Performance Analysis of CNN Models in the Detection and Classification of Diabetic Retinopathy

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Abstract. This study focuses on investigating different CNN architectures and assessing their effectiveness in classifying Diabetic Retinopathy, a diabetes-associated disease that ranks among the primary causes of adult blindness. However, early detection can significantly prevent its debilitating consequences. While regular screening is advised for diabetic patients, limited access to specialized medical professionals can hinder its implementation. To address this challenge, deep learning techniques provide promising solutions, primarily through their application in the analysis of fundus retina images for diagnosis.

Several CNN architectures, including MobileNetV2, VGG16, VGG19, InceptionV3, InceptionResNetV2, Xception, DenseNet121, ResNet50, ResNet50V2, and EfficientNet (ranging from EfficientNetB0 to EfficientNetB6), were implemented to assess and analyze their performance in classifying Diabetic Retinopathy. The dataset comprised 3662 Fundus retina images. Prior to training, the networks underwent pre-training using the ImageNet database, with a Gaussian filter applied to the images as a preprocessing step. As a result, the Efficient-Net stands out for achieving the best performance results with a good balance between model size and computational efficiency. By utilizing the EfficientNetB2 network, a model was trained with an accuracy of 85% and a screening capability of 98% for Diabetic Retinopathy. This model holds the potential to be implemented during the screening stages of Diabetic Retinopathy, aiding in the early identification of individuals at risk.

Keywords: Diabetic retinopathy · Deep Learning · Classification · Detection · Convolutional neural network (CNN)

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1 Introduction

Diabetic retinopathy (DR) is caused by the long-term effects of diabetes. This is a common disease that was estimated, in 2020, to affect 103.12 million people worldwide, and by 2045 this number is projected to increase to 160.50 million [1].

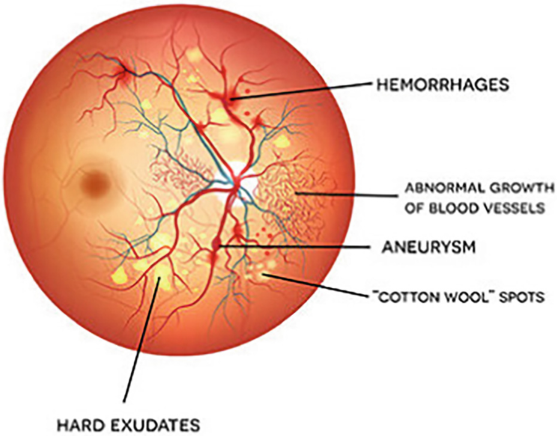

Fig. 1. Diabetic Retinopathy diagram. Image source: [24]

Diabetic retinopathy is characterized by high levels of glucose in the bloodstream causing the vascular formation of retinal microaneurysms and hemorrhages (Fig. 1), complications that may lead to cotton wool spots, hard exudates and tractional retinal detachment [25]. It is a serious public health problem being the leading cause of blindness. However, it is possible to prevent vision loss, with timely interventions and early detections, achieved by performing regular eye screenings.

The diagnosis is typically conducted by an ophthalmologist who classifies its severity into five stages (Fig. 2), according to the Diabetic Retinopathy Severity Scale [2]. DR screening is performed through fundus photography that captures the images of the retina, optic nerve head, macula, retinal blood vessels, choroid, and the vitreous [26]. Although fundus cameras have become more accessible in primary hospitals, a shortage of experienced ophthalmologists capable of conducting regular screenings, as recommended (at least annually) [3], remains a challenge. Consequently, there is a growing need for automated techniques, such as Deep Learning, to assist in DR diagnosis. The development of Deep Learning applications, in a variety of clinical settings, plays a critical role for accurate DR detection and classification. It can assist DR referrals and slow down the disease progression of patients in remote or poor areas. It can also assist clinicians in confirming their diagnosis [12].

This study aims to compare the performance of Deep Learning models for diabetic retinopathy detection and classification.

