SHORT REVIEW

Diabetic Retinopathy Diagnosis using Machine Learning Techniques

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ABSTRACT

Diabetes mellitus affects vital organs of the human body including heart, kidneys but also eyes. The majority of patients have blood sugar fluctuations which may result in several ocular problems. Patients with history of diabetes mellitus for more than ten years may develop, indeed, eye-related diseases such as cataract, nerve tissue destruction, maculopathy and retinopathy. Visual deficit and visual impairment are, in fact, eminent problems among working-age adults. Diabetic retinopathy is a common retinal condition secondary to diabetes that if neglected, might result in serious eye damage. To avoid irreversible visual loss, effective identification, analysis and treatment are required at an early stage of diabetic retinopathy. Diabetic patients should actually have regular eye exams to confirm the non-appearance of diabetic retinopathy abnormalities. In the realm of medical discipline, computer vision and image treating methods play a major part in diabetes and recent ophthalmology. A Computer Aided Diagnosis's major purpose is to distinguish the initial indications of a certain disease from a medical picture that physicians can hardly notify with their naked eyes. Digital image treating is the processing of pictures in which the input is a video or image and the output is an image or a set of features connected to that picture. It most commonly relates to numerical picture processing.

This review resumes identification methods of diabetic retinopathy based on the severity of its stages using different learning algorithms such as Support Vector Machine, multilayer perceptron, and Convolution neural networks.

Key words: Diabetic Retinopathy, Computer Aided Diagnosis, learning algorithm, eye, image.

INTRODUCTION

Diabetes, also known as Diabetes Mellitus, is series of metabolic illnesses characterised by an excess of glucose in the blood over long time. If diabetes is not managed, it can lead to serious consequences such as eye, heart, skin, and hearing difficulties, diabetic neuropathy, and kidney complications [1]. Diabetic retinopathy (DR) is an eye condition that damages blood vessels in the light-sensitive tissue known as the retina. It is a prevalent cause of vision loss in diabetics and one of the primary causes of blindness and vision degradation in those below the age of seventy[2]. The major cause of diabetic retinopathy is an inconsistent rise in blood glucose levels, which causes endothelial damage and increases retinal vascular permeability. Diabetic retinopathy progresses, resulting in retinal detachment.

The early discovery of Diabetic retinopathy allows ophthalmologists to administer proper therapy and therefore save the patients' eyesight. The treatment of Diabetic retinopathy entails recognising symptoms such as haemorrhages, microaneurysms, and exudates in the retinal region [3].

Microaneurysms are the earliest indicator of diabetic retinopathy, and detecting these microaneurysms early may prevent Diabetic retinopathy development and visual loss [4]. Microaneurysms are slight red spots initiated through saccular

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capillary dilatation. Retinal haemorrhage is the abnormal bleeding of blood vessels in retina, which is the light-sensitive muscle in the back of the eye. Vascular Blood leaking is initiated through pre-capillary arterioles. Exudates are known by the existence of bright lipids and spilled liquid from blood vessels [5]. At the advanced phase of Non-Proliferative Diabetic Retinopathy (NPDR), the injured blood vessels may escape yellowish liquid and an insignificant amount of blood into eye. As the illness advances, the number of exudates increases. The early stage of exudates is referred as hard exudates, while the severe phase is referred ~~to~~ as soft exudates. Hard exudates have well-defined sharp edges, a granular consistency, a yellow colour, and a globular form[6].

Diabetic retinopathy is divided into five classes: minor, restrained, severe, proliferative, and no disease [7]. The initial stages of diabetic retinopathy can be treated with laser photocoagulation, perhaps preventing visual damage [3]. For patients with diabetic retinopathy history who are unaware of any symptoms until vision damage grows, the less operational therapy will be used.

Diagnosis and Treatment

Diabetic patients should have regular eye exams to confirm the non-appearance of diabetic retinopathy abnormalities. These abnormalities include diabetic macular oedema, age-related macular degeneration, conjunctivitis, cataract, and glaucoma [8].

The ophthalmologist diagnoses Diabetic retinopathy when the dilated eye exam reveals serious deviations in retina, such as leaky or newly formed blood vessels and enlargement of the macula. Diabetic retinopathy is diagnosed using the following imaging modalities:

- **Ophthalmoscopy or Colorfunduscopy** is the most often used diagnostic technique for viewing the arrangements within the eye. Ophthalmologists can use this tool to examine the retina, blood vessels, optic disc, and any irregular injuries created through diabetic retinopathy [9]. It‘s also the basis of diabetic retinopathy‘s staging.

- **Fluorescein angiography (FA):** the retinal angiography picture is acquired by inoculating a fluorescent dye. It is beneficial to analyse the transition from NPDR to PDR. It clearly identifies microaneurysms, artery blockages, and blood and fluid leaks [10].

