DIABETIC RETINOPATHY DIAGNOSIS CATEGORIZATION USING DEEP LEARNING

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Abstract Diabetic retinopathy is a leading problem throughout the world and many people are losing their vision because of this disease. The damage in the retinal blood vessel eventually blocks the light that passes through the optical nerves which makes the patient with Diabetic Retinopathy blind. Therefore, in our research we wanted to find out a way to overcome this problem and thus using the help of Convolutional Neural Network, we were able to detect multiple stages of severity for Diabetic Retinopathy. Diabetic Retinopathy (DR) is a degenerative disease that impacts the eyes and is a consequence of Diabetes mellitus, where high blood glucose levels induce lesions on the eye retina. Early detection of Diabetic Retinopathy is crucial in order to sustain the patient's vision effectively. The main issue involved with DR detection is that the manual diagnosis process is very time, money, and effort consuming and involves an ophthalmologist's examination of eye retinal fundus images. The latter also proves to be more difficult, particularly in the early stages of the disease when disease features are less prominent in the images. In our research we wanted to find out a way to overcome this problem and thus using the help of Convolutional Neural Network, we were able to detect multiple stages of severity for Diabetic Retinopathy. one such process is manual screening. With photos of eyes as input, the goal of this project is to create a new model, ideally resulting in realistic clinical potential.

1. INTRODUCTION

Diabetic Retinopathy (DR) is a degenerative disease that impacts the eyes and is a consequence of Diabetes mellitus, where high blood glucose levels induce lesions on the eye retina. There are other processes present to detect Diabetic Retinopathy and one such process is manual screening, but this requires a skilled ophthalmologist and takes up a huge amount of time. Thus our automatic diabetic retinopathy detection technique can be used to replace such manual processes and the ophthalmologist can spend more time taking proper care of the patient or at least decrease the severity of this disease. Diabetes Mellitus is a chronic disease where blood glucose levels tend to increase due to the lack or inability of the pancreas to produce or secrete sufficient blood insulin. Diabetes incidents have risen rapidly over the past decades, from 108 million in 1980 to 422 million in 2014. Adverse effects of diabetes on human organs include the liver, heart, kidneys, joints, eyes, etc. The detrimental vision loss due to DR occurs primarily when there is retina central swelling. According to the World Report on Vision, an estimated 11.9 million suffer from vision impairment, whether mild or severe, by virtue of glaucoma, trachoma, and DR, which is the focus of our paper. In order to avoid complications associated with chronic diseases such as Diabetes, early detection is vital. Abnormal growth of blood vessels in the retina is a potential consequence of DR, which can cause scarring or bleeding from the retina and consequently blindness. This can result in progressive vision loss with possible blindness at advanced stages. Globally, DR amounts to 2.6% of causes for blindness.
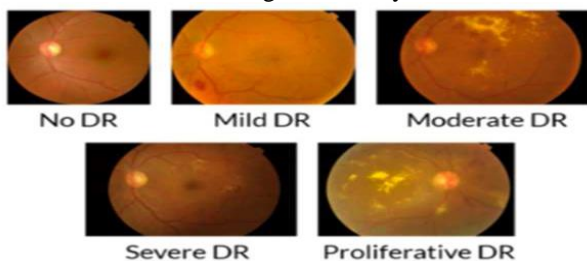
The amount of time a patient is diabetic, high hemoglobin A1c, and high blood pressure readings are considered to be the highest risk factors associated with the development of DR. Regular screening is crucial for diabetic patients to ensure that DR is detected at an early stage. DR detection traditionally involves a physician's examination of retinal imaging for the shape and appearance of different types of lesions. Generally, the four types of lesions diagnosed are Microaneurysms (MA), Haemorrhages (HM), soft and hard exudates (EX).

EXISTING SYSTEM

The need for a comprehensive and automated method of diabetic retinopathy screening has long been recognized, and previous efforts have made good progress using image classification, pattern recognition, and machine learning. With photos of eyes as input, the goal of this project is to create a new model, ideally resulting in realistic clinical potential. Proliferative DR represents the latter stages of DR and represents an antigenic retinal response, in which angiogenesis is a physiological process in which new vessels form from pre-existing blood vessels. Neovascularization of the retina can be commonly viewed as the growth of new vessels along what is referred to as vascular arcades in the retina. As a future direction, upcoming studies should focus on leveraging SSL methods to not only generalize but also be able to generate new fundus images based on the learned features using generative networks. Generative adversarial networks (GAN) and Variation auto-encoders (VAE) can be combined with existing networks to synthesize a whole range of enhanced fundus images that can be made available for training. As an example, DALL-E proposed is capable of generating images from text, such a model could potentially generate large collections of DR fundus images that can be trained and tested on.

