Diabetic Retinopathy using Deep Learning

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***Abstract*— If diabetes problems are not managed, diabetic retinopathy can result in permanent blindness. The main obstacle is early identification, which is necessary for a successful course of treatment. Regretfully, precise staging of diabetic retinopathy is challenging and necessitates knowledgeable fundus imaging interpretation. Simplifying the application procedure is crucial and might help millions of people. CNN have been effectively used for a variety of relevant themes, including as diabetic retinopathy self-diagnosis. Nevertheless, these systems' efficacy is diminished by the high expense of annotated datasets and the variability of physicians. In this, we would provide a single human brain image-based automatic self-learning technique to diagnose diabetic retinopathy. Furthermore, we provide a multi-phase method for transfer learning that makes use of comparable datasets with distinct IDs. With a second weighted kappa value of 0.925466, this technique can be employed as a screening tool for the early diagnosis of diabetic retinopathy among 2943 competing diseases in the APTOS 2019 blind list (13,000 photos). Its demonstrated sensitivity and specificity are both 0.99. 54.**

I. INTRODUCTION

DR is one of the most dangerous complications of diabetes, in which the retina is damaged and causes blindness. It damages the blood vessels in the retinal tissue, causing fluid and distorting vision. According to statistics from the United States, the United Kingdom and Singapore (NCHS, 2019; NCBI, 2018; SNEC, 2019), DR is one of the most common diseases besides blinding diseases such as cataract and glaucoma.

There are four stages of DR:

- Mild non proliferative retinopathy, the first stage in which only micro aneurysms can develop;
- Disease progression to reduce non proliferative retinopathy explained by blood loss. the ability of a vessel to carry blood As a result of movement and swelling;
- Severe non proliferative retinopathy blocks blood flow to the retina due to increased vascular occlusion, which causes new blood vessels to grow in the retina.
- Proliferative diabetic retinopathy is an early stage of growth. Retinal excretory conditions activate the growth of new blood vessels that grow along the retinal covering within the vitreous skin and fill the eye.

Since each stage has its own unique features and characteristics, doctors may not recognize some of them, which can lead to an incorrect diagnosis. That is why the idea was born to create an automatic solution for DR detection.

At least 56% of new cases of this disease can be reduced by proper and timely treatment and eye examination (Rohan T, 1989). However, this disease has no early warning signs and is very difficult to detect in its early stages. In addition, in some cases, well-trained surgeons could not examine and evaluate the characteristics of the patient's diagnostic background images (according to a Google study (Krause et al., 2017), see Figure 1). At the same time, doctors agree on the diagnosis of the disease. In addition, traditional diagnostic methods are not very effective due to the long diagnostic time and the number of ophthalmologists involved in solving the patient's problem. These problems of inconsistency lead to misdiagnosis and an insufficient basis for implementing automatic solutions to assist the investigation.

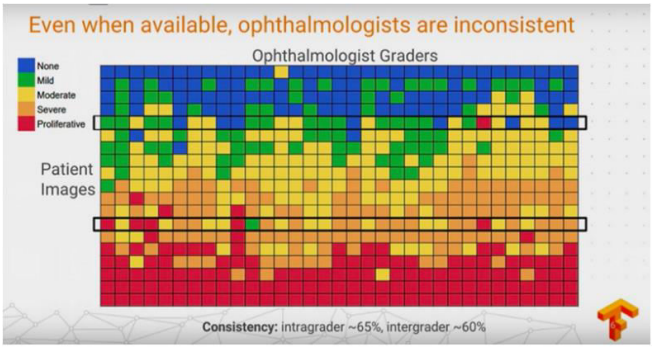

Figure 1: Google showed that ophtalmologists' diagnoses differ for same fundus image.

Therefore, DR detection algorithms are starting to emerge. The first algorithm is based on different computer vision and threshold transformations. However, in recent years, deep learning approaches have been more successful than other algorithms for object classification and retrieval tasks (Harry Pratt, 2016). In particular, CNN have been successfully used in

many projects related to diabetic retinopathy self-diagnosis (Shaohua Wan, 2018; Harry Pratt, 2016).

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II. BACKGROUND

DR is a debilitating complication of diabetes characterized by retinal vascular damage caused by long-term exposure to elevated blood glucose levels. It is the leading cause of vision loss and blindness worldwide, especially among working adults. Early detection and timely intervention are critical to prevent irreversible vision loss and alleviate the socioeconomic burden associated with this disease.

