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Research Article

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A comparison between the VGG16, VGG19 and ResNet50 architecture frameworks for classification of normal and CLAHE processed medical images

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Abstraction

In this paper, we chose to focus our study on finding the right convex neural network model specifically for the binary classification task for normal contrast medical image type and enhanced by CLAHE technique. We made a comparison of the architectures of VGG16, VGG19 and Resnet50 in terms of their accuracy, F1 score and Recall for a set of selected brain images of normal and CLAHE enhanced contrast cases. After running 10 experiments in two modes: with and without Data augmentation while keeping the same parameters of the simulations, we came to the conclusion that VGG16 obviously presents the best architecture for medical image classification, the results in the light of Data augmentation mode, the use case the normal contrast images, the three models provided the accuracies 0.78, 0.66 and 0.69 respectively for VGG16, VGG19 and Resnet50, and for the use case the contrast images enhanced by the CLAHE technique, the accuracies being 0,78, 0.76 and 0.72 respectively for VGG16, VGG19 and Resnet50. For the no Data augmentation mode, the use case normal contrast images, the three models provided the accuracies 0.88, 0.79 and 0.75 respectively for VGG16, VGG19 and Resnet50, and for the use case CLAHE-enhanced contrast images, the accuracies being 0.86, 0.87 et 0.65 respectively for VGG16, VGG19 and Resnet50.

Keywords : Transfer learning, classification by CNN, CLAHE, Convolutional Neural Networks.

I. Introduction

Brain tumors are considered a dangerous pathology for all age categories of man, the latest statistics suggest that the rate of patients is increasing, in fact, the groups of infants and young children recognize the second form of cancer that is brain tumors, for adolescents and young adults, brain tumors went from the fifth to the eighth most common cancer. Overall for the elderly population, brain tumors either primary or metastatic is increasing, in fact, for primary have a prevalence of 14.7 per 100,000 in the United States, also that there are about 80,000 to 100,000 new metastatic brain tumors each year *[1]*.

At present, the science of AI is making a remarkable birth to the discipline of oncology, specifically in the treatment of cancerous tumors, thanks to deep learning algorithms such convolutional neural networks CNN, it becomes easy to detect and classify tumors according to the kind and intensity of danger. *[2]*

In our study, we have highlighted several studies carried out in the context of arriving at the best architecture for detecting and classifying medical images, in fact, (Sheldon Mascarenhas and Mukul Agarwal) demonstrate in their study that the VGG16 model presents the best accuracy compared to the VGG19 and Resnet50 models for the case of image classification *[3]*, but this study was not carried out on a precise type of image, knowing that each type of image it has specific properties.

(Parepalli Likhitha Saveri; Sandeep Kumar) have shown that the Resnet50 model gives more accurate results than VGG16 and VGG19 for classification of lung cancer types using non-contrast enhanced medical images *[4]*, this study seems interesting except that it does not target the case of enhanced medical images. In the same context, (Nur Syahmi Ismail and Cheab Sovuthy) made a concrete study on the detection of breast cancer based on a deep learning technique, in fact, they reached the result that the VGG16 model performs better than Resnet50 where the rates were 94% and 91.7%, knowing that this study applied on unenhanced medical images *[5]*. (Hassan Ali Khan et al) conducted an important study on brain tumor classification using CNN, they built a model based on CNN and compared it with VGG16, Resnet50 and INCEPTION-V3 models, the study arrived at results in consecutive 100%, 96%, 89% and 75% for accuracy measure *[6]* . (Muhammed Talo et al) make an interesting study in the same direction of our work, it was a comparison of 4 CNN models for the detection of multi-class brain diseases using MRI image, they achieve that the ResNet-50 model offers the best classification accuracy of 95.23% ± 0.6 better than AlexNet, Vgg-16, ResNet-18, ResNet-34 *[7]* .

After our state of the art, to our knowledge, there are no studies performed at the research stage comparing the VGG16, VGG19 and Resnet50 architecture models for medical images enhanced by the CLAHE technique where all studies performed focus on normal unenhanced medical images.

II. Methods and materials

Following the studies carried out, in the framework of arriving at the right model for the classification of cancerous tumors, we have continued to enrich the actors of this field through a concrete and relevant study. To understand our work, our study will be used a set of medical images of normal contrast that will be exploited to generate a second set of images of contrast enhanced by the technique of CLAHE in order to elaborate three systems of classification each one of which includes an architecture of model VGG16, VGG19 and Resnet50 Note that the contrast enhancement of medical images is done by using the code of python.

The two sets of images of different contrast are used in the three classifiers in two modes with data augmentation and without data augmentation in order to conclude the best model for each case treated.

To carry out this work, we have chosen to subdivide it in five essential steps where each one will be explained in detail in the continuation of paper, the figure (*figure 1*) also summarizes all the steps of our study.

