IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 13, No. 1, March 2024, pp. 417~429
ISSN: 2252-8938, DOI: 10.11591/ijai.v13.i1.pp417-429

An improved dynamic-layered classification of retinal diseases

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Article Info

Article history:

Received Nov 16, 2022
Revised Jan 28, 2023
Accepted Mar 10, 2023

Keywords:

Choroidal neovascularization
Deep learning
Diabetic macular edema
Drusen
Improved dynamic-layered classification

ABSTRACT

Retina is main part of the human eye and every disease shows the effect on retina. Eye diseases such as choroidal neovascularization (CNV), DRUSEN, diabetic macular edema (DME) are the main retinal diseases that damage the retina and if these damages are identified in the later stages, it is very difficult to reverse the vision for these retinal diseases. Optical coherence tomography (OCT) is a non-nosy image testing for finding the retinal diseases. OCT mainly collects the cross-section images of retina. Deep learning (DL) is used to analyze the patterns in several complex research applications especially in the disease prediction. In DL, multiple layers give the accurate detection of abnormalities in the retinal images. In this paper, an improved dynamic-layered classification (IDLC) is introduced to classify retinal diseases based on their abnormality. Image filters are used to filter the noise present in the input images. ResNet is the pre-trained model which is used to train the features of retinal diseases. Convolutional neural networks (CNN) are the DL model used to analyze the OCT image. The dataset consists of three types of OCT disease datasets from Kaggle. Evaluation results show the performance of IDLC compared with state-of-art algorithms. A better performance is obtained by using the IDLC and achieved the better accuracy.

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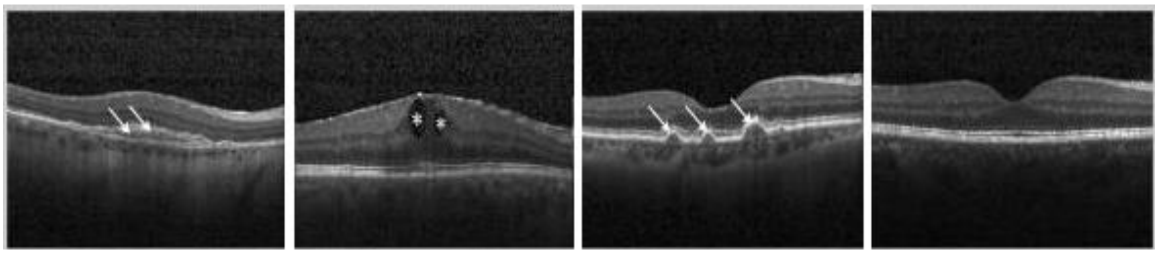
1. INTRODUCTION

The eye is a very sensitive part of the human body. It is very important to maintain the accurate vision of the human eye. Retina plays a major role in maintaining the vision perfectly. The retina contains the photosensitive layer of one tissue, which is located on the inner surface of the eyeball. The focus light is received by this layer and converted into neural signals. Macula is the significant part of retina which is the main region for sensing purposes. The special layers present in the photoreceptor nerve cells are used to detect the color, intensity of light, and visualization. Finally, the visualization of data is analyzed by the macula in the retina and sent to the brain by using the optic nerve. Medical imaging plays a major role in clinical diagnosis and proper treatment of eye diseases. High-resolution images are used to analyze the abnormalities in the given samples. Over the past many years, several imaging approaches are developed rapidly with corrective treatments. Nowadays imaging technology is increasing very fastly to diagnose and detect complex diseases such as retinal diseases because of the increasing number of patients and observations that are recorded for single patients. Based on the professional experience of experts several traditional diagnostic techniques lead to mismatched results and the destruction of medical data.

Machine learning (ML) is the advanced domain used to identify the eye diseases such as choroidal neovascularization (CNV), diabetic macular edema (DME), and Drusen. Figure 1 shows the different type's retinal diseases such as (a) choroidal neovascularization, (b) diabetic macular edema, (c) DRUSEN and

(d) normal. ML is the sub-domain of artificial intelligence (AI) which uses to learn the data and made predictions. ML classifications are of two types such as supervised and unsupervised learning. In ML, the training is done with the previous data which is labeled by the humans to estimate the accurate output which can solve the classification and regression issues. Supervised learning approaches are more time-consuming to process the data because it requires labeled data which is manual.



(a) (b) (c) (d)

Figure 1. Shows the different type's retinal diseases such as (a), (b), (c) and (d) showing the types of retinal diseases; (a) CNV: choroidal neovascularization, (b) DME: diabetic macular edema, (c) DRUSEN and (d) normal

The unsupervised learning approach provides the labeled data externally without the influence of humans. It is divided into two types such as clustering and association rule mining and also it works only for small datasets and these approaches are failed to achieve accurate results for complex datasets because of their manual selection of features. DME is a common disease that will cause loss of vision disability and blindness in diabetic patients. By using several diagnoses this can be prevented in the early stages. But regular diagnoses are not enough to detect this disease [1]. Figure 2 explains the overall process of detecting the retinal diseases.

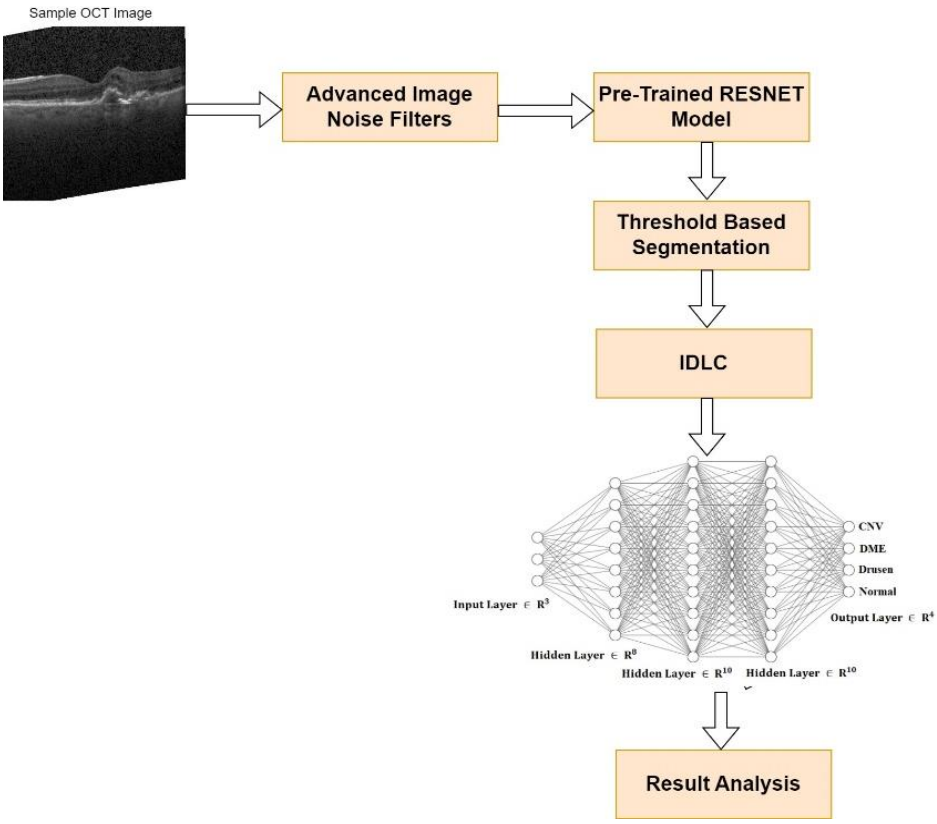


Figure 2. Architecture diagram for improved dynamic-layered classification (IDLC)

