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An Efficient Frame Box for Detection of Human Disease using Fundus Images Based on Deep Learning Method

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***Abstract*—Diabetes Mellitus, or Diabetes, is a disease in which a person's body fails to respond to insulin released by their pancreas, or it does not produce sufficient insulin. People suffering from diabetes are at high risk of developing various eye diseases over time. As a result of advances in machine learning techniques, early detection of diabetic eye disease using an automated system brings substantial benefits over manual detection. A variety of advanced studies relating to the detection of diabetic eye disease have recently been published. This article presents a systematic survey of automated approaches to diabetic eye disease detection from several aspects, namely: i) available datasets, ii) image pre-processing techniques, iii) deep learning models and iv) performance evaluation metrics. The project provides a comprehensive synopsis of diabetic eye disease detection approaches, including state of the art held approaches, which aim to provide valuable insight into research communities, healthcare professionals and patients with diabetes.**

***Index Terms*— Diabetic eye disease, diabetic retinopathy, deep leaning, glaucoma, image processing, macular edema, transfer learning.**

I. Introduction

Diabetic Eye Disease (DED) comprises a group of eye conditions, which include Diabetic Retinopathy, Diabetic Macular Edema, Glaucoma and Cataract. Serious DED begins with an irregular development of blood vessels, damage of the optic nerve and the formation of hard exudates in the macula region. Four types of DED threaten eye vision, and they are briefly described in the following subsection.

Diabetic Retinopathy (DR) is caused by damage to blood vessels of the light sensitive tissue (retina) at the back of the eye. The retina is responsible for sensing light and sending a signal to brain. The brain decodes those signals to see the objects around. There are two stages of DR: early DR and advanced DR. In early DR, new blood vessels donot develop. Advanced DR is called proliferative diabetic retinopathy (PDR). In this case, the damaged blood vessels leak the transparent jelly-like fluid that fills the centre of the eye (vitreous) causing the development of abnormal blood vessels in the retina. Pressure can build up in the eyeball because the newly grown blood vessels interrupt the normal flow of the fluid. This can damage the optic nerve that carries images from the eye to the brain, leading to glaucoma.

Glaucoma (Gl) is an ocular disease that damages the optic nerve that links the eye to the brain. When the fluid pressure inside the eye, known as intraocular pressure (IOP), is high, the optic nerve is impaired. An increase in

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blood sugar doubles the chances of Gl, which leads to blindness and a loss of vision if not detected early. *Diabetic Macular Edema*(DME) occurs when fluid buildsup in the centre of the retina (macula) due to damage to theblood vessels. The macula is responsible for sharp, straight ahead vision. Fluid build-up causes swelling and thickening of the macula which distorts vision.
Cataract (Ca) is the degeneration of the lens protein due to high sugar level causing blurry lens growth, which in turn leads to blurred vision. Diabetic people are more prone to growing cloudy lenses and developing Ca earlier than nondiabetic people. Patients suffering from diabetes display a significantly higher predisposition develop DED.

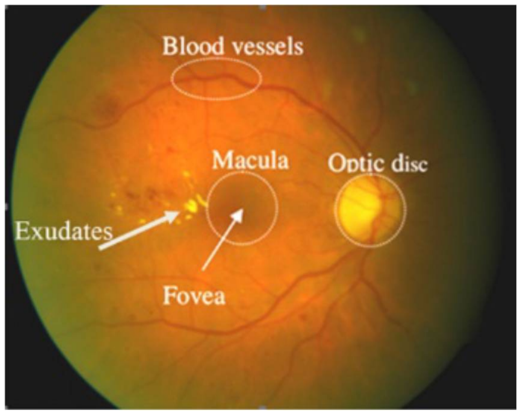


Figure 1. Original fundus image and its main anatomical features.

