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Analysis Of Ophthalmic Disorders For Retinal Images Using Deep Learning: A Review

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ABSTRACT.A summary of deep learning applications for ophthalmic disorders for retinal fundus images is given. Retinal Detachment, Macular Bunker, Retinoblastoma, Diabetic Retinopathy (DR), Age-Related Macular Degeneration (AMD), and Retinitis Pigmentosa are only a few of the retinal diseases that can be detected and categorized using retinal image analysis. Automated retinal disease detection is a major measure toward prior analysis and avoidance of disease exacerbation. Several state-of-the-art methods for automated segmentation and recognition of retinal landmarks and pathologies have been developed in the past. However, recent breakthroughs in deep learning and the contemporary imaging process in ophthalmology have opened up an entirely new world of possibilities for analysts. This paper is a study of deep learning techniques for automatic detection of diseases including age-related macular degeneration(AMD), glaucoma, diabetic retinopathy(DR), retinal landmarks, and anatomy using 2-D(two-dimension) fundus and 3-D (three dimensions) Optical Coherence Tomography (OCT) retinal images. The techniques are evaluated in terms of area under the ROC curve, sensitivity, accuracy, specificity, and F score.

Keywords: Deep learning, ophthalmic disease, Diabetic retinopathy, age-related macular disease, retinal images, ophthalmology, fundus photos, glaucoma, retinal disease classification, image segmentation, Convolution neural network.

1 INTRODUCTION

In telemedicine, automatic categorizing of ophthalmologic and cardiovascular disorders using retinal image processing has become commonplace. Manual segmentation was used previously, which was tedious, prolonged, inappropriate, labor-demanding, gazer-dependent, and needed expert expertise while computer-assisted identification of retinal abnormalities is profitable, attainable, objective, and does not necessitate the use of a well-trained psychiatrist to order the images. Early analysis and instantaneous classification of retinal disorders like retinitis pigmentosa, age-related macular degeneration (AMD), retinoblastoma, diabetic retinopathy (DR), macular bunker, and retinal detachment are aided by the development of screening systems [1]. The most prevalent retinal disorders are age-related macular degeneration, diabetic retinopathy, and. Glaucoma. Glaucoma is one of the most common sources of blindness. This disease is divided into two types: open-angle and angle-closure glaucoma. Main open-angle glaucoma affects nearly 90% of those impacted. The ratio of the optic cup to optic disc has traditionally been used to diagnose glaucoma. Ophthalmologists also use vision fields, hard exudates, neuroretinal rim loss, soft exudates, and retinal nerve fiber layer disorders to diagnose patients. Another frequent source of blindness in humans is diabetes retinopathy (DR). The count of diabetic-affected patients worldwide is projected to grow from 2.8 percent in 2000 to 4.4 percent by 2030. Diabetes is very normal among people over the age of thirty; untreated diabetes may result in DR. It is distinguished by a variety of retinal anomalies, including microaneurysms (MA) and

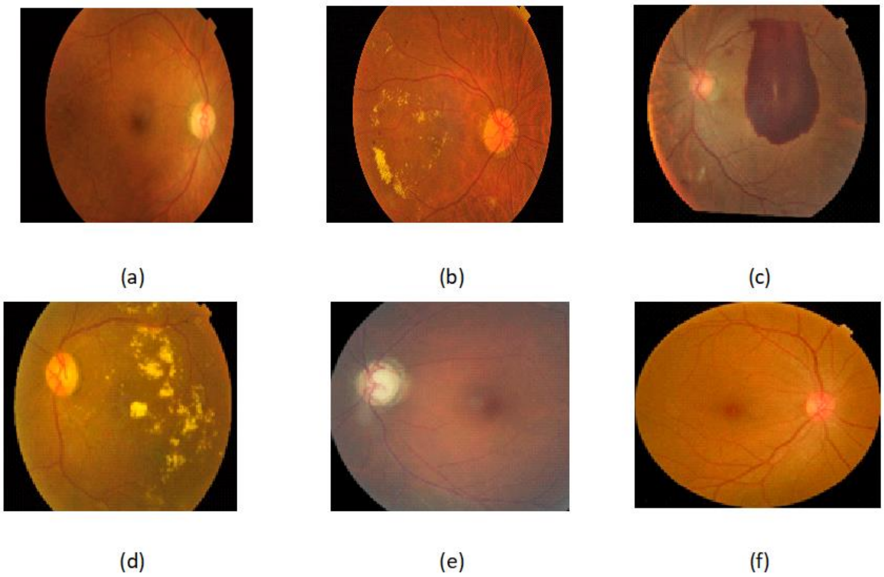

Fig. 1. Retinal images showing a) Mild DR b) Moderate DR c) Proliferate DR d) Severe DR e) Glaucoma f) AMD

other minor lesions that result in the breakup of weak retinal capillaries; those were the early signs of DR. Strong exudates, cotton wool spots (CWS) or delicate exudates, macular edema (ME), hemorrhages (HEM) and neovascularization (NV) are some of the other symptoms. Fig.1.shows the difference between the persons having normal retina and diabetic retinopathy affected retina. Another widespread reason for vision loss condition is age-related macular degeneration (AMD). It may result in blindness at the center of the visual field of the human eyeball, and over the period, it can cause total loss of central vision.[2].

