Classification of Retinal Diseases from OCT images using 2D-Convolutional Neural Networks

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Abstract

Purpose: Diabetic macular edema (DME) is the primary cause of vision loss among individuals with diabetes mellitus (DM). An approach for detection of Diabetic Macular Edema (DME) retinal diseases from Optical Coherence Tomography (OCT) images in diabetic patients using 2D-convolutional neural networks (CNN), a commonly used deep learning network model has been presented. Classification of optical coherence tomography (OCT) images can be achieved with high accuracy using convolution neural networks (CNN), a commonly used deep learning network for computer- aided diagnosis. We developed, validated, and tested a deep learning (DL) system for classifying DME using OCT images using optical coherence tomography (OCT) devices.

Methods: In this study, we used 300 B-Scan OCT images (DME and Normal) to evaluate the model. There were 200 sample data in the training and for testing a total of 100 retinal OCT images datasets containing (50 normal and 50 DME affected) are used for detection and classification. All the data are OCT images of retina. The proposed model was constructed based on a deep neural network to diagnose the images accurately and for better accuracy of classification. It was trained using the training dataset and the test dataset was used to evaluate the trained model.

Result: Our study shows that the classification of OCT images using deep learning method achieved accuracy score of 93% and 24% of score of loss respectively. In this study, as per the comparison it can be seen that our 2D-CNN model exhibited higher accuracy than those of the other traditional SVM and Random forest machine learning method.

Conclusion: The proposed deep learning model helps us in better classification of DME from the OCT images. This will help the eye doctor to initiate early and proper treatment. Future research is needed to validate DL algorithms to get faster better accuracy of big data of OCT images and get more details of disease changes in all retina layers.

Keywords- Retinal diseases, Convolution Neural Networks (CNN), Deep learning model, Diabetic Macular Edema (DME), Optical Coherence Tomography (OCT).

I. INTRODUCTION

The macula is the central part of the retina and responsible for the visual acuity or sharpness of vision, color vision etc. When this macular area is affected by any disease process it will have

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a direct impact in the quality of sight by reduction of visual acuity, color perception and other parameters [1]. Swelling or fluid build-up in this portion of macula due to leaking fine blood vessels called microanurysms is called diabetic macular edema (DME). DME can cause permanent visual loss in diabetes patients with diabetic retinopathy [2]. Involvement of the macula can cause of severe vision loss that occurs in a variety of pathologic conditions, such as age-related macular degeneration, diabetic retinopathy, epiretinal membrane or vitreomacular traction and oedema as a complication of intraocular surgery. Diabetic macular oedema known as DME is one of the leading causes of treatable blindness all over the world, more in developed countries with the developing countries rapidly catching up, hence the importance of early detection is of paramount [3-5].

According to available data, the number of diabetic patients in all the age groups in the world will reach a figure 693 million by the year 2045; this will also lead to rise of deaths to the complications of diabetes to about five million per year. It is well known that the quality of life is significantly reduced by the complications of long standing and uncontrolled diabetes [6]. Diabetic retinopathy is known to cause permanent visual impairment and significant visual disability if left undetected and untreated. According to the study, a large majority portion can be treated and complication prevented by early detection and treatment [7–11]. DME patterns are classified into focal, diffuse, cystoid with or without associated traction. Optical coherence tomography (OCT) images of the retina can accurately show the anatomical structure leading to a good understanding of the physiological properties of the retina, and any change detected in situ in different disease conditions helps in knowing its impact on the functions, thus leading it to become one of the gold standards for diagnosis, prognosis and treatment of eye diseases worldwide [12, 13]. The current gold standard for DME diagnosis is based on optical coherence tomography (OCT) image evaluation [14,15] which is often not available for screening in the rural and semi urban areas in most parts of the world due to its the high cost and technical limitations [16]. The use of OCT in the confirmation of the presence or absence of macular oedema including DME is universal. In addition use of automated report generation for detection of DME will help greatly reduced pressure on the medical infrastructure and focus only on patients who need treatment [17-19]. It is an important research field is to continuously improve the OCT machines and algorithms used for automatic analysis of the medical images for better patient care [20]. Artificial intelligence (AI) is now on its way to revolutionize disease diagnosis and management by performing classification from pooled big data which may not be possible at by individual or small groups of human experts. There are still lot of challenges to be overcome as the AI undergoes rapid refinements to get better results. Artificial intelligence (AI) can achieve similar diagnostic performance to human experts but in a very short time. Hence AI has a great potential to revolutionise the medical field by automation and wider reach of diagnostic tools at the door step. Deep learning is a technique to learn the features present in neural networks. During recent years, deep learning models have been used in nonlinear information processing for feature extraction and transformation, as well as for pattern analysis and classification [21, 22]. One of the deep learning frameworks is a convolutional neural network (CNN), which is applied to images for the recognition of abnormalities, classification and other tasks. Multilayer neural networks use

