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Review of Glaucoma Disease Diagnosis-based Deep Learning Network

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A B S T R A C T

The glaucoma is a disease that leads to the irreversible loss of sight after its onset. In the area of medicine, glaucoma diagnosis is a crucial problem that must be addressed. Only a few studies were carried out with a view to early detection of blue. However, the implementation of this law has not succeeded in identifying glaucoma using the many methods currently available. Moreover, the old ways to identify retrograde gland disease require a much greater time commitment. Knowledge of glaucoma in colored images (fundus) is a difficult task that requires years of experience as well as knowledge. The preferred method of analyzing medical images soon became deep educational algorithms. A series of studies have been undertaken within the time period between 2018 and 2023 and these reports have shown how critical elements, such as architecture, size of data sets, and application of transport learning compared with the newly established structures, can affect performance more accurately and time-consumingly using a set of new networks (CNN).

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1. Introduction

A group of eye conditions known as glaucoma's damage the optic nerve by burning the neurofibrils that carry information from the eye to the brain because of elevated intraocular pressure. Permanent blindness is a result of malignant gland cancer, and early illness identification is difficult. Age-related muscular deterioration, glaucoma, diabetes, pulmonary morbidity, and katrakes are four in-kind diseases that typically cause additional severe vision impairments and blindness. When an atmospheric cancer first appears, it may not cause any symptoms, but it can cause blindness. Early diagnosis is essential for successful therapy; without it, there would be total blindness. Early detection and treatment are the only ways to stop this disease from progressing. Even in wealthy nations, the

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detection rate for glaucoma was relatively low—less than 50%. Blue disease so continues to be a significant public health issue. Worldwide, an estimated 116 million people are predicted to be impacted by the illness by 2040. In underdeveloped nations, where there is a shortage of skilled professionals, the evaluation manual poses a problem. Thus far, an ophthalmologist has used the biomicroscope of the cracks to make a clinical diagnosis of the glacier. Because of this strategy's extreme manuality and reliance on clinical experience, there may be a significant rate of change between screening and false positives diagnostics and the squandering of medical data. The economy and the populace both benefit from these strategies. This study demonstrates that glacial screening can be more affordable for vulnerable populations (those with a family history of black ethnicity, advanced age, etc.) and can be enhanced by utilizing an automated initial classification that is then followed by a skilled evaluation by a specialist. The field of ophthalmology is greatly impacted by industrial intelligence, mostly in the form of precise and proficient picture interpretation.

It alludes to the field of computer science, which represents the potential of human mind. The auto-learning model is the primary source of inspiration for artificial intelligence technology (ML). Artificial Intelligence (AI) computer techniques enable computers to function in a self-learning manner without explicit programming, perhaps paving the way for future technological advancements. Deep learning algorithms (DL) are currently a subset of machine learning (ML) that show promise in the medical field and are gaining traction in fields like OCD. The only category type created from machine learning (ML) that uses multiple layers of non-linear information processing units to extract supervised and unsupervised features from a training data set and provide precise predictions is deep learning (DL). The researchers suggested the computational models of neural networks in 1943. Jan predicted that it will be a certain kind of artificial neural network model in 1988 called CNN. The architecture of CNN is based on the idea of the visual cortex and is congruent with the shape of a neuronal connection in the human brain. Only a small portion of visual space is used by individual neurons to react to stimuli, indicating that it is acceptable. To fill the whole visual field, a collection of these fields passes through. To be more precise, there are four different sorts of layers in the network: convolutional layer, ReLU layer, subsampling layer, and the output or fully connected layer. Generally speaking, the images are built as a matrix of pixels, and these pixels are supplied as input values for an input layer (for nonlinearity) [5].

2. Glaucoma

If left untreated, glaucoma, an eye ailment linked to the loss of retinal ganglion cells, can cause permanent vision loss as a result of the axons of these cells gradually deteriorating over time. This disease affects 80 million people worldwide of various ages, and in 2020 it was anticipated to be the leading cause of blindness. An imbalance in the drainage and flow of aqueous humor fluid is the primary cause of this disease and can lead to elevated intraocular pressure, a significant risk factor for this condition. Age, race, and family history are additional factors that may raise the risk of developing glaucoma. Diagnosing glaucoma requires a thorough examination of the optic nerve head, visual field tests, and extensive eye exams employing tonometry. However, these tests are typically expensive, time-consuming, and require specialized knowledge and equipment. Owing to these drawbacks, the use of deep learning algorithms for automated fundus image-based glaucoma detection is becoming more popular. Fundus imaging is a readily available, noninvasive technology that offers vital information about the eye and optic nerve heads, including structural abnormalities that signal the existence of glaucoma. Every feature of the retina is captured in depth in in this image, including the dimensions, forms, and colors of important areas like the fovea, blood vessels, optic disc (OD), and optic cup (OC). The key features in the retinal fundus picture are displayed in Figure 1.

