Deep Learning-Based Automatic Detection of Central Serous Retinopathy using Optical Coherence Tomographic Images.

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***Abstract*—Central Serous Retinopathy (CSR), also known as Central Serous Chorioretinopathy (CSC), occurs due to the clotting of fluids behind the retinal surface. The retina is composed of thin tissues that capture light and transform into visual recognition in the brain. This significant and critical organ may be damaged and causes vision loss and blindness for the individuals. Therefore, early-stage detection of the syndrome may cure complete loss of vision and, in some cases, may recover to its normal state. Hence, accurate and fast detection of CSR saves macula from severe damage and provides a basis for detecting other retinal pathologies. The Optical Coherence Tomographic (OCT) images have been used to detect CSR, but the design of a computationally efficient and accurate system remains a challenge. This research develops a framework for accurate and automatic CSR detection from OCT images using pre-trained deep convolutional neural networks. The preprocessing of OCT image enhances and filters the images for improving contrast and eliminate noise, respectively. Pre-trained network architectures have been employed, which are; AlexNet, ResNet-18, and GoogleNet for classification. The classification scheme followed by preprocessing enhances the foreground objects from OCT images. The performance of deep CNN has been compared through a statistical evaluation of parameters. The statistical parameters evaluation has shown 99.64% classification accuracy for AlexNet using Optical Coherence Tomography Image Database (OCTID). This shows the suitability of the proposed framework in clinical application to help doctors and clinicians diagnose retinal diseases.**

Keywords— Central Serous Retinopathy (CSR), Optical Coherence Tomography (OCT), Convolutional Neural Network (CNN), Retinal Surface , Healthcare

I. INTRODUCTION

The retina is composed of thin layer ocular tissues and is situated at the eyeball's back in the optic nerve's vicinity [1]. The retina's primary function is to capture the light from the lens's focal length and transform it to message signals for visual recognition in the brain. Therefore, the retina is considered a significant part of an eye and plays a significant role in recognizing various neighboring objects. Any abnormality or damage to the retinal surface can lead to the sightlessness visual impairments of the subject.

Vision loss and blindness may be caused by one of the diseases commonly known as Central Serous Retinopathy (CSR) that has infected millions of people worldwide. The core reason behind CSR occurrences is the clotting of liquid material on the retinal surface, causing widespread damage to individuals' eyesight [2]. Accurate CSR detection in the early stages can help treatment planning and diagnostic procedures prevent loss of sight. For this purpose of CSR detection, several imaging technologies, including the Fluorescein Angiography (FA), Fundus Photography, and Optical Coherence Tomography Angiography (OCTA), are employed. It is considered the most effective and advanced imaging technique among all OCT-based detection of numerous retinal pathologies.

The OCT imaging technique is like ultrasound imaging; however, it possesses a slight difference in detection. In contrast to sound waves that capture the ultrasound image, OCT imaging employs light waves [3]. High dimensional images of the retinal surface area produced from OCT using a combination of endoscopes and catheters. OCT image with no sign of CSR or any other retinal syndrome is shown in Fig. 1, and OCT image of the subject affected with CSR is shown in Fig. 2. The discrimination between OCT images of healthy subjects and CSR-affected individuals could be seen in the choroid, the thickness of fovea, serous retinal detachment, and Inner Limiting Membrane (ILM).

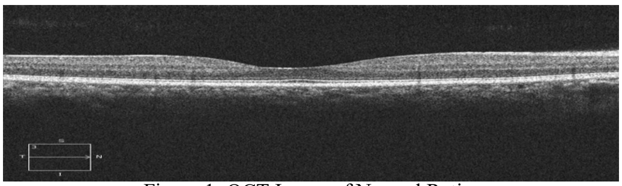

Figure 1: OCT Image of Normal Retina

Figure 2: OCT Image of CSR affected Retina

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Traditionally, the process of detection of CSR has been conducted by expert examiners that may cause a human error, which makes it not only inefficient but also time-consuming. There exist some automated systems to detect retinal abnormalities, including [4], [5], [6], [7] and [8]. Still, there is a research gap to develop a fully automated and reliable system for detecting Central Serous Retinopathy through OCT images. This research is a milestone towards the automatic detection of CSR through OCT images.

