

## A Survey on Deep Learning Models in Glaucoma Detection using Fundus Images(Feasibility Study of Semi-Supervised Learning)

C. Gobinath<sup>[1]</sup>, M. P. Gopinath<sup>[2]\*</sup>

<sup>1,2</sup> School of Computer Science and Engineering, VIT University, Vellore, Tamil Nadu, India  
Email:gobinath.c@vit.ac.in, mpgopinath@vit.ac.in\*

**Abstract**-In the human world today is affected by numerous diseases that lead to damage to body parts or degrade their pace of operation.As main factors, eye disorders include loss of vision due to glaucoma and diabetic retinopathy.As a result of technological advances in deep learning, fundus early detection of glaucoma with an automated approach offers significant advantages.This article addresses deep learning models that are useful for glaucoma detection and to identify opportunities for using Semi-Supervised deep learning models over supervised deep learning methods.Using both labelled and unlabeled data on fundus images, the Semi-supervised GAN model consists of a SegNet, real data generator, and classifier to improve segmentation performance.

**Keywords** - Optic Disc(OD), Optic Cup(OC), Cup to Disc ratio(CDR), Deep Learning (DL), Convolutional Neural Network (CNN), Generative Adversarial Network (GAN).

### I. INTRODUCTION

Glaucoma in today's world is one of the most common eye conditions that cause irreparable harm to the human eye. It is an optic neuropathy that causes damage to the optic nerve head.This damage is incremental and can also cause total loss of vision. [14] Glaucoma is an irreparable eye disorder that affects the optic nerve. The optic nerve is impaired due to improper fluid pressure inside the eye.This is due to the imbalance in the amount of fluid range created i.e. 22mmHg and the amount of excess fluid that is exhausted.Since the lacrimal glands in eye is unable to expel the excess fluid, so fluid pressure varies within the gland, causing nerve fibre damage.The retinal nerve fibre layer deteriorates as a result of the weakened nerve fibers, contributing to an increased CDR ratio and OD value or optic nerve head ratio. Peripapillary atrophy (PPA) was recognized with area of marked waste away of the retinal pigment epithelium with thinning of the chorioretinal tissues. Studies have shown that accelerating glaucoma may lead to an increase in PPA.PPA, on the other hand, can be linked to high myopia. [16]. The structure of a regular and glaucomatous eye is depicted in Figure 1.The fluid flow blockage, which finally leads to optic nerve degradation, can be seen in the figure, and the obstruction will not be in the circular lymphatic vessel[16]. It results in CDR and OD modification. The disc size in the glaucoma image is puffy compared to the disc size in the usual fundus image.

Open-angle glaucoma: As it is pain free and leads to sever vision damage because of zero symptoms to the patients, Peripheral vision is severely affected leads to limited focus of objects.It is caused by the impoverished blocking of waste materials because liquid is not properly exhausting as shown in Fig.

1. Because of that vision loss, the person will not be able to see the objects until these blockages influence the focal vision. Angle-closure glaucoma: It requires immediate medical treatment as it leads to quick vision loss. Extreme eye and head torment are symptoms of angle closure glaucoma. It is likewise known as extreme glaucoma due to an unusual blockage of watery leakage. The retinal size increases fast aggravating the loss of retinal vision quickly. The waste point is limited due to pathetic and watery iris.