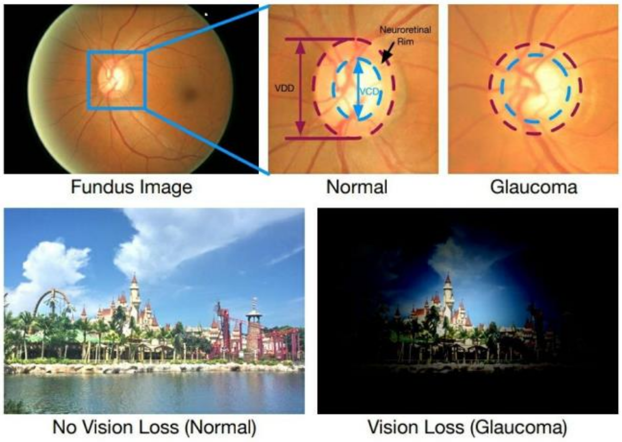

Figure 1. Structure of the normal eye and the eye with glaucoma [3]

There are three different kinds of glaucoma: normal-tension, angle-closure, and open-angle glaucoma. The most prevalent kind of glaucoma, known as open-angle glaucoma, is brought on by a gradual decrease in the drainage angle of the eye, which raises intraocular pressure. Conversely, angle-closure glaucoma happens when the iris enlarges and obstructs the drainage angle, causing an abrupt rise in intraocular pressure. A less common kind of glaucoma called normal-tension glaucoma develops when the optic nerve is harmed despite the eye pressure being within normal limits. Depending on the kind and severity of the condition, glaucoma patients can choose from a variety of treatments, including medication, surgery, eye drops, and laser therapy.

Glaucoma is diagnosed by a doctor according to the following procedure:

1. Measuring intraocular pressure, also called tonometry.
2. Examination to detect optic nerve damage with dilated fundus examination and imaging tests.
3. Examination of areas of vision loss, also called visual field testing.
4. Corneal pachymetry examination.
5. Examination of the drainage angle, known as gonioscopy.

3. *Deep learning*

Deep learning is a branch of machine learning that consists of three or more layers of neural networks. By "learning" from vast volumes of data, these neural networks aim to mimic the activity of the human brain, albeit far from approaching its capacity. A neural network with only one layer can still generate educated guesses, but it can be optimized and refined for accuracy with the help of more hidden layers. Numerous artificial intelligence (AI) services and apps that increase automation in carrying out physical and analytical tasks without human interaction are powered by deep learning. Both emergent and commonplace technologies—like voice-activated TV remotes, digital assistants, and credit card fraud detection—as well as self-driving automobiles are powered by deep learning technology. The deep learning architecture is shown in Figure 2.