After section I of the Introduction, the rest of the paper's organization is as follows; the very next section II discusses the most recent studies to classify OCT images. A detailed and comprehensive description of the proposed framework for detecting CSR from OCT images has been discussed in section III. Section IV discusses the evaluation and comparison of the proposed classification scheme for CSR detection. The conclusion and prospects have been discussed in section V.

II. Literature Review

The advancement in computer-aided diagnostic systems, algorithms based on image processing, machine learning, and deep learning have been proposed in the literature. A detailed and comprehensive review of algorithms for detecting the CSR method has been referred to in [19]. S. Weng in [9] proposed a detection scheme called Optical Coherence Tomographic Angiography (OCTA) to detect retinal pathologies. The proposed system has been evaluated from the data of 70 subjects. Loosely Coupled and Locally Adaptive CSR detection approach has been presented in [10] and achieved an overall True Positive Rate (TRP) of 0.96. An advanced and robust artificial intelligence-based classification algorithm has been proposed by SG Odaibo et al. in [11] using cloud computing. A comparative study has been conducted in [12] to access the classified performance of algorithm based on Color Fundus Photography (CFP) and Multicolored Imaging (MC). A machine learning-based classification approach called Support Vector Machine (SVM) had been employed in [13] to detect CSR. The feature vector in the proposed scheme consists of five characteristics extracted from 30 OCT scans. The classification accuracy of 98.88% has been attained in [14] while detecting CSR from 3-D OCT images. Random forest classification model combined with max-flow optimization algorithm was evaluated on a dataset of 37 retinal in [15]. The proposed algorithm by the author was successful in achieving a classification accuracy of 95%. Deep learning-based segmentation of OCT images for CSR detection was carried out in [16] and [17] using self-activating technique and U-Net deep CNN, respectively. U-Net Deep Convolutional Neural Network was proven to be very effective in accurately detecting CSR from OCT images. The self-activating algorithm's error rate was 5.5%, while the total classification accuracy of U-Net network architecture was 97.87%. A robust algorithm was also proposed in [18] based on fully convolutional networks (FCN). Table I shows a summary of previous studies made for the detection of CSR. The classification of OCT images has been proposed significantly in the literature; however, it has been identified that preprocessing data is essential to obtain accuracy in detecting CSR. Therefore, in this study, transfer learning-based comparative analysis has been made on multiple pre-trained networks. The preprocessing phase, to eliminate noise and enhance foreground objects from OCT images, has been followed by the classification scheme. The preprocessing phase enhances the foreground of OCT images and effectively extracts the most beneficial information from images to feed the deep Convolutional Neural Networks.

TABLE I. SUMMARY OF PREVIOUS STUDIES

Paper	Year	Authors	Dataset	Results
[9]	2016	S. Weng, Xiang et al.	70 OCT eye scans of patients	97.77% Accuracy
[10]	2016	Z. W. Jelena Novosel et al.	74 Retinal OCT image	0.96 TRP
[11]	2019	SG Odaibo et al.	90 Time Domain OCT images	97% Sensitivity
[12]	2020	M. Lu He et al.	75 SD-OCT eyes scans	92% Detection Rate
[13]	2016	Hassan B et al.	34 OCT Scans	97.77% Accuracy
[14]	2016	A. M. Syed et al	3-D OCT Images	98.88% Accuracy
[15]	2017	M.Wu Xiang et al	37 retinal SD-OCT	95% Accuracy
[16]	2018	J De Fauw et al.	887 SD-OCT scans	5.5% Error Rate
[17]	2019	B. Hassan et al	30 OCT Images	97.87% Accuracy
[18]	2019	K. Gao et al	52 SD-OCT scans	96.4% PPV

III. Proposed Methodology

The framework proposed in detecting Central Serous Retinopathy (CSR) using OCT images is based on deep Convolutional Neural Networks. The proposed algorithm for the classification of Central Serous Retinopathy is shown in Fig. 3. OCT images' available database has been primarily augmented to increase the number of images that are the prerequisite for training deep convolutional neural networks. The enhancement of contrast images and noise removal is then conducted in the preprocessing phase to have a more useful OCT images database. The performance of multiple architectures of CNN has been compared based on statistical evaluation of the parameters.

