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Abstract. Diabetic Retinopathy (DR) is the leading cause of visual impairment among working-aged adults. Screening and early diagnosis of DR is essential to avoid visual acuity reduction and blindness. However, a worldwide limited access to ophthalmologists may prevent an early diagnosis of this blinding condition. In this paper, we propose a novel method for screening DR from smartphone-captured fundus images. The main challenges are to perform higher accurate detection even with reduced quality of handheld captured fundus images and to provide the result into the smartphone used for acquisition. For such a need, we apply transfer learning to the lightweight deep neural network "NasnetMobile" which is used as a feature descriptor, while configuring a multi-layer perceptron classifier to deduce the DR disease, in order to take benefit from their lower complexity. A dataset composed of 440 fundus images is structured, where the acquisition and statement are performed by expert ophthalmologists. A cross-validation process is conducted where 95.91% accuracy, 94.44% sensitivity, 96.92% specificity and 95.71% precision in average are achieved. In addition, the whole processing flowchart is implemented into a mobile device, where the execution time is under one second whatever the fundus image is. Those performances allow deploying the proposed system in a clinical context.

Keywords: Diabetic retinopathy, Deep learning, Transfer Learning, Mobile-health.

1. Introduction

Diabetic Retinopathy (DR) is an ocular disease registered for 30% of diabetes-affected patients (Sabanayagam, 2019). Based on the world health organization report, 146 million suffer from DR (Pan, 2018). Advanced stages of DR may lead to severe visual acuity impairment and blindness (Ting, 2016; Chalakkal, 2020), with 37 million blind persons worldwide. Therefore, DR screening is mandatory for the early diagnosis and

initiation of appropriate treatment to improve the visual outcome and to prevent blindness. Fundus examination is the main clinical approach to screen DR.

Actually, a heavy workload is requested from ophthalmologists, where a ratio of 50 per million persons worldwide is required to ensure early screening and timely management of DR. However, only 21 countries have verified the targeted ratio, where the actual global ratio is about 29 ophthalmologists per million persons (Resnikoff, 2020; Singh, 2018). Consequently, in many countries, there is a lack of periodical DR screening, hence an important delay of DR diagnosis.

Recently, several optical lens-based devices have been proposed, which can be snapped into smartphones to capture fundus images. Those devices are distinguished by their low-cost and mobility, which are associated to the smartphone availability in terms of connectivity, data storage and processing (Panwar, 2016; Bolster, 2014; Russo, 2016). The mobile devices ensure capturing fundus images with sufficient quality compared to those captured by conventional fundus cameras. However, blurs and noise are always deduced caused by the handheld aspect of the mobile capturing. Several clinical studies have been performed and have shown similar DR detection accuracy from smartphone-captured fundus images and conventional fundus cameras-captured images (Akil, 2019; Prassana, 2013; Monjur, 2019).

Previous studies have aimed to automatically screen DR from smartphone-captured fundus images (Hacisoftaoglu, 2020; Kashyap, 2017; Kalpiyapan, 2018). Some work has addressed the problem of limited quality of fundus images, where the different limitations were highlighted in (Hacisoftaoglu, 2020). To outperform those problems, the methods have been based on intensive computational processing. In (Mueller, 2020), DR detection was provided though a multiple instance for the AlexNet Deep Convolutional Neural Network (DCNN) architecture, while the method suggested in (Hacisoftaoglu, 2020) used the ResNet50 neural network as a feature descriptor. Such processing could not be run into embedded or smartphone devices, due to the limited material resources.

Other methods have aimed to run DR screening into smartphones where the main contribution was based on suggesting low complexity processing. In (Boukadida, 2021; Elloumi, 2020), features were extracted though linear computational complexity, where the DR stages were detected using the SVM classifier. Elsewhere, lightweight DCNNs were employed such as mobilenet-V2 and inception-V3, respectively used in (Suriyal, 2018; Hagos, 2019; Majumder, 2020). However, these methods did not consider the decreased quality of smartphone-captured fundus images, where they were validated using database images acquired by classical conventional fundus cameras. Little work has addressed both challenges, hence failing to achieve higher performance, such as the one described in (Kashyap, 2017) where 62% precision was registered.