Fig. 2. Five classes according to the Diabetic Retinopathy Severity Scale. The first stage (No DR) corresponds to a healthy patient while Proliferative DR is the end-stage of advanced diabetic eye disease with vision-threatening complications.

1.1 Literature Review

The field of DR detection and classification has witnessed significant advancements through Machine Learning (ML) and Deep Learning (DL) techniques, with several noteworthy studies contributing to this progress. Giroti et al. [8], Dutta et al. [5], Revathy [6], Zhang and Nabil [9] and Alabdulwahhab et al. [4] harnessed ML and DL to address the need for automation in DR diagnosis.

Alabdulwahhab et al. [4] conducted a significant study focusing on ML techniques for DR classification. Their research aimed to address challenges in DR screening, including high patient volume and limited resources. They employed various ML algorithms, achieving 86% accuracy with the ranger random forest classifier.

In a parallel effort, Revathy [6] utilized a machine learning approach, emphasizing crucial feature extraction. Their dataset of 1000 Kaggle-sourced images underwent preprocessing, including color space conversion and filtering. For classification, they employed a hybrid approach that integrated Support Vector Machine (SVM), K Nearest Neighbors (KNN), Random Forest, Logistic Regression, and Multilayer Perceptron Network, achieving a testing accuracy of 82%. This approach demonstrates ML and image processing potential in enhancing DR detection.

Dutta et al. [5] proposed an automated knowledge model that leveraged a range of deep learning models, encompassing backpropagation Neural Networks (NN), Deep Neural Networks (DNN), and Convolutional Neural Networks (CNN). Significantly, their deep learning models outperformed the conventional NN model, underscoring the importance of intricate neural architectures for feature quantification. Furthermore, Dutta et al. [5] highlighted the significance of image preprocessing, including grayscale conversion and noise reduction through filters, which notably improved their results.

Similarly, Giroti et al. [8] conducted thorough data preprocessing, involving resizing, cropping, noise reduction, and feature detection, to enhance image quality and emphasize critical features. Their approach incorporated the EfficientNet model, aiming for an ambitious accuracy range of 87-95%. This research holds pivotal significance as it addresses the imperative need for automation in DR

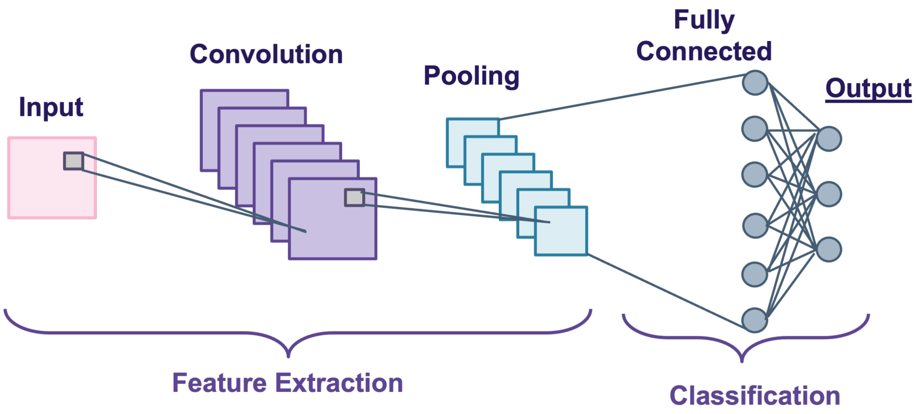

Fig. 3. Convolutional Neural Networks Diagram.

diagnosis, given the expected surge in data volume and limited availability of highly skilled professionals.

Additionally, Zhang and Nabil [9] introduced two distinct solutions to the challenge of Diabetic Retinopathy (DR) classification. In their initial approach, they introduced a shallow neural network architecture, which performed admirably in classifying the most frequent classes but faced challenges with less frequent ones. In their second approach, they leveraged a transfer learning-based method, employing the Efficientnet-B3 architecture, which significantly outperformed their shallow neural network architecture, particularly in classifying less frequent DR categories. This research underscores the superiority of transfer learning and the significance of utilizing pre-trained models on extensive datasets. It offers compelling advantages in improving DR classification accuracy, even for classes with limited representation in the dataset.

