Diabetic Retinopathy Detection using the Genetic Algorithm and a Channel Attention Module on Hybrid VGG16 and EfficientNetB0

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ABSTRACT

Diabetic Retinopathy (DR), a result of diabetes, requires early detection to reduce the impact of the disease on vision. This study introduces a new system whose architecture is based on a combination of VGG16 architecture with EfficientNetB0 as well as an added body structure, which is the Channel Attention Module (CAM), to strengthen the channel maps and thus achieve improved classification accuracy. For further efficiency and consistency, the system employs a genetic algorithm for image normalization. The system shows great potential for improving clinical decision making and patient examination results when used in the diagnosis of DR. The evaluation results confirm the reliability of the system and the feasibility of using it in daily practice to address the acute challenge of early detection of DR. The model is well trained with a test dataset of 2900 images and demonstrates high accuracy of 95%. This high accuracy clearly shows the high reliability of the proposed hybrid model which is also confirmed by the precision and recall values. The achieved precision is 0.96 for class 0 and 0.94 for class 1, and the achieved recall is 0.94 for class 0 and 0.97 for class 1.

Keywords-diabetic retinopathy; hybrid model; VGG16; EfficientNetB0; Channel Attention Module; genetic algorithm; image alignment

I. INTRODUCTION

Diabetic Retinopathy (DR) is a macrovascular complication of diabetes mellitus. It is expressed as damage to the blood vessels of the retina and can lead to vision loss and blindness. There is a global trend of high incidence of diabetes, which implies high incidence of DR, requiring improvement of the screening and diagnostic methods. Compared to conventional techniques, the diagnostic reliance on ophthalmologists to review retinal images is downright slow and error prone. As a result, there is a growing trend to develop automated and accurate methods for diagnosing DR to prevent disease progression and complications. Given the advances in deep learning and computer vision, there are opportunities to automate the diagnostic process for medical conditions such as DR. Convolutional Neural Networks (CNNs) have been extensively used in most image classification tasks [1]. VGG16 and EfficientNetB0 are two CNN architectures that are believed to have the strongest feature extraction capability and are efficient in performance. Thus, a higher performance can be achieved while maintaining a relatively small number of parameters [2].

This work presents a new hybrid architecture that combines the advantages of both VGG16 and EfficientNetB0 architectures. A Channel Attention Module (CAM) is also incorporated to enhance the ability of the model to pay attention to the most relevant features in retinal images. A very critical component of our approach is the use of a genetic algorithm for image preprocessing in an initial step. The genetic algorithm has been used to align images to a reference standard, thereby reducing variability and increasing uniformity in the input data [3]. The objectives of this research are:

- Apply genetic algorithms in image preprocessing to align images to a reference image.
- Implement the CAM in the model, adding the ability to focus on the most critical features for diagnosing DR.

- Design a hybrid deep learning model that combines the best of VGG16 and EfficientNetB0 architectures to improve feature extraction and classification accuracy.

II. PREVIOUS WORK

Previous studies have provided important solutions and proposed systems for this problem, but with limitations. Tymchenko et al. in [4] presented a scheme for diabetic retinopathy stage detection from a single fundus photograph. Their methodology was a multi-stage transfer learning procedure. According to the current research, the authors make their experiments appear highly and stably enhanced for generalization and low variance. Deep learning was applied to different stages of DR by Khan et al. in [5]. Incremental improvements were achieved by applying a method known as known as VGG-NiN architecture with transfer learning and Spatial Pyramid Pooling (SPP). Here, the dataset used is EyePACS, therefore the result is incredible with less computational load compared to previous techniques. A new method for identifying DR has recently been described by Luo et al. in [6]. Their method is based on a CNN architecture and incorporates long-range units to help correlate long-range patches for improved sensitivity to global properties in addition to local properties that are well captured by the CNN. In the view of the extensive exploration of the study, Kalyani et al. in [7] paid aggressive efforts towards developing and incorporating the Capsule Network (CapsNet) architecture to classify different stages of DR. The authors used the Messidor dataset of 1200 RGB fundus images, for which contrast enhancement and noise removal operations were performed by the authors themselves.