The originality of our work is to describe an automated method that (1) ensures higher performant DR screening from smartphone-based fundus photography and which (2) has a low complexity to be implemented into a smartphone associated with a mobile device. The whole hardware and software tool presents an end-to-end mobile system from fundus image acquisition to DR screening. For such a need, a preprocessing is performed to enhance the image quality. Then, the DCNN “Nasnet-Mobile”

is used as a feature descriptor, which is characterized by its higher performance, light-weight processing and fast convergence even with a reduced database size. Then, the extracted features are provided to a Multi-Layer Perceptron (MLP) classifier with a single hidden layer, to deduce the DR disease. This work is a part of project leading to mobile computer-screening system for DR which we already developed in (Akil, 2019, Elloumi, 2020; Boukadida, 2021).

The suggested method is introduced in the rest of the paper. Section 2 describes the automated method for DR screening. The experimental evaluation of the detection performance and the execution time is presented in section 3. The conclusion and some future work are detailed in section 4.

2. Novel Method for DR Screening

2.1. Pre-processing and Data processing

Basically, the dataset images must be resized to (224×224×3) to be provided to the NasNet-Mobile. Preprocessing aims to enhance the fundus image quality in order to promote DR screening. In fact, the handheld capture of fundus images leads to a blurred illustration of retinal components, especially the DR lesions characterized by a small size such as micro-aneurysms or hard exudates. Thus, the point spread function is applied to clearly model the retina (Boukadida, 2021), as shown in fig.1(b). The variability on the light source causes a non-balanced contrast of the smartphone-captured fundus images. To resolve this problem, the Contrast Limited Adaptive Histogram Equalization (CLAHE) approach (Chalakkal, 2017) is applied, as illustrated in fig.1(c).

Thereafter, a data augmentation is applied in order to increase the dataset size and enhance the DL model robustness. For this purpose, all images are flipped and shifted horizontally and vertically, rotated with angle 30°, zoomed and contrast-adjusted with respect to the varied contrast of the smartphone-captured fundus images (Blaiech, 2019, Elloumi, 2021).

(a) (b) (c)

Figure 1: Fundus images: (a) captured with Volk-inView, (b) after deblurring, (c) after contrast enhancement

2.2. Nasnet-Mobile Architecture

The Nas Network (NasNet) is a CNN architecture provided by the neural architecture search (Nas) framework (Gupta, 2021, Cogan, 2019)). It a research algorithm that designs an optimal convolutional architecture is for a given dataset, through a scalable method. The framework is based on a controller recurrent neural network (RNN) where networks are iteratively generated and trained using the provided dataset. Then , their accuracies are returned to the controller to enhance the next versions of architectures (Cogan, 2019; Bahri, 2020). The research leads to compose the network by convolutional layers called “normal cell” and “reduction cell” having identical structure with different weights. The first cell type generates a feature map preserving the same resolution than the input. the second one reduces the feature map size through a stride =2. Using the "ImageNet" dataset that contains 1,000 categories (Li, 2019), the Nas framework was provided an architecture where the selected cells are as modelled in Fig.2. We note that Nas framework may provide a lightweight architecture called “NasNet-Mobile” made up of only four million parameters (Bahri, 2020), which is able to perform an accurate classification (Winoto, 2020).

2.3. Transfer Learning of Nasnet-Mobile Architecture

The available dataset is composed of few hundreds of smartphone-captured fundus images. To ensure reliable performance, the transfer learning method is endorsed (Bouden, 2021), where the NasNet-Mobile model, initially trained with the "ImageNet" dataset that contains 1,000 categories (Li, 2019), is retrieved. The classification layer is interchanged by the four ones, as described in fig.2. The first layer consists of an Average Pooling where the input feature map is spatially partitioned into a grid of square blocks with side 2, and average over each blocks are stored in the output feature map. Then, a flatten is performed to align all features into a single row. The third layer applies a dropout function to prevent overfitting, with a threshold equal to 0.7. The last one is a dense layer with a ReLU function where the feature vector size is reduced to 32, while decreasing the error through back-propagation.

