DeepCNN- A NOVEL DEEP LEARNING BASED RETINAL IMAGE SEGMENTATION

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ABSTRACT

Medical imaging has fully changed the cost-effective health care and efficient disease evaluation in all major disease fields. This leads to the identification of treatable diseases too early, resulting in substantially reduced treatments available. This is especially relevant when it comes to retinal imaging. Segmentation is a problem with separating an image into similar parts. The conventional methods of segmentation using handcrafted features with supervised trainable classifiers. When machine learning can produce better performance, parameter tuning is difficult. Hence it is important to find a value-efficient method to identify those at risk at the early stages of the disease. A novel DeepCNN method for the segmentation of retinal images is proposed in this study. On our own database, we test the method which includes a dataset of 50 color images. Our method achieves an average accuracy of 0.9642 for normal image and 0.9542 for abnormal images compared to traditional methods.

Keywords

Deep Learning, Machine Learning, Medical Imaging, Retina, Segmentation.

1. INTRODUCTION

Medical imaging has become the most useful method in the social health care sector, owing to the visual documentation and record preservation of patients and their ability to produce information on many pathogens. There were 5 billion diagnostic imagery investigations worldwide as of 2010.Sometimes, medical imaging has been seen as marking the set of techniques that produce stereotactic depictions of the inner dimension of the body. Although imagery of extracted organs and tissues may be performed for health purposes, such procedures are generally considered to be part of pathology rather than medical imaging.Many serious eye disorders as well as systemic diseases develop themselves in the retina. There are also many applications for retinal image analysis, such as diabetic retinopathy, where it may be used in early stages due to its essential roles in detecting such diseases Ganguly et al.[2010]; Verma et al.[2013].Retina forms a vital part of the human eye, and statistics indicate that retinal disorders affect a large global population because early signs are not observed. Most retinal disorders are positive in nature, and for years they remain passive together without causing any visible sign of dysfunction to the subject. The illnesses cause no sudden loss of vision. It should be remembered that the apparent migration of significant to extreme vision deficiency in the patient is very mild and thin, and even an ophthalmologist will find it hard to recognize at first. Automated and intelligent methods of processing retinal scanned images are important for improving accuracy and diagnosis Lam et al.[2008];Binooja et al. [2015].

The morphology of the blood vessels in retinal fundus photos is an important indicator of conditions like glaucoma, hypertension, and diabetic retinopathy. Retinal image analysis typically requires blood vessel segmentation, optical disk segmentation and fovea segmentation to identify and determine any abnormalities. The accuracy of segmentation of the retinal blood vessels determines the quality of retinal image analysis used in diagnostic procedures of modern ophthalmology. It is based on the fundamental assumption that the transformation from manual and conventional methods to automated systems aims to increase accuracy by resolving manual detection method errors while at the same significantly minimizing the expertly long time taken by the manual evaluation and recognition process Elbalaoui et al. [2017].

In recent times, retinal fundus images for blood vessels have indicated multiple automatic segmentation techniques, ranging from the use of inexpensive and easily trainable filters to complicated neural networks, and even deep learning. Reliability for segmentation focuses on consistency of contrasts over image. Deep learning was demonstrated to exhibit a small improvement over strategies to machine learning but was found to differ from high performance for larger data sets and provide accuracy at the cost of the processing time Fengshou Yin et al. [2012].

The diagnosis strategies for modern retinal disease are focused on the extremely subjective and error-prone manual test. Thus, the need for digital tools to eliminate the downside of traditional methods is significantly high in the medical industry. The accuracy of strategies to classify diseases automatically should be high. The strategies should also have a rapid convergence rate in addition to being accurate which makes them suitable for real-time applications. Based on these two performance measures, various automated retinal disease detection techniques are developed Gehad Hassan et al. [2015].

The automatic system for detecting disease is not one operation. The success rate of each and every stage is extremely important to ensure the high quality of the method. In addition, the advantages and demerits of these various works are addressed in detail in order to determine the suitability of these approaches for disease detection. Retinal disease detection retrieves and segments Retinal disease regions from cluttered images created either from video images or from still images. This has diverse applications in different fields such as surveillance and safety control systems, content-based image recovery, video conferencing, and human computing intelligent design Gramatikov et al.[2014];Hassanien et al. [2015].

In comparison to the problem of detecting Retinal Disease in video, the task of detecting Retinal Disease in still images is more nuanced and complicated as emotional information may lead to probable regions where Retinal Disease may be located. Retina disease therapies are now a must, because if such diseases are not identified at an early stage, many people would eventually become blind Kavitha et al.[2010]. Nowadays, as the amount of patient data rises, clinical procedure concerns like diagnosis, treatment, and monitoring are added. Retinal conditions can be detected accurately by using the deep learning methodology. This paper's key contribution is to show the high efficacy of the deep learning approach to the segmentation of the blood vessels in fundus images. With this detailed introduction Section 2 reviews the background work; Section 3 shows the system methodology of proposed work and results in Section 4 followed by conclusion.

