



Detection of Diabetic Retinopathy Based on Convolutional Neural Networks: A Review

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Authors' contributions

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ABSTRACT

A major cause of human vision loss worldwide is Diabetic retinopathy (DR). The disease requires early screening for slowing down the progress. However, in low-resource settings where few ophthalmologists are available to care for all patients with diabetes, the clinical diagnosis of DR will be a considerable challenge. This paper, review the most recent studies on the detection of DR by using one of the efficient algorithms of deep learning, which is Convolutional Neural Networks (CNN), which highly used to detect DR features from retinal images. CNNs approach to DR detection saves time and expense, and is more efficient and accurate than manual diagnostics. Therefore, CNN is essential and beneficial for DR detection.

Keywords: Diabetic retinopathy; retinal images; detection; convolutional neural networks.

1. INTRODUCTION

Diabetic retinopathy is considered the major reason that causes blindness among working-

age individuals in developing countries. According to the World Health Organization (WHO), 347 million people are suffering from diabetes over the world and this number will be

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increased to 552 million people in 2030. The person who has diabetes is at high risk of eyes disease; include DR diabetic retinopathy, Diabetic Macular Edema (DME) glaucoma and cataract [1-4]. To process this information, the brain needs to light signal to penetrate the eyes through the shape on the retina and lenses. This process can be disturbed easily by different diseases which prevent the correct explication of a visual signal, and this disorder is DR diabetic retinopathy which is an accompanying disorder of diabetes disease [5,6]. According to early detection of DR diabetic retinopathy, the process of eyes injury might be slow down and even stopped surgically, while without any treatments it will be caused irreversible damage and blindness in advanced stages [6,7]. Therewith, the process of retinal detection is difficult manually and spend time-consuming, so the system that can be analyzed the retina automatically and observe the development of disease will highly help both patients and ophthalmologists [8].

Recently, deep learning has been enhanced to the purpose of computer vision in diagnostic and classification of images and is the key device has been used to automate a task in people life [9]. The Convolution Neural Networks CNN consistently have been developed to detect the objects, segmentation and classification [10,11]. CNN is a class of artificial neural networks that are proven to be highly effective in cases like image classification and recognition [12,13]. CNN has been successful used in analyzing visual imagery, identifying persons and objects [14]. Furthermore, CNN has been used effectively to solving various medical image problem [15,16]. CNN is one of the important methods to fix an automatic analysis of retinal images. The CNNs is used to classified retinal injury to an appropriate degree and also to extract features of retinal damage. Many studies are focusing on the anomalies ordinarily known as (Exudates) or light lesions [17-20]. Another way to assess entire retinal images is labelled then as a suitable degree of diabetic retinopathy [21-25]. For this process, they use different image pre-processing ways to extract several important features and classified to their particular classes. And can be implementing CNNs to detect the five degrees of retinal damage DR. At last, use the specificity, accuracy, sensitivity, (ROC) Receiver Operating Characteristic and (AUC) Area Under Curve for performance evaluation the proposed models [26-28]. In addition, can get the best publicly

available datasets of images to train for its models.

This paper aims to review the most important recent studies about using CNN to detect DR, as well as to present the importance of this algorithm and how to use this technique for DR detection efficiently.

This paper is organized as follows. The DR is explained in section 2, the dataset of the RD is presented in section 3, In section 4 the CNNs types are presented, And the performance metrics explained in details in section 5, Section 6 is reviewed many studies and research on DR detection used CNN followed by the section 7 with a discussion. The conclusion of this paper is presented in section 8.

2. DIABETIC RETINOPATHY

Based on an international clinical diabetic retinopathy disease severity scale, the presence of DR can be graded into 5 divisions (None, Mild, Moderate, Extreme, Proliferative). Examples of the Mild DR [29], distinguished by the existence of micro-aneurysms, are seen in (Fig. 1), Micro-aneurysms typically have a diameter of (10 μ m - 100 μ m), which is less than the main veins' diameter in the eyes. Several eye retina objects are close to the shape and size of micro-aneurysms, which often makes it difficult to diagnose them appropriately [30].

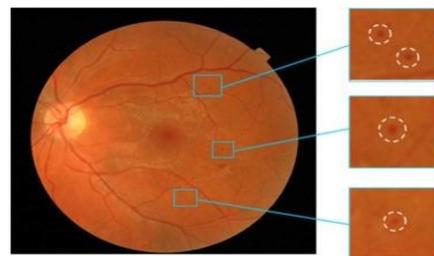


Fig. 1. Microaneurysms

The intermediate stage between severe and mild retinopathy is a moderate DR [31]. Certain symptoms that cause the eyes to be classified in this category cannot be described by an international clinical DR disease severity scale. The loss of description detailed of this class can cause significant difficulty to CNN in its classification.

If one of these symptoms occurs, diabetic retinopathy is considered a strong DR [32]:

- a. Comprehensive intra-retinal bleeding in each of the four quadrants of the retina.
- b. Special expansion of the retina veins that like a string of pearls, or at least in two-quarters of the eyes it is known as venous beading.
- c. Outstanding Intraretinal microvascular abnormalities (IRMA).

Fig. 2 shows the important example about venous beading is, the area of this symptom is marked with the black arrow [33].

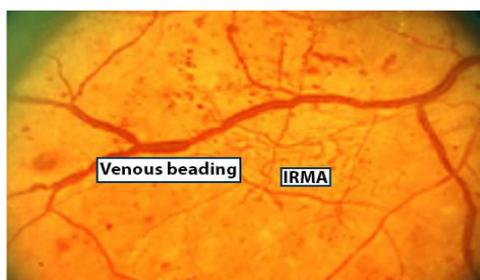


Fig. 2. Venous beading

While Fig. 3 shows IRMA jointly with venous beading, and these abnormalities characterized by retinal degeneration and petechiae and are more difficult to differentiate from neovascularization [34].