CNV is a retinal disease that can grow abnormal blood vessels in the choroid layer of the retina [2]. The macula is the central part of the retina in the human eye. If the patient is affected with Diabetic Macular Edema leads to the inflation of fluid in the macula part [3]. This is caused due to the leakage of a blood vessel in the retina. 30% of diabetic retinopathy patients converted to DME in the last stage. Drusen is the other retinal disease that causes vision issues. The early signs of drusen create issues in vision, but high drusen may lead to the development of age-related macular degeneration (AMD). Drusen also form the yellow-white spots that are placed in the back side of retinal pigment epithelium (RPE) cells [4]. Thus, clinically an automated approach is required to diagnose and detect retinal diseases. This paper mainly focused on classifying the optical coherence tomography images based on their diseases. Every disease has its own properties to find the features of the specific disease. The proposed approach consists of multi layers that are used to find the abnormalities in the OCT images. A better pre-trained approach ResNet is also used for training. An improved feature extraction, pre-processing with image filters is used to remove the noise from the OCT images is also used to improve the diseases detection rate. Another approach which is used to segment the input OCT image is threshold segmentation. Figure 3 shows the default retinal layers present eye sample belongs to healthy person.

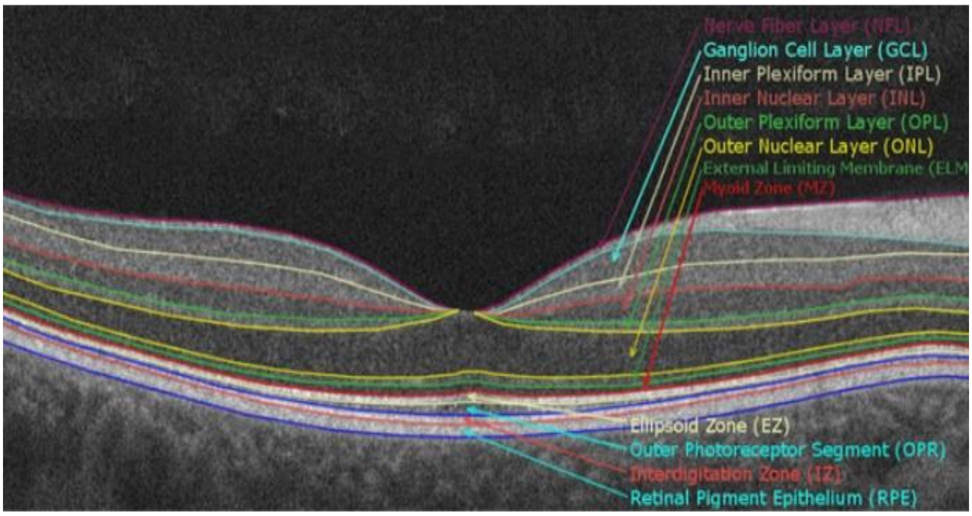


Figure 3. Showing the 12 layers of OCT retinal image belongs to healthy person

2. LITERATURE SURVEY

Huang *et al.* [5] proposed the novel layer-guided convolutional neural networks (LGCNN) developed to find the three types of retinal diseases. The proposed approach is mainly used to create segmented maps based on the retinal layer. The proposed classification obtained the results based on lesion-related layer regions. The LG-CNN takes more time to find the abnormal regions and this is considered as the drawback of LGCNN. Rasti *et al.* [6] presented the ensemble approach which classifies the two types of diseases such as disease-related malnutrition (DRM), DME and normal. This approach is also called a multi-scale convolutional mixture of experts (MCME). This is a data-driven model which is integrated with the convolutional neural networks applied by using multiple sub-scale images. MCME is used for the training dataset. The MCME achieved a precision of 98.86% and AUC of 99.85% on average. This approach is limited to small datasets and it should work better on large datasets. Seebock *et al.* [7] proposed the model which is mainly focused on finding the early prediction of AMD disease in patients. This also detects late AMD. For better results, the multi-scale deep denoising auto-encoder is used for training the AMD disease and normal images with the merging of one-class SVM used to find the malicious data. The proposed approach achieved an receiver operating characteristic (ROC) of 0.944. This approach should focus on increasing the parameters and improving the performance.

Ma *et al.* [8] proposed the multi-scale class activation map (MS-CAM) to highlight the affected regions based on the diseases such as AMD and geographic atrophy (GA). The segmentation for GA is applied to spectral domain-optical coherence tomography (SD-OCT) images. For the extraction of multi-features, the scaling and up sampling (SUS) is used to extract the various scales. The proposed approach achieved the accuracy in detecting the images. The MS-CAM should extract the accurate features that show the huge impact on output performance. Wang *et al.* [9] proposed the low-performed supervised learning approach that solves the classification of macula-related diseases. The proposed approach uses the two-step formula for detecting accurate diseases and a robust instance classifier is also developed to classify the abnormal samples. The proposed approach limited to detect only the DME disease. This should work for detecting the multiple diseases. Rong *et al.* [10] developed a surrogate-assisted classification (SAC) based on CNN. The noise is reduced by the image preprocessing technique. To extract the masks from the image threshold is applied. Finally, the output is shown after training the CNN model on the surrogate images. The training samples are to be increased more and advanced training is required for the increase of performance.

Yan *et al.* [11] proposed the segment level-based approach that analyzes the denser vessels in the training process. By utilizing the vessel segmentation more effective features are extracted to reduce the complexity. Still there is a lack of accuracy in this approach and advanced models are to be adopted for improving the performance. Wang *et al.* [12] proposed the content-based multi-model approach which is used to detect the segmentation of vessels, detection of features, and description. The proposed approach was applied to color fundus images with retinal properties. The proposed approach achieved the accuracy with disease detection rate and dice coefficient. The robustness of this system should be improved in terms of computation time. Ma *et al.* [13] introduced the OCTA-Net used to detect retinal diseases based on the segmentation of images. Better performance is obtained from the segmentation and shows the difference between health and Alzheimer's disease (AD) diseases. In future the OCTA-Net focused detecting the multiple diseases.