- **Optical coherence tomography (OCT) scanning**: Optical coherence tomography is a device that scans the picture of the retina using an array of light. It catches the retina’s innermost tissue layers. It estimates the retina thickness and compares it to the healthy retina thickness in order to detect macular oedema and swelling, secondary to capillary fragility [11].

- 1.4. **B-scan ultrasonography**: This imaging technology captures the eye picture via a sound wave with high frequency. A transducer sends a sound wave to the target tissue, which creates a 2-D picture of eye. It is mostly used to diagnose complications of proliferative diabetic retinopathy such as tractionnal adherences of the vitreous body, vitreous haemorrhage and retinal detachment [12].

Computer Aided Diagnosis System

The Computer Aided Diagnosis (CAD) technique is primarily intended to aid medical practitioners in evaluation of medical pictures. In radiology, Computer Aided Diagnosis is rapidly increasing and continually improving its picture interpretation capability with improved precision [13]. A Computer Aided Diagnosis’s major purpose is to distinguish the initial indications of a certain disease from a medical picture that physicians can hardly notify with their naked eyes. An assortment of algorithms in a Computer Aided Diagnosis system identifies the suspicious area in a picture and assesses it to anticipate the probable illness [14]. Retinal fundus images, Computed tomography (CT) ultrasound imaging, magnetic resonance imaging (MRI), and other imaging modalities have been assessed via Computer Aided Diagnosis arrangements[15].

Besides, an automated computer-aided diagnosis approach consists of three major steps using several technologies:

- Picture Segmentation and Processing: The medical picture quality is improved in this module by reducing noise and increasing visuals. Numerous picture-enhancing techniques are available. The segmentation approach is then applied to identify suspicious candidate patterns or lesions [16]. Morphological filters, Fourier analysis, various image examination techniques, wave analysis, and artificial neural networks are some of the often-used segmentation methods [16].

- Feature Extraction: Computer Aided Diagnosis’s initial observation is established on physician’s personal interpretations. The physician’s information is supplied into the Computer Aided Diagnosis so that it can distinguish among unusual features or lesions and normal structures or features [17]. Following the picture improvement and segmentation procedures, the selected attributes are measured in terms of form, size, and contrast. Using mathematical formulas, several characteristics may be retrieved.

- Classification: In the final stage, data are studied to discriminate between abnormal and normal patterns, based on retrieved characteristics. In general, a rule-based strategy is used to distinguish between aberrant and normal lesions/features. In addition to the rule-based methodology, other classification approaches such as discriminate analysis, decision trees, and artificial neural networks can be commonly utilised [18].

Machine Learning Algorithms for Diabetic Retinopathy Diagnosis

Machine learning is a computational approach that enables an algorithm to program itself through learning from a huge number of examples that demonstrate the preferred comportment, eliminating the requirement to express clearly the guidelines [19]. Using different classification algorithms and verified datasets to determine the presence or absence of diabetic retinopathy will help both patients and clinicians evaluate more cases. Although training the neural network is a time-consuming operation, using machine-learning techniques has the benefit of solving a medical image-processing problem rather well [20].

SVM Classifier

A Support Vector Machine (SVM) is a very effective tool for performing linear or nonlinear regression, classification, and outlier identification. It works well for difficult categorization with small or medium datasets [21]. A supervised learning approach analyses training data to identify the best solution for classifying pictures as normal, minor, reasonable, or severe. A training example is made up of label and feature sets that are represented by points in space and correspond to distinct classes [22]. Linear SVM classifiers and nonlinear SVM classifiers are the two types of SVM classifiers. A hyper plane is built and projected to space in the linear SVM classifier to separate the various classes. It predicts that the hyper plane with the highest margin will have a good separation in view, resulting in minimal generalisation error of the SVM classifier [23]. The support vectors are the spots closest to the decision surface. The datasets of various classes are close together and scattered to some extent in the non-linear SVM classifier. A conventional hyper plane is not favoured for dividing these distinct sorts of classes in order to overcome this problem[24].

Multilayer perceptron Classifier

The multilayer perceptron (MLP) is a type of feed forward artificial neural network. Multilayer perceptron is made up of at least three layers of nodes. Except for the input nodes, each node is referred to as a neuron since it employs a nonlinear activation function [25]. For training, it employs a supervised learning approach known as back propagation. It differs from linear perceptron in that it has numerous layers and non-linear activation. The adequate training algorithm for neural networks was stochastic gradient descent. The input to this method is the row of data presented to the system at a time [26]. The network processes the showing input through firing the neurons upstream in a loop that repeats until an output value is produced. This is known as a forward pass. The Artificial neural network composition is showed in Figure 1.