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the various convolutional layers and the fully-connected layers, which can learn on its own to perform classification without being programmed by certain task-specific rules [23]. Before an image is classified, the pixels in it are predefined into different classes, the pixels in the images under study are matched to these classes and thus categorised to create classifications. This forms the fundamentals of image processing also known as computer vision tasks like detection, localization and segmentation. This sort of classification is visual and natural to the humans but its quite challenging for an automated system. One of the methods is to use machine learning algorithms, which contain supervised and unsupervised learning approaches. Supervised learning is learning a function that maps an input to an output based on training dataset [24]. An example is following the neural networks of different life forms- it's an inspired programming method enabling a computer to learn from observational data [25][26][27]. The unsupervised method is learning to produce inferences from datasets consisting of input data without labelled responses. An example is cluster analysis, which has a set of objects in such a way that objects can be grouped according to their similarity easily and thus multiple classes created.

In this study, in order to achieve the above objectives, the two-dimensional convolutional deep neural network has been proposed. As per the comparison, the traditional training methods requires lot of time and economic cost but 2D-convolutional neural networks (CNN) can use the filters to quickly and from images tiny features extract automatically[28]. This method of automatically extracting features overcomes the subjectivity and one-sidedness of traditional manual diagnosis, reduces the overall cost of obtaining medical resources, and alleviates the contradiction of uneven distribution of medical resources. Deep learning is an advanced machine learning and artificial intelligent computing method to process data with multiple layers as in neural networks and Deep learning neural network research in the early 2000s introducing a number of elements which is easier to train of deeper networks [29]. The advantages of deep learning are: (1) significantly good results than other solutions in multiple domains, (2) does not need to do feature extraction and time consumption with the use of graphic processing units (GPUs), and (3) quickly adapts to a new problem. Hence, deep learning is readily used in bioinformatics and computational biology research.

In this paper, 2D CNN deep learning classifier is used for labelling optical coherence tomography (OCT) retina images into two classes (NORMAL and DME). In the field of medical image classification with deep learning OCT image classification has been studied the most. In this study we prepared and processed a relatively 300 dataset of retinal OCT images captured in real-time setting. This was followed by the use of four improved ResNet50 to automatically classify the data as either abnormal as DME or normal without DME. In this study we have used the 2D CNN also known as two dimensional convolutional neural networks which is a popular deep learning neural network program for processing the images. The CNN can be used for training to analyze the normal and abnormal DME from the retinal OCT images and label them. We expect our method will lead to a significant improvement when compared to traditional other machine learning techniques in the bioinformatics field.
The remaining of this paper is organized in the following manner as; the Section 2 gives an introduction to the retina OCT images. The next Section 3 describes the network architecture

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and the next Section 4 deals with processing data using the 2D-CNN program and getting the output. The last two sections 5 and 6 shows the experimental results and conclusions of the study.

II. METHODOLOGY

In my study, used a deep-learning model called 2D CNNs and implemented it to find its efficacy as a framework for identifying normal and abnormal (DME) images. The framework consists of four steps of processing: data collection, feature extraction, CNN generation, and model evaluation. Figure 1 presents the flowchart of our framework, and its details are described as follows.