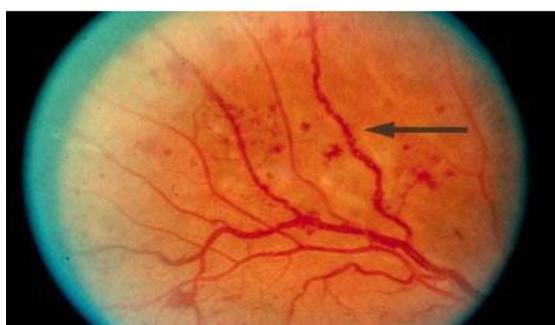


Fig. 3. IRMA

The defective blood vessels have been produced in the absence of treatment and fibrous tissue is growing in the retina. Proliferative DR, the last stage of a disease characterized by neovascularization is the process through which new blood vessels form. Other symptoms of proliferative DR are often vitreous haemorrhages that haemorrhage into the vitreous body of the skin, and the vitreous body is translucent like a gel material stuffing the space between the eyes and the retina of the lens and the eyes form retina preservation [35]. Vitreous haemorrhage

and neovascularization have been seen in each symptom Fig. 4.

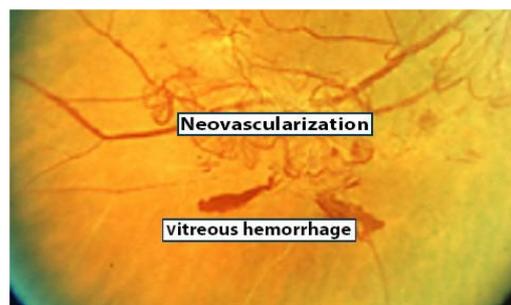


Fig. 4. Neovascularization and vitreous hemorrhage

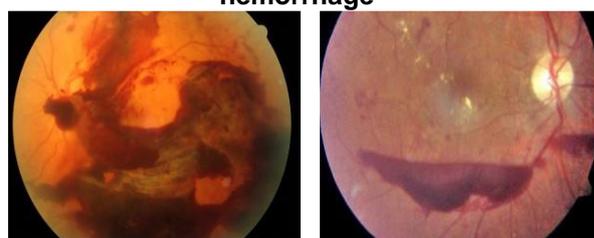


Fig. 5. Hemorrhages

Another form of haemorrhage that sometimes occurs in proliferative DR is the pre retinal haemorrhage and the shape of the boat-like pre retinal haemorrhage, as shown in Fig. 5 in both forms of haemorrhage that can occur in proliferative DR [36].

The key symptoms of the DR Stage have been seen, although other indications of DR are shown, such as cotton wool spots, which are seen in Fig. 6.



Fig. 6. Cotton wool spots

The classification of multiclass is necessary because the various treatment ways depend on the disease stages, while is more complex than simple detection by the presence and absence of

disease. It's recommended to control blood pressure and glucose in all potentially endangered DR, therefore, a moderate DR patient must be consulted by an ophthalmologist, and recommended laser therapy for individuals who have serious DR, in particular, if retinopathy is identified as proliferative the laser treatment is strongly recommended. While in the state of neovascularization or vitreous haemorrhage in the head of the optic nerve, the therapy must be performed immediately [13].

3. RETINA DATASETS

In general, there are several publicly available retina datasets for DR detection and vessels, typically used to test systems, verify trains, and compare the performance of systems with other systems. The important types of retinal imaging are fundus colour images and Optical Coherence Tomography (OCT). The image OCT is a 2 and 3-dimensional of the retina datasets has been taken with low cohesion light and provides a lot of information about the thickness and structure of the retina, but the images of the fundus are 2 dimensional of the retina and taken with reflected light [37,38]. There are several datasets of fundus images that are commonly used and available publicly, they are as follows:

- Kaggle: It contains 88,702 high-resolution images with a various resolution, ranging from 433 X 298 pixels to 5184 X 3456 pixels. It is collected from different cameras [39,40]. All images are classified into five DR stages. Only training images ground truths are publicly available. Kaggle contains many images with poor quality and incorrect labelling [36,41].
- DIARETDB1: it contains 89 publicly available retina fundus images with size 1500 X 1152 pixels obtained in the 50-degree FOV field of view, and including 84 DR images and 5 normal images annotated with 4 medicinal experts [38].
- DDR: this type of dataset contains 13,673 fundus images obtained in the 45-degree FOV annotated to 5 DR stages, and 757 images from the dataset annotated to DR lesions [36].
- E-ophtha: it includes E-ophtha M and E-ophtha EX, the E-ophtha MA contains 148 images with MA and 233 normal images, while the E-ophtha EX contains 47 images with EX and 35 normal images [42].
- DRIVE: this type of dataset used for the segmentation of blood vessel, and

containing 40 images obtained at 45 degrees FOV, the images with the size 565 X 584 pixels, 7 of them are mild DR image are presented, and the remaining includes the images of the normal retina [43].

- Messidor-1: this dataset contains 1200 fundus color images obtained at degree FOV annotated at 4 stages DR [44].
- Messidor-2: this dataset contains 1748 images obtained at 45-degree FOV [45].
- HRF: this type is also supplied to blood vessel segmentation and includes 45 images with size 3504 X 2336 pixels, there are 15 DR images, 15 glaucomatous images and 15 healthy images [46].
- STARE: this dataset is used for the segmentation of blood and includes 20 images obtained at 35-degree FOV, the images with the size 700 X 605 pixels, and there are 10 normal images among them [47].
- ROC: this type of dataset contains 100 retina images obtained at 45-degree FOV, with size ranging from 768 X576 to 1389 X1383 pixels, the images annotated for detecting MA, and only training ground truths are available [48].
- CHASE DB1: this type of dataset is provided with the segmentation of blood vessel, and contains 28 images with size 1280X960 pixels, obtained at 30-degree FOV [49,50].
- Indian DR image dataset (IDRiD): this dataset contains 516 fundus images obtained at 50-degree FOV, annotated to 5 DR stages [50].
- DR2: this dataset contains 435 retina images with size 857X569 pixels, providing referral annotation for images, and 98 images have been classified as referral [51].

In addition, many studies have been used types of publicly available fundus images datasets such as; the study [52] was used DIARETDB1 dataset for detecting DR lesions, the study [49,53] (E-ophtha) and (DIARETDB1) were used for the detection of the red lesion, while the study [50,54] was used these datasets for detecting (MA). Furthermore, the study [2] was used (DIARETDB1) to detect (EX), the studies [52] [18,55-58] were used (Kaggle dataset) to classify (DR) stages, while the study [59] were used (DRIVE, HRF, STARE and CHASE DB1) to detect segment the blood vessels.

