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PAPER

Classification of Ocular Diseases Related to Diabetes Using Transfer Learning

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ABSTRACT

Although artificial intelligence enables the detection of abnormalities in medical images and is widely used as a computer vision technology, many researchers have focused on the detection of only one disease related to diabetes, which is diabetic retinopathy. In fact, patients face a significant risk of two other illnesses: cataract and glaucoma. In this article, we examined the diagnosis of these three eye diseases caused by diabetes and compared four approaches to classify these conditions. The proposed approaches are based on the transfer learning technique. We started by filtering, preparing, and augmenting the dataset, then applied transfer learning for feature extraction using two different architectures: VGG16 and RESNET50. We also investigated the impact of using contrast limited adaptive histogram equalization on the accuracy and precision of the models. This filter was used in a pre-training step for diabetic retinopathy diagnosis and in this paper proved its efficiency for glaucoma and cataract too. The final layers were replaced by Random Forest for classification. Models performed acceptable accuracies of 89.17% and 85.64% without operating contrast-limited adaptive histogram equalization and achieved better results when applying contrast-limited adaptive histogram equalization, with an accuracy of 97.48% and 96.66% for VGG16 and RESNET 50, respectively.

KEYWORDS

transfer learning, diabetic, ophthalmology, computer-aided, machine learning, deep learning, artificial intelligence

1 INTRODUCTION

Medical imaging plays an important part in clinical diagnosis, identification of abnormalities in the human body and treatment assessment for patients. Many researchers are interested in studying medical images of the brain, breast, lungs, and eyes [1]. Studies on medical images aim to classify and measure features of a particular organ. Consequently, many researches have focused on the construction and interpretation of medical images to promote disease identification and facilitate the detection of lesions. Diabetes can lead to many allied health problems. It can

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cause eye damage leading to vision impairment or blindness. However, with diabetes care and early diagnosis, it is possible to prevent diabetic eye disease. In this paper we are concerned about three diabetes complications: diabetic retinopathy (DR), glaucoma and cataract. Diabetic retinopathy is a disorder related to abnormal blood sugar levels, which causes damage to the retinal region. This disease is assessed according to the lesions represented on the fundus images, namely microaneurysm, cotton wool spots, hemorrhage, exudates, and neovascularization [2]. The warning signs of DR are the blurred spots and dark strings floating in the patient's vision [3]. When glaucoma starts to develop, the patient progressively loses peripheral vision. Glaucoma is categorized into three classes: open-angle glaucoma, closed-angle glaucoma caused by intra-ocular pressure and normal-tension glaucoma diagnosed by damage signs in the optic nerve. Ocular pathology, which progressively deteriorates the nerve fibers and hence leads to progressive damage of the neuro-retinal rim and the optic nerve head (ONH), occurs with a significant rise of intraocular pressure [4] and clustering vessels in the border of the optic disc. Glaucoma is characterized by a significantly enlarged area of the optic disc, and an optic cup can be observed in the fundus images. Once it starts to develop, the patient will loss peripheral vision progressively, which is why early diagnosis is crucial to avoid irreversible complications [5]. Patients with cataract experience glassy denseness to their vision. Cataract disease has a vitreous opacity feature, which is caused by protein denaturation. In consequence, cataract leads to the blurring of the basic fundus structures. In general, it develops with aging and unfortunately is not detected until it blocks light [6]. Figure 1 illustrate the vision of patients with each disease compared with a normal vision.

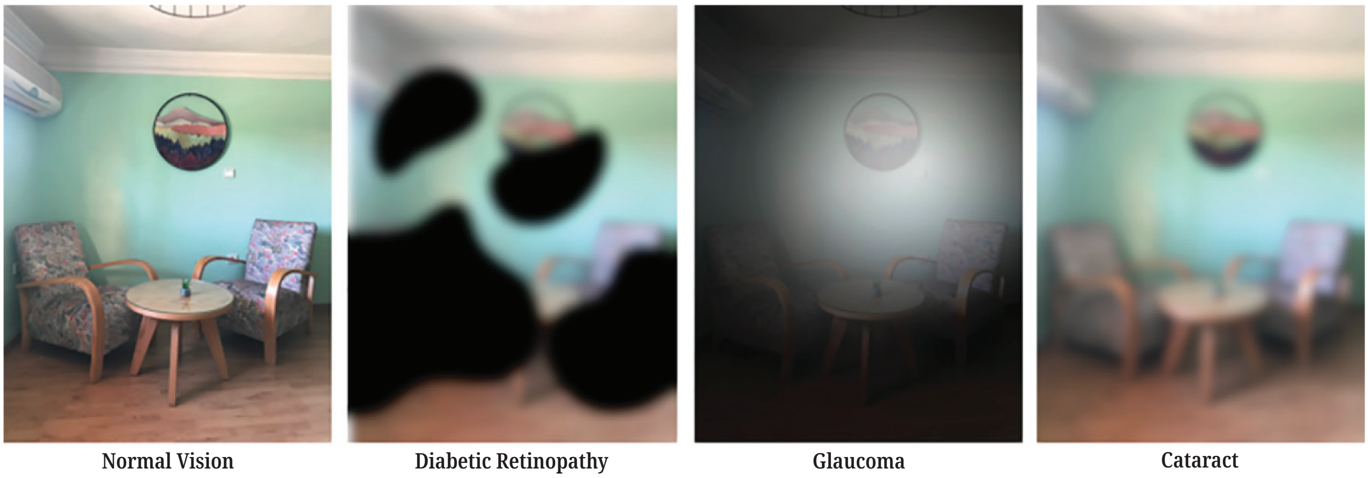

Fig. 1. Vision of a person without eye disease compared with patients suffering from diabetic retinopathy, glaucoma, and cataract

Machine learning plays an important part in the development of computer-aided diagnosis tools that support the healthcare industry. In this paper we use fundus images for the diagnosis of three illnesses that affect diabetic patients: diabetic retinopathy, glaucoma, and cataract. We rely on machine learning (ML) and particularly on transfer learning for the analysis and classification of these images. This paper investigates the multiclassification problem of eye diseases related to diabetes into glaucoma, cataract, and DR. We use a model for filtering, preparing and augmenting the dataset, then we apply transfer learning for feature extraction using two different architectures VGG16 and RESNET50. We add a final layer for classification using Random Forest and compare the results of the two approaches.