As a consequence, early detection of DED has become paramount in preventing vision loss in adults and children. Studies have already shown that 90% of patients with diabetes can avoid DED development through early detection. Manual detection of DED involves no computer assistance, resulting in longer waiting times between early diagnosis and treatment. Moreover, the initial signs of DED are so minute that even an expert may struggle with its identification. Advancements in Artificial Intelligence (AI) offer many advantages to automated DED detection over the manual approach. They include a reduction in human error, time efficiency and detection of minute abnormalities with greater ease. Automated DED detection systems can be assembled through joint image processing techniques using either Machine Learning (ML) or Deep Learning techniques (DL). In DL approaches, images with DED and without DED are collected. Then, the image pre-processing techniques are applied to reduce noise from the images and prepare for the feature extraction process. The pre-processed images are input to DL architecture for the automatic extraction of features and their associated weights to learn the classification rules. The features weights are optimized recursively to ensure the best classification results. Finally, the optimized weights are tested on an unseen set of images. This type of architecture demands a large number of images for training. Therefore, a limited number of images can severely restrict its performance. DL techniques require a substantial amount of computational memory and power. Normally, to develop and evaluate the classification model, DL architecture requires a Graphical Processing Unit (GPU). In real world DL applications, this assumption does not always hold. Training images using the DL model can be costly, challenging in terms of *annotated* data collection, and time and power consuming.

II. Literature Survey

Title: Computer-Aided Diagnosis of Glaucoma Using Fundus Images: A Review
Author: Yuki Hagiwara , Joel En Wei Koh
Year:2018
Description: Glaucoma is an eye condition which leads to permanent blindness when the disease progresses to an advanced stage. It occurs due to inappropriate intraocular pressure within the eye, resulting in damage to the optic nerve. Glaucoma does not exhibit any symptoms in its early stage and thus, it is important to diagnose early to prevent blindness. Fundus photography is widely used by ophthalmologists to assist in diagnosis of glaucoma and is cost-effective. Methods: The morphological features of the disc that is characteristic of glaucoma are clearly seen in the fundus images. However, manual inspection of the acquired fundus images may be prone to inter-

observer variation. Therefore, a computer-aided detection (CAD) system is proposed to make an accurate, reliable and fast diagnosis of glaucoma based on the optic nerve features of fundus imaging. In this paper, we reviewed existing techniques to automatically diagnose glaucoma.

Title:Image Processing, Textural Feature Extraction and Transfer Learning based detection of Diabetic Retinopathy
Author: Anjana Umapathy
Year:2019
Description: Diabetic Retinopathy (DR) is one of the most common causes of blindness in adults. The need for automating the detection of DR arises from the deficiency of ophthalmologists in certain regions where screening is done, and this paper is aimed at mitigating this bottleneck. Images from publicly available datasets STARE, HRF, and MESSIDOR along with a novel dataset of images obtained from the Retina Institute of Karnataka are used for training the models. This paper proposes two methods to automate the detection. The first approach involves extracting features using retinal image processing and textural feature extraction, and uses a Decision Tree classifier to predict the presence of DR. The second approach applies transfer learning to detect DR in fundus images. The accuracies obtained by the two approaches are 94.4% and 88.8% respectively, which are competent to current automation methods. A comparison between these models is made. On consultation with Retina Institute of Karnataka, a web application which predicts the presence of DR that can be integrated into screening centres is made.

Title: Deep Transfer Learning Models for Medical Diabetic Retinopathy Detection
Author: Nour Eldeen M. Khalifa
Year:2019
Description: Diabetic retinopathy (DR) is the most common diabetic eye disease worldwide and a leading cause of blindness. The number of diabetic patients will increase to 552 million by 2034, as per the International Diabetes Federation (IDF). Aim: With advances in computer science techniques, such as artificial intelligence (AI) and deep learning (DL), opportunities for the detection of DR at the early stages have increased. This increase means that the chances of recovery will increase and the possibility of vision loss in patients will be reduced in the future. Methods: In this paper, deep transfer learning models for medical DR detection were investigated. The DL models were trained and tested over the Asia Pacific Tele-Ophthalmology Society (APTOS) 2019 dataset. According to literature surveys, this research is considered one the first studies to use of the APTOS 2019 dataset, as it was freshly published in the second quarter of 2019. The selected deep transfer models in this research were AlexNet, Res-Net18, SqueezeNet, GoogleNet, VGG16, and VGG19. These models were selected, as they consist of a small number of layers when compared to larger models, such as DenseNet and InceptionResNet. Data augmentation techniques were used to render the models more robust and to overcome the overfitting problem.