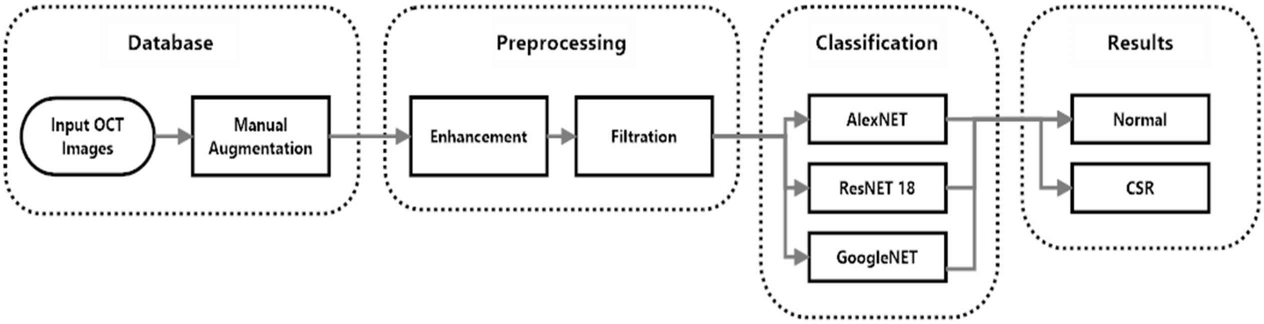

Figure 3: Workflow Diagram of Proposed Methodology

A. Dataset

In this research, a publicly available dataset called Optical Coherence Tomography Image Database (OCTID) has been imported from [20]. The database of OCTID comprises a total of 309 samples, of which 102 OCT images of CSR and 207 normal subjects. OCT images' resolution in this database has been maintained at 512x1024 and collected using raster scan protocol. The images flipped concerning the x and y-axis during the process of augmentation. In Fig. 4, numbers of images from each discrete class used for training and validation of Deep CNN have been depicted. This database requires the classification system to handle class imbalance issues to achieve better accuracy.

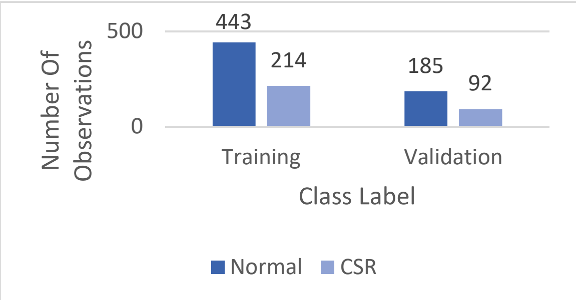

Figure 4: Training and Validation Databases

B. Preprocessing

In preprocessing phase, the contrast of OCT images has been enhanced, and noise has been eliminated using the median filtration method. This has been performed due to low contrast and huge noise in OCTID database images. The noise has been removed to allow the network to fetch valuable information from OCT images.

1) Enhancement: The enhancement of OCT images has been performed using the process of intensity transformation. The intensity transformation operation saturates the top 1% and the bottom 1% of all pixel images to increase the difference of background and foreground objects. The enhanced OCT image of CSR has been shown in Fig. 5.

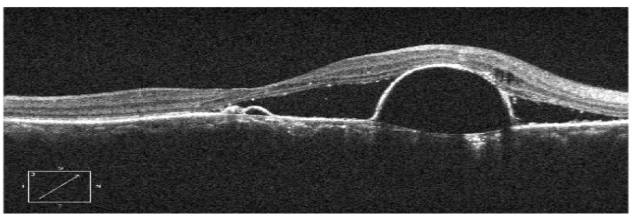

Figure 5: Enhanced OCT Image

2) Filtration: The filtration process has been required due to background contamination of enhanced OCT images with salt and pepper that may mislead the classification's deep networks. As the background noise has maximum similarity with salt and pepper noise, so median filter has been used in the filtration process due to its effectiveness in removing such noise. The median filter having a kernel size of 5x5 has been referred to filter the images effectively. Image filtration using a median filter is a non-linear technique that decides the output pixel value based on a 5x5 neighborhood pixel's median value within the input image. The filtered image has been shown in Fig. 6.

