundus photography. Fundus photography is far less intrusive and readily available when compared to other techniques for capturing pictures of the eye. For example, slit lamp microscope examinations are often used by ophthalmologists when diagnosing glaucoma. However, these examinations are far more intrusive than fundus photography. Therefore, it is more beneficial to use retinal fundus images. There are two sample images from the data in the figures below. One is an example of a retinal fundus that is normal and the other image shows a retinal fundus that has glaucoma.

In the retinal fundus image, opthamologists are concerned with two key elements, the optic disc and the optic cup. These two elements are shown in the figure. Using image processing, the computer program detects the location of both the optic disc and cup. From this, the optic cup to disc ratio, abbreviated as CDR, is calculated. This ratio is helpful in determining whether the retinal fundus pictured has glaucoma or not.

Next, the computer program segments the optic disc into four quadrants. These quadrants are the inferior, superior, nasal, and temporal quadrants. The quadrants can also be seen in the figure, abbreviated using the first letter from the specific quadrant name. After identifying these quadrants, the computer program calculates the ISNT Quadrant Ratio and apply the ISNT rule. The ISNT rule states that in normal eyes, the thickness of the neuroretinal rim along the cardinal meridians of the optic disc, that is the rim width, decreases in the order inferior (I) > superior (S) > nasal (N) > temporal (T), and that the neuroretinal rims in glaucomatous optic discs violate this quantitative. In essence, if the retinal fundus image does not adhere to the ISNT rule and the rim width does not decrease in the correct order, then the retina in the image has glaucoma.

This computer program relies on machine learning. Machine learning is concerned with algorithms that learn from data. In other words, machine learning algorithms do not involve explicit instructions, but rather draw inferences from patterns in data. One type of machine learning system is supervised learning. In supervised learning, algorithms learn from labeled data. After understanding the data, the supervising learning algorithm determines which label should be given to new data by associating patterns to the unlabeled new data. This computer program uses a certain type of supervised learning algorithm called a classification algorithm. Classification algorithms analyze sets of training data and assign that data to preset categories. The visual in the figure demonstrates the essence of a classification algorithm. The group of different colored shapes enter the brain and the brain then sorts them into finite categories.

For this specific project and computer program, binary classification was used. The data, which is retinal fundus images, was divided into two preset categories, either glaucomatous or normal. During this project, four different types of classification algorithms were used on the data. The first algorithm was logistic regression. Logistic regression is the standard method for binary classification problems and relies on the concept of probability. The second algorithm was random forest. Random forest consists of many decision trees that rely on bagging and feature randomness. The third algorithm was K-Nearest Neighbors. K-nearest neighbors classifies new data based on similarity measures and classification is done by a majority vote to its neighbors. The fourth and final algorithm used was a support vector machine. Support vector machines are based on the margin maximization principle and perform structural risk minimization. This improves the complexity and enhances the general performance of the classifier. Finally, the computer program utilizes ensemble learning, which is a technique that combines several machine learning models into one comprehensive model. In other words, the four machine learning techniques above were combined into one. This was helpful because it decreased the variance, decreased the bias, and improved the prediction accuracy of the computer program.

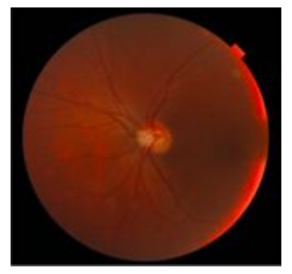

Figure 1. Sample normal image

Figure 2. Sample glaucomatous image

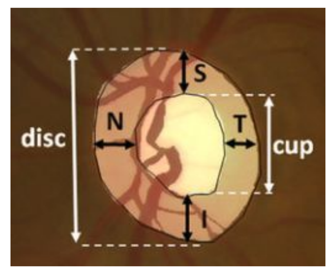

Figure 3. Anatomy of the Optic Disc

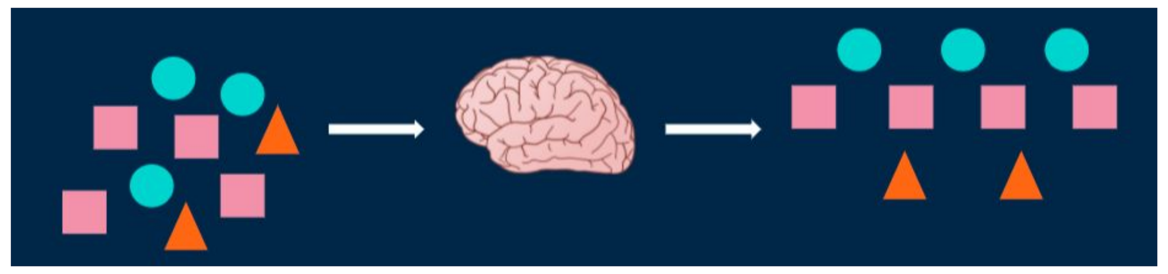

Figure 4. Essence of a Classification Algorithm

Results

The performance and accuracy of the computer program was tested and visualized with a confusion matrix. A confusion matrix is used to describe the performance of a classification algorithm on a set of test data for which the values are unknown. In other words, the confusion matrix tests to see how well the algorithm is as recognizing patterns in data the algorithm was never seen before. The confusion matrix for this computer program is shown in the figure. The predicted values are shown on the y axis and the true condition is shown on the x axis. A scale is provided on the right hand side for reference. Overall, the computer program has a sensitivity rate of 64.1%, a specificity rate of 77.1%, and an accuracy rate of 72.3%. Each of these values can be improved by implementing a more complex and comprehensive algorithm, along with adding more variable and representative data.

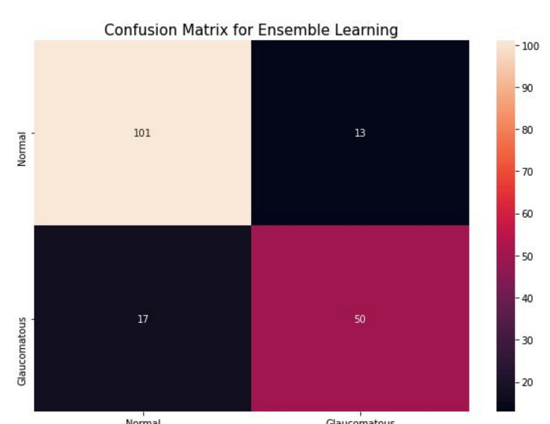

Figure 5. Confusion Matrix

Acknowledgements

I would like to thank Dr. Zacharias for all of his guidance and support throughout this project.

Conclusions

At first, I had not planned to use ensemble learning, but after researching and realizing that the different algorithms were not sufficiently accurate on their own, ensemble learning seemed like the obvious choice. Each of the separate algorithms consistently marked similar images incorrectly. Ensemble learning combined the different algorithms to address this issue. In the future, I hope that researchers are able to train a wider range of algorithms and classification models to improve the the accuracy, sensitivity, and specitivity rate of the final model. I wonder how well the algorithm performs in comparison to an opthamologist or other experienced professional. This project can also be expanded upon to determine whether an individual may be susceptible to glaucoma. This would change the computer program from binary classification to multiclass classification and may change some of the classification models used. I also wonder how soon these computer programs can be implemented in actual medical settings. Hopefully researchers are able to expand on this work and develop computer programs that can effectively and efficiently detect eye diseases.

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