A Comprehensive Survey On Deep Learning Based Automated Diabetic Retinopathy Detection

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Abstract: **People who are diabetic for many years get a type of eye disease called Diabetic Retinopathy (DR). It is a dangerous disease to eyes leading to blindness. Hence detection in its early stage is required but it is very difficult. At present, evaluation of color fundus images helps to detect diabetic retinopathy which requires experienced clinicians. This type of diagnosis needs a complex grading system which is a time-consuming and difficult task. A deep learning technique which is a part of machine learning that can also be used to detect the diabetic retinopathy detection provided we have a required data sets. In this paper, We carried out a comprehensive survey of the latest diabetic retinopathy identification techniques. We have identified the previous work done in this field and analyzed based on the following parameters such as the type of algorithms used for classification of DR stages, objective, advantages, and shortcomings. We find that Convolutional Neural Network (CNN) is the most popular deep learning method which gives promising results. We concluded the paper with a summary and future directions in the area of diabetic retinopathy.**

***Keywords*: Deep Learning, CNN, Diabetic Retinopathy,Fundus images,Image Classification.**

I. Introduction

The people who have diabetes for a long time may lead to an eye disease that causes damage to the retina this disease is known as Diabetic Retinopathy (DR). This disease is very common among them and around 80% of the diabetic patients affected in the last 20 years. 75% of them between 20-64 years old will be a chance for becoming blind. As per World Health Organization(WHO),347 million people in the world suffering from DR. [1] International Diabetes Federation reports that about 366 million adults are diabetes. By 2030 this number is expected to increase to 552 million. Based on a survey conducted in 2000, type 2 diabetes and diabetic retinopathy are high in numbers in India (31.7 million), China (20.8 million), and the USA (17.7 million).

Color fundus photograph are the basic photograph taken by the ophthalmologists. Manually interpreting color fundus photographs of retina and detection of DR needs trained clinicians and its a time-consuming process. This becomes very challenging in rural areas where there is a lack of experienced clinicians and knowledge in handling complicated equipments[2]. Improving the infrastructure helps to tackle the growing number of population with diabetics. For classic DR image classification systems, much preparation is needed which requires domain expertise. The main task is to annotate the images which require the service of the skilled ophthalmologists. Figure 1 Illustrates retinal images of DR at different stages of the disease[3].

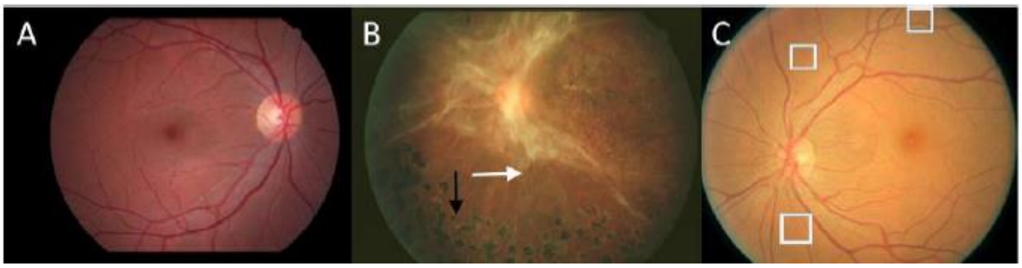

Figure 1: Illustrative retinal images of DR at different stages of the disease

as labeled A-normal, B-Last phase, C-Starting phase.

Deep Learning is a part of machine learning which is composed of hidden layers of multiple neural networks. It works on unsupervised data and is known to provide accurate results than traditional Machine Learning algorithms. The fast development of deep learning methods is possible due to the advancements in software and hardware algorithms and the availability of large datasets. High dimensional data can be learned by deep learning algorithms which is a primary advantage. In other words, deep neural networks can learn extract features of the data during the training and to incorporate this knowledge in the form of weights and biases the parameters of the neural network. Therefore, deep neural networks can operate on raw images with just a little preprocessing like resizing or cropping.

In the field of medical imaging, CNN which is a division of deep learning plays a significant role in image analysis and interpretation[4]. Challenging image recognition with numerous object classes to a remarkable standard is successfully done by large CNNs. It has huge parameters that are adjustable and the numbers even vary in millions and even billions but shallow networks consist of only hundreds or thousands of parameters.The deep learning uses in Medical Imaging are image classification,object detection,Segmentation ,registration ,and other tasks[6].

