A Review on the Detection of Diabetic Retinopathy through the Use of Deep Learning

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Abstract
One of the most common and complicated forms of diabetes, diabetic retinopathy (DR) is now recognised as the major cause of blindness on a global scale. It is also one of the most commonly observed forms of the disease. The development of DR is associated with a degeneration of the blood vessels in the retina. Over the course of the past few years, numerous approaches to DR detection have been put forward as a result of the growing recognition that an early diagnosis is critical to effective treatment. However, research done in recent times has revealed a fact that deep learning-based CNN structures and Transfer Learning-based Medent's are widely employed in DR detection because of their superior performance in the medical sector. This is a reality that has been brought to light as a result of recent developments. This article presents a study on automated ways that are used to diagnose diabetic retinopathy utilising image processing and disease classification techniques as a result of such improvements in Deep Learning methodology. These advancements have led to the writing of this article.

Keywords: diabetic retinopathy, deep learning, fundus images, glaucoma, transfer learning

Introduction

The presence of diabetes in an individual is the primary cause of diabetic retinopathy. This happens because the blood vessels are unable to expand as they should. This results in damage to the eyes and an increase in the size of the capillaries in the retina, a condition known as ischemia [1]. Ischemia in the retina increases the synthesis of cytokine protein, which encourages the construction of new blood vessels from the existing ones and leads to distortion of the retinal surface. Ischemia in the retina also causes a loss of function in the retina. This ultimately results in the creation of an internal gravity, which in turn encourages the tissue to expand, which ultimately leads to a loss of vision. Damage to a person's retina has a direct and immediate effect on their ability to see [2], as the fundamental purpose of a retina is to detect light and transmit specific signals about that light to the brain. According to the findings of a number of experts in the field of research, a DR can be identified at either of the two stages: the first stage involves an early detection of the DR, and the second stage involves an advanced detection of the same. This leads in the dilatation of the blood vessels. However, therapy for it is available, and the severity of the condition can be further broken down into mild, moderate, and severe categories. Glaucoma can be caused by the advanced stage of the disease, also known as advanced diabetic retinopathy. This stage of the disease is characterised by an increase in intraocular pressure, which in turn causes

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damage to the optic nerve and raises the risk of developing glaucoma [4]. According to the figures compiled from all around the world, an estimated number of 464 million people have been diagnosed with diabetic retinopathy, and it is anticipated that this number will rise to 552 million by the end of the year 2035 [5]. Therefore, it is the primary factor that contributes to the widespread occurrence of vision impairment all over the world. The following examples of retinopathy, which can be identified at various stages of the disease, are shown in the figure below:

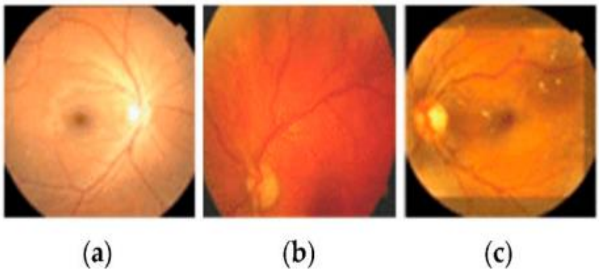

Figure 1: The prevalence of retinal diseases in normal (a), mild (b), and moderate (c) eyes

Finding and evaluating DRs in the early stages of the project is a time-consuming process that requires the assistance of technical specialists. In addition, the manual evaluation of patients with DR reveals a large lot of variation in practise from one practitioner to the next. Roughly 80% of people who have DR live in impoverished or underdeveloped nations, which suffer from a dearth of ophthalmologists and a failure to implement even the most fundamental DR detection procedure [6]. As a consequence of this, it has been observed and demonstrated that manual screening methods are still unable to keep up with the expanding demand for diagnostic methods of DR all over the world. Research researchers have developed a wide variety of automated systems in response to the significant breakthroughs that have been made in the field of computer vision. Nevertheless, advancements in computer-aided diagnostic (CAD) systems face substantial hurdles, such as recognising lesions from a retina, subdividing the head of the optic nerve, segmenting arteries, and other similar tasks.

