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Deep Learnıng Technıques On Fundus, B-Scan And Oct Imagıng Modalıtıes For Retınal Detachment Classıfıcatıon

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Abstract

Retinal Detachment is an eye disorder. It detaches itself from the other layers of the eye. It occurs due to loss of vision in the eye. In image processing applications, state-of-the-art-technology deep learning in artificial intelligence plays an important role in biomedical and satellite image processing for object identification and object recognition. The proposed method is to detect retinal abnormality by using computer-aided diagnosis from advanced imaging modalities such as Optical Coherence Tomography (OCT) system, Fundus image and B-Scan system have emerged as a powerful new methodology. This method employs a deep learning Convolutional neural network by RDNet for automated abnormality identification. Deep network RDNet architecture is applied to the fundus, OCT and B-Scan systems. This data set consists of 2 categories including a normal and abnormal image of the retina. The proposed deep learning model is compared with other deep learning models such as Resnet, Inception-v3 on Fundus, OCT systems. The proposed model was trained on the Agarwal Eye Hospital's image dataset consists of 1117 images. The proposed method achieves an accuracy of 96%, the precision of 93%, recall of 1% and F1 score of 96%.

1.0 INTRODUCTİON

Retinal detachment causes its cell to seriously affect due to a lack of oxygen. Generally, retinal detachment affects 0.6%to 1.8% of total people. Retinal detachment affects all age groups. Accurate identification of eye diseases needs advanced imaging techniques. Fundus photographic imaging modality is used for retinal diseases [1-2]. OCT is mainly used to view and find even tiny changes in the retinal images. Many eye-related problems are identified using the OCT system [3-5]. CNN model is used for Classifying the OCT system automatically. CNN is a supervised approach [6]. This type of classification technique is considered as standard in medical image processing, for diagnosing and assessment of the eye diseases. Accurate identification of retinal detachment abnormalities is achieved in OCT imaging technology. CNN's are also utilized in the area of Handwritten digit recognition such as MNIST dataset and image classification. B-scan is an imaging modality for identifying the lesions of the posterior pole of the eye. This modality accurately evaluates diseases like cataract, vitreous degeneration, retinal detachment, ocular trauma, choroidal melanoma and retinoblastoma B-Scan imaging modality essential roles in diagnosing retinal detachment. Recently, in the medical image processing community, the automatic localization and detection of retinal anatomical structures from the digital fundus photography image have increased attention [7-8]. This can help Computer-Aided Diagnostic (CAD) software for improved retinal disease supervision. It is novel and promising to use a deep convolutional neural network to identify retinal landmarks [13]. This novel method produces fast results and does not want user input [9-10].

1. The proposed method named as Residual RDNet is independent method and does not depend on other methods such as segmentation or other landmarks.
2. No need for manual handcrafted features for extracting the features of retinal detachment and there is no need of the technical person to identify those features.
3. The proposed network finds out more than one position at a time with high accuracy.
4. This approach is reliable and even works with the poor quality of the image.

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5. The deep network is a refinement of object identification and Localization which removes the redundant background from the neural network.
6. The recommended model reveals gained knowledge to teach other models
7. Testing incorporating various measures to achieve high accuracy.

BACKGROUND

Residual Neural Network (ResNet) is a type of Convolutional Neural Network. CNN is a backbone for many computer vision tasks [11]. The network consists of 50 deep layers and also classify images into 1000 object category. Resnet trains on 23 million trainable parameters. It consists of 5 stages each associated with a 3-convolution block and 3 identity blocks. Each Convolution block also contains 3 convolution layers and each identity block consists of another 3 convolution layers. The main aim of this resnet-50 is to maintain the Stochastic Gradient Descent (SGD).To avoid loss of information, an identity matrix is used. Resnet architecture is creating more layers. Resnet uses the pretrained models which are developed by Caffe. This method uses TensorFlow to convert the weights. Resnet is a fully connected layer, which is applied for any size of the input.

Inception-v3 is a classical type of transfer learning method in machine learning. It utilizes the pre-trained models for the starting point of the computer vision task and is reused with the second task. It is divided into two parts. In the first part, feature extraction is associated with a CNN which is used to extract the general features in an image. Classification associated with CNN is used to classify images based on those features. It also classifies images into1000 object categories [12-13].

2.0 RELATED WORKS

Acharya et al. [14], focused on a hybrid system-based radon transform method is employed for the identification of macular edema.

S. Wang et al. [15], developed a trainable hierarchical feature extractor performed by a convolution neural network and as a trainable classifier by Random Forest (RF). For feature extraction, it has a convolution of 6 layers followed by the sampling layers. For the classifier ensemble method, the random forest algorithm has been utilized and introduced in the retinal blood vessel segmentation. Around 0.98 and 0.97 is achieved by using this architecture in the database of DRIVE AND STARE.

Mrinal Halai [16], focused on a new computer-aided deep learning system for microaneurysm detection. It requires less pre-processing and vessel extraction. Convolution, Maxpooling and Softmax layers are some of the fine-tuning layers. It consists of the Softmax layer that comes with additional dropout training for improving accuracy. A low false-positive rate is achieved and 96 % accuracy with 0.96 specificities and 0.97 sensitivity is the performance.

M. Melinscak et al. [17], suggested blood vessels in fundus images that are segmented automatically. The blood vessels are segmented by deep max pooling convolutional neural networks. For achieving maximum accuracy, a 10-layer architecture is deployed but worked with small image patches. For Testing and reshaping the fundus image, a pre-processing is done. In vessel segmentation, it carries around 4 convolutional and 4 max-pooling layers with 1 additional fully connected layer. Around 0.94 accuracies are achieved by this method.

Gardner et al. [18], proposed a fruit method of diabetic retinopathy using an artificial neural network with a pre-processing technique. Features are learned from the sub-images in this method. It’s relied on a backpropagation neural network.

Sohini Roychowdhury et al. [19], proposed a novel two stage hierarchical classification algorithm for automatic detection and classification. Novel two-step hierarchical binary classification is used for automated detection. GMM, SVM, KNN and AdaBoost methods are used for the classification of lesions from non-lesions. Major and minor axis length, variance of Ired channel, Igreen channel, mean pixels for Ired, Igreen ,solidity ,intensity etc. are some of the top 30 features that are taken into account. 59.54 to 3.46 is the average computation time for DR severity per mage.