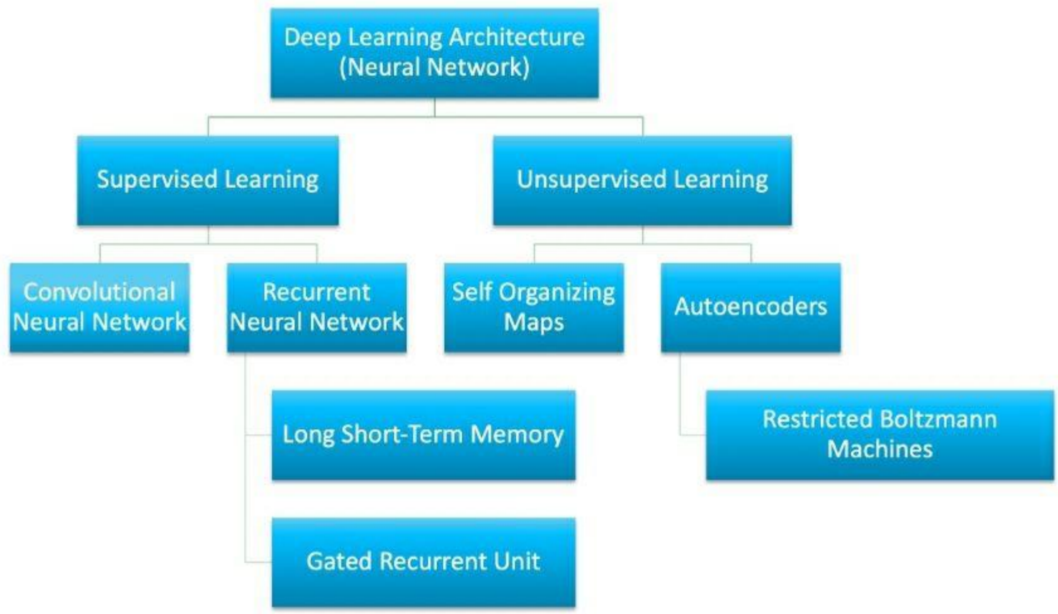

Figure 2. Deep learning architecture [32]

A convolutional neural network has tens or even hundreds of layers, each of which is trained to identify a distinct feature of an image. Each training image is filtered at different resolutions, and the output of each convolved image is used as the layer's input. The filters can begin with relatively basic criteria, such as edges and brightness, and progress in sophistication to include features that specifically identify the object.

Transfer learning is a machine learning technique that involves applying a model created for one job to another task. In deep learning, transfer learning is a popular method because it allows deep neural networks to be trained with less data than if a model had to be created from the beginning. A model requires a significant investment of time and processing power to train. Reducing both is aided by beginning with a pre-trained model.

Typically, machine learning algorithms are designed to tackle discrete tasks. Through transfer learning, methods are developed for using information from one or more of these source tasks to improve learning in a related target task. For knowledge from a machine learning model that has already been trained to be transferable, it must be similar to the new task. For instance, in a supervised machine-learning system, the skills learned to identify a dog image may be applied to a new system designed to identify cat photos. The new method will exclude pictures that it already knows to be of dogs.

Transfer learning is the process of using information from one task to enhance learning in another. A negative transfer occurs when the new task performs less well as a result of the transfer mechanism. Ensuring positive transfer between related activities while preventing negative transfer between less related jobs is a major difficulty in the development of transfer systems.

A neural network might be employed to sift through medical photos and identify possible diseases or conditions. When there is not enough data to train the network, transfer learning may be able to assist in identifying certain illnesses utilizing pre-trained models.

4. *Deep learning with glaucoma diagnosis*

Oscar Perdomo et al proposed that OD and PC are segmented in the first stage using a 15-layer DCCN. The two segmentations produced by the first stage are supplied into the second stage, which stacks a third image mask to build a 3D-binary mask that corresponds to the union of the OD and PC segmentations. This mask is then fed into a 12-layer DCNN. The third stage uses a multilayer neural network to provide the final prediction[1]. Anindita et al. proposed a texture-based analysis used in the publication to describe an automated technique for detecting the retinal nerve fiber layer (RNFL). Two texture features—correlation and autocorrelation—derived from a co-occurrence matrix are used in the suggested method[2]. The researchers used two cutting-edge deep-learning algorithms the first technique is a multi-label segmentation network known as M-Net. M-Net computes the vertical cup-to-disc ratio (CDR). DENet is the second technique; it combines the local optic disc region with the global fundus picture context. Without segmenting the image[3]. The researchers suggested reliable fuzzy c-means clustering algorithm (FRFCM) is employed. The FRFCM is an enhanced form of the FCM method, the clustering algorithm combines membership filtering with morphological reconstruction (MR). This technique suppresses various noises without taking noise kinds into account[4]. Researchers used a 13-layer CNN trained on a dataset. The process was made simpler by using Google Colab to develop the algorithm. To make the dataset larger, it was split up into (training, validation and testing sets) [5]. Researchers used to assess how well 3 convolutional neural networks (CNN) models perform while using various learning techniques and assess how successful they are in diagnosing glaucoma. Using both label and label data, the study applies transfer learning and semi supervised learning approaches [6]. Researchers used the performance metrics derived from the image classification. Modified architectures were employed for the Inception-V3, VGG-19 and ResNet50models. To determine the best training parameters, the real activation function is used for the internal layers [7].