Despite the fact that machine learning-based frameworks have shown resilience in DR detection, the efficacy of these frameworks is strongly dependent on handmade features that are still challenging to generalise. Deep learning (DL) algorithms, on the other hand, have presented automatic feature extraction strategies derived from fundus images as a means of overcoming these disadvantages. When using a technique that is based on DL, all of the necessary photos are retrieved from the data repository, and then image processing methodologies are used to the dataset that is subsequently generated. Because the raw data that is collected is unbalanced and contains noise, the dimensionality of the data needs to be decreased before it can be given to the hidden neurons and have useful features automatically extracted from it. After that, each of the features is given a weight and then optimised in a recursive manner so that the classification can be as accurate as possible. However, all of the techniques that follow the notions of DL require a certain amount of computational memory in addition to a certain level of processing power. There will be occasions when you will find this to be difficult.

Related Works

The research that was carried out as part of this section provide evidence for the classification of the DR Dataset into two distinct groups. The classification was carried out by the authors of [7] utilising the CNN network that was available from the Kaggle repository. Dimensionality reduction was performed on the dataset, which consisted of photos obtained from DR patients and had been collected over time. After cutting down each image to a dimension of 224 by 224 by 3, the next step in the process was to apply the idea of augmentation to those photos. This step was carried out primarily with the intention of expanding the dataset by utilising modifications such as turning and rotating the data. However, the implementation of the CNN design consisted of 14 input layers, and the activation function was applied to the very last layer using the Softmax algorithm. The experiment that was carried out yielded an accuracy rating of 94.5 percent.

All of the input photos that were retrieved from the repository were categorised as either having positive or negative DR when they were used in a study that was carried out by G. Quellec et al. in [8]. The model was trained on a CNN network, and in the pre-processing stage, dimensionality reduction was carried out. As part of this procedure, the images were scaled down to a resolution of 448 by 448 pixels. The implementation of the CNN architecture was further coupled with the ideas of the AlexNet model, which is based on transfer learning. When a Gaussian filter was utilised for the purpose of augmentation, the trained model reached an overall accuracy of 95%.

The basics of ResNet34 were utilised by M. T. Esfahan and colleagues in [9], along with the development of the CNN model. Because ResNet34 was a heavily trained model, an enormous number of photos were utilised and scaled down to 512 pixels by 512 pixels. The authors' work was effectively contributed to the achievement of an accuracy of 85% by applying a similar set of pre-processing procedures, which were successfully used. The authors of [10] advocated automating a model that was constructed using CNN architecture and a VGG-16 model that was based on transfer learning. In addition to this, they resized the input image to a resolution of 512 pixels on each side before carrying out their trials. The cross-validation methods were also utilised. The technique of initialization of different weights was applied to the model so that the issue of over-fitting could be circumvented as much as possible. The experiment was carried out using the dataset that was taken from the Kaggle repository, and the trained model was then balanced through the use of augmentation before being further categorised as either DR positive or DR negative. The accuracy of the model that was proposed reached a level of 98.8 percent.

Methodologies Used

A Image Processing

Images from several devices, each of which is responsible for capturing the DR Dataset using a unique camera and utilising its own unique adjustment settings are included in the dataset that was acquired during the initial phase. In addition to this, the image possesses noise in the form of fluctuating pixel intensities, which, as a result, needs to be removed in order to avoid inconsistency. Therefore, in order to address this problem, a stage of pre-processing the data is carried out, and a collection of photos that are considered to be standard are utilised. In the beginning, an interpolation of the fundus images is carried out across a pixel value of 4 by 4 and a sample of the retinal images is formed. This particular interpolation is highly recommended because it preserves image quality and additionally fixes the aspect ratio. Within the scope of this part, the researchers

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addressed a variety of pre-processing techniques, and this section provides an overview of those techniques. When contrasted with the other channels, the green channel in the RGB colour space provides a greater degree of differentiation.