The model is finetuned in order to update the weights of neurons during training, where the chosen learning rate is 0.000005 (Li, 2019; Mateen, 2020). The optimal weight is stored after each epoch, to guarantee converging the model. Training is performed into 150 epochs, and the weights are updated following the "Adam" optimizer (Boudegga, 2021). The "categorical-cross entropy" loss function is adopted, where the loss is based on the sum of all computed ratios. The main hyper parameters used for training are summarized in Table 1.

Table 1: Hyper parameters of training NasNet-Mobile model

Parameter	Value
Optimizer	Adam optimizer
Learning rate	0.000005
Regularization	Dropout (0.7)
Mini-batch size	2
Epoch	200
Loss function	Binary cross-entropy

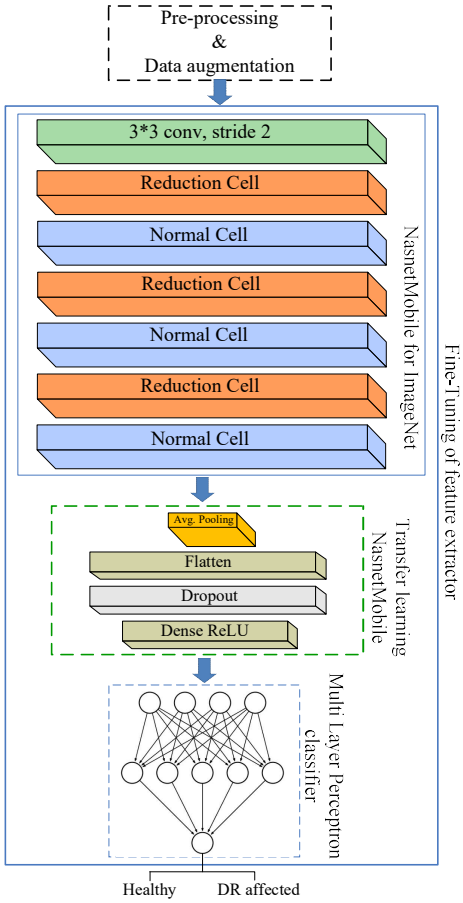


Figure 2: Processing flowchart of the proposed DR screening method

2.4. MLP Configuration

The classifier must retrieve a feature map from the NasNet-Mobile deep learning model in order to ensure a performant classification, through low-complexity processing. Based on those constraints, the MLP classifier is chosen to ensure the classification of DR-affected fundus images. It is considered as a neural network where the weights are randomly predefined. Indeed, it is widely employed in medical classification problems. The MLP can be configured in terms of number of hidden layers and number of neurons inside. We choose a single hidden layer to reduce the computational complexity. After that, we perform an experimental study where the neuron number is varied. Then, training and testing processes are iteratively performed to evaluate the current MLP, as detailed in Table 2. Based on the experiment results, we deduce that a hidden layer with 10 neurons will allow achieving the best classification result.

Table 2: performance classification in terms of neuron number of hidden layer

neuron number of hidden layer	8	10	12
Sens	88.57	94.44	94.29
Spec	91.67	96.15	85.42
Acc	89.83	95.4.45	90.68
Prec	93.94	94.44	90.41