III. METHODOLOGY:

To provide a structured and comprehensive overview of the state of the art in DED detection systems using DL, the proposed paper surveys the literature from the following perspectives:

1) Datasets available for DED
2) Pre-processing techniques applied to fundus images for DED detection
3) DL approaches proposed for DED detection
4) Performance measures for DED detection algorithm evaluation.

A. Image Pre-processing Techniques:

*I*mages are subjected to numerous image pre-processing steps for visualization enhancement. Once the images are brighter and clearer, a network can extract more salient and unique features. The resizing of an image is a popular method of image pre-processing. The image is scaled down to a low-resolution image according to the appropriate system. The resolution of an image is resized into the resolution required by the network in use. Researchers often have to eradicate and mask the blood vessels and optical discs so that they are not classified as wrong DED lesions. Many DED datasets consist of images with a black border, with researchers generally preferring to segment the meaningless black border to focus on the region of interest (ROI). Image augmentation is applied when there is an imageimbalance (as typically observed in real world settings). Images are mirrored, rotated, resized and cropped to produce cases of the selected images for a class where the number of images is lower than the other large proportion of healthy retina images in comparison with DED retina images. Augmentationis a common strategy for enhancing outcomesand preventing overfitting.

B. Diabetic Eye Disease Classification Technique:

In this section, we review the DL based approaches for DED detection. DL is defined as the extension of the ML with a multilayer network for extracting features. In DL architecture the term "deep" refers to the depth of the layers. The classification process is as follows: (i) The annotated dataset is split into testing and training samples for DL architecture, (ii) The dataset is pre-processed using image pre-processing techniques for quality enhancement and (iii) The pre-processed images are fed into DL architecture for features extraction and subsequent classification. Each layer in DL architecture considers the output of the previous layer as its input, Finally, the last layer of the architecture produces the required result, i.e., classification of DED as for the scope of the study. Out of 65 studies, 38 used TL, 21 used their proposed DL and six used a combination of DL and ML classifiers such as Random Forest (SF), Support Vector Machine (SVM), Backpropagation Neural Network (BPNN).

Diabetic Retinopathyused a CNNmodel based on *AlexNet*with Random Forests classifier for the detection of DR. Using Messidor-2 data they achieved area under the curve (AUC) of 98.0%, sensitivity of 96.8%, specificity of 87.0% and the predictive negative value was 99.0%.GlaucomaA number of research studies have beenconducted for the automated detection of Gl using TL.Phan*etal.*applied the Deep Convolutional NeuralNetwork to 3,312 images, which consisted of 369 images of Gleyes, 256 Gl-suspected images and 2687 images of non-glaucoma eyes. 3 The AUC achieved was 90%. Ghamdi*et al.* presented a semi-supervised TL CNN model for automatic detection of Gl. They used the RIM-ONE database and achieved an Accuracy of 92.4%, specificity of 93.3% and sensitivity of 91.7%.

