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Review Article

Diabetic Retinopathy Detection with Deep Learning Techniques on Fundus Photographs: A Review

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Abstract: Diabetic retinopathy (DR) is an ocular condition that can affect individuals with diabetes mellitus (DM) and may lead to reduced vision or even blindness if not detected on time. Delay in diagnosis and disagreement in interpretation of retinal images by different health experts are some of the challenges that can occur during screening for DR. Deep learning (DL) techniques are currently used for classification of images across various domains including the ophthalmic imaging field. The implementation of this cutting edge technology for detection of DR could lead to improvement of existing eye care services for diabetic individuals. This paper discussed the publicly available datasets of retinal images of diabetic individuals used for training DL models. The efficiency of several convolutional neural networks (CNNs) created for the detection of different classes of DR was also reviewed. Furthermore, the achievements and the challenges faced in the application of DL techniques for the DR detection were discussed. Finally, future works that can be performed in this research area has been suggested.

Keywords: Diabetic Retinopathy, Fundus photography, Deep Learning, Retinal Images, Convolutional Neural Networks.

1. INTRODUCTION

Diabetes mellitus (DM) is a situation in which there is presence of elevated blood sugar in an individual. This is as a consequence of the body not being able to produce adequate amount of insulin, or because there is no response by the cells of the human body to the insulin that is being made. The retinal microvasculature may be affected in individuals with DM leading to progressive damage of the eyes. This condition known as Diabetic retinopathy (DR) could lead to symptoms like cloudy vision, dark spots in the field of view and even blindness. DR can be categorized into Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). Clinical Signs of NPDR include microaneurysm, hard exudates, hemorrhages, and venous beading. NPDR is divided into mild, moderate and severe DR. Proliferative Diabetic Retinopathy, a more severe form of DR, occurs because of production the of new fragile blood vessels that can leak and lead to retinal detachment and blindness. Several risk factors for DR include high-level hemoglobin A1C (HbA1c), long duration of diabetes and elevated blood pressure [1]. Globally, diabetes mellitus will be present in 600 million individuals by the year 2040, with one-third presumed to present with diabetic retinopathy [1]. This could lead to challenges in manual inspection of morphological changes in retinal images as experienced clinicians can have difficulty keeping up with the demand for screening programs [2, 3]. Variability in the interpretation of images by human observers suggest that current methods of screening for DR can miss a sizeable number of cases [4]. Dilated eye examinations should be conducted on diabetic individuals annually to detect DR at its early stage [5]. The need for regular and improved eye screening for diabetic individuals has resulted in the creation of automated methods of detection of DR. This technique allows the computer to learn automatically and become better from experience without specifically programmed. As such, computer programs look for patterns in data such as retinal fundus photographs and make better decisions in the future based on the data that has been provided. Applying automated methods for DR detection will eventually help to reduce the workload of eye care professionals as more focus will be on treatment of DR rather than diagnosis of DR. The purpose of this paper is to review various methods of detection of DR

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using deep learning techniques. The paper is divided as shown below. Section 2 shows a description of fundus photography used for retinal image acquisition and different publicly available datasets of DR. Section 3 describes the performance measures of deep learning methods. Section 4 describes the training and validation of various DL algorithms on different data sets of DR. Section 5 describes the successes and limitations of automated methods of detection of DR using DL. Section 6 describes future works that should be conducted.