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Lachure et al. [20], proposed the SVM classifier process that involves pre-processing and morphological operations. Abnormality of images such as retinal microaneurysms, hemorrhages, exudates and cotton wool spots are detected from the fundus image. In digital fundus photographs, red and black lesions are identified. GLCM feature and structural features are extracted for classification.100% and 90% is the optimized sensitivity in this SVM classifier.

Priya et al. [21], foused on Probabilistic Neural Network and SVM to diagnostic retinopathy. Grayscale conversion, adaptive histogram, equalization, discrete wavelet transform matched filter and fuzzy c-means segmentation are used for the pre-processing of the input color retinal images. Pre-processing image features were extracted for classification. 89.6% of accuracy is 97.608 of achieved with SVM classifier

Giraddi et al. [22], proposed an identification of exudates, which aids to take care of color variability and brightness of retinal images in the process. For the earliest detection comparative analysis is made from SVM and KNN classifier. To obtain the reduced number of false positive in GLCM, texture feature extraction is utilized. Around 83.4 % are the true positive rates for SVM classifier and around 92% for KNN classifier. SVM is outperformed in color as well as texture features by KNN.

Srivastava et al. [23], developed a key idea during training process to randomly drop units together with their connection. Over fitting is significantly reduced in this work and improvements has been given over other regularization techniques. Performance of neural networks in vision document classification, speech recognition has been improved.

Joseph et al. [24], recommended a mechanics based mathematical model for retinal detachment. It considers retina with and without central tears, numerical simulations are performed.

Ganesh et al. [25], proposed a giant magnetoresistance magnetometers sensor is utilized for glaucoma identification. Complexity is also increased by adding more steps and processing stages such as deblurring algorithm prior to detection, blood vessel segmentation, rotating cross section, enhancing light intensity of mathematical model, morphological renovation.

3.0 PROPOSED METHOD:

CNN

Convolutional Neural Network, is a supervised technique. CNN uses Keras Library for image classification. Generally, CNN contains the 3 parts.

DEEP LEARNING

CNN Architecture

CNN is a combination of several layers to perform a classification task. CNN contains several layers as follows as

Input Layer

The first layer of CNN is the input layer. It takes raw images and these images are forwarded to the further processing of feature extraction.

Convolutional Layer

The input layer is found before the convolutional layer. .In the convolution layer, a filter is applied to images to extract the features from images. These extracted features employed to find the matches of images at the testing phase.

ReLU.

The next layer is the Rectified Linear Unit. The negative number of the Convolutional layer is replaced with zero by ReLU. It is used to increase the speed with accurate training.

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Pooling Layer

The pooling layer takes care of the extracted features. It reduces the image size and number of parameters. The pooling layer is used to maintain important information. It preserves a maximum value for each window.

Fully Connected Layer

High level filtered images are taken from a fully connected layer and translated into a label with categories. This is the final layer.

Softmax layer

After the fully connected layer is the Softmax layer. Its main purpose is for classification of images into categories. This layer provides a decimal probability between 0 to 1 for each class. The first 4 layers are extraction layers. The last 2 layers are classification layers.

Deep Learning libraries supporting of image handling

1. TFLearn- This deep learning library is used to create several customized layers
2. NumPy – To handle the image matrices
3. Open-CV – Handling of image processing and Grayscale conversion.
4. Matplotlib – Predictive outcome result display.
5. TensorFlow -Compare the loss and Adam curve of result
6. Keras- Python library to create a deep learning model and train a model

Pre-processing

Data augmentation

Different types of imaging modalities were Fundus, SD-OCT, B-scan. It is captured from different camera with varying perspectives, lack of clarity, dim, difference in illumination and image size. In the process of data augmentation, adjustment of brightness and contrast of the images are made.

In image processing, pre-processing is an essential step for image segmentation and classification. Its main use is to improve an image feature for further classification. The proposed retinal detachment classification architecture is in fig.1.The proposed method is worked on images acquired using various imaging modalities. The pre-processing step is needed for image resizing. The python software is used to read an image. The proposed network model is created using residual RDNet CNN which fine-tunes the images having a constant size.

Deep learning architecture consists of 3 Residual RD blocks. Every Residual RD block has 5 layers such as 3 convolutional layer,1 additional layer and 1 max pooling layer. Each block is convolved by a different number of feature maps such as 32,64,128. Each convolution layer filter size is as follows

First convolution layer with a 1x1 filter size

Second convolution layer with a 3x3 filter size

Third convolution layer with a 1x1 filter size.

After that one more convolution layer is added. In this layer filter size is 1x1. Next, it followed by 1 Global average max pooling layer with a filter size of 256.The max pooling layer is followed by 2 dropout layers with 0.5 as a drop out ratio. Next, it is followed by 2 fully connected layers with output size of 256. Finally, Softmax layer is added as the 10^{th} layer to classify the image as normal or affected by retinal detachment.

Residual RD BlocksResidual RD Blocks are a special type of highway network. It is implemented as the output of one layer with the input of the earlier layer. Residual RD blocks are designed as double- or triple-layer skip connection that contains nonlinearities (ReLU) and batch normalization in middle. Skip a few layers of training during the training process is achieved via skip connections. The flow of data is from the initial layer to the last layer. Residual RD blocks are so called “Identity shortcut connection”. In each convolution layer, there is an accumulation of residual blocks. A residual block consists of a convolution layer with 3 filter sizes such as

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1x1,3x3,1x1 which is called bottleneck design. In this step, the output feature map size is to be reduced to half when each convolution layer begins as the residual blocks accumulate, the first residual block of convolution layer 1x1 with stride is set to 2. It is a reduced form of a feature map size. In the first attempt, a 1x1 convolution with batch normalization operation is equal to the number of channels in each convolutional layer is added to the feature map size The Skip connection block diagram is represented as below.