The paper deals with the following topics:

1. What is Deep learning and why?

2. What are the available architectures in deep learning?

3. What are the available deep learning framework and its applications?

4. What are the various classification algorithm used in Diabetic Retinopathy?

5. Which type of datasets has been used for Diabetic Retinopathy?

II. Overview of Deep Learning

Deep learning is a part of the superclass of machine learning in Artificial Intelligence(AI). Deep learning uses a hierarchical level of artificial neural network. Artificial Neural Network (ANN) is built like the human brain, with neuron nodes connected like a web. This is accomplished by studying all minute details of how a human brain thinks, learns, decides, and works while trying to solve a problem. [11] The motivation behind building a neural network is the biological neuron. The neurons have dendrites that receive information, the nucleus in the cell operates (summation), and the processed information is then moved to axons or terminals which fires the output.

In machine learning, the model is trained by passing multiple inputs and outputs. Then the model automatically predicts the output for any given input based on what it learned during training. In general machine learning uses algorithms to parse data, learn from it, and then decide or prediction. The machine is trained using large amounts of data and algorithms that give it the ability to learn how to perform the task.

The name deep here is used to indicate that the given machine learning algorithms are being taken further by accessing more nuanced technologies such as neural networks. These technologies are very useful in building any form of model for any general-purpose with more accuracy and higher intuitive specificity. The adjective "deep" in deep learning comes from the use of multiple layers (more than one hidden layer) in the network. The neural network must contain one input layer (first layer) followed by many intermediate hidden layers, and then the output layer (last layer). The artificial neural network is designed such that, when multiple inputs are passed, the neural network multiplies each input with a random weight value, and then sums up all the input values and forwards it to the activation function, which has a threshold value. If the value forwarded is larger than the threshold value then the output is fired. If there is a difference in the output then the weight values get updated by a method called backpropagation.

Deep learning is used to build the model and not machine learning because of the following reasons: (i) Machine learning has a high dimensionality problem. This is overcome in deep learning by projecting the input data into a lower-dimensional space, or using dimensionality reduction techniques like feature extraction, removing missing values and by using filters. (ii) In machine learning, the model automatically extracts features to train the model such that it can predict, but in deep learning, it extracts only useful, meaningful, and required information to train the model. (iii)In machine learning, if an AI algorithm returns an inaccurate prediction, then an engineer has to step in and make adjustments. While in a deep learning model, an algorithm can determine on its own if a prediction is accurate or not through its neural network. (iv) Machine learning is mainly used for structured data. structured data will be enough for the machine learning algorithm to learn, and it will continue working based on the labels it understood, and classify as per the features it learned through the said labels. While in deep learning networks it does not necessarily need to be structured/labeled data.

A.Deep learning architectures

There are various types of deep learning architectures some of them described below[7]:

- CNN-Convolutional Neural Network
- RNN-Recurrent Neural Networks
- LSTM-Long Short-Term Memory
- DBN-Deep Belief Networks
- DSN-Deep Stacking Networks

CNN

A CNN is an image processing architecture where we have various layers performing various functions as required. Here the first layer is the convolution layer which is very useful for creating the pattern identification filters, Relu layer is used to normalize the values of images to be in a positive vector. The next layer is the flatten and fully connected layers where the flatten converts the 2d array to a 1d array which is passed to the fully connected layers which work similar to ANN’s and then produce as many results as desired.