Ngo *et al.* [14] proposed the dynamic segmentation approach for OCT images without human-biased feature learning regression. The proposed approach is based on the potency and slope used to learn the features and predict the relevant retinal boundary pixel. This shows the performance of proposed approach is 0.612 which is less than a 1-pixel variation. Several issues are identified such as scalability and discontinues layers are identified. This should be improved in future. Seebock *et al.* [15] proposed the Bayesian deep learning approach which is used to detect the anomaly deviations from the training set. The pre-trained model such as Bayesian U-Net is also used for better performance. To detect the blob-shaped segments a unique post-processing method is used. The segmentation separated the health and diseases with late wet AMD, dry geographic atrophy (GA), DME, and retinal vein occlusion (RVO). The proposed approach should improve the accuracy and detection rate to detect the biomarker detection.

Li *et al.* [16] presented the integrated approach with the combination of CNN and attention mechanism consisting of general U-Net and attention module which is utilized to capture the overall information about the features by using with future fusion. The proposed approach achieved better accuracy and it is applied on 5 public available datasets. Huang *et al.* [17] introduced a unique unbalanced DL which is combined with the ResNet which is proposed to work on arterial spin labeling (ASL) images. This is mainly focused on detecting dementia diseases which are gradually increased with the performance obtained with the new model. The experiments are conducted on 355 patients with dementia.

2.1. Segmentation techniques used for detecting retinal images

Hassan *et al.* [18] presented the residual learning-based framework (RASP-Net) combined with several preprocessing techniques and merged with the segmentation and analysis of 11 chorioretinal biomarkers (CRBMs). Overall 7k scans are used for training, testing, and validation of RASP-Net. To increase the disease detection, rate the 3D macular approach is adopted that shows the impact on final output. Based on the performance the proposed model shows an accuracy of 91.6%, an intersection of 63.4%, and a dice score of 77.6%. Sarhan *et al.* [19] discussed several machine learning algorithms that are utilized for the detection of retinal vessel segmentation, techniques of retinal layers, and segmentation of fluids. This survey is mainly focused on applying the ML algorithms to color fundus images. Performances of various ML algorithms are also discussed by the authors.

Soomro *et al.* [20] discussed various DL approaches that are used to analyze retinal image diseases. Numerous retinal diseases lead to permanent blindness if they didn't take proper treatment. For example, Diabetic retinopathy (DR) is one of the eye diseases that will damage the retinal blood vessels. By using segmentation and feature extraction methods the diseases are identified. Qin *et al.* [21] presented the localized technique that combined with the various segmented approaches. This is the integrated approach that finds the probe location in the given OCT input image. The drawback of this approach is finding the mismatched probe location. Imran *et al.* [22] introduced the segmented model to segments the blood vessels that are present in the retina. This approach is focused on detecting and diagnosing cardiovascular (CVD) and retinal diseases. The proposed approach is also called a system-based diagnosis approach (SBDA) which helps the experts' diagnosis easily. Abbood *et al.* [23] introduced the technique to find intensity of input images if the noise is removed and contrast is increased. In this model, two phases are used such as cropping the image and applying the Gaussian filter to increase the brightness and removing the noise particles from the input image. This is applied to two real-time datasets. The proposed approach is also tested in some hospitals with the help of the internet of medical things (IoMT) application. Table 1 gives the detailed deep learning (DL) models that process the OCT images for disease detection.

Table 1. Several segmentation, preprocessing and classification of retinal diseases using OCT images approaches with performance analysis

Authors	Training model	Preprocessing and feature extraction techniques	Proposed models	Performance metrics
Schurer-Waldheim *et al.* [24]	U-Net	Normalization	A fully automated fovea centralism detection (FAFCD)	P-Value-0.153, Mean-0.122
Girish *et al.* [25]	Intra-retinal cysts (IRCs)	Unbiased fast non-local means (UFNLM)	Fully convolutional network (FCN) model	PR-0.74, RC-0.73, DS 0.72
Wang [26]	Segmentation convolution neural network (CNN)	Image feature extraction	Optimized convolution neural network (CNN)	ACC-96.65%,
Das *et al.* [27]	Cross-scale model	Scale specific feature extraction	Deep multi-scale fusion convolutional neural network (DMF-CNN)	ACC-96.13% for UCSD dataset ACC-99.62% NEH dataset
Fang *et al.* [28]	CNN	Lesion detection network	Lesion-aware convolutional neural network (LACNN)	ACC-98.67%
Das *et al.* [29]	Hybrid training	Advanced noise removal approach	Generative adversarial network (GAN)	ACC-96.54%
Das *et al.* [30]	Advanced training approach	Speckle noise removal	Data-efficient semi-supervised generative adversarial network-based classifier	ACC98.26%, SE-96.98%, SP-99.13%
Mishra *et al.* [31]	Deep CNN	Multi-level feature extraction	A multi-level dual-attention model	ACC-97.98%, SP-99.56%, SE-98.78%
Pan *et al.* [32]	Hybrid training	Advanced pre-processing approach	3D registration approach	ACC-97.89%
Wei and Peng [33]	Advanced training	Hybrid preprocessing	Full CNN with depth max pooling (DMP)	ACC-96.89%
Liu *et al.* [34]	DCNN	Novel segmentation	Deep feature enhanced structured random forests classifier	ACC-98.89%, SE-97.56%, SP-98.45%

Note: ACC: Accuracy, SE: Sensitivity, SP- Specificity, PR-Precision

3. OUR CONTRIBUTION

This research work makes a significant contribution to the field of retinal disease by focusing on the processing and classification of these conditions. Firstly, it employs advanced image processing techniques to enhance retinal images and extract relevant features. Secondly, it utilizes state-of-the-art deep learning algorithms to classify retinal diseases accurately, enabling early detection and prompt treatment. Finally, the research provides valuable insights into the development of automated systems that can aid healthcare professionals in diagnosing and managing retinal diseases effectively. The following steps explains the contribution of this research work.

- The dataset OCT images are collected from online sources consists of retinal diseases such as CNV, Drusen, DME and normal.
- The dataset is available in [35].
- The first step is focused on training the model. In this step, the pre-trained model ResNet-18 that contains 72-layer architecture consisting of 18 deep layers. This model aims to process complex data such as disease prediction by using convolutional layers to work effectively.
- In pre-processing step, the speckle noise is identified and to remove this noise the threshold-based segmentation is used.
- After this, CNN is applied to process the OCT image samples. This CNN consists of 4 layers such as deep convolutional neural network (DCNN) layer, pooling layer, rectified linear unit (ReLU) layer and fully connected layer.
- The CNN model classifies the diseases based on the selected datasets.
- To validate the classification results, improved dynamic layered classification (IDLC) is used. This is the classification model that analyzes the results and validate with the actual values of the retinal diseases.
- Finally, confusion matrix is applied to find the accuracy and the other performance metrics.