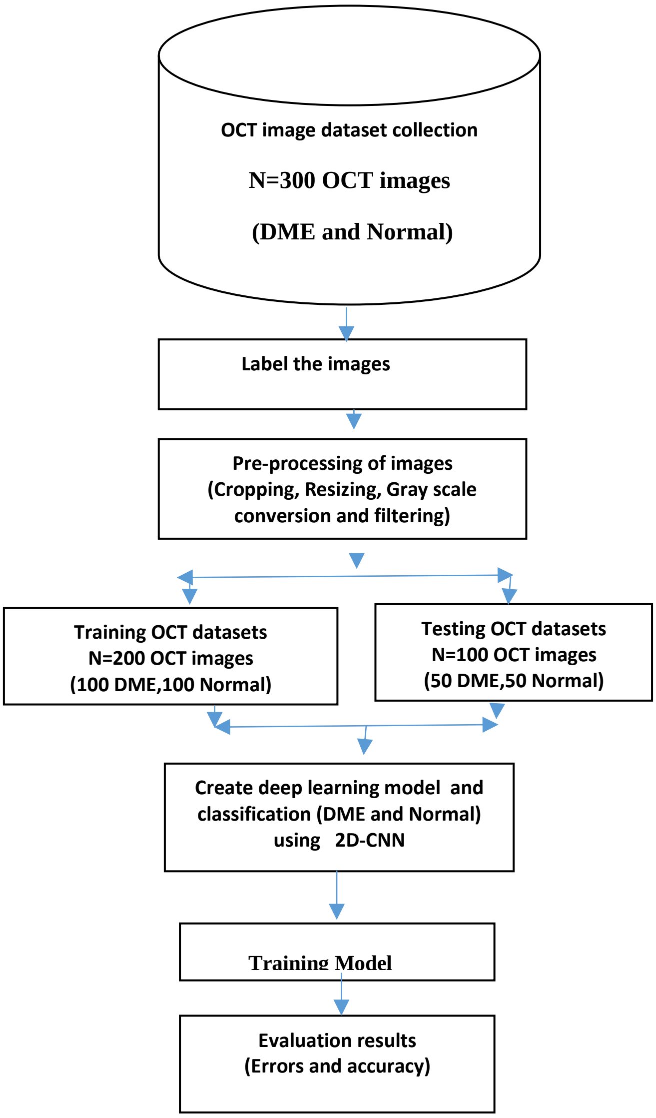

Fig. 1. Methodology for classification of retinal images

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A. OCT image datasets

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In this study, for algorithm development, retinal 300 B-Scan OCT images datasets containing (normal and abnormal DME) were obtained from diabetic patients presenting to the retina clinic at Jyoti Eye Care Hospital, Puducherry. Only cases those were willing for treatment for both intravitreal injections and lasers if required were used. OCT images were obtained using the CIRRUS 5000 Spectralis B-Scan SD-OCT (Heidelberg Engineering GmbH, Heidelberg, Germany) imaging device. Initially collected DICOM format OCT images are converted into JPEG format for further processing. The proposed problem was the binary classification between Normal and DME affected diseases. In this study, there were 200 sample data in the training and for testing a total of 100 retinal OCT images datasets containing (50 normal and 50 DME affected) are used for detection and classification shown in the Table1.

Class	Training Images	Test Images
DME	100	50
NORMAL	100	50

Table 1: The datasets contain 300 retina OCT images were labelled as two classes.

Diabetic macular edema (DME): It is an accumulation of fluid in the macula. Macula is the part of the retina that is responsible for sharpness of vision and color perception. Any fluid leaking from the nearby fine blood vessels results in swelling or increase in thickness of the layers of the macula, as shown in Figure 2(a). These results in impairment of the functions of the layers of the macula resulting in reduction in visual function fall in visual acuity, distortion, washing of the color perception.

In addition to the above diseases in the retina, Figure 2(b) shows the original OCT image of the normal retinal. From above figure, we can observe that there is a minute difference between normal and the DME classes.