MODULE DESCRIPTION

Data Training
The data originates from a competition. However, is an atypical Kaggle dataset. In most Kaggle competitions, the data has already been cleaned, giving the data scientist very little to preprocess. With this dataset, this isn't the case. All images are taken of different people, using different cameras, and of different sizes. Pertaining to the preprocessing section, this data is extremely noisy, and requires multiple preprocessing steps to get all images to a useable format for training a model.

Exploratory Data Analysis
The very first item analyzed was the training labels. While there are five categories to predict against, the plot below shows the severe class imbalance in the original dataset. Of the original training data, 25,810 images are classified as not having retinopathy, while 9,316 are classified as having retinopathy. Due to the class imbalance, steps taken during preprocessing in order to rectify the imbalance, and when training the model. Furthermore, the variance between images of the eyes is extremely high. The first two rows of images show class 0 (no retinopathy); the second two rows show class 4 (proliferative retinopathy).

Neural Network - First Model
Our first models used 120x120 rescaled input and I stayed with that for a decent amount of time in the beginning (first 3-4 weeks). A week or so later our first real model had an architecture that looked like this (listing the output size of each layer).

Neural Network - Second Model
First, I wanted to take into account the fact that for each patient we get two retina images: the left and right eye. By combining the dense representations of the two eyes before the last two dense layers (one of which being a soft max layer) I could use both images to classify each image. Intuitively you can expect some pairs of labels to be more probable than others and since you always get two images per patient, this seems like a good thing to do. Using higher leakiness on the leaky rectify units, max (alpha*x, x), made a big difference on performance. I started using alpha=0.5 which worked very well. In the small tests I did, using alpha=0.3 or lower gave significantly lower scores. Instead of doing the initial downscale with a factor five before processing images, I only downscaled by a factor two. It is unlikely to make a big difference but I was able to handle it computationally so there was not much reason not to. The oversampling of smaller classes was now done with a resulting uniform distribution of the classes. But now it also switched back somewhere during the training to the original training set distribution. This was done because initially I noticed the distribution of the predicted classes to be quite different from the training set distribution. However, this is not necessarily because of the oversampling (although you would expect it to have a significant effect!) and it appeared to be mostly because of the specific kappa loss optimisation (which takes into account the distributions of the predictions and the ground truth). It is also much more prone to overfitting when training for a long time on some samples which are 10 times more likely than others. Maxout worked slightly better or at least as well as normal dense layers (but it had fewer parameters).

CONCLUSION

While DR cannot be cured, it is important to detect it in its early stages to prevent further damage. For example, no proliferative DR stages will almost always contain early indicators of DR and the ability to detect and classify those stages using a proper evaluation technique could mean saving one's eyesight. In our research we wanted to find out a way to overcome this problem and thus using the help of Convolutional Neural Network, we were able to detect multiple stages of severity for Diabetic Retinopathy. one such process is manual screening. With photos of eyes as input, the goal of this project is to create a new model, ideally resulting in realistic clinical potential. In this review paper, a major portion of the work focuses on the study of hemorrhages, micro aneurysms and exudates. Results from multiple studies show an accuracy average of about 91% and promising classification performance overall. Screening systems being developed today could incorporate these DL based approaches to enhance and classify the DR stage using lesion detection techniques across multiple fundus images. The main issue addressed in the reviewed studies is the manual diagnosis that has to occur after screening, which is typically a lengthy process prone to ophthalmologists' bias. Moreover, dataset limitations restrict fundus image variations that can be used in the assessment of indicators.

FUTURE WORK

Lastly, Transformers introduced more explainable methods that can help overcome the limitations of no generalizability. Hidden indicators can now be detected more accurately, thanks to the various context enrichment approaches used in patching and embedding of fundus images. Screening systems being developed today could incorporate these DL based approaches to enhance and classify the DR stages. Ultimately, transformer-based models enable better interpretability for researchers and future work.

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