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# Classifications of CNV, DME, Drusen and Normal in Retinal Optical Coherence using CNN

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**Abstract**

In this research, the importance of Optical Coherence Tomography (OCT) in diagnosing and monitoring various retinal disorders, including Drusen, Diabetic Macular Edema (DME), and Choroidal Neovascularization (CNV), is highlighted. These conditions can have a significant impact on retinal health and vision. The research presents a technique that utilizes batch normalization for preprocessing OCT images. For classification of retinal disorders, the research employs the Inception v3 architecture, which is known for its effectiveness in image classification tasks. The performance of the proposed technique is evaluated using performance metrics such as sensitivity, specificity, accuracy, and precision. In this work, a total of 3,133 images were obtained from Kaggle.com. Among these, 710 images were classified as CNV, 895 as DME, 725 as drusen, and 804 as normal retinal images. Python was used for both designing and Google colab was used for executing the algorithm.

**Keywords:** Retinal Imaging, Automated Classification, Deep Learning, Drusen Retinal OCT image


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## 1. Introduction

CNV diseases in the retina are a group of conditions where new, abnormal blood vessels grow underneath the retina and macula, the central part of the retina responsible for detailed central vision. These abnormal blood vessels can leak fluid and blood, leading to distorted or blurred vision, and if left untreated, can cause severe vision loss. DME is a complication of diabetes that affects the macula. High blood sugar levels can damage the blood vessels in the retina, causing them to leak fluid and leading to swelling in the macula. Drusen are small yellow or white deposits that accumulate under the retina. They are often associated with aging and are a hallmark of early AMD. Drusen themselves may not cause vision loss, but their presence can increase the risk of developing advanced AMD, including CNV [3,4].

In this study, using OCT images to detect DME, drusen, and CNV in the retina for detecting the diseases in eye. OCT is a non-invasive imaging technique that provides high-resolution, cross-sectional images of the retina, allowing for detailed analysis of retinal structures [5 , 6]. The limitation of the method is the lack of detail regarding the preprocessing steps applied to the retinal OCT image before classification. Therefore, in this work, the focus will be on using classification methods to address this limitation.

## 2. Review of Literature

In this study the author presented a novel technique dubbed MF-FDOG for collecting retinal blood vessels. For increased accuracy, this approach combines the first-order derivative of the Gaussian (FDOG) with the matching filter (MF). Applying a threshold to the retinal image's response to the MF and adjusting it based on the image's response to the FDOG allows for the identification of retinal vessels. [7,8]

A parallel implementation for segmenting retinal blood vessels method analyses larger datasets and higher-resolution photos faster while maintaining accuracy comparable to the ITK serial version. The main difficulty in implementing the parallel segmentation algorithm is keeping communication cost to a minimum of all present. In order to reduce communication, the authors present a novel method in which the image is split up into smaller images, making sure that some areas overlap. They show that this methodology maintains accuracy while speeding up the segmentation of the process [1,2].

The technique for retinal vascular segmentation was proposed. This process makes use of matched filters with multiwavelet kernels (MFMK), a vessel improvement approach. These kernels are intended to detect and isolate vessels from bright, localized characteristics such as lesions and clutter edges. The blood vessel segmentation utilizing multi-scale quadrature filtering was proposed. This method effectively detects both clear vessels and distinct vessel walls. By integrating energy optimization techniques for segmentation, the authors demonstrated promising results in both 2D and 3D medical [11,12].

The main objective of the work is given below [9,10]

- To classify CNV, DME, Drusen and Normal in retinal OCT Image
- To determine the performance metrics

## 3. Methodology

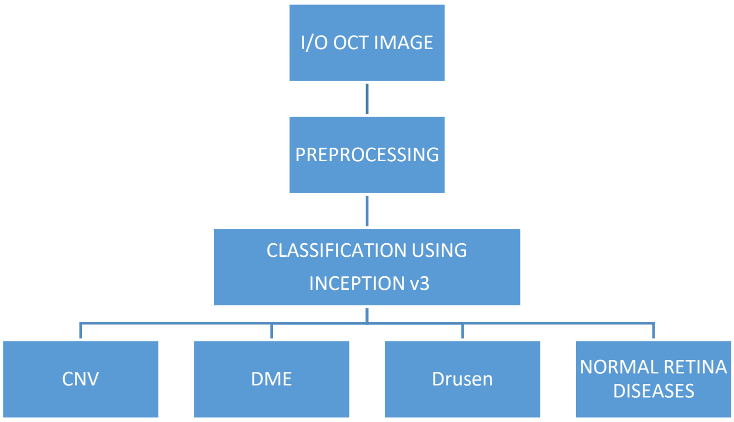


**Figure 1.** Proposed Block Diagram

Figure 1 shows the proposed block diagram for the system. The input to the system is a retinal OCT image, which undergoes preprocessing steps including batch normalization. The preprocessed image is then classified using the Inception-v3 architecture. The classification result categorizes the image into two classes: normal and diseased. The diseased category further classifies the type of disease present, such as CNV, DME, or DRUSEN.