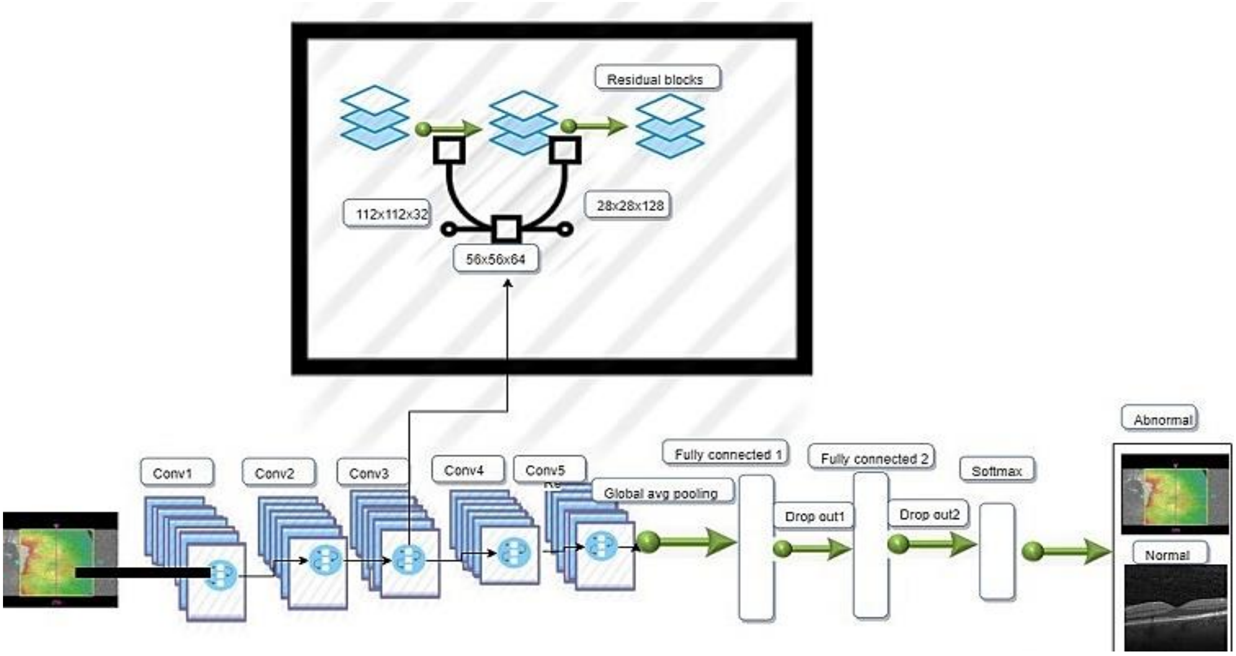

Fig 1. Residual RDnet architecture

Deep learning model mapping is denoted as M, then Mapping from an input layer x to an output layer y

1. M(x)=y

The residual function is used to find the difference between mapping applied to an input x and original input, x

2. F(x)=M(x)-x

Then uses skip connection is expressed as

3. M(x)=F(x)-x |

y=F(x)+x

At last, residual function is compared to the original Mapping M(x). The network learns mapping process by itself as x -> F(x) + G(x) instead of

x -> F(x). The dimension of both Input x, output G(x) is the same. G(x) = x is an identity function. The weights are set with zero at the intermediate layer during the training process. It is easier to set out 0 rather than thrust them 1. Network skip weights are learned through an additional weight matrix.

Residual RDNet

Each layer in Residual RDNet consists of the Convolutional layer, Rectified Linear Unit(ReLU) and Batch normalization layers.

ReLU

ReLU consists of an activation function that forced sparsity in the hidden units. Compared to sigmoid and logistic regression, deep CNN trained efficiently.

f(x)= max(0,x) where x is input to the neuron

Skip connections do the work of identity mapping. Identity mapping outputs, stacked layer outputs are added together. Dimension reduction can be achieved through 1x1 convolutional layers and also responsible for data

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augmentation. Keras is a Deep Learning library in python to support image augmentation. After that deep networks are constructed by residual stacked layer. 3x3 convolutional layer is fast and also reduces the computational complexity.

Convolutional layer

Convolution layer 1 to convolutional layer 3 is the convolutional layer group. Local receptive fields and shared weights are the strengths of the convolutional neural network.

Local Receptive Field

In image recognition, the local receptive field is a multiple layer collection of small neurons group which are a small part in an input image.

Shared weights and bias

CNN's each feature map shared the same weights and bias values. This value represents the same feature overall image. Feature map generation is diverse depending upon the application. Features are derived via convolutional layers for image classification. The convolution operation of the proposed method selects a smaller matrix that provides a filter. The movement of these filters along with an image extract the features and creates a new activation map or layer. Each activation map serves as a dwelling place to Important features. Finally, at the end of the operation, it obtains one number by summing up the products. A similar operation is carried out after it moves to the right position in one unit. In this way, across all locations in an image, filters be in motion. Finally, the obtained matrix is smaller than the input matrix.

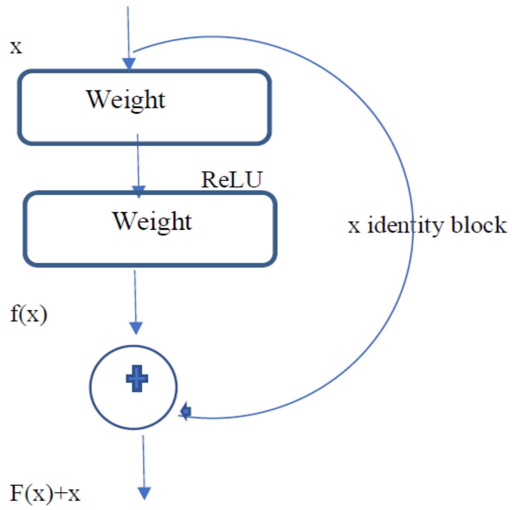

Fig 2. Single Residual RD block: A block diagram

Global Average Pooling (GAP)

Object localization is done with the help of GAP layer. Its main objective is to finding out the main objects and their border and it divides the activation map into the number of rectangular regions. The feature map with the dimension 28x28x256 is appeared in the stacked layer. Among the dimensions, the first two dimensions are précised as a spatial dimension and several feature maps will be generated in the process which is specified in the last one. Each sub-region holds a maximum value of 256.During the training process,

The gap layer helps to evade the overfitting in the model by minimizing the number of parameters.