The researchers used to increase accuracy and prevent overfitting, the study examines three distinct CNN architectures (Inception-v3, VGG19, and ResNet50) and uses a variety of data pre-processing and augmentation approaches. Data pre-processing methods like dilation and Contrast Limited Adaptive Histogram Equalization (CLAHE) are used [8]. The researchers in Local this paper use the local Binary Pattern (LBP) and Support Vector Machine (SVM) methods. LBP was used to extract local features from the images, while SVM was used for classification [9]. Researchers used to elucidate their method of employing order-one 2D- FBSE-EWT to split fundus images into sub-images using the ResNet-50 model to extract deep features. After that a soft max classifier receives these features for classification [10]. The researcher suggests a deep learning approach that combines the u-net architecture with pre-train transfer learning models. They retrieve in classify features using the DNSCNET 2 101 deep convolution neural networks [11]. using optical coherence to myography images the researchers examine several properties and added a new optical nerve head feature 12. The researchers used an algorithm for the automatic area of interest. ROI detection mentioned in the document which enhances the accuracy of glaucoma diagnosis [13]. Research suggested, provides research on the efficacy of a convolutional nerve. CNN classifier for glaucoma detection that was trained on a small set of high-quality fund images [14]. Researchers used an ensemble model created for early glaucoma detection. The model suggests extracting feature information from the images using a convolutional neural network. Two categories are created from the data testing and training [15].

According to Thisara et al., there are three CNN architectures that are recommended for attention U-Net models: Inception-V3, Visual Geometry Group 19 (VGG19), and Residual Neural Network 50 (ResNet50) for segmenting fundus images[16]. The researchers suggested searching for learning discriminative features and merging them for grading, the program uses convolutional neural networks and deep learning to mimic human grading[17]. The researchers used a computer-aided diagnostic (CAD) system that uses fundus images and artificial intelligence in conjunction with image processing techniques to diagnose eye illnesses[18]. The researchers used two stages. The first stage involves supervised machine learning without feature selection and the application of a superpixel algorithm. Feature selection methods are used in the second phase to boost efficiency[19]. The researchers suggested assessing critical variables and techniques to enhance fundus photos' ability to identify glaucomatous optic neuropathy (GON) they constructed convolutional neural networks (CNNs) based on transfer learning with VGGNet [20]. A 3D convolutional neural network (CNN) was created by the researchers, and it was trained on a real-world glaucoma dataset that showed evidence of class imbalance—that is, a glaucoma case class with a much higher number of samples than a healthy case[21]. The researchers used the construction of a CNN model from scratch, comprising two max pooling layers and five convolutional layers. A pre-trained model was Repurposed and improved for the job classification application of learning 22 researchers used a small data of 30 high resolution fund. Retinal images. Research the performance of various models, including CNN random forest, RF, DT and support vector machine. SVM 23 researchers use the technique to analyses fundus photos in two stages, using convolutional neural networks. CNN. The optic disc region is first identified by the system using a CNN architecture known as you only look once (YOLO). The second phase involves classifying cases into "glaucomatous" and "non-glaucomatous" categories using the MobileNet architecture [24]. The researchers evaluate the performance of Vision Transformers (ViTs), a more recent architecture that was initially intended for Natural Language Processing (NLP) but was modified for image analysis, against Convolutional Neural Networks (CNNs), which have been extensively utilized for image processing [25]. The researchers used medical images and pre-trained residual convolutional networks ResNet-50 to construct an early detection approach segmentation algorithm from digitized retinal fundus pictures[26]. The researchers suggested the RC-DNN created, and thanks to its residual connectivity, it can conduct robust segmentation by utilizing previous picture pre-processing[27]. Researchers used Google Cloud Auto ML, a code-free deep learning tool, was used to create a convolutional neural network. Working with data locally and then uploading.csv files with the image file's cloud location and the grader-assigned image quality was made feasible by the AutoML platform[28]. The researchers used multiple steps in the suggested hybrid paradigm for glaucoma screening. Using a modified dichromatic reflection model, a preprocessing step is first conducted to reduce reflection from distorted fundus images. The next phase involves segmenting the data using a modified U-Net CNN[29]. Ayesha et al. suggested the following phases:

* Gather the fundus photos from various publically accessible sources.

* Apply grayscale to the fundus photos.

* After splitting the dataset into training and testing sets, use the data augmentation technique to multiply the number of photos by flipping, rescaling, and rotating them.