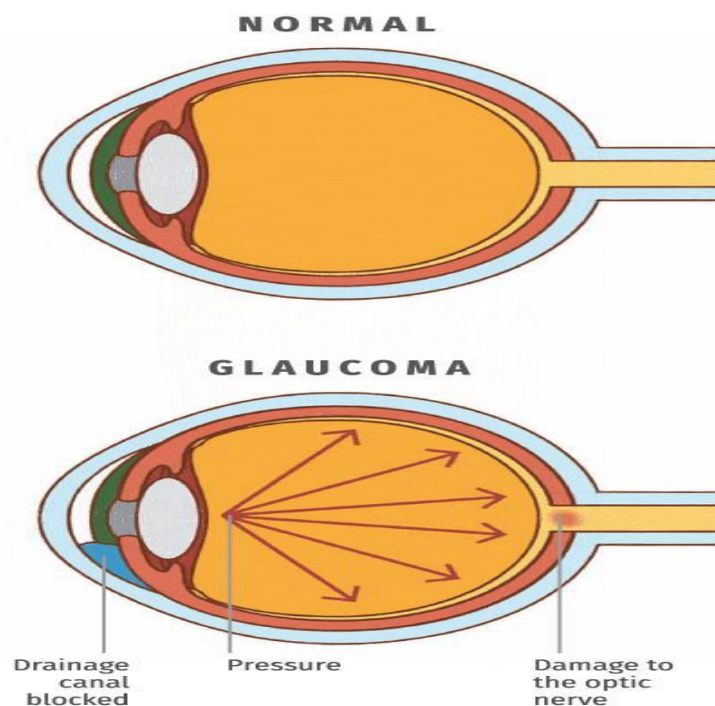


Fig. 1 The examination of a normal and glaucoma-affected eye

## II. DIAGNOSTIC APPROACHES

The medical diagnostic approaches consist of a number of special tests administered by an ophthalmologist. The key to avoiding glaucoma after 40 years is doing frequent eye check-ups. [19]

Confocal scanning laser ophthalmoscopy (CSLO): The CSLO uses a low level light laser with optical microscope to fabricate a three dimensional photograph of the optic nerve and retina. The successful CSLO system that is commercially available in the Heidelberg optical diagnostic procedure which gives 3-dimensional images of retina. Optical Coherence diagnostic procedure: This is a non-invasive cross-sectional instrument using low-consistency interferometry to generate a quick-diagnostic optical dispersion image of the retina. Low light laser or Scanning Laser Polarimetry (SLP): Using retinal laser ellipsometry, the SLP tests RNFL thickness which acquires images rapidly. The three basic imaging techniques used to identify nerve fiber loss and changes to the optic disc of glaucoma are CSLO, OCT and SLP. [16]

The medical diagnosis of the eye using the aforementioned methods takes time and includes inter-observer variability. For monitoring the development of blood sugar level retinal damage, fluid pressure and damage of

macula, fundus images taken using a fundus camera in fixed size can be used successfully. The clinical manifestations of the retinal vision, optics, ophthalmic artery and a central retinal artery, and so on can be visibly identified in fundus imagery. Furthermore, the fundus low power microscope is precise, cheaper and easier to work. It is capable of measuring various formations such as transition between the OC and the OD, point of exit, cup level diameter, etc. The relation between vertical cup chords to vertical disc chord is CDR measurement. Fundus pictures can also appropriately be used to diagnose retinal safety and eye abnormalities via a single fundus image. [19] Through complex, large-scale networks, deep learning combines extraction and classification of features and can achieve promising results.

### III. REVIEW WORK IN DEEP LEARNING MODELS

#### Research Method

This study focuses on a systematic literature review using Deep Learning Models on glaucoma fundus images, thus formulating several research questions:

Q1: Is it enough to train or learn features using supervised deep models with the datasets used in the existing deep learning literature?

Motivation: The purpose is to understand the importance of the data set size, the class balance and the dataset labelled.

Q2: How can domain knowledge be incorporated into significant model learning to improve model performance?

Motivation: The importance of the domain knowledge should be incorporated into the deep models to achieve higher performance.

Q3: What alternative training methods with the limited quantity of data are available?

Motivation: A new method with semi-supervised learning using undefined data for training is being proposed to develop a broader knowledge of the existing controlled learning scheme.

Q4: Whether it is possible to apply transfer or own model?

Motivation: Decide whether a new model should be constructed or whether existing models should be used for transfer learning.

#### Semi-Supervised Learning:

Rongchang et al. [1] discussed on the depiction of the point of exit through a deep learning technique, the method directly depicts CDR value from fundus images while skips intermediate segmentation process. The method consists of two stages of a converters approach one is unsupervised fundus image representation mechanism with convolutionary neural networks and other one is random forest regressor CDR value regression which constructs decision tree to identify CDR value.