Traditionally, the diagnosis of DR was based on manual evaluation of retinal fundus images by trained ophthalmologists. The process is resource-intensive, subject to inter- and intra-observer variability, and often unavailable in underserved areas. The increasing prevalence of diabetes and increasing demand for diabetic eye exams highlight the need for scalable, efficient and objective diagnostic solutions.

In the context of diabetic retinopathy, deep learning offers the opportunity to develop automated screening systems capable of analyzing retinal images and detecting subtle abnormalities that indicate earlystage disease. Harnessing the power of deep learning can improve the efficiency and scalability of diabetic eye care programs, facilitate early detection, and improve long-term outcomes for patients with diabetes.

The significance of this study is that it can address critical challenges in DR diagnosis and management by developing Deep Diag, a new deep learning framework specifically adapted for automatic DR detection and fundus image classification. Using the latest techniques of deep learning, transfer learning and custom modules for damage detection and severity assessment, Deep Diag aims to achieve better diagnostic accuracy, efficiency and scalability compared to current methods.

In addition, this study contributes to the field of automated DR diagnoses by providing insights into the interpretability and robustness of deep learning models for medical imaging. Through extensive testing and analysis, we aim to validate Deep Diag's performance, identify limitations, and outline future directions to improve the effectiveness and applicability of automated DR examination tools.

Overall, this study could have a significant impact on the early detection and treatment of diabetic retinopathy, ultimately improving patient outcomes, reducing health inequalities and alleviating the global burden of vision loss associated with this common and debilitating disease.

III. DIABETIC RETINOPATHY AND DEEP LEARNING

Here is a detailed explanation of deep learning and its use in predicting diabetic retinopathy:

1. *Neural Networks:*

   Neural networks consist of interconnected layers of neurons organized as an input layer, one or more hidden layers and an output layer.

   Each neuron in the network receives input from neurons in the previous layer, uses a weighted sum of the inputs, adds. bias, and passes the result through an activation function to produce an output.

   Neuron weights and the biases are randomized and adjusted during training using optimization algorithms such as gradient descent, backpropagation, or variations thereof to minimize the variance. between the predicted and the actual output (i.e the loss function).

2. *Deep Learning Architectures:*

   Convolutional Neural Networks (CNN): CNNs are widely used in image recognition tasks, including the detection of diabetic retinopathy. They consist of twisted layers, converging layers and fully connected layers. Convolutional layers use filters to extract features from input images and capture spatial hierarchies of visual patterns.

   Recurrent Neural Networks (RNNs): RNNs are powerful for sequential computing operations. They have feedback connections that allow them to assimilate information from previous time steps, making them suitable for tasks involving temporal dependencies. Although RNNs are less commonly used to predict diabetic retinopathy, they can be used to analyze longitudinal retinal images or clinical data.

3. *Training and Optimization:*

   Data augmentation techniques such as rotation, scaling, and translation can be applied to artificially increase the diversity of the training data set and improve the generalization ability of the model.

   Transfer learning is often used in deep learning for medical imaging tasks. Pretrained CNN models trained on large-scale image datasets such as ImageNet are fine-tuned to exploit features of smaller medical image datasets and accelerate convergence.

4. *Prediction of Diabetic Retinopathy:*

   Predicting diabetic retinopathy involves analyzing fundus images of the retina to detect signs of disease such

as micro aneurysms, hemorrhage, exudate, and neo vascularization.

Deep learning models are trained to classify retinal images according to different degrees of diabetic retinopathy (eg, mild). , moderate, severe) or detect specific lesions indicative of the disease.

After training, the deep learning model can be used to analyze new retinal images and predict the occurrence and severity of diabetic retinopathy.

Model predictions can help healthcare professionals in early diagnosis, patient risk stratification and treatment planning, improving clinical outcomes and reducing the risk of vision loss in patients with diabetes.

In conclusion, deep learning methods, especially CNNs, provide powerful tools for automatic prediction and diagnosis of diabetic retinopathy based on retinal fundus images. Using large data sets, complex architectures and optimization algorithms, deep learning models can learn complex patterns and features that are important for disease detection, thereby improving patient care and management.