* For categorization, DL architecture that has already been trained, like the ResNet-50, is utilized[30]. The researchers suggested an approach that combines Xcep-Dense classification with U-Net segmentation workable for glaucoma detection. The encoder and decoder components of the U-Net CNN architecture is used in the segmentation step. The U-Net architecture segments the optic disc and optic cup, two crucial aspects for glaucoma detection, with good accuracy and recall [31].

5. *Results and discussion*

After we conducted a survey on a group of research papers related to deep learning and its use in diagnosing glaucoma, the time period ranges exclusively from the year 2018 to the year 2023, and the most prominent results we obtained are shown in Table 1. Each of [7],[8],[11],[12],[16],[19],[28],[30] achieved distinguished results in diagnosing people with glaucoma, the best of which was [16], in which the researchers used a technique U-Net with (Inception V3, VGG19, ResNet50) and they suggested focus AG is combined with U-Net architecture for every skip connection. They replaced the original encoder of the standard U-Net in the contraction path with pre-trained networks, specifically VGG19, Inception-v3, and ResNet50 as backbones independently, to determine the best segmentation performances. The three networks have the same decoders: convolutional, up-sampling, and concatenation. The encoder's feature maps are combined with the up-sampled output by the concatenation layers. One the other hand, the results were less accurate [1] and [23] where it used a small number of images, amounting to 30 images in [23].

Table 1 - Comparison of some related works.

Ref. id	Author	Year	Data set	Proposed techniques	Accuracy
[1]	Oscar at el	2018	Rim-one & DRISHTI-GSI	Segmentation the OD & physiological cup	89%
[7]	Thisara at el	2022	RIM-ONE	The segmentation models on U-Net & 3 CNNs (VGG19, Inception-V3, ResNet 50	With ResNet 99.58% With Inception-V3 98.79%

[8]	Thisara at el	2022	ACRIMA & RIM-ONE	Classification image by (Inception-V3)	98.52%
[11]	Ramgopal at el	2022	Glaucoma_dataset	DenesNet-201 DCNN used	98.82%
[12]	Nahida at el	2022	200 images from center for eye Health UNEW Sydney	Deep learning (DL) VS Logistic regression (LR)	98.6%
[16]	Thisara at el	2022	RIM-ONE	U-Net with (Inception V3, VGG19, ResNet50)	99.53%
[19]	Osama at el	2023	RIM-ONE r3	SVM with supervised machine learning	98.5%
[23]	Rohit at el	2023	ORIGA	SVM with RF & DT	80%
[28]	Ella Bouris at et	2023	2377 images	CNN	98.5%
[30]	Ayesha Shoukat at el	2023	G1020, DRISHTI-GS, RIM-ONE, ORIGA	ResNet-50	98.48%

6. *Conclusions*

Recent studies unequivocally demonstrate that the analysis of eye-bed images using deep learning algorithms has greatly advanced the early diagnosis of glaucoma. High-accuracy pathology identification and complex feature extraction have been demonstrated using CNNs and RNNs.
As part of the preparation procedures, the quality of the images input into the models was enhanced by improving image variation using methods like CLAHE (Contrast Limited Adaptive Histogram Equation). The outcomes also shown how applying this kind of pre-treatment might greatly improve model accuracy and lower the percentage of false positives and false negatives.

Nonetheless, there are still issues with the enormous diversity and high caliber of picture data. Therefore, it is essential to create novel data processing techniques and enhance model performance on a variety of data sets. Furthermore, to increase diagnosis accuracy and ease the integration of deep learning approaches into routine clinical applications, future research endeavors should concentrate on combining these methods with clinical decision support systems.

In summary, deep learning methods present intriguing opportunities for improved glaucoma early detection, providing fresh directions for future study and useful applications.

References

[1] O. Perdomo, V. Andrearczyk, F. Meriaudeau, H. Müller, and F. A. González, "Glaucoma Diagnosis from Eye Fundus Images Based on Deep Morphometric Feature Estimation," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 11039 LNCS, pp. 319–327, 2018, doi: 10.1007/978-3-030-00949-6_38.

[2] A. Septiarini, A. Harjoko, R. Pulungan, and R. Ekantini, "Automated detection of retinal nerve fiber layer by texture-based analysis for glaucoma evaluation," *Healthc. Inform. Res.*, vol. 24, no. 4, pp. 335–345, 2018, doi: 10.4258/hir.2018.24.4.335.