4. CONVOLUTIONAL NEURAL NETWORKS (CNN)

CNN is a type of deep neural networks that are specifically created to interpret image information directly from its pixels. It is possible to describe CNN layers as dark and light, positions, forms, colors, margins, and artefacts [59]. There are many drawbacks of utilizing CNN, such as the process need for further training database, the active learning is a lengthy and complicated neural hyper-parameter network method [22,60,61].

The first layer of CNN architecture is the input layer that emerged as seen in Fig. 7 for encoding and interpreting image pixels, and then the data are interpreted by the coevolutionary layer series reflecting lineaments of image filters. The first layer of CNN senses simpler picture characteristics such as borders and shifts in brightness, but subsequent layers may be identified as a dynamic function and part of the artefacts. [62-64].

Clustering methods are used to decrease the size of the function diagram, thereby reducing the parameters and computational complexity. Pooling layers operate on any stage separately [65,66].

During the process, these pooling layers are divided into planes having edges and their outputs become function maps that are centred on the previously sorted frames [67].

The final classification was done by fully joined layers classifying the inputs, and the output layer supplying the results of the classification is the final component of this chain.

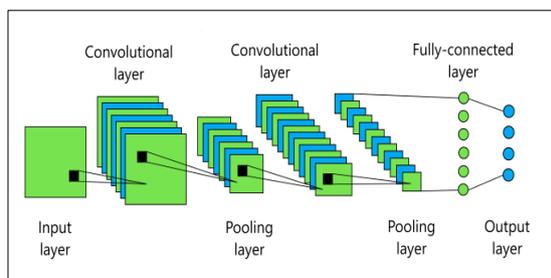


Fig. 7. Architecture of CNN

4.1 Types Deep CNN Architectures

4.1.1 AlexNet

It was first included in the competition for ImageNet [61,68], which ignited the attention of the computer vision community to work on improving the CNN design framework for image recognition challenges. There are 5 convolution layers in this architecture, two of which are binding layers and three are pooling layers. AlexNet has influenced and used many of CNN's architectures through transfer learning. As seen in (Fig. 8), AlexNet's simple architecture.

4.1.2 GoogLeNet/ Inception

This model was first used in [69], this network architecture is totally deep and dynamic, and a new layer known as Its emerged (Inception). Each layer of Inception consisted of 6 convolutions and only one lake. GoogLeNet has recently gained attention because of its network

Infrastructure and the application of data analytics in many problems. Some implementations of GoogLeNet are available and can be used for image classification.

4.1.3 VGGNet

The neural network was ranked first in the ImageNet competition in 2014 [70]. VGG is designated for the visual geometry community, and the structure was created to decide how the depth of a network influences its accuracy.

This network can be used for classification tasks and localization of images. The basic architecture of ResNet -50. is as seen in Fig. 9.

4.1.4 ResNet-50

To achieve a meaningful result in the ImageNet database classification, Residual Network- 50 is a deep convolutionary neural network [71]. ResNet-50 consist of many sizes of convolutional filters to decrease.The basic architecture of ResNet is the time of preparation and management of the degradation case due to the deep structure.



Fig. 8. Basic architecture of AlexNet

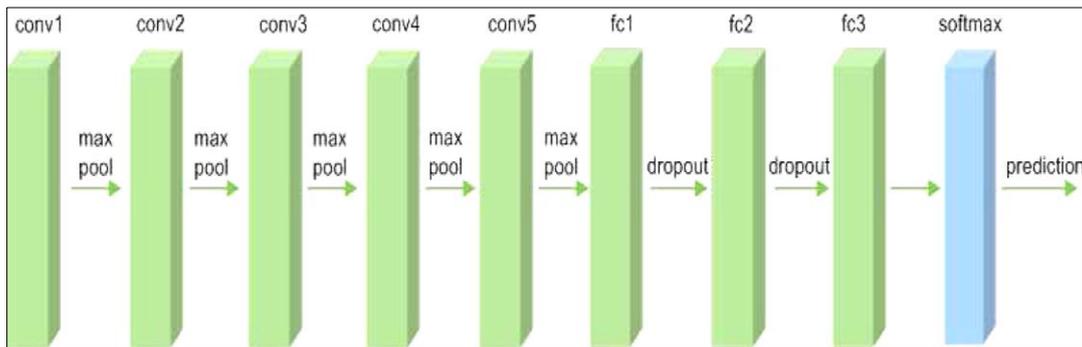


Fig. 9. Basic VGGNet-19 architecture

The overall system for detecting DR is seen in (Fig. 10). It consists of Three critical components: the classification network, the preprocessing step and the post prediction. In addition, the preprocessing stage can be divided into the ROI identification of the interest area and the enhancement of the image. The identification of ROI filters out useless material, while the enhancement of the image emphasizes characteristics such as haemorrhage and microaneurysms related to DR signs. The classification network aims to classify the DR scales of severity. Finally, the post forecast deals with the issue of multiple DR structures being graded [1].

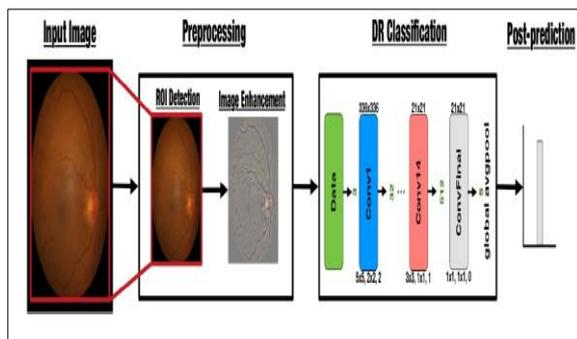


Fig. 10. System Overview of DR Recognition Based on CNN

4.2 Performance Metrics

The fundus images captured submit an additional step known as preprocessing for detecting DR. Many of the preprocessing steps such as median filtering contrast enhancement and histogram equalization. In the medical state applications, the data divided considerably into 2 types; healthy and unhealthy, and the same case applied to detecting DR. Usually deep learning model used for the analysis of classification problems, and there are only a few standard metrics to assess the classifiers. The algorithms correctness has been reviewed through analysis of the following Metrics [65,72]:

- True positive TP= total number of the correct identification as unhealthy.
- True negative TN= total number of the correct identification as healthy.
- False-positive FP= total number of incorrect identifications is unhealthy.
- False-negative FN= total number of incorrect identifications as healthy.