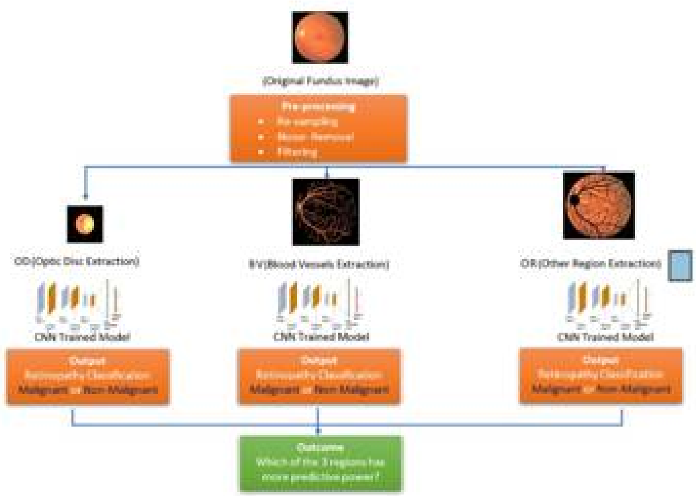


Fig.2 The three different regions this work investigate

Out of 65 studies, six proposed a combination of DL and ML classifiers. Table shows the studies in which the authors applied a combination of DL and ML classifiers namely: Random Forest (RF), Support Vector Machine (SVM) and Backpropagation Neural Network (BPNN) based architectures for DED detection. Abbas *et al.* [71] developed a DLNeural Network (DLNN) to discover the severity degree of DR in fundus images using studying Deep Visual Features (DVFs). For feature extraction, they used Gradient Location Orientation Histogram (GLOH) and Dense Color Scale Invariant Feature Transform (DColor-SIFT). They converted the features through the use of Principle Component Analysis (PCA). Afterwards, a three-layer deep neural network was used to learn these features and subsequently, an SVM classifier was applied for the classification of DR fundus images into five severity stages, including no-DR, moderate, mild, severe NPDR (Nonproliferative Diabetic Retinopathy) and PDR (Proliferative Diabetic Retinopathy). They obtained sensitivity of 92.18%, specificity of 94.50% and AUC of 92.4% on three publicly available datasets (Foveal Avascular Zone Messidor [77], DIARETDB1) and one extraordinarydataset (from the, Hospital Universitario Puerta del Mar, HUPM, Cádiz, Spain). Orlando *et al.* [72] combined ML and DL for the detection of lesions (red). They used three public datasets, namely Messidor [77], DIARETDB1 and eophtha. They extracted intensity and shape as features usingknowledge transferred LeNet architecture, which consists of 10 layers.

IV. Analysis and Review of Performance Evaluation Metrics:

In the majority of listed academic papers, the authors used specificity, sensitivity, accuracy and AUC as their assessment metrics to evaluate the efficiency of the classifier. The combined effect of performancemetrics found to be used frequently was Sensitivity,Specificity and Accuracy. This variation was used 12 times out of a total 60 trials, accompanied by 12 uses of and Sensitivity, Specificity, AUC and two use of Sensitivity, Specificity, Accuracy and AUC. Instead of Sensitivity, some researchers used Recall. We accommodated Recall under Sensitivity, rather than using it as another success indicator. The performance measurements frequently used include Sensitivity (32 times), Specificity (25 times), Accuracy (26 times), and AUC (25 times). Other performance metricsnot commonly used by research groups were: F-Score(twice), Precision (twice), PABAK (once), Kappa Score (3 times), Positive PredictiveValue (once) and GMean (once).

V. Discussions and Observations:

AI is one of the most intriguing technologies used in the material science toolset in recent decades. This compendium of statistical techniques has already shown that it is capable of significantly accelerating both fundamental and applied research. ML, already has a rich history in biology, and chemistry, and it has recently gained prominence in the field of solid-state materials science. Presently, DL models in ML are effectively used in imaging for classification, detection, segmentation and prepossessing. The most famous and commonly employed DL architecture in the selected 65 studies is CNN, which is used in 64 cases, while DBN is implemented once. We can infer that CNN is currently the most preferred deep neural network, particularly for the detection of DED as well as the diagnosis of other pathological indications from the medical images. We have noticed that DL performed well on binary classification tasks (e.g., DR and Non-DR), whereas its performance significantly dropped when the number of classes increased.

DED	Model	Layers	Features	Ref.	Classifier	Results
DR	*CNN*	3	DColor-SIFT, GLOH	[71]	Softmax	$AUC = 92.4\%, SE = 92.18\%, SP = 94.50\%$
	CNN	10	Shape, Intensity	[72]	RF	$AUC = 93.47\%, SE = 97.21\%$
	DBN	3	Shape, Intensity	[73]	SVM	$ACC = 96.73\%, SE = 79.32\%, SP = 97.89\%$
Gl	*CNN*	23	-	[74]	RF	$ACC = 88.2\%, SE = 85\%, SP = 90.8\%$
Ca	*DCNN*	17	Shallow, residual, pooling	[75]	RF	$ACC = 90.69\%$
	CNN	2	Wavelet, Sketch, Texture	[76]	SVM, BPNN	$ACC = 93.2\%, 84.5\%$

Legend: CNN = Convolutional Neural Network, DBN = Deep Belief Network, RF = Random Forests, SVM = Support Vector Machine, BPNN = Back-Propagation Neural Network, SE = Sensitivity, SP = Specificity, AUC = Area Under Curve, Acc = Accuracy, DColor-SIFT = Dense Color Scale-Invariant Feature Transform, GLOH = Gradient Location Orientation Histogram.

