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Detection on Glaucoma Using Neuro evolution of Augmenting Topology with Conventional Neural Network

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Abstract

If glaucoma is not detected in its early stages, it can cause irreparable blindness. It is the second most prevalent cause of blindness in the eyes. The fundus camera is a modern imaging device that is used to examine the inside anatomy of the eye. Among the methods used to diagnose glaucoma include the retinal nerve fiber layer analyzer, the Topcon image net methodology, and optical coherence tomography. The optic cup to disc ratio is a useful tool for diagnosing glaucoma, despite its high cost and paucity of studies. The degree of glaucomatous damage is mostly determined by the appearance of the optic cup. The majority of the disc space is occupied by glaucoma as it advances and gets bigger. The diameter of the optical cup and the overall diameter of the optical disc are related by the ratio of the optical cup to the optical disc. The manual inspection of an optic disc and cup is time-consuming. Thus, a system for diagnosing glaucoma automatically is developed. Due to a genetic component, optic cupping can enlarge without glaucoma; so, the enlargement of the optic cup by itself is not indicative of the condition.

Introduction

Glaucoma is simply a complex neurological condition that causes progressive vision loss over time, accounting for 66.8 million blind people globally. The detection and management of glaucoma, as well as the assessment of potential risk factors, are too slow. The intraocular pressure (IOP), or elevated blood pressure within the eye, increases dangerously as the sickness progresses and separates the optic nerve axon. Therefore, the primary risk factor for the development of glaucoma is an increase in IOP pressure. This will eventually lead to blindness and accelerate visual loss. Glaucoma and intraocular hypertension are similar in the way they harm the visual nerve. The brain was not able to receive picture data from the light receptors because the optic nerve was damaged. The physiologist's complaint is optic nerve cell degeneration in both the optic nerve head and the visual region. Even though glaucoma damage cannot be reversed, ophthalmologists advise early diagnosis and treatment to reduce the chance of vision loss. The diameters of glaucoma eyes vary more than those of healthy eyes because of fluid pressure. Glaucoma is a disease of the optic nerve that worsens with time. It usually occurs as fluid accumulates in front of our eyes. The pressure in an eye's fluid is typically less than 21 mm Hg. When the fluid level rises, the pressure inside our eyes rises as well, damaging the visual nerves. Rapid disease progression may result in bilateral blindness. Nonetheless, blindness associated with glaucoma can also be avoided with early detection and treatment. In its early stages, glaucoma normally exhibits no symptoms and develops within the eye.

Objectives

- Collecting images of human eyes from a variety of sources, including as image databases and hospitals, using the appropriate image- capturing equipment.
- Glaucoma can be identified by measuring the ratio of the optic disc to the optic cup in an optical picture and using CNN to segment the image.

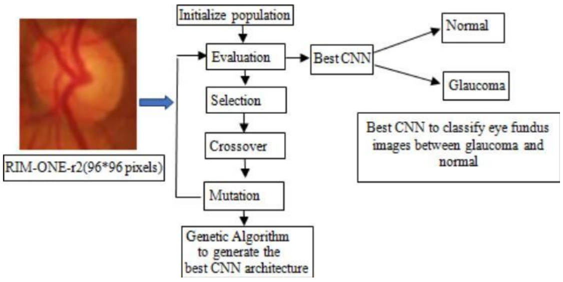
Issue Statement

To create and implement glaucoma detection in order to ascertain whether patients have an ocular health issue.

Creating Systems

Three steps comprise the method of this assignment: pre-processing, run of GA (finding the simplest CNN architecture), and run of CNN (classifying glaucoma). Rim-One, which was used in this study, illustrates the steps of the recommended procedure. Rim-One is a freely available database that acts as a guide for creating the optic nerve segmentation algorithm and contains images of the I fundus in RGB (Red, Green, and Blue) format.

System Architecture



In our research, we used the Rim- One dataset version r2, which includes pictures from the "standard" class as well as those from the "glaucoma and suspicious" class. There are 455 images in the collection; 255 belong to the regular class and 200 to the "glaucoma and suspected" class. Pre-processing RIM-ONE-r2 with varying widths and heights resulted in the images. The specific pre-processing method used in this study aims to cover the size of all images up to 96x96 pixels with a black pixel using a technique called zero- padding and input volume pixels. Therefore, it is beneficial to include zeroing the image's format's edge for a correct classification.