Of particular interest is the EfficientNet model, which has emerged as a standout performer in this field. EfficientNet not only achieves remarkable accuracy but also operates with exceptional efficiency, surpassing the capabilities of traditional Convolutional Neural Network (CNN) architectures [8,9,20]. This demonstrates its capacity to address the intricate challenges associated with DR diagnosis.

2 Methods

For the performance analysis of using Deep Learning in the detection and classification of diabetic retinopathy, there were trained and tested 16 Convolutional Neural Networks (CNN) models.

The CNN architectures are specifically designed to process and analyze visual data, such as images. This is possible due to their ability to accept 2D arrays as input. Their inspiration came from the human visual system [7]. Similarly, to the human visual system, CNNs are designed by multiple layers in a hierarchical manner. Their architectural concept is based on layers that apply convolutional operations, which involve sliding small filters across the input data to extract and learn relevant features. For this reason, the convolution layers are often referred to as "the feature extraction layers" of the network, while the remaining part of the network is responsible for classification (Fig. 3) [7].

2.1 Dataset

The dataset comprises 3662 publicly available retina fundus images sourced from the Kaggle APTOS 2019 Challenge, ranking as the third-largest dataset for Diabetic Retinopathy (DR) [7]. These images were collected at Aravind Eye hospital in India's rural areas and every subject is represented by images of both their right and left eyes [8]. The data was captured from a variety of equipment operated by different professionals, under various non-typical conditions. Consequently, the dataset exhibits variability in terms of image size, brightness, and, occasionally, focus. All these factors contribute to noise which causes difficulties for the algorithms to accurately classify DR. Precisely to reduce the noise from the dataset, and to achieve better color constancy, a Gaussian filter was systematically applied to all images [9]. The images were also resized into 224×224 pixels so that they can be readily used with pre-trained deep-learning models. Samples of the outcome of the pre-processing procedure are depicted in Fig. 4. Nevertheless, considering the presence of low-quality images that accurately represent the actual data, the algorithm can be effective in practical clinical applications [10].

Every image is annotated and sorted according to the stages of DR (Fig. 5). One limitation of this dataset is the large class imbalance, especially between the "No DR" and all the other classes (Fig. 6). This will heavily influence the capacity of the model to correctly classify the stages of diabetic retinopathy. The dataset was partitioned into three distinct subsets, training, validation, and testing, in order to facilitate the respective stages of model development and evaluation, as seen in Fig. 7. This procedural step has significant importance as it ensures impartial evaluation and mitigates the risk of overfitting.

2.2 CNN Architectures

In this study, a total of 16 Convolutional Neural Network (CNN) models were trained and evaluated, each employing a distinct architecture. The applied architectures were the following:

MobileNetV2. Is a network with the aim to optimize CNN architecture for mobile and embedded devices by creating a compact, power-efficient design that maintains high performance [13]. This was achieved by implementing'depthwise separable convolution,' which decomposes the standard convolution into two distinct layers: depthwise convolution and pointwise convolution. The primary objective of testing this network was to assess whether a "lightweight" network could achieve satisfactory results in the classification of diabetic retinopathy.

VGG16 and VGG19. Are CNN models comprising 16 and 19 layers, respectively, which consist of repeated sequences of 3×3 convolutional and 2×2 pooling layers. Their uniform structure simplifies model comprehension and implementation, making them widely used choices for image classification and feature extraction [10,14].