- **Preprocessing:**

In this work, Batch normalization is used as a preprocessing step. It is a technique used to improve the training of deep neural networks by normalizing the input of each layer to have a mean of zero and a variance of one. This helps to stabilize and speed up the training process. In the term of preprocessing, batch normalization is typically applied as a layer within the neural network architecture rather than as a separate preprocessing step. It is usually inserted after the linear transformation and before the activation function in each layer of the network.[11,12].

Batch normalization is typically applied to the output of a layer before the activation function. Let's denote the input to the batch normalization layer as $x$, the mean of the batch as $\mu$, and the variance of the batch as $\sigma 2$. The normalized output of the batch normalization layer is denoted as $\hat{\boldsymbol{x}}$, and the parameters learned by the batch normalization layer are $\gamma$(scale parameter) and $\beta$ (shift parameter).

The equations for batch normalization are as follows:

Normalization:

$$\hat{\boldsymbol{x}} = \frac{\boldsymbol{x}-\boldsymbol{\mu}}{\sqrt{\boldsymbol{\sigma}^{2}+\boldsymbol{\epsilon}}} \qquad (1)$$

where $\epsilon$ is a small constant (e.g., $10^{-5}$) added for numerical stability.

Scale and Shift:

$$\boldsymbol{y} = \boldsymbol{\gamma}\hat{\boldsymbol{x}} + \boldsymbol{\beta} \qquad (2)$$

where $\gamma$ and $\beta$are learnable parameters that allow the network to scale and shift the normalized output.

- **Inception V3:**

Inception v3 is a classifier that performs multiple parallel convolutions of different sizes on the same input and concatenates their results. This allows the network to capture features at various scales without significantly increasing the number of parameters. To reduce the computational cost of the network, Inception v3 uses factorized convolutions, including 1x1 and 3x3 convolutions, instead of traditional 5x5 convolutions. This strategy decreases the number of parameters and operations required while still maintaining expressive power. Table 1 indicates the various hyper tuning parameters of inception-v3 architecture.[13]

**Table 1.** Hyper Tuning Parameters of Inception-v3

| S.No. | Model Parameters | Hyper Tuning Values |
|---|---|---|
| 1 | Total params | 3,903,471 |
| 2 | Trainable params | 3,903,471 |
| 3 | Non-trainable params | 0 |
| 4 | Activation function | Sigmoid |
| 5 | Layer | Sequential |
| 6 | Optimizer | RMSprop |
| 7 | Learning Rate | 0.001 |
| 8 | Loss Function | Sparse Categorical Cross Entropy |
| 9 | Classes | 4 |
| 10 | Types | 'CNV','DME','DRUSEN','NORMAL' |
| 11 | Epoch | 20 |
| 12 | Accuracy | 0.96 |
| 13 | Loss | 0.4 |

