Xi'an Shiyou Daxue Xuebao (ZiranKexue Ban)/
Journal of Xi'an Shiyou University, Natural Sciences Edition
ISSN:1673-064X
E-Publication: Online Open Access
Vol: 65 Issue 06 | 2022
DOI 10.17605/OSF.IO/E37GT

DIABETIC RETINOPATHY DETECTION USING 'ForeseeGAN': A DEEP LEARNING APPROACH

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ABSTRACT

Diabetic retinopathy (DR) is an ailment affecting the eyes of a diabetic person. It may lead to loss of eyesight if left untreated for a long time. To aid the detection of DR in an early stage, we came up with the idea of applying a semi-supervised Generative Adversarial Network (GAN) for designing an automated diagnostic model. The model, named 'ForeseeGAN,' is capable of data augmentation and classification as a step for diagnosis, with an accuracy of 95.920%. The automated working capability and promptness mark the excellence of this study. The existing studies were capable of either classification using machine learning or deep learning techniques. However, ForeseeGAN has the capability of data augmentation, thus making it capable of accurate analysis even with fewer data. Our study can be of immense use to the medical community in detecting retinal diseases from the image without a huge dataset.

Keywords: Diabetic retinopathy (DR), Generative Adversarial Network (GAN), Data augmentation, automated diagnosis

1. INTRODUCTION:

Diabetic Retinopathy (DR), a consequence of long-term diabetes mellitus, is one of the most prevalent causes of vision loss and blindness [1]. Several anomalies in the eye fundus, such as microaneurysms and dot hemorrhages, vascular hyperpermeability indications, exudates, and capillary closures, impact the retinal microvasculature early stages of this disease. DR lesions are thought to be reversible, and retinopathy progression can only be slowed in the early stages of the illness[2]. During the progression of DR, the loss of vision might vary. Non-proliferative DR (NPDR) and proliferative DR (PDR), characterized by neovascularization or vitreous or preretinal bleeding, are the two basic stages of DR. Up to 10% of diabetic individuals with no DR will acquire NPDR each year. At the same time, patients with severe NPDR had a 75% chance of acquiring PDR in a year. The transition from normal status (no visible abnormalities in the retina) to PDR might take years. As a result, NPDR is sometimes categorized into three stages: mild, moderate, and severe. These five phases make up the 'International Clinical Diabetic Retinopathy Disease Severity Scale,' widely used[3]. Based on the prior studies related to DR, five severity scales have been proposed as an international clinical categorization system: no visible retinopathy (no

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DR), mild non-proliferative DR (NPDR), moderate NPDR, severe NPDR, and proliferative DR (PDR).[8] Laser photocoagulation, for example, is the most effective treatment for DR at an early stage. As a result, it is critical to identify and stage the severity of DR in clinical practice so that DR patients can receive personalized treatment early, which often depends on the grading system.

By 2040, an estimated 600 million people will have diabetes, with one-third of them developing diabetic retinopathy (DR), the primary cause of visual loss in working-age individuals worldwide [4]. According to the American Diabetes Association, DR impacted more than 4.4 million Americans aged 40 and above between 2005 and 2008, with about 0.7 million (4.4 percent of people with diabetes) having advanced DR resulting in serious vision loss[5].

According to statistics, 60% of individuals who require laser surgery to avert blindness do not receive it. Inadequate referrals, financial constraints, and lack of access to proper eye care are the main causes of this screening and treatment gap. Telemedicine has enhanced access to screening and follow-up therapy, including distributed remote retinal fundus imaging and grading at either local primary care offices or centralized grading remotely by eye care specialists[5].Deep learning techniques have recently enabled computers to learn from massive datasets in ways that far transcend human skills. Several deep learning algorithms with high specificity and sensitivity have been created to classify or identify certain illness disorders based on medical images, especially retinal scans [6]. However, with a very list no of the dataset, training a deep learning model is difficult; hence lots of work have already been done in recent decades with machine learning and deep learning algorithm technique in which the extracted features include morphological characteristics, temporal and frequency domain features, and many more. The issue is assembling a dataset that can be used to train a neural network model rapidly. To address this problem, we proposed an architecture that leverages a semi-supervised Generative Adversarial Network (GAN) [7] to augment a small or standard-sized dataset with a much bigger dataset to train a neural network model accurately. This proposed architecture is named 'ForeseeNet.' With a 95.920% accuracy, this model can augment the dataset several times. The same discriminator model was harnessed to classify and detect DR's presence automatically. This vast augmentation power combined with such a detection model of this architecture could serve as a foundation stone for future research on this subject.