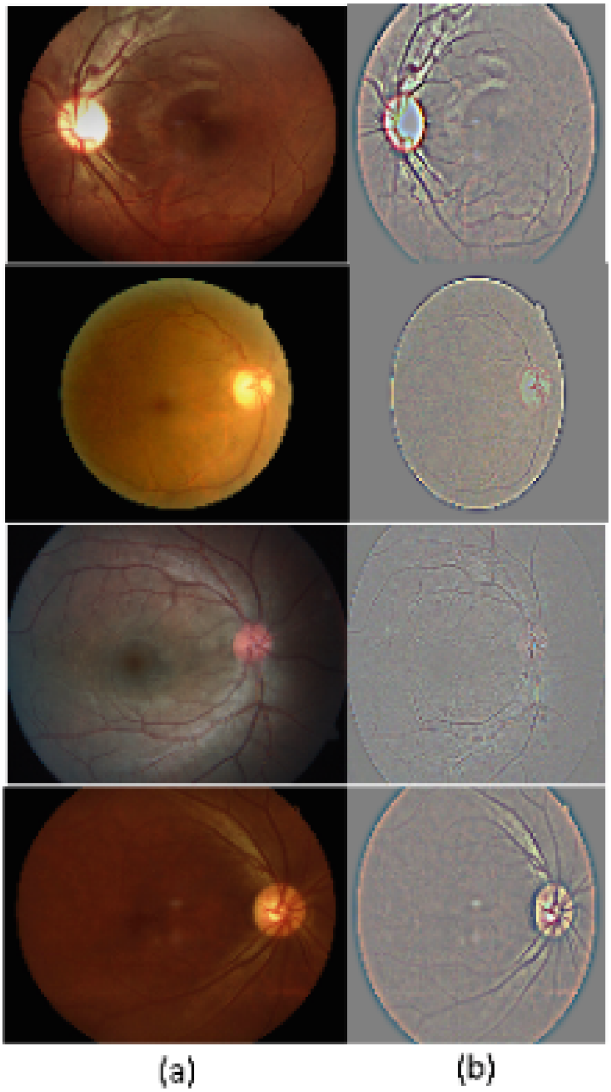

Fig. 4. (a) Sample of fundus image from APTOS 2019; (b) Corresponding sample, processed with a Gaussian filter and resized to dimensions of 254×254 pixels.

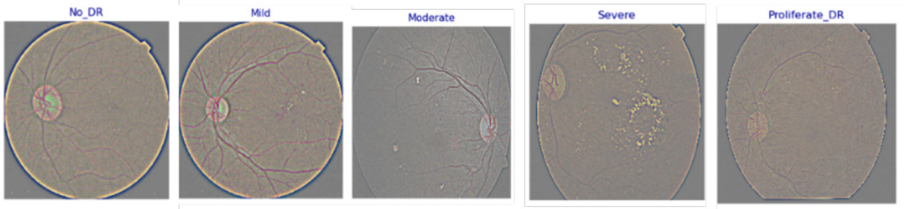

Fig. 5. Sample images from dataset after Pre-processing

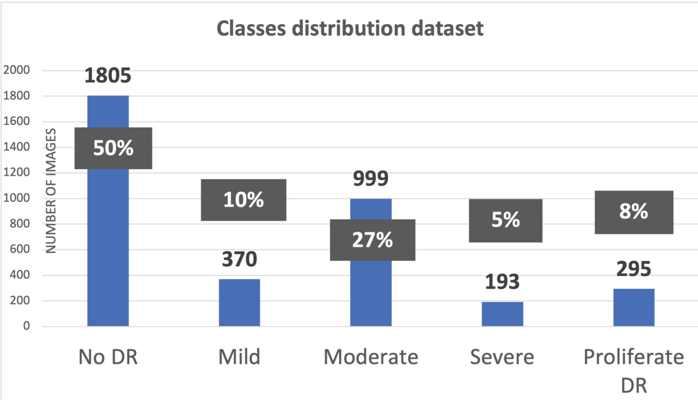

Fig. 6. Visual representation of classes distribution of the dataset; There are 3662 images in total, in which the No DR represents close to 50%.

InceptionV3 and InceptionResNetV2. Both architectures are based on inception modules, comprising parallel convolutional layers with various filter sizes, enabling multi-scale and multi-level feature extraction. InceptionResNetV2 goes a step further by incorporating residual connections [15]. While achieving strong performance, InceptionResNetV2 can demand more computational resources compared to InceptionV3 [11].