This paper is organized as follows. Section 2 explores related work, Section 3 introduces the architecture of the model, including preprocessing data, feature extraction, and classification. Section 4 presents the experiments conducted and the results obtained. Finally, Section 5 is the conclusion and summary.

2 RELATED WORK

2.1 Artificial intelligence, machine learning, and deep learning

Scientists thought in the early 1950s that they could create an intelligent entity by coding, as much as possible, rules for transforming inputs into specific outputs. As researchers became interested in solving more complex and fuzzy systems, such as image classification, machine learning emerged. Alan Turing introduced concepts that shaped the artificial intelligence of today and came to the conclusion that machines are able to learn. Therefore, machine learning appeared from the assumption that computers would be able to go beyond what we know about how to perform a specific task or learn from available data. The difference between artificial intelligence and machine learning is that for artificial intelligence we code the rules and the operations that manipulate inputs in order to generate outputs, but in the case of machine learning, a computer needs both inputs and the expected outputs to deduce the rules. Machine learning looks for statistical structure and meanings in both inputs and outputs fed to the system. These rules can then be applied to new datasets to generate results. In machine learning, machines are trained, not programmed. Machine learning is applied to handle image datasets with millions of pixels that would be impossible to handle using simple statistics. In other words, we can define machine learning as a procedure of predictions guided by data. Many fields have taken advantage of this technique for classification of objects and even humans [7]. Deep learning is also a very popular technique to extract information from images. It is a subset of machine learning and has proved its efficiency, especially in medical imaging, where it has achieved considerable performance compared with human experts. Direct learning is known for image segmentation and classification use [8]. Neurons are the smallest unit of any intelligence. They are organized into layers, and each layer performs a specific transformation. Through those layers, inputs are processed in different ways to approach the desired output. The convolutional neural network (CNN) is the most used technique for image-processing algorithms such as classification and segmentation. It aims to extract features of an image and is widely used for problems such as identification and classification or detection of abnormalities in fundus images [9]. Figure 2 illustrates a general configuration of a CNN.

CNNs excel at capturing patterns within medical images, thanks to their ability to learn spatial features [10]. By automatically extracting relevant features from complex medical images, CNNs enable accurate diagnosis, disease detection, and treatment planning. Additionally, CNNs can leverage pre-trained models on large datasets, such as ImageNet, allowing them to transfer learned representations to medical image analysis. While deep neural networks (DNNs) and recurrent neural networks (RNNs) have their applications in medical image analysis [11], CNNs stand out due to their performance and specialized focus on spatial features in medical images [12].

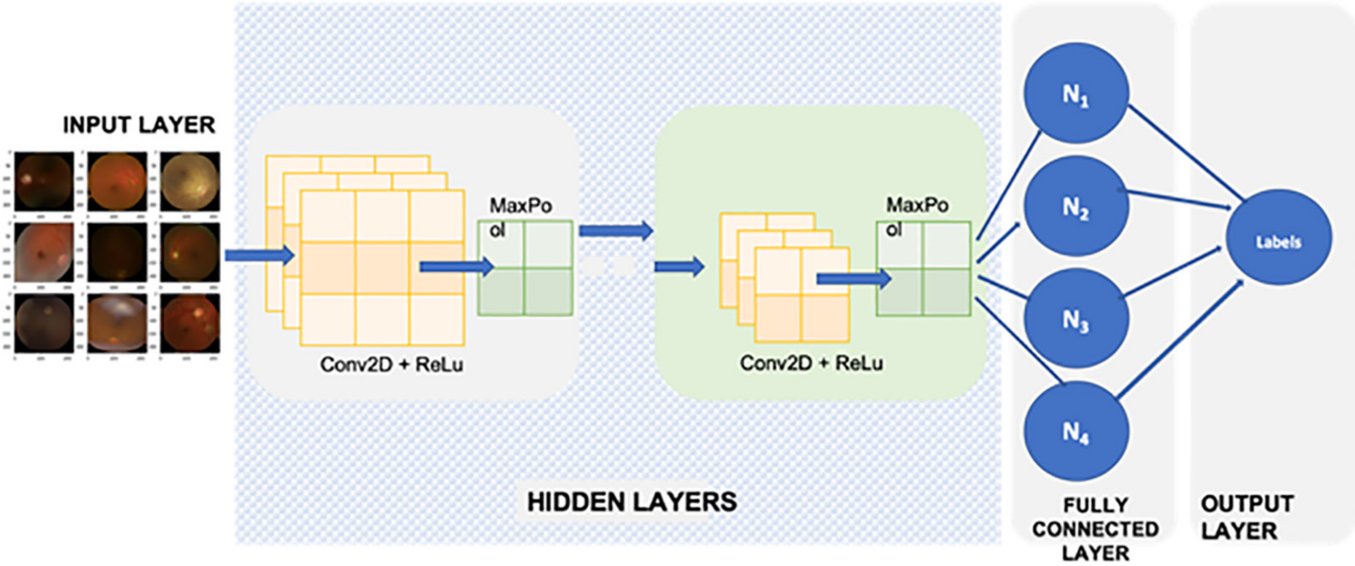

Fig. 2. Organization of a CNN

2.2 Detection of eye abnormalities using machine learning

Several methods based on machine learning have been used to detect abnormalities in fundus images. Some were focused on the multiclassification of eye diseases; others were more concerned about one abnormality. DR is one of the most studied eye diseases in artificial intelligence. Models have been conceptualized not only to detect DR but also to classify it as proliferative DR, non-proliferative DR, or diabetic macular edema [13]–[15] and, depending on its complexity, further classify it as mild, moderate, or severe [16]. For example, 124 retinal photographs were analyzed to identify four groups (normal and three levels of DR groups) in [17] using a three-layer feed-forward neural network. Authors in [18] used another approach, a morphological component analysis (MCA) algorithm, to distinguish normal from pathological retinal structures, with a sensitivity of 92.01%. Another study [19] was concerned about detecting and marking harmed zones of DR eye and classify them using transfer learning and attention mechanism; the results of this approach exceeded 99% accuracy.