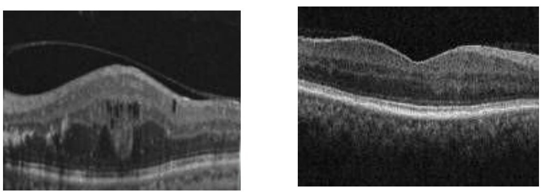

Fig 2 Original OCT image of (a) DME (b) Normal

A. Pre- Processing Of OCT images

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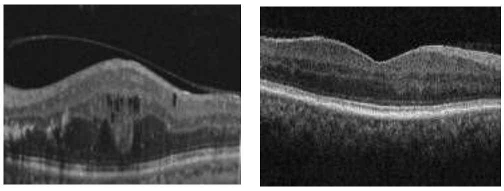
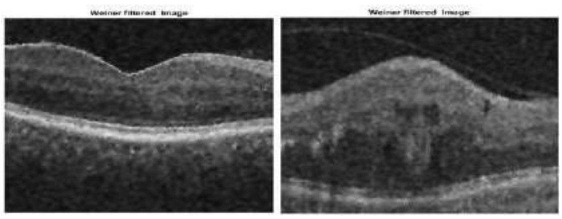


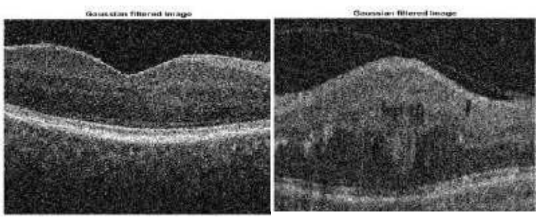
Fig 2 Original OCT image of (a) DME (b) Normal

A. Pre- Processing Of OCT images

The OCT images are corrupted by speckle noise due to high frequency sound waves, so it is better to denoise them. This will be help to reduce the effect of noise on the detection and classification results. In this work, Gaussian and adaptive wiener filters types of filters method was used to denoise and smooth the speckle noise of the OCT images shown in Figure 6(a) to (d).



(a) (b)



(b) (d)

Fig.6. Filtering image (a) Gaussian Normal image (b) Gaussian DME affected image.(c) Wiener normal image and (d) Wiener DME affected image

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B. 2D-Convoutional Neural Network (CNN) architecture

In this study, the two-dimensional convolutional deep learning image classifier is developed for two classes Normal and abnormal (DME). The architecture of 2D CNN is described in the following Figure 8.

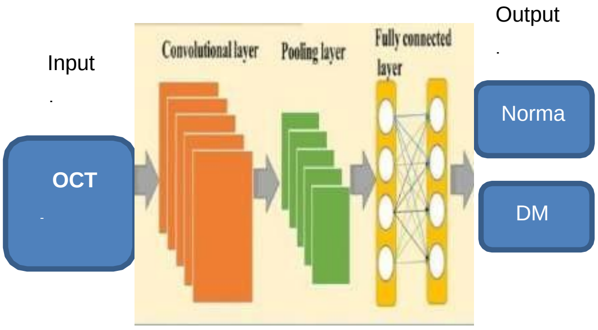

Fig 8 Diagram for classifying OCT images using 2D- convolutional deep learning neural network

The 2D-CNN architecture is a set of neurons and collection of three layers i.e. input layer, hidden layers and an output layer. The hidden layer consists of convolutional layer and some other layers such as pooling layer and fully connected layers. A CNN has a number of filters. The filter does convolution operation as follow in Figure 7.and each filter detects a small pattern.

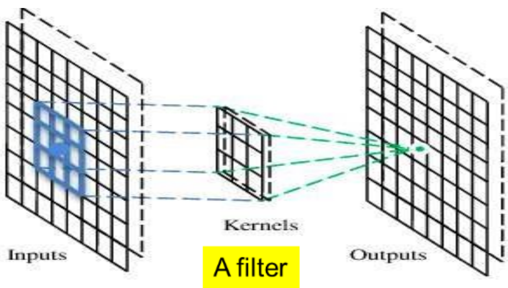

Fig.7. Convolution operation using filter.

In this model, the input image organised as a pixel format and pixel are arranged in matrix format and each pixel is the input of neuron. CNN is used to learn the features automatically from the original OCT image using filters and learning feature calculation principle is shown in the following equation,

$$\mathbf{O} = \sigma(\textstyle\sum_l \sum_m w_{l,m} I_{j+l,k+m} + b) \qquad (1)$$

The convolution of the convolution layer is to produce a feature map. Then after the convolutional layer the pooling layer is used to reduce the size, reduces the number of parameters and reduces the computation. Then in the max pooling layer using pooling technique for the selected images filter of N X N maximum size of operation is applied.