3.1. Pre-trained model ResNet

ResNet 18 is the pre-trained model used for the classification of eye diseases. ResNet 18 uses the ImageNet dataset. Every layer in ResNet 18 consists of residual blocks. Every residual block contains two convolution layers with a size (3×3). Using ResNet 18 for the training of the OCT image dataset helps the proposed model to improve the disease detection rate. This network mainly uses the unique connections among the layers with normalization after every convolution layer. In this model, skip connections are also used to optimize and takes the activation from one layer to another layer. In RESNET, the pre-processing step mainly focused on resizing images, extraction of green channels, and feature extraction stage. In place of the pooling layer the fully connected layer is used for global averaging and IDLC is used for final classification. Figure 4 shows the system architecture of ResNet model.

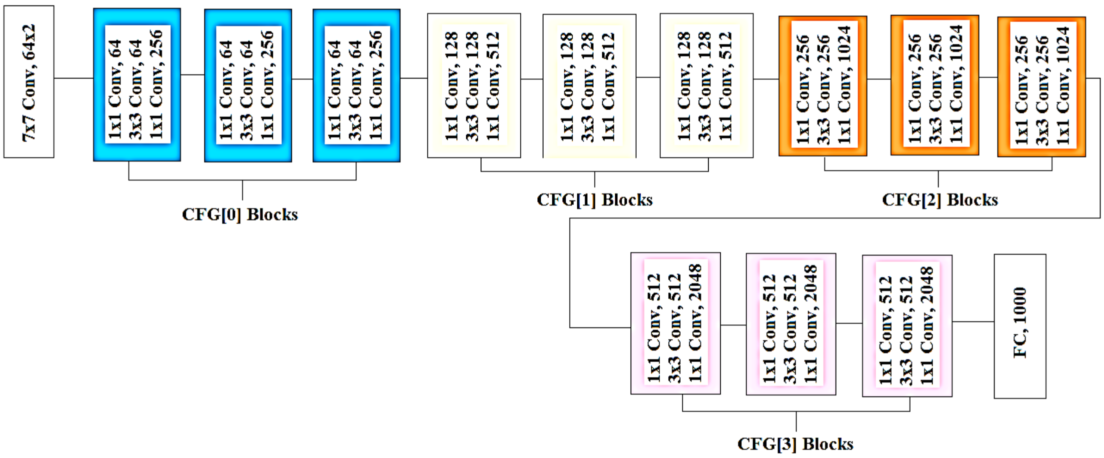


Figure 4. System architecture for ResNet

ResNet is based on the ImageNet database. ImageNet contains thousands of image data which is used for classification. In this paper, ResNet is trained with the OCT images dataset to extract the significant features from the OCT images dataset. Transfer learning is used to transfer the knowledge of OCT images to ImageNet which is called ResNet in this paper. Figure 5 clearly shows the transfer learning process by using layers.

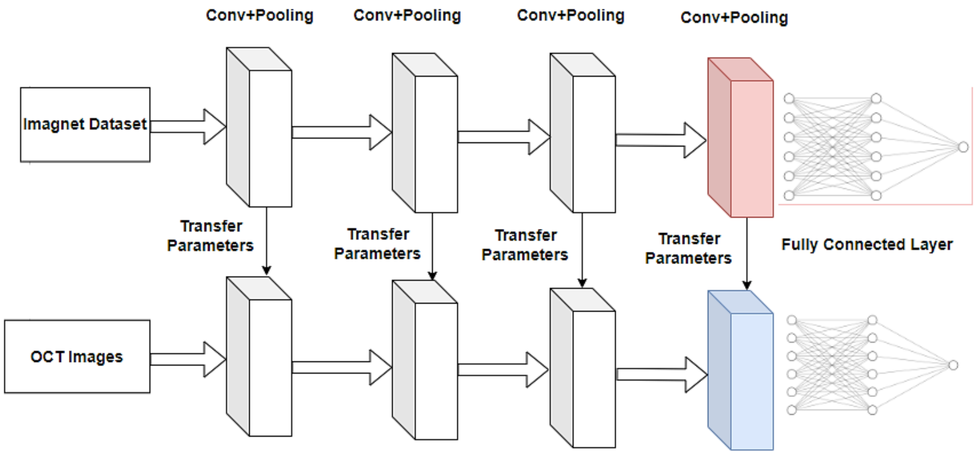


Figure 5. Transfer learning architecture

4. PRELIMINARIES

4.1. Speckle noise or fixed noise

This noise is also called generative noise or fixed noise. This noise is like the white dots between the pixels and shows the unevenness in the pixel distribution. This noise follows the gamma distribution. This type of noise occurs in various images such as medical images, magnetic resonance imaging (MRI) images, and synthetic aperture radar (SAR) images. All these images are grey-scale images. The mathematical equation of this image is given as,

$$G(a,b) = g(a,b) * \gamma(a,b) + \eta(a,b) \tag{1}$$

where, G(a,b) is final image, γ(a,b) is the generative noise image and g(a,b) is noise free image η(a,b) is the adaptive noise image [36]. By using the threshold-based segmentation the noise is removed.

4.2. Threshold based segmentation

In Image segmentation, the threshold technique is a significant technique and this is given as,

- This is a very simple technique.
- Based on the intensity value the pixels are divided.
- By using the $T_h$value the global threshold is used.

$$g(a,b) = \begin{cases} 1, & \text{if } (a,b) > T_h \\ 0, & \text{if } (a,b) \le T_h \end{cases} \tag{2}$$

A global (Single) threshold is used where the intensity among the objects of foreground and background are very dissimilar. In this scenario, both objects are converted by using a single value. In this scenario, the value of threshold T is based on the feature of the pixels and gray level value present in image. Steps for global (single) threshold method:

- T_h is initialized.
- Segmentation initialized by following variablesT_h: I G1, pixels brighter thanT_h; I G2, pixels darker than (or equal to) T_h.
- Average intensities m1 and m2 of G1 and G2 are calculated.
- The value of threshold is represented as,

$$T_{new} = \frac{m_1 + m_2}{2} \tag{3}$$

- If $|T_h - T_{new}| > \Delta T_h$, back to step 2, otherwise stop,

4.3. Deep convolutional neural network layer

This layer contains set of understandable filters that are having small responsive line; hence, the feature extraction is obtained by expanding the filters by using full depth input volume. The formula is given as,

$$\sum_{k=1}^{n} \sum_{x=1}^{k_h} \sum_{y=1}^{k_\omega} I^k_{r-k_{h+1,c-k_\omega+y}} \times W^k_{x,y} + b \tag{4}$$

here, r-row and c-represent column of the feature map, n-input channels, the height k_h and width $k_w$belongs to kernel, $W^k_{x,y}$ represents the weights of the x[th] row and y[th] column in the k[th] channel, $i^k_{x,y}$ is the input of the x[th] row and y[th] column in the channel, and is the bias.