2. RELATED WORK

Over the ages, image processing has encountered a wide variety of applications, and its importance in the medical and healthcare sectors has seen tremendous growth in recent times. In the medical field, different types of digital images predominate, such as computer tomography images (CTs), magnetic resonance images (MRIs), etc.Each imaging modality has its own way of conveying information through appropriate methods of processing. Efficient processing of such diagnostic images assists in the early identification of various anomalies and conditions, thereby helping to eradicate them by early and effective methods of treatment Wong et al.[2008]; Peter et al.[2009].

It is important to note that these photos not only reflect the disorders related to the component being studied but also help to predict and determine the onset of certain other disorders. In the case of retinal photos, the best example could be found which helps to relay useful information about the onset of diabetic conditions in the patient.Comprehensive analyses of retinal blood vessels, their structure, scale, and spatial parameters help predict the development of associated disorders, thereby helping to diagnose and avoid them early Pinao et al.[2013].The primary purpose of this report to diagnose retinal disorders with utmost precision was segmentation of the retinal image. Cataracts, diabetic retinopathy, glaucoma, corneal opacities, age-related macular disorders and child blindness are disorders.

Diagnosis of certain conditions involving the eye and choroid inside it would require the use of the fundus camera to take a series of fundus images. These images are to be examined for better diagnosis and treatment planning. Retinal image segmentation is much required to identify certain characteristics that can assist in diagnosis and treatment. It is also very important to analyze retinal images in retrieving motion parameters which help to formulate a complete map for the retina as well as retinal tracking Gwetu et al.[2014].

They are primarily responsible for converting specula reflective impulses into information which is ultimately transmitted to the human brain via the neural system. Retina is a very sensitive and membranous coating located in the back of the eye and is associated with the focusing and impulse transfer processes. So it is critical for both preventive and prompt physician diagnosis to recognize any conditions promptly. This could result in permanent loss of vision if ignored Ravichandran et al. [2014]; Meenu Garg et al. [2016]; Anjali et al. [2017].

Anushikha Singh et al. [2016] implemented the technique of detecting the object of large bright intensity in the fundus image. Kaiser Window was applied in the fundus image green channel to localize the optic disk area. The morphological technique was used to remove the blood vessels, followed by the in-printing process. Patitapaban Rath et al. [2017] have implemented diverse image processing and pattern recognition algorithms and techniques to recognize and distinguish the normal eye from the infected eye. Automatic detection and testing of various retina diseases has been proposed which helps doctors to more accurately recognize the disease. The dissertation also briefly addresses retinal vessel identification, in which the techniques of image processing and machine learning are taken into account. It offers a review of research performed in the field of automatic recognition of retinal vessels and various retinal diseases Brooks et al.[2016].

Hideharu Ohsugi et al. [2017] Indicated that rhegmatogenous retinal detachment (RRD) is a serious condition that can cause blindness, but is highly infectious with timely and proper treatment. So early detection and treatment of RRD is critical. Deep learning, a machine-learning technique, uses ultra-wide fundus images to classify RRD, and its performance has been investigated. The deep learning model exhibits a significant sensitivity of 97.6, and the area under curve has a high specificity of 96.5 and 0.988. This model would improve medical care in remote areas where no eye clinics are accessible by the use of ultra-wide fundus ophthalmoscope to diagnose RRD accurately. Early diagnosis of RRD may protect blindness.

Detailed literature provides a thorough overview of the theory and implementation of profound learning in retinal image analysis. In the absence of adequate clinical diagnosis and medical care many eye conditions also lead to blindness. With developments in image processing and artificial intelligence, computer-based vision methods have been applied quickly and broadly in the field of medical image analysis and are becoming a safer way of practice to improve ophthalmology. More recently, machine learning has been successfully implemented in this field, especially in deep learning. Since 1982, the relevant publications, which include more than 80 papers for identification of retinal vessels from segmentation to classification, have been available. While deep learning has been successfully applied in other fields, so far we find very few papers focusing on the segmentation of retinal blood vessels.