1. METHODS AND MATERIALS:

1.1. DATASET COLLECTION:

The IDRiD dataset [8] is a collection of retinal images from natives of India. The database consists of 516 images categorized into two parts: retinal images with the signs of Diabetic Retinopathy (DR) and Diabetic Macular Edema (DME). Moreover, the second category is normal retinal images (without signs of DR or DME).

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The Pixel level annotations of typical diabetic retinopathy lesions and the optic disc, Image level disease severity grading of diabetic retinopathy, diabetic macular edema, and Optic Disc and Fovea center coordinates mark the characteristics of the chosen dataset.

1.2. METHODOLOGY:

The images from the dataset were directly fed to ForeseeGAN after reshaping all the images to a uniform dimension. The semi-supervised model was trained on just 60 epochs to beget such accuracy. If the model had been trained on more epochs, the accuracy would have increased significantly. The generator model used a labeled dataset, thus resulting in supervised learning, while the discriminator model was semi-supervised. With the amalgamation of both, ForeseeGAN emerges to be an effective semi-supervised model for automated diagnosis of DR. The discriminator model comprises layers of strided convolution with LeakyReLu activation with zero padding in all the layers to prevent the loss of any feature or biased learning. The discriminator has two outputs, one for classifying the real from fake images generated from the generator model and the other output for distinguishing the presence of DR in the image. The distinction of the real images is performed in a supervised method while the other output results from unsupervised learning, thus ensuring better feature extraction capability. Furthermore, the results from the convolution strides were down-sampled twice. The sparse categorical cross-entropy loss function has been used here, with the presence of SoftMax activation after flattening the data points in the penultimate layer of the discriminator model.

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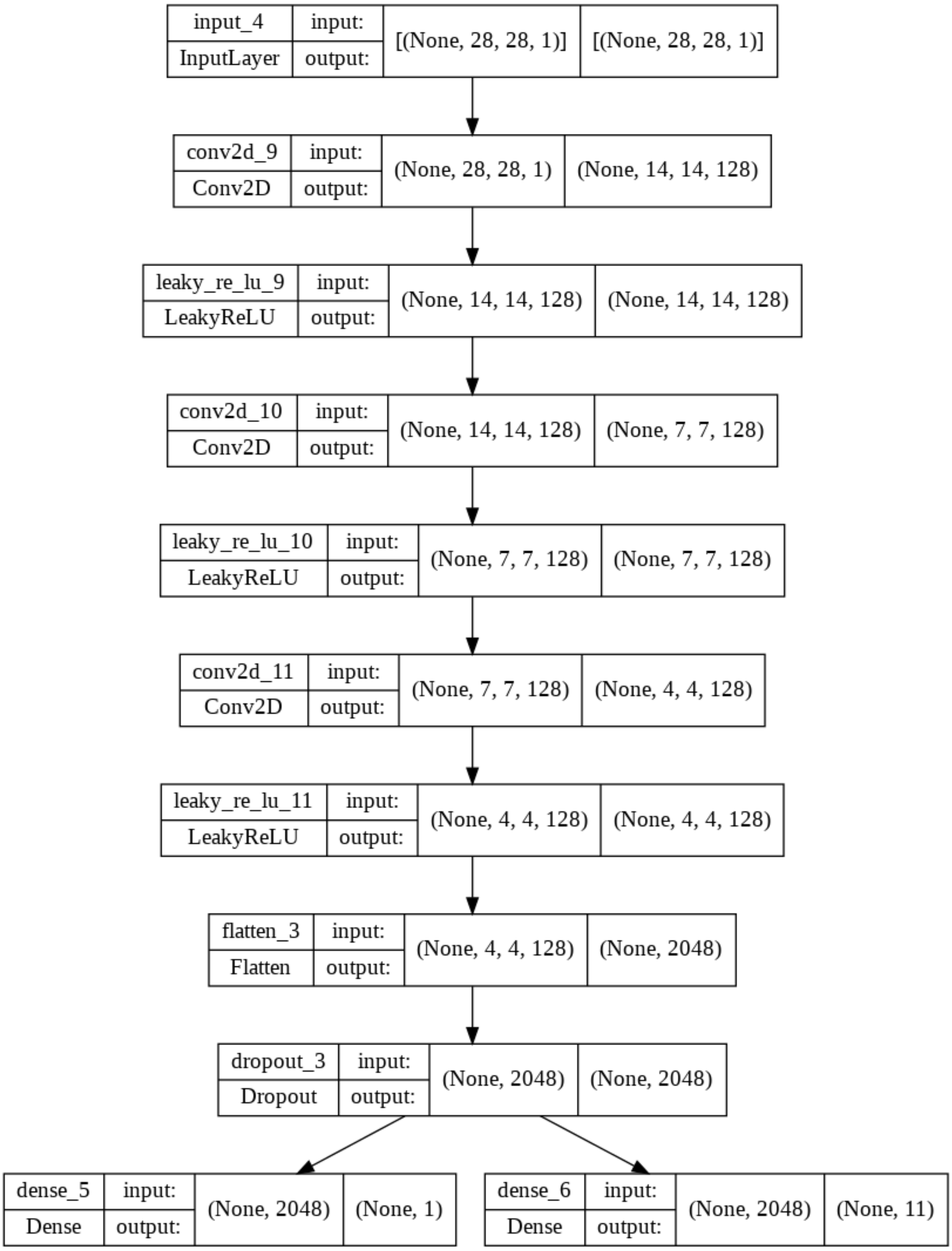