Other studies have been concerned about the early detection of cataract, which is crucial to prevent serious complications. Authors of [20] adopted a CNN algorithm for detection of early signs of cataract. The performance of this approach was a 70% exact integral agreement ratio. In [21], researchers combined CNN to extract features then applied support vector machine (SVM) to explore those features and concluded with a Softmax classifier. Up to 97% sensitivity was achieved, plus grading of the cataract was supported. For the identification of glaucoma, techniques have been designed to evaluate the optic disc thickness using optical coherence tomography [22]. In [17], researchers studied the use of deep learning to detect glaucoma based on fundus images and achieved high sensitivity of 83.7% and specificity of 88.2%, while sensitivity performed by an ophthalmologist was between 61.3% and 81.6%. More recently, studies have been conducted on the multiclassification problem, such as in [23], where the authors state that their model performed better than the original Xception network in the classification of fundus images into eight categories, with an accuracy, precision, F1 value, and kappa score of the DSRA-CNN of 87.90%, 88.50%, 88.16%, and 86.17%, respectively. In [24] authors handled the data imbalance in the ODIR dataset by converting the multiclassification into binary classification and using the same number of images for each class. Table 1 represents some of the most relevant studies with a summary of the techniques used, diseases inspected, and reported accuracies.

Table 1. Most relevant research studies with reported accuracies

Ref.	Targeted Diseases	AI Techniques	Preprocessing Techniques	Accuracy
[14]	DR	DCNN	De-noising CLAHE	**98.80%**
[25]	DR	Bottleneck U-NET: saliency and shape detection, then classification using SVM	Resized images to 576×576	**97.1%**
[26]	DR	Hybrid SVM NAÏVE-BAYES	Normalization, then intensity conversion followed by de-noising, logic statistics with wiener-2 and CLAHE	**98.60%**
[27]	Squint, Chalazion, C	CNN: VGG16, VGG19, MobileNet, Xception, Inception and DenseNet121	Resize into 224×224 Data augmentation: zooming in, zooming out, shearing by 20%, flipping horizontally by 20%, rotating by 40°	VGG16 **95.63%** VGG19 **94.20%** MobileNet **97.49%** Xception **95.10%** InceptionV3 **95.33%** DenseNet121 **96.92%**
[18]	DR	MCA algorithm	Pre-screening algorithm to assess the quality of the image	**92.01%**
[19]	DR	Transfer learning using CNN	Determine first region of interest: lesions using fast RCNN	**99.1%**
[21]	C	Alex Network followed by SVM classifier instead of Softmax	Automatic localization of region of interest from slit-lamp photography	**96.83%**
[22]	GL	CNN	—	**91.2%**
[23]	N, DR, GL, C, AMD, H, M, O	DSRA-CNN	Data screening, black-border cropping, data amplification and normalization	**87.90%**
[24]	N, DR, GL, C, AMD, H, M, O	Transformed the multiclassification problem into binary classifications by coupling each disease with normal eyes and using VGG19 and transfer learning	Over-sampling and down-sampling to overcome unbalanced data	**98.13%**
[28]	N, DR, GL, C, AMD, H, M, O	Inception Resnet + Discriminative Kernel Convolution Network	Over-sampling and down-sampling to overcome unbalanced data	**96.08%**
[29]	N, DR, GL, C, AMD, H, M, O	ResNet50 with attention mechanism	Image augmentation module composed of: image cropping, image selection, image enhancement: rotation, up/down flip, left/right inversion	**94.23%**

Abbreviations: AMD, age-related macular degeneration; C, cataract; CLAHE, contrast limited adaptive histogram equalization; CNN, convolutional neural network; DCNN, Deep Convolutional Neural Network; DR, diabetic retinopathy; DSRA-CNN, Depthwise Separable Residual Attention Convolutional Neural Network; GL, glaucoma; H, hypertension; M, myopia; MCA, morphological component analysis; N, normal; O, other diseases; RCNN, Region-Based Convolutional Neural Network; SVM, support vector machine

2.3 Multiple eye-disease datasets

With the multitude of studies applying deep learning to detect and classify abnormalities using fundus photography, public datasets have arisen. The MESSIDOR [30] dataset is a collection of 1200 images and was used for detection of exudates. A second version, MESSIDOR-2 [31], contains 1748 images, which were used for the diagnosis of DR. EYEPACS [32] is a set of 9963 images to diagnose DR. DDR [33], with 13673 images, was used for detection of exudates, microaneurysms, hard exudates, and DR. REFUGE [34] has 1200 images to diagnose glaucoma. LAG [35] contains 11760 images used for OD/OC segmentation and glaucoma detection. ODIR [23], with 10000 images, is used for the classification of eight eye diseases. AREDS [36] holds 206,500 images for DR diagnosis, and ICHALLENGE-AMD [37], for OD/OC segmentation and DR diagnosis.

3 METHODS

The proposed framework is illustrated in Figure 3. This approach was composed of three steps: preprocessing images, feature extraction, and classification.