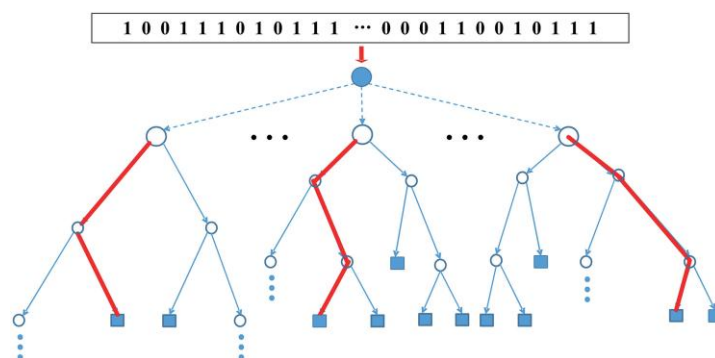


Fig. 2 Decision tree of regression forest to predict CDR value

**Transfer Learning:**

Rubina Sarki et al. [2] made a comprehensive survey of several aspects of Diabetic eye disease automatic approaches with available types of data in digital image preprocessing, empowerment model of learning and efficiency assessment measurements. The survey provides a detailed overview of approaches to diabetic eye disease identification, including creative approaches to research groups, health professionals and diabetes. Ruben Hemelings et al. [7] discussed the effect of training with pictures selected from an active method of learning minimizes labeling costs. These findings indicate the advantages of deep learning focused on optic disc-centered fundus images for automatic glaucoma detection. The combined use of transfer and active learning will increase the output of DL models while minimizing domain-specific labeling costs. Glaucoma specialists can assess their decisions by using the maps created by the deep learning classification. Serener et al. [22] suggested various deep learning approaches, ResNet-50 performs well on advanced glaucoma fundus image classifications, and GoogLeNet also works well. The efficiency of the two models is assessed from the precision, responsiveness, specificity and region underneath the ROC curve. The findings indicate that GoogleNet surpasses ResNet-50 for early, advanced and total detection of glaucoma.

**Multitask Learning:**

Nooshin Mojab et al. [10] suggest an Interpretable Glaucoma Detector (InterGD) for the detection of glaucoma for comprehensible multi-task model. Two main complementary elements, segmentation and prediction modules, make up InterGD. The segmentation module deals with the absence of clinical information by positioning the disc and optical cup regions in a glaucoma image. In order to increase the efficiency of the segmentation task and thus reduce the issue of limited labeled data in the segmentation module, the prediction module uses a larger data set. Effectively incorporated into a cohesive multi-task system, the two components allow end-to-end training.

**Supervised learning:**

Mohammed Mujahid et al. [3] suggested U-Net-based structures for object segmentation and utilization of these networks in medical sectors for retina based vessel segmentation. It also contrasts the different AUC and F1 score-based architectures. Retinal vascular disorders are essential and efficient genetic markers of many

cardiovascular and eye diseases, including diabetic based retinopathy, open and closed angle glaucoma, macular degeneration, and more. Many experiments have been done with the purpose of automatically deriving details of the retinal vessel from the fundus image for segmentation of vessels. Neda Faraji et al. [4] suggested CDR based glaucoma evaluation by segmenting the optic centre and optic disc of fundus image in this article. For this purpose, a revised U-Net architecture using the pre-trained SEResNet50 as its down sampling layers implements segmentation. Finally, CDR is evaluated due to cup and disc areas obtained from the proposed segmentation step. This model has been trained in the Drishti-GS1 and RIMONE v3 databases and is performed on the Drishti-GS1 database test images.

WangMin Liao et al. [5] proposed a new clinical interpretable ConvNet architecture by marking the dissimilar regions predictable by the network on its own. The system proposed results in glaucoma activations that support the gap between the precise position and the global semantime diagnosis. Contrary to earlier works on the diagnosis of clinically interpretable glaucoma, separation of local regions can be found on fundus images. This method is not only used to diagnose glaucoma accurately, but is also used to ensure more transparency. Ryo Asaoka et al. [6] proposed the Residual Network (ResNet) deep learning automated system for validation of fundus photography and to diagnose glaucoma. Dataset is collected by means of various fundus cameras at multiple institutes. The size of the training samples was arbitrarily increased by making minor changes to the original figures, known as "image augmentation."

