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Enhancing Diabetic Retinopathy Detection using Transfer Learning

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Abstract - Diabetic retinopathy (DR) is a visual disease caused by hyperglycemia that can lead to blindness. The early detection of this disease is crucial to prevent and avoid serious and permanent complications. In this context, machine learning techniques and deep learning have proven to be a promising solution to address this pressing issue. However, there are currently no optimal techniques offering the best performance. Our work is within this context and represents an interesting contribution to the early detection of DR. In this paper we propose a new model based on deep learning by using transfer learning to achieve an efficient detection of DR. We have trained our proposed model on two different datasets, EyePACS and APTOS, and evaluated it using image pre-processing techniques. Our model significantly outperforms previous approaches in terms of accuracy, F1_score and Recall.

Keywords – Deep Learning, Transfer Learning, Diabetic Retinopathy (DR), Convolutional Neural Networks (CNN), Diabetic Retinopathy Detection.

I. INTRODUCTION

Diabetic retinopathy (DR), commonly known as the diabetic eye disease, is the leading cause of sight loss among mid-aged diabetic population. Globally, the third of diabetic patients have a form of DR. DR damages Blood vessels (BV) causing fluid leakage within the retinal tissue and or abnormal BV growth on the surface of the retina [1]. In Figure 1 the fundus image on the left depicts the normal retina condition, and the fundus image on the right depicts a retina with diabetic retinopathy symptoms [2].

Unfortunately, once DR reaches a severe stage, the damages are irreversible, which typically results in partial or total vision loss [3]. To preserve the patient's vision and prevent disabilities, early and accurate detection of the disease is urgently required [3,4]. The widespread prevalence of diabetes and diabetic retinopathy has resulted in significant costs and a

heavy workload for specialists. Hence, there is a pressing need for automated and precise methods to enable early detection of DR. Indeed, with automated technics, the efficiency of both diagnosis and treatment would be enhanced. Moreover, this would reduce the burden on specialists and improve the quality of patient care [3].

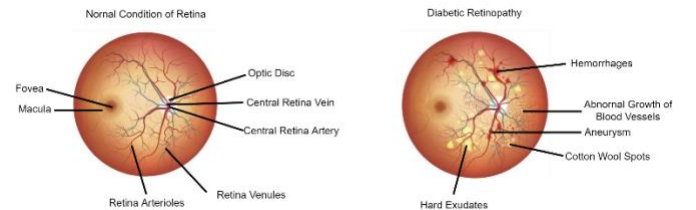


Figure 1 Illustration of the entire retina image. [2].

The detection of Retinopathy requires automatic classification of fundus images, and machine learning (ML) has emerged as the preferred approach for this task [5]. Image classification necessitates a preceding segmentation phase, which enables the extraction of distinctive features for pathology recognition. Indeed, traditional machine learning approaches do not inherently support image segmentation, often requiring ophthalmologists to manually extract features from images prior to utilizing them. In recent years, Deep Learning (DL) has emerged as a promising solution to address these limitations. Specifically, convolutional neural networks (CNNs), a type of DL technique, have gained significant popularity. CNNs have the ability to automatically extract relevant features from images without the need for manual intervention. However, it is important to note that CNN-based methods require a substantial amount of labeled images for training, validation, and testing, as well as a considerable time for model training [6]. To address these limitations, transfer learning which consists of pre-trained networks, has been widely adopted in image segmentation. Transfer learning

utilizes a pre-trained model as a basis for constructing a new model, facilitating the transfer of pre-existing weights to the classification task. This approach offers significant benefits, including accelerated training and reduced data requirement.

Model-based transfer learning for neural networks has two stages. The first one is to pre-train the network using reference datasets, such as ImageNet, and the second to refine the pre-trained network using specific target datasets related to the specific medical imaging task. The first stage is used for segmentation and the second one for the classification.

In this paper, we have built a new model based on transfer learning and a multilayer CNN for DR classification to improve the accuracy.

To determine the best classifier, we experienced four transfer learning architectures: Vgg16, Resnet50, Xception, and InceptionV3. Two distinct datasets, EyePACS and APTOS, were used to train and evaluate the models. Experimental results reveal that the ResNet50 classifier achieves superior performance in binary classification. It surpasses previous approaches in terms of accuracy, F1 score, and recall, highlighting its effectiveness in detecting diabetic retinopathy.