This study reveals the research gap for more rigorous approaches to the development of multiclass DED classification problems. Furthermore, we have observed that binary classification is mostly conducted between the normal and the affected DED cases. Thus, there is a need for classifiers that perform equally well for mild stages of DED developments, where the lesions are tiny and difficult to detect. Early detection of DED or mild DED is especially necessary to take effective preventive steps and to avoid possible blindness due to deterioration condition over time. As we can see, DL has shown an extensive capacity in the field of health care and especially in the field of DED detection. However, there are some limitations in its large-scale implementation. In terms of the validation of the proposed methods, the authors predominantly used Accuracy, Specificity, and Sensitivity to report their classification performance. However, data imbalance has been solved using geometric transformation (augmentation techniques) or re-sampling images from each class.

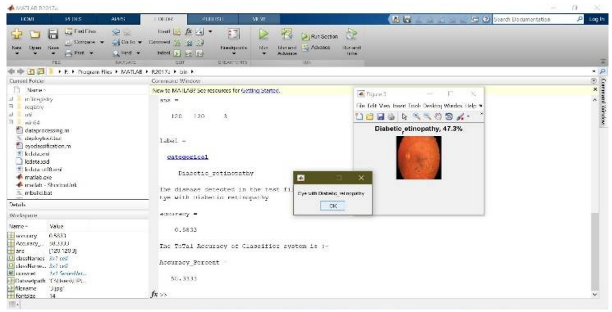
V. Output

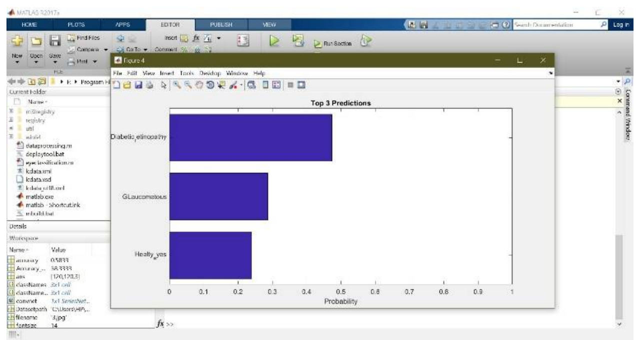
The following is the output of our project.
In the output simulation, it provides the condition of the human eye affected by Diabetes. It will identify whether the eye is healthy or affected by Glaucoma or affected by Diabetic Retinopathy using the Deep Learning Method.

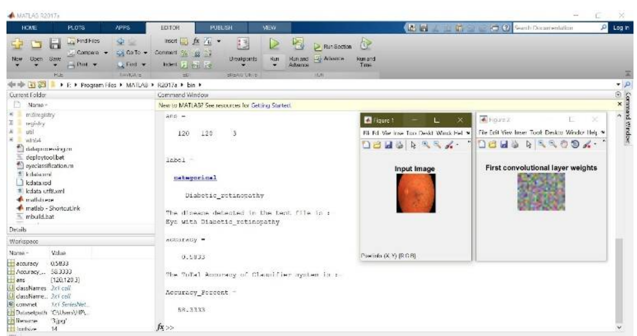
VII. Conclusion

This review paper provides a comprehensive overview of the state of the art on Diabetic Eye Disease (DED) detection methods. To achieve this goal, a rigorous systematic review of relevant publications was conducted. After the final selection of relevant records, following the inclusion criteria and quality assessment, the studies have been analysed from the perspectives of 1) Datasets used, 2) Image pre-processing techniques adopted and 3)Classification method employed. The works were categorized into the specific DED types, i.e., DR, Gl for clarity and comparison. In termsof classification techniques, our review included studies that 1) Adopted TL, 2) Build

DL network architecture and 3) Used combined DL and ML approach. Furthermore, we hope that our research can be further expanded in the future to include an all-encompassing and up to-date overview of the rapidly developing and challenging field of DED detection.







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