For any of the above ailments requires handcrafted feature extraction, for which explicit domain awareness is needed. The majority of the time, the findings collected from them were more specialized on datasets and don't want to achieve generalization. Recent innovations in deep learning-based vision[52-57] perception have energized analysts to apply these methods often in the field of ophthalmology. Deep learning can be used to achieve automatic recognition of intricate pusses from retinal images. For all the images like color fundus images, RGB images, B-scans, 2-D (two dimensions) fundus images, and 3-D (Three dimensions) Optical Coherence Tomography (OCT) photos, the retinal image processing focused on deep learning outperformed conventional approaches. This study looks at how advanced deep learning techniques can be put to use to analyze all the above-mentioned types of images of the retina for automatic prediction of retinal landmarks, anatomy, and disorder type. We compared and evaluated techniques using a variety of key performance metrics such as sensitivity, precision, accuracy, and area under the ROC curve. The aim of this paper is to use deep learning approaches to summarise recent progress in the field of ophthalmology [1].

1.1 Literature-searching technique

For this review, a systematic technique for searching the literature has been established. The steps of this formal approach are as follows:

- Defining the study challenge
- Finding related papers that follow the pre-determined inclusion requirements
- Collecting appropriate data from papers
- Assessing the collected data's consistency

This survey looked at all of the literature that was available at the time found by repetitious and systematic searches in the databases mentioned below:

1. ScienceDirect, (http://www.sciencedirect.com/)
2. American Academy of Ophthalmology, (http://www.aaojou rnal.org/)
3. The JAMA Network, (http://jamanetwork.com/journals/jam a)
5. Eye-Nature (https://www.nature.com/eye/)
6. IEEE Xplore Digital Library, (http://ieeexplore.ieee.org)
7. Springer Link, (http://link.springer.com/)

This analysis covered both journal articles and conference papers that were presented in the proceedings of the bibliographic databases listed above.

1.2 Conditions for inclusion

The cue sentence for literature search is 'Deep learning for retinal image processing.' Both article's abstracts and titles are collected and compared to the research cue, and only those publications that include deep learning techniques based on segmentation and disease recognition of anatomical composition of the retina are chosen. This survey includes all related content up to 2021.

1.3 Condition for exclusion

This survey's primary objective is to explore approaches for retinal image recognition based on deep learning. As a result, papers with algorithms that aren't focused on deep learning principles are not considered for this survey. Besides, papers that have high-impact factors and respected conferences were chosen for this study. We didn't have any articles that were written in local magazines or conferences.

1.4 Selection of papers

The papers were chosen after a thorough review of the inclusion and exclusion requirements. Selected papers were saved in pdf format after being downloaded. The publication year, journal name or conference name, editor, primary author's name, and titles are all used in the nomenclature to save selected articles. This form of nomenclature aided in the indexing of papers and allowed for quick retrieval in response to queries. Many of the papers' citations were downloaded and stored in the EndNote library.

2 DIAGNOSTIC ANALYSIS OF RETINAL PHOTOS

2.1 Retinal imaging modalities

For visualization that is non-destructive of retinal anatomical properties, several imaging modalities have been established. Fundus photography is successful in the early identification and evaluation of the three better solemn sources of vision loss in the developed world namely macular degeneration, glaucoma, and diabetic retinopathy (DR). Preliminary fundus cameras' 2-D representations of the retinal environment lacked the capability to comprehend depth while fundus image analysis, resulting in an inaccurate diagnosis of some retinal pathologies (example. cotton wool spots). This issue has been solved using tomography-based imaging. OCT is now being successfully used to create a three-dimensional image of the retina[1].

2.1.1 Fundus photography.

The method of taking serial photos within your eye via the pupil is known as fundus photography. The optic disc, retina, and lens are examined using a fundus camera, which is a specialized less-power microscope mounted to a camera. It's a quick and painless procedure that only takes a minute or two. Rather than inspecting the eye directly, stereoscopic fundus photos make it easier to see the features of the retina (within the surface of the eye). It gives the doctor an outlook of whole layers of the retina (the eye's inner surface) and helps a doctor to make the most precise diagnosis possible. Present fundus images employ the succeeding imaging technique:

Color fundus photography.

Color fundus photography is a diagnostic technique that involves capturing colored photographs of the internal surface of the eye with a system called a fundus camera. The aim of this procedure is to keep track of whether or not there are any diseases and how they change over time. The macula, optic disc, retinal blood vessels, retina, and posterior pole are among the eye structures recorded. Optic nerve disorders, glaucoma, color vision defects, age-related macular degeneration(AMD), macular edoema, diabetic retinopathy(DR), and retinal detachment are all conditions that can be kept on track with color fundus imaging. The technique aids in the mapping of each eye's human life cycle and wellbeing. It offers a bird's eye outlook of the retina's within layers due to the strong imaging. It can also be used to observe disease progression added, allowing for more precise treatment plans.