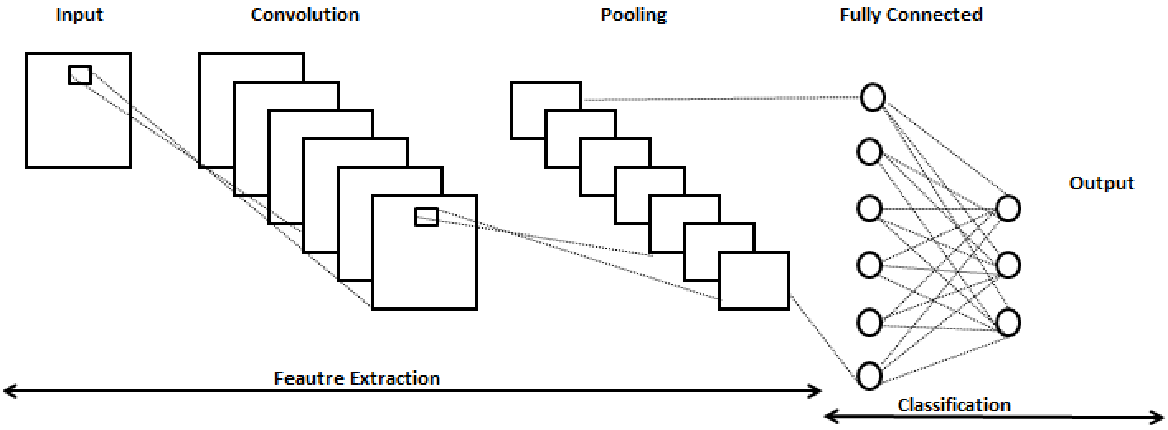

Figure 2. Schematic diagram of Basic Convolutional Neural Network (CNN) architecture [10].

RNN

RNN is similar to an ANN but here rather than having a set of constant feedforward connections in nodes it has feed backward connections merged in as well. Both types of connections can be occurring in between various nodes of the layers. It also has access to context layers along with having hidden layers keeping only the input and output layers as the same.

LSTM

LSTM is an architecture derived from RNN. It primarily removes the features where the neurons exist and replace it with a new technology called memory cell. The memory cell can retain its value for a short time or a long time as a function of inputs. There are 3 gates in place to control the flow of information to or from a memory cell, which are the input gate, output gate and forget gate.

DBN

DBN is a simple network that includes a novel training algorithm. It is multilayered where each pair of layers are connected to a restricted Boltzmann machine (RBM). Each RBM is trained to reconstruct all sensory inputs received from the input layer and then pass this input to the hidden layers. Which can be done using unsupervised learning and output layers can be trained using supervised layers to give affine tuned result.

DSN

DSN is otherwise called a deep convex network. A DSN consists of the modules, where each module is itself a network in the DSN. Consider an instance of this model where 3 modules are created in one DSN. Every module consists of 3 layers which are the input, single hidden, and an output layer. Modules are layered on top of each other, here the inputs of one module are the output of the prior layer or the previous layer behind it and the original input vector. Using this form of layering allows the network to learn more efficiently. Where this form of model allows for some complex classification to be easily accomplished without any burden on any single module.

B. Deep Learning Framework and its applications

A framework is an environment that is built by system software to give a platform to programmers for developing and deploying the applications. Deep Learning framework enables programmers to build the deep learning models and test those applications. Many open-source deep learning frameworks are available in the market such as TensorFlow, Keras, Caffe, Torch, PyTorch etc.[9] Some of the most commonly used frameworks are listed in Table 1 Each row in the table 1 corresponds to one open-source framework which is attributed based on Developer's group, supported language, and best suitable application. Table 1 gives a clear view that based on the language known we can select a framework.

Deep Learning Framework	Developed by	Release Year	Language	Architecture	Applications
TensorFlow	Google Brain Team	2015	C, C++, Python, Java, R	• Convolutional Neural Networks (CNNs)	• Speech Recognition • Self-driving cars • Text Summarization • Image and Video Recognition • Sentiment Analysis
Keras	Francois Chollet, Google Engineer	2015	Python, R	• VGG16 • VGG19 • InceptionV3 • Mobilenet	• Prediction • Feature extraction • Image Classification
PyTorch	Facebook AI Research group	2016	Python, C	• Convolutional Neural Networks (CNNs)	• Predictive algorithms • Images (Detection, Classification, etc.) • Forecast time sequences • Text generation • Reinforcement Learning
Caffe	Berkeley AI Research(BAIR), Communit y	2013	C++,Python ,Matlab	• Convolutional Neural Networks (CNNs)	• Speech and robotics applications • Computer Vision • Translation of text • Large Scale

					visual classification
Deeplearning4j	Machine Learning group headquartered in San Fransisco	2014	C++, Java, Scala, Kothline and Clojure	• Convolutional Neural Networks (CNNs) • Recurrent Neural Networks (RNNs) • Long Short-Term Memory (LSTM) and many other architectures.	• Security Applications • Recommender Systems • Parallel and distributed applications

Table 1 Deep Learning Framework and its applications

III. Automatic DR Detection

DR categorization using Automatic computer-aided solution is still an evolving field for research. Fast retinal evaluation is done by an automatic image-based DR detection system which helps in the timely detection of some DR problems[8]. Here, we will discuss about the phases of DR, kinds of DR lesions, Comparative analysis of various classification algorithms, and the datasets used for DR detection.