After experiencing poor performance for a different size, 96x96 pixels (28x28, 32x32, 64x64 pixels) were calculated. Furthermore, experiments involving more than 96x96 pixels were carried out, but memory constraints prevented our GPU's (Nvidia GeForce GTX 1060) RAM from supporting these tests. The entire image was used as the input ROI (region of interest) for our method in this particular RIM-One dataset. This approach considered all available data, containing the data found in the interior parts of the OD as well as the excavation, macula, and blood vessels. This work uses a genetic algorithm and training approach to create automated CNN structures. Its foundation is the neuroevolutionary technique known as NEAT (Neuroevolution of Augmenting Topology). Using the NEAT technique, the components, topology, and hyperparameters are optimized. The effectiveness of the formed network depends on how well it can be trained using gradient descent to achieve the classification function. The genetic code is driven by natural selection, which is a vampire. It was first proposed by John Holland in 1975, and by relying on bio- inspired operators like mutations, crossings, and selection, it is widely used to generate great solutions to optimization and discovery problems.

To assess GA, each CNN that was built was trained using the same dataset partition: test data with 136 images, validation data with 92 images, and train data with 227 images. This phase likewise lasted for more than 200 epochs, with a bath size of 16. Each model was constructed using the adapter function as an optimizer, and binary cross-entropy was used for loss because our task is a binary classification problem. To expedite development and implementation, the Cairns API was utilized to conduct all activities in Python. To start our GA, a random initial population of 20 people was formed. With at least one layer, batch normalization, determination, relay activation, and dropout should occur in 50% of this population (likely to be of additional layers). The likelihood of our GA crossing is 30%. According to Utation, the algorithm can have a wider range of population types, boosting the opportunity to explore for perplexing areas in the search space and obtaining better solutions. To carry out the mutation, the following options are randomly assigned to each element of the chromosome array: dropping out, adding or deleting determination clauses, changing the order in which punishment blocks are ordered, changing the inputs of punishment blocks, changing the output of large blocks, etc. Switch up the huge blocks' placements. The test process on the test set data of the RIM- ONE-R2, the validation set data on the test procedure, and the training procedure on the train set data were all employed to evaluate each CNN.

Implementation

- The test image input is gathered, subjected to initial processing, and then converted into an array for comparison in the ensuing step.
- After properly preparing the selected database, it is renamed and placed into the relevant folders.
- Preprocessing is required even when hemorrhage is difficult to detect in order to obtain a clear, noise-free, and contrast-enhanced image.

The methods for identifying hemorrhages, which involve preprocessing, are as follows:

a) Enlarge the image to 512 by 512

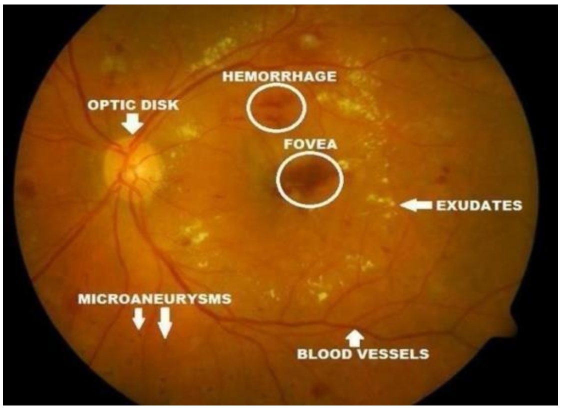
pixels.

b) Convert an RGB image to a greyscale image.

c) Use median filtering to get rid of artifacts.

d) Level up the image and increase contrast.

- Categorization occurs when the model has been suitably trained using CNN.
- After comparing the test image and training model, the result is shown.



Hemorrhages and exudates in the retina Since the green channel makes the

affected area visible and easy to see, we begin by deleting it from the image. Next, we create a backdrop by applying an 8- pixel-radius median filter to the image, which we then subtract from the original. An image of blood vessels and bleeding is created as a result. We eliminate the vessel that ends during the picture when a vessel mask recommends taking a picture of hemorrhages.

Exudates detection

Our approach to identifying exudates on the human retina is based on the work described in [20]. The data set has completely different properties because humans have evolved in many different ways. As a result, we shall describe each step along with its rationale. Here, we should note that we have utilized a library provided by [21]. This detection is comprised of the following phases, which we carried out with MATLAB version 2017a:

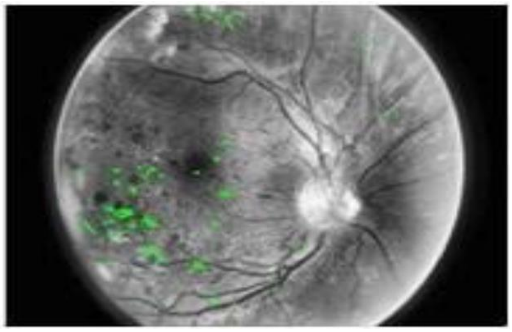
- Image pre-processing.
- Locating the point and other objects.
- the identification of optic disc exudates and artifacts.