Red free photography

Using a filter with a wavelength of 500 nm, red-free fundus photography was designed to compare rhodopsin contents in the retina during light and dark adaptations. To prevent a possible photographic artifact, half of the fundus is irradiated after dark adaptation, either top or bottom half, and a red-free light fundus photograph is taken. This is useful for detecting pale lesions (exudates and drusen), hemorrhages, retinal blood vessels, epiretinal membranes, and defects in the retinal nerve fiber sheet.

Stereo fundus photography

Because of its improved depth resolution, it aids in the documentation of retinal structures. It is possible to diagnose macular edoema (ME) and subretinal neovascularization using this method of photography, which requires concurrent or successive visualization of the retina by dual cameras with separate angles of view, causing the least amount of discomfort to the sick person.

Hyper-spectral imaging

Hyperspectral imaging, like other types of spectral imaging, gathers and processes data from all parts of the electromagnetic spectrum. The aim of hyperspectral imaging is to obtain the spectrum for each pixel in a scene image in order to locate objects, recognize materials, or detect processes. The use of hyperspectral photography in the early detection of retinopathy and macular edoema before eye damage occurs. A decrease in oxygen intake in the retina can be detected by the metabolic hyperspectral camera, indicating the presence of disease. An ophthalmologist will then be able to use injections to treat the retina and avoid any further damage.

Scanning Laser Ophthalmoscopy (SLO)

SLO (scanning laser ophthalmoscopy) is a technique for examining the eye. It uses confocal laser scanning microscopy to image the retina and cornea of the human eye for diagnostic purposes. It is useful in the diagnosis of glaucoma, macular degeneration, and other retinal disorders as a tool for imaging the retina with a high degree of spatial sensitivity. It's also been paired with adaptive optics technology to create clearer retinal images.

Adaptive Optics SLO

AOSLO (adaptive optics scanning laser ophthalmoscopy) is a procedure for assessing the count of living retinal cells. Adaptive optics is used to eliminate optical aberrations from retinal images produced by scanning laser ophthalmoscopy.

Angiography.

The technique of angiography is used to investigate the tiny blood vessels which are present in the eye. The technique is used to assist in the detection of some eye disorders. Fluorescein is a dye that is inserted into a vein in your arm or hand. When the dye enters the blood vessels in the eye, it passes rapidly through the bloodstream and a series of photographs are taken. Any abnormal or leaking blood vessels that may be causing your eye problems are noticeable in the images.

2.1.2. 3-D optical coherence tomography (OCT)

The most quickly developing retinal imaging technique in ophthalmology is optical coherence tomography. OCT technology can produce cross-sectional images including an axial resolution of up to 2 m for research-grade apparatus by calculating the echo time lag and amplitude of back-distributed or back-emulated radiation. The B-scan images which are obtained by cross-sectional of the retina act as “optical biopsies” of their target tissues, similar to histologic sections.

3 RETINAL DISEASE CLASSIFICATION

3.1 AMD Classification

Below are some of the most recent findings on AMD disease classification using fundus images. The outcome of deep learning-based automatic evaluation of AMD from fundus images is comparable to the human performance standard[3]. It is demonstrated that deep-learning-based techniques can be utilized successfully to grade and detect AMD in the retina and also demonstrates that neural networks are used with specific instruction with fundus shows substantially greater outcomes than pre-trained networks [4]. By combining the ensemble network method with cutting-edge network architectures, it is shown that the performance is vastly improved comparing to the previous model[5]. Without a segmentation algorithm, an accurate computational deep-learning technique for differentiating AMD from standard OCT images and categorizing AMD based on the existence or absence of exudative difference [6]. A new method for predicting AMD-related disorders from a very broad variety of ophthalmoscope color fundus images has been released. On pre-processed retinal images, three convolutional layers including the ReLU unit and max-pooling layers were applied to carry out this analysis. Six ophthalmologists compared the accuracy of DCNN using photographs to human scoring[7].[8] detected AMD, using 14-layer CNN. This work used three completely linked layers, four max-pooling layers, and seven convolutional layers. [9] thirteen classes were described, and several convolutional deep learning architectures were trained. The accuracy of prediction was enhanced by using a combination of network architectures. By employing a transfer learning algorithm the existence of initial AMD biomarkers was identified from OCT B-scans[10]. Color fundus images of particular eyes have been identified by AREDS harshness rate using automated deep learning (DL) systems[11]. For classification of dry AMD (dAMD) and neovascular AMD (nAMD) VGG16 (Visual Geometry Category with 16 Layers) convolutional neural network model is used[12]. Validate the performance for joint detection of AMD and DR using CNN[13]. Applies a multi-scale learning method to make a fine segmentation prediction of AMD[14]. [15] all baseline OCT scans were segmented using a deep learning algorithm and also calculate the volume of segmented features and the thickness of the central subfield.[16] introduces a multiscale CNN model for distinguishing AMD or normal images and this model validate huge volume of local structures with numerous filter size. [17] developed combined Squeeze-and-Excitation blocks along accompanied by U-Net called SEUNet to segregate fluid sector and label OCT B-scan images into AMD or normal image.