Figure 6: Filtered OCT Image

C. Classification

The preprocessed OCT images obtained from previous steps have been considered for automatic detection of Central Serous Retinopathy. A comparison has been made between the performance of multiple pre-trained deep network architectures to attain accuracy. Using transfer learning, the architectures of AlexNet, ResNet, and GoogleNet have been modified according to the discrete classes involved in OCT image classification. These classifiers' selection has been made based on their exemplary performance in pattern recognition and classification problems.

1) AlexNet: AlexNet is one of the successful network architectures used in object recognition and classification applications. The architecture of AlexNet consists of 8 layers, including three is fully connected layers and five convolutional layers. The Max Pooling layers have been integrated before the first, second, and fifth convolutional layers. The third and fourth convolutional layers of this architecture are directly connected. The activation function used in all eight layers is ReLU. The softmax function is used in the last layer to assign the probabilities for classification in each class. A comprehensive detail about the architecture of AlexNet can be seen in [21].

2) ResNet18: ResNet-18 is also a pretrained network like AlexNet and has been trained on around 1 million images from the classification of 1000 discrete classes. This network architecture has the edge over other networks due to its applicability in real-life applications. There are 18 deep layers in the architecture of ResNet-18. The detailed architecture of ResNet-18 can be seen in [22].

3) GoogleNet: The GoogleNet architecture has been presented to solve computer vision problems like classification to detect objects efficiently. There are 22 layers in the architecture of GoogleNet, and the size of the input layer is 224x224. Moreover, there are five pooling layers and nine inspection modules in this deep network. A simple and effective introduction to GoogleNet can be seen in [23].

IV. Results and Discussions

The performance of deep convolutional neural networks in CSR detection has been conducted through several experiments. This experimentation helps decide which networks have optimized the results that depict each network competence and clinical application reliability.

Before the OCT image input in networks, all the preprocessed images have been resized according to the respective network architecture's input layers. In AlexNet Deep CNN, the dimensions of input images have been kept at 227x277. Whereas, in ResNet18 and GoogleNet images resolution of 224x244 has been provided. Approximately 70% of the preprocessed OCTID database is used to train the network, and the remaining 30% is employed for validation. For all three classifiers, the initial learning rate is 1x10-4, and the maximum number of training iterations is set to 96.

The classification accuracy and loss curve against each iteration for AlexNet Deep CNN has been shown in Fig. 7. It has been observed from the curves that the network has rapidly started learning from OCT images in the 1st to 20th iteration. In twenty-four iterations, Alexnet achieves maximum accuracy for validation data later flattens the curve. Also, the classification error or loss curve approximately converges to zero during its first few iterations.