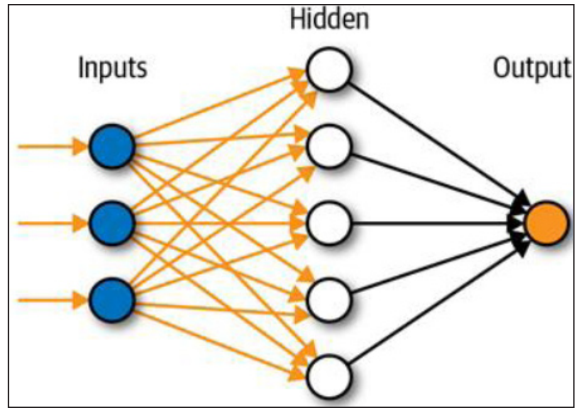

Figure 1. Artificial Neural Network structure

After the network has been trained, the forward pass is used to generate predictions on new data. An error is computed by comparing the network output with predicted output. This error is transmitted via the network, and the weights are changed while keeping the volume they contributed to the error. This is known as back propagation algorithm [27]. This procedure is done for each picture in the training data. Epoch is the network's update for the training duration. The network can be trained over tens of thousands, hundreds of thousands, or even millions of epochs. The weights can be changed based on mistakes determined for each training session [28]. The errors for all training pictures may be stored, and the network can then be updated. This is known as batch learning. To estimate a model on unseen data, predictions can be conducted on test or validation data. It can be arranged operationally and produce repetitive forecasts.

Convolutional Neural Network

Deep Learning (DL) is a subtype of machine learning that employs many layers to extract and change features. Each layer's input makes use of the preceding layer's output. It will learn its characteristics on each layer [29]. Deep Learning achieves greater precision than ever before. In contrast, Deep Learning needs a significant quantity of categorised data as well as high-performance GPUs capable of reducing training time to hours or even minutes [30]. Large amounts of data are used to train Deep Learning models, and the neural network studies the parameters from data without any prior information about data through feature extraction.

In this scenario, we are employing one of the most widely used neural networks, Convolutional Neural Networks (CNN). Its structure is showed in Figure 2.

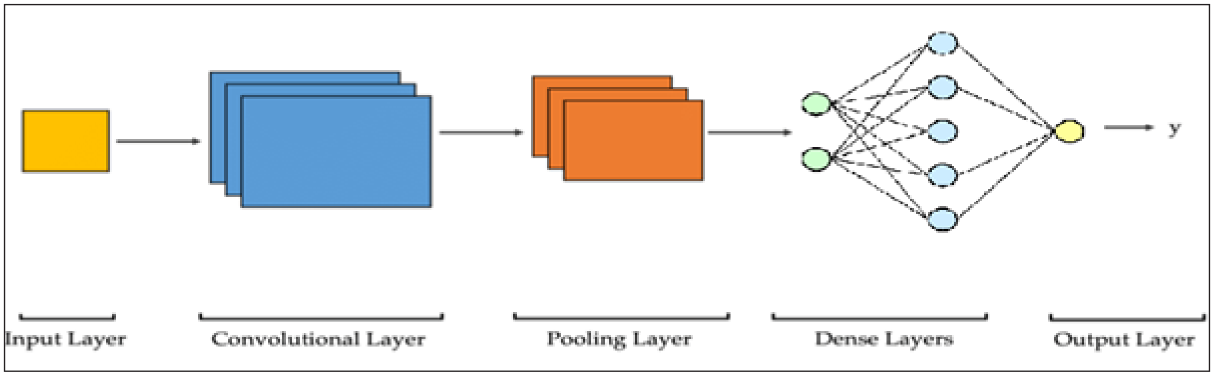

Figure 2. Convolutional Neural Networks structure

It contains the mathematical features of the construction components, which include convolutional layers, pooling layers, activation functions, and fully linked layers. Convolutional neural networks are a subclass of deep neural networks (DNN), which are neural networks with several hidden layers that extract characteristics from an input. When the data has a grid-like form, Convolutional Neural Networks are most typically utilised [31]. A picture is an example of a grid-like structure since the image is made up of pixels that are mapped to a two-dimensional array or grid. Convolutional Neural Networks have been shown to be effective in picture analysis, classification, and segmentation tasks [32]. Convolutional Neural Network is made up of three layers: input, hidden, and output. It comprises of alternating convolution and pooling operations in hidden layer to minimise computation time and build up spatial and configuration invariance; the final limited layers (near to outputs) will be entirely linked normalising layers and one-dimensional layers. Each hidden layer is employed to determine different aspects of a picture [33].

CONCLUSION

The main goal of Computer Aided Diagnosis is to differentiate the preliminary signs of a given disease from a medical image that doctors can hardly inform with macroscopic vision. A collection of algorithms in a Computer Aided Diagnosis organisation recognises the suspicious part in a representation and measures it to anticipate the possible disease. Diverse classification algorithms and datasets used for determining the absence or presence of diabetic retinopathy will aid both clinicians and patients to estimate more cases. The statement to use machine-learning methods as Support Vector Machine, multilayer perceptron, and Convolutional neural networks has the advantage of resolving a therapeutic image-processing problem rather well.

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