Table 1. Outline of AMD prediction results

Paper	Architecture	Dataset	Accuracy	Sesnsitivity	Specificity	Area under curve
[3]	DCNN approach	AREDS dataset	90.7%	-	-	-
[4]	VGG-16 layer	AREDS dataset	92.5%	-	-	-
[5]	Ensemble		95.3%	-	-	-

	learning(Inception-ResNet-V2 and Xception)	AREDS dataset				
[6]	CNN model(First model) CNN model (second transfer learning model)	-	99.0% 93.9%	100% 98.4%	91.8% 88.3%	-
[7]	DCNN	Tsukazaki hospital	-	-	-	99.76%
[8]	CNN	Kasturba Medical lege	95.45%	96.43%	93.43%	-
[9]	CNN and Random Forest ensemble	AREDS dataset	63.3%	-	-	-
[10]	DCNN	Doheny Eye Centers	87%	-	-	-
[11]	DeepSeeNet	AREDS dataset	67.0%	-	-	-
[12]	VGG-16 layer	Keras Image Data Generator	73.21%	-	-	-
[13]	CNN	DR-AMD dataset, AREDS dataset	-	91.8%	87.5%	94.9 %
[14]	the multi-scale deep learning model	Kangbuk Samsung Hospital, STARE	0.993%	0.995%	0.674%	-
[15]	The deep learning-based segmentation algorithm	Moorfields AMD dataset	54.7%	-	-	-
[16]	Multiscale CNN	Mendeley, OCTID, Duke, SD-OCT Noor dataset	Mendeley-99.73 OCTID98.08% Duke-96.66% SD-OCT Noor-97.95%	-	-	-

3.2 Glaucoma Classification

The following are some of the most recent findings on Glaucoma disease classification using fundus images. It was the first to suggest a technique for combined segmentation of OD(optic disk), OC(optic cup), and glaucoma prognosis in one technique. CNN functions are shared for various functions which were used in this approach to ensure enhance learning and avoid more fitting. The sections that were shared from the model with U-net had eight times lesser CNN filters better than the regular U-net. It is utilized as an encoder network to undersample the function before restoring the image size with a decoder network. For OC and OD segmentation, two separate convolutional layers were added to the decoder network's performance. The segmentation masks from the OC and OD were combined into different channels and added CNN to them. To predict glaucoma, the CNN and encoder outputs were connected and boost into a sole neuron[18]. Glaucomatous optic neuropathy was detected using the Inception-v3 architecture. Before using the algorithm, the researchers had the images graded by qualified ophthalmologists. To account for varying illumination, pre-processing used local space average color subtraction[19]. On the basis of the collection of fundus images gathered from different hospitals, a system was presented that incorporated both domain awareness and characteristics studied from a deep learning model [20]. [21]utilized curriculum information in DCNNS to produce greater outcomes with a limited number of training instances. [22] put forward the G-EyeNet architecture, that manifests to be highly stable based on low-quality image performance. AG-CNN, a new deep learning system for mechanized glaucoma detection and pathological region localization on fundus images, has been proposed[23]. [24] proposed that in the medical community, integrating transfer and active learning will boost the efficiency of DL models while lowering the cost of labeling discipline-specific mavens. [25] put forward an algorithm that depends on Deep Convolutional Neural Network architecture called Glaucoma Network (G-Net) to segment the Optic Disc(OD) and the Optic Cup(OC) from retinal fundus images. [26] demonstrate that ImageNet-trained techniques appear to be a reliable choice for an automated glaucoma screening process. [27] uses different fundus cameras to verify a deep residual learning technique for diagnosing glaucoma from fundus images.[28] proposes a two-stage framework. The first stage uses sectors with Convolutional Neural Network (RCNN) to locate and extract the optic disc out of retinal fundus image, while the next stage employs Deep Convolutional Neural Network to categorize the obtained disc as normal or glaucomatous. [29] constructed a deep learning technique to analyze glaucoma by utilizing fundus images by building a basic logistic classification and convolutional neural network and fine-tuning it with the GoogleNet Inception v3 model. [30] uses monoscopic fundus images, to build and check the efficiency of a deep learning-based model for glaucomatous disc recognition.[31] developed a convolutional neural network(CNN) classifier to build and test a deep learning (DL) methodology to predict early glaucoma out of discipline-specific optical coherence tomography (OCT) images. A Convolution neural network (CNN) has skilled in full images to detect bounding boxes additionally with their analogous contingency and confidence values[32]. [33] entrenched a hierarchical deep learning model which depends on a lesser number of cases and this model can be used to extract the biological features of fundus images and the presence of retinal nerve fiber layer to predict glaucoma.[34] proposed dynamic framework to sector the optic disc and cup using two separate CNN architecture to discover (CDR)

Cup-to-Disc-Ratio.A unique model was developed for distinguishing glaucoma out of colored fundus images using hill-climbing methodology unified with stochastic gradient descent with momentum (SGDM) model [35].[36] approaches a model which is used to differentiate the retinal images depending on the disease pattern and for the purpose of classification, it uses a neural network whereas for prediction and extraction various features of images are used.