Enhancing the contrast of an image is one of the pre-processing procedures that is used most frequently. The utilisation of contrast enhancement helps to highlight the difference that may be seen in an image with a green channel. In order to achieve a higher contrast, this technique is applied to the green channel of the image [11]. Exudates from a green Chromecast are more likely to become visible as a result of this. After the contrast in the image has been increased, lighting correction is typically used in order to further improve the picture's brightness and clarity. After that, a noise reduction filter, such as a Gaussian Filter, is applied to the image in order to smooth it out. Image scaling is yet another method that is widely utilised during the pre-processing stage of image editing. The image is shrunk down to a low resolution and its size is decreased so that the efficient framework can function properly.

B Lesion based Classification

For instance, the authors of the paper [12] used DL approaches in conjunction with domain expertise for feature learning in order to identify only red lesions in a DR image. The accuracy of the categorization was then improved through the application of the Random Forest approach. After retrieving the photos from the MESSIDOR repository, a Gaussian filter was applied to the model's input layers. The results were then examined. After that, the photos were shrunk to 32 × 32 pixels, and the design of the CNN included a total of 8 hidden layers.

In a study that was very similar to this one, P. Chudzik and colleagues [13] proposed the implementation of CNN architecture using three different datasets, each of which contained one hundred images. After undergoing transformations and resizings to achieve the appropriate amount of pixels, the datasets were subjected to the process of feature extraction, which was then followed by batch normalisation. After that, the recovered features were compared to the input photos, and a morphological function was applied utilising three layers of max-pooling.

The authors of [14] were able to identify red DR lesions by merging their model with a LeNet architecture that was based on transfer learning. The RGB image that was obtained in this manner from the dataset was subjected to the process of noise reduction by having a Gaussian filter applied to it. The random forest algorithm served as the classifier, while morphological approaches were applied in the analysis.

The concept of detecting multiple instances of DR lesions in retinal pictures was proposed by H. Wang and colleagues in [15]. The author did his research using the HEI-MED dataset as well as the E-Optha dataset, and he combined the concepts of CNN and random forest. In order to handle the dataset, crop rotation, adjusting the camera aperture, and employing morphological constructions were some of the methods used. However, the implementation of the model produced an accuracy of 92 percent overall and comprised eight hidden layers.

T. Li and colleagues emphasised the implementation of GoogleNet, ResNet, DensNet, and VGG-16 in their paper [16], and at the end of the paper, they carried out a comparative analysis to determine which type would produce the most optimal results. Due to the fact that all transfer learning networks have extensive prior training, the dataset that is necessary for implementation has been dramatically decreased. All of the fundus photos were pre-processed and scaled to 224 by 224

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pixels before being supplied to the succeeding layers of transfer learning variants in the first step of the procedure. When compared to other models, it was found that the Inception model produced the highest accuracy, which was equal to 82%.

C Retina Dataset

There are many different sets of data that are open to the public that can be used to detect DR and vessels in the retina. It is common practise to make use of these datasets while training, validating, and testing systems, as well as when comparing the effectiveness of one system to that of others. Imaging of the retina consists of colour images of the fundus as well as optical coherence tomography (OCT). The majority of the time, various datasets comprised of fundus images that are open to the public are used. The following is a list of the image datasets available through Fundus:

- Kaggle: It includes 88,702 slightly tilted photographs that were acquired from a variety of cameras and have dimensions ranging from 433 x 289 pixels to 5184 x 3456 pixels. The name of the website is Kaggle. On the other hand, a significant number of the photographs hosted on Kaggle suffer from both low image quality and erroneous labelling
- Messidor: This data set includes 1200 fundus colour images that were captured with a field of view of 45 degrees and evaluated according to four distinct DR phases
- IDRiD stands for the Indian Diabetic Retinopathy Image dataset. This data set contains 516 fundus pictures with a field of view of fifty degrees that have been reported up to five different DR phases