Figure 1: The discriminator model

The generator model starts with a dense layer of convolution followed by two layers of convolution strides resulting in upsampling back to the original dimension. Each of these layers was LeakyReLuactivated and zero-padded from all dimensions. The penultimate

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layer was activated using the sigmoid function, thus resulting in the proper training of the generator model.

The compiled GAN model was optimized using an Adam optimizer and binary cross-entropy loss function.

2. RESULTS AND DISCUSSION:

The ForeseeGAN stands out with its remarkable augmenting capability embellished with the automated detection of DR in an early stage of the ailment. Semi-supervised learning aided in performing two tasks in a single network independently, thus accounting for efficient computing. The model has been compared with prior yet similar tasks [Table-1]. In the comparison, we can see that most statistical or artificial intelligence-based techniques were less accurate than our model or based on probabilistic output instead of deterministic outputs. However, the work of Roychowdhury, Sohini et al. [5] begets more accuracy. Our model proves itself to be far more superior in terms of feature learning when compared to any machine learning technique. Moreover, the capability of data augmentation marks the innovation that has never been put to use in the genre of detecting the presence of DR.

Author	Method	Accuracy	Classification Result
Hua, Cam-Hao[1]	Twofold Feature augmentation	94.8	That feeding multi-modal inputs from the same instance into a CNN architecture with strong feature regularisation can be a viable alternative to relying on large amounts of labeled data.
[5]Roychowdhury, Sohini	Machine Learning	99.7	the individual performance of the three steps of the DR screening systems
*[9]*Li, Xiaomeng;	Cross-disease Attention Network	NA	Combining two attention modules in a deep network to provide disease-specific and disease-dependent features, as well as to jointly maximize overall performance for grading DR and DME
Ibrahim Abdurrazaq[10]	Morphology Approach for Features Extraction	NA	The diagnosis can be simplified by using image processing methods to reduce the number of specialists required and the time spent on each examination.

Our proposed architecture	Implementation of GAN	95.920	Many diabetic people have been found to have irregular diabetic retinopathy (DR)

Table 1: Comparison table

3. CONCLUSION:

The results reflect the reliability and accuracy of ForeseeGAN and mark the areas of excellence of the model. The integral focus of our study was centered on the amount of data and the accuracy of the results. Methods involving statistical methods, machine learning methods, and deep learning have already been discovered, capable of performing accurately. However, all the existing methods either require the user to perform some manual tasks for processing, or they may not function properly under the deficit of a large dataset. In ForeseeGAN, all the user needs to do is feed the data in the model. The rest of the task will be performed automatically, thus marking the user-friendliness of ForeseeGAN. Therefore, the accuracy, reliability, stability, feasibility, and promptness distinguish our study for aiding the early detection of DR, thus taking a step forward to save the eyesight of many diabetic patients. Our study is mainly aimed at helping the medical community and education sector by advancing the domain of research. In the near future, our study can be extended to be of use in other image processing techniques involving the necessity of data augmentation.

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