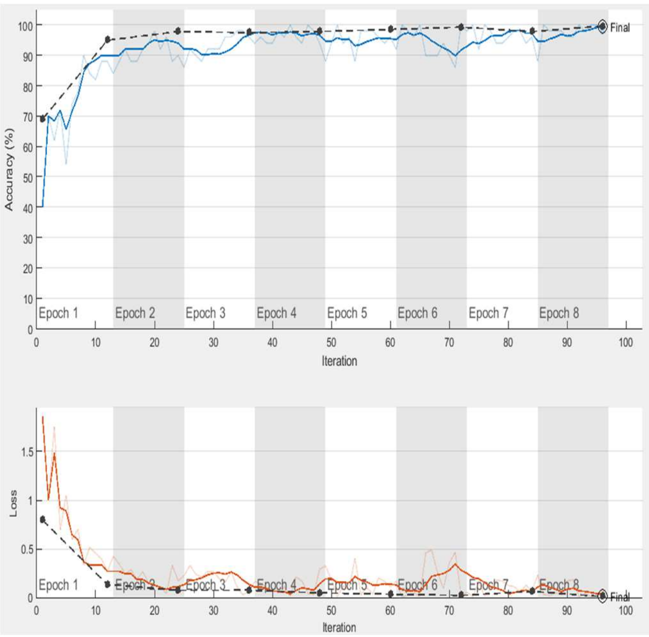

Figure 7: Classification Accuracy and Loss Curves

The confusion matrix for Alexnet Classifier is shown in Fig. 8. According to this confusion matrix, 91 OCT images of Central Serous Retinopathy have been classified accurately out of a total of 92 images, while no normal OCT image has been classified incorrectly. The incorrect classification is due to the massive similarity between two discrete classes of OCT images.

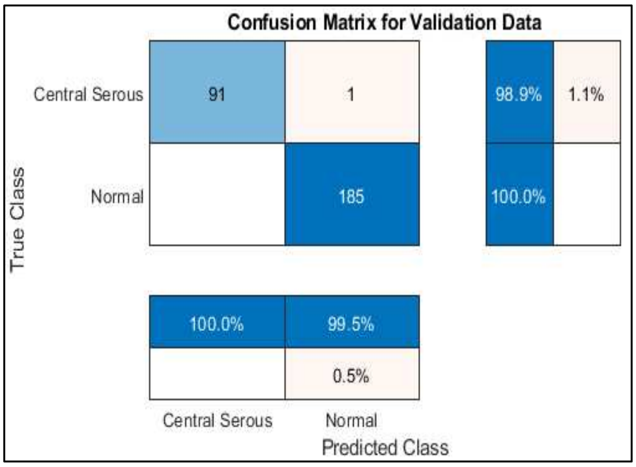

Figure 8: Confusion Matrix for AlexNet

A. *Evaluation Parameters*

The general investigation of the networks on validation data, statistical evaluation parameters have been considered. These standard evaluation parameters have been commonly used to assess the performance of classification systems.

1) Accuracy: The total classification accuracy has been illustrated as the number of correct detected subjects to that of the total subjects.
TP has been referred to as true positive, FN is false negatives, TN is a true negative, and FP is a false positive emotion classification system.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{(\text{TP} + \text{FN} + \text{TN} + \text{FP})} \times 100$$

2) Precision: It is referred to as the measure of actual positive from the true predicted values. It depicts the exact and truthful a classification model can measure the correctness of signal classification when a false positive value is high. Precision is computed from the confusion matrix as.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

3) Recall: The ratio of true positive values to the sum of true positives and false negatives is referred to as recall or sensitivity and is generally applied to evaluate classifiers in pattern recognition and binary classification applications. This feature estimates the number of the true positives in the classification model that have been truly classified.

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

4) F1-score: The function of precision and recall is referred to as F1. This significant statistical parameter evaluates to find the difference between precision and accuracy. F1 has been utilized in an unequal distribution of classes and is assumed to be a good measure in need of equilibrium between Precision and Recall. The formula for the calculation of the *F1 score* is given below.

$$F1 - score = 2 \text{ x } \frac{Precision \text{ x } Recall}{Precision + Recall}$$

TABLE II. COMPARISON OF PROPOSED METHOD

Method	Classifier	Accuracy	Precision	Recall	F1-score
[13]	SVM	97.77%	93.33%	100%	---
[14]	SVM with B-scan	98.88%	96.66%	100%	---
[15]	Random Forest	95%	---	---	---
Proposed Model	**AlexNet**	**99.64%**	**98.91%**	**100%**	**99.45%**
	ResNet18	**98.19%**	**94.57%**	**100%**	**97.21%**
	GoogleNet	**96.39%**	**92.39%**	**96.59%**	**94.44%**

The performance of the proposed model based on evaluation parameters has been presented in Table II. A comparison in the form of bar graph can also be seen in Fig. 9. It has been observed that the AlexNet classifier exhibits better performance compared to ResNet18 and GoogleNet, thus, achieving 99.64% accuracy, 98.91% precision, 100% recall, and 99.45% f1. Based on total classification accuracy, the proposed classification algorithm exhibits better performance than previous techniques presented in Table I. The methodologies proposed by researchers in these studies employed small and local datasets for validation purposes. Moreover, all the three classifiers' evaluation parameters have values above 90%, which shows the capability of deep learning-based algorithms in the classification and detection of Central Serous Retinopathy from OTC images.