Shulin Zhang et al. [8] proposed dual-modal fundus images in this paper to build a cascade re-net U-net (CRU-net) to enhance arteriovenous segmentation. The two monochrome imagery gives the venula and arteriole a lot richer detail. Our suggested CRU-net will fully utilize the data in the double data set and achieve the latest results. The accuracy of the arteriovenous rating assessed on the vessels instantaneously detected is 97.27%. Mamta Juneja et al. [11] propose an expert method of Artificially Intelligent Glaucoma focused on optic disc and optic point segmentation. The architecture of deep learning is produced with CNN operating at its heart to automate glaucoma detection. Two neural networks operating in combination with the segment optic cup and the disk are used in the proposed method. The model was tested and accurately achieved on fifty fundus images with a disc accuracy of 95.8 percent and cup segmentation of 93 percent. Anirban Mitra et al. [12] suggested a Convolution Neural Network (CNN) equipped to predict imaginary boxes together with their analogue chance and confidence values on complete images. For the training of the network, the publicly accessible MESSIDOR and Kaggle datasets were used. To expand our data set our network's sensitivity to noise has been reduced by implementing various data augmenting strategies. From a greater perception each image is broken into a 13 X 13 cells of grid. Each grid cell provides five bounding boxes along with the known class success score and a trust attainment. Using a distance metric response based on the set Intersection over the ground-info imaginary boxes, anchors are initialized by grouping k-means on the original data set. Baidaa Al-Bander et al. [13] proposed a fully automated convolutionary neural network (CNN) system, to differentiate diagnostic decisions between normal and glaucoma patients. The features are automatically collected by CNN from raw images and then transferred to the SVM classifier for normal or abnormal images, unlike conventional approaches where the optic disc features are handcrafted. In

comparison with the state-of-the-development but at much lower computing costs, we show an accuracy, specificity and sensitivity of 88.2 percent, 90.8 percent and 85 percent, respectively.

Raghavendra et al. [19] proposed a deep learning method CAD tool for early analysis of fundus images. A 18-layer convolutionary neural network (CNN) is clearly focused to extort local features from the color fundus images. These characteristics are distinguished as normal and glaucoma infected fundus images during testing. The best result of 98.13 per cent is achieved with 1426 fundus images. dos Santos Ferreira et al. [20] discussed a technique for the self-detection of glaucoma in ocular images and the analysis in phylogenetic diversity metrics of texture attributes, using a deepConv learning approach. The image generation is done by RIM-ONE, DRIONSDB and DRESHTI-GS databases, track by working out on the convolutionary neural networks for retinal disc segmentation. It is significant to remove the blood flow vessels after this segmentation, after which extraction of the feature on the RGB channel images and the grey levels has been applied. Borwankar et al [21] proposed a low-cost digital system that is better than previous strategies to diagnose glaucoma, and the ResNet output proposed is comparatively similar to an ophthalmologist which makes it easier and cheaper for a patient to handle. The accuracy of this algorithm is 98.9% and the F1 scoring is 98.8% for the glaucoma infected sample.

Touahri et al. [23] proposed two different classification methods, the first focused on the TWSVM system and the subsequent one describes two dissimilar CNN classifier structures. We used them to classify automatic Glaucoma fund images added to the RimOne colour image as an assisted computer diagnostic method. We suggested three convolutionary layers of CNN architecture for the CNN approach. Three separate families of features are used for the classical approach describing the TWSVM classifier. Increase in the numeral fundus images data has been used, which supports for regularisation and data enhance techniques. It involves vertical, horizontal flip, rotation of 30 and translation with a 0.2 range, which results in 421 glaucoma and 511 non-glaucoma images, both horizontal and vertical. At the end of an increase, we classify the data set into testing, training and validation data, 70% of the fundus images are intended for training, 20% of the total images into the test data set, and 10% of the total images into the validation dataset. Renith and Senthilselvi [29] explained diabetic retinopathy disease detection using deep learning network. Mohammed thaha et al. [30] used Convolutional Neural Network for brain tumor detection and classification. Image denoising [31] plays important role in all kind of image processing researches. Senthilselvi et al. [32, 33, 34] explained image denoising using fuzzy logic and optimization algorithms. Senthilselvi et al. [35] explained image de-noising using ANFIS (Adaptive Neuro Fuzzy Inference System). R Nivetha and A Senthilselvi [36] explained the usage of feature extraction and feature matching process in forgery detection.

