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A Deep Learning Approach for the Detection and Identification of Neovascularization in Fundus Images

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Abstract – *Diabetic patients are at a high risk of developing a retinal disorder called Proliferative Diabetic Retinopathy (PDR). In PDR Neovascularization is considered as one of the major conditions in which there is an abnormal random growth of blood vessels on the retina. Neovascularization can cause severe vision loss and blindness if it is not detected and treated in its early stages. Fundus images include the images of the rear of an eye. Using these fundus images Neovascularization can be detected and classified into several stages. Neovascularization has a small size and random abnormal growth pattern. This could be a challenging task to detect with normal Image processing techniques. Deep learning methods can be used to detect Neovascularization because of their ability to perform automatic feature extraction on objects with complex features. The proposed system is implemented based on the performance of popular pre-trained deep neural networks such as Inception ResNetV2, DenseNet, ResNet50, ResNet18, AlexNet, and VGG19 networks. The best Convolutional Neural Network (CNN) model can be used to build and implement the Neovascularization detection and classification Model.*

***Key Words*: CNN, Deep Learning, Neovascularization, Fundus Images, Pre-trained Networks.**

1. INTRODUCTION

Neovascularization is the formation of abnormal blood vessels in the retina, which can be a complication of various retinal diseases, including diabetic retinopathy. The presence of neovascularization can lead to severe vision loss and blindness if left untreated. Thus, early detection and timely intervention are crucial for preventing or minimizing the damage caused by this condition. The Neovascularization is further classified into 5 conditions - Healthy Eye, Mild, Moderate, Proliferate, and Severe.

Fundus images correspond to the retinal view of an eye which represents the rear of an eye. These images are mostly used for detecting eye-related disorders. Fundus images are commonly used for the screening and diagnosis of diabetic retinopathy. However, detecting neovascularization in these images can be challenging due to the presence of various confounding factors such as image noise, variability in image quality, and the presence of other retinal abnormalities. Hence, developing automated and accurate methods for detecting neovascularization in fundus images is essential.

Deep learning techniques, particularly convolutional neural networks (CNNs), have shown remarkable success in various image-processing tasks, including medical image analysis. These techniques can learn complex features from the input images and detect the presence of Neovascularization and also classify them into different categories(Mild, Moderate, Healthy, Proliferate, Severe).

The proposed approach for neovascularization detection in fundus images combines deep learning and image processing techniques to develop a reliable and accurate system. By using a minimum amount of fundus image dataset, the deep learning model can learn to identify and classify the condition of neovascularization in fundus images with a finer accuracy. Overall, the proposed approach can help improve the early detection and management of neovascularization, leading to better patient outcomes and reduced healthcare costs.

1.1 LITERATURE SURVEY

Several research studies have proposed divergent image processing methods to detect Neovascularization in fundus images. But it is still a challenging task to detect Neovascularization due to its abnormal random growth and small size pattern. Recently, Deep learning techniques are getting immensely popular due to their advancement in Artificial Intelligence in Biomedical Image Processing. These methods can be employed to train a CNN model to detect and classify Neovascularization in fundus Images.

1) By the literature survey of the research papers, the existing system methods which include image processing and machine learning algorithms provide preferable accuracy for detecting Neovascularization, but this is limited. The abnormal random growth pattern of Neovascularization

must be detected and identified so that the condition of Neovascularization can be classified accurately.

2) The existing image processing techniques are better suited for detecting the Neovascularization based on the training data samples. The growth pattern still remains challenging to detect and also it changes from patient to patient. The growth pattern is abnormal and small. The detection mechanism must be able to learn the behavior of the growth pattern of blood vessels in order to detect and classify it properly.

3) The existing systems with image processing techniques can be improved by employing deep learning methods for feature extraction and classification. The deep learning models can be trained to learn the behavior of the random growth pattern of the blood vessels formation and can be able to detect and classify the condition of Neovascularization by training the model with an ample amount of training dataset and validating the model with a validation dataset consisting of different growth patterns of blood vessels. These models can be used to act as a base to build the system for detecting and classifying the Neovascularization from the fundus images.