Dropout

The problem of overfitting can be averted through dropout and stochastic models. The excess number of parameters generation is eradicated through drop out layer's nearby layer which is a fully connected layer. The drop out layer is set to 0.5 to avoid overfitting. The neurons are cascaded to the next layer when the value is less than 0.5. In the deep neural network, a significant part of each stacked layer is accountable for parameter handling. Drop out is one of the regularization techniques for deep learning. It mainly utilized to avoid excessive

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parameter generation.

Fully Connected Network

In network structure, 2 fully connected layers emerge after the cascaded convolutional and max | average pooling. These fully connected layers help us to extract high-level features for classification. All neurons in the previous layer have been collected by FCN from global average pooling and connect its neurons.

Softmax layer

The last layer of the proposed architecture is the Softmax layer. The function of the Softmax layer is stacking the previous layers. The previous layers are stacked and applied for the classification of the OCT image in the end after receiving the output of a fully connected layer.

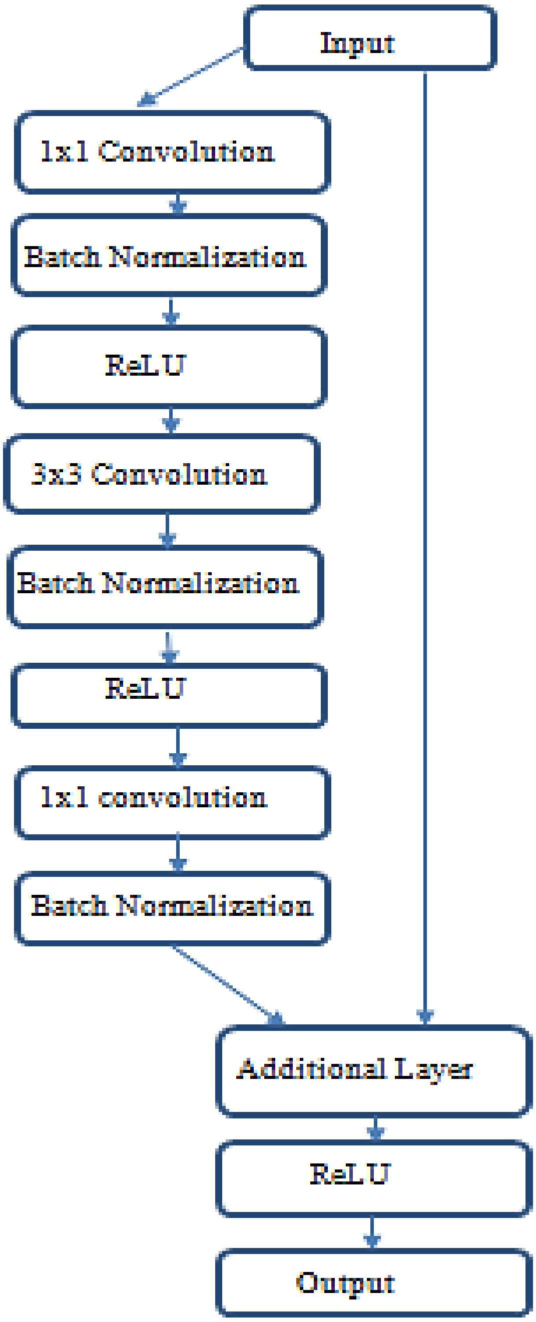

Fig 3. Residual block

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4.0 PERFORMANCE EVALUATION

Three performance evaluation measures are used to identify whether the person's eye has an abnormal or normal vision. Resnet, Inceptionv3 models are compared to the proposed designed work. The automated classification method is essential for handling disease affected areas. Images are tested and evaluated from Agarwal's Eye hospital standard data set. Anaconda Python 3.7 Spyder environment is needed to run on the single server with NVIDIA GeForce GTX1080TI graphics cards only.

Accuracy

The performance metric for the classification model is evaluated using accuracy. It is the ratio of the number of correctly predicted positives divided by the total number of predictions. Accuracy is calculated in terms of True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN). It is a significant inequality of TP and TN labels. It works well for each class an equal number of samples.

TP = It works with predicted = yes, actual class =yes.

TN = It worked both predicted and actual classes are no value.

FP = when one predicted class =yes, another actual class =no.

FN = In this case predicted class =no, actual class=yes.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of examples.}}$$

Precision

It is a ratio for calculating accurately predicted positive observations divided by predicted positive numbers of observation.

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

Recall

The recall is calculated using the following formula. It is simply a measure of the accurately identified positive cases divided by all the actual positive cases.

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

F1 score

It is a weighted mean between precision and recall. This F-measure takes the values of FP and FN for performance evaluation. F1 score's best value is 1 and the worst score is 0. The test's accuracy is calculated using the F1 score.

$$\text{F1 Score} = 2 \text{ X } \frac{\text{precision x recall}}{\text{Precision + recall}}$$

5.0 CONCLUSIONS AND FUTURE WORK

Other existing algorithms need more preprocessing, post-processing and segmentation for identifying normal or abnormal classes and previously developed algorithms compulsorily need a feature extraction algorithm to identify the diseases whereas the proposed algorithm is a solution for all the above problems. There is no compulsion to define the feature extraction algorithm. Drop out layer is used to prevent a model from overfitting using regularization technique. A single drop out layer can be used to trigger multiple architectures in a random aspect to drop out nodes at the time of training. Drop out techniques are highly supportive to improve the overall

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accuracy. In this network, residual blocks are used to create own custom blocks as well as the entire model. Residual blocks are retaining an image border without any loss of information. It is a skip connection model.