Table1. Medical Image Analysis based on various deep learning models

Year	Authors	Objectives	Model used	Data set used / size
2020	Rongchang. [1]	Cup to Disc Ratio (CDR) Estimation	Semi-Supervised Learning	Custom dataset- 421 Images

2020	Rubina Sarki. [2]	Diabetic eye disease detection in fundus images	Transfer Learning	Kaggle dataset- 80k Images
2020	Mohammed Mujahid. [3]	Retinal Vessel Segmentation using U-Net model	Supervised learning	DRIVE CHASE DB dataset- 68 Images
2020	Neda Faraji. [4]	CDR based Glaucoma Diagnosis	Supervised learning	Drishti-GS1 dataset-1.2k Images
2020	WangMin Liao. [5]	Transparent interpretation by highlighting the distinct regions	Supervised learning	Custom dataset- 650 Images
2020	Borwankar. [21]	CNN based feature extraction and classification of fundus images	Supervised learning	REFUGEE, DRISHTI dataset- 101 Images
2019	Ryo Asaoka. [6]	Deep residual learning algorithm to diagnose glaucoma	Supervised learning	Custom dataset- 3.1 Images
2019	Ruben Hemelings. [7]	Glaucoma identification by active learning strategy	Transfer Learning	Custom dataset- 8.4k Images
2019	Shulin Zhang. [8]	Vessel segmentation	Supervised learning	DRIVE dataset-40 Images. Custom dataset-30 Images
2019	Shaopeng Liu. [9]	OD and OC segmentation	Semi-Supervised GAN	ORIGA dataset- 650 Images. Custom dataset- 650 Images
2019	Nooshin Mojab. [10]	Segmentation and prediction using fundus images	Multitask Learning	Custom dataset- 10k Images
2019	Mamta Juneja. [11]	Segmentation of OD and OC	Supervised learning	Custom dataset- 50 Images
2019	Serener, A. [22]	ResNet-50 and GoogLeNet based classification of fundus images	Transfer Learning	Custom dataset- 1.5k Images
2018	Raghavendra, U. [19]	Future extraction of fundus images using 18 layer CNN	Supervised learning	Custom dataset- 1426 Images
2018	dos Santos Ferreira, M. V. [20]	CNN based optic disk and vessel segmentation	Supervised learning	RIM-ONE, DRISHTI-GS dataset-380 Images
2018	Touahri. [23]	CNN based auto feature generation	Supervised learning	RIM-ONE dataset-300

				Images
2018	Anirban Mitra. [12]	Glaucoma identification by active learning strategy	Supervised learning	Kaggle dataset-6k Images
2017	Baidaa Al-Bander. [13]	Automatic feature learning technique for detecting glaucoma	Supervised learning	RIM-ONE dataset-455 Images

#### IV. RESEARCH FINDINGS IN THE REVIEW OF LITERATURE

In this review, Table-1 summarized the literature review findings. The study of different deep models proposed for the detection and classification of glaucoma exposes the difficulties of insufficient labelled model training datasets, the inclusion of domain information for decision-making in deep models. The analysis was dropped to explore the possibilities for designing smart solutions using unlabelled data in deep models, integrating domain information into decision-making and understanding model behaviour using support systems. It is observed that neither the benchmark dataset nor the data evaluation metrics were considered for performance analysis after carefully evaluating the review process, so it is difficult to compare the deep models proposed for fundus image analysis.

#### Semi-Supervised Deep Model using Generative Adversarial Network:

To overcome this constraint, we suggest an inventive optic point and disc segmentation technique from the semi-supervised conditional Generative Adv Nets (GAN). Most of the methods used are difficult to obtain sufficient segmentation efficiency, as a large number of annotated pixel levels of data are often not available during training.