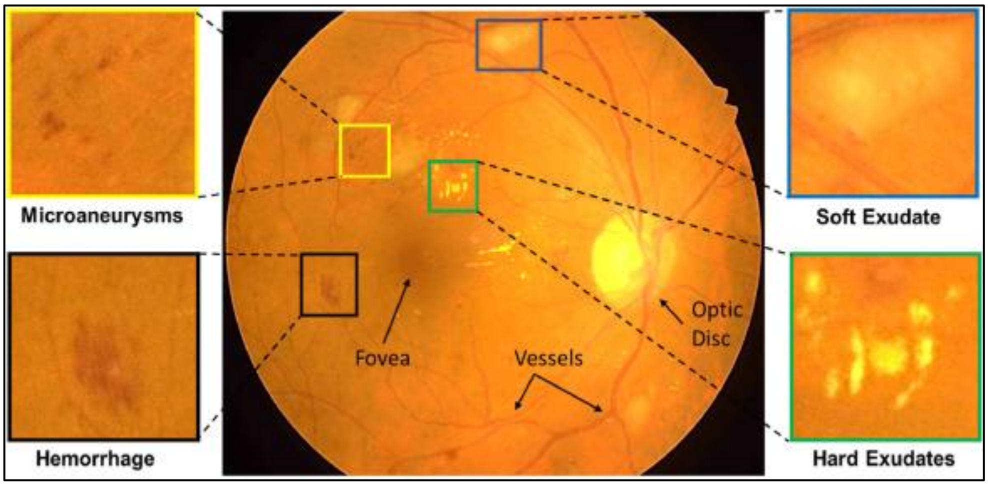

Figure 1: Clinical Features of Diabetic Retinopathy [6]

2. Fundus photography and publicly available datasets of DR

Fundus photography is a technique used for acquiring the image of the posterior aspect of the eye with a fundus camera. The back of the eye consist of the retina, blood vessels, macula and optic nerve head. Fundus cameras could be mydriatic (requires dilation of the pupils), non-mydriatic (does not require dilation of the pupils) or hybrid (mydriatic and non-mydriatic). Fundus cameras are in form of desk top, portable or smartphone imaging device. Fundus photography aids in early detection, proper monitoring and treatment of various eye diseases including DR. This procedure is carried out by trained health care professionals. The application of a dilating eye drops during fundus photography decreases the number of ungradable images and enhances sensitivity and specificity in the diagnosis of DR [7-10].

Various fundus photographs of diabetic individuals who have undergone DR screening programs in different countries have been compiled into DR datasets. These DR datasets are used for training and validation of different DL models developed by researchers in the retinal imaging field. Below is a list of some publicly available DR datasets.

Table 1: Diabetic retinopathy datasets

Name	Type of fundus camera	Field of view	No of retinal images
Messidor [11]	Topcon TRC NW6 non-mydriatic fundus	45 degree	1200 images
Messidor 2 [11]	Topcon TRC NW6 non-mydriatic fundus camera	45 degree	1748 images
Kaggle /EYEPACS [12]	Different fundus cameras	Different field of view	88,702 images
Indian diabetic retinopathy Image Dataset (IDRiD) [13]	Kowa VX-10α fundus camera	50 degree	516 images
ROC (Retinopathy online challenge) [14]	-	-	100 images
E ophtha [15]	-	-	463 images
DIARETDB1[16]	-	50 degree	89 images
DRIVE [17]	Canon CR5 non-mydriatic 3CCD camera	45 degree	40 images
The Asia-Pacific Tele-Ophthalmology Society APTOS [18]	-	-	3662 images

3. Performance Measures

The following measurement are used for the assessment of deep learning models

- Area under the curve (AUC): is a graph that plots the sensitivity against the specificity
- Accuracy: is the number of correct predictions made by the model

$$= \frac{(TP + TN)}{(TP + FP + FN + TN)}$$

- Sensitivity: is the rate of actual positives over all predicted values that are actually positive.

$$= \frac{TP}{TP + FN}$$

- Specificity: Specificity measures the True negatives over the sum of true negatives and false positives

$$= \frac{TN}{TN + FP}$$

True Positive (TP) – In this case, the model correctly predicts a diseased image
True Negative (TN) - In this case, the model correctly predicts a normal image
False Positive (FP) - In this case, the model wrongly predicts a diseased image
False Negative (FN) - In this case, the model wrongly predicts a normal image