The rest of the paper is organized as follows: the related works is presented in Section II where we provide an overview of recent research on DR detection and their results. Section III describes our proposed methodology. Section IV presents a detailed discussion of the obtained results and the comparison with other methods. Finally, in Section V, we summarize the conclusions drawn from our study.

II. RELATED WORKS

The detection and diagnosis of diabetic retinopathy (DR) have been extensively studied in the literature. Several research works have proposed various approaches that tackled the DR detection challenges [3,5,8,9].

In [7], the authors have used traditional machine learning (ML) approaches to diagnose DR. Although these approaches showed promising results, they still required the involvement of healthcare professionals. This was impractical given the high prevalence of diabetes.

However, in recent years, Deep Learning (DL) techniques have emerged as a solution to overcome these limitations. A comprehensive review in [9] summarizes various research works that have explored the application of DL techniques in the detection and diagnosis of DR.

In a study conducted by M. T. Esfahan et al. [10], a convolutional neural network (CNN) architecture was proposed for binary classification of fundus images from the EyePACS dataset [12]. The architecture incorporated the pretrained ResNet34 model [11]. The 35000 images used in this study were preprocessed to enhance their quality. The authors reported a sensitivity of 86% and an accuracy of 85% for their proposed model.

K. Xu et al. [13] proposed a CNN technique for binary classification in the detection of diabetic retinopathy (DR). The authors utilized the EyePACS dataset with 1000 images.

Preprocessing techniques such as data augmentation and resizing were applied. The model achieved 94% accuracy.

Kaushik et al. [14] developed a stacked model composed of three CNN models. The model achieved a high binary classification accuracy of 97.92% when evaluated on the EyePACS dataset. The images were preprocessed in two ways: normalization and data augmentation.

MR Islam et al. [16] used a CNN architecture based on Xception [17] to classify images as normal or DR. To enhance the image quality before the training phase, the authors employed the Contrastive Limited Adaptive Histogram Equalization (CLAHE) method to preprocess a total of 5590 images from the APTOS 2019 [18] and Messidor-2 [19] datasets. The proposed CNN model achieved remarkable performance, with an accuracy of 98.36% and an area under the curve (AUC) score of 98.50% for binary classification.

III. METHODOLOGY

Our proposed approach aims to achieve an early detection of retinopathy disease. As shown in Figure 2, it is composed of:

- a pre-processing phase,
- a pre-trained network such as VGG16, Inception, Resnet%0 and Exception, for a segmentation
- A Neural Network for a classification

Initially, each image from the dataset is preprocessed before inputted into the pre-trained network to extract relevant features. These extracted features are then fed into the neural network which we have defined and connected to the pre-trained models. This network comprises fully-connected layers that enable us to predict the probability of disease occurrence. Further details of these phases are described in the following subsections.

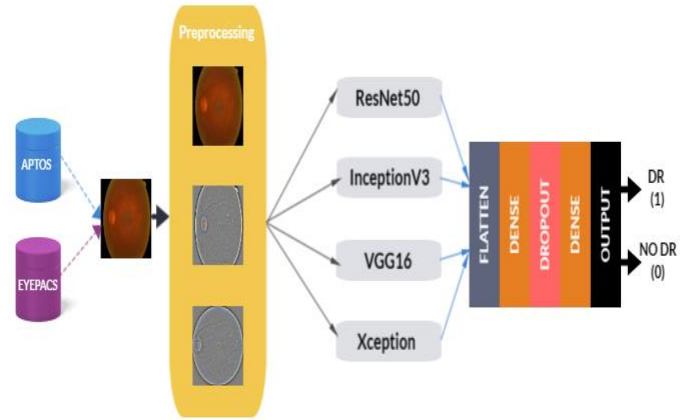


Figure 2 Schematic Diagram of the Proposed Approach

A. Data Description

All the models, we have developed are trained using the APTOS [18] and EYE PACS [12] datasets, which contain 3662 and 88507 images, respectively. Both datasets are divided into five classes: No DR (0), Mild (1), Moderate (2), Severe (3), and

Proliferative DR (4), The number of images for each stage of infection is presented in Table 1.