3. Experimental Results

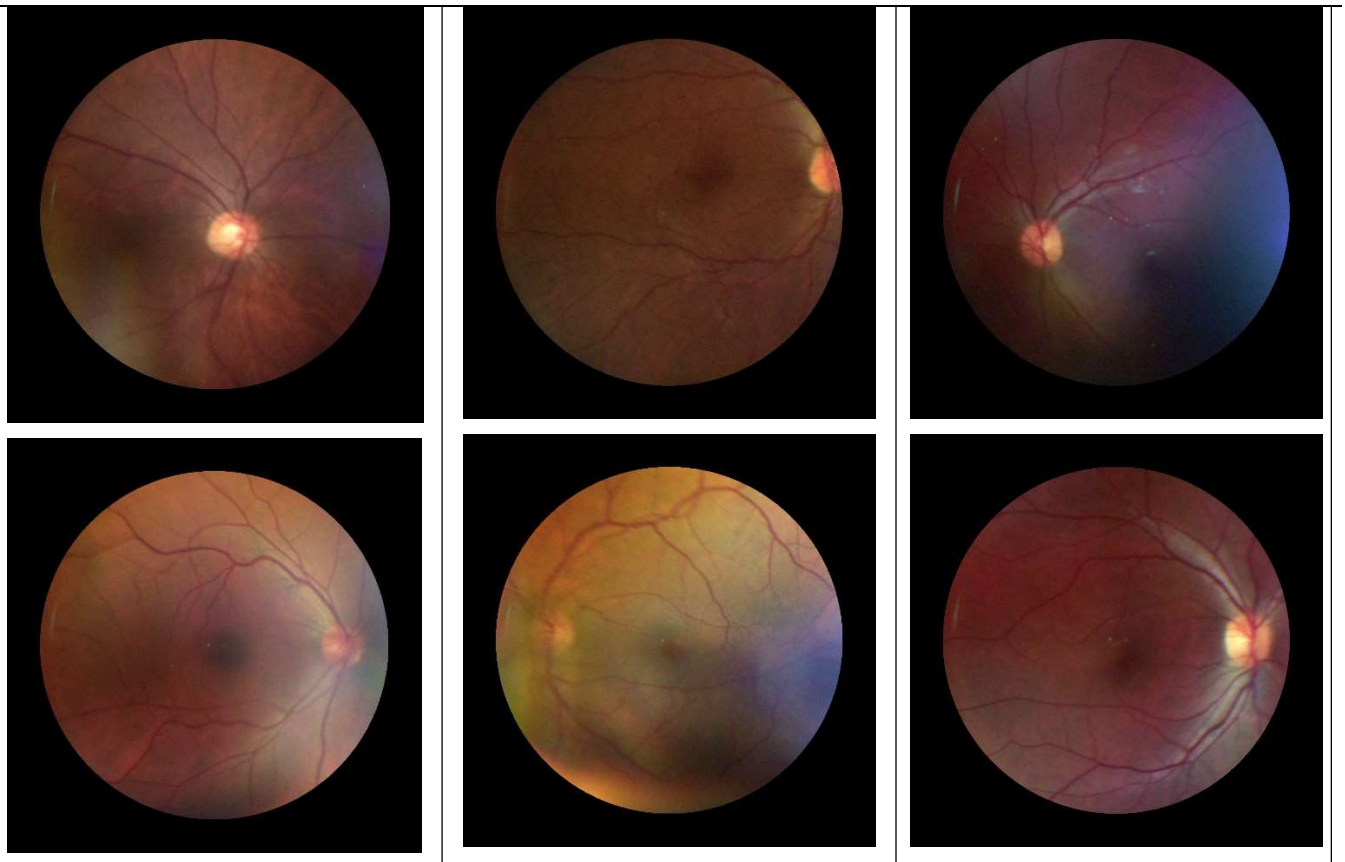
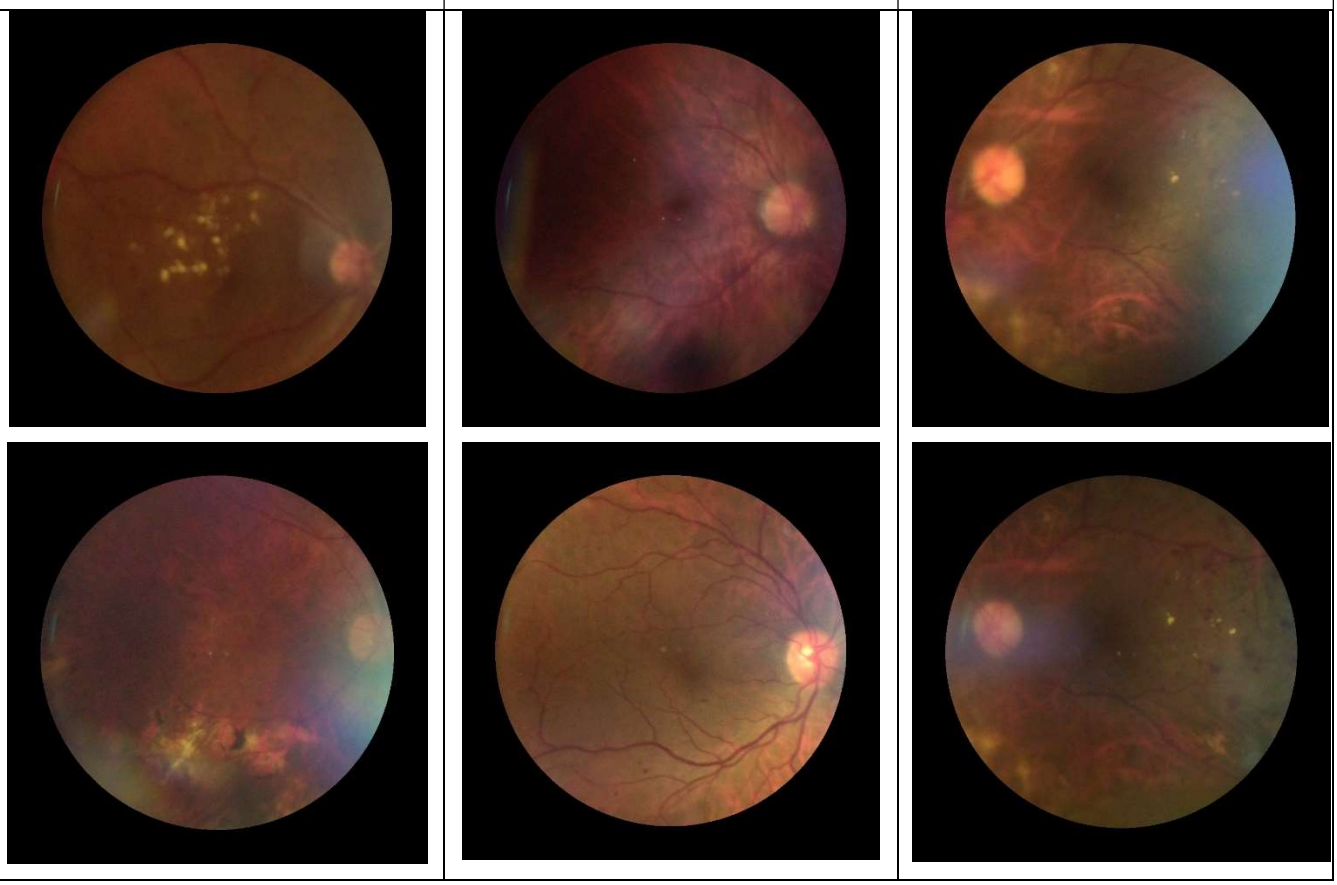
3.1. dataset