A. Phases of Diabetic Retinopathy

There are four phases of diabetic retinopathy[5]:

Mild Nonproliferative Retinopathy – These are called also microaneurysms which can cause vessels to leak into the eye. This is the initial stage of diabetic retinopathy, and it's categorized by balloon-like swelling in the retina's blood vessels.

Moderate Nonproliferative Retinopathy – Blood vessels supplying blood to the retina swells and after sometimes it is blocked. It leads to building up of fluid in the macula region of the retina and called Diabetic macular edema (DME).

Severe Nonproliferative Retinopathy – More blood vessels are blocked which are supplying blood to the retina. Brain signals the retina to build new blood vessels so that the supply of blood to the retina can be done.

Proliferative Diabetic Retinopathy (PDR) – New blood vessels grow in the retina which gives vitreous gel causing the retina to grow bulky and results in retinal detachment tearing away the retina from the underlying tissue. This is the last stage of diabetic retinopathy leading to poor eyesight, light flashes, and even severe loss of vision.

B. Kinds of Lesions

The size of microaneurysms(MA) is less than 125 microns and seen as red spots with sharp borders. It is formed by large leakage of blood in retinal vessels and it is the initial medical mark of DR[5]. When the walls become weak, it finally breaks causing hemorrhages (HMs) but larger in size. It is called as dot and blot due to their asymmetrical borders. Furthermore, bleeding can lead to Splinter hemorrhage and further damage of capillaries can appear yellow irregularity surface on the retina leading to exudates(EXs). There are two kinds of EXs: hard and soft exudates.

Hard exudates (HEs) are white or white-yellow in color with sharp borders formed as blocks or in circles. It is the leakage of retinal vessels and made of lipoproteins and other proteins. It is found on the retina’s outer layers[5].
Soft exudates are whitish-grey in color with appears cloud-like shape or cotton wool spots(CWS) MAs and HMs are dark lesions and EXs are bright.
The next type of lesions are called Neovascularization (NV) formed because the brain signals to find alternate blood pathways because the normal routes are blocked. To get the alternate routes it generates elements such as sorbitol
When retinal vessels becomes preamble, leakage occurs around macula called Macular edema (ME).

Optic disc (OD) plays a vital role to detect DR which has more contrast between the circular shape regions[5]. Serious eye pathologies such as glaucoma, optic disc pit, and optic disc drusen can be diagnosed using an Optic disc which is used as a landmark and frame of reference. Structures such as fovea can be detected by OD. Edges of OD are perfect and well defined in the normal retina.

C. Related Work
The overall framework for detection and classification of DR comprises detailed steps such as explores the data analysis, pre-processing and data augmentation, opting for a suitable classification technique, and lastly evaluating the performance of the results. [22]Various algorithms used in the classification of DR stages such as Support Vector Machine, K-Means Clustering, Naïve Bayes Analysis. Table 2 shows the Comparative Analysis of Various CNN algorithms.

References	Algorithm / Method or Tool	Objective	Advantage	Shortcomings	Datasets Used
[12]	K-Means clustering, (NPRTOOL).	Classification of images to predict Diabetic Retinopathy.	The sensitivity rate, Specificity rate, and Accuracy are increased. The misclassification rate is decreased.	Small dataset with low-resolution images.	Standard Diabetic Retinopathy Database
[13]	Fully convolutional neural network.	Classification of images to predict Diabetic Retinopathy.	Accuracy is more and computational complexity is less.	The images can be classified to only three classes	HRF
[14]	Deep Learning-based CNN, AlexNet, VGG16,	Classification of images to predict Diabetic	Heterogeneity is achieved and noise-related issues are	Abnormal blood vessels are not considered,	Kaggle