In paper [73] and [74] the algorithms that reviewed the use of performance metrics such as (SP or FPR) Specificity or false positive rate [75],

(SE or TPR) sensitivity or true positive rate, (Acc) Accuracy [76], and (AUC) Area under curve characteristic. Also, a few algorithms prefer the usage (F1) F1-score as a performance metrics on the others. As seen in the Table 1, the classification problems used as the diversion matrix to explain the efficiency of the classifiers are the combination of TP, FP, FN and TN [77]. Values such as Acc, AUC, SE and SP may easily be acquired [78,79]. The formation of the uncertainty matrix is a simplified way of performance evaluation.

For each metric used in the detecting algorithms, the formulas are as follows:

$$Acc = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$SE = \frac{TP}{TP+FN} \quad (2)$$

$$SP = \frac{TN}{TN+FP} \quad (3)$$

		Predicted		
		Positive	Negative	
Actual	Positive	TP	FN	SP (TN/TN+FP)
	Negative	FP	TN	SE (TP/TP+FN)
		PPV (TP/TP+FP)	NPV (TN/TN+FN)	Acc (TP+TN / TP+TN+FP+FN)

Fig. 11. Example of the confusion matrix

5. RELATED WORKS

The most important studies related to deep learning CNN method for detection of (DR) were conducted by many researchers and have been presented automatically retinal images analysis tools include.

Kadam et al. [31] suggested the CNN algorithm of machine learning has been used to detecting (DR) by using thermal images and pre-processed the images by converting from (RGB) to (GRAY) depended on the required features that extracted.

Pao et al. [80] proposed the entropy image computed using the green portion of the fundus images and the image enhancement by (UM) unsharp masking was applied to the preprocessing before the entropy images were calculated, and the bi-channel CNN was suggested to apply

(UM) and grey level entropy images to the features of each green component preprocess to improve the detection efficiency of (DR) by deep learning.

Manta et al. [11] proposed a color fundus photograph focused on transfer learning CNN architecture that performs comparatively well on far smaller datasets for warped groups of (418) validation images and (3060) training images to identify (DR) classes from blood vessels, texture and rough exudates.

Chen et al. [81] suggested the approach to retinal image classification is focused on the application of multi-scale shallow CNNs. Experiments indicate that the proposed approach can increase the classification accuracy by 3% on public data sets, on limited datasets, relative to current representative applied CNN learning methods, the proposed approach will boost the accuracy of the classification by 3% to 9%. Compared with other representative methods, such as conventional LCNN, CNN and VGG16noFC, on a broader dataset.

Saranya and Prabakaran [82] used a convolution neural network to automate detection and grading of non-proliferative Diabetic Retinopathy (DR) from retinal fundus images and tested this model on 2 public datasets includes (IDRiD) and (MESSIDOR).

Mateen et al. [2] pre-trained architecture based on CNN was proposed for the detection of exudates. Furthermore, the position of the interest region ROI used to locate exudate characteristics and then transfer learning is carried out to retrained CNN models for extraction of features (Visual Geometry Group Network-19, Residual Network-50 and Inception-V3) they used 2 good-known publicly accessible databases as (E-Ophtha and DIARETDB1), the output of the proposed system was evaluated. Experimental results show that the proposed CNN-based pre-trained system outperforms the current exudate detection techniques.

Xu et al. [83] explored the use of deep convolutional neural network technic for the automatic classification of diabetic retinopathy detection using color fundus image, and 94.5% precision was obtained on their dataset, surpassing the findings obtained using classical approaches.

Chen et al. [1] suggested a recognition pipeline based on the deep CNN they and they designed lightweight networks called SI2DRNet-v1 along

with six methods to further boost the detection performance in their pipeline. Based on the DCNN for detecting DR they presented a framework, and for the RDR and DR states on the Messidor dataset, the proposed framework achieves 0.965 AUC.

Gulshan et al. [84] have been used certain deep learning ways for automated (DR) detection and used CNN ways for image classification and trained its algorithm with Inception-v3 architecture with about (128175) image using Eye-PACS and Messidor-2 dataset. In addition, they have been mentioned the type of (DR) problem like (DME) referable Diabetic Macular Edema, (rDR) referable Diabetic Retinopathy and (vtDR) vision-threatening Diabetic Retinopathy and based on their results, they suggested that the CNN network gives the best result when the network trained with (60,000) image in terms of specificity and sensitivity.

Pratt et al. [18] proposed a CNN technique to diagnose DR from digital fundus images and reliably characterize its severity. They trained this network on the publicly accessible Kaggle dataset using a high-end graphics processing unit (GPU) and showed amazing outcomes, particularly for a high-level classification mission. On a data set of 80,000 images used, the proposed CNN achieves a sensitivity of 95% and a precision of 75% on 5,000 validation images.

Abramoff et al. [56] have been developed an Iowa detection program for detection of (rDR) and used their own (DR) databases and overtly available (Messidor-2) dataset for the training and testing respectively, and based on results on (Messidor-2) dataset, they have achieved 87.0% specificity and 96.8% sensitivity for detection of (rDR).

Gargeya et al. [85] they have used a specific CNN technique for detecting (DR), and trained this system with (75127) images from the dataset and examined with (Messidor-2) and (E-Opha) datasets, then they classified these images into 2 categories; one with healthy eyes and other with worse (DR) stage, in result they obtained 98% specificity and 94% sensitivity and 98% specificity from their dataset.

Kajan et al. [23] the automated identification and classification of DR symptoms with pre-trained CNN has been suggested, and they acquired datasets in the EyePace DR database of retinal images. The proposed images used as data for

testing and training. The accuracy of the classification of three various pre-trained neural networks was compared and chosen as the most effective.

Carson et al. [41] for detecting (DR) inserted CNN base deep-learning technique and used different classification models such as (2-ary, 3-ary, and 4-ary), and Pre-trained (AlexNet) and (GoogLeNet) model have been inspected and transfer learning approach was applied by using (KaggleEyePACS) and (Messidor-1) dataset, then they proposed using image treating technique for increasing effectiveness accuracy for detecting of mild (DR) includes contrast adjustments and image normalization by using histogram equalization. Also, they increased the retina image for increasing the number of the images in the training set and preventing overfitting, in result have received 94% sensitivity in the validation group and accuracy in the testing group was 75.5%, 69.7%, and 51.25% for (2-ary, 3-ary, and 4-ary) models respectively.