Table 2. Outline ofGlaucoma prediction results

Paper	Architecture	Segmentation	Dataset	Accuracy	Sensitivity	Specificity	Area under curve
[18]	Multi-task CNN	OD segmenta-tion by U-net	REFUGE	-	-	-	.9456
[19]	Inception – V3	NA	Private-48000+		95.6%	92.0 %	.986
[20]	MB-NN	OC and OD using CNN	Private-2554	91.5%			
[21]	DCNN	OD and OC using CNN	RIM-ONE-v1 RIM-ONE-v3 DRISHTI-GS1	89.4%(RIM-ONE-v1)	-	-	0.82(DRISHTI-GS)
[22]	Autoencoder with CNN classifier	OD segmentation using U-Net	DRIONS-DB	-	-	-	0.923
[23]	-	-	large-scale attention-based glaucoma (LAG) database, RIM-ONE database	96.2%	95.4%	96.7 %	0.983
[24]	CNN, ResNet-50 encoder pre-trained on ImageNet	-	-	-	98.0%	91%	0.995
[25]	CNN Model, Glaucoma	OD and OC segmentation	DRISHTI-GS dataset	95.8% for OD and	-	-	-

	network (G-net), modified version of U-net			93% for OC			
[26]	ImageNet-trained models (VGG16,VGG 19, InceptionV3, ResNet50 and Xception)	-	ACRIMA database, HRF database, Drishti-GS1 database, RIM-ONE database		0.8580	0.93 46	0.960
[27]	Residual Network (ResNet), VGG11, VGG16 and Inception-v3	-	Datasets were obtained across multiple institutes	-	-	-	(with out aug-men-tation) 87.7% (with aug-menta -tion) 94.5%
[28]	Regions with Convolutiona l Neural Network (RCNN) and Deep Convolutiona l Neural Network(DC NN)	-	ORIGA dataset	-	-	-	0.874
[29]	Convolutiona l Neural Network, GoogleNet Inception v3	-	Kim's Eye Hospital	87.9%	-	-	0.94

[30]	ResNet50	-	Eye Associates, Macquarie University Ophthalmology Clinic, and University of New South Wales Optometry Clinic	-	89.3%	97.1 %	0.97
[31]	CNN	-	The Japanese Archives of Multicentral Images of Glaucomatous Optical Coherence Tomography database.	-	-	-	93.7%
[32]	CNN	-	Kaggle and MESSIDOR datasets	99.05 for Kaggle and 98.78% for MESSIDOR	-	-	-
[33]	DNN	-	Beijing Tongren hospital hospita	-	-	-	0.942
[34]	CNN	OC and OD segmentation	DRISHTI-GS database	98% for OD and 97% for OC	-	-	-
[35]	CNN	-	DRISHTI, RIM-ONE r2 datasets	DRISH-TI dataset 90.1%	96.5% DRISHTI-98.6%	-	0.999 DRISHTI-0.91
[36]	Neural networks	OC and OD segmentation	MESSIDOR	93%	100%	88%	-

3.3 Diabetic retinopathy Classification

This part lists many implementations of deep learning techniques for the prediction of diabetic retinopathy(DR).[37] introduced a model that creates feature maps faster and more competently using entropy images as a replacement for original fundus images. [38]uses a deep transfer learning method and the Inception-v3 network, and also used a 10-fold cross-validation method for evaluating and refining the design for automatic diabetic retinopathy (DR) determination in fundus images.[39] discovered that preprocessing using contrast limited adaptive histogram equalization and assuring dataset reliability by expert confirmation of class labels increases identification of delicate features.[40] classified the DR fundus images into different severity categories, a Synergic Deep Learning (SDL) model was used. [41]analyze how AlexNet, VggNet, GoogleNet, and ResNet, along with transfer learning and hyper-parameter regulation techniques execute with DR image classification. [42] introduces the HPTI-v4 (Hyperparameter Tuning Inception-v4) methodology for the automatic identification and classification of diabetic retinopathy from fundus images. [43] proposes GraNet, a novel Convolutional Neural Network (CNN) technique for nuclear cataract distinguishing using AS-OCT photos, is proposed. In the GraNet, implement a grading block that uses the pointwise convolution method to learn high-level attribute depiction. The most significant prognostic regions in this cross-sectional analysis were lesions commonly seen in examples of referable diabetic retinopathy (exudate, hemorrhage, or vessel abnormality) were recognized[44].[45] proposed o_O Solution which was used to address a process for detecting referable DR along with lesions with the ConvNet architecture. [46] used GoogleNet architecture, for grading various stages of the existence of DR. Unlike other formerly available methodologies, the authors categorize the photos physically to ensure that the methodology was accurate. The model was created in two ways: first, manually mount ternary color photographs (AI1), and then manually mount only a single color photograph (AI2) (AI2). Five top layers were removed from the GoogleNet model, the crop volume was increased, and the batch volume was decreased. AI1 was also trained with a ResNet model for comparison, and 20 fold cross-validation was used.[47] demonstrated that method of automated imaging recognition device VeriSeeTM had strong sensitivity and specificity in predicting DR.[48] presented a new methodology for classifying all five levels of DR from the fundus images by utilizing a multitasking deep neural network architecture.[49] reformed capsule network is created for distinguishing and categorizing diabetic retinopathy. The characteristics from the fundus images are taken out by making use of the convolution and primary capsule layers, and the possibility that the image belongs to a particular class is evaluated using the class capsule layer and softmax layer.[50] established a feature dependent on retinal image exploration approach that mainly focuses to reinforce pliable grading and control evolution. [51] manifest a different CAD system to predict early DR with the usage of non-descent OCT B-scans and also the system evaluates various segregate architecture and reflectivity markers from retinal layers which were impulsively segmented.