Fundus Image

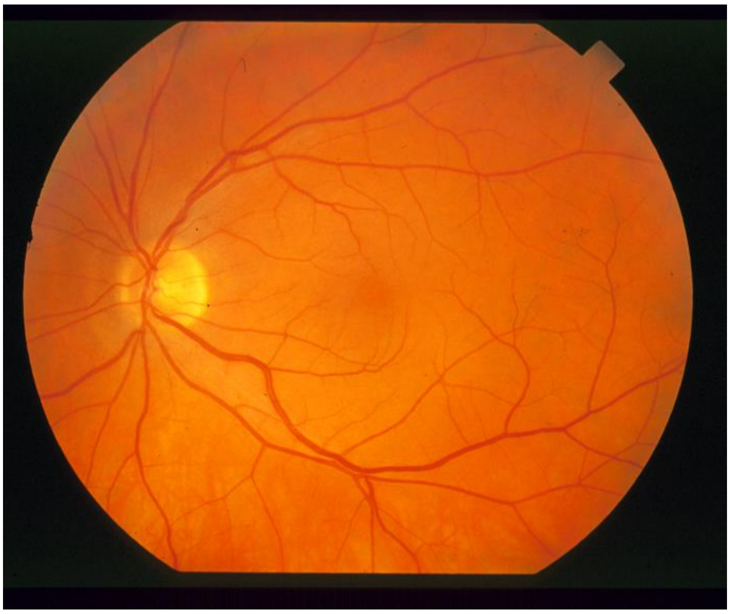

Fig 4. Normal Fundus image

Fig 5. Retinal Detachment fundus image

Metrics	Resnet	Inception_v3	Proposed
Accuracy	0.870968	0.854839	0.903226
Precision	0.787474	0.769231	0.872340
Recall	1.000000	1.000000	1.000000
F1 score	0.882353	0.869565	0.931818

Table 1 Performance evaluation of the proposed fundus image.

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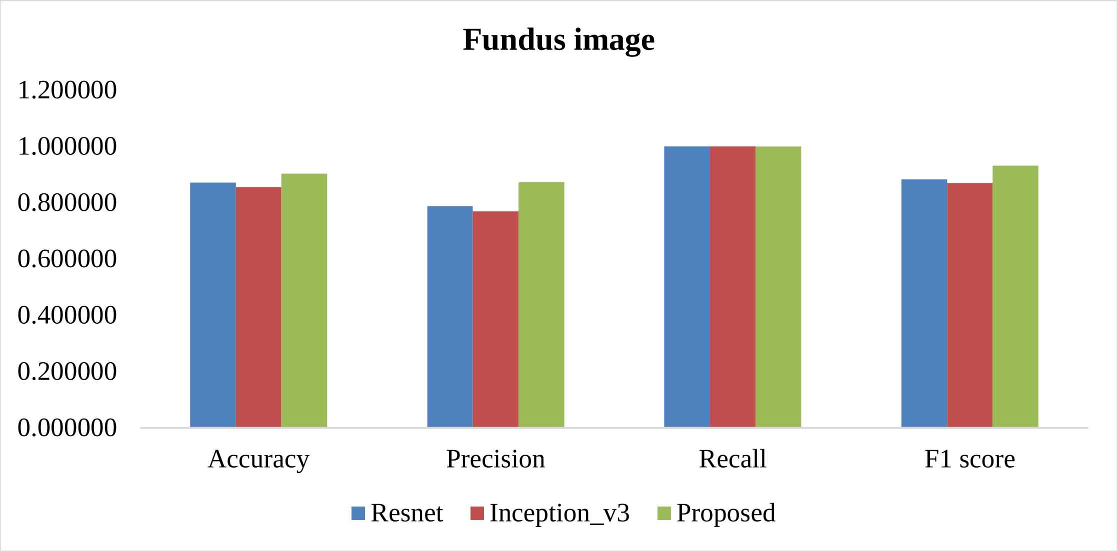