4. Application of DL for diabetic retinopathy (DR) detection

Deep learning is a technique in machine learning which is used to train a neural network to carry out a task such as image classification prediction [19, 20]. A multitude of images are needed to train a neural network with the severity of a disease such as DR already known [20]. This enables the network to slowly modify their weight parameters to model and distinguish the stages of DR [21].Convolutional neural network (CNN) is a form of neural network in deep learning that is developed for analyzing mainly two- dimensional images [22, 23]. CNN is common in different computer vision tasks and is drawing a lot of interest across various disciplines [24]. ResNet, AlexNet, VGGNet, Inception v3, DenseNet are some examples of pretrained CNN architectures that have been employed for training large number of images from ImageNet dataset. Pre-trained CNN architectures provides a simpler and faster way of training using randomly initialized weights [25]. DR detection from fundus photographs has a rich and lengthy history in the analysis of the retina [2]. The classification of DR is a rather complicated activity which that demands the assessment of clinical signs like microaneurysms, exudates and haemorrhages leading to a reasonable amount of discrepancy in grading [26-28]. Several research works have recently developed algorithms for screening for diabetic disease using CNNs [29]. During the early development of these DL algorithms, many organizations assessed the performances of CNN in advanced countries mainly among people in United States [20, 30]. In a study done by Xu *et al*., 2016 [31], an accuracy of 94.5% with CNN for detection of DR was ranked as the highest when compared to earlier automated methods of classification using hand-crafted features, like: microaneurysm, blood vessel and exudate detection. Pratta *et al*., 2016 [32] developed a network using CNN architecture to diagnose DR from retinal images. Colour normalisation was implemented on the image. Thereafter the dataset was downsized to 512x512 pixels. Kaggle dataset was used for training and a sensitivity and accuracy of 95% and 75% was reported respectively. Gulshan *et al*., 2016 [20] trained a neural network known as inception-v3 architecture to detect referable diabetic retinopathy (moderate nonproliferative diabetic retinopathy or worse) using fundus photographs from EyePACS and three eye clinics located in United States and India respectively. Two datasets EyePACS 1 and Messidor 2 was used for validation. The sensitivity and specificity of the EyePACS 1 dataset was 90.3% and 98.1% respectively. The sensitivity and specificity of the Messidor 2 dataset was 87.0 % and 98.5 % respectively. García *et al*., 2017 [31] developed a computer-assisted tool using CNN architecture to identify micro-aneurysms, hemorrhages and exudates in fundus images. Training was done with labeled retinal images provided by EyePACS. The network showed an accuracy of 83.7% and specificity of 93.7% on validation process. Gargeya and Leng *et al*., 2017 [30] created a DL algorithm for the detection of DR. Publicly available datasets were used for training and assessment. The sensitivity and specificity of the algorithm with a local dataset was 94% and 98% respectively. An accuracy of 94% and 95% was achieved with MESSIDOR 2 and E-Ophtha datasets respectively. Ting *et al*., 2017 [21] trained a CNN architecture with fundus images of diabetic individuals from Singapore National Diabetic Retinopathy Screening Program (SIDRP) 2010-2013. The area under the curve (AUC) for referable DR and vision-threatening DR was 93.6%, and 95.8% respectively when internally validated on diabetic patients who participated in SIDRP 2014 - 2015. The range of AUC of referable DR was between 88.9% to 98.3% when external validation was done on 10 additional multi-ethnic cohorts of diabetic patients from various backgrounds. Li *et al*., 2018 [34] developed a DL algorithm for detecting referable DR using retinal images obtained from an online, crowdsourcing platform (LabelMe, Guangzhou, China). The Images were resized to a resolution of 299 × 299 pixels. The algorithm was validated using retinal images from Malay, Caucasian Australians, and Indigenous Australians population and reported a sensitivity, and specificity of 92.5%, and 98.5%, respectively. Lam *et al*., 2018 [29] detected different stages of DR using CNN architectures on Kaggle and Messidor datasets. AlexNet, VGG16 and GoogLeNet architectures were trained on Kaggle dataset. The GoogLeNet model has the best sensitivity of 95% and specificity of 96% for detection of referable DR. It was also observed that there was misclassification of Mild DR as normal because of CNNs inability to recognize subtle signs of DR. Deep CNNs (Alexnet, VGG16, InceptionNet V3)techniques were employed by Wang *et al*., 2018 [35] for classification of DR. The accuracy of VGG16, InceptionNet V3, Alexnet, was 50.03%, 63.23% and 37.43% for a 5 classification task.