IV. PROBLEM DESCRIPTION

4.1 Dataset:

Image data used in this study are taken from several materials. We trained the CNN using the Kaggle Diabetic Retinopathy Removal Challenge 2015 dataset (EyePACs, 2015). A total of 35,126 photographs were taken of the left and right eyes of Americans with signs of diabetic retinopathy.

- Sen diabetic retinopathy (label 0)
- Mild diabetic retinopathy (label 1)
- Diabetic retinopathy (label 2)
- Severe diabetic retinopathy (label 3)
- Melancholy diabetic retinopathy (label 4).

We also used another small dataset, the Indian Diabetic Retinopathy Image Data (IDRID) (Sahasrabuddhe and Meriaudeau, 2018), which used 413 background images and MESSIDOR (Retinal Field Segmentation and Analysis). . Ophthalmology) (Decencire et al., 2014) consisting of 1200 fundus images. Since the original MESSIDOR dataset has different markers than other datasets, we used a version that was re-marked by a group of opticians with standard markers (Google Brain, 2018).

When the evaluation changed to be done using the Kaggle APTOS 2019 Blindness Detection (APTOS2019) material (APTOS, 2019), we reached the most effective part of the training. The complete dataset contains 18,590 fundus images, which can be divided into 3,662 schools, 1,928 validations, and 13,000 control images across the Kaggle competition organizers. All datasets have comparable class distributions; The APTOS2019 distribution is demonstrated in Figure 2. nSince the distribution of unique datasets is comparable, we considered it as an important part of this type of data. We did not make changes to the distribution of the dataset (under sampling, oversampling, etc.).

The smallest local length of all datasets is 640 x 480. An example from APTOS2019 is shown in Figure 3.

4.2 Evaluation Index

Cohen's team weighted score was used as the main index in this study. The kappa score measures the agreement between two ratings. The weighted kappa square is calculated between the score given by the human rater and the predicted score. This scale ranges from -1 (complete disagreement between raters) to 1 (complete agreement between raters). The definition of κ is as follows:

$$\kappa = 1 - \frac{\sum_{i}^{k-1}\sum_{j}^{k-1} w_{ij} o_{ij}}{\sum_{i}^{k-1}\sum_{j}^{k-1} w_{ij} e_{ij}}, \qquad (1)$$

where k is the number of components, oi j and ei j are the elements of the observation and expectation matrix. wi j is

$$w_{ij} = \frac{(i-j)^2}{(k-1)^2}, \qquad (2)$$

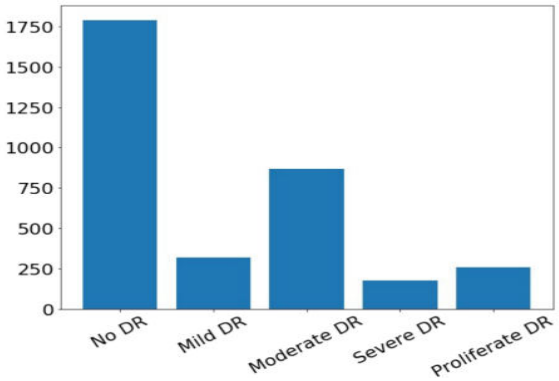

Figure 2: Classes distribution in APTOS2019 dataset.

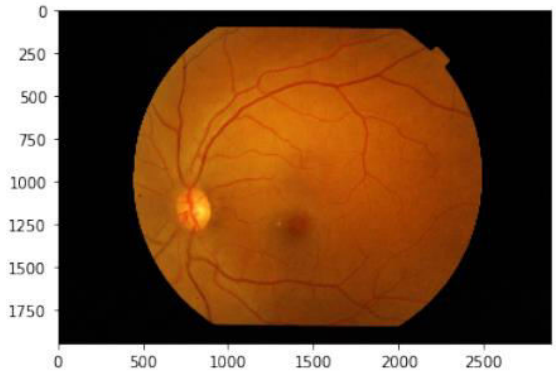

Figure 3: Sample of fundus photo from the dataset.

Due to nature of Cohens Kappa, researchers should interpret this relationship with caution. For example, if you consider two pairs of players with the same pass percentage but different rating percentages, consider that this will significantly affect the team ratio.

The reason for using the kappa ratio is that validation and test data identifiers are not included. Kappa values for these data sets are obtained by submitting the model and solution code to

the positioning system Kaggle. There is also no clear access to images of the test dataset.
We calculated the macro F1 score, accuracy, sensitivity and specificity for the 736shape image retention dataset extracted from the APTOS2019 training data and Kappa scores.