4.4. Pooling layer for feature reduction

Step 2: To extract the features very effectively, maximum moving strides are initialized as 1; yet, hence this setup requires more functionality. Thus, this layer is combined with the CNN to reduce the total operations. In (5) shows the measurement of max (MP) and average pooling (AP),

$$O_{r,c} = \begin{cases} MP\left(\max\left(I_{a,b}\right)\right|, \begin{cases} r \le x < r + P_h \\ c \le x < c + P_w \end{cases}), \\ AP\left(\sum_{x=r}^{r+p_h} \sum_{y=c}^{c+pw} \frac{I_{x,y}}{(P_w \times P_h)}\right), \end{cases} \tag{5}$$

4.5. ReLU layer

Step 3: A significant feature maps are obtained and shows the huge impact on this. The component-based function arranges the negative pixels to '0' in this layer. To find the accurate features this layer consists of ReLU and convolutions.

$$R(z)=\max(O, z) \tag{6}$$

4.6. Fully connected layer

Step 4: Calculating the high-dimensional feature maps by using FCNN. In this layer, many pre-trained networks are used such as,

$$P = O_c \times (I_c + 1) \tag{7}$$

hence, I_c→ input and O_c →output channels.

In (7) shows the parameters based on given dimensions. If the dimension reduction is not applied, the input channels are more and more, huge parameters are created. The fully connected layers (FCL) are disposed to over-fit the conception potential of total network. The CNN architectures are replaced with FCL and global average pooling. All the steps from previous and present sections explain the detecting and diagnosing the retinal diseases. The segmentation methods used in this research work segments the OCT input image by dividing the input image into high intensity values like white and black colors.

5. METHOD

The proposed classification approach mainly focused on validating the results that are obtained from the CNN model. This classification is used to classify the diseases based on the values acquired by the model. Every disease has its values (threshold value) that define the stage of the disease. The threshold values are initialized based on the disease severity. Proposed approach flows few steps to process the retinal diseases. By finding the probability the retinal diseases are identified. The algorithm steps are given,

Algorithm:
Input: Dataset containing OCT images of retinal diseases (I_1,..,I_n)
Output: Type of diseases ($class_i$)
Step 1: Calculate pixel conversion (color to grey) usingpixel $(p) = dpi * \frac{mm}{25.4mm}$ (1 in)
Step 2: initialize the values of_cnv, _dme, _drusen and _normal is 1;
Step 3: Process the input Image
For each image i = 1 to n do:
if(type_=='oct'):
test_image = imageio.imread(name) #Read image using the PIL library
test_image = resize_image_oct(test_image) #Resize the images to 128x128 pixels
test_image = np.array(test_ image) #Convert the image to NumPy array
test_image = test_image/255 #Scale the pixels between 0 and 1
test_image = np.expand_dims(test_image, axis=0)#Add another dimension because the model was trained on (n,128,128,3)
data = test_image
end for
Step 4: For each image *img* in data do:
$class_i$= img.flatten().tolist()[0] * 100
end for;
Step 5: if ($class_i$<200Mn) then
Msg("Type of Disease:CNV")
else if ($class_i$>63Mn)
Msg("DME:Detected")
else if ($class_i$<125Mn)
Msg("Drusen:Detected")
else if (s<50Mn)
Msg("No Disease found")

Experimental Setup - The experimental setup of this project is given,

Software and hardware	Name of the Technology
Programming Language	Python 6.5.4
IDE	IDLC
Libraries	NumPy, Pandas, Keras, Matplotlib, TensorFlow
RAM	16 GB
Hard Drive	1 TB
Processor	I5/I7

6. EXPERIMENTAL RESULTS

The OCT-Imagenet dataset contains 5,000 images with 4 categories. This dataset contains 5,000 training and 5,000 testing [37]. This is labeled dataset contains CNV, DRUSEN, DME and normal**1250** each. The system hardware 8 GB RAM is required for the processing of large datasets. Figure 6 shows the processing of OCT images dataset. From the large dataset, the random sampling is applied to divide the samples into training 5k and texting 5k.

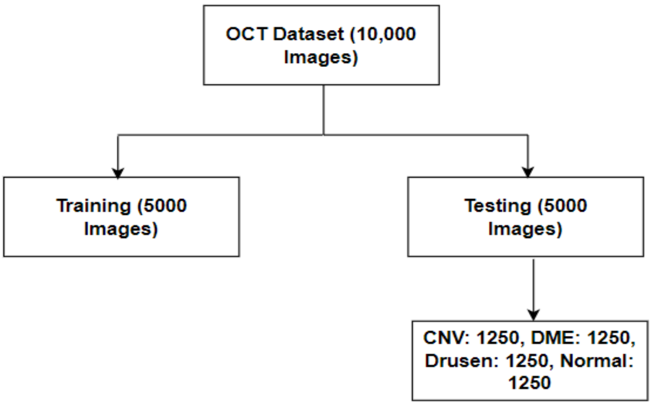
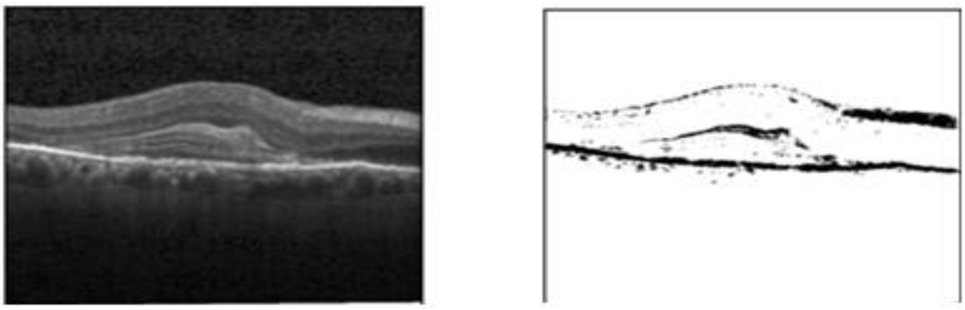


Figure 6. Details of dataset with training and testing sample images

The testing set consists of 1,250 samples of every disease such as CNV, DME, Drusen and normal. Figure 7 shows the OCT image where Figure 7(a) is the input image and (b) is the segmented image and shows the edges of the image. The segmented image is binary image with high intensity values which are normally black and white colors. Black represents the '0' and white represents the '1'. The abnormality of the CNV disease is shown in the Figure 7(b).