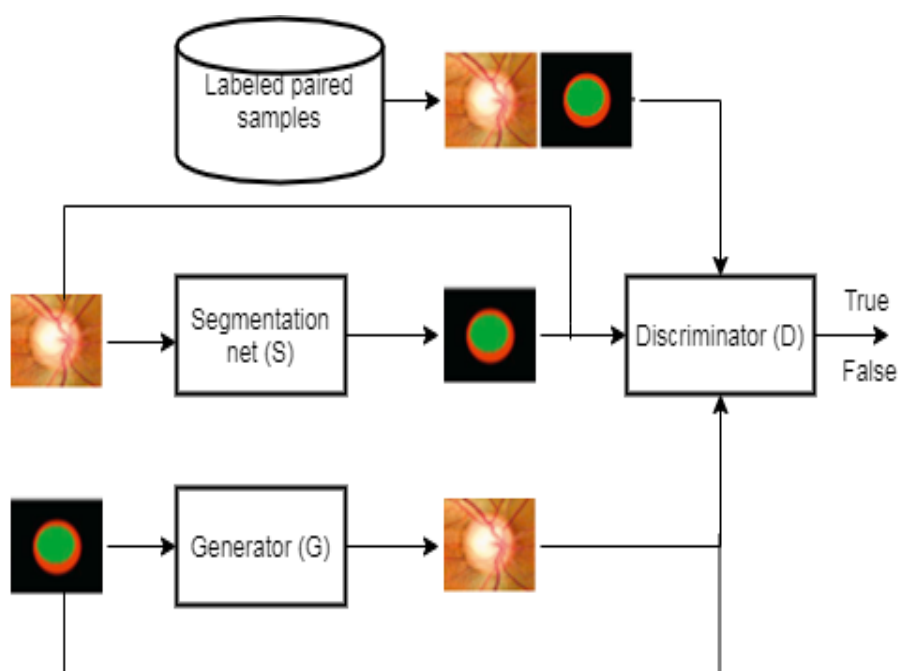


Fig 3. Design of semi-supervised segmentation conditional GANs



Our architecture comprises SegNet, generator and classifier in order to study how to map the glaucoma images with the equivalent segmentation record. Furthermore, we use both well defined and improper data to advance segmentation efficiency. Detailed tests show that both ORIGA and REFUGE data sets are available [9]; our system delivers high-tech segmentation results for optical discs and cups. We have a data set with limited samples for cup and disc segmentation, where  $x$  marks an image of spotted input glaucoma image and  $y$  refers to the equivalent disc and optic point map segmentation. Our goal is to learn the unlabeled pixel based data dissimilarities and to introduce higher order consistency types. Fig. 3 illustrates retinal optic point and cup partitioning procedures with overall flowchart, which includes an SegNet  $S$ , a generator  $G$  and a classifier network  $D$ . Together SegNet and generator are designed to study multimodal mappings between glaucoma images and segmentation maps, while classifier is trained to distinguish two forms of fake data pairs from actual data pairs.

## V. DISCUSSION

The study of deep models used in fundus images for detecting glaucoma was discussed. The importance of using deep models for fundus image analysis also discusses the data collection, merits and drawbacks considered. It is noted that in supervised learning, current deep models use limited quantities of labeled training data. Due to the class imbalance the quality of the training data is found to be poor. By using unlabelled data for model training, the Semi-supervised GAN addresses the inadequate labeled dataset problem and thus increases the overall accuracy of classification by comparing other supervised models. In the future, it will be possible to integrate domain information into deep models to improve model decision-making.

## REFERENCES:

- [1] Zhao, R., Chen, X., Liu, X., Chen, Z., Guo, F., & Li, S. (2019). Direct cup-to-disc ratio estimation for glaucoma screening via semi-supervised learning. *IEEE journal of biomedical and health informatics*, 24(4), 1104-1113.
- [2] Sarki, R., Ahmed, K., Wang, H., & Zhang, Y. (2020). Automatic Detection of Diabetic Eye Disease Through Deep Learning Using Fundus Images: A Survey. *IEEE Access*, 8, 151133-151149.
- [3] Islam, M. M. U., & Indiramma, M. (2020, September). Retinal Vessel Segmentation using Deep Learning—A Study. In *2020 International Conference on Smart Electronics and Communication (ICOSEC)* (pp. 176-182). IEEE.
- [4] Maadi, F., Faraji, N., & Bibalan, M. H. (2020, November). A Robust Glaucoma Screening Method for Fundus Images Using Deep Learning Technique. In *2020 27th National and 5th International Iranian Conference on Biomedical Engineering (ICBME)* (pp. 289-293). IEEE.
- [5] Liao, W., Zou, B., Zhao, R., Chen, Y., He, Z., & Zhou, M. (2019). Clinical interpretable deep learning model for glaucoma diagnosis. *IEEE journal of biomedical and health informatics*, 24(5), 1405-1412.