	0	1	2	3	4	TOTAL
APTOS	1805	370	999	193	295	3662
EYEPACS	65343	6205	13153	2087	1914	88702

As mentioned before, our objective is to detect retinopathy in its first stage. To achieve this, we specifically focused on differentiating between two classes: class 0, which indicates the absence of DR, and class 1, which represents the presence of DR. So, we combined all the other classes (1, 2, 3, 4) into a single class. This consolidation resulted in a balanced distribution of data among the classes, eliminating the need for data augmentation. Figures 3 and Figure 4 show the number of images obtained for each class after the aggregation process.

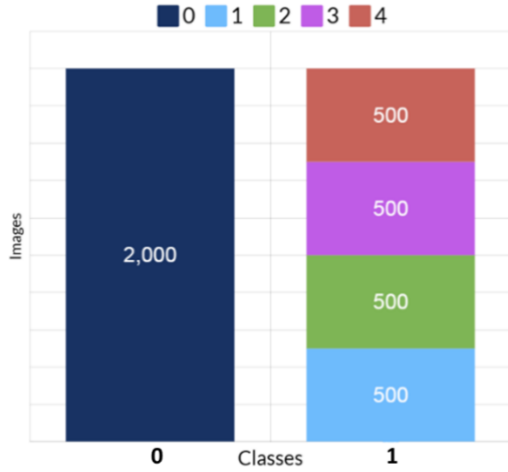


Figure 3 EyePacs dataset after aggregation step.

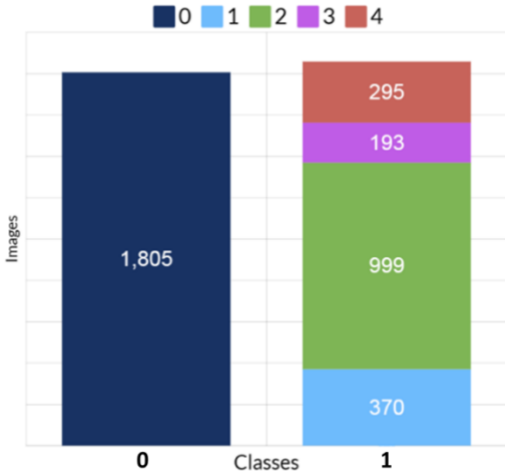


Figure 4 APTOS dataset after aggregation step.

B. Preprocessing

Due to the large volume of data and the variation in image quality and sizes, it is necessary to apply pre-processing techniques to resize the images and emphasize relevant features

that aid in the identification of diabetic retinopathy (DR). The preprocessing includes resizing and enhancing image quality.

B.1 Resizing the images

Due to the diverse sources and time periods of image collection in the datasets, the images exhibit variations in terms of size and storage memory. To ensure optimal performance during the training and evaluation processes, we have employed a normalization technique to resize all the images to a standardized dimension of 224x224 pixels.

B.2 Grey Scale & Gaussian Blur

In order to improve the performance of the training model, it is crucial to enhance the quality of the images and make their features easily extractable. Initially, we converted the color images to grayscale images, simplifying subsequent analysis. Then, we applied a Gaussian blur filter to reduce image noise and improve its clarity. Subsequently, we have used weighted masking to sharpen the edges of the image obtained after gaussian blur [1].

B.3 Circle Crop

In order to enhance the learning performance of the model, we implemented a circular cropping technique. It aimed to remove unnecessary black pixels, representing the background, and focus solely on the relevant region containing the eye's fundus. To apply circular cropping, we used a mask on the image to keep only the pixels inside the circle and eliminate the rest [1].

After applying the preprocessing step, the quality of the images has been significantly improved in comparison to the original images (see Figure 5).

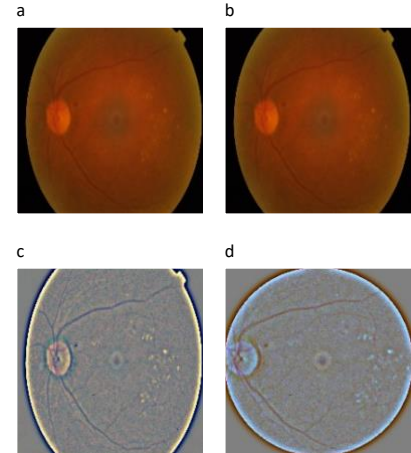


Figure 5 Preprocessing phases : (a) original image. (b) Resized image. (c) filtered image. (d) Circle cropped image.