V. LITERATURE REVIEW

In [8], researchers propose a deep learning method that uses CNN to extract features from retinal images and classify them into different DR categories. The results of the system showed that the system outperformed other advanced methods in terms of accuracy and speed. It has proven to be very accurate in detecting DR and accurately classifying the different stages of the disease. This study shows an encouraging way to automatically detect and classify diabetic retinopathy, which can help health professionals to diagnose and treat the disease early [19].

A model developed in [9] is a DNN model for DR classification of retinal images [21]. Trained and tested on a large dataset of retinal images and evaluated on a test set, we show that deep neural network models outperform traditional machine learning methods in terms of accuracy.

In [10], researchers proposed a Deep Learning Ensemble method for DR detection. This paper presents a method to improve DR detection accuracy by training deep neural network models and combining their predictions. A large dataset of retinal images is used to train and evaluate the approach. The results show that deep learning approaches outperform individual DNN models in DR detection accuracy [19][23].

In [11], researchers use a Siamese binocular CNN architecture to detect DR. It requires the use of two separate CNNs to extract features from a patient's two eyes and compare them to obtain predictions. A large dataset of retinal images was used to train and evaluate the approaches used. This method outperforms other state-of-the-art methods in accuracy by 94.6%.

In [12], researchers present a CNN architecture for DR detection and classification based on a pre-trained ImageNet model used for image extraction and user-defined classification for DR prediction. The model uses a large dataset of retinal images. According to the research results, the CNN architecture achieved 93.5% DR detection accuracy and 82.5% DR classification accuracy.

Other methods for DR detection and estimation using convergence and transfer learning (SVM) [13] and deep convolutional neural network (DCNN) [14] use different feature extraction and transformation techniques. [18] [20] [22].

VI. RESEARCH METHODOLOGY

This section briefly describes the research methods used for this model, including experimental methods and settings.

The dataset used in this study is "APTOS 2019 Blindness Detection" [15]. This Diabetic Retinopathy (DR) detection and diagnosis dataset was developed by the Asia Pacific Tele-Ophthalmology Society (APTOS) and is now freely available. It was collected in collaboration with various clinics and eye clinics in various countries of the Asia-Pacific region. This dataset contains more than 5,000 high-quality retinal images of various types of diabetic retinopathies, making it a valuable resource for researchers and professionals in the fields of ophthalmology and computer vision. Ophthalmologists carefully recorded each image and graded it according to the nature and severity of symptoms of diabetic retinopathy. This disease is the leading cause of blindness in the world.

The APTOS 2019 dataset is important for several reasons. First, it provides a large and diverse collection of high-quality retinal images, which are essential for training and testing machine learning algorithms. Second, the data provided by ophthalmologists is a high-quality, reliable and consistent way to evaluate the performance of these algorithms. Finally, researchers have the opportunity to address global issues that have a significant impact on human health by developing algorithms that can aid in the early detection of diabetic retinopathy and other retinal diseases.

The APTOS dataset contains fundus images, which are high-resolution images of the back of the eye, including images of the retina, optic nerve, and macula. These images were obtained from patients with DR varying in severity from no DR to severe disease, graded on a scale of 0-4. In our study, we divided them by two parameters 0 and 1.0, which represent the entire dataset. Example dataset 1 represents a healthy eye, ie. images without DR, and 1 represents a defective eye (ie, images with mild or severe DR) and is shown in Figure 1.

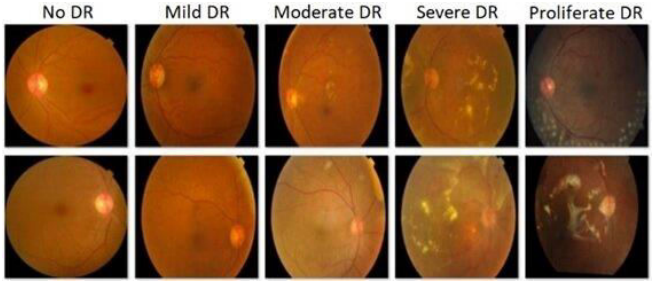

Figure. 4. A sample from APTOS dataset with images categorized as healthy or defected.