In this work, filter layers with different kernel sizes 3x3 in each filter is applied. Then the fully connected layer combines the features learned by the convolution and pooling layers and feed it to the

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next fully connected layer. At the end, the last fully-connected layer combines all the features learned by the previous layers to classify the images into Normal and DME. The last fully-connected layer will have the number of neurons same as the number of classes in classification. To speed of the training of network and reduce the sensitivity to network initialization using both normalization layers normalizes the activations and gradients propagating through a network. Then the SoftMax activation function normalizes the output of the fully-connected layer to be positive numbers that sum to be one and using the probabilities the final classification layer is to assign the input to one of the mutually exclusive classes and also compute the loss and the loss rate is shown in Figure 10.

In this study, few of the parameters need to setup for training the neural network. In this study, we set a total of 1,212,513 trainable parameters in this model. In the following Table 2 all the layers of the 2D CNN build model and trainable parameters are listed after experiment.

Table 2. 2D-CNN sequential model with all the layers and trainable parameters of the 2D CNN (Layers in CNN -convolutional layer, Relu, Pooling layer, fully connected layer (Dense)

Layer No.	**Layer (type)**	**Output Shape**	**Param #**
1	conv2d(Conv2D)	(None, 148, 148, 32)	896
2	activation(Activation)	(None,148,148,32)	0
3	max_pooling2d(MaxPooling2D)	(None,74,74,32)	0
4	conv2d_1 (Conv2D)	(None, 72, 72, 32)	9248
5	activation_1 (Activation)	(None, 72, 72, 32)	0
6	max_pooling2d_1 (MaxPooling2D)	(None,36,36,32)	0
7	conv2d_2 (Conv2D)	(None, 34, 34, 64)	18496
8	activation_2 (Activation)	(None, 34, 34, 64)	0
9	max_pooling2d_2 (MaxPooling2D)	(None,17,17,64)	0
10	flatten (Flatten)	(None, 18496)	0
12	dense (Dense)	(None, 64)	1183808
13	activation_3 (Activation)	(None, 64)	0
14	dropout (Dropout)	(None, 64)	0
15	dense_1 (Dense)	(None, 1)	65
16	activation_4 (Activation)	(None, 1)	0
	Total params:	**1,212,513**	
	Trainable params:	**1,212,513**	
	Non-trainable params:	**0**	

In this study, the convolutional layers 1, 4,7,13 and 16 are arranged for the rectified linear unit (ReLu) activation function. Then max pooling layers 3, 6 and 9 are arranged. Then set the flatten layer as 10 and dense layer as 12 and dropout layer as layer 14 and then arrange the fully connected layer.

Before the model is fitted for training, the stochastic gradient descent with momentum (SGDM) is used to optimizing the neural network. The learning rate is 0.001 will be used and the number of epochs is 10. Train the model for 10 epoch and shuffle the training data at every epoch. The number of epochs is low because we do not want to change the weights of our pre-trained neural network. Accuracy metrics measurement obtains the prediction accuracy rate on each and every epoch. The learning rate of 0.001 is set, which is small enough to slow down the learning in the transferred layer. So, in the fully-

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connected layer the learning speed is increased and this became to faster learning in the newer layer and slower in the other layers.

I. PERFORMANCE EVALUATION AND EXPERIMENT RESULTS

The purpose of this study was to predict whether or not a DME affected diseases. Therefore, the "positive" is assign to define Normal retina and "negative" is assign to define the DME diseases affected retina. In this study, training the model was done using 10-fold cross validation technique on the training dataset. Based on the 10-fold cross-validation results, hyper-parameter optimization process was employed to find the best model for each dataset. At last, the datasets was used to assess the predictive ability of current model. To train the model the OCT images was randomly separated in to multiple 10-fold cross validations to estimate and optimize the model [30].

After training the OCT image dataset the analysis of training model accuracy with 10 epochs versus the number of iterations for the 2D CNN model shown in the Figure 9 and the training loss rate with 10 epochs versus the number of iterations for the 2D CNN model shown in Figure 10. In this study, the accuracy score of test dataset is 93% and loss score of test dataset is 24% of respectively.