(a) (b)

Figure 7. Shows the OCT image; (a) Input image and (b) Segmented image

6.1. Performance metrics

To analyze the performance of the classification algorithm the confusion matrix is used on OCT image data obtained from the algorithm and is shown in Figure 8. The confusion matrix is applied on all the diseases data. Measuring the performance with a confusion matrix gives a better for find accurate errors. A confusion matrix mainly defines the positive and negative classes. The positive class defines the abnormal and the negative class defines the normal class. In this paper, the dataset is classified into two classes positive and negative. Table 2 shows the performance of detecting the overall OCT input samples classified as CNV. The comparision between CNN, ResNet with IDLC is given. Among the existing models IDLC achieved the better classification results. Table 3 shows the classification performance of DME. CNN, ResNet compared with IDLC which acheived the better classification results. Table 4 gives the classification results for the drusen disease and also compared with existing models such as CNN and ResNet, and Table 5 shows the normal samples classification and Table 6 shows the overall classification results for all the diseases.

Accuracy: Accuracy shows the total number of predictions that is correct. Actual and predicted values are correct. It is represented with formula.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \tag{8}$$

Precision (P): This is also called as positive predictive value, the percentage of positive values from total predicted positive values.

$$\text{P} = \frac{\text{TP}}{\text{TP+FP}} \tag{9}$$

Sensitivity (Sn): This metric analyzes the ability of the proposed approach to estimate the TP's of a given dataset.

$$\text{S}_\text{n} = \frac{\text{TP}}{\text{TP+FN}} \tag{10}$$

Specificity (Sp): The percentage of negative values count from total negative values.

$$\text{S}_\text{p} = \frac{\text{TN}}{\text{TN+FP}} \tag{11}$$

Duration: This shows the processing time for every input image.

$$\text{Time (T)} = \text{Starttime(St)} - \text{Endtime(ET)} \tag{12}$$

Predicted Values

Actual Values	CNV	DME	Drusen	Normal
CNV	1250	0	0	0
DME	10	1240	0	0
Drusen	8	0	1242	0
Normal	0	0	0	1250

Figure 8. Confusion matrix

Tables 2-6 show the comparison between the state-of-art and IDLC. The proposed approach shows the improvement of 10% in all the parameters. This shows the huge on disease detection rate. The tables show the overall data belongs to CNV, DME, Drusen, and Normal retinal cases. Table 7 shows the duration (milliseconds) comparison between the state of art and IDLC. Figures 9-12 shows the graphical representation of performance of Deep learning algorithms for the detection of CNV, DME, Drusen and Normal cases. In this research work, the proposed model is combined with noise filters, segmentation, DCNN and IDLC. IDLC is used to classify the OCT input images. Figure 13 shows the visualization performance of existing and proposed algorithms. The overall performance of all the diseases is shown in Table 6. The graphical representation is shown in Figure 14.

Table 2. Performance of deep learning algorithms for detection of CNV

	CNN	ResNet	IDLC
Sensitivity (SE)	77.22	86.76	98.98
Specificity (SP)	81.54	85.76	98.56
Precision (PE)	80.65	85.43	98.34
Accuracy (ACC)	81.66	87.52	97.76
F1-Score	82.12	87.53	97.58

Table 3. Performance of deep learning algorithms for detection of DME

	CNN	ResNet	IDLC
Sensitivity (SE)	78.32	86.78	98.96
Specificity (SP)	81.34	87.34	98.12
Precision (PE)	82.34	88.43	98.44
Accuracy (ACC)	82.45	87.12	98.12
F1-Score	83.12	88.43	98.56

Table 4. Performance of deep learning algorithms for detection of DRUSEN

	CNN	ResNet	IDLC
Sensitivity (SE)	79.32	87.64	98.89
Specificity (SP)	82.34	87.87	97.12
Precision (PE)	82.34	88.53	97.34
Accuracy (ACC)	83.45	86.12	98.12
F1-Score	84.12	87.43	98.56

Table 5. Performance of deep learning algorithms for detection of normal input images

	CNN	ResNet	IDLC
Sensitivity (SE)	78.34	88.64	97.67
Specificity (SP)	81.56	86.90	98.97
Precision (PE)	83.76	89.56	98.34
Accuracy (ACC)	83.65	88.87	98.12
F1-Score	82.45	88.23	98.09

Table 6. Overall Performance of deep learning algorithms for detection of retinal diseases

	CNN	ResNet	IDLC
Sensitivity (SE)	78.12	85.34	98.56
Specificity (SP)	80.34	86.34	97.34
Precision (PE)	81.34	87.43	99.34
Accuracy (ACC)	82.45	86.12	99.45
F1-Score	82.12	86.43	98.56

Table 7. The average time taken for every input image for processing

Algorithms	Duration (millisecond)
CNN	23.12
ResNet	19.23
IDLC	9.23

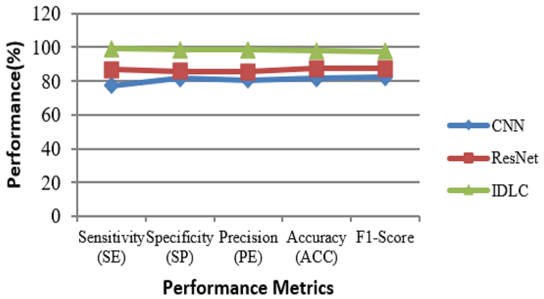


Figure 9. Performance of deep learning classification models for CNV disease

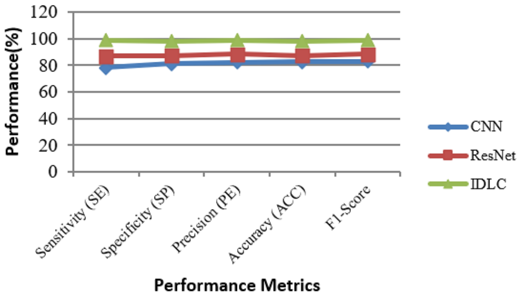


Figure 10. Performance of deep learning classification models for DME disease

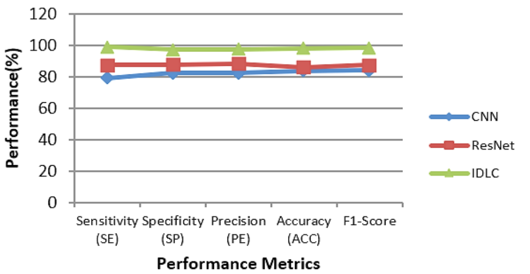


Figure 11. Performance of deep learning classification models for drusen disease

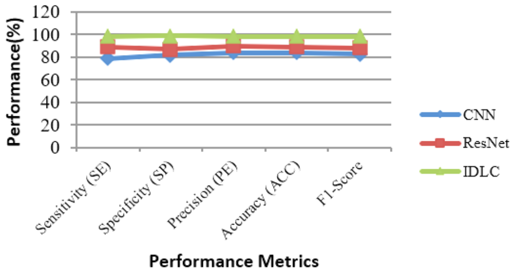


Figure 12. Performance of deep learning algorithms for detection of normal input images