Table 3. Outline ofDiabetic retinopathy prediction results

Paper	Architecture	Dataset	Accuracy	Sensitivity	Specificity	Area under curve
[37]	CNN	Kaggle	86.10%	73.24%	93.81%	-
[38]	CNN (Inception v3 network)	Messidor-2dataset	93.49%	96.93%	93.45%	-
[39]	CNN (GoogLeNet and AlexNet models from ImageNet)	Messidor and MildDR fundus folder	66.03%	95%	-	-
[40]	Synergic Deep Learning(SDL) model	Messidor DR dataset	99.28%	98.54%	99.38%	-
[41]	CNN(AlexNet,VggNet ,GoogleNet,ResNet)	Kaggle dataset	95.68%	-	-	-
[42]	HPTI-v4 model	Messidor DR dataset	99.49%	98.83%	99.68%	
[43]	CNN model (GraNet., AlexNet, VGGNet16, VGGNet19, RetNet18, ResNet34, ResNext50, GoogleNet, and EfficientNet)	AS-OCT image dataset CIFAR-100 dataset	75.82%	-	-	-
[45]	ConvNet	EyePACS, e-optha, DiaretDB1	-	-	-	.954, .949, .955
[46]	CNN (GoogleNet, ResNet)	9939 images	80%	-	-	-
[47]	CNN (Resnet and Inception-V4)	NTUH		89.2%	90.1%	-
[48]	DNN	EyePACS and APTOS dataset	0.85	0.79	-	-
[49]	Capsule networks (CapsNet)	Messidor dataset	97.98%	-	-	
[50]	CNN	Kaggle dataset	85%	-	-	-
[51]	CNN	Datasets collected	97.69%	-	-	-

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4 CONCLUSION AND DISCUSSIONS

This analysis looked at various deep learning applications in ophthalmic diagnosis. Based on our review of retinal image interpretation, we can conclude that CNN performed better than all other methods for the classification of ophthalmic diseases namely age-related macular disease, glaucoma, and diabetic retinopathy.CNN network is incredibly deep, with the potential to retrieve much more complex features than conventional approaches and with better performance metrics. There are no restrictions on the number of layers or the design of a neural network and network architecture is selected practically based on the problem domain. Also supervised learningapproaches outperformed unsupervised learning methodologies since supervised learning networks grasp the scaling more effectively because of the existence of ground truth data. Deep learning applications for ophthalmic disorders using retinal images are extremely beneficial and efficient. Since the methodologies are predominantly data-based, they lessen the want for physical function extraction. While research into the eradication of retinal landmarks and pathologies has been performed, the pinnacle of this model has yet to be glimpsed.

5 REFERENCES

1. Badar, M., M. Haris, and A. Fatima, *Application of deep learning for retinal image analysis: A review.* Computer Science Review, 2020. **35**: p. 100203.
2. Jager, R.D., W.F. Mieler, and J.W. Miller, *Age-related macular degeneration.* New England Journal of Medicine, 2008. **358**(24): p. 2606-2617.
3. Burlina, P.M., et al., Automated grading of age-related macular degeneration from color fundus images using deep convolutional neural networks. JAMA ophthalmology, 2017. **135**(11): p. 1170-1176.
4. Govindaiah, A., et al. Deep convolutional neural network based screening and assessment of age-related macular degeneration from fundus images. in 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018). 2018. IEEE.
5. Govindaiah, A., R.T. Smith, and A. Bhuiyan. A new and improved method for automated screening of age-related macular degeneration using ensemble deep neural networks. in 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 2018. IEEE.