Graham. [86] preprocessed the retina image to reduce illumination differences and he used Sparse-ConvNet, CNN and random forest to classifying by raising the retina image to increase the number of images in the training group. In particular, with increased computing power and developments in deep learning algorithms (CNNs).

Rajalakshmi et al. [87] compared conventional fundus devices and proposed to use (FOP) Remidio Fundus Phone devices to capture high-quality retina pictures.

Pires et al. [88] suggested the solution to detecting (rDR) by using data-driven approaches and have been used transfer learning technique to be implemented in CNN, and they have applied on training stages to data increasing, multi-resolution, per-patient analysis, feature extraction and examining their solution with cross dataset logic by using (Kaggle EyePACS) as the training, and by (Messidor-2) dataset for testing, in result, they acquired 98.3% (ROC) Receiver operating characteristic for prediction (rDR).

M. hamzah abed et al. [90] built a classification model based on CNN to classify the retina images from three datasets DiaretDB0, DiaretDB1 and DrimDB to healthy and unhealth state. The accuracy is used as a evaluation metric. The model achieved 100% for DiaretDB0,

99.495% for DiaretDB1 and 97.55% for DrimDB dataset.

Y. Sun [91] speed up and enhanced classification accuracy using CNN-based method combining with the BN layer to one-dimensional unrelated datasets. The proposed work solved the problem of convolution one-dimensional

irrelevant data. The model training accuracy was 99.85% and a testing accuracy was 97.56%.

6. COMPARISON AND DISCUSSION

In this section, we discussed the comparison between 14 important recent studies on convolutional neural networks for DR detection, as shown in Table 1.

Table 1. Summary of literature review papers

Authors	Year	Methods	Datasets	Results
Quellec et al [4]	2017	CNN on Image-level with pixel-level visualization, an ensemble of CNNs.	Kaggle& DIARETDB1	AUC= 0.954 Need for referral on Kaggle test-set
Wan et al [26]	2018	convolutional neural networks , adopt by AlexNet, VggNet, GoogleNet, ResNet	Kaggle	AlexNet AUC= 0.7968 ACC =73.04% VggNet, AUC=0.7938 ACC 82.17% GoogleNet AUC=0.7756 ACC=86.35% ResNet AUC=0.8266 CC=0.7868%
Chen et al [1]	2018	A pipeline of recognition based on CNN. and Lightweight networks called SI2DRNet-v11 have been designed.	Messidor	AUC=0.959 ACC=0.905 For SI2DRNet-v1
Orlando et al [53]	2018	Selection of classical candidate, patch-based CNN followed by random forest with added manually designed features	Messidor DIARETDB1 E-Ophtha	Screening DR on Messidor AUC = 0.893% SE = 0.9109% need for referral on Messidor
Hajabdollahi et al [89]	2019	A hierarchical pruning method for addressing the problem of reducing CNN's structural complexity	Messidor	AUC= 0.973 Accuracy = 0.938
Y. Sun [91]	2020	apply the CNN method to one-dimensional unrelated data sets	3500 fundus images from 301 hospitalized patients	Training accuracy of 99.85% Testing accuracy of 97.56%
Mateen et al [2]	2020	Pretrained CNN-based framework	e-Ophtha DIARETDB1 Database	Accuracy 98.43% Accuracy 98.91%
Kajan et al [23]	2020	CNN Using Transfer Learning	25 790 Various retinal	The Inception-v3 network achieved the average best performance, achieving

Authors	Year	Methods	Datasets	Results
			images from the EyePacs Database for DR	90.97% training and 70.29 testing accuracy
Saranya&Prabakaran [84]	2020	CNN layers	MESSIDOR	SP= 96.30 % Se=88.75% Accuracy =90.89%
			IDRiD	SP= 96.89 % Se=88.75% Accuracy=90.29%
Kadam et al [31]	2020	CNN algorithm- using the thermal images	images thermal	These images are pre- processed by converting them from RGB to GRAY based on which the required features are extracted. To detect the diabetic retinopathy
Chen et al [83]	2020	Approach classification of retinal images based on the inclusion of multi-scale shallow CNNs	3000, 3500,35000 images of platform Kaggle	Accuracy of 35000 =0.92%, Accuracy of 3500 = 0.86% , Accuracy of 3000 = 0.85%
Nazir et al [82].	2020	Fast Region-based CNN (FRCNN) algorithm with fuzzy k-means (FKM) clustering	ORIGA DR-HAGIS MESSIDOR HRF	SP= 0.965% SE= 0.961% ACC= 0.95% AUC=0.967%
Samanta et al [11]	2020	Transfer learning based on CNN on a small dataset	419 fundus images	Accuracy=84.10%
M. hamzah abed et al. [90]	2020	Visual enhancement at pre-processing phase, classification images to the healthy and unhealthy cases .	DiaretDB0, DiaretDB1 and DrimDB	DiaretDB0 is 100%, DiaretDB1 is 99.495% DrimDB is 97.55%

The above table shows that each research used CNN for DR detection in different methods and datasets. Most of them used public datasets such as (ORIGA, DR-HAGIS, MESSIDOR, HRF, Kaggle, EyePacs), and others used various methods and architecture of CNN as (AlexNet, VggNet, GoogleNet, ResNet, SI2DRNet-v1, FRCNN). As shown in those studies the classification performance was different when using different CNN architectures. The [51] showed the accuracy difference in each architecture and performance of overall classification is low. In [11] the results of the accuracy shows 98.43% and 98.91% in both datasets for the retinal exudates detection. As well as, the proposed pretrained CNN based framework technique was better than the current individual methods. In paper [17] the overall

performance assessment of the proposed method the images from the MESSIDOR dataset obtained 90.89% accuracy, 96.3% precision, 88.75% sensitivity and 0.48 only a loss. An accuracy of 90.29% and 96.89% specificity, 88.75% sensitivity and 0.475 loss were obtained on the (IDRiD) images. As indicated in the table, some of the studies used a few numbers of the dataset, while others used many datasets, so in the result, the accuracy percentage can be different according to the set of images used, and based on the analyses and experimental results, the using of few numbers of datasets gives accurate results and enhances the speed of operation.