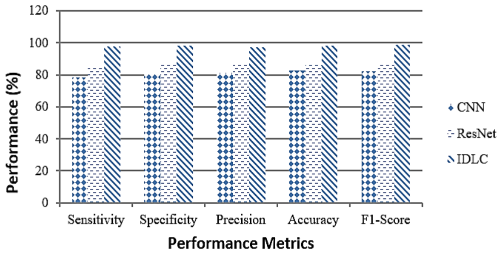


Figure 13. Performance graph for CNN, ResNet and IDLC

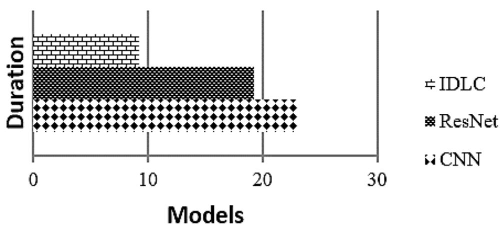


Figure 14. Performance of processing time (duration) using CNN, ResNet and IDLC

7. CONCLUSION

In this paper, the proposed approach is called an integrated approach. This is the combination of several existing algorithms such as CNN, ResNet, and the proposed approach IDLC. The classification of retinal diseases is based on the properties of the diseases such as CNV, DRUSEN, DME, and Normal by using the OCT images, and it is shown in the algorithm. Here the abnormality plays the significant role in finding the affected regions in the given samples. The average duration for the processing of OCT input image is 9.23 milli seconds for the proposed approach IDLC. The sensitivity is 98.98%, specificity is 98.56%, precision is 98.34% and accuracy is 97.76% and the proposed approach achieved better performance compared with the existing approaches.

REFERENCES

[1] T. Y. Wang *et al.*, "Diabetic Macular Edema Detection Using End-to-End Deep Fusion Model and Anatomical Landmark Visualization on an Edge Computing Device," *Frontiers in Medicine*, vol. 9, p. 851644, Apr. 2022, doi: 10.3389/fmed.2022.851644.

[2] J. Kim and L. Tran, "Retinal disease classification from OCT images using deep learning algorithms," *2021 IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology, CIBCB 2021*. IEEE, 2021, doi: 10.1109/CIBCB49929.2021.9562919.

[3] S. R. Cohen and T. W. Gardner, "Diabetic retinopathy and diabetic macular edema," *Developments in Ophthalmology*, vol. 55, pp. 137–146, 2015, doi: 10.1159/000438970.

[4] M. Subramanian, K. Shanmugavadivel, O. S. Naren, K. Premkumar, and K. Rankish, "Classification of Retinal OCT Images Using Deep Learning," *2022 International Conference on Computer Communication and Informatics, ICCCI 2022*. IEEE, 2022, doi: 10.1109/ICCCI54379.2022.9740985.

[5] L. Huang, X. He, L. Fang, H. Rabbani, and X. Chen, "Automatic Classification of Retinal Optical Coherence Tomography Images with Layer Guided Convolutional Neural Network," *IEEE Signal Processing Letters*, vol. 26, no. 7, pp. 1026–1030, 2019, doi: 10.1109/LSP.2019.2917779.

[6] R. Rasti, H. Rabbani, A. Mehridehnavi, and F. Hajizadeh, "Macular OCT Classification Using a Multi-Scale Convolutional Neural Network Ensemble," *IEEE Transactions on Medical Imaging*, vol. 37, no. 4, pp. 1024–1034, 2018, doi: 10.1109/TMI.2017.2780115.

[7] P. Seebock *et al.*, "Unsupervised Identification of Disease Marker Candidates in Retinal OCT Imaging Data," *IEEE Transactions on Medical Imaging*, vol. 38, no. 4, pp. 1037–1047, 2019, doi: 10.1109/TMI.2018.2877080.

[8] X. Ma, Z. Ji, S. Niu, T. Leng, D. L. Rubin, and Q. Chen, "MS-CAM: Multi-Scale Class Activation Maps for Weakly-Supervised Segmentation of Geographic Atrophy Lesions in SD-OCT Images," *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 12, pp. 3443–3455, 2020, doi: 10.1109/JBHI.2020.2999588.

[9] X. Wang *et al.*, "UD-MIL: Uncertainty-Driven Deep Multiple Instance Learning for OCT Image Classification," *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 12, pp. 3431–3442, 2020, doi: 10.1109/JBHI.2020.2983730.

[10] Y. Rong *et al.*, "Surrogate-assisted retinal OCT image classification based on convolutional neural networks," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 1, pp. 253–263, 2019, doi: 10.1109/JBHI.2018.2795545.

[11] Z. Yan, X. Yang, and K. T. Cheng, "Joint segment-level and pixel-wise losses for deep learning based retinal vessel segmentation," *IEEE Transactions on Biomedical Engineering*, vol. 65, no. 9, pp. 1912–1923, 2018, doi: 10.1109/TBME.2018.2828137.

[12] Y. Wang *et al.*, "Robust Content-Adaptive Global Registration for Multimodal Retinal Images Using Weakly Supervised Deep-Learning Framework," *IEEE Transactions on Image Processing*, vol. 30, pp. 3167–3178, 2021, doi: 10.1109/TIP.2021.3058570.

[13] Y. Ma *et al.*, "ROSE: A Retinal OCT-Angiography Vessel Segmentation Dataset and New Model," *IEEE Transactions on Medical Imaging*, vol. 40, no. 3, pp. 928–939, 2021, doi: 10.1109/TMI.2020.3042802.

[14] L. Ngo, J. Cha, and J. H. Han, "Deep Neural Network Regression for Automated Retinal Layer Segmentation in Optical Coherence Tomography Images," *IEEE Transactions on Image Processing*, vol. 29, pp. 303–312, 2020, doi: 10.1109/TIP.2019.2931461.

[15] P. Seebock *et al.*, "Exploiting Epistemic Uncertainty of Anatomy Segmentation for Anomaly Detection in Retinal OCT," *IEEE Transactions on Medical Imaging*, vol. 39, no. 1, pp. 87–98, 2020, doi: 10.1109/TMI.2019.2919951.