Sengupta *et al*., 2019 [36] presented a DL method for detection of DR. Kaggle data was used for training and the assessment of the algorithm was done using Messidor dataset. An accuracy of 90.4%, sensitivity of close to 90% and specificity of 91. 94% was achieved with the model. Sarki *et al*., 2019 [37] conducted experiments with 13 CNN architectures that were pre-trained on ImageNet in order to detect mild DR. Messidor and Kaggle dataset were used for training and testing. An accuracy of 86% for No DR/Mild DR classification was achieved for ResNet50. Bellemo *et al*., 2019 [38] trained a VGGNet and a residual neural network (ResNet) using fundus images from diabetic patients who were examined in SIDRP. Clinical validation study was performed on diabetic patients that participated in a mobile screening program in urban regions located in Copperbelt district of Zambia. Heat maps was used to emphasize the region of the details in the retinal photographs that mostly led to the predicted diagnoses of the DL system. The AUC for detecting referable DR, vision threatening DR was 97.3%, and 93.4% respectively. Sahlsten, *et al*., (2019) [39] trained an Inception-v3 architecture to detect referable DR using non-open anonymized dataset of graded DR retinal images provided by Digifundus Ltd in Finland. Seventy percent of retinal images was used for training while 10% and 20% was used for tuning and primary validation. The AUC, sensitivity and specificity on the primary validation set was 98.7%, 89.6% and 97.4% respectively. The finding in this study also revealed that the accuracy of DL algorithms was improved when using high quality retinal images. Costa *et al*., 2019 [40] suggested EyeWeS for DR detection. EyeWeS is a combination of Multiple Instance Learning (MIL) and Transfer Learning for CNNs. This technique detects DR and also highlight the area of the fundus photographs that presents with lesions, while even though the training was done with only labelled retinal images. Messidor data set was used for training and testing to distinguish healthy images from DR. EyeWeS enhanced the results of Inception V3 architecture from 94.9% AUC to 95.8% AUC. The model was also able to obtain 97.1% AUC in a cross-dataset (E-ophtha MA dataset) experiment. Deep Convolutional Neural Network-based Diabetic Retinopathy Detection (DCNN-DRD) model has been proposed by Saranya *et al*., 2019 [41] to classify retinal images as healthy or DR. (DCNN-DRD) learns distiguishing signs of DR using the intensities of pixel values and does not require preprocessing. A portion of retina photographs from the ROC and MESSIDOR dataset was used for training. An accuracy of 97% was achieved with this model. A DL algorithm developed and trained with images from EyePACS, Messidor-2, and a local populace [42]. For validation, retinal images acquired from database of local DR screening program were evaluated by a DL algorithm and four senior retina ophthalmologists for detecting any-DR and referable-DR. The sensitivity and specificity for detecting any DR was 96.7% and 0.97.6%. The sensitivity and specificity for detecting referable DR was 99.8% and 96.8%. Transfer learning has been applied to divide DR into 2 stages with smaller dataset for training compared to earlier DR classification methods [43]. They applied pre-trained Inception-V3 on retinal images from the Kaggle dataset and validated on a previously unseen data subset. The accuracy of the model was 90.9%. Sharma *et al*., 2019 [44] applied CNN for the detection of DR. An accuracy of 74.04% was achieved with a 5 class classification task. They stated that accuracy can be better when the dataset size is increased because a portion of the data set was used as a result of limitation of hardware. Deep CNN was developed for DR detection by Housen *et al*., 2020 [45]. After the network was trained and validated, an accuracy of 96.3% and validation of 94.9% was observed with the DL algorithm. In a study done by Thiagarajan *et al*., 2020 [46], DL methodologies was applied for the detection of DR. An accuracy of 80% was achieved for the DL techniques compared to the Machine learning (ML) that resulted in an accuracy of 48% on the same Dataset. Shah *et al*., 2020 [47] validated a DL algorithm on dataset of 1,533 retinal images collected retrospectively from an Indian Eye hospital. The AUC was 99.1% and 96.9% for detecting any DR and referable DR respectively. The concession between two retinal specialists that graded the fundus images was 99.5% and 99.2% for detecting DR and referable DR respectively. Hemanth *et al*., 2020 [48] suggested a hybrid technique of detecting DR with image processing and deep learning and image processing. Four hundred fundus photographs available in the MESSIDOR dataset was used for validation. The AUC, sensitivity and specificity was 97.0%, 94.0%, and 98.0% respectively. Gadekallu *et al.