M. C. S. Tang, S. S. Teoh, H. Ibrahim, and Z. Embong, in "A Deep Learning Approach for the Detection of Neovascularization in Fundus Images Using Transfer Learning"[1] proposed a deep learning neural network that is capable of detecting the Neovascularization in fundus images. The performance of the transfer learning technique is evaluated using four pre-trained networks AlexNet, GoogLeNet, ResNet18, and ResNet50, and used to build the proposed system for detecting the presence of Neovascularization in fundus images. The combination of ResNet18 and GoogLeNet pre-trained models is used in building the proposed system for detecting the presence of Neovascularization in fundus images.

S. C. Munasingha, K. K. Priyankara, R. G. Upasena, and A. Ikeda in "A Novel Method of Detecting Neovascularization Regions in Digital Fundus Photographs" proposed novel methods to detect Neovascularization using image processing techniques. The proposed system incorporates image processing techniques and machine learning methods on the fundus images to segment the regions with Neovascularization. This segmentation can help find the region of abnormal growth of blood vessels and can be able to detect Neovascularization.

H. Huang, X. Wang, and H. Ma in "An Efficient Deep Learning Network for Automatic Detection of Neovascularization in Color Fundus Images" proposed a deep learning network to automatically detect Neovascularization in fundus images. The model is developed using Feature Pyramid Network and Vovnet and the model is evaluated with fundus images from the real-time cases. The experimental results with testing showed that it has less training and test time and high accuracy when compared with Mask R-CNN.

2. METHODOLOGY

The proposed network to detect and classify Neovascularization in fundus images is developed using deep learning methods and transfer learning approaches. The popular pre-trained networks are evaluated on the training and validation sets of fundus images and the model with the best accuracy metrics is considered as the base model for developing the proposed network for the detection and classification. The proposed system employs two tasks - Detection and Classification.

DETECTION:

The detection stage includes training the neural network model to precisely detect Neovascularization in fundus images. The abnormal random growth of blood vessels makes it challenging to detect. The model should be capable of learning the behavior of the random growth of the blood vessels and should be able to detect the presence of Neovascularization. The image processing techniques and feature extraction methodologies can be combined with neural networks to accurately detect the presence of Neovascularization in fundus images. This detection stage helps in further classifying the stage and condition of neovascularization detected in the eyes of the patient.

CLASSIFICATION:

The classification stage of the proposed system enables the model to predict the condition of Neovascularization in fundus images. Neovascularization can lead to permanent vision loss if not treated early. The early detection of Neovascularization can help patients with their treatment and recovery. There are 5 stages in Diabetic Retinopathy - (Healthy/Normal, Mild, Moderate, Severe, and Proliferative). the presence of Neovascularization is detected in the Detection stage and after the detection stage the condition is classified based on the growth of the abnormal blood vessels on the retina in the Classification stage. This helps the patients to get the conventional and right treatment for their condition detected through their fundus images. The model should be able to learn the random growth patterns of the 5 stages and accurately detect the right condition of the detected Neovascularization in the retina.

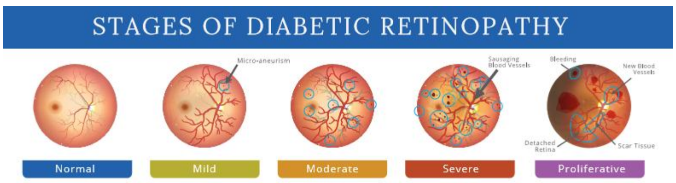


Fig -1: Stages of Neovascularization

SYSTEM ARCHITECTURE:

System architecture refers to the high-level design or blueprint of the entire conceptual model of the proposed system. It provides a structural overview of how the system is built and organized. The proposed system is built on top of the pre-trained neural networks using transfer learning approaches. The underlying architecture for implementing the proposed system is given below.