	InceptionNetV3.	Retinopathy.	overcome.	CNN based object detection methods are not used for classification.	
[15]	Deep convolutional neural networks (CNN), VGG-D.	Classification of images to predict Diabetic Retinopathy.	Fast Diagnosis of Diabetic Retinopathy.	A small dataset is used; hence it is less accurate.	EyePACKS
[16]	Support vector machine (SVM).	Classification of images to predict Diabetic Retinopathy.	Accurate determination of number and area of Microaneurysms	Soft exudates and abnormal blood vessels as features from colour fundus images are not considered.	DIARETDB 1
[17]	Convolutional neural networks (CNN).	Classification of images to predict Diabetic Retinopathy.	They accurately classified images into two groups: Healthy eye and Anomaly eye.	Less number of training data is used thus decreasing accuracy.	Messidor
[18]	Convolutional neural networks (CNN).	Diabetic retinopathy image classification using CNN based transfer learning	Better classification results with small datasets, using knowledge learned from larger datasets.	Less number of training data is used and is not concentrated much on accuracy.	DR1 and Messidor
[19]	GPU accelerated Deep Convolutional Neural Networks	Automatic diagnosis of the disease into stages using deep learning	It classifies the images and also finds a misclassification rate to penalize the accuracy score accordingly.	Accuracy of 38.6% is obtained which is very less when compared to other models.	EyePACs
[20]	Decision tree, Artificial Neural Network (ANN), and Support vector machine (SVM).	Decision about the presence of disease.	It could detect the presence of disease with greater accuracy.	The model was designed to just detect the disease but not to identify in which stage the disease is.	Messidor

[21]	Neural Networks (NNET), Random Forest, K-Nearest Neighbour (KNN), Support Vector Machine (SVM)	Classification of images to predict Diabetic Retinopathy.	Automatic feature selection, feature generation and parameter selection	SVM – 57.93% KNN -66.74% Random Forest-66% NNET – 72.61% Accuracy is low, Classified into only two classes.	Messidor

Table 2 Comparative Analysis of Various Classification algorithms in DR detection

D. Datasets Description

In this division, we will see the some of the datasets having retinal fundus images used for diverse DR detection tasks are tested and learned. The public domain benchmark datasets are DRIVE, STARE, e-ophtha, Kaggle, Messidor-1, Messidor-2, DeepDR, IDRiD. Table 3 shows the datasets for Retinal Images.

Dataset Name	Total Number of images	Resolution/Size	Image format	Camera name/Degree of View
DRIVE[23]	40 color eye fundus images.	768 by 584 pixels.	.jpg format.	Canon CR5 3CCD camera with a 45-degree field of view.
STARE [24]	20 eye fundus images.	Image resolution is 700*605.	NA	TopCon TRV camera with a 35-degree field of view.
E-ophtha [25]:	148 images in e-ophtha-MA and 233 images in e-ophtha-EX.	NA.	.jpeg/.png format.	NA.
Kaggle dataset[26]:	35126 training images and 53576 test images.	1024px.	.jpg format.	NA
Messidor-1 dataset[27]:	1200 color images.	1440*960, 2240*1488, or 2304*1536 pixels.	TIFF format.	45-degree field of view with 8 bits per color plane.
Messidor-2 dataset[28]:	1748 images.	NA.	spreadsheet.	45-degree field of view.
DeepDR (Deep Diabetic Retinopathy)[29]:	2696 images.	Regular retinal fundus images-1956×1934	.jpg format.	Regular retinal fundus images-digital fundus

		pixels, 778 KB in size, and Ultra-widefield retinal images-3900×3072 pixels, 2 MB in size.		camera which is made by TOPCON and Ultra-widefield retinal images-Optomap P200Tx (Optos, Dunfermline, UK).
IDRiD dataset[30]:	516 images.	4288×2848 pixels and a size of 800 KB.	.jpg file format.	digital fundus camera with a 50-degree field of view.