Patients' data were collected in the department of ophthalmology belonging to Fattouma Bourguiba University Hospital (Tunisia), between 2019-2020. Image acquisition was performed after preliminary eye examination and dilating pupil of patient eyes using mydriatic substance. Fundus images were captured using a Volk-InView dispositive, as shown in Fig.3, allowing a field of view of 50°. Several clinical studies have attested the higher quality of fundus images captured by Volk-InView, compared to other optical lenses such as D-Eye, Retina Peek and Welch Allyn (Karakaya, 2020). All anonymized captured images were evaluated by two independent masked retina specialists (NA and IK). Screening the DR lesions of retinal photographs using the "International Clinical Diabetic Retinopathy Classification Severity Score" was performed, where images were graded as non DR and DR.
The dispositive was snapped into an "Ipod Touch" device where the camera resolution was about 8 Mp. The dataset was composed of 440 images, where 260 were classified as healthy and 180 contained DR lesions. The image resolution was 892*892 pixels with 96 dpi, where some healthy and DR affected captured retina are shown in Table 3. It is easy to distinguish retinal components, such as the optic disk, the macula and DR lesions, even those having small sizes.
The evaluation is performed through a five-fold cross validation approach to guarantee a reliable evaluation, where the dataset is partitioned into 5 subsets. To overcome the problem of the reduced dataset size, four subsets representing 80% of fundus images are dedicated for training. The fifth subset is partitioned equitably between validation and testing sub-sets, as illustrated in Fig.3.