Xception. Short for "Extreme Inception", enhances the Inception architecture by employing depthwise separable convolution. This innovative approach separates spatial and channel-wise features [16], reducing parameters and operations, leading to faster training and inference. It enables the network to capture fine-grained spatial details while maintaining expressive power.

DenseNet121. Was developed to enhance information flow and parameter efficiency in deep CNNs by introducing densely connected blocks [17], where each layer connects to every other layer using "skip connections" in a feed-forward manner. It also employs bottleneck layers with 1×1 convolutions to reduce model complexity, achieving a balanced trade-off between complexity and performance.

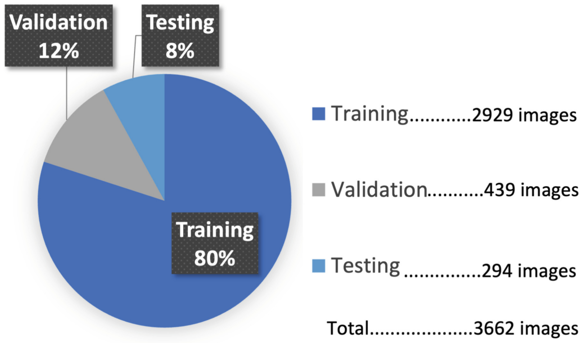

Fig. 7. Visual representation of the percentage of data splitting of the dataset.

ResNet50 and ResNet50V2. ResNet50 was developed to address the problem of vanishing gradients in deep neural networks by introducing skip connections. These connections facilitate gradient flow throughout the network, enabling the model to learn meaningful representations and enhance performance [18].

ResNet50V2, an improved iteration of ResNet50, incorporates enhancements like the pre-activation variant of residual blocks, adjusted layer ordering, and diverse weight initialization schemes for improved performance [19].

EfficientNet: EfficientNetBO to EfficientNetB6. EfficientNet was designed to improve accuracy and efficiency in image classification by employing compound scaling, which uniformly scales network width, depth, and resolution. This approach acknowledges that larger input images necessitate increased depth for capturing broader spatial information and increased width for finer pattern details [20].

In this study, seven variants of EfficientNet, ranging from EfficientNetB0 to EfficientNetB6, were trained and tested, differing primarily in network scale. EfficientNetB0 is the smallest with fewer parameters, while EfficientNetB6 is the largest variant with the most parameters. Scaling from B0 to B6 increases depth, width, and resolution, enhancing model expressiveness. However, this larger scale also demands higher computational resources.

Overall, EfficientNet has revolutionized the design of convolutional neural networks, providing a scalable and efficient solution for image classification tasks. Its wide adoption and impressive performance have solidified its position as a main choice for researchers and practitioners in the field of deep learning [21–23].

2.3 Model Training

Transfer Learning. In this study, to overcome the challenge posed by limited data, resulting in class imbalance, it is employed a technique known as transfer learning [9]. Transfer learning is a technique that enables the transfer of knowledge acquired from one task to improve learning in another task, even if the

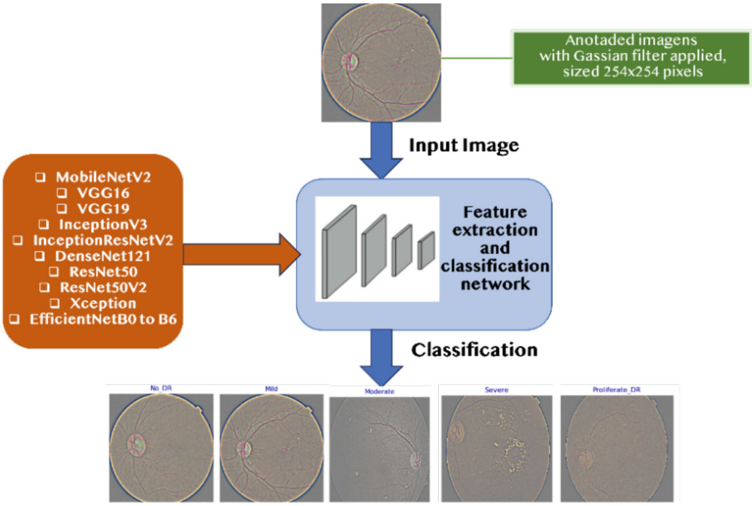

Fig. 8. Diabetic Retinopathy classification model.