7. CONCLUSION

Convolution Neural Networks has been shown that have high potential and accurate results to be training for detection of the features of DR in the fundus images and to the automated retinal images analysis. The CNN technic for detection DR is saving time and cost at the same time, and it is more efficient and accurate than the manual diagnosis, and also CNN very important and useful for DR clinicians.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Chen Y-W, Wu T-Y, Wong W-H, Lee C-Y. Diabetic retinopathy detection based on deep convolutional neural networks. 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2018;1030–1034.
2. Mateen M, Wen J, Nasrullah N, Sun S, Hayat S. Exudate detection for diabetic retinopathy using pretrained convolutional neural networks. Complexity; 2020.
3. Shaw JE, Sicree RA, Zimmet PZ. Global estimates of the prevalence of diabetes for 2010 and 2030. Diabetes Research and Clinical Practice; 2010;87(1):4–14.
4. Zeebaree DQ, Abdulazeez AM, Zebari DA, Haron H, Nuzly H. "Multi-level fusion in ultrasound for cancer detection based on uniform lbp features," Computers, Materials and Continua. 2021;66(3):3363–3382.
5. Price LD, Au S, Chong NV. Optomap ultrawide field imaging identifies additional retinal abnormalities in patients with diabetic retinopathy. Clinical Ophthalmology (Auckland, NZ); 2015;9:527.
6. Zebari DA, Haron H, Zeebaree DQ, Zain AM. A Simultaneous Approach for Compression and Encryption Techniques Using Deoxyribonucleic Acid. In 2019 13th International Conference on Software, Knowledge, Information Management and Applications (SKIMA). IEEE. 2019;1-6.
7. Gao Z, Li J, Guo J, Chen Y, Yi Z, Zhong J. Diagnosis of diabetic retinopathy using deep neural networks. IEEE Access. 2018;7:3360-3370.
8. Zago GT, Andreão RV, Dorizzi B, Salles EOT. Diabetic retinopathy detection using red lesion localization and convolutional neural networks. Computers in Biology and Medicine. 2020;116:103537.
9. Ahmed O, Brifcani A. Gene Expression Classification Based on Deep Learning. In 2019 4th Scientific International Conference Najaf (SICN). IEEE. 2019;145-149.
10. Gadekallu TR, Khare N, Bhattacharya S, Singh S, Maddikunta PKR, Srivastava G. Deep neural networks to predict diabetic retinopathy. J. Ambient Intell. Humaniz. Comput ; 2020.
11. Samanta A, Saha A, Satapathy SC, Fernandes SL, Zhang YD. Automated detection of diabetic retinopathy using convolutional neural networks on a small dataset. Pattern Recognition Letters.
12. Ian Goodfellow, YoshuaBengio, and Aaron Courville. (2016). Deep Learning. MIT Press; 2020. Available:http://www.deeplearningbook.org
13. Zeebaree DQ, Haron H Abdulazeez AM. Gene selection and classification of microarray data using convolutional neural network. In 2018 International Conference on Advanced Science and Engineering (ICOASE). IEEE. 2018;145-150.
14. Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. In Advances in Neural Information processing systems. 2012;2:1097–1105.
15. Bekker AJ, Greenspan H, Goldberger J. A multi-view deep learning architecture for classification of breast microcalcifications. In Proceedings -International Symposium on Biomedical Imaging. 2016;726–730.
16. Roth HR, Lee CT, Shin HC, Seff A, Kim L, Yao J, Summers RM. Anatomy-specific classification of medical images using deep convolutional nets. In 2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI). IEEE. 2015;101-104.
17. Prentašić P, Lončarić S. Detection of exudates in fundus photographs using convolutional neural networks. In 2015 9th International Symposium on Image and Signal Processing and Analysis (ISPA). IEEE. 2015;188-192.

18. Pratt H, Coenen F, Broadbent DM, Harding SP, Zheng Y. Convolutional neural networks for diabetic retinopathy. *Procedia Computer Science*. 2016;90:200-205.
19. Andonova M, Pavlovičová J, Kajan S, Oravec M, Kurilov'a V. Diabetic Retinopathy Screening Based on CNN. 59th International Symposium. Zadar, Croatia. 2017;51-54.
20. Zeebaree, Diyar Qader, Habibollah Haron, Adnan Mohsin Abdulazeez and Subhi RM Zeebaree. "Combination of K-means clustering with Genetic Algorithm: A review." *International Journal of Applied Engineering Research*. 2017;12(24):14238-14245.
21. Sadek I, Elawady M, Shabayek AER. Automatic classification of bright. 2017.
22. Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. *Communications of the ACM*. 2017;60(6):84-90.
23. Gargeya R, Leng T. Automated identification of diabetic retinopathy using deep learning. *Ophthalmology*. 2017;124(7):962969.
24. Kajan S, Goga J, Lacko K, Pavlovičová J. Detection of Diabetic Retinopathy Using Pretrained Deep Neural Networks. In 2020 *Cybernetics & Informatics (K&I)*. IEEE. 2020;1-5.
25. Abdulazeez, Adnan Mohsin, Diyar Qader Zeebaree, Dildar Masood Abdulqader. "Wavelet Applications in Medical Images: A Review." *Transformation (DWT)*. 2020;21:22.
26. Wan S, Liang Y, Zhang Y. Deep convolutional neural networks for diabetic retinopathy detection by image classification. *Computers and Electrical Engineering*. 2018;72:274-282.
27. Zebari, Dilovan Asaad, Diyar Qader Zeebaree, Adnan Mohsin Abdulazeez, Habibollah Haron, Haza Nuzly Abdull Hamed. "Improved Threshold Based and Trainable Fully Automated Segmentation for Breast Cancer Boundary and Pectoral Muscle in Mammogram Images." *IEEE Access* 8. 2020;203097-203116.
28. Zebari NA, Zebari DA, Zeebaree DQ, Saeed JN. Significant features for steganography techniques using deoxyribonucleic acid: A review. *Indonesian Journal of Electrical Engineering and Computer Science*. 2021;21(1):338-347.
29. Kwasigroch A, Jarzembinski B, Grochowski M. Deep CNN based decision support system for detection and assessing the stage of diabetic retinopathy. In 2018 *International Interdisciplinary PhD Workshop (IIPhDW)*. IEEE. 2018;111-116.
30. Sehirlı E, Turan MK, Dietzel A. Automatic detection of microaneurysms in RGB retinal fundus images. *Studies*. 2015;1(8):1-7.
31. Kadam S, Pradhan V, Kate K. Convolution neural network-based method for automatic detection of diabetic eye disease using thermal Images. 2020;07(05):5.
32. Kwasigroch A, Jarzembinski B, Grochowski M. Deep CNN based decision support system for detection and assessing the stage of diabetic retinopathy. In 2018 *International Interdisciplinary PhD Workshop (IIPhDW)*. IEEE. 2018;111-116.
33. "Ophthalmology | School of Medicine | University of Colorado Denver; 2018. (Accessed: 09-Feb-2018)." [Online]. Available:<http://www.ucdenver.edu/academics/>
34. Kwasigroch A, Jarzembinski B, Grochowski M. Deep CNN based decision support system for detection and assessing the stage of diabetic retinopathy. In 2018 *International Interdisciplinary PhD Workshop (IIPhDW)*. IEEE. 2018;111-116.
35. Stewart MW. Human immunodeficiency virus and its effects on the visual system. *Infectious Disease Reports*. 2012;4(1).
36. Li T, Gao Y, Wang K, Guo S, Liu H, Kang H. Diagnostic assessment of deep learning algorithms for diabetic retinopathy screening. *Information Sciences*. 2019;501:511-522.
37. Abramoff MD, Garvin MK, Sonka M. Retinal imaging and image analysis. *IEEE reviews in biomedical engineering*. 2010;3:169-208.
38. Kauppi T, Kalesnykiene V, Kamarainen JK, Lensu L, Sorri I, Raninen A, Pietilä J. The diaretdb1 diabetic retinopathy database and evaluation protocol. In *BMVC*. 2007;1:1-10).
39. Kaggle dataset [Online]; 2002.