The method consists of five distinct parts: data collection, data processing, model selection, model construction and training, and model testing. Each step is explained below:

A. Data collection

The Kaggle program "APTOS 2019 Blindness Detection"[15] was used in the study. Having dead eyes wallpapers DR. These images were scored on a scale of 0-4 based on the severity of DR. In our example, 2000 images were used.

B. Data Processing

• As with real data sets, the collected images must be processed before they can be used together. This image processing ensures the same size and resolution, making it easier for deep learning models to process images and extract the most important features.

• Scaling and normalization: Since the dataset contains images of different sizes, all images are scaled to 256 and scaled to. Online training time.

• Class Comparison: We consider the binary classification of diabetic retinopathy, i.e whether the patient has DR or not, so we divide the entire dataset into two classes: 0 and 1, 0 indicating healthy eyes. One image shows the defective eye without DR, i.e mild to severe DR.

C. Model Selection

CNN is a type of deep learning algorithm widely used in image classification, object detection and segmentation. CNNs are considered a new technology in image classification due to their ability to recognize image elements without pre-processing and their ability to tune and refine parameters through cross-training. Therefore, in this study, we chose the original CNN model and ResNet50 architecture for binary classification of diabetic retinopathy.

• CNN: The main algorithm used in medical diagnosis is a CNN [16]. A CNN consists of several basic layers, including a communication layer (CONV), an advertisement layer, an activation layer, and a full link layer (FC). To detect local features, an additional layer processes the input image using a set of learning filters. To create nonlinearity in the model, a nonlinear function, such as the ReLU function, is introduced in the activation layer. Spatial levels reduce the spatial size of data and preserve important information. Finally, the connection layer uses all the extracted features for prediction.

• ResNet: ResNet is a deep learning architecture first introduced in 2015. It aims to solve the problem of missing gradients in deep networks, and the networks can eventually be trained for hundreds or hundreds of thousands of layers. the results are better. Compared to power grids, it has better accuracy and efficiency. The concept of residual learning is at the heart of ResNet. This means that the network learns the difference between the input and the desired output, rather than mapping it itself. This is achieved by adding shortcuts between the input and output layers of each network block to facilitate information dissemination. The architecture of ResNet consists of several blocks, each block consists of several layers of convolution, batch processing, activation and other important layers. Residual connectivity allows the network to avoid cross-layer effects.

D. Construction and Training

• For training, the network splits the training and test datasets in the ratio of 80:20. We build a hierarchical CNN model by first stacking four pairs of Convolution and MaxPooling layers using the ReLu activation function, followed by two convolution, one smooth layer and two layers (see Figure 2). For the final prediction, we only need to classify between two classes, so the sigmoid function is used. Figure 2 shows the architecture of the model and a summary of all layers. The model is run with the death function 'Categorical_Crosentropy' and the moderator 'Adam'. The sample was run for 50 generations with a batch size of 32.

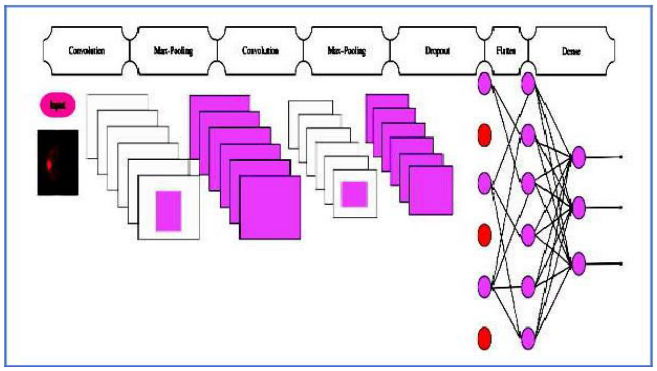

Figure. 5. CNN Architecture

• Another model we created is ResNet50. The ResNet50 architecture has a total of 50 layers, including 64 different kernels and a 7x7 convolution kernel with 2-step size and a high convolution layer for 2 steps. Nine additional layers are sent three times, including 3x3, 64-core convolution, 1x1, 64-core convolution, and 1x1256-core convolution. Figure 3 shows the architecture of the model and a summary of all layers. We then build a model using 'Categorical_Crosentropy' as the mortality function and 'Adam' as the moderator. The sample was run for 100 generations with a set size of 128.