Table 3: Datasets for Retinal Images

IV. Discussions

One of the main challenging task that arises during the design of the deep learning and the deeper CNN model architecture is the collection of the huge volume datasets consisting of the fundus images that are annotated in the pixel and the image level. Another alternative is to introduce the deep CNN learning models that learn the model using lesser parameters. Tajbia Karim., et al. [12] Some of these features include obtaining high-resolution images which could increase the sensitivity rate and also decrease the misclassification rate. Arkadiusz Kwasigroch., et al. [15] If a larger number of training images are considered then it could increase the accuracy to classify images. More features can be considered like cotton wool spots, minute blood vessels, and other features to implement the fine-grained DR stage classification. Monika Andonová ., et al. [17] Larger number of convolutional kernels could also be used to obtain the higher computational accuracy. Xiaogang Li ., et al. [18] If larger datasets is not available then the knowledge learned from the source domain with large datasets could also be used to improve the target task with a low number of dataset images. The second important challenge is the image processing related to fundoscopy is the lack of similarity between the different images. Fundus images suffer from the illumination problem that occurs due to the non-uniform diffusion of light and angle on the retinal surface. The third challenge arises in the fundoscopy which is due to the different resolution of the images captured.In the kaggle datasets[25] the images taken with different camers,so the images are different resolution,light and angle.Working with various image pre-processing techniques we can resolve the above problems like different resolution,light ,angle and noise.

V. Conclusions

The main bourne of this paper is to review the previous work in diabetic retinopathy as in terms of deep learning architecture, framework, and the large number of datasets used for development in this field..In this survey, We reviewed the methods which enhance the accuracy of the classification of diabetic retinopathy. The main appeal for the need to use deep learning architectures in this DR detection lies in its broad application domain.Deep learning is preferable compared to traditional machine learning algorithms due to its nature of learning the networks , handling of large and diversified data sets such as text ,image ,audio and video and produces accurate results.

REFERENCES

[1] Chandrakumar, Kathirvel, Classifying Diabetic Retinopathy using Deep Learning Architecture, International Journal of Engineering Research & Technology(IJERT), Vol.5 Issue 06, June 2016.

[2] Ratul Ghosh, Kuntal Ghosh, Sanjit Maitra. "Automatic detection and classification of diabetic retinopathy stages using CNN", 2017 4th International Conference on Signal Processing and Integrated Networks (SPIN), 2017.

[3] Carson Lam. MD, Darvin Yi, Margaret Guo, Tony Lindsey, Ph.D.Biomedical Informatics Department, Stanford University, Palo Alto, CA; School of Medicine, Stanford University, Palo Alto, CA; 3NASA Ames Research Center, Mountain View, CA. Automated Detection of Diabetic Retinopathy using Deep Learning.

[4] HarryPratt, Frans Coenen, Deborah M Broadbent, Simon P Harding, Yalin Zheng. Convolutional Neural Networks for Diabetic Retinopathy, Procedia Computer Science 90(2016)200-205.

[5] Vishaka Chandore, Shivam Asati, Automatic detection of diabetic retinopathy using deep Convolutional Neural Network, International Journal of Advance Research, Ideas and Innovations in Technology, ISSN 2454-132X 2017.

[6] Geert Litjens, Thijs Kooi, Babak Ehteshami Bejnordi, Arnaud Arindra Adiyoso Setio, Francesco Ciompi,Mohsen Ghafoorian, Jeroen A.W.M. vander Laak, Bram van Ginneken, Clara I. S´anchez. A Survey on Deep Learning in Medical Image Analysis, Pages 1-30, 2017.

[7] Daniele Ravi, Charence Wong, Fani Deligianni, Melissa Berthelot, Javier Andreu-Perez, Benny Lo, and Guang-Zhong Yang. Deep Learning for Health Informatics, IEEE Journal of Biomedical and Health Informatics, Vol.21, no.1, 2017.

[8]Madhura Jagannath Paranjpe, M N Kakatkar, Review Of Methods For Diabetic Retinopathy Detection And Severity Classification IJRET: International Journal of Research in Engineering and Technology, Vol.3 Issue 03, Pages 619-624, March 2014.

[9]MamtaArora,SanjeevDhawan,KulvinderSingh,DeepLearning:Overview,Architecture,Framework and Applications. International Journal of Latest Trends in Engineering and Technology Vol.(10)Issue(1), pp.379-384 DOI: http://dx.doi.org/10.21172/1.101.69 e-ISSN:2278-621X.

[10] Phung,V.H;Rhee,E.J.A Deep Learning Approach for Classification of Cloud Image Patches on Small Datasets.J.Inf.Commun.Converg.Eng.2018,16,173,178,DOI:10.6109/jicce. 2018.16.3.173.

[11] Tom M. Mitchell, Machine Learning, India Edition 2013, McGraw Hill Education.