6. Motozawa, N., et al., Optical coherence tomography-based deep-learning models for classifying normal and age-related macular degeneration and exudative and non-exudative age-related macular degeneration changes. Ophthalmology and therapy, 2019. **8**(4): p. 527-539.
7. Matsuba, S., et al., Accuracy of ultra-wide-field fundus ophthalmoscopy-assisted deep learning, a machine-learning technology, for detecting age-related macular degeneration. International ophthalmology, 2019. **39**(6): p. 1269-1275.
8. Tan, J.H., et al., Age-related macular degeneration detection using deep convolutional neural network. Future Generation Computer Systems, 2018. **87**: p. 127-135.
9. Grassmann, F., et al., A deep learning algorithm for prediction of age-related eye disease study severity scale for age-related macular degeneration from color fundus photography. Ophthalmology, 2018. **125**(9): p. 1410-1420.
10. Saha, S., et al., Automated detection and classification of early AMD biomarkers using deep learning. Scientific reports, 2019. **9**(1): p. 1-9.
11. Peng, Y., et al., DeepSeeNet: a deep learning model for automated classification of patient-based age-related macular degeneration severity from color fundus photographs. Ophthalmology, 2019. **126**(4): p. 565-575.
12. Heo, T.-Y., et al., Development of a deep-learning-based artificial intelligence tool for differential diagnosis between dry and neovascular age-related macular degeneration. Diagnostics, 2020. **10**(5): p. 261.
13. González-Gonzalo, C., et al., Evaluation of a deep learning system for the joint automated detection of diabetic retinopathy and age-related macular degeneration. Acta ophthalmologica, 2020. **98**(4): p. 368-377.
14. Pham, Q., et al., Automatic Drusen Segmentation for Age-Related Macular Degeneration in Fundus Images Using Deep Learning. Electronics, 2020. **9**(10): p. 1617.
15. Moraes, G., et al., Quantitative Analysis of OCT for Neovascular Age-Related Macular Degeneration Using Deep Learning. Ophthalmology, 2020.
16. Thomas, A., et al., A novel multiscale convolutional neural network based age-related macular degeneration detection using OCT images. Biomedical Signal Processing and Control, 2021. **67**: p. 102538.
17. Chen, Z., et al., Automated segmentation of fluid regions in optical coherence tomography B-scan images of age-related macular degeneration. Optics & Laser Technology, 2020. **122**: p. 105830.
18. Chakravarty, A. and J. Sivswamy, A deep learning based joint segmentation and classification framework for glaucoma assesment in retinal color fundus images. arXiv preprint arXiv:1808.01355, 2018.
19. Li, Z., et al., Efficacy of a deep learning system for detecting glaucomatous optic neuropathy based on color fundus photographs. Ophthalmology, 2018. **125**(8): p. 1199-1206.
20. Chai, Y., H. Liu, and J. Xu, Glaucoma diagnosis based on both hidden features and domain knowledge through deep learning models. Knowledge-Based Systems, 2018. **161**: p. 147-156.
21. Perdomo, O., et al., Glaucoma diagnosis from eye fundus images based on deep morphometric feature estimation, in Computational pathology and ophthalmic medical image analysis. 2018, Springer. p. 319-327.

22. Pal, A., M.R. Moorthy, and A. Shahina. G-eyenet: A convolutional autoencoding classifier framework for the detection of glaucoma from retinal fundus images. in 2018 25th IEEE international conference on image processing (ICIP). 2018. IEEE.
23. Li, L., et al., A large-scale database and a CNN model for attention-based glaucoma detection. IEEE transactions on medical imaging, 2019. **39**(2): p. 413-424.
24. Hemelings, R., et al., Accurate prediction of glaucoma from colour fundus images with a convolutional neural network that relies on active and transfer learning. Acta ophthalmologica, 2020. **98**(1): p. e94-e100.
25. Juneja, M., et al., Automated detection of Glaucoma using deep learning convolution network (G-net). Multimedia Tools and Applications, 2019: p. 1-23.
26. Diaz-Pinto, A., et al., CNNs for automatic glaucoma assessment using fundus images: an extensive validation. Biomedical engineering online, 2019. **18**(1): p. 1-19.
27. Asaoka, R., et al., Validation of a deep learning model to screen for glaucoma using images from different fundus cameras and data augmentation. Ophthalmology Glaucoma, 2019. **2**(4): p. 224-231.
28. Bajwa, M.N., et al., Two-stage framework for optic disc localization and glaucoma classification in retinal fundus images using deep learning. BMC medical informatics and decision making, 2019. **19**(1): p. 1-16.
29. Ahn, J.M., et al., A deep learning model for the detection of both advanced and early glaucoma using fundus photography. PloS one, 2018. **13**(11): p. e0207982.
30. Liu, S., et al., A deep learning-based algorithm identifies glaucomatous discs using monoscopic fundus photographs. Ophthalmology Glaucoma, 2018. **1**(1): p. 15-22.
31. Asaoka, R., et al., Using deep learning and transfer learning to accurately diagnose early-onset glaucoma from macular optical coherence tomography images. American journal of ophthalmology, 2019. **198**: p. 136-145.
32. Mitra, A., et al., The region of interest localization for glaucoma analysis from retinal fundus image using deep learning. Computer methods and programs in biomedicine, 2018. **165**: p. 25-35.
33. Xu, Y., et al., A hierarchical deep learning approach with transparency and interpretability based on small samples for glaucoma diagnosis. NPJ digital medicine, 2021. **4**(1): p. 1-11.
34. Veena, H., A. Muruganandham, and T.S. Kumaran, A novel optic disc and optic cup segmentation technique to diagnose glaucoma using deep learning convolutional neural network over retinal fundus images. Journal of King Saud University-Computer and Information Sciences, 2021.
35. Singh, H., S. Saini, and V. Lakshminarayanan, Rapid Classification of Glaucomatous Fundus Images. arXiv preprint arXiv:2102.04400, 2021.
36. Shalini, S. and N. Srinivasan, Retinal image classification by glaucoma based on ANFIS classifier. Materials Today: Proceedings, 2021.
37. Lin, G.-M., et al., Transforming Retinal Photographs to Entropy Images in Deep Learning to Improve Automated Detection for Diabetic Retinopathy. Journal of Ophthalmology, 2018. **2018**: p. 2159702.
38. Li, F., et al., Automatic detection of diabetic retinopathy in retinal fundus photographs based on deep learning algorithm. Translational vision science & technology, 2019. **8**(6): p. 4-4.
39. Lam, C., et al., Automated detection of diabetic retinopathy using deep learning. AMIA summits on translational science proceedings, 2018. **2018**: p. 147.