[3] H. Fu, J. Cheng, Y. Xu, and J. Liu, "Glaucoma Detection Based on Deep Learning Network in Fundus Image," *Adv. Comput. Vis. Pattern Recognit.*, no. September, pp. 119–137, 2019, doi: 10.1007/978-3-030-13969-8_6.

[4] P. Elangovan, M. K. Nath, and M. Mishra, "Statistical Parameters for Glaucoma Detection from Color Fundus Images," *Procedia Comput. Sci.*, vol. 171, no. 2019, pp. 2675–2683, 2020, doi: 10.1016/j.procs.2020.04.290.

[5] A. Balasopoulou *et al.*, "Symposium Recent advances and challenges in the management of retinoblastoma Globe - saving Treatments," *BMC Ophthalmol.*, vol. 17, no. 1, p. 1, 2017, doi: 10.4103/ijo.IJO.

[6] M. Alghamdi and M. Abdel-Mottaleb, "A Comparative Study of Deep Learning Models for Diagnosing Glaucoma from Fundus Images," *IEEE Access*, vol. 9, pp. 23894–23906, 2021, doi: 10.1109/ACCESS.2021.3056641.

[7] T. Shyamalee and D. Meedeniya, "Glaucoma Detection with Retinal Fundus Images Using Segmentation and Classification," *Mach. Intell. Res.*, vol. 19, no. 6, pp. 563–580, 2022, doi: 10.1007/s11633-022-1354-z.

[8] T. Shyamalee and D. Meedeniya, "CNN Based Fundus Images Classification For Glaucoma Identification," *ICARC 2022 - 2nd Int. Conf. Adv. Res. Comput. Towar. a Digit. Empower. Soc.*, no. February, pp. 200–205, 2022, doi: 10.1109/ICARC54489.2022.9754171.

[9] F. NURFAJAR, R. MAGDALENA, and S. SA'IDAH, "Deteksi Glaukoma pada Citra Fundus Retina menggunakan Metode Local Binary Pattern dan Support Vector Machine," *ELKOMIKA J. Tek. Energi Elektr. Tek. Telekomun. Tek. Elektron.*, vol. 10, no. 4, p. 769, 2022, doi: 10.26760/elkomika.v10i4.769.

[10] P. K. Chaudhary, S. Jain, T. Damani, S. Gokharu, and R. B. Pachori, "Automatic Diagnosis of Type of Glaucoma Using Order-One 2D-FBSE-EWT," *2022 24th Int. Conf. Digit. Signal Process. its Appl. DSPA 2022*, no. March, 2022, doi: 10.1109/DSPA53304.2022.9790762.

[11] R. Kashyap, R. Nair, S. M. P. Gangadharan, M. Botto-Tobar, S. Farooq, and A. Rizwan, "Glaucoma Detection and Classification Using Improved U-Net Deep Learning Model," *Healthc.*, vol. 10, no. 12, 2022, doi: 10.3390/healthcare10122497.

[12] N. Akter, J. Fletcher, S. Perry, M. P. Simunovic, N. Briggs, and M. Roy, "Glaucoma diagnosis using multi-feature analysis and a deep learning technique," *Sci. Rep.*, vol. 12, no. 1, pp. 1–12, 2022, doi: 10.1038/s41598-022-12147-y.

[13] I. G. Classification, U. Fundus, and D. Learning, "ib," vol. 42, no. 3, pp. 28–41, 2021.

[14] Y. C. Ko *et al.*, "Widen the Applicability of a Convolutional Neural-Network-Assisted Glaucoma Detection Algorithm of Limited Training Images across Different Datasets," *Biomedicines*, vol. 10, no. 6, 2022, doi: 10.3390/biomedicines10061314.

[15] S. Joshi, B. Partibane, W. A. Hatamleh, H. Tarazi, C. S. Yadav, and D. Krah, "Learning for Classification," vol. 2022, 2022.

[16] T. Shyamalee and D. Meedeniya, "Attention U-Net for Glaucoma Identification Using Fundus Image Segmentation," *2022 Int. Conf. Decis. Aid Sci. Appl. DASA 2022*, no. May, pp. 6–10, 2022, doi: 10.1109/DASA54658.2022.9765303.

[17] M. Lin *et al.*, "Automated diagnosing primary open-angle glaucoma from fundus image by simulating human's grading with deep learning," *Sci. Rep.*, vol. 12, no. 1, pp. 1–11, 2022, doi: 10.1038/s41598-022-17753-4.