C. Proposed Architecture

The proposed Architecture, uses the pre-trained models for the convolution part to extract features from the input images. These features are then flattened into a one-dimensional vector. This vector is then fed into a series of fully connected dense layers. Specifically, there are three dense layers: the first one is composed of 1024 neurons and ReLU activation, followed by a dropout of 0.3 to prevent overfitting.

The second dense layer is 512 neurons and ReLU activation. The last one has two neurons, utilizes sigmoid activation. The sigmoid function allows the classification of images into either class 0 or class 1.

IV. RESULTS

The experiment was conducted using the Python environment on a server equipped with an Intel(R) Xeon(R) CPU @ 2.20GHz processor, 13 GB of RAM, and a GPU P100 16GB provided by Kaggle platform. The hyperparameters used in this experiment includes batch size, base learning rate, dropout rate, epoch size, and number of iterations, as presented in Table 2.

Table 2 Model's Training Hyperparameters

Parameters	Value
Validation set	20% of dataset
Test set	30% of Validation set
Image size	224x224
Batch size	32
Warmup epochs	5
Warmup learning rate	0.00001
epochs	30
Learning rate	0.0001
Weight decay	0.02
Early stopping patience	15
Reduce learning rate patience	5

The experiment conducted in this study involved the evaluation of all four models using two distinct datasets to assess their performance in detecting the retinopathy disease. Specifically, a total of 220 images from the APTOS dataset and 240 images from the EYEPACS dataset were selected as the test set to assess the capabilities of the models.

To assess our approach, we considered various performance parameters such as accuracy (Acc), precision, recall, F1 score, true positive rate (TPR), and false positive rate (FPR). these performance measures are defined in terms of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) and are presented in Table 3.

The results of the training phase using the APTOS dataset demonstrated the effectiveness of our method, with an impressive accuracy of 99.23% achieved when utilizing the ResNet50 model. This high accuracy indicates the strong capability of our method to accurately detect retinopathy in the APTOS dataset. On the other hand, when applying our method to the EYEPACS dataset, the accuracy was comparatively lower at 71.79% when employing the Xception model.

Table 3 Performance parameter formula [15]

Performance Parameter	Formula
Accuracy (Acc)	$Acc = \frac{TP+TN}{TP+TN+FP+FN}$
Precision	$precision = \frac{TP}{TP+FP}$
Recall	$recall = \frac{TP}{TP+FN}$
F1 score	$f1_score = \frac{2*precision*recall}{precision+recall}$
False Positive Rate (FPR)	$FPR = \frac{FP}{FP+TN}$
Binary Loss	$H(q) = -\frac{1}{N} \sum_{i=1}^N (y_i \log(P(y_i)) + (1 - y_i) \log(1 - P(y_i)))$

This observation suggests that the images in the APTOS dataset exhibit higher quality compared to those in the EYEPACS dataset. It highlights the significance of dataset quality in deep learning approaches and emphasizes the need for high-quality images.

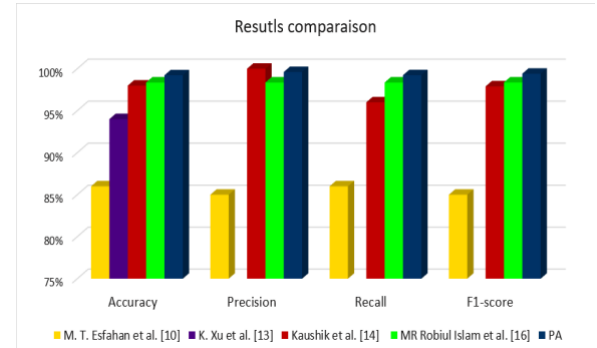


Figure 6. Comparison of the proposed approach with previous research works

Table 4 Binary classification Results

		ResNet50	InceptionV3	VGG16	Xception
APTOS	Accuracy	0.9922	0.9805	0.9903	0.9883
	Precision	0.9961	0.9807	0.9885	0.9984
	Recall	0.9923	0.9807	0.9923	0.9884
	F1_Score	0.9941	0.9807	0.9804	0.9884
EYEPACS	Accuracy	0.7075	0.6693	0.6929	0.7179
	Precision	0.7026	0.6302	0.7429	0.7117
	Recall	0.6377	0.7125	0.5693	0.6496
	F1_Score	0.6686	0.6655	0.6446	0.6792

Additionally, we compare our results to other existing methods mentioned in the related works section. As illustrated in Table 5 and Figure 6, our Proposed Approach (PA) outperforms all of them, affirming its efficacy in accurately detecting diabetic retinopathy from fundus images.