*, 2020 [49] used firefly algorithm and principal component analysis (PCA) on Diabetic Retinopathy Debrecen dataset. Principal Component Analysis (PCA) was applied to select the important features in the dataset. The Firefly algorithm was then applied for dimension reduction. The accuracy, sensitivity and specificity of this method was 97.0%, 92.0% and 95% respectively. It was noted that the same achievement may not be noticed in the instance of reduced dimensional dataset with likelihood of the model being overfitted. Mateelm *et al.*, 2020 [50] evaluated the performance of CNN architectures (Visual Geometry Group Network-19, Inception-v3, Residual Network-50,) for the detection of exudate. The region of interest (ROI) localization was applied to pinpoint the characteristics of the exudates. The accuracy of Inception-v3, ResNet-50, and VGG-19 was 93.7%, 97.8%, and 95.8%, respectively using the e-Ophtha dataset. Furthermore the accuracies achieved was 93.6%, 97.9%, and 95.5%, respectively using the DIARETDB1 dataset. It was suggested that this technique can also be used for the detection of microaneurysms and hemorrhages and for DR. Shaban *et al*., 2020 [51] applied an adapted version of the VGG-19 architecture to classify DR into No DR, Moderate DR, and severe DR. The architecture was trained with Kaggle dataset and an accuracy, sensitivity and specificity of 88%-89%, 87%-89%, and 94%-95% respectively was reported. Yip *et al*., 2020 [52] assessed the technical and image-related factors for the detection of referable DR. A similar performance was found among ResNet, VGGNet, Densenet, Ensemble models. The performance of DL was found to be lower when the size of the retinal photograph was lower than 250 KB. It was observed that different image-related factors played more remarkable roles than technical factors for the detection of referable DR. Deep residual learning has been proposed by Rahman *et al*., 2020 [53] due to the challenge of time and space complexity while efficiently detecting DR. About 66.66% of kaggle dataset was used to train Resnet50 architecture while the remaining dataset was used for validation. An accuracy of 93.2% and sensitivity of 95.6% was achieved with this model. In the study done by Pao *et al*., 2020 [54], a bichannel CNN was trained using the characteristics of both the entropy retinal photographs from the gray level and the green aspect of retinal images preprocessed with unsharp masking to enhance the detection of referable DR. The sensitivity, and specificity of the proposed bichannel CNN model are 77.81%, and 93.88%, respectively. CNN and the technique of enhanced learning was employed by Wang *et al*., 2020 [55] to enhance the accuracy of a Deep DR model for classifying DR. An accuracy of 99.7%, 98.4% and 98.1% was achieved for the detection of microaneurysm, haemorrhage and hard exudates respectively in retinal images of two Eye Centers. An accuracy for accurate staging of retinal images from community screening was 91.79%. Qomariah *et al*., 2021 [56] employed a novel deep learning network that modifies UNet using residual units with modified identity mapping (MResUNet) to perform microaneurysm segmentation. The proposed architecture was assessed using the IDRID and DiaretDB1 datasets. The experimental results show that the architecture (MResUNet) achieved accuracy values of 61.96% and 85.87% on the IDRID and DiaretDB1 datasets, respectively. El Houby 2021 [57] used a pretrained VGG 16 for the detection of different classes of diabetic retinopathy. Kaggle dataset was used for training and testing. The accuracies achieved for 2-class, 3-class, 4-class and 5-class were 50%, 80.50%, 63.5% and 73.7%, respectively.