[18] A. Zyout, H. Alquran, W. A. Mustafa, M. Alsalatie, A. Al-Badarneh, and W. Khairunizam, "Automated Diagnosis of Eye Fundus Images," *Proc. Int. Conf. Artif. Life Robot.*, pp. 56–61, 2023, doi: 10.5954/icarob.2023.os1-7.

[19] O. M. Kamara, A. H. Asad, and H. A. Hefny, "Automated Diagnoses Glaucoma Approach in Retinal Fundus Images Using Support Vector Machine," *Lect. Notes Data Eng. Commun. Technol.*, vol. 184, pp. 368–379, 2023, doi: 10.1007/978-3-031-43247-7_33.

[20] J. Surendiran and M. Meena, "Deep learning-Assisted Glaucoma Diagnosis and Model Design," *Int. J. Intell. Syst. Appl. Eng.*, vol. 11, no. 1, pp. 269–276, 2023.

[21] A. Abbasi, B. J. Antony, S. Gowrisankaran, G. Wollstein, J. S. Schuman, and H. Ishikawa, "Can Glaucoma Suspect Data Help to Improve the Performance of Glaucoma Diagnosis?," *Transl. Vis. Sci. Technol.*, vol. 12, no. 8, pp. 1–7, 2023, doi: 10.1167/tvst.12.8.6.

[22] K. Devkota and A. Acharya, "Deep Convolutional Neural Network and Transfer Learning to Classify Cataract Based on Fundus Images Deep Convolutional Neural Network and Transfer Learning to Classify Cataract Based on Fundus Images," no. August, 2023.

[23] R. Thanki, "Deep Learning Based Model for Fundus Retinal Image Classification," *Commun. Comput. Inf. Sci.*, vol. 1788 CCIS, pp. 238–249, 2023, doi: 10.1007/978-3-031-27609-5_19.

[24] S. Saha, J. Vignarajan, and S. Frost, "A fast and fully automated system for glaucoma detection using color fundus photographs," *Sci. Rep.*, vol. 13, no. 1, pp. 1–11, 2023, doi: 10.1038/s41598-023-44473-0.

[25] S. Alayón, J. Hernández, F. J. Fumero, J. F. Sigut, and T. Díaz-Alemán, "Comparison of the Performance of Convolutional Neural Networks and Vision Transformer-Based Systems for Automated Glaucoma Detection with Eye Fundus Images," *Appl. Sci.*, vol. 13, no. 23, p. 12722, 2023, doi: 10.3390/app132312722.

[26] M. S. Puchaicela-Lozano *et al.*, "Deep Learning for Glaucoma Detection: R-CNN ResNet-50 and Image Segmentation," *J. Adv. Inf. Technol.*, vol. 14, no. 6, pp. 1186–1197, 2023, doi: 10.12720/jait.14.6.1186-1197.

[27] K. Aurangzeb, "A residual connection enabled deep neural network model for optic disk and optic cup segmentation for glaucoma diagnosis," *Sci. Prog.*, vol. 106, no. 3, pp. 1–22, 2023, doi: 10.1177/00368504231201329.

[28] E. Bouris, T. Davis, E. Morales, L. Grassi, D. Salazar Vega, and J. Caprioli, "A Neural Network for Automated Image Quality Assessment of Optic Disc Photographs," *J. Clin. Med.*, vol. 12, no. 3, 2023, doi: 10.3390/jcm12031217.

[29] S. Lenka and Z. L. Mayaluri, “Hybrid glaucoma detection model based on reflection components separation from retinal fundus images,” *EAI Endorsed Trans. Pervasive Heal. Technol.*, vol. 9, pp. 1–13, 2023, doi: 10.4108/EETPHT.9.3191.

[30] A. Shoukat, S. Akbar, S. A. Hassan, S. Iqbal, A. Mehmood, and Q. M. Ilyas, “Automatic Diagnosis of Glaucoma from Retinal Images Using Deep Learning Approach,” *Diagnostics*, vol. 13, no. 10, pp. 1–17, 2023, doi: 10.3390/diagnostics13101738.

[31] A. Desiani and S. Priyanta, “Multi-Stage CNN : U-Net and Xcep-Dense of Glaucoma Detection in Retinal Images,” vol. 5, no. 4, pp. 211–222, 2023.

[32] Samaya Madhavan, M. Tim Jones, "Deep learning architectures" from IBM, 24 April 2024.