Val. Test	Training	Training	Training	Training
Training	Val. Test	Training	Training	Training
Training	Training	Val. Test	Training	Training
Training	Training	Training	Val. Test	Training
Training	Training	Training	Training	Val. Test

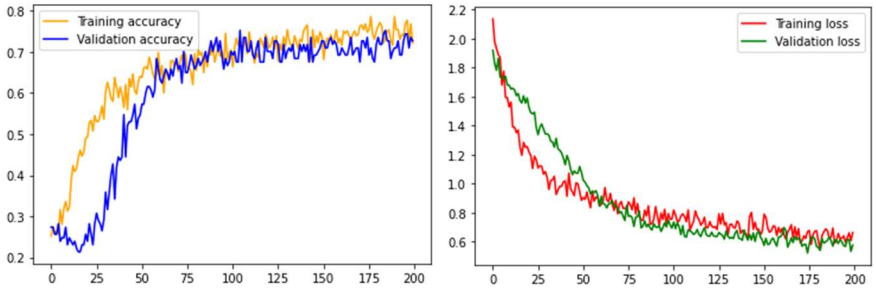
Figure 3: Dispatching of subsets for 5-fold cross validation

Table 3: Healthy and DR-affected fundus images

Healthy fundus images	
DR-affected fundus images	

3.2. ML Implementation

The method is coded using the Python language. Preprocessing is performed using the OpenCV library, while NasNet-Mobile and MLP are implemented using the "Keras" API. The training and testing steps are executed on the cloud service "google Colab". The curve slopes of accuracy and loss for both training and validation are retrieved as depicted in Fig.4. It is deduced that both accuracy (resp. loss) curves increase (resp. decrease) progressively to become almost constant.



(a) (b)

Figure 4: Evaluation of training performance in terms of epochs: (a) Training and validation accuracy values; (b) Training and validation loss values

3.3. Evaluation Metrics

The performance of our method is evaluated through the Accuracy (Acc), Sensitivity (Sens), Specificity (Spec) and Precision (Prec) metrics, which are computed as indicated in equations 3, 4, 5 and 6.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

$$Specificity = \frac{TN}{TN + FP} \quad (4)$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (5)$$

$$Prec = \frac{\text{TP}}{\text{TP+FP}} \quad (6)$$

where TP (True Positive) is the number of images classified correctly as DR-affected, TN (True Negative) is the number of images classified correctly as healthy, FP (False Positive) is the number of healthy images identified as DR, and FN (False Negative) is the number of DR-affected images classified as healthy.

3.4. Performance Evaluation of Proposed Method

This method is evaluated using all cross-datasets, where the performance metrics of each one are shown in Table 4. We deduce that our method carries out higher accuracy, which achieves 97.73%. Even with an equitable partition between healthy and DR-

affected images, sensitivity and specificity have higher values whatever the cross dataset is.

Table 4: DR screening performances in terms of cross-datasets

	Acc (%)	Sens (%)	Spec (%)	Prec (%)
First cross-database	97.73	94.44	100.00	100.00
Second cross-database	93.18	88.89	96.15	94.12
Third cross-database	95.45	94.44	96.15	94.44
Fourth cross-database	97.73	94.44	100.00	100.00
Fifth cross-database	95.45	100.00	92.31	90.00

The performances of cross-validation sets are illustrated through the box plots represented in Fig.5. The reduced plot sizes justify the sustainability of the DR screening whatever the image set, either used for testing or for training. Consequently, it reflects the method robustness and confirms its capacity to be used as a mobile aided screening system for DR.