[16] X. Li, Y. Jiang, M. Li, and S. Yin, "Lightweight Attention Convolutional Neural Network for Retinal Vessel Image Segmentation," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 3, pp. 1958–1967, 2021, doi: 10.1109/TII.2020.2993842.

[17] W. Huang *et al.*, "Arterial Spin Labeling Images Synthesis from sMRI Using Unbalanced Deep Discriminant Learning," *IEEE Transactions on Medical Imaging*, vol. 38, no. 10, pp. 2338–2351, 2019, doi: 10.1109/TMI.2019.2906677.

[18] B. Hassan, S. Qin, T. Hassan, R. Ahmed, and N. Werghi, "Joint Segmentation and Quantification of Chorioretinal Biomarkers in Optical Coherence Tomography Scans: A Deep Learning Approach," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–17, 2021, doi: 10.1109/TIM.2021.3077988.

[19] M. H. Sarhan *et al.*, "Machine Learning Techniques for Ophthalmic Data Processing: A Review," *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 12, pp. 3338–3350, 2020, doi: 10.1109/JBHI.2020.3012134.

[20] T. A. Soomro *et al.*, "Deep Learning Models for Retinal Blood Vessels Segmentation: A Review," *IEEE Access*, vol. 7, pp. 71696–71717, 2019, doi: 10.1109/ACCESS.2019.2920616.

[21] X. Qin *et al.*, "Indoor Localization of Hand-Held OCT Probe Using Visual Odometry and Real-Time Segmentation Using Deep Learning," *IEEE Transactions on Biomedical Engineering*, vol. 69, no. 4, pp. 1378–1385, Apr. 2022, doi: 10.1109/TBME.2021.3116514.

[22] A. Imran, J. Li, Y. Pei, J. J. Yang, and Q. Wang, "Comparative Analysis of Vessel Segmentation Techniques in Retinal Images," *IEEE Access*, vol. 7, pp. 114862–114887, 2019, doi: 10.1109/ACCESS.2019.2935912.

[23] S. H. Abbood, H. N. A. Hamed, M. S. M. Rahim, A. Rehman, T. Saba, and S. A. Bahaj, "Hybrid Retinal Image Enhancement Algorithm for Diabetic Retinopathy Diagnostic Using Deep Learning Model," *IEEE Access*, vol. 10, pp. 73079–73086, 2022, doi: 10.1109/ACCESS.2022.3189374.

[24] S. Schurer-Waldheim, P. Seebock, H. Bogunovic, B. S. Gerendas, and U. Schmidt-Erfurth, "Robust Fovea Detection in Retinal OCT Imaging Using Deep Learning," *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 8, pp. 3927–3937, 2022, doi: 10.1109/JBHI.2022.3166068.

[25] G. N. Girish, B. Thakur, S. R. Chowdhury, A. R. Kothari, and J. Rajan, "Segmentation of intra-retinal cysts from optical coherence tomography images using a fully convolutional neural network model," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 1, pp. 296–304, 2019, doi: 10.1109/JBHI.2018.2810379.

[26] J. Wang, "OCT Image Recognition of Cardiovascular Vulnerable Plaque Based on CNN," *IEEE Access*, vol. 8, pp. 140767–140776, 2020, doi: 10.1109/ACCESS.2020.3007599.

[27] V. Das, S. Dandapat, and P. K. Bora, "Automated Classification of Retinal OCT Images Using a Deep Multi-Scale Fusion CNN," *IEEE Sensors Journal*, vol. 21, no. 20, pp. 23256–23265, 2021, doi: 10.1109/JSEN.2021.3108642.

[28] L. Fang, C. Wang, S. Li, H. Rabbani, X. Chen, and Z. Liu, "Attention to lesion: Lesion-Aware convolutional neural network for retinal optical coherence tomography image classification," *IEEE Transactions on Medical Imaging*, vol. 38, no. 8, pp. 1959–1970, 2019, doi: 10.1109/TMI.2019.2898414.

[29] V. Das, S. Dandapat, and P. K. Bora, "Unsupervised Super-Resolution of OCT Images Using Generative Adversarial Network for Improved Age-Related Macular Degeneration Diagnosis," *IEEE Sensors Journal*, vol. 20, no. 15, pp. 8746–8756, 2020, doi: 10.1109/JSEN.2020.2985131.

[30] V. Das, S. Dandapat, and P. K. Bora, "A Data-Efficient Approach for Automated Classification of OCT Images Using Generative Adversarial Network," *IEEE Sensors Letters*, vol. 4, no. 1, pp. 1–4, 2020, doi: 10.1109/LSENS.2019.2963712.

[31] S. S. Mishra, B. Mandal, and N. B. Puhan, "Multi-Level Dual-Attention Based CNN for Macular Optical Coherence Tomography Classification," *IEEE Signal Processing Letters*, vol. 26, no. 12, pp. 1793–1797, 2019, doi: 10.1109/LSP.2019.2949388.

[32] L. Pan *et al.*, "Octrexpert: A feature-based 3D registration method for retinal OCT images," *IEEE Transactions on Image Processing*, vol. 29, pp. 3885–3897, 2020, doi: 10.1109/TIP.2020.2967589.

[33] H. Wei and P. Peng, "The Segmentation of Retinal Layer and Fluid in SD-OCT Images Using Mutex Dice Loss Based Fully Convolutional Networks," *IEEE Access*, vol. 8, pp. 60929–60939, 2020, doi: 10.1109/ACCESS.2020.2983818.

[34] X. Liu *et al.*, "Automated Layer Segmentation of Retinal Optical Coherence Tomography Images Using a Deep Feature Enhanced Structured Random Forests Classifier," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 4, pp. 1404–1416, 2019, doi: 10.1109/JBHI.2018.2856276.

[35] C. a. Duarte-Salazar, andres E. Castro-Ospina, M. a. Becerra, and E. Delgado-Trejos, "Speckle Noise Reduction in Ultrasound Images for Improving the Metrological Evaluation of Biomedical applications: an Overview," *IEEE Access*, vol. 8, pp. 15983–15999, 2020, doi: 10.1109/aCCESS.2020.2967178.

[36] Y. A. Bayhaqi, A. Hamidi, F. Canbaz, A. A. Navarini, P. C. Cattin, and A. Zam, "Deep-Learning-Based Fast Optical Coherence Tomography (OCT) Image Denoising for Smart Laser Osteotomy," *IEEE Transactions on Medical Imaging*, vol. 41, no. 10, pp. 2615–2628, 2022, doi: 10.1109/TMI.2022.3168793.

[37] D. Kermany, K. Zhang, M. Goldbaum, and others, "Labeled optical coherence tomography (oct) and chest x-ray images for classification," *Mendeley data*, vol. 2, no. 2, p. 651, 2018.

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