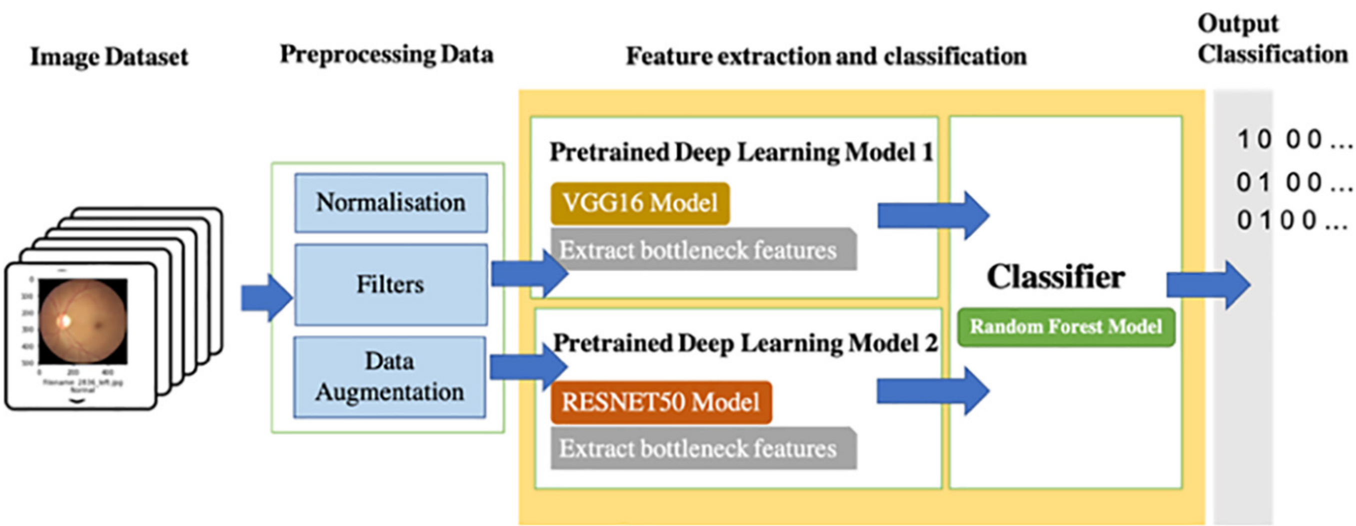

Fig. 3. Proposed general approach for our experiments

3.1 Preprocessing fundus images

The dataset used for experimentation is ODIR, representing 5000 patient's left and right eyes from different types of cameras, categorized into eight ocular diseases: DR, AMD, glaucoma, cataract, hypertension, pathological myopia and other abnormalities. For these experiments, we selected a total of 3098 fundus images labeled Normal, 265 images of cataract, 224 fundus images of glaucoma, and 1406 images of DR. The unbalance in the dataset is clear, with normal and DR class representing the majority from the total images. Figure 4 represent the distribution of the eight ocular diseases in ODIR dataset.

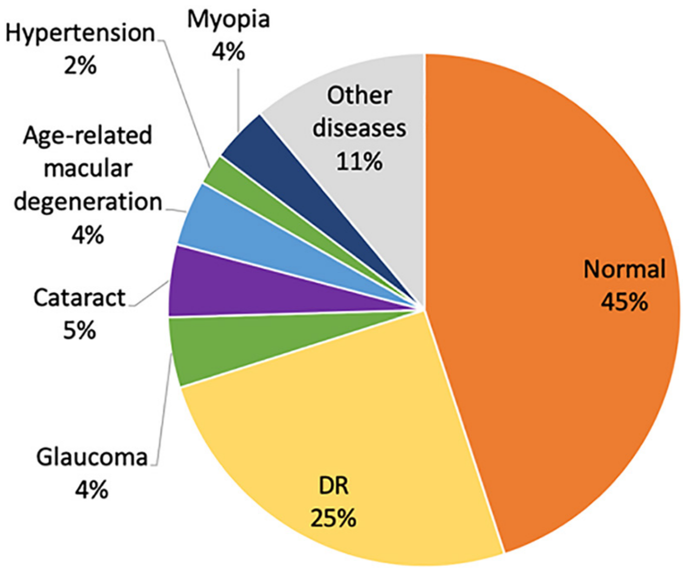

Fig. 4. Distribution of the 8 diseases in the ODIR dataset

The dataset was shared between three subsets, where 70% was used for training, 20% for validation, and 10% for tests. To keep the same ratio for each application, we stratified a train-test split. We also needed to face the unbalance problem that generated bias toward DR and Normal classes because they were highly represented, which led to over-predicting these two categories. Sampling strategies solved this issue by balancing the distribution in the dataset. We used the image augmentation technique to increase the size of our dataset by rotating 90°, flipping vertically, and flipping horizontally. We followed the results of [38] and applied the contrast limited adaptive histogram equalization (CLAHE) algorithm and illumination equalization to obtain uniform background and high-contrast images. Figure 5 illustrates a sample of images from the ODIR dataset before and after the preprocessing step.