[12] Tajbia Karim, Md. Salehin Riad, Rehnuma Kabir, "Symptom Analysis of Diabetic Retinopathy by Micro-Aneurysm Detection Using NPRTOOL", 2019 International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), 978-1-5386-8014-8/19/$31.00 ©2019 IEEE.

[13]Manaswini Jenad, Smita Prava Mishra, Debahuti Mishra, "Detection of Diabetic Retinopathy Images using A Fully Convolutional Neural Network", IEEE, 2018 2 nd International Conference on Data Science and Business Analytics.

[14] Xiaoliang Wang, Yongjin Lu, Yujuan Wang, Wei-Bang Chen, "Diabetic RetinopathyStage Classification using Convolutional Neural Networks", 2018 IEEE International Conference on Information Reuse and Integration for Data Science, 978-1-5386-2659- 7/18/$31.00 ©2018 IEEE DOI 10.1109/IRI.2018.00074.

[15] Arkadiusz Kwasigroch, Bartlomiej Jarzembinski, Michał Grochowski, "Deep CNN based decision support system for detection and assessing the stage of diabetic retinopathy",978-1-5386-6143-7/18/$31.00 ©2018 IEEE.

[16] Shailesh Kumar, Basant Kumar, "Diabetic Retinopathy Detection by Extracting Area and Number of Microaneurysm from Colour Fundus Image", 2018 5th International Conference on Signal Processing and Integrated Networks (SPIN), 978-1-5386-3045-7/18/$31.00 ©2018 IEEE.

[17] Monika Andonová, Jarmila Pavloviþová, Slavomír Kajan, Miloš Oravec, Veronika Kurilová, "Diabetic Retinopathy Screening Based on CNN", IEEE, 59th International Symposium ELMAR-2017,18-20September2017, Zadar, Croatia.

[18] Xiaogang Li, Tiantian Pang, Biao Xiong, Weixiang Liu, Ping Liang, Tianfu Wang,"Convolutional Neural Networks Based Transfer Learning for Diabetic Retinopathy FundusImage Classification", 2017 10th International Congress on Image and Signal Processing,Biomedical Engineering and Informatics (CISP-BMEI 2017), 978-1-5386-1937-7/17/$31.00©2017 IEEE.

[19] Darshit Doshi, Aniket SheQoy Sardar Patel, Deep Sidhpura, Dr. Prachi Gharpure, "Diabetic Retinopathy Detection using Deep Convolutional Neural Networks", 2016 International Conference on Computing, Analytics and Security Trends (CAST) College of Engineering Pune, India. Dec 19-21, 2016, 978-1-5090-1338-8/16/$31.00 ©2016 IEEE.

[20] Karan Bhatia, Shikhar Arora, Ravi Tomar, "Diagnosis of Diabetic Retinopathy Using Machine Learning Classification Algorithm", 2016 2nd International Conference on Next Generation Computing Technologies (NGCT-2016) Dehradun, India 14-16 October 2016, 978-1-5090-3257-0/16/$31.00 ©2016 IEEE.

[21] Yogesh Kumaran, Chandrashekar M. Patil, "A Brief Review of the Detection of Diabetic Retinopathy in Human Eyes Using Pre-Processing & Segmentation Techniques", International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-7 Issue-4S2, December 2018.

[22]Kajaree Das,Rabi Narayan Behera,A Survey on Machine Learning:Concept,Algorithms and Applications,International Journal of Innovative Research in Computer and Communication Engineering,ISSN (Online):2320-9801 ,Vol.5,Issue 2,February 2017

[23] Drive dataset[online]: https://drive.grand-challenge.org/

[24] STARE dataset[online] : http://cecas.clemson.edu/~ahoover/stare/

[25] E-ophtha dataset[online]: http://www.adcis.net/en/third-party/e-ophtha/

[26] Kaggle dataset[online]: https://www.kaggle.com/c/diabetic-retinopathy-detection/data.

[27] Messidor1 dataset[online]:https://www.kaggle.com/google-brain/messidor1-dr-grades

[28] Messidor2 dataset[online]: http://www.adcis.net/en/third-party/messidor2/

[29] DeepDR [online]: https://isbi.deepdr.org/data.html

[30] IDRiD [online]:https://idrid.grand-challenge.org/Data

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