- Available:<https://kaggle.com/c/diabetic-retinopathy-detection>
40. Abdulazeez A, Salim B, Zeebaree D, Doghramachi D. Comparison of VPN Protocols at Network Layer Focusing on Wire Guard Protocol; 2020.
 41. Lam C, Yi D, Guo M, Lindsey T. Automated detection of diabetic retinopathy using deep learning. AMIA Summits on translational science proceedings. 2018;147.
 42. Decenci re E, Cazuguel G, Zhang X, Thibault G, Klein JC, Meyer F, Chabouis A. Tele Ophtha: Machine learning and image processing methods for teleophthalmology. IRBM. 2013;34(2):196-203.
 43. Staal J, Abr moff MD, Niemeijer M, Viergever MA, Van Ginneken B. Ridge-based vessel segmentation in color images of the retina. IEEE transactions on medical imaging. 2004;23(4):501-509.
 44. Budai A, Bock R, Maier A, Hornegger J, Michelson G. Robust vessel segmentation in fundus images. International Journal of Biomedical Imaging; 2013.
 45. Decenci re E, Zhang X, Cazuguel G, Lay B, Cochener B, Trone C, Klein JC. Feedback on a publicly distributed image database: The Messidor database. Image Analysis and Stereology. 2014;33(3):231-234.
 46. Hoover AD, Kouznetsova V, Goldbaum M. Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response. IEEE Transactions on Medical Imaging. 2000;19(3):203-210.
 47. Owen CG, Rudnicka AR, Mullen R, Barman SA, Monekosso D, Whincup PH, Paterson C. Measuring retinal vessel tortuosity in 10-year-old children: Validation of the computer-assisted image analysis of the retina (CAIAR) program. Investigative Ophthalmology and Visual Science. 2009;50(5):2004-2010.
 48. Younis ZA, Abdulazeez AM, Zeebaree SR, Zebari RR, Zeebaree DQ. mobile ad hoc network in disaster area network scenario: A review on routing protocols. International Journal of Online and Biomedical Engineering. 2021;17(3).
 49. Porwal P, Pachade S, Kamble R, Kokare M, Deshmukh G, Sahasrabuddhe V, Meriaudeau F. Indian diabetic retinopathy image dataset (IDRiD): A database for diabetic retinopathy screening research. Data. 2018;3(3):25.
 50. ROC dataset [Online]; 2007. Available:<http://roc.healthcare.uiowa.edu>
 51. DR2 [Online]; 2016. Available:https://figshare.com/articles/Advancing_Bag_of_VisualWords_Representations_for_Lesion_Classification_in_Retinal_Images/953671
 52. Quellec G, Charri re K, Boudi Y, Cochener B, Lamard M. Deep image mining for diabetic retinopathy screening. Medical Image Analysis. 2017;39:178-193.
 53. Orlando JI, Prokofyeva E, del Fresno M, Blaschko MB. An ensemble deep learning-based approach for red lesion detection in fundus images. Computer methods and programs in biomedicine. 2018;153:115-127.
 54. Chudzik P, Majumdar S, Caliv  F, Al-Diri B, Hunter A. Microaneurysm detection using fully convolutional neural networks. Computer Methods and Programs in Biomedicine. 2018;158:185-192.
 55. Esfahani MT, Ghaderi M, Kafiyeh R. Classification of diabetic and normal fundus images using a new deep learning method. Leonardo Electron J Pract Technol. 2018;17(32):233-248.
 56. Abr moff MD, Lou Y, Erginay A, Clarida W, Amelon R, Folk JC, Niemeijer M. Improved automated detection of diabetic retinopathy on a publicly available dataset through integration of deep learning. Investigative Ophthalmology and Visual Science. 2016;57(13):5200-5206.
 57. Dutta S, Manideep BC, Basha SM, Caytiles RD, Iyengar NCSN. Classification of diabetic retinopathy images by using deep learning models. International Journal; 2018.
 58. Wang X, Lu Y, Wang Y, Chen WB. Diabetic retinopathy stage classification using convolutional neural networks. In 2018 IEEE International Conference on Information Reuse and Integration (IRI). IEEE. 2018;465-471.
 59. Lu J, Xu Y, Chen M, Luo Y. A coarse-to-fine fully convolutional neural network for fundus vessel segmentation. Symmetry. 2018;10(11):607.
 60. Kandel I, Castelli M. Transfer learning with convolutional neural networks for diabetic retinopathy image classification. A