40. Shankar, K., et al., Automated detection and classification of fundus diabetic retinopathy images using synergic deep learning model. Pattern Recognition Letters, 2020. **133**: p. 210-216.
41. Wan, S., Y. Liang, and Y. Zhang, Deep convolutional neural networks for diabetic retinopathy detection by image classification. Computers & Electrical Engineering, 2018. **72**: p. 274-282.
42. Shankar, K., et al., Hyperparameter tuning deep learning for diabetic retinopathy fundus image classification. IEEE Access, 2020. **8**: p. 118164-118173.
43. Zhang, X., et al. A Novel Deep Learning Method for Nuclear Cataract Classification Based on Anterior Segment Optical Coherence Tomography Images. in 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC). 2020. IEEE.
44. Keel, S., et al., Visualizing deep learning models for the detection of referable diabetic retinopathy and glaucoma. JAMA ophthalmology, 2019. **137**(3): p. 288-292.
45. Quellec, G., et al., Deep image mining for diabetic retinopathy screening. Medical image analysis, 2017. **39**: p. 178-193.
46. Takahashi, H., et al., Applying artificial intelligence to disease staging: Deep learning for improved staging of diabetic retinopathy. PloS one, 2017. **12**(6): p. e0179790.
47. Hsieh, Y.-T., et al., Application of deep learning image assessment software VeriSee™ for diabetic retinopathy screening. Journal of the Formosan Medical Association, 2021. **120**(1): p. 165-171.
48. Majumder, S. and N. Kehtarnavaz, Multitasking Deep Learning Model for Detection of Five Stages of Diabetic Retinopathy. arXiv preprint arXiv:2103.04207, 2021.
49. Kalyani, G., et al., Diabetic retinopathy detection and classification using capsule networks. Complex & Intelligent Systems, 2021: p. 1-14.
50. Al-Turk, L., et al., Automated feature-based grading and progression analysis of diabetic retinopathy. Eye, 2021: p. 1-9.
51. Sharafeldeen, A., et al., Precise higher-order reflectivity and morphology models for early diagnosis of diabetic retinopathy using OCT images. Scientific Reports, 2021. **11**(1): p. 1-16.
52. Suganthe, R. C., Latha, R. S., Geetha, M., & Sreekanth, G. R. (2020). Diagnosis of Alzheimer's Disease from Brain Magnetic Resonance Imaging Images using Deep Learning Algorithms. Advances in Electrical and Computer Engineering, 20(3), 57-64.
53. Latha, R. S., Sreekanth, G. R. R., Suganthe, R. C., & Selvaraj, R. E. (2021, January). A survey on the applications of Deep Neural Networks. In 2021 International Conference on Computer Communication and Informatics (ICCCI) (pp. 1-3). IEEE.
54. Latha, R. S., Sreekanth, G. R., Suganthe, R. C., Geetha, M., Swathi, N., Vaishnavi, S., &Sonasri, P. (2021, January). Automatic Fruit Detection System using Multilayer Deep Convolution Neural Network. In 2021 International Conference on Computer Communication and Informatics (ICCCI) (pp. 1-5). IEEE.
55. Latha, R. S., Sreekanth, G. R., Suganthe, R. C., Rajadevi, R., Karthikeyan, S., Kanivel, S., &Inbaraj, B. (2021, January). Automatic Detection of Tea Leaf Diseases using Deep Convolution Neural Network. In 2021 International Conference on Computer Communication and Informatics (ICCCI) (pp. 1-6). IEEE.
56. Maheswaran, S., Vivek, B., Sivaranjani. P., Sathesh, S., and Vignesh, K P., "Development of Machine Learning Based Grain Classification and Sorting with Machine Vision Approach for Eco-Friendly Environment," Journal of Green Engineering*,* vol. 10, no. 3, pp. 526-543, 2020.
57. Sathesh, S., Pradheep, V A., Maheswaran, S., Premkumar, P., Gokul Nathan, S., and Sriram, P., "Computer Vision Based Real Time Tracking System to Identify Overtaking Vehicles for Safety

Precaution Using Single Board Computer.” Journal of Advanced Research in Dynamical and Control Systems, vol. 12, no. SP7, July 2020, pp. 1551–61. *DOI.org (Crossref)*, doi:10.5373/JARDCS/V12SP7/20202258.