domains differ [7]. In this approach, a pre-trained model, originally trained on the diverse ImageNet dataset, was fine-tuned for the task of diabetic retinopathy classification from fundus images, leveraging its high-level representations and feature extraction capabilities.

Fine-Tuning. For the performance analysis and comparison of CNN architectures in the classification of diabetic retinopathy, the model involved inputting already pre-processed data (Fig. 5, fundus images with a Gaussian filter applied and resized to 254×254 pixels) into a pre-trained feature extraction and classification network (Fig. 8). The model has trained with 80% of the dataset, validated with 12%, and tested with 8% (Fig. 7). For training the model, the batch size was set to 32 and was set for 40 epochs, however, the training would stop if there was no notable improvement after making three adjustments to the learning rate.

Evaluation Metrics. To evaluate the performance of the model, several metrics were utilized, including the calculation of the confusion matrix, accuracy, and F1-score. The confusion matrix provides insights into the classification results, showcasing the number of true positives, true negatives, false positives, and false negatives. Accuracy measures the overall correctness of the model's predictions, while the F1-score assesses the model's balance between precision and recall. These metrics collectively provide a comprehensive assessment of the model's performance in classifying diabetic retinopathy (DR).

3 Results and Analysis

In this study, were trained multiple CNN models to identify the most accurate architecture classifier for diabetic retinopathy. To determine the model that achieves the highest classification performance in DR classification, were employed a range of evaluation metrics, including accuracy, to assess the performance of each model.

Accuracy. In the context of this research, accuracy measures the ability of the trained models to correctly classify diabetic retinopathy cases compared to the ground truth labels. A higher accuracy value would indicate, in general, a more reliable classification performance.

The Table 1 presents the accuracy results obtained for each model, as well as the number of parameters. The experimental results confirm that, similar to the state-of-the-art studies discussed earlier, the EfficientNet networks consistently achieve the highest accuracy scores among the models tested [8,9]. EfficientNetB5 and EfficientNetB2 emerge as the top performers, achieving accuracy rates of 85.37% and 84.69%, respectively. It is worth noting that EfficientNetB2 achieves accuracy close to EfficientNetB5, with 3,6 times fewer parameters. As expected, MobileNetV2 performs poorly with only 56% accuracy.

In the performance graph (Fig. 9), it is visually evident that the EfficientNet networks achieve better accuracy results while utilizing fewer parameters. The densenet121 network also stands out, as it achieves a considerable accuracy value while using a low number of parameters, although it never surpasses the efficiency of the EfficientNet.

From the 294 images of the testing set, 50% of the images belong to the “no DR” class, with only 5% and 10% belonging to the “Severe” and “Proliferate DR”, respectively (Fig. 10). Due to the highly imbalanced nature of class distribution on the dataset, evaluating performance with accuracy alone will not provide much information about the individual class-wise performance of the model in diabetic retinopathy classification. Therefore, confusion matrices were generated to gain insights into the model’s performance for each specific class.

Confusion Matrix. In the context of this study, the confusion matrix will help understand how well the model is able to correctly identify different levels of retinopathy severity because it allows analyzing the distribution of correct and incorrect predictions across the classes.

By examining the confusion matrix (Fig. 11), it becomes apparent that the models are accurately classifying the most prevalent class, “No DR”. However, they fall short of achieving comparable results for the less frequent classes such as “Severe”, “Mild” and “Proliferate DR”.

F1-Score. To assess the overall effectiveness of the models in accurately classifying diabetic retinopathy, it was analyzed the f1-score of each individual class.