- [6] Asaoka, R., Tanito, M., Shibata, N., Mitsuhashi, K., Nakahara, K., Fujino, Y., ... & Kiuchi, Y. (2019). Validation of a deep learning model to screen for glaucoma using images from different fundus cameras and data augmentation. *Ophthalmology Glaucoma*, 2(4), 224-231.
- [7] Hemelings, R., Elen, B., Barbosa-Breda, J., Lemmens, S., Meire, M., Pourjavan, S., ... & Stalmans, I. (2020). Accurate prediction of glaucoma from colour fundus images with a convolutional neural network that relies on active and transfer learning. *Acta ophthalmologica*, 98(1), e94-e100.
- [8] Zhang, S., Zheng, R., Luo, Y., Wang, X., Mao, J., Roberts, C. J., & Sun, M. (2019). Simultaneous arteriole and venule segmentation of dual-modal fundus images using a multi-task cascade network. *IEEE Access*, 7, 57561-57573.
- [9] Liu, S., Hong, J., Lu, X., Jia, X., Lin, Z., Zhou, Y., ... & Zhang, H. (2019). Joint optic disc and cup segmentation using semi-supervised conditional GANs. *Computers in biology and medicine*, 115, 103485.
- [10] Mojab, N., Noroozi, V., Philip, S. Y., & Hallak, J. A. (2019, July). Deep multi-task learning for interpretable glaucoma detection. In *2019 IEEE 20th International Conference on Information Reuse and Integration for Data Science (IRI)* (pp. 167-174). IEEE.
- [11] Juneja, M., Singh, S., Agarwal, N., Bali, S., Gupta, S., Thakur, N., & Jindal, P. (2019). Automated detection of Glaucoma using deep learning convolution network (G-net). *Multimedia Tools and Applications*, 1-23.
- [12] Mitra, A., Banerjee, P. S., Roy, S., Roy, S., & Setua, S. K. (2018). The region of interest localization for glaucoma analysis from retinal fundus image using deep learning. *Computer methods and programs in biomedicine*, 165, 25-35.
- [13] Al-Bander, B., Al-Nuaimy, W., Al-Taei, M. A., & Zheng, Y. (2017, March). Automated glaucoma diagnosis using deep learning approach. In *2017 14th International Multi-Conference on Systems, Signals & Devices (SSD)* (pp. 207-210). IEEE.
- [14] Soorya, M., Issac, A., & Dutta, M. K. (2018). An automated and robust image processing algorithm for glaucoma diagnosis from fundus images using novel blood vessel tracking and bend point detection. *International journal of medical informatics*, 110, 52-70.
- [15] Saba, T., Bokhari, S. T. F., Sharif, M., Yasmin, M., & Raza, M. (2018). Fundus image classification methods for the detection of glaucoma: A review. *Microscopy research and technique*, 81(10), 1105-1121.
- [16] Hagiwara, Y., Koh, J. E. W., Tan, J. H., Bhandary, S. V., Laude, A., Ciaccio, E. J., ... & Acharya, U. R. (2018). Computer-aided diagnosis of glaucoma using fundus images: A review. *Computer methods and programs in biomedicine*, 165, 1-12.
- [17] Kumar, P. J., Li, X., Binford, T., Yuan, Y., Hu, W., Yung, Y., ... & Ruby, J. (2019). Intelligent detection of glaucoma using ballistic optical imaging. *Advanced Engineering Informatics*, 40, 107-129.
- [18] Zheng, F., Wu, Z., & Leung, C. K. (2018). Detection of Bruch's membrane opening in healthy individuals and glaucoma patients with and without high myopia. *Ophthalmology*, 125(10), 1537-1546.