Table 2: Different DL techniques used for the classification of DR

Studies	**Deep Learning Techniques**	**Dataset**	**DR Detection**	**AUC**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
Xu *et al*., 2016	CNN	Local	DR	-	95.54	-	-
Pratta *et al*., 2016	CNN	Kaggle	DR	-	75.00	30.00	95.00
Gulshan *et al*., 2016	CNN (Inception V3)	EYEPACS 1	RDR	0.991	-	90.30	98.10
		Messidor 2	RDR	0.990	-	87.00	98.50
García *et al*., 2017	CNN	EYEPACS	DR		83.63	-	93.65
Gargeya and Leng *et al*., 2017	CNN	Local	DR	0.970	-	94.00	98.00
		Messidor 2	DR	0.940	-	-	-
		E- Ophtha	DR	0.950	-	-	-
Ting *et al*., 2017	CNN	Local (SIDRP)	RDR	0.936	-	90.50	91.60
		10 Datasets of different ethnicity	RDR	0.889 to 0.983	-	91.80 to 100	81.30 to 92.20
Li *et al*., 2018	CNN (InceptionV3)	Local (Label Me)	VTDR	0.989	-	92.50	98.50
		3 Datasets of different ethnicity	VTDR	0.937 to 0.969	97.11 to 99.13	89.76 to 94.59	97.57 to 99.17
Lam *et al*., 2018	CNN (GoogleLeNet)	Kaggle	No DR Mild DR Severe DR	-	-	98.00 93.00 7.00	-
		Messidor	No DR Mild DR Severe DR	-	-	85.00 75.00 29.00	-
Wang *et al*., 2018	CNN (AlexNet VGG InceptionNet V3)	Kaggle	DR (5 classes)	-	37.43 50.03 63.23	-	-
Sengupta *et al*., 2019	CNN (Inception-v3)	Kaggle Messidor	RDR	0.880 0.910	86.80 90.40	80.00 89.26	96.20 91.94
Sarki *et al*., 2019	(CNN) VGG ResNet	Kaggle Messidor	Mild DR	-	 81.30 81.60	-	-