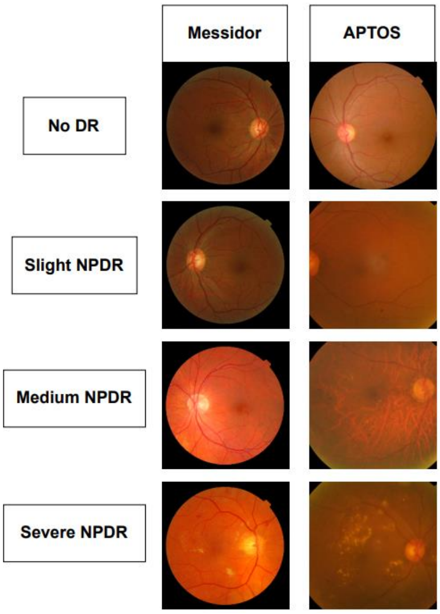

Figure 2: Sample images from the dataset

Metrics Of Evaluation

A wide number of performance indicators are utilised in order to determine whether or not DL approaches for categorization are successful. In DL (AUC), some measures that are widely employed are accuracy, sensitivity, specificity, and area under the ROC curve. It is referred to as

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sensitivity when the proportion of unusual images that are classified as abnormal, and it is referred to as specificity when the percentage of natural images that are classified as normal. An area under the curve (AUC) graph is created by plotting sensitivity and specificity. The following figure illustrates the proportion of performance metrics that have been utilised in many studies.

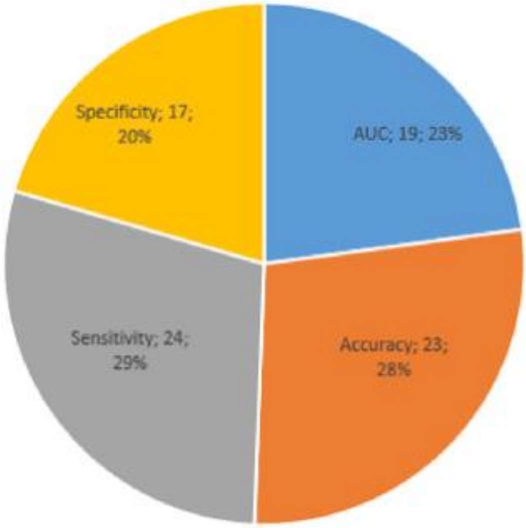

Figure 2: Sample images from the dataset

Conclusions

Automated diagnostic procedures significantly reduce the amount of time that must be spent making diagnoses. This not only saves ophthalmologists time and money but also enables patients to obtain treatment sooner. As a result, automated DR detection systems are absolutely necessary for identifying DR at a more advanced stage. The types of lesions that occur on the retina are what determine the stages of diabetic retinopathy (DR). In order to accomplish this goal, a comprehensive and methodical analysis of all relevant articles was carried out. We have provided a quick introduction to deep learning methods and characterised the datasets that are available to the public that are part of the common fundus DR. CNN has been utilised by the vast majority of researchers for the purpose of picture categorization and detection due to the efficiency with which it performs these tasks. The current investigation involved the review of a number of different studies. In order to automate the diabetic retinopathy screening system, the techniques of deep learning were utilised in each of the aforementioned experiments included in the current work. Recent increases in the number of people diagnosed with diabetes have increased the urgency with which reliable diabetic retinopathy screening systems are required. Utilising DL for both the detection and classification of DR provides a solution to the problem of selecting trustworthy features for ML. The following list includes some upcoming scientific projects that deserve more attention:

- When training with a limited amount of data for the purpose of learning, deep learning software will usually use a large number of retinal fundus images. If the training dataset is small, it is possible that the performance it produces in terms of accuracy will not be sufficient. There are two possible responses to this question. The second step is to obtain the training data by utilising a variety of augmentation techniques, such as cropping, rotating, and shifting the data, and utilising weak learning algorithms. Additional study suggests that

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Generative Adversarial Networks (GANs) can be used for training generation, which makes it possible to train the DL architecture with more robustness and distinguishing features

- When it comes to healthcare, particularly telemedicine services, cloud computing, and deep learning, remote places struggle with a shortage of human resources. Therefore, in situations like these, telemedicine has the potential to play a key role in overcoming this barrier. In the not-too-distant future, retinal degeneration (RD) could be diagnosed from eye fundus images by employing neural networks, cloud computing, and remote monitoring

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