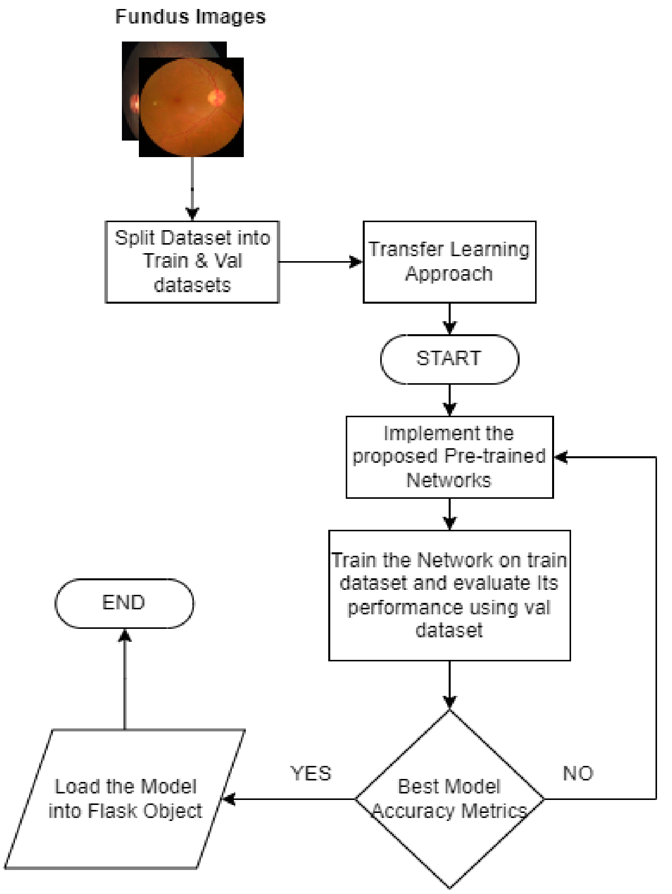


Fig -2: System Architecture

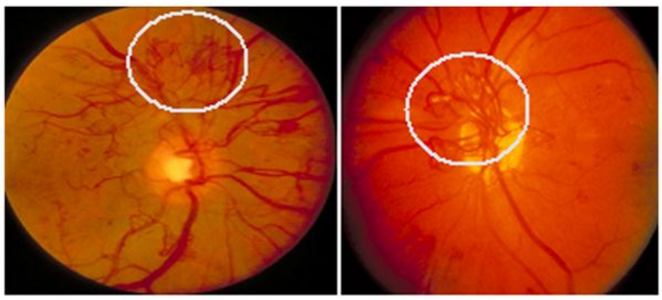
WORKING PRINCIPLE:

The fundus image dataset is collected according to the 5 stages - (Healthy, Mild, Moderate, Proliferate, and Severe). In the image processing techniques, the ground truths of the fundus images are obtained for the model training. The dataset is split into training and validation sets to evaluate the model performance over its training time. the proposed network is developed using a transfer learning approach. The pre-trained networks are loaded and trained over the train and validation datasets and the model with the best performance metrics is employed for developing the proposed system to detect and classify Neovascularization in fundus images. The popular pre-trained networks used include - Inception ResNetV2, DenseNet, ResNet50, RestNet18, AlexNet, and VGG19 networks. The model is then loaded into a flask object to provide an interface for the patient/user to interact with the system and upload their fundus image to check their condition.

2.1 MODEL TRAINING:

I. IMAGE PROCESSING:

The fundus image dataset is collected according to the 5 stages - (Healthy, Mild, Moderate, Proliferate, and Severe). In the image processing techniques, the ground truths of the fundus images are obtained for the model training. The dataset is split into training and validation sets to evaluate the model performance over its training time. the proposed network is developed using a transfer learning approach. The pre-trained networks are loaded and trained over the train and validation datasets and the model with the best performance metrics is employed for developing the proposed system to detect and classify Neovascularization in fundus images. The popular pre-trained networks used include - Inception ResNetV2, DenseNet, ResNet50, RestNet18, AlexNet, and VGG19 networks. The model is then loaded into a flask object to provide an interface for the patient/user to interact with the system and upload their fundus image to check their condition.



(a) New vessels elsewhere (NVE) (b) New vessels on disc (NVD)

Fig -3: Abnormal blood vessels growth in the retina

Ground truth images are essential for evaluating the performance of neovascularization detection algorithms or systems. They are used as a reference for comparing the results obtained from automated image analysis methods, such as segmentation and classification algorithms, to determine the accuracy, sensitivity, specificity, and other performance metrics of the algorithms.

II. FEATURE EXTRACTION & CLASSIFICATION:

The feature extraction method comprises extracting relevant features or attributes from the segmented blood vessels. This information can be used to discriminate and understand normal blood vessels and their growth with the abnormal growth of blood vessels in the retina. This can identify the severity of the Neovascularization detected in the eye of the patient. The features extracted could include vessel diameter, vessel tortuosity, vessel branching patterns, and other shape, intensity, and texture features.