	NASNetLarge				81.50		
Bellemo *et al.*, 2019	CNN (VGGNet ResNET)	Local	RDR	0·973	-	92·25	89·04
			VTDR	0·934	-	99·42	89·04
Sahlsten, *et al.*, 2019	CNN (Inception-v3)	Messidor	RDR	0.987	-	89.60	97.40
Costa *et al.*, 2019	CNN (VGG ResNet Inception- v3)	Messidor	DR	0.900 0.953 0.959	-	-	-
Saranya *et al.*, 2019	CNN	Messidor and ROC	DR	-	97.00	-	-
Romero-Aroca, *et al.*, 2019	CNN	Local	DR RDR	-	-	96.70 99.80	97.60 96.80
Hagos and Kant 2019	CNN (Inception-V3)	Kaggle	DR	-	90.90	-	-
Sharma *et al.*, 2019	CNN	Kaggle	DR (5 classes)	-	74.04	-	-
Housen *et al.*, 2020	CNN (DenseNet)		DR		94.90	-	-
Thiagarajan *et al.*, 2020	CNN	IdiRD	DR		80.00	-	-
Shah *et al.*, 2020	CNN	Local Messidor	DR RDR DR RDR	0.991 0.969 0.907 0.960	- -	99.71 98.98 90.37 94.68	98.50 94.84 91.03 97.40
Hemanth *et al.*, 2020	CNN	Messidor	DR		97.00	94.00	98.00
Gadekallu *et al.*, 2020	DNN	Diabetic Retinopathy Debrecen	DR	-	97.00	92.00	95.00
Mateelm *et al.*, 2020	CNN (Inception-v3, ResNet, and VGGNet).	e-Ophtha	Exudates	-	93.67 97.80 95.80	-	-
		DIARETDB1		-	93.57 97.90 95.50	-	-
Shaban *et al.*, 2020	CNN	Aptos 2019	DR (No DR, Moderate DR and Severe DR)	0.950	88.00	87.00	94.00
Yip *et al.*, 2020	CNN (VGGNet ResNet DenseNet Ensemble)	Local (SIDRP)	RDR	0.938 0.936 0.941 0.944		92.10 91.90 92.80 94.00	91.00 90.90 90.90 90.70
Rahman *et al.*, 2020	CNN(ResNet)	Kaggle	DR	-	-	95.60	93.20
Pao *et al.*, 2020	CNN	Kaggle	RDR	0.930	87.83	77.81	93.88
Wang *et al.*, 2020	CNN	Local	DR Microaneurym Haemorrhage Hard exudates	0.9327	91.79 99.70 98.40 98.10	80.58	95.77
Quomariah *et al.*, 2021	CNN ((MResUNet)	IDRID DiaretDB1	Microaneurym	-	99.76 99.75	61.96 85.87	99.81 99.77
Elhouby *et al.*, 2021	CNN (VGG16)	Kaggle	2 class 3 class 4 class 5 class	-	86.50 80.50 63.50 73.50	-	-

5. DISCUSSION

A total of 31 papers that applied DL techniques for detection of DR were reviewed in this study. Majority of the studies reported different levels of accuracy, sensitivity and specificity in detecting any DR, referable DR, vision threatening DR and five stages of DR. This automated method of detection of DR will play a significant role in screening of diabetic individuals for the purpose of identifying diabetic individuals who are in need of additional examination and treatment. It was also noted that the performance of DL algorithms tends to reduce when used for a multi-class classification task. Although DL techniques had better performance compared to traditional ML techniques, large numbers of images are usually needed for training. When the data volume of dataset is limited, deep learning algorithms often perform poorly [19]. DL techniques depends more on computers with graphical processing units (GPUs) due to large computational operations during training. The retinal images used for the development of DL algorithms in most of the studies were acquired from publicly available databases. The classes of retinal images available for training are usually unbalanced, with high number of no DR compared to the remaining four classes. Image resolution and number of field of view used for training can affect the performance of DL algorithms [52]. The various CNN architectures had similar rates of performance for the detection of DR. However the present CNN architectures have been optimized to detect moderate features as the signals used for classification reside in a part of the image clearly visible to the human observer [59, 29]. DL algorithm uses numerous levels of representation to access each retinal image without revealing the features of DR such as microaneurysms, exudates, haemorrhages [21]. This black box method of disease detection results in an output specified simply as a negative or positive response [60]. Hence, it may be that the DL algorithm is making use of features previously not known to humans [20]. Recent studies have attempted to overcome this challenge by highlighting areas of the retinal fundus used for classification. Such visualizations represent important explanations that could assist in developing trust in DL models [38].

6. CONCLUSION AND FUTURE WORKS

Incorporating automated methods of detection of DR will reduce delay in the diagnosis and treatment of DR leading to improved eye care delivery for diabetic individuals. Majority of the studies reviewed achieved high performance in binary classification task for the detection of DR. Algorithms that can be created from training small dataset and detecting a higher number of classes using novel techniques in DL should be considered. Validation of DL algorithms with independent data sets is necessary to access their performance in real life situations as many factors may affect the performance of DL algorithms.

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