DRFEC is an early DR detection system proposed by Das et al. in [8]. The authors trained several deep learning CNN models and DenseNet201 achieved the highest training accuracy whereas EfficientNetB4 performed the best in the validation set. Mobile-based structures were found to be more effective than the residual networks and inception modules. They used attention mechanisms for lesion detection, and for fine-tuning the model in terms of overfitting and generalization. Wan et al. in [9] suggested an automated way to detect DR using fundus images and by utilizing CNNs such as AlexNet, VggNet, GoogleNet, and ResNet with transfer learning and hyperparameter optimization. An automated DR detection system for fine-tuning the CNN using Nesterov momentum and dealing with insufficiently annotated data using data augmentation techniques was described by Pires et al. in [10]. In their work, Carrera et al. in [11] were interested in developing a CAD system for early diagnosis of DR using retinal images. The image processing technique was proposed by Ishitaq et al. in [12], where the acquired features were quantified and the SVM classifier was applied using the obtained quantitative input features. Wang et al. in [13] presented a new deep learning approach for DR using CNN with a Regression Activation Map (RAM) layer. After the global averaging pooling layer their innovation is the RAM layer which helps the model to locate discriminative areas in the retinal images and provides insights into the severity of DR. Similar approaches have been proposed by the authors in [14-17].

III. PROPOSED SYSTEM

The proposed system, as demonstrated in Figure 1, first loads and preprocesses images from the dataset. It preprocesses the dataset images by retrieving them from the specified directories and converting them to grayscale, and it performs image alignment using a genetic algorithm and a reference image. It the transforms the aligned images into the RGB color space and adjusts their dimensions to 224×224 pixels. This is followed by a normalization that sets the pixel values in the range [0, 1]. A CAM and a global average pooling are applied after the VGG16 feature extraction. In the case of EfficientNetB0 feature extraction, only a global average pooling is applied. The features are then concatenated and the dense layer, the batch normalization and dropout layer are applied. The system is evaluated using metrics such as accuracy, precision, recall, and F1 score.

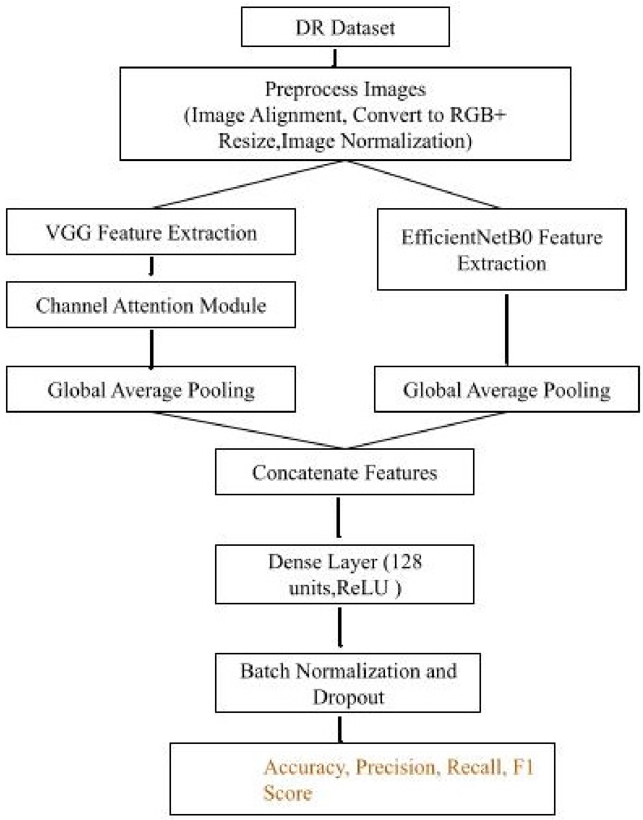


Fig. 1. The proposed system.