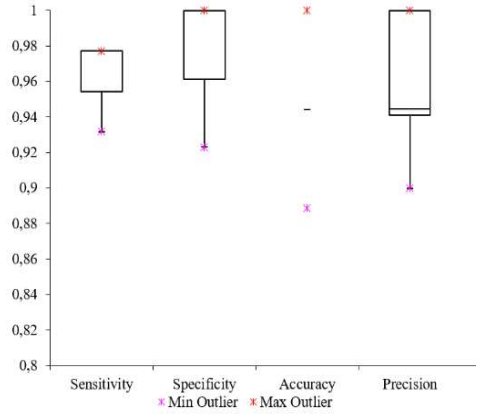


Figure 5: Performance visualization using box plots

3.5. Execution Time Evaluation of the Mobile-Aided Screening System

The trained Nasnet-Mobile model associated to the MLP classifier must be updated to be suitable for smartphone uses. Therefore, the method is implemented as an android app through an Android Studio 4.2 and JAVA Development Kit (JDK) 15.0.2. Therefore, the “TFLiteConverter” class of the public “tf.lite” API is used to convert the trained “TensorFlow” model into a “TensorFlowLite” model. The NasNet-Mobile is converted into a FlatBuffer file (.tflite) and stored into a ”TensorFlowLite” model to be called through the “TensorFlow Lite Android Support” library. The MLP classifier and the image enhancement processing are implemented using the predefined function of the "Open Source Computer Vision (OpenCV)" multiplatform library which is compiled by an Android Native Development Kit (NDK).
Thereafter, we evaluate the computational performance of DR screening when run in a mobile device as an app. For such a need, 10 images (partitioned equitably on healthy

and DR-affected fundus images) are randomly selected from the dataset and tested through the app executed into a "Samsung Galaxy A31" smartphone having an octa-core processor (2 x 2GHz & 6 x 1.95GHz) and 4 Go RAM. We deduce that all execution time is above one second, as depicted in Fig. 6. In addition, close values are registered where the average value is equal to 0.894 second. Accordingly, we deduce that the computational performance is adequate to promote using our system in clinical contexts.

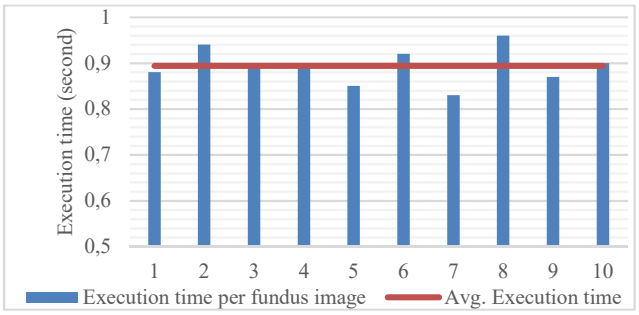


Figure. 6: Execution time of DR screening application in terms of fundus images

4. Conclusion

DR is a major cause of blindness worldwide. Our challenge consists in screening DR using a mobile CAD system, while ensuring all tasks from the fundus image acquisition to the decision generation. For such a requirement, we have proposed a preprocessing to enhance the image quality. Then, we have employed a lightweight DL architecture and a low complexity classifier to carry out higher performant DR screening. The experimentation has been proved respecting the clinical constraints in terms of screening performance and execution time.

In our future work, we aim to extend the dataset size by continuous collaboration with the expert ophthalmologist team. Afterwards, the provided system will be extended to ensure fundus image grading into DR severity. Otherwise, the system will be oriented to other ocular pathologies such as glaucoma, aged macular degeneration or hypertensive retinopathy. Furthermore, the lightweight processing principle can be carried out into other mobile-health domains (Khessiba, 2021).

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