- [19] Raghavendra, U., Fujita, H., Bhandary, S. V., Gudigar, A., Tan, J. H., & Acharya, U. R. (2018). Deep convolution neural network for accurate diagnosis of glaucoma using digital fundus images. *Information Sciences*, 441, 41-49.
- [20] dos Santos Ferreira, M. V., de Carvalho Filho, A. O., de Sousa, A. D., Silva, A. C., & Gattass, M. (2018). Convolutional neural network and texture descriptor-based automatic detection and diagnosis of glaucoma. *Expert Systems with Applications*, 110, 250-263.
- [21] Borwankar, S., Sen, R., & Kakani, B. (2020, July). Improved Glaucoma Diagnosis Using Deep Learning. In *2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT)* (pp. 1-4). IEEE.
- [22] Serener, A., & Serte, S. (2019, October). Transfer learning for early and advanced glaucoma detection with convolutional neural networks. In *2019 Medical Technologies Congress (TIPTEKNO)* (pp. 1-4). IEEE.
- [23] Touahri, R., Azizi, N., Benzebouchi, N. E., HAMMAMI, N. E., & Moumene, O. (2018, November). A Comparative Study of Convolutional Neural Network and Twin SVM for Automatic Glaucoma Diagnosis. In *2018 International Conference on Signal, Image, Vision and their Applications (SIVA)* (pp. 1-5). IEEE.
- [24] Bajwa, M. N., Singh, G. A. P., Neumeier, W., Malik, M. I., Dengel, A., & Ahmed, S. (2020, July). G1020: A Benchmark Retinal Fundus Image Dataset for Computer-Aided Glaucoma Detection. In *2020 International Joint Conference on Neural Networks (IJCNN)* (pp. 1-7). IEEE.
- [25] Zhang, H., Yang, J., Zhou, K., Li, F., Hu, Y., Zhao, Y., ... & Liu, J. (2020). Automatic Segmentation and Visualization of Choroid in OCT with Knowledge Infused Deep Learning. *IEEE Journal of Biomedical and Health Informatics*, 24(12), 3408-3420.
- [26] Pandey, A., Patre, P., & Minj, J. (2020, October). Detection of Glaucoma Disease using Image Processing, Soft Computing and Deep Learning Approaches. In *2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC)* (pp. 1-7). IEEE.
- [27] Gopinath, M. P., & Prabu, S. (2018). An EM-MPM algorithmic approach to detect and classify thyroid dysfunction in medical thermal images. *International Journal of Computer Aided Engineering and Technology*, 10(5), 513-529.
- [28] Malathi, V., & Gopinath, M. P. (2021). Classification of pest detection in paddy crop based on transfer learning approach. *Acta Agriculturae Scandinavica, Section B—Soil & Plant Science*, 1-8.
- [29] G. Renith, A Senthilselvi , “Accuracy Improvement in Diabetic Retinopathy Detection using DLIA”, Journal of Advanced Research in Dynamical and Control Systems, titled Volume 12, Issue 7, July 2020
- [30] Mohammed Thaha .M, Pradeep mohankumar .K Murugan .B.S, Dhanasekar .S, Vijay Karthick , P,Senthilselvi.A “Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images”,Journal of Medical Systems, Volume 43 No 9 July 2019
- [31]A Senthilselvi, R Sukumar,” A survey on image restoration technique”, International Journal of Emerging Engineering Research and Technology, volume2, issue 8,November 2014.

- [32] Senthilselvi.A , Sukumar. R &Senthil Pandi S“Hybrid Fuzzy Logic and Gravitational Search Algorithm based multiple filters for Image Restoration”, International journal of data analysis Techniques and strategies, Vol.12 No.1, pp.76 – 97, Feb 2020,
- [33] Senthilselvi.A&Sukumar. R, “Removal of salt and pepper noise from images using Hybrid Filter (HF) and Fuzzy Logic Noise Detector (FLND)”, Concurrency and Computation: Practice and Experience, Volume 31 No 12 June 2019,
- [34] Senthilselvi. A, Pradeep mohankumar. K, Dhanasekar. S, Uma Maheswari .P, Ramesh. S, Senthil Pandi. S “Denoising of images from salt and pepper noise using hybrid filter,fuzzy logic noise detector and genetic optimization algorithm (HFGOA)”, Multimedia Tools and Applications, Volume 78 No 14 July 2019,
- [35] Senthilselvi, A., Duela, J.S., Prabavathi, R. et al. Performance evaluation of adaptive neuro fuzzy system (ANFIS) over fuzzy inference system (FIS) with optimization algorithm in de-noising of images from salt and pepper noise. J Ambient Intell Human Comput (2021). <https://doi.org/10.1007/s12652-021-03024-z>
- [36] R Nivetha, A Senthilselvi, “Hybrid Feature Matching for Image Forgery Detection”,International Journal of Engineering Science and Computing, volume 7, issue 3, p. 5075 – 5080, 2017