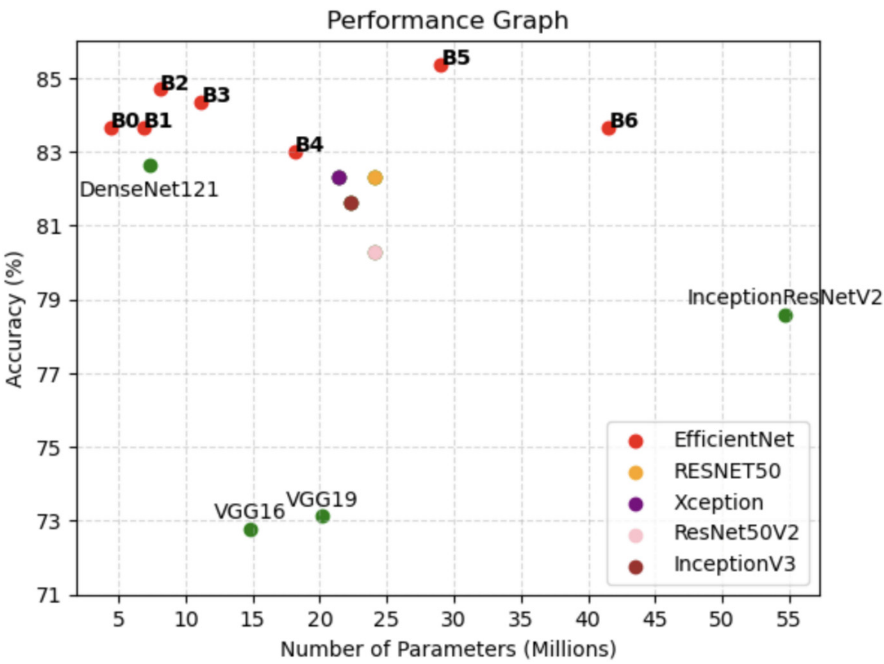

Fig. 9. Model size vs Accuracy; EfficientNet stands out as the best performance overall

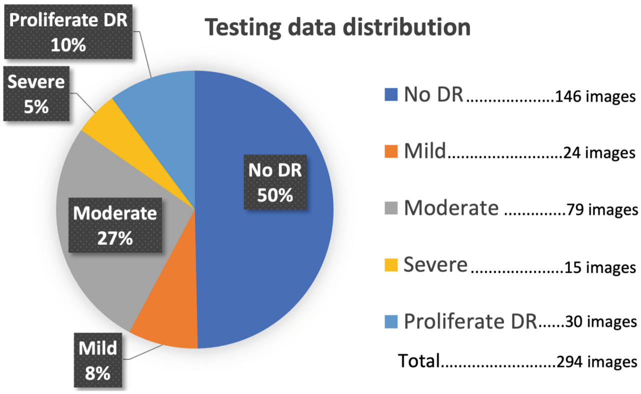

Fig. 10. Visual representation of classes distribution of the testing dataset; There are 294 images in total, in which the No DR represents 50%.

Table 2 displays the f1-score values for each class obtained by the different models. It confirms the observations made in the confusion matrices, where the models performed well in classifying the most represented class, "No DR", with the EfficientNetB6 model achieving an f1-score of 0.99. For the least represented

Table 1. Performance of the classification models: Accuracy and Number of Parameters

Architecture	Accuracy(%)	Number of Parameters(Millions)
EfficientNetB5	85,37	29,05
EfficientNetB2	84,69	8,14
EfficientNetB3	84,35	11,18
EfficientNetB0	83,67	4,38
EfficientNetB1	83,67	6,91
EfficientNetB6	83,67	41,56
EfficientNetB4	82,99	18,14
DenseNet121	82,65	7,31
RESNET50	82,31	24,12
Xception	82,31	21,49
InceptionV3	81,63	22,34
ResNet50V2	80,27	24,10
InceptionResNetV2	78,57	54,74
VGG19	73,63	20,16
VGG16	72,79	14,85
MobileNetV2	56,12	2,59