Classification techniques are applied in the neural network models to train in categorizing the segmented blood vessels into 5 classes of diabetic retinopathy stages. The Convolutional Neural network is trained on the image datasets for classification. These neural networks are trained on labeled datasets to learn the pattern, growth, and features of the healthy and abnormal blood vessels and make predictions on the new fundus images.

III. TRANSFER LEARNING:

Transfer learning is a machine learning technique that leverages knowledge learned from one task or domain to improve the performance of another, related task, or domain. It involves training a pre-trained model, typically trained on a large dataset for a different task, on a smaller dataset, or on a different task, to benefit from the learned representations and features. Transfer learning has gained significant attention and popularity in recent years due to its ability to overcome data limitations and improve the performance and efficiency of machine learning models in various domains, including image recognition, natural language processing, and speech recognition, among others.

One of the key advantages of transfer learning is that it allows models to leverage the knowledge and representations learned from a large dataset to perform well on a smaller dataset with limited labeled data. This is especially beneficial in scenarios where obtaining large, labeled datasets for training is challenging, time-consuming, or expensive. By utilizing a pre-trained model, transfer learning can help overcome the limitations of limited data, resulting in more accurate and robust models. Transfer learning can be implemented in different ways, depending on the specific task and domain.

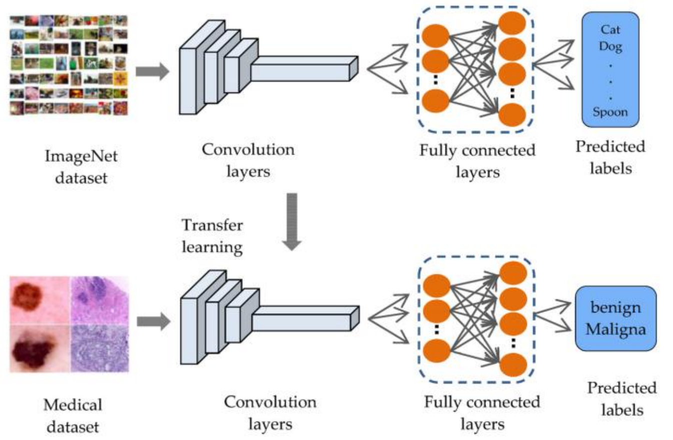


Fig -4: Transfer Learning Approach

The proposed system is constructed using the transfer learning approach. In this approach, the pre-trained model is used as a fixed feature extractor, where the layers of the pre-trained model are used to extract relevant features from the input data. These features are then fed into a separate classifier or model for the target task. This allows the model to benefit from the learned representations and features from the pre-trained model, which may have already learned generic patterns or high-level features that are transferable to the target task. The deep architecture of layers of the pre-trained neural network models helps the system to learn the features from the datasets and understand the behavior of the growth pattern of the blood vessels. However, it is important to carefully select the appropriate pre-trained model, consider the domain and task similarity between the source and target tasks, and evaluate the performance of the transferred model to ensure its effectiveness for the specific target task.

2.2 PRE-TRAINED NEURAL NETWORKS:

I. INCEPTION RESNETV2:

Inception ResNetv2 is a deep convolutional neural network (CNN) architecture that combines the Inception module and the residual connections from ResNet. Inception ResNetv2 is a pre-trained network that has been trained on a large dataset to learn the features from images, making it a powerful tool for a wide range of computer vision tasks. The Inception module in Inception ResNetv2 is designed to extract features at multiple scales by using convolutional layers with different filter sizes (1x1, 3x3, and 5x5) and pooling operations, and then concatenating the outputs. This allows the network to capture both local and global contextual information, making it more robust to variations in object scales and orientations. Residual connections allow for the efficient training of very deep networks by alleviating the vanishing gradient problem, which can occur in deep neural networks. Residual connections also help to improve the accuracy and stability of the network during training by allowing the network to learn both the residual and the identity mapping, which can facilitate the flow of gradients and information across the layers.

II. DENSENET:

DenseNet, short for Densely Connected Convolutional Networks, is a deep Convolutional Neural Network (CNN) architecture. It is known for its unique dense connectivity pattern, where each layer receives input from all previous layers, resulting in highly connected and densely packed feature maps. DenseNet is a pre-trained network, meaning it has been trained on a large dataset to learn meaningful features from images, making it a powerful tool for various computer vision tasks. The dense connectivity pattern in DenseNet allows for efficient feature reuse and gradient flow throughout the network, as each layer has access to the feature maps of all previous layers. This dense connectivity leads to better feature propagation, reduces the number of parameters needed, and enhances the gradient flow during training.