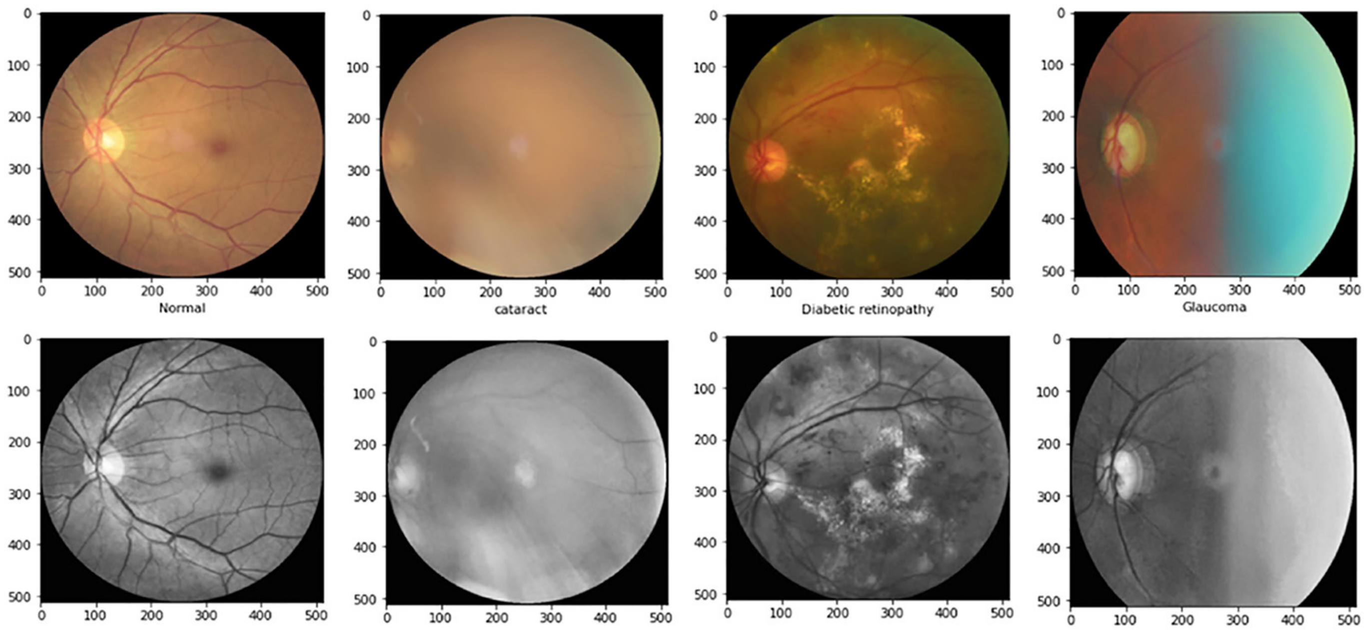

Fig. 5. Results of preprocessing fundus images

3.2 Feature extraction

Our approach is based on transfer learning and fine-tuning. Collecting a large database in the medical field is a tedious and a difficult task. Collecting enough labeled data requires a considerable effort from experts. Transfer learning aims to leverage information from pre-trained architectures, regardless of the domain for which they were primarily trained. Transfer learning takes a pre-trained machine learning model and repurposes it for another task for faster development, especially if the dataset is small [39].

VGG16 stands for Visual Geometry Group from Oxford. It is a CNN model with 16 layers trained on more than a million images from the ImageNet database. VGG16 can classify images into 1000 object classes [40]. The image input size is $224 \times 224 \times 3$. Figure 6 illustrates the layers architecture of VGG16 with 15,135,624 training parameters.

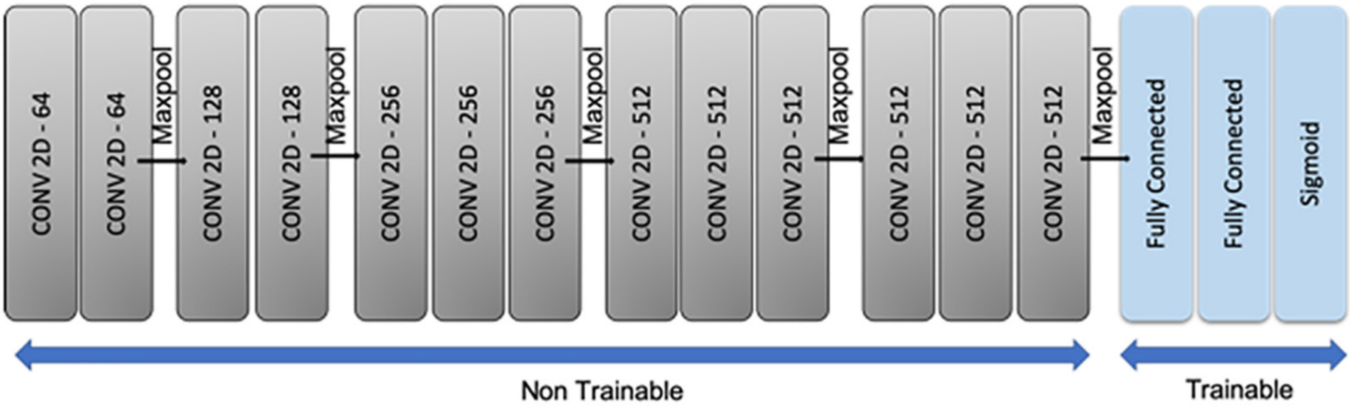

Fig. 6. VGG16 architecture

RESNET50 stands for Residual Network, which is a CNN that is 50 layers deep, with 23,519,360 training parameters, and was introduced in 2015 [41]. This specific architecture is a form of an artificial neural network (ANN) and is illustrated in Figure 7.