3. SYSTEM MODEL

The exponential development of digital imaging and computer vision has broadened ophthalmology's ability to integrate advances in image processing. The imaging processing technologies are used in normal clinical procedures for the production of medical diagnostic systems.The retinal images provide good informative knowledge about the state of the sensory portion of the visual system. Retinal diseases, such as glaucoma, diabetic retinopathy, age-related macular degeneration, Stargardt 's disease, and premature retinopathy which result in decreased blindness manifested as artefacts in the retina picture Yorston et al.[2003].An automated system can be used to get standardised, low-cost, large-scale screening capable of taking human mistakes, providing facilities to remote areas, as well as safe bias and fatigue in accessibility.Retinal disease care is available; but the aim is to find a value-efficient solution with high rates of complication that can be delivered timely to large populations to identify those at risk at the early stages of the disease.

3.1 Preprocessing

In general, preprocessing makes the data more relevant to a particular application. Preprocessing is undertaken particularly in deep learning to reduce the range of intensities and highlight the region of interest. Reduction in intensity range decreases the overhead of computation during preparation.

- The first preprocessing technique is to transform RGB images into grayscale single-channel images. By decomposing the RGB color image into three-channel color image of red , green and blue, it can be shown that there is a greater degree of distortion in the green channel between both the blood vessels and the background, and that the monochrome image of the red and blue sources has more distortion and low contrast.

- The second technique of preprocessing is normalization of the data. Standardizing the image will increase the convergence speed of the standardization model. Z-score refers to setting zero-mean and unit-variance for each dimension of the data X.
- The final preprocessing technique is to use gamma correction to boost the image quality even more.

The preprocessed images have approximately half the intensity spectrum and clearly illuminated portions of the blood vessels compared with images subtracted by mean value.

3.2 Proposed DeepCNN Approach

Deep CNNs are a series of convolutionary, profound, and completely connected layers.

- Deep CNN can map input samples into output class probabilities using multiple hierarchical layers to extract features, and multiple fully connected layers to classify extracted functions.
- 2D filtering is implemented in every convolutional layer between the input images and a filter bank. It affects the new image collection.
- As in completely convolutionary maps of representation of input output are often combined linearly.
- After that a nonlinear activation function is applied.
- Deep layers are set, and no training is required. They take square blocks of convolutional layers and decrease their production into one element.

The selected function is the most promising provided that deep learning takes place over the convolutionary block. Completely convolutional layers are the normal layers of the neural network where the output neurons are linked to all the input neurons, with each connection having a parameter weight.

Segmentation

To do segmentation, image blocks are taken to specify the class (vessel or non-vessel) of the central pixel (with an odd number of pixels-the central pixel plus neighborhood). Network testing is conducted on patches derived from a collection of images for which there is manual segmentation.

Training and Testing

The network can be used after such training to identify each pixel in the new image examples after alternating four phases of convolutionary and deep layers, two completely convolutional layers further combining the outputs into a 1D feature vector. The last layer is always a completely convolutional layer with one neuron per class (two, because of binary classification in our case).

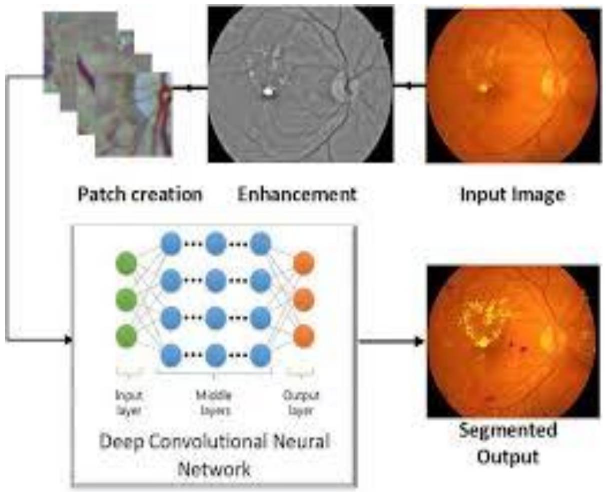


Figure 1. General architecture for proposed DeepCNN

Through the use of Softmax activation function, the output activation of each neuron can be taken as the likelihood of a given pixel in the output layer.

4. EXPERIMENTAL RESULTS

Our laptops' hardware environment includes Intel Core i7-7700HQ CPU@2.80 GHz CPU, 32 GB RAM and Linux Ubuntu OS 16.04 running. Every training and testing was done in the same hardware environment. As per the initialization process, we initialize the network and use the Adam optimizer to train the system and the Softmax function for final prediction. The back propagation and the size of a mini-batch are approximately 0.001 and 256. Binary segmentation is accomplished by thresholding a map of likelihood to 0.49. The height of the pitch is 5.

The proposed method was tested on a database that includes a dataset of 50 color images in the RGB range with 768 rpm pixels, taken from a Canon CR5 camera and saved in JPEG format. Segmented images are used in the test and training data collection, and the collection is contrasted with typical model results. In this, the first set of 25 images is anomalous, and the second 25 are normal.