Fig 6. Comparison chart of the proposed fundus image

OCT Image

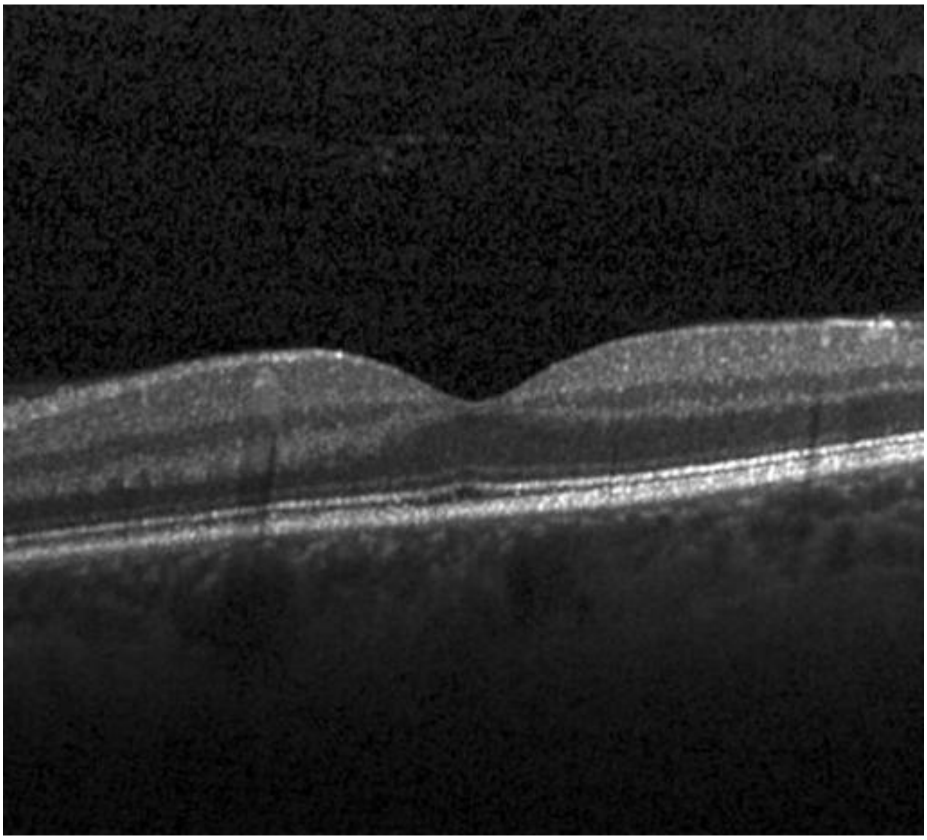

Fig 7. OCT Normal image

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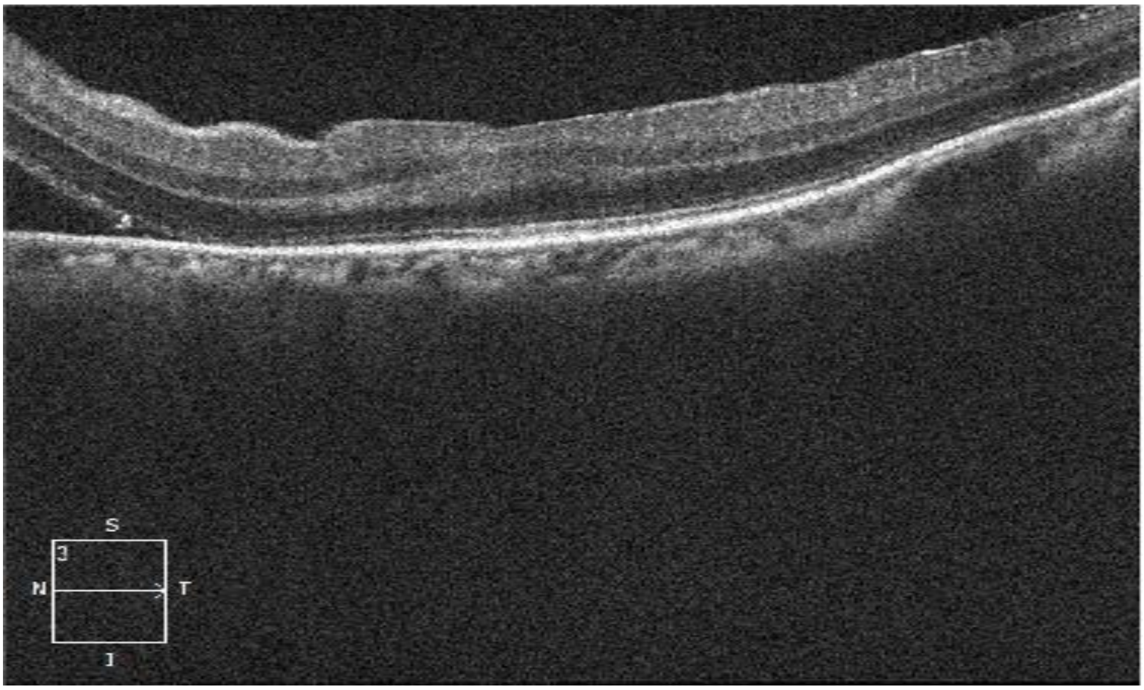

Fig 8. Retinal Detachment OCT image

Metrics	Resnet	Inception_v3	Proposed
Accuracy	0.962963	0.944444	0.962963
Precision	0.935484	0.900000	0.939394
Recall	1.000000	1.000000	1.000000
F1 score	0.966667	0.947368	0.968750

Table 2. Performance evaluation of the proposed OCT image

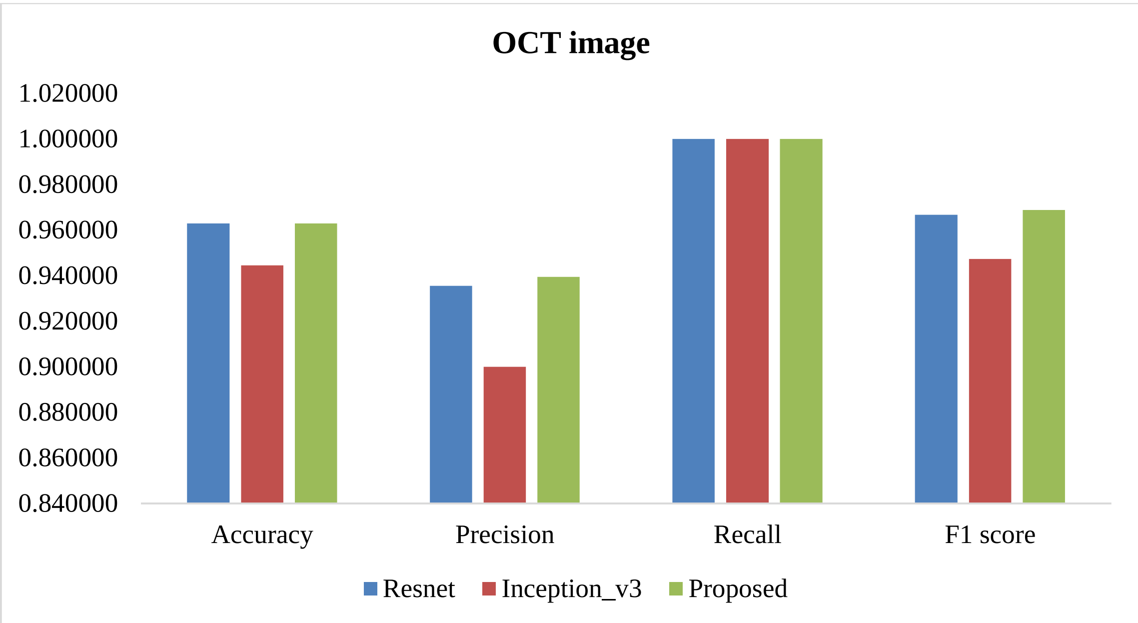

Fig 9. Comparison chart of the proposed OCT method

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Metrics	Resnet	Inception_v3	Proposed
Accuracy	0.670886	0.645570	0.721519
Precision	0.670886	0.636364	0.717949
Recall	1.000000	1.000000	1.000000
F1 score	0.803030	0.777778	0.835821