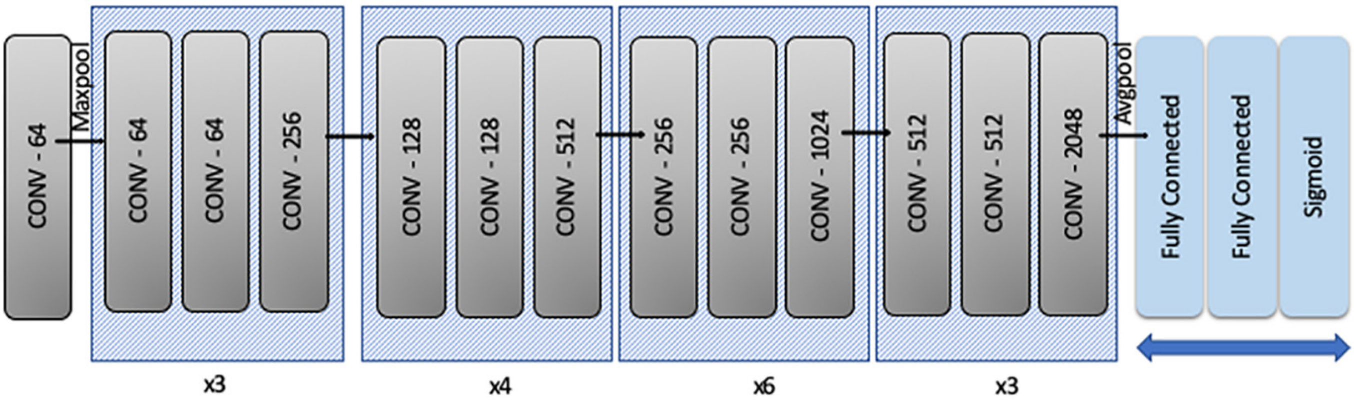

Fig. 7. RESNET50 architecture

In this paper, the first model based on VGG16 was labeled and referred to as Model 1, and the second model based on RESNET50 was referred to as Model 2.

3.3 Classification

Random forest (RF) is a technique based on machine learning that constructs a forest of classification entities; the trees. Each entity is developed on a sample of the data, and attributes for each node are selected from a random subset of all attributes. The ultimate classification is the result of voting for every tree in the forest.

Our approach consisted of extracting the features and using them as inputs for RF. Finally, the activation function used was sigmoid combined with binary cross-entropy loss function. The sigmoid function limited the prediction values between 0 and 1, and the loss function measured the distance between true and predicted values for each class [42]. For each epoch, we considered the averaged class-wise error, and the weights were updated based on the loss. We used stochastic gradient descent optimizer (SGD) and a learning rate of 0.0001.

4 RESULTS AND DISCUSSION

The proposed approaches were implemented on the training set, validated on the validation set, and tested on the testing set of ODIR dataset. The predicted labels were compared with ground truth labels and evaluated using the confusion matrix, accuracy, recall, precision, and F1-score. *Accuracy* represents the fraction of correct prediction to the total of predictions. *Recall* is the ratio of true positives to the total positives in the ground truth. *Precision* is the proposition of positive findings that was actually correct. $\mathrm{F1}_{score}$ is the harmonic mean of recall and precision, where T_n represents true negatives, T_p true positives, F_n false negatives, and F_p false positives.

$$Accuracy = \frac{Tn + Tp}{Tn + Tp + Fn + Fp} \tag{1}$$

$$Recall = \frac{Tp}{Tp + Fn} \tag{2}$$

$$Precision = \frac{Tp}{Tp + Fp} \tag{3}$$

$$\mathrm{F1}_{score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

For a better visualization of the quality of prediction on the test set, we organized the metrics into classification reports. After 50 epochs, we achieved the results in the classification reports represented in Tables 2 and 3. On one hand, for Model 1 we attained on the testing set an overall accuracy of 89.17% without using CLAHE and 97.48% using CLAHE. On the other hand, Model 2 achieved 85.64% for the same metric without using CLAHE and 96.66% using CLAHE. Model 1 based on VGG16 attained better results compared with Model 2, based on RESNET50. Also using CLAHE significantly improved both models. The precision obtained on Normal and Glaucoma were also better than Cataract and DR for both cases.

Table 2. Classification report for Model 1 on testing set

	Accuracy		Precision		Recall		$F1_{score}$	
CLAHE	No	Yes	No	Yes	No	Yes	No	Yes
Cataract	89.17%	97.48%	0.83	0.94	0.76	0.96	0.79	0.95
Normal	98.49%	99.75%	0.94	0.99	1.0	1	0.97	0.99
Glaucoma	94.71%	98.49%	0.96	1.0	0.85	0.94	0.90	0.97
DR	95.97%	99.24%	0.84	0.97	1.0	1.0	0.91	0.98
Accuracy	89.17%	97.48%						

Table 3. Classification report for Model 2 on testing set

	Accuracy		Precision		Recall		$F1_{score}$	
CLAHE	No	Yes	No	Yes	No	Yes	No	Yes
Cataract	87.66%	97.17%	0.81	1.0	0.72	0.9	0.76	0.94
Normal	97.48%	98.97%	0.95	0.98	0.95	0.98	0.95	0.98
Glaucoma	92.7%	98.46%	0.90	0.94	0.83	1.0	0.87	0.97
DR	93.45%	98.71%	0.78	0.95	0.96	1.0	0.86	0.97
Accuracy	85.64%	96.66%						

We can observe from Figure 8 that using CLAHE for both approaches significantly improved the accuracy for each class. This is due to using this filter that made fundus images more contrasted and with less noise, for a better extraction of common and smallest details of each disease. We also observed that CLAHE had a significant impact on increasing the accuracy, particularly for Cataract, with 8.31% for Model 1 and 9.51% for Model 2, which makes this filter, widely used for DR, also adequate for cataract. This is important, since we wanted to ensure minimum use of preprocessing techniques for all the input images and, at the same time, to achieve better accuracy.