- Review. Applied Sciences. 2020;10(6):2021.
61. Hasan DA, Abdulazeez AM. A modified convolutional neural networks model for medical image segmentation. Learning. 2020;20:22.
 62. Zeebaree, Diyar Qader, Habibollah Haron, Adnan Mohsin Abdulazeez, Dilovan Asaad Zebari. "Trainable Model Based on New Uniform LBP Feature to Identify the Risk of the Breast Cancer." In 2019 International Conference on Advanced Science and Engineering (ICOASE), IEEE. 2019;106-111.
 63. Adem K. Exudate detection for diabetic retinopathy with circular Hough transformation and convolutional neural networks. Expert Systems with Applications. 2018;114:289-295.
 64. Bargarai Faiq, Adnan Abdulazeez, VolkanTiryaki, Diyar Zeebaree. "Management of Wireless Communication Systems Using Artificial Intelligence-Based Software Defined Radio." 2020;107-133.
 65. Kwasigroch A, Jarzembinski B, Grochowski M. Deep CNN based decision support system for detection and assessing the stage of diabetic retinopathy. In 2018 International Interdisciplinary PhD Workshop (IIPhDW), IEEE. 2018;111-116.
 66. Taha MS, Rahim MSM, Hashim MM, Khalid HN. Information Hiding: A Tools for Securing Biometric Information. Technology Reports of Kansai University. 2020;62(04):1383-1394.
 67. Abdulazeez AM, Hajy DM, Zeebaree DQ, Zebari DA. Robust watermarking scheme based on LWT and SVD using artificial bee colony optimization. Indonesian Journal of Electrical Engineering and Computer Science. 2021;21(2):1218-1229.
 68. Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. Communications of the ACM. 2017;60(6):84-90.
 69. Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, Rabinovich A. Going deeper with convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2015;1-9).
 70. Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. 2014;Xiv. Preprint arXiv: 1409.1556.
 71. Yu Y, Lin H, Yu Q, Meng J, Zhao Z, Li Y, Zuo L. Modality classification for medical images using multiple deep convolutional neural networks. J. Comput. Inf. Syst. 2015;11(15):5403-5413.
 72. Thanati H, Chalakkal RJ, Abdulla WH. On Deep Learning based algorithms for Detection of Diabetic Retinopathy. In 2019 International Conference on Electronics, Information, and Communication (ICEIC), IEEE. 2019;1-7.
 73. Hossin M, Sulaiman MN. A review of evaluation metrics for data classification evaluations. International Journal of Data Mining and Knowledge Management Process. 2015;5(2):1.
 74. Sokolova M, Lapalme G. A systematic analysis of performance measures for classification tasks. Information Processing and Management. 2009;45(4):427-437.
 75. Abdulqader DM, Abdulazeez AM, Zeebaree DQ. Machine learning supervised algorithms of gene selection: A review. Machine Learning. 2020;62(03).
 76. Zeebaree DQ, Haron H, Abdulazeez AM, Zebari DA. Machine learning and Region Growing for Breast Cancer Segmentation. In 2019 International Conference on Advanced Science and Engineering (ICOASE), IEEE. 2019;88-93.
 77. Al-Zebari A, Sengur A. Performance Comparison of Machine Learning Techniques on Diabetes Disease Detection. 2019 1st International Informatics and Software Engineering Conference (UBMYK). 2019;1-4. Available:<https://doi.org/10.1109/UBMYK48245.2019.8965542>
 78. Costa P, Araújo T, Aresta G, Galdran A, Mendonça AM, Smailagic A, Campilho A. eyes: weakly supervised pre-trained convolutional neural networks for diabetic retinopathy detection. In 2019 16th International Conference on Machine Vision Applications (MVA), IEEE. 2019;1-6.
 79. Adnan Mohsin Abdulazeez, Sulaiman MA, Zeebaree Diyar Qader. Evaluating Data Mining Classification Methods Performance in the Internet of Things Applications. Journal of Soft Computing

- and Data Mining. 2020;1(2):11-25.
80. Pao SI, Lin HZ, Chien KH, Tai MC, Chen JT, Lin GM. Detection of Diabetic Retinopathy Using Bichannel Convolutional Neural Network. *Journal of Ophthalmology*; 2020.
81. Chen W, Yang B, Li J, Wang J. An Approach to Detecting Diabetic Retinopathy Based on Integrated Shallow Convolutional Neural Networks. *IEEE Access*. 2020;8:178552-178562.
82. Saranya P, Prabakaran S. Automatic detection of non-proliferative diabetic retinopathy in retinal fundus images using convolution neural network. *Journal of Ambient Intelligence and Humanized Computing*. 2020;1-10.
83. Xu K, Feng D, Mi H. Deep convolutional neural network-based early automated detection of diabetic retinopathy using fundus image. *Molecules*. 2017;22(12):2054.
84. Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, Webster DR. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *Jama*. 2016;316(22):2402-2410.
85. Gargeya R, Leng T. Automated identification of diabetic retinopathy using deep learning. *Ophthalmology*. 2017;124(7):962-969.
86. Graham B. Kaggle diabetic retinopathy detection competition report. The University of Warwick; 2015.
87. Rajalakshmi R, Arulmalar S, Usha M, Prathiba V, Kareemuddin KS, Anjana RM, Mohan V. Validation of smartphone-based retinal photography for diabetic retinopathy screening. *PloS one*. 2015;10(9):e0138285.
88. Pires R, Avila S, Wainer J, Valle E, Abramoff MD, Rocha A. A data-driven approach to referable diabetic retinopathy detection. *Artificial Intelligence in Medicine*. 2019;96:93-106.
89. Hajabdollahi M, Esfandiarpour R, Najarian K, Karimi N, Samavi S, Soroushmehr SR. Hierarchical Pruning for Simplification of Convolutional Neural Networks in Diabetic Retinopathy Classification. In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE. 2019;970-973.
90. hamzah abed M, Muhammed LAN, S. J. a. e.-p. Hussein Toman, "Diabetic Retinopathy Diagnosis based on Convolutional Neural Network." 2008;00148
Accessed on: July 01, 2020.
Available: <https://ui.adsabs.harvard.edu/abs/2020arXiv200800148H>
91. Sun Y. "The Neural Network of One-Dimensional Convolution-An Example of the Diagnosis of Diabetic Retinopathy," in *IEEE Access*. 2019;7:69657-69666.
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