Table 5 Numerical comparison Results

metrics	[10]	[13]	[14]	[16]	PA
Accuracy	86%	94%	97,99%	98,36%	99,22%
Precision	85%	/	100%	98,36%	99,61%
Recall	86%	/	96%	98,36%	99,23%
F1_Score	85%	/	97,90%	98,37%	99,41%

In the following, we present the model's performance prediction in terms of confusion matrix and ROC curve. Figure 7 and Figure 8 show the results obtained using APTOS dataset, whereas Figure 9 and Figure 10 summarize the results with EYEPACS dataset.

True Label		ResNet50		InceptionV3		VGG16		Xception	
		0		1		0		1	
		97.9%	2.1%	97.9%	2.1%	96.8%	3.2%	96.8%	3.2%
1		2.4%	97.6%	4%	96%	4%	96%	3.2%	96.8%
		0	1	0	1	0	1	0	1
		Predicted Label							

Figure 7 Prediction results for APTOS trained models.

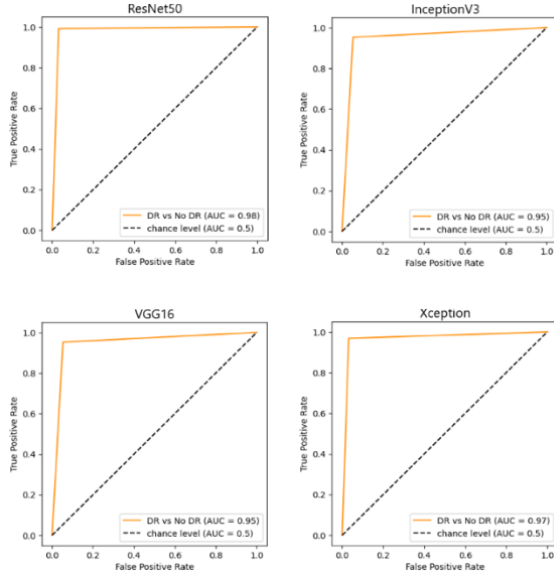


Figure 8 : ROC curve for models trained with APTOS dataset

True Label	ResNet50		InceptionV3		VGG16		Xception		
	0	80.4%	29.6%	55.4%	44.6%	71.4%	28.6%	86.6%	13.4%
	1	39.8%	60.2%	30.5%	69.5%	35.9%	64.1%	36.7%	63.3%
	0	1	0	1	0	1	0	1	
Predicted Label									

Figure 9: Prediction results for EyePACS trained models

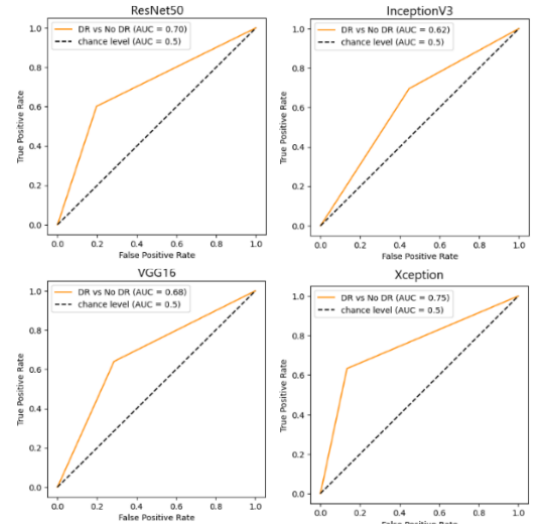


Figure 10: ROC curve for the model's trained with EYEPACS dataset

V. CONCLUSION

Our study aimed to evaluate the performance of several pre-trained CNN models for retinopathy detection using two publicly available datasets, APTOS and EyePACS. We proposed an approach based on DL and transfer learning. We conducted several experiments using two publicly available datasets, namely APTOS and EyePACS. The obtained results showed that our proposed method achieved a high accuracy of 99.23% on the APTOS dataset, indicating its potential for effective detection of retinopathy. However, the accuracy dropped to 71.79% with the EyePACS dataset, suggesting that the quality of the images could have impacted the results. This highlights the significance of dataset quality in deep learning approaches and emphasizes the need for high-quality images. Further research can be conducted, particularly in the context of multiclass classification.

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