First, we take an image and extract its intensity components during the preprocessing phase. We are choosing grayscale photos to tour this study since they best display exudates. Then, median filtering is used to reduce the noise, and histogram equalization is used to improve brightness and contrast. Blind spot identification is aided by the created image, which exudes appropriately. This acts as an input image. An optic disc and exudates both have high intensities. When traveling for the purpose of detecting exudates, we would want to look for blind spots in order to differentiate between the optic disc and exudates outside and inside the blind spot area. The most important and circular element in our actions and methods is time. near the picture's brightest region. The Gray Scale is applied. Closing of blood vessels, particularly in the vicinity of the blind spot, eliminates blood vessels from the retina. We'll employ a structural element including an eight-radius radius and a flat disk shape. After thresholding the image, it is binarized by using the generated image as a mask. The mask is then slightly inverted before being overlaid on top of the original image. Next, we apply reconstruction by dilation to the superimposed image. We threshold the image and execute the algorithm to compare the reconstructed image with the original image. As a result, a high-intensity moment is identified and relaxation periods are eliminated.

In this section, we used this approach to an infinite problem. Using the grey scale closure, vessels were eliminated at the start of the strategy, and the image that resulted from that original image was subsequently recreated. We will therefore be traveling to the goal region in order to rebuild ships. There doesn't seem to be a single large circular blind area, which is our problem. At this level, however, we are observing two or three large connected components. We additionally enlarged the last word mask in order to get around this problem. The end effect is a ring-shaped connection between the different parts. The scene is already full of items and various vibrant places, as can be seen. Therefore, if we use too much dilation, the blind spot can converge with those locations. It was believed that a structural feature with a radius of four that was flat and disc-shaped may provide the necessary additional dilatation. We have estimated values for every part of the mask to help separate the features because the optic disc and some light artifacts are detected during this process. These extra values are referred to in scores.

Area circularity = score That gives us a result of 3. You must pay attention to this situation. We decided to give circularity more weight because of a situation when the feature instead of the point can grow much larger than the blind region. We handle components with a Think of a scale of less than 1100 pixels as an artifact, and the remaining pixels as a blind spot. In this case, small areas that can develop exudates are not regarded as objects. After identifying the artifact and extracting the points, we will now look for exudates. Grey scale closure removes high-intensity blood vessels once again. Next, we decide to depict regular deviation in a way that emphasizes the salient features of nearly ordered exudates. By grey scale closing, high-intensity blood vessels are eliminated once more. Thus, we choose to create an image with a regular deviation that best depicts the original image.

Original image

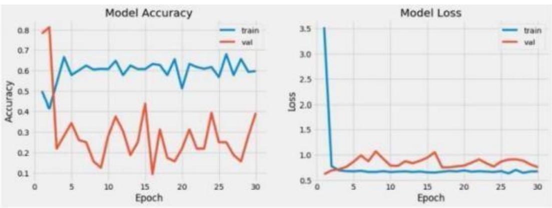


Exudates detection

We will now do binary classification after completing the feature extraction procedure in its entirety. In this case, two input layers and one output layer—a total of three layers—are used in deep neural networks. To do this, we have created a feed-forward back propagation network (newff). The acronyms "newfit" and "newpr," respectively, stand for regression and classification. All together, they are referred to by the generic term "newff," which is still in use and produces better results in our classification.

First and foremost, we have built a two- stage feed forward network. Three "transit" neurons make up the first layer, while one "purelin" neuron makes up the second. Thus, (p,t,[3,1]); net = newff; is what we have.

Here, p denotes the matrix of input vectors, while t is the matrix of goal vectors. The three input vector components that we used were the exudates mask, objects mask, and blind spot mask. The network is then simulated, and the results are plotted. This means that y = sim (net, p); After 5000 training epochs, the network's train- parameter objective is set to 0.01. A.After training is complete, a mat file is created and loaded to test our datasets. If they are loaded, we can tell them apart. the difference between a good and a bad image. The corr2 library function is then used to determine the correlation between the four sets of photographs. The test image belongs to the category in which it most closely correlates.



Accuracy

Conclusion:

We have introduced a novel deep learning technique, CNN, for automatic glaucoma recognition and problematic area localization on fundus photos. The glaucoma classification, pathological region localization, and attention prediction subnets make up our CNN model. We constructed the LAG database with 5,824 fundus images that had been identified as having either positive or negative glaucoma in order to train the CNN model.

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