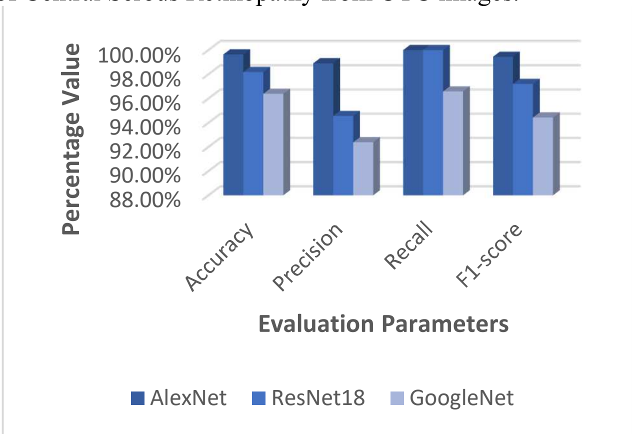

Figure 9: Comparison of Networks

V. CONCLUSION

An automatic classification scheme for CSR detection, one of the most common molecular syndromes in the retina, has been proposed in this paper. The computationally efficient detection system has been designed with the pre-trained network that depicts competitive results due to incorporating learned architectures' and parameters. Before the classification, the preprocessing has enhanced the low contrast OCT images and filtered noisy elements that supported the performance enhancement. The statistical evaluation of networks from the OCTID database depicts the developed algorithm's better performance and advanced methodology that may be preferred in real-time medical applications. This system can also be used as a decision support system for planning treatment and diagnosing the patient affected by CSR. Most of the previous research studies rely on a small and local dataset for validation of their proposed algorithm, but in this work, extensive experimentation using OCTID, which is a large and standard dataset, is carried out to test the classification system.

The fusion of the three networks, including AlexNet, ResNet-18, and GoogleNet, can be considered in the future to advance the accuracy in results while making a little compromise in complexity. Besides, the combination of imaging technologies such as Fluorescein Angiography (FA), Fundus Photography, and Optical Coherence Tomography Angiography (OCTA) may be used simultaneously for validation of discrete class of networks at the output.

CONFLICT OF INTEREST

The authors of this paper have no conflict of interest.

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REFERENCES

[1] A. Rehman, "Light microscopic iris classification using ensemble multiclass support vector machine", *Microscopic research & Technique*, 2021.

[2] A. Jamal, M. Hazim Alkawaz M, A. Rehman, T. Saba "Retinal imaging analysis based on vessel detection". *Microsc Res Tech*.vol. 80, no. 17,799-811, 2017.

[3] J. Amin, M. Sharif, A. Rehman, M. Raza, M.R. Mufti. Diabetic retinopathy detection and classification using hybrid feature set. *Microscopy research and technique*, vol. 81, no. 9, 990-996, 2018

[4] S. Akbar, M. U. Akram, M. Sharif, A. Tariq, and U. Ullah Yasin, "Arteriovenous ratio and papilledema based hybrid decision support system for detection and grading of hypertensive retinopathy," *Computer methods and programs in biomedicine* vol. 154, pp. 123-141, 2018.

[5] S. Akbar, M. U. Akram, M. Sharif, A. Tariq, and U. Ullah Yasin, "Decision support system for detection of papilledema through fundus retinal images," *Journal of medical systems* vol. 41, no. 4, p. 66, 2017.

[6] S. Akbar, M. U. Akram, M. Sharif, A. Tariq, and S. A. Khan, "Decision support system for detection of hypertensive retinopathy using arteriovenous ratio," *Journal of medical systems* vol. 90, pp. 15-24, 2018.