The most commonly used metrics in medical science are sensitivity and specificity; the higher the specificity and responsiveness values, the better the diagnosis. The sensitivity represents the algorithm's ability to detect pixels of the vessels, while the precision dictates the algorithm's ability to detect non-vessel pixels. The characteristics are Sensitivity and Specificity.

Sensitivity= TP (TP+FN) (1)

Specificity= TN (TP+FN) (2)

Accuracy= (TP+TN) (TP+FN+FP+TN) (3)

Precision= TP (TP+FP) (4)

Where TP is True Positive, FP is False Positive, FN is False Negatives, and TN is True Negatives.

The number of true negatives is obtained by calculating dependent values for the picture and the segmented field. A performance comparison for normal images of the proposed model is given in Table 1. Table 2 provides distinction for abnormal images. Table 3 gives the comparison of proposed DeepCNN model and Artificial Neural Network (ANN) accuracy for normal and abnormal samples.

Table 1 performance comparison of proposed model

[Normal Images]

S.No	Method	True Positive	False Positive
1	ANN	0.8245	0.0242
2	Proposed DeepCNN	0.8962	0.0157

Table 2 performance comparison of proposed model

[Abnormal Images]

S.No	Method	True Positive	False Positive
1	ANN	0.6542	0.0523
2	Proposed DeepCNN	0.7642	0.0220

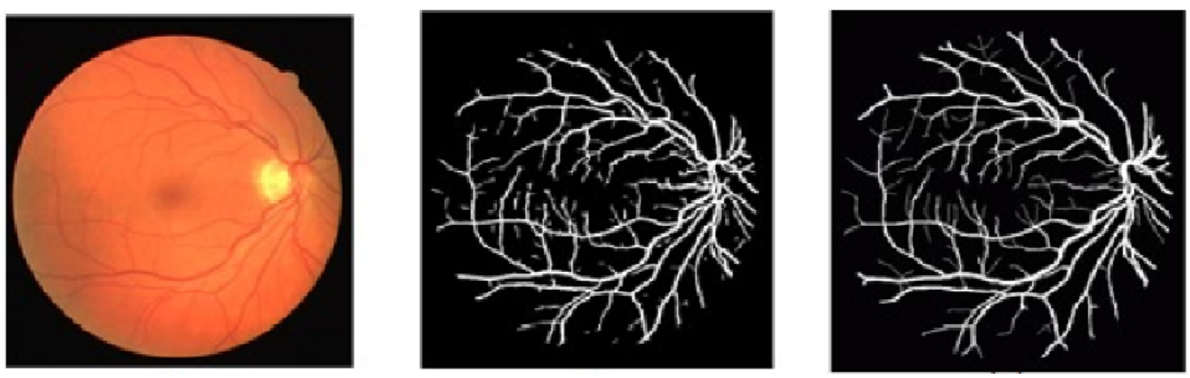
Table 3 Accuracy comparison

S.No	Model	Normal Sample	Abnormal Sample
1	ANN	0.9133	0.9024
2	Proposed DeepCNN	0.9642	0.9542

Based on the results of the training set and the data, the performance is described, in particular the efficiency of the proposed model and ANN model. Figure 2 gives a comprehensive description of the proposed model findings in terms of the retinal image and segmented outcomes and ground picture for the normal sample. For an irregular sample the same is given in Figure 3.

a. Retinal Image b.DeepCNN c. Traditional ANN

Figure 2. Normal Image



a. Retinal Image b.DeepCNN c. Traditional ANN

Figure 3. Abnormal Image

The final analysis is focused on the calculation time provided for the proposed DeepCNN, as opposed to supervised and decision-based segmentation models. The efficiency and reduction in computation time were measured against the number of images in the dataset ranging from 10 to 100 and in each case the proposed DeepCNN model outperforms conventional ANN and shows improvement in accuracy. It was observed a reduction of up to 28 per cent over fuzzy C and 30% over ANN segmentation methods. The size of the data set has been varied, and the proposed DeepCNN is found to show optimum computation time in each case. However, decreased computation time is observed over own data-set images at the expense of reducing segmentation accuracy.

5. CONCLUSION

The major causes of global blindness are eye disorders such as diabetes retinopathy (DR) and diabetic maculopathy (MD). MD has a long preclinical period in which the visual acuity is not impaired and the vision loss will always not be restored until the patient returns to the eye clinic. Early detection can preserve vision and avoid disease progression. The deep learning methods provide better results for retinal blood vessel detection. Failure to observe the progression of diabetes leads to the development of a separate abnormality in the retinal vessels that damage the retina, and eventually to losing vision. In this work, a novel DeepCNN approach is proposed for retinal image segmentation and demonstrated the accuracy which outperforms the traditional ANN.

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