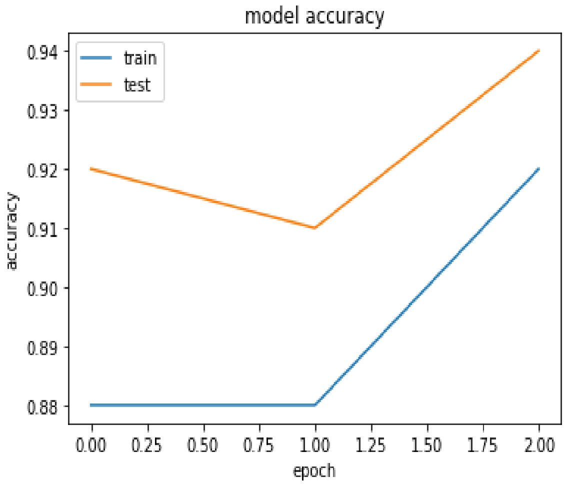

Fig.9 The plot of validation accuracy score for CNN model

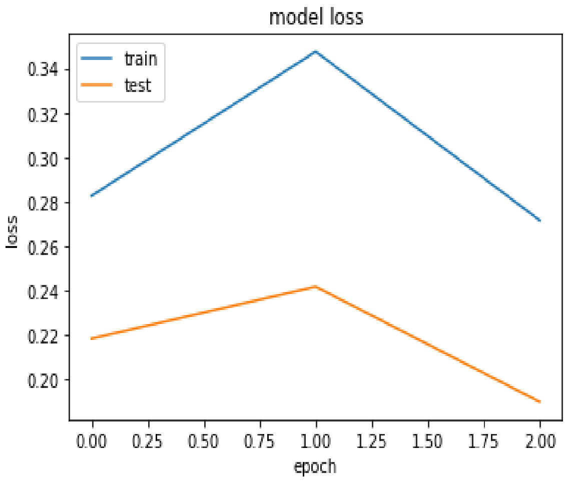

Fig 10. The plot of validation loss score for CNN model

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It is important to take into consideration the quality and reliability of the modelling techniques of research in any study. Initially, we designed an experiment by analysing data, perform calculations and take various comparisons in the results.

In this study, using package Keras with Tensorflow the 2D-CNN model is implemented. Then we did a comparison of the performance indices with that of traditional machine learning algorithms with the present study using 2D-CNN deep learning model.

We compared the performance indices of different machine learning classifiers for DME like Random Forest and support vector machine (SVM)) and evaluated and compared 2D CNN results with them. To get a good comparison, we needed to use the optimal parameters for all the classifiers in all the experiments. Table 3 shows the comparison results of between our method and other machine learning algorithms. It can be seen that our 2D CNN exhibited higher accuracy 93% performance than those of the other traditional accuracy 62% of SVM and 72% of Random forest machine learning techniques. Especially, our 2D CNN outperformed other algorithms when using the independent OCT dataset.

Table 3. Comparison result of proposed method with machine learning method.

Method	**Accuracy**
SVM	62%
Random forest	75%
2D-CNN(Proposed)	93%

VI. CONCLUSION AND FUTURE WORKS

In conclusion, our 2D-CNN deep learning model demonstrated good accuracy for the detection and classification of the Normal and abnormal disease presence of DME from the OCT images. In this study, five convolutional layers and a fully connected two dimensional deep learning neural network model is built. In this experiment, the 2D-CNN classifier's accuracy performance of the test dataset was found to be better as compared to other traditional classifier SVM and random forest classifier. According to the classification of OCT images this model helps to make therapy with the best response and highest safety for patients with DME affected diseases. This result is to give special attention of artificial intelligence in assisting clinical decision-making processes to help to analyse and reach a diagnosis of OCT images data of normal or DME affected patients. The next step is to study the deep learning programs ability to classify further the subtypes of DME and the severity levels. This can further be linked to known standardised treatment protocols according to the type and severity of disease process. Future research is needed to validate DL algorithms to get faster better accuracy of big data of OCT images and get more details of disease changes in all retina layers. Further integrating these programs into the patient management protocol will simplify the decision making process for the patient and medical technician bringing in better compliance. The contribution of this study helps for further research to promote the use of 2D-CNN in biological data.

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