E. Model Testing

` For training, the network splits the dataset for training and testing in the ratio of 80:20. We tested the above two training models on the test set to evaluate their performance on unseen data. The results of these tests can be compared and analyzed to draw conclusions about the performance of the CNN and ResNet50 models in binary classification for diabetic retinopathy detection.

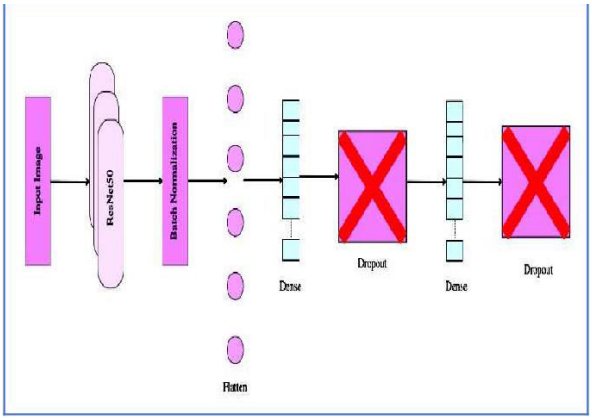

Figure. 6. ResNet 50 Architecture

VII. RESULT

Our testing phase was carefully divided into two distinct segments: local testing and Kaggle testing. In the local testing phase, we found that the composite method turned out to be the best alternative. The method was then rigorously evaluated against Kaggle validation and test suites to ensure its effectiveness. In our local testing involving a dataset of 736 images, we found an interesting observation: the performance

of the composite method decreased slightly when Test Time Augmentation (TTA) was used. This was in contrast to the much larger dataset of 13,000 images used in Kaggle's testing. In this case, the integration of TTA at the n-level proved to be useful because it improved the generalization ability of the model on unseen images, indicating better performance in a wider context.

The results were quantitatively impressive. For the trimmed mean set without TTA, we obtained a Quadratic Weighted Kappa (QWK) score of 0.818462 on the validation set and an excellent 0.924746 on the test set. In contrast, the average TTA ensemble received a QWK of 0.8265567 in the validation set and was intriguingly coded "46triW" in the test set, which appears to be a typo or miscommunication.

Model	QWK	Macro F1	Accuracy	Sensitivity	Specificity
EfficientNet-B4	0.966	0.806	0.902	0.809	0.977
EfficientNet-B5	0.963	0.812	0.902	0.807	0.976
SE-ResNeXt50 (512x512)	0.971	0.853	0.928	0.868	0.983
SE-ResNeXt50 (380x380)	0.962	0.799	0.899	0.798	0.976
Ensemble (mean)	0.968	0.827	0.917	0.828	0.980
Ensemble (trimmed mean)	0.969	0.840	0.919	0.840	0.981
Ensemble (trimmed mean, binary classification)	0.986	0.993	0.993	0.993	0.993

Figure. 7. Result.

In addition, we extended our evaluation to binary classification and distinguished the presence and absence of diabetic retinopathy (DR) to confirm the effectiveness of the model as a screening tool. This analysis, detailed in the table, emphasized the remarkable stability of the TTA, ranking consistently 58th and 54th among 2,943 participants in the validation and testing data.

This consistency underlines the reliability of the ensemble method and its potential as a robust tool in medical screening applications.

VIII. CONCLUSION

In summary, the prevention of vision loss in individuals with diabetes mellitus depends critically on the prompt recognition and prompt treatment of diabetic retinopathy. Fundus imaging is a useful diagnostic technique that directs suitable interventions and offers crucial information about retinal health. Machine learning have led to the development of automated techniques for fundus imaging-based diabetic retinopathy diagnosis, which hold promise for increasing diagnostic process efficiency and accuracy.

In particular, deep learning methods—particularly CNN and ResNet architectures—have demonstrated a great deal of promise for raising the machine-learning identification of diabetic retinopathy's accuracy. These models enable earlier intervention and improved patient outcomes through recognizing subtle illness signals using the wealth of information found in fundus pictures.

Because deep learning techniques are still being developed and many imaging modalities are being harmonious, this field has a very bright future. These advancements are expected to enhance the availability, efficacy, and precision of analytical instruments utilized in the diagnosis of diabetic retinopathy. We can continue to push the limits of medical innovation and eventually enhance the lives of people suffering from diabetes worldwide by utilizing profound learning and new imaging approaches.

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