III. RESNET50:

ResNet50 is a popular pre-trained Convolutional Neural Network (CNN) architecture. ResNet stands for Residual Network, and 50 in ResNet50 refers to the depth of the network, which consists of 50 layers. ResNet50 is known for its residual connections, which allow for the efficient training of deep networks and have been shown to improve accuracy and stability during training. ResNet50 is organized into blocks, where each block contains multiple convolutional layers followed by batch normalization and activation functions, with residual connections across the blocks. The basic building block of ResNet50 is the bottleneck block, which consists of three convolutional layers with different filter sizes (1x1, 3x3, and 1x1) to reduce computational complexity, followed by batch normalization and activation functions.

IV. RESNET18:

ResNet stands for Residual Network, and 18 in ResNet18 refers to the depth of the network, which consists of 18 layers. ResNet18 is known for its residual connections, which allow for the efficient training of deep networks and have been shown to improve accuracy and stability during training. The basic building block of ResNet18 is the basic block, which consists of two convolutional layers with the same filter size (3x3), followed by batch normalization and activation functions. The residual connections in ResNet18 skip one or more convolutional layers and directly connect the input of the block to the output, allowing for efficient feature propagation and reuse.

V. ALEXNET:

AlexNet is a pioneering pre-trained convolutional neural network (CNN) architecture. AlexNet is known for its deep architecture, use of rectified linear units (ReLU) as activation functions, and introduction of dropout regularization to mitigate overfitting. AlexNet consists of five convolutional layers followed by three fully connected layers. The convolutional layers are responsible for extracting hierarchical features from the input image, while the fully connected layers are used for classification. The architecture of AlexNet is characterized by its depth, with a total of eight layers, which was considered deep at the time of its introduction. ReLU introduces non-linearity into the network, allowing it to learn complex patterns and representations from the input data.

VI. VGG19:

VGG19 is known for its simplicity and uniformity in design, consisting of 19 layers, with 16 convolutional layers and 3 fully connected layers. VGG19 is widely used for image recognition tasks, such as image classification and object detection, due to its strong performance and ease of implementation. The main characteristic of VGG19 is its deep architecture, with multiple convolutional layers stacked on top of each other, followed by fully connected layers for classification. VGG19 uses small convolutional filters (3x3) in all its convolutional layers, which allows for a deeper network with a smaller number of parameters compared to larger filters. This leads to a more efficient and computationally feasible architecture. VGG19 also has a uniform design, where all the convolutional layers have the same number of filters (64, 128, 256, or 512) and the same padding (same) to maintain the spatial dimensions of the input. This uniformity in design makes it easier to implement and fine-tune the network.

3. CHALLENGES

The proposed system to detect and classify Neovascularization in fundus images is developed based on deep learning methods. Various challenges are faced when training a deep neural network on a fundus image dataset. Some of those challenges include:

I. DATA AVAILABILITY:

Fundus images of patients with neovascularization are relatively rare, making it challenging to obtain a large dataset for training deep learning models. This can result in models with limited generalization capabilities and reduced accuracy and performance.

II. VARIABILITY IN GROWTH PATTERNS:

Neovascularization can manifest in different patterns, such as fine or coarse vessels, which can vary in size, shape, and appearance. This variability makes it challenging to develop a robust deep learning model that can accurately detect neovascularization across different patterns and stages. The abnormal growth patterns of the blood vessels in the retina makes it challenging to develop the model to learn the behavior of the growth pattern and predict the condition.

III. NOISE AND ARTIFACTS:

Fundus images can be affected by various artifacts, such as uneven illumination, blur, and noise, which can affect the accuracy of neovascularization detection. Deep learning models need to be robust to these artifacts to achieve reliable detection performance.

IV. INTERPRETABILITY:

Deep learning models are often considered as "black box" models, making it difficult to interpret and explain the rationale behind their predictions. In the context of Neovascularization detection, interpretability is important for gaining trust and acceptance from clinicians and stakeholders.