Table 3. Performance evaluation of the proposed

B-Scan Image

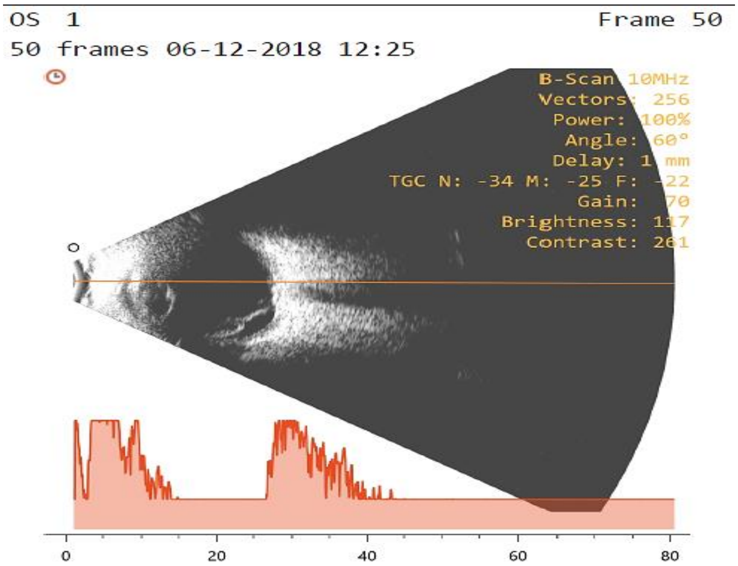

Fig 10. B-Scan normal image

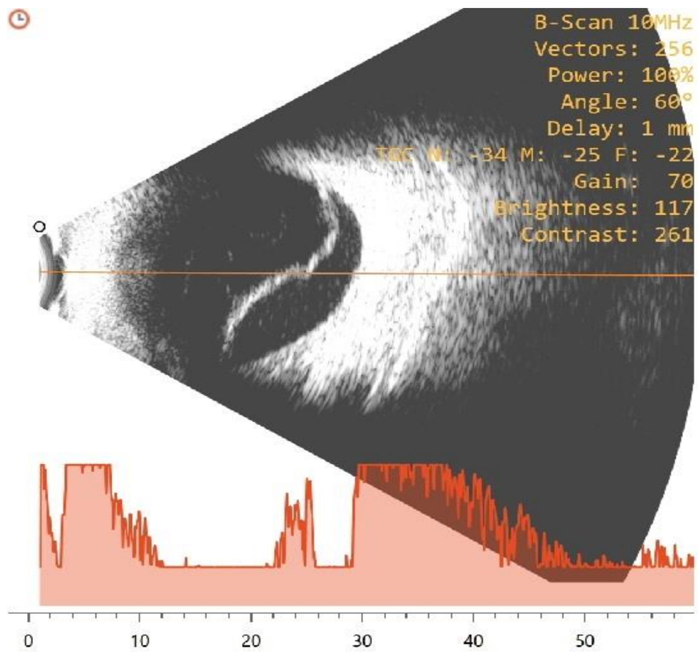

Fig 11. B-Scan abnormal image

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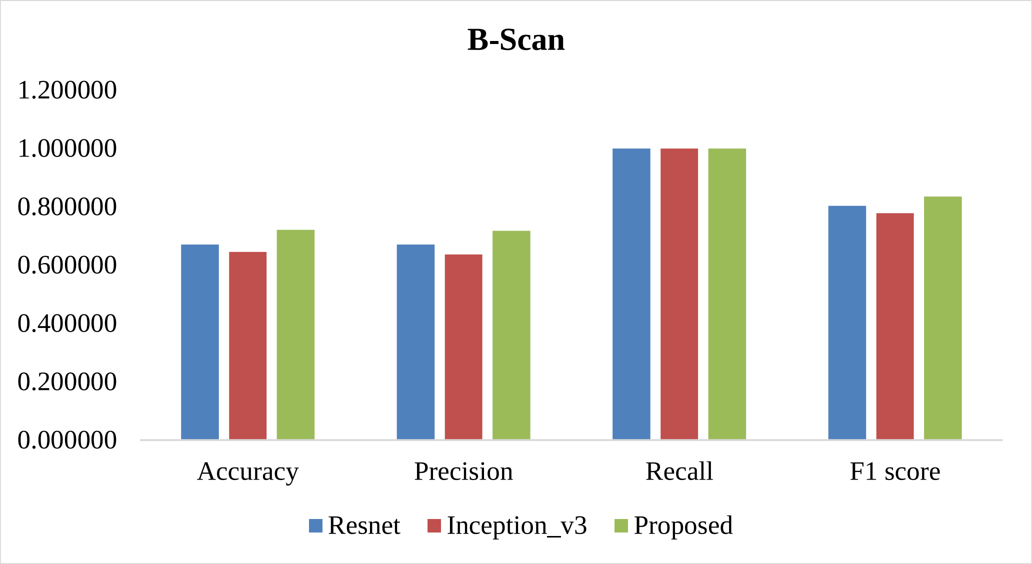

Fig 12. Performance chart of the proposed B-scan image

Metrics	Fundus	B-Scan	OCT image
Accuracy	0.903226	0.721519	0.962963
Precision	0.872340	0.717949	0.939394
Recall	1.000000	1.000000	1.000000
F1 score	0.931818	0.835821	0.968750

Table 4. Comparison evaluation metrices of the best proposed method

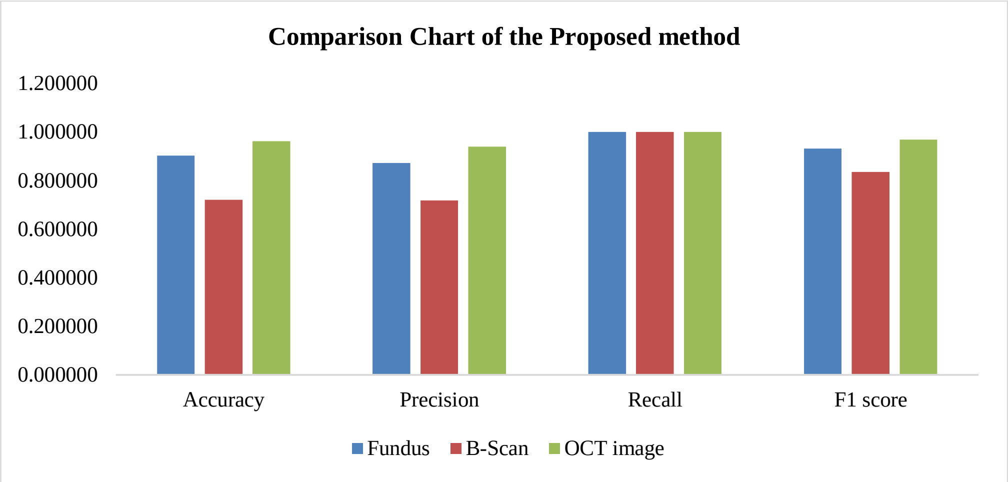

Fig 10. Comparison chart of the best proposed method

References:

[1] M. Adeel, M. Usman Akram, Takir Akram, Mohamad Muzammal, and Shehzad Kahlid, "Fundus Images-based Detection and Grading of Macular Edema Using Robust Macula Localization', IEEE Access, vol. no 6, pp. 58784-58793, 2018.