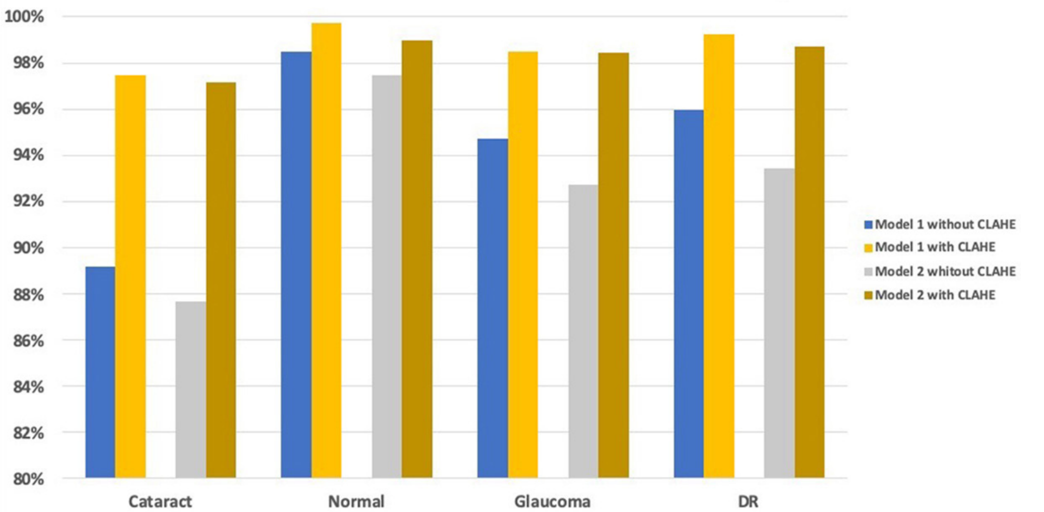

Fig. 8. Comparing the accuracies obtained before and after using CLAHE

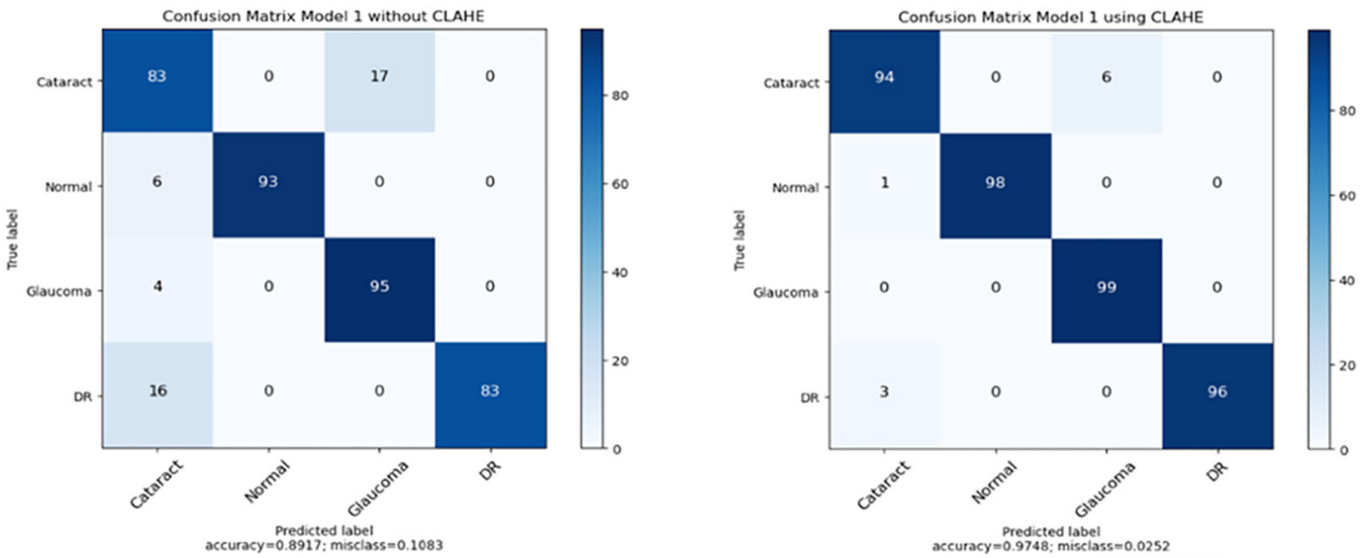

Fig. 9. Confusion matrices for Model 1without CLAHE and using CLAHE

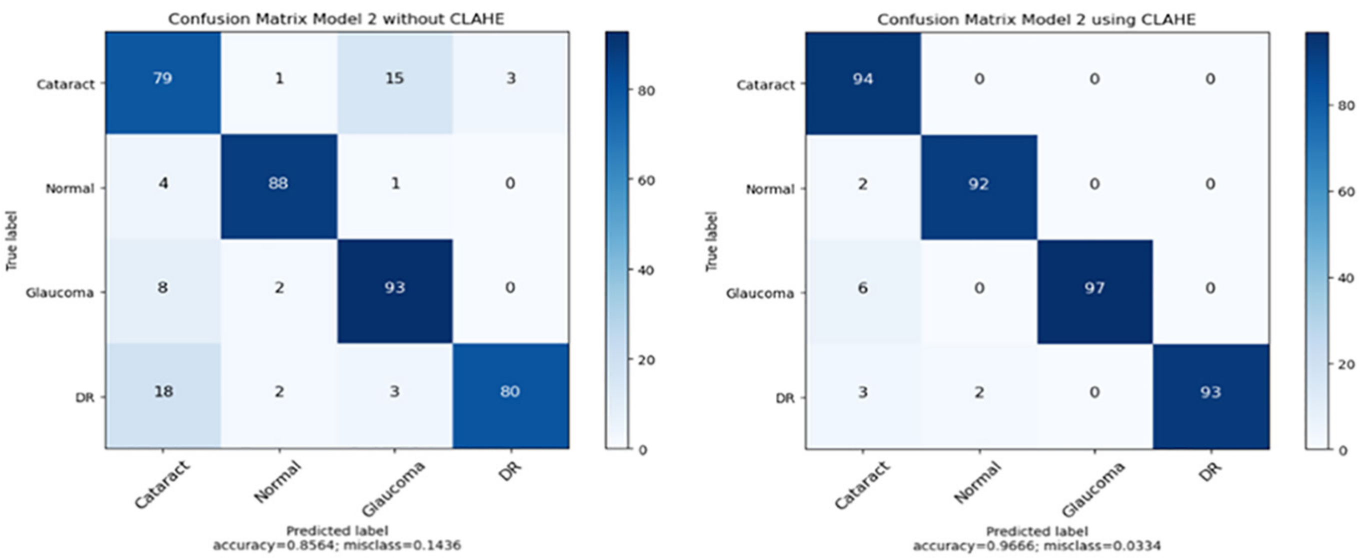

Fig. 10. Confusion matrices for Model 2 without CLAHE and using CLAHE

Figures 9 and 10 represent the confusion matrices for Models 1 and 2, respectively. In Model 1, when using CLAHE, our misclassification drops from 0.1083 to 0.0252. For Model 2, the misclassification of 0.1436 drops to 0.0334 when utilizing CLAHE.