## 4. Results and Discussion

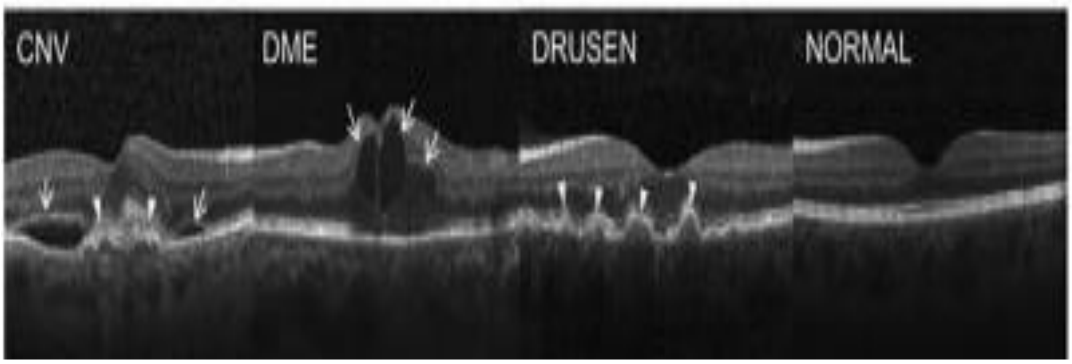


**Figure 2.** Input OCT Retinal Image [14]

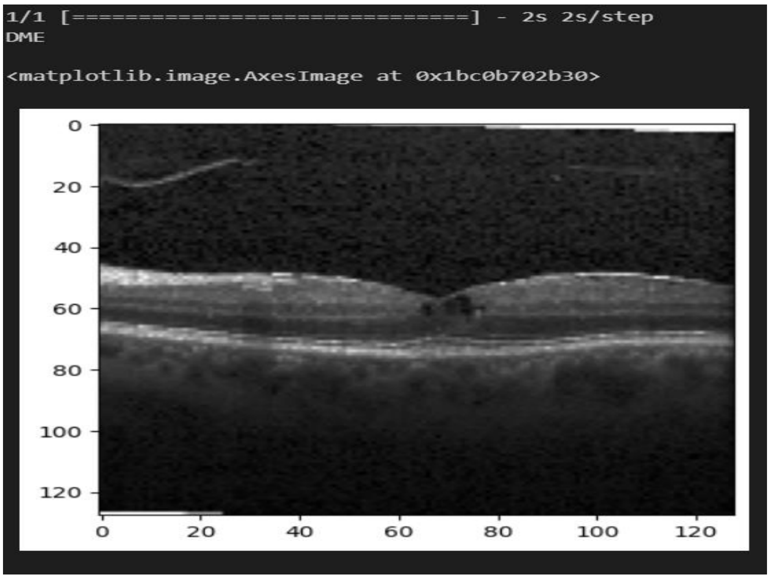


**Figure 3.** Output Image

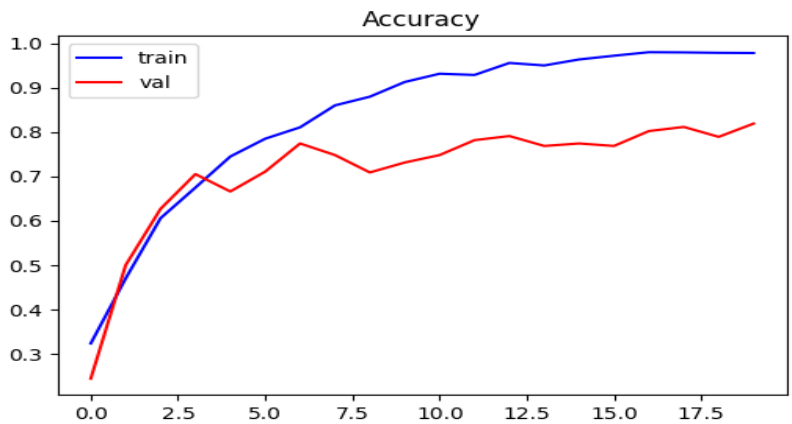


**Figure 4.** Epochs vs Accuracy

Figure 2 displays the original retinal image before any processing or analysis. It serves as the starting point for the classifier to detect and classify features. Figure 3 indicates the output of the classifier after processing the input retinal image. It may highlight areas of interest, such as regions indicative of diabetic macular edema (DME), drusen, or choroidal neovascularization (CNV). The Figure 4 illustrates how the accuracy of the classifier changes over the Epochs. The plot typically shows two lines: one for training accuracy and another for validation accuracy. These lines represent how well the classifier performs on the training data and unseen validation data, respectively. The sensitivity, specificity, accuracy and precision values of classifier is 98%, 97%, 96% and 95% respectively.

## 5. Conclusion

In this work, the focus is on diagnosing retinal disorders such as Drusen, Diabetic Macular Edema (DME), and Choroidal Neovascularization (CNV) using OCT images. The preprocessing step involves batch normalization to improve the training process. For classification, the Inception v3 architecture is utilized, aiming to achieve high accuracy in identifying these disorders from OCT images. In future, the plan is to collect more real-time datasets from ophthalmologists. This data will be used to analyse and potentially develop different customized deep learning architectures. These efforts aim to further enhance the accuracy and effectiveness of the diagnostic process for these retinal disorders using OCT Imaging.

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