IV. METHODOLOGY

This section presents the overall proposal of the methodology of the system proposed in the previous section. This is shown in the following Algorithm 1.

```
Algorithm 1: Proposed methodology
Input: Eᵢₙ :  Raw image ( image for
alignment, image path, model input shape)
Output: Eₒᵤₜ: Model predictions (metric
scores)
```

```
Begin
//Initialize genetic algorithm parameters
Define fitness calculation function:
Fitness ← mean(image 1, image 2)
Matrix transformation: M′ ← transform_
matrix(M)
Generation of initial population: P′ ←
translate(M′, PS)
//Evaluation of fitness for population:
For each generation g ∈ {1,…,
num_generations} do:
   Find the fittest among the population
End
//Selection:
For I ∈ {1,…,polulation_size} do:
   probabilities ← normalize_fitness
   (fitness_scores)
End
Implement crossover and mutation.
Finalize population and apply
transformation: apply_transformation(img,
best_transformation)
//CAM:
For each feature_map in the model:
   avg_pool ← GlobalAveragePooling2D
   (feature_maps)
   avg_pool ← BatchNormalization(avg_pool)
   max_pool ← GlobalMaxPooling2D(feature_
   maps)
   attention ← σ(avg_pool + max_pool)
   output ← feature_maps × attention
End
//Model architecture (hybrid model):
Inputs ← Input(input_shape)
vgg_base ← VGG16(inputs), CAM
effnet_base ← EfficientNetB0(inputs)
concatenated_features ← BatchNormalization
(concatenated_features)
//Train the model:
model ← train(model,processed_images,
labels)
//Evaluate using precision, recall, and
F1-score:
E_out ← evaluate(model, metrics(precision,
recall, F1))
```

A. Dataset Preprocessing with Genetic Algorithm

This subsection focuses on the preprocessing of the dataset. The images of the dataset are aligned using a genetic algorithm and then normalized. They are converted to RGB and resized to 224×224.

1) Image Alignment using Genetic Algorithm

Uniform alignment of all images is an important task in medical image analysis, as it allows all images to be properly aligned, facilitating comparison and analysis. This alignment process can be performed efficiently using a genetic algorithm. The goal is to maximize the use of the transformed images while reducing image misalignments. The fitness function measures how well the transformed image $I(t)$ matches the reference image $I(r)$ by comparing the Mean Squared Error (MSE) between the two images. The number of iterations required is determined by the fitness function defined in (1).

$$\mathrm{Fitness}(I(t), I(r)) = -\frac{1}{N}\sum_{i=1}^{N}(I(t,i) - I(r,i))\text{^}2 \quad (1)$$

The genetic algorithm iteratively evolves a population of transformations $T = [t(x), t(y)]$ by applying crossover and mutation operations to generate new candidate transformations [18]. Figure 2 presents the steps of the genetic algorithm, where parameters such as population size are initialized, followed by fitness evaluation. Selection is followed by crossover and mutation of characters. After replacement with mutated factors, the process is terminated.

Fig. 2. Architecture of the genetic algorithm.

2) Dataset Normalization

This process involves modifying the images by resizing, standardizing, and aligning them. First, each image I is resized to a standard size (H, W) using bilinear interpolation, as shown in (2), to ensure consistent dimensions throughout the dataset.

$$I(\mathrm{resized}) = \mathrm{resize}(I, (H, W)) \quad (2)$$

Pixel value normalization is performed to rescale the intensity values within the range [0, 1], which helps to achieve faster convergence during the model training [19]. This is done by dividing each pixel value by the highest possible pixel value (255 for 8-bit images), as shown in (3).

$$I(\mathrm{normalised}) = \frac{I(\mathrm{resized})}{255.0} \quad (3)$$

B. Feature Extraction with Multi-Model Channel Attention

We further improve the feature extraction process for our proposed hybrid deep learning model, which adopts both VGG16 and EfficientNetB0 models, by incorporating multi-model channel attention. The CAM simply improves the essential channel by modifying its importance along the respective channel. This is accomplished using a global average pool followed by a global maximum pool over the feature maps. This is followed by common dense layers that are used to learn ways to reconstruct the responses of the features. We have incorporated this form of attention mechanism into the VGG16 model to potentially enhance its ability to pay even more attention to the regions in the images of the retina that appear to be more characteristic of DR.

1) VGG16

VGG16 uses a 3×3 gap convolution that remains constant across all layers of the network. It allows the identification of more detailed features and structures inherent in the images fed into the network. It has the following characteristics:

- Convolutional layers:

$$Z_{i,j,k} = \sum X_{i+m,j+n} \cdot W_{m,n,k} + b_k \tag{4}$$

where $Z_{i,j,k}$ is the output feature map, $X_{i+m,j+n}$ is the input feature map, $W_{m,n,k}$ are the filter weights, and b_k is the bias term.

- ReLU activation:

$$A_{i,j,k} = \max(0, Z_{i,j,k}) \tag{5}$$

where $A_{i,j,k}$ is the activation output.