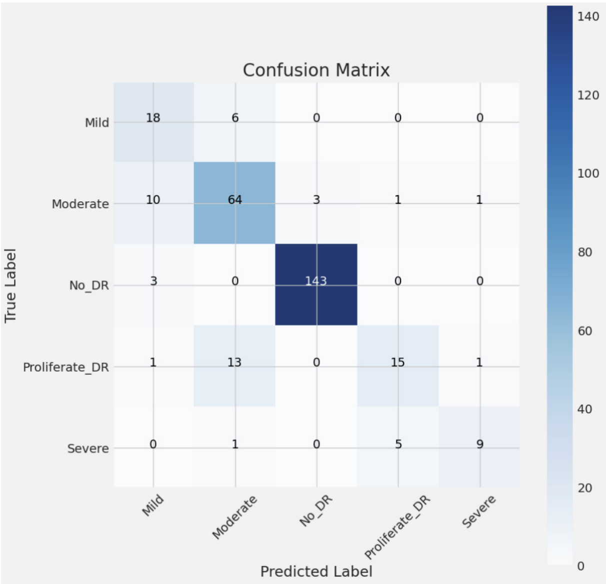

Fig. 11. Confusion Matrix of the model EfficientNetB2; The diagonal line indicates that its prediction is the same as the true value, and the more accurate the predictions are, the darker the color.

Table 2. F1-score values for each class obtained by the models

Architecture	No DR	Mild	Moderate	Severe	Proliferate DR
EfficientNetB5	0,98	0,62	0,82	0,43	0,68
EfficientNetB2	0,98	0,64	0,79	0,69	0,59
EfficientNetB3	0,98	0,60	0,78	0,55	0,65
EfficientNetB0	0,98	0,63	0,78	0,72	0,47
EfficientNetB1	0,98	0,62	0,77	0,64	0,60
EfficientNetB6	0,99	0,61	0,77	0,48	0,61
EfficientNetB4	0,98	0,62	0,77	0,45	0,57
DenseNet121	0,98	0,58	0,78	0,48	0,49
RESNET50	0,97	0,60	0,77	0,57	0,47
Xception	0,97	0,59	0,78	0,61	0,45
InceptionV3	0,98	0,53	0,76	0,57	0,42
ResNet50V2	0,96	0,54	0,75	0,59	0,39
InceptionResNetV2	0,96	0,52	0,52	0,55	0,21
VGG19	0,96	0,08	0,66	0,00	0,00
VGG16	0,95	0,31	0,65	0,00	0,00
MobileNetV2	0,81	0,31	0,20	0,00	0,14

class, "severe", the best f1-score is 0.72, achieved by the EfficientNetB0 model. The class with the lowest classification performance is "Mild", with the highest f1-score of 0.64 obtained by the EfficientNetB2 model.

Overall, the EfficientNetB5 and EfficientNetB2 models demonstrate superior performance in DR classification, as indicated by the f1-score values.

4 Conclusion

In conclusion, it can be stated that the models trained with the EfficientNet architecture achieve the best performance results with a good balance between model size and computational efficiency. Among the trained models, EfficientNetB2 demonstrates the best performance. It achieves higher overall accuracy and more specific classification for each class while utilizing a smaller number of parameters, making it the most efficient and effective model for the classification of diabetic retinopathy.

Although the models excel in classifying individuals without DR, achieving an accuracy rate of approximately 97% across all trained networks, addressing the classification challenges for less represented classes such as "Severe" and "Proliferate DR" remains a priority for future research.

Furthermore, to ensure the practical applicability of these models in clinical settings, collaboration with healthcare professionals is essential. Integrating these AI-driven solutions into clinical workflows offers a valuable solution for accurate early disease screening, particularly in cases of a deficiency of specialized doctors. Such collaborations can significantly contribute to preventing visual impairment in diabetic individuals, as DR remains one of the leading causes of blindness in adults.

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