V. MODEL OVERFITTING:

Deep learning models are prone to overfitting, where they may learn to memorize the training data instead of generalizing from it. This can result in poor model performance on unseen data, including fundus images with Neovascularization.

VI. COMPUTATIONAL RESOURCES:

Deep learning models typically require significant computational resources, including powerful hardware and large amounts of memory, for training and inference. Access to such resources may be limited in some settings, posing challenges in developing and deploying deep learning models for neovascularization detection in resource-constrained environments.

4. TESTING AND RESULTS

The pre-trained networks are trained on the fundus image dataset. The image dataset is divided into training and validation dataset and each pre-trained network is trained on those datasets. The validation dataset is used to evaluate the performance metrics and accuracy of the model in detecting and classifying the Neovascularization in fundus images. The model with the best accuracy metrics is adopted for constructing the deep neural network for detecting and classifying the stage of Neovascularization.

The pre trained networks employed for developing the proposed network are trained over 3000+ images of training data and validated over 300+ images of validation dataset. The network which performs best under optimal conditions and gives a better accuracy for less training time is considered for building the proposed system. The testing stage here includes the accuracy testing of each pre trained network to find the best model architecture to build the system.

4.1 MODEL COMPARISION:

PRE-TRAINED MODEL	MODEL ACCURACY
Inception ResNetv2	**86%**
DenseNet	74%
ResNet50	72%
ResNet18	71%
AlexNet	72%
VGG19	72%

Table-1: Performance of Neural Networks

The Inception ResNetV2 Model has shown the high accuracy of 86% with less training time over a less training dataset compared to other models. This pre trained network Inception ResNetV2 is used for building the proposed system for detecting and classifying the Neovascularization.

4.2 RESULTS

From the model training and validation, the Inception ResNetV2 model has better accuracy of prediction when compared to other CNN Models. This forms the base for developing the proposed system and the proposed model is loaded into a Python Flask object to create a web interface for the users to upload fundus images and classify its stage.

Fig -5: Prediction Result on New Image

5. CONCLUSION

The Neovascularization detection and classification of diabetic retinopathy in fundus images using deep learning methods has a great impact in advancing the field of ophthalmology. Through leveraging pre-trained models and utilizing deep learning techniques, researchers and clinicians have been able to achieve remarkable results in automating the detection of Neovascularization, a critical feature in various retinal diseases such as diabetic retinopathy. Transfer learning has been found to be an effective approach in overcoming the limitations of limited annotated data and reducing the need for large datasets, which are often challenging to obtain in medical imaging. By leveraging pre-trained models, such as convolutional neural networks (CNNs), that are trained on large datasets from other tasks, transfer learning allows for the extraction of meaningful features from fundus images and enables the development of accurate and robust neovascularization detection models with relatively smaller datasets.

The integration of transfer learning with deep learning approaches has further improved the accuracy and robustness of neovascularization detection models. By fine-tuning pre-trained CNNs with domain-specific data, transfer learning allows for the adaptation of the model to the specific characteristics of the fundus images, leading to improved performance in detecting Neovascularization.

The performance of six pre-trained convolutional neural networks, which are Inception ResNetV2, DenseNet, ResNet50, ResNet18, AlexNet, and VGG19, was investigated for building the best CNN model for developing the neovascularization detection model through transfer learning. Evaluation results show that the transfer learning approach yields superior performance. The Inception ResNetV2 Model architecture is considered the best model for developing the proposed system and the model is trained and loaded into a flask object to classify the fundus images into 5 classes of Neovascularization conditions (Healthy, Mild, Moderate, Severe, and Proliferate).

6. FUTURE SCOPE

- More fundus images can be added to the training and validation datasets to increase the accuracy of detection and classification. The fundus images of patients in real-time can be served as new validation sets to fit the model training and improve its accuracy of prediction.
- The detection model incorporated on the website gives the patients the chance to check their condition and get immediate treatment.
- The model training over large fundus image datasets to build a much more accurate detection model could be efficient when the system is connected to a GPU, allowing it to run smoothly and reduce the model training time.
- The detection model can also be embedded into an IOT device for real-time detection and classification purposes in the Medical Industry.
- Continued research and development in this field, along with careful validation and standardization, will contribute to the further advancement and integration of these approaches into clinical practice, ultimately benefiting patients and improving the management of retinal diseases.

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