- Dense layer:

$$F_i = g\left(\sum w_{ij} - x_j + b_i\right) \tag{6}$$

where F is the output vector, W is the weight matrix, X is the input vector, and b is the bias vector.

- Pooling Layers:

$$P_{i,j,k} = \max(A_{2i,2j,k}, A_{2i+1,2j,k}, A_{2i,2j+1,k}, A_{2i+1,2j+1,k}) \tag{7}$$

where $P_{i,j,k}$ is the pooled feature map.

- Fully connected layers:

$$F_i = \sum W_{ij} \cdot X_j + b_i \tag{8}$$

where F_i is the fully connected layer output, W_{ij} is the weight, and b_i is the bias term.

VGG16 is very effective for all types of image classification, such as DR, because it uses multiple small-sized convolutional layers. First, feature extraction is performed using these convolutional layers. Then, the class activation map is applied to the output of each of the convolutional layers to enhance the feature maps by highlighting the most informative channels. This model takes advantage of better features because the feature maps for the subsequent layers are rescaled as follows. Since the process of selecting primary features is aided by the morphology of the CAMs, feature extraction increases the ability of the model to detect salient features. As the model focuses on key channels, it becomes more accurate in diagnosing DR by identifying key diagnostic features. The architecture of the VGG16 with channel attention network is shown in Figure 3.

2) EfficientNetB0

EfficientNetB0 is a member of the EfficientNet model developed by Google. The primary advancement in EfficientNetB0 is the compound scaling method, in which the depth, width, and resolution of a simple network are uniformly scaled using a predefined set of scalars. This scaling also ensures that the networks are well optimized in terms of efficiency and performance for both large and small scales. By integrating compound scaling of EffNetB0 with MBConv blocks in conjunction with SE blocks, the design becomes both significantly more efficient and powerful enough for image classification:

- Convolutional layers:

$$Z_{i,j,k} = \sum X_{i+m,j+n} \cdot W_{m,n,k} + b_k \tag{9}$$

where $Z_{i,j,k}$ is the output feature map, $X_{i+m,j+n}$ is the input feature map, $W_{m,n,k}$ are the filter weights, and b_k is the bias term.

- MBConv block:

$$Z_{i,j,k} = \sum X_{i+m,j+n} \cdot W_{m,n,k} \tag{10}$$

- Swish activation:

$$\mathrm{Swish}(x) = x \cdot \sigma(x) \tag{11}$$

Adding attention mechanisms to models such as VGG16 with EfficientNetB0 increases the highly accurate detection and comprehensive classification of DR in the retinal images.

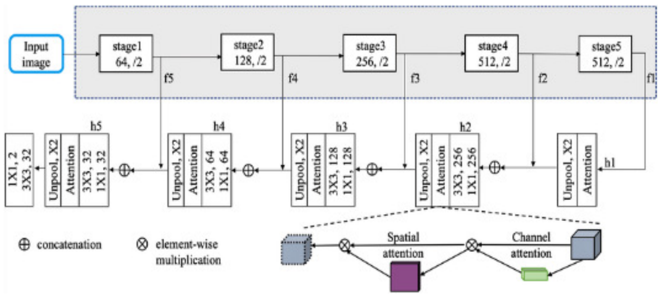


Fig. 3. VGG16 with channel attention network architecture.

3) Channel Attention

With the addition of channel attention, our proposed architecture of combining VGG16 and EfficientNetB0 increases the performance and efficiency of the model. To focus on the parts of the VGG16 feature maps that are most relevant to DR, our model applies the CAM only when needed. The importance of each channel is adjusted using global contextual data, and then the common dense layers are applied. The model emphasizes the most critical channels for feature identification and reduces the influence of irrelevant information. Although the structure is intentionally driven in some respects, the ability of the model to detect the subtle patterns and irregularities present in the retinal images is enhanced, thereby improving the diagnostic results and reliability. Therefore, incorporating channel attention increases the model's ability to differentiate between accuracy and robustness in diagnosing DR. The metrics used to evaluate the performance of the model are as follows:

$$\mathrm{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{12}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (13)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (14)$$

$$\text{F1 Score} = \frac{2*\text{Recall}*\text{Precision}}{\text{Recall+Precision}} \quad (15)$$