[2] J. Long, E. Shehamer, and Darrell. T, "Convolutional Networks for Semantic segmentation," Proceedings of the IEEE Conference on computer Vision and Pattern Recognition, pp. 3431-3440.

[3] M. K Garvin and M. Sonka , "Intraretinal layer segmentation of Macular spectral-domain Optical

ISSN: 2233-7857 IJFGCN

Coherence Tomography images,”, IEEE Transactions on Medical imaging, vol. 28, pp. 1436-1347, 2009.

[4] K. M. Lee, “Segmentations of the intraretinal surfaces, optic disk and retinal blood vessels in 3D-OCT scans,” Dissertations & thesis, University of Lowa, 2009.

[5] F. Shi, X. Chen, W. Zhu, D. Xiang, E. Gao, et al., “Automated 3-D Retinal Layer Segmentation of Macular Optical Coherence Tomography Images with Serous Pigment Epithelial Detachments,” IEEE Transactions on Medical Imaging, vol. 34, no. 2, pp. 441-452, 2015.

[6] Hoo- Chang shin, R. Holger, Mingchen Gao, Le Lu, Ziyue Xu, Isabella Nogues, et al., “Deep convolutional Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning”, IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1285-1298, 2016.

[7] Qinghua. H, Bowen W, Jiulong L, Xuelong. L, “Fully Automatic Three-Dimensional Ultrasound based on Conventional B-Scan”, IEEE Transactions on Biomedical Imaging, vol. 12, no. 2, pp. 426-436, 2018.

[8] M. Streho, F. Perrenoud, N. Abrham,. K. Hawa, M. Puech and A. Giocanti-Auregan, “Predominantly Superior Retinal Tears Detected by B-Scan Ultrasonography”, Journal of Ophthalmology, pp. 1-5, 2019.

[9] O. Ronneberger, P. Fischer, and T. Brox, 2015, ‘U-net: networks for Biomedical image segmentation’, International conference on Medical Image Computing and computer-Assisted Intervention, pp. 234-241, 2015.

[10] Tianming Zhao, Yuanning Liu, Guang Huo, Xiaodong Zhu, “ A Deep Learning Iris Recognition Method Based on Capsule Network Architecuture,” IEEE Access, vol. 7, pp. 49691-49701, 2019.

[11] Ajay Shrestha, Ausif Mahmood, “Review of Deep leaning Algorithms and Architectures,” IEEE Access, vol. 7, pp. 53040-53065, 2019.

[12] Sarfaraz Masood, Tarun Luthra, Himanshu Sundriyal, Mumtaz Ahmed, “Identification of diabetic Retinopathy in eye images using transfer learning,” IEEE, Access, 2017 International conference on Computing and Communication and Automation(ICCCA), 2017.

[13] Ibaa Jamal, Usman Akram, M, Anam Tariq, “Retinal image preprocessing: Background and Noise Segmentation,” Indonesian Journal of Electrical engineering and Computer Science, Vol. 10, no. 3, pp.537-544, 2012.

[14] U.R. Acharya , M.R.K. Mookiah ,Joel. E. W. Koh, J. H.Tan, V. Sulatha S.V. Bhandary, A.K. Rao, Y. Hagiwara, C.K. Chua, A. Laude, “Automated Diabetic Macular Edema(DME) Grading system using DWT, DCT features and Maculopathy Index,” ‘Computers in Biology and medicine’, Vol. 84, no. 1, pp. 59-68, 2017.

[15] Shuangling Wang, Yilong Yin, Guibao Cao, Benzheng Wei, Yuanjie Zheng, Gongping Yang, “Hierarchical retinal blood vessel segmentation based on feature and ensemble learning,” Neuro Computing, Vol. 149, no. part B, pp. 708-717, 2014.

[16] Mrinal Haloi, “Improved Microaneurysm detection using Deep Neural Networks,” Cornel University Library, arXiv:1505.04424, 2015.

[17] Martina Melinscak, Pavle Prentasic, Sven Loncaric, “Retinal Blood Vessel Segmentation using Deep Neural Networks,” 10th International Conference on Computer Vision Theory and Applications (VISAPP), pp. 577-582, 2015.

[18] G.G. Gardner, D. Keating, T. H Williamson, A. T. Elliott “Automatic detection of diabetic retinopathy using an artificial neural network: a screening Tool,”, British journal of Ophthalmology, vol. 80, no. 11, pp. 940-944.

[19] Sohini Roychowdhury S, Koozekanani Dara D, Keshab K Parhi, 2014, “DREAM: Diabetic Retinopathy Analysis using Machine Learning,” IEEE Journal of Biomedical and Health Informatics, vol. 18, no. 5, pp. 1717-1728.

[20] J. Lachure, A. V . Deorankar, S. Lachure S. Gupta, R. Jadhav , “Diabetic Retinopathy using Morphological operations and Machine Learning,” IEEE International Advance computing Conference(IACC), 2015.

[21] R. Priya, P. Aruna, “SVM and Neural Network based Diagnosis,” International Journal of Computer

ISSN: 2233-7857 IJFGCN

Applications, vol. 41, no.1, pp. 6-12, 2012.

[22] S. Giraddi, J. Pujari, S. Seeri, "Identifying Abnormalities in the Retinal Images using SVM Classifiers," International Journal of Computer Applications, vol. 111, no. 6, pp. 5-8, 2015.

[23] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, R. Salakhutdinov, "Dropout: A Simple way to prevent Neural networks from overfitting," Journal of Machine Learning Research, vol. 15, no. 56, pp. 1929-1958, 2014.

[24] M. Joseph Lakawicz, William J. Bottega Jonathan L Prenner Howard F Fine, "An analysis of the mechanical behaviour of a detaching retina," Mathematical Medicine and Biology: A Journal of the IMA, vol. 32, no.2, pp. 137-161, 2015.

[25] E. Ganesh, N.R. Shanker, M. Priya, "Non-Invasive Measurement of Glaucoma disease at earlier stage through GMR Sensor AH Biomagnetic Signal from Eye and RADWT algorithm," IEEE sensors Journal, vol. 19, no. 14, pp. 5404-5412, 2019.

ISSN: 2233-7857 IJFGCN