We note that the number of cataract fundus confused with DR then normal and glaucoma for Model 1 is the highest, and the same is the case for Model 2. We can deduce that our models have a difficulty in predicting cataract fundus but are highly capable of distinguishing a normal and DR eye, especially using Model 1. This is partially due to the representation of each class in the ODIR dataset. We observed unbalanced categories, with images of normal eyes being represented the most and cataract the least in the dataset. This makes the models fail to recognize the minority categories, even with the sampling strategy where we had to reconsider the number of highly represented classes to balance the distribution.

The model should look for the differences representing each class. In fundus with cataract, the image is hazy and cannot permit a clear view of the disc, macula and vascular arcades. DR images show microaneurysm with dot and blot hemorrhages, hard exudates, venous beading, and neovascularization. Glaucoma shows a cup disc ratio higher than 0.5 with nasalization of vessels, and normal fundus does not show any of the anomalies cited above. To ameliorate the visualization of these differences in the dataset, an image-processing technique is needed to enhance the dominant features of the four classes. CLAHE, which is a sharpening filter, increased the contrast of fundus images. This filter is commonly used for DR and glaucoma to enhance the low-contrast regions, especially the contrast enhancement of microaneurysms and small blood vessels, and we show in this paper that it is a very effective filter for cataract as well.

It is important to develop instruments for an early diagnosis of ocular diseases. Unfortunately, we face some key challenges to build accurate ocular disease detection tools. These include the lack of public data, handling different images from different types of cameras, and analysis of fundus images by experts to provide a rich and reliable dataset for models of machine learning. A reliable and unbiased training set is very important to avoid any variability in the results of the deep learning model. We demonstrated in this paper that the right choice of filter significantly impacts the accuracy of the training model.

Table 4. Comparison with previous studies using the same dataset ODIR for multiclassification

Ref	Method	Disease Classification	Accuracy	F1_score
Proposed Model 1	VGG16 Random Forest with CLAHE	DR, GL, C, N	97.48%	97.49%
Proposed Model 2	RESNET50 Random Forest with CLAHE	DR, GL, C, N	96.66%	96.68%
[28]	Inception Resnet + DKC Block	N, DR, GL, C, AMD, H, M, O	96.08%	94.28%
[29]	ResNet50 with attention mechanism	N, DR, GL, C, AMD, H, M, O	94.23%	99.16%
[17]	DSRA-CNN	N, DR, GL, C, AMD, H, M, O	87.90%	88.16%

Abbreviations: AMD, age-related macular degeneration; C, cataract; CLAHE, contrast limited adaptive histogram equalization; CNN, DR, diabetic retinopathy; DSRA-CNN, Depthwise Separable Residual Attention Convolutional Neural Network; GL, glaucoma; H, hypertension; M, myopia; N, normal; O, other diseases.

Table 4 compares the accuracy obtained from our method with the results obtained in [17], [28], [29]. These papers investigate the multiclassification problem using the same ODIR dataset we chose for our experiments. The results show that preprocessing fundus images using CLAHE and the training the model on VGG16 combined with Random Forest gave a significant result in detecting DR, glaucoma and cataract. Our results demonstrate that our approach outperforms previous methods and has potential for clinical application in diagnosis of eye diseases, especially for diabetes patients.

In order to help doctors deliver cutting-edge medical care, smartphones and mobile Ccinical decision support systems (MCDSS) may be used [43]. These systems can provide real-time assistance to ophthalmologists, especially non-experimental ones, by helping them in the diagnosis of these diseases related to diabetes and thus save their patients' sight. For future work, we aim to implement our solution and evaluate the effectiveness of MCDSS in improving the accuracy of diagnosis and treatment among ophthalmologists.

5 CONCLUSION

Many studies have been conducted using fundus images and on different data sets. Different training parameters are used in the literature, and one method cannot be claimed to be the best. Also, it is more difficult to accomplish high performance in multiclassification tasks than in binary classification tasks. The quality and complexity of the images certainly impact the results. In fact, we lost many images during the preprocessing step, especially during sampling. Even with these drawbacks, we consider that both models performed with acceptable overall accuracy on the testing set. The accuracies achieved were 89.17% and 85.64% without operating contrast limited adaptive histogram equalization, and when applying contrast limited adaptive histogram equalization, were 97.48% and 96.66% for VGG16 and RESNET 50, respectively. One of the advantages of VGG16 is the number of its training parameters, which is lower than RESNET50.

To improve the recognition rate, it is necessary to improve the quality of images and feed the model with a diverse but balanced dataset. Plus, it is important to investigate the impact of different filters applied during preprocessing step, because, as demonstrated in this paper, that makes the model achieve a better accuracy. We are aware that developing software for detecting and grading ocular diseases leads to more efficient screening and will help practitioners to save more diabetic patient from blindness. Therefore, we aim through the continuity of this work and as a perspective of this paper to improve the proposed model to obtain better results by testing a different approach in the preprocessing step, i.e., transfer learning, and testing the model with a classifier other than Random Forest. Finally, we aspire to implement the solution that gives the best accuracy on the test set to provide a computer-aided tool for practitioners.

6 DATA AVAILABILITY

The dataset is available at https://www.kaggle.com/datasets/andrewmvd/ocular-disease-recognition-odir5k

7 CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

8 ACKNOWLEDGMENTS

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