V. EVALUATION RESULTS

The dataset used in this study consists of a large, comprehensive database of a total of 2900 high-resolution retinal images acquired under various imaging settings to closely mimic real-life situations [20]. Each image in the dataset was medically reviewed to determine the presence or absence of DR. This grading is done using the binary grading system, where a score of 0 indicates the presence of DR and a score of 1 indicates the absence of DR. It provides high reliability and practically accurate ground truth data, which are important factors for training and evaluating the proposed deep learning models. Figure 4 shows randomly shuffled images selected from the dataset for the DR and no DR classes. Figure 5 shows a comparison of some random original images from the dataset with their aligned image using a genetic algorithm in RGB format and resized. When the attention mechanism was applied to the hybrid VGG16 and EfficientNetB0 model, the model achieved an accuracy of 95%. Table I shows the achieved evaluation metrics, and Figure 6 demonstrates the training and validation loss and accuracy, respectively. In addition, Figure 7 presents the ROC curve of the proposed multi-model.

The results provide a clear and comprehensive evaluation of how well our system can diagnose DR, and they indicate that the proposed system correctly distinguishes between positive and negative cases of DR. A graphical representation of the metric scores obtained by the proposed system is presented in Figure 8.

TABLE I. EVALUATION METRICS

Class	Precision	Recall	F1-Score	Accuracy
0	0.96	0.94	0.95	0.93
1	0.94	0.97	0.95	0.96

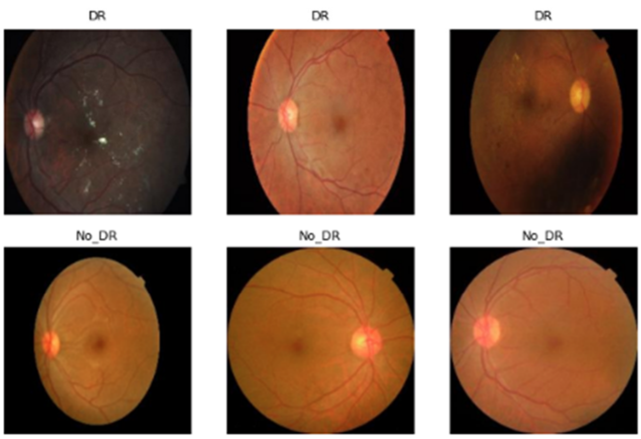


Fig. 4. Image samples from the dataset.

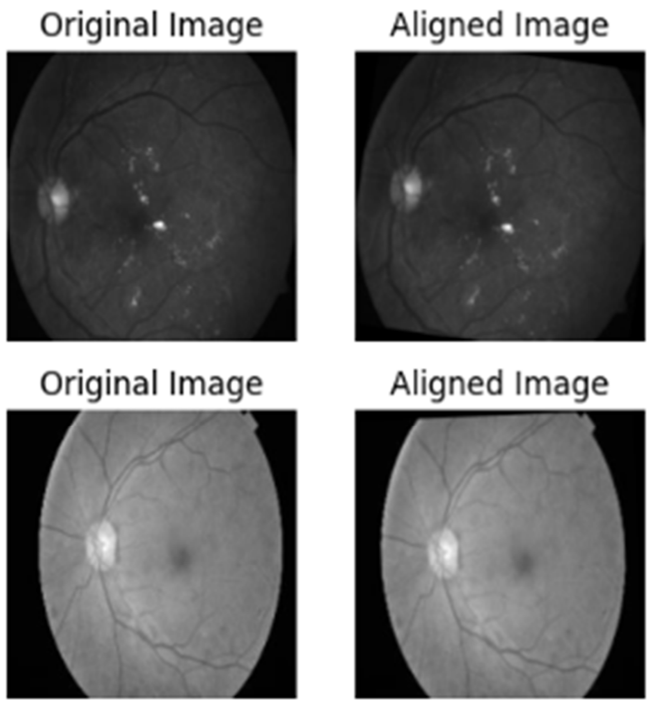
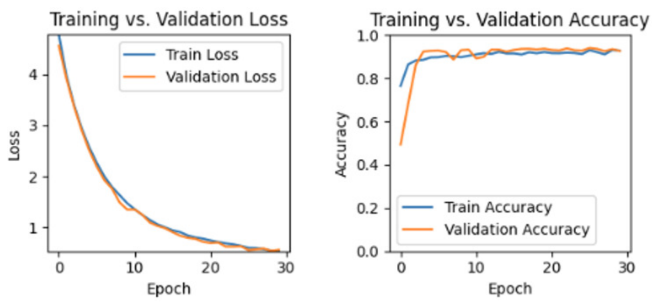


Fig. 5. Original and aligned images from the dataset.