[7] S. Akbar, M. Sharif, M. U. Akram, T. Saba, T. Mahmood, and M. Kolivand, "Automated techniques for blood vessels segmentation through fundus retinal images: A review," *Microscopy research and technique* vol. 82, no. 2, pp. 153-170, 2019.

[8] M. U. Akram, S. Akbar, T. Hassan, S. G. Khawaja, U. Yasin, and I. Basit, "Data on fundus images for vessels segmentation, detection of hypertensive retinopathy, diabetic retinopathy and papilledema," *Data in brief* vol. 29, p. 105282, 2020.

[9] S. Weng, L. Mao, S. Yu, Y. Gong, L. Cheng, and X. Chen, "Detection of choroidal neovascularization in central serous chorioretinopathy using optical

coherence tomographic angiography," *Ophthalmologica* vol. 236, no. 2, pp. 114-121, 2016.

[10] J. Novosel, Z. Wang, H. de Jong, M. Van Velthoven, K. A. Vermeer, and L. J. van Vliet, "Locally-adaptive loosely-coupled level sets for retinal layer and fluid segmentation in subjects with central serous retinopathy," in *2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI)*, 2016, pp. 702-705: IEEE.

[11] S. G. Odaiba, M. MomPremier, R. Y. Hwang, S. J. Yousuf, S. L. Williams, and J. Grant, "Mobile artificial intelligence technology for detecting macula edema and subretinal fluid on OCT scans: Initial results from the DATUM alpha Study," *arXiv preprint arXiv:1902.02905* (2019).

[12] L. He, C. Chen, Z. Yi, X. Wang, J. Liu, and H. Zheng, "Clinical application of multicolor imaging in central serous chorioretinopathy," *Retina* vol. 40, no. 4, pp. 743-749, 2020.

[13] B. Hassan, G. Raja, T. Hassan, and M. U. Akram, "Structure tensor based automated detection of macular edema and central serous retinopathy using optical coherence tomography images," *JOSA* vol. 33, no. 4, pp. 455-463, 2016.

[14] A. M. Syed, T. Hassan, M. U. Akram, S. Naz, and S. Khalid, "Automated diagnosis of macular edema and central serous retinopathy through robust reconstruction of 3D retinal surfaces," *Computer methods and programs in biomedicine* vol. 137, pp. 1-10, 2016.

[15] M. Wu *et al.*, "Three-dimensional continuous max-flow optimization-based serous retinal detachment segmentation in SD-OCT for central serous chorioretinopathy," *Biomedical optics express* vol. 8, no. 9, pp. 4257-4274, 2017.

[16] J. De Fauw *et al.*, "Clinically applicable deep learning for diagnosis and referral in retinal disease," *Nature medicine* vol. 24, no. 9, pp. 1342-1350, 2018.

[17] B. Hassan and T. Hassan, "Fully automated detection, grading and 3D modeling of maculopathy from OCT volumes," in *2019 2nd International Conference on Communication, Computing and Digital Systems (C-CODE)*, 2019, pp. 252-257: IEEE.

[18] K. Gao *et al.*, "Double-branched and area-constraint fully convolutional networks for automated serous retinal detachment segmentation in SD-OCT images," *Computer methods and programs in biomedicine* vol. 176, pp. 69-80, 2019.

[19] G. Quin, G. Liew, I. V. Ho, M. Gillies, and S. Fraser‐Bell, "Diagnosis and interventions for central serous chorioretinopathy: review and update," *Clinical & experimental ophthalmology* vol. 41, no. 2, pp. 187-200, 2013.

[20] P. Gholami, P. Roy, M. K. Parthasarathy, and V. Lakshminarayanan, "OCTID: Optical coherence tomography image database," vol. 81, p. 106532, 2020.

[21] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Computers & Electrical Engineering* vol. 25, pp. 1097-1105, 2012.

[22] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770-778.

[23] C. Szegedy *et al.*, "Going deeper with convolutions," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015, pp. 1-9.