(a) (b)

Fig. 6. Loss and accuracy graphs.

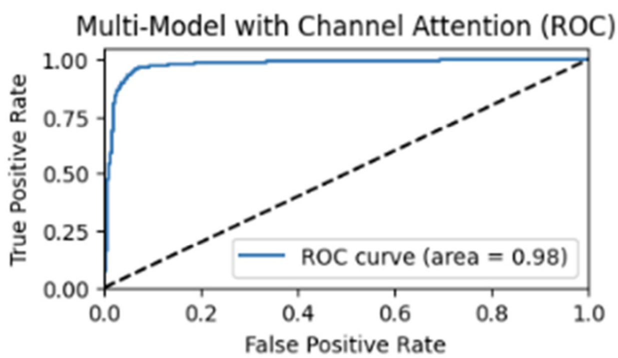


Fig. 7. ROC curve.

Table II and Figure 9 show a comparison of the metric scores obtained in previous research with the metric scores obtained with the proposed model.

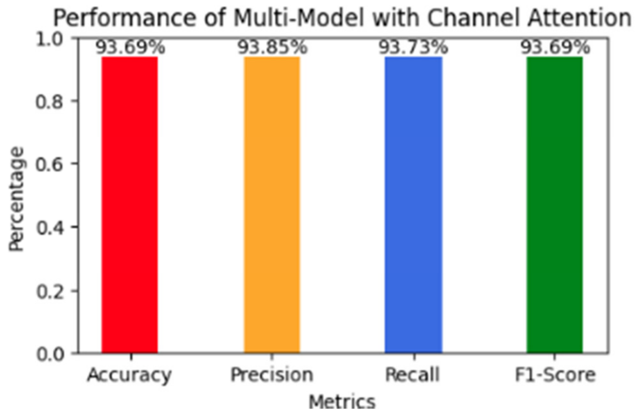


Fig. 8. Illustration of the metric scores obtained by the multi-model system with channel attention.

TABLE II. COMPARATIVE ANALYSIS

Study	Dataset	Model	Metrics
[14]	Retinal fund images	VGG16 and MobileNetV1	Accuracy: 93% Best performing algorithm: MobileNetV1
[21]	DDR	CNN512 and YOLOv3	Accuracy: 94.3% Best performing algorithm: CNN512 and YOLOv3
[22]	Diabetic macular edema DR images	CNN and VGG16	Accuracy: 94.3% Best performing algorithm: CNN
Proposed architecture	2900 high-resolution retinal images	Hybrid VGG16 and EfficientNetB0 model with multi-channel attention	Accuracy: 95% Best performing algorithm: Hybrid VGG16 and EfficientNetB0

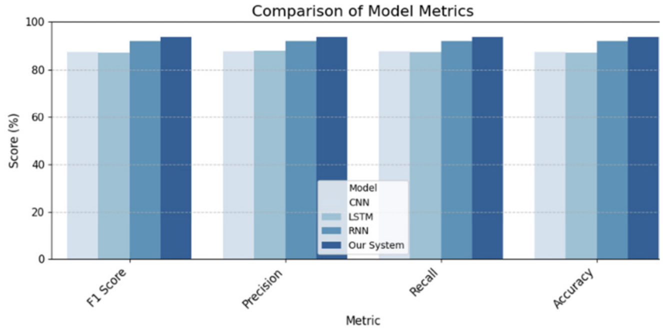


Fig. 9. Performance comparison of the proposed model.

VI. CONCLUSION

In the present study, a hybrid model has been proposed by combining VGG16 and EfficientNetB0 architectures, further enriched by adding a Channel Attention Module (CAM), which achieves remarkable results in the field of Diabetic Retinopathy (DR) detection, supported by the power of deep learning and artificial intelligence. It combines all the feature extraction capabilities offered by Convolutional Neural Networks (CNNs) and improves the classification, resulting in a high overall accuracy of 95%. The high diagnostic accuracy of the model is also characterized by good precision and recall scores in for both positive and negative cases. Such an approach describes how deep learning is slowly transforming the healthcare sector, especially eye health. This study can be further developed in the future to classify DR using additional datasets.

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