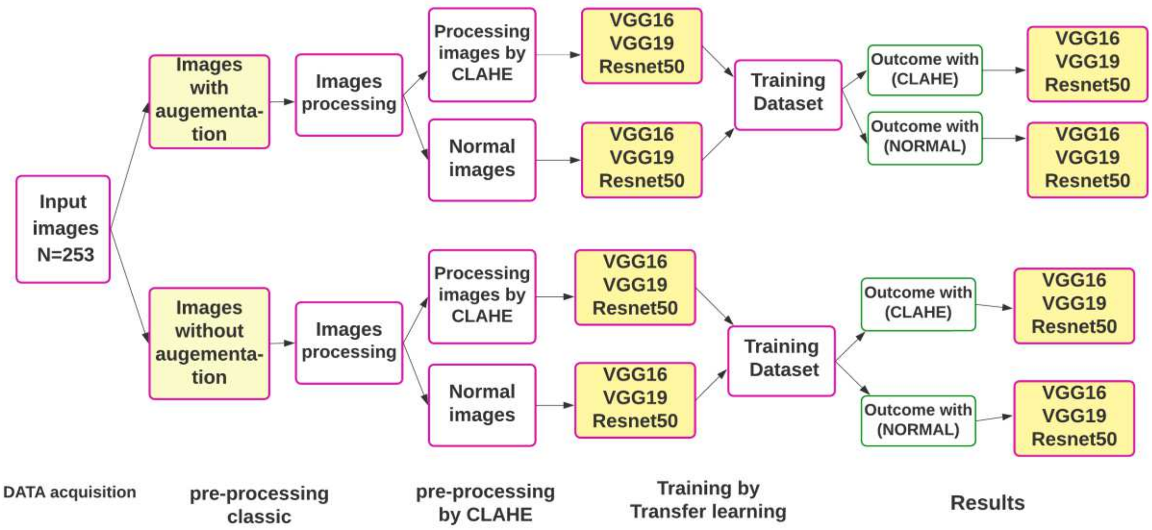

Figure 1: Flow chart of all classification process steps.

1. Dataset

In this study The set of medical images that has chosen is of normal contrast of the brain structure of 253 images *[8]*, in fact, it includes two classes where 253 images present the normal sign brain state (no) and 98 images of the sign brain tumor state (yes). Generally it seems clear that the set of images taken is not sufficient to achieve high accuracy but the objective of our work is focused on discovering a model that gives good performance for the classification of medical images enhanced by CLAHE. The second set of contrast enhanced images obtain by submitting the first set to the CLAHE technique via a python programmed algorithm.

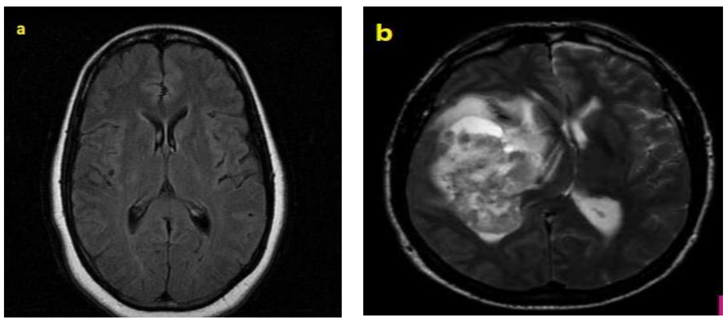

Figure 2: Example of images, (a) normal case (b) cancerous case

2. Image preprocessing

The preprocessing of DATA is an indispensable process for deep learning applications, especially to have correct and delicate results, for our case of MRI medical images often they are in low quality also not usable because of several bills like Gaussian noise, salt and pepper noise *[9]*. For all reasons, we have chosen two procedures to preprocess the set of images that they are the Data augmentation to generate several images and procedure aimed the image quality improvement to help the classifiers to classify correctly the introduced cases.

a. Data augmentation

Among the most widely used strategies to generate many images is the data augmentation, in fact, it comes to cover the problem of insufficient data especially the case where it is difficult to access, in this study we have added several attributions that generate other images, the following table shows the added parameters. *[10]*

Method	Setting
Rotation	40°
shearing	0.2
Image zoom	0.2
Image height range	0.2
Image width range	0.2
Image Horizontal	True
Image Vertical	True
Fill mode	'nearest'

Table 1 : Parameter setting for traditional data augmentation method.

b. Contrast Limited Adaptative Histograme Equalization (CLAHE)

Is a technique to be applied originally to improve the quality of contrast of images especially of low contrast, Indeed, it is also used to solve the problem of noise amplification that result by the application of HE techniques, practically, it divides the image into small regions called blocks have a dimension often of 8x8 in order to equalize each region in specific histogram. On the other hand, the CLAHE technique includes two important parameters are the block size (BS) and the clipping limit (CL) which mainly control the quality of the enhanced image. Indeed, the image becomes brighter when CL is increased, because the input image has a very low intensity with larger CL, which makes the histogram flatter. When the clipping limit is larger, the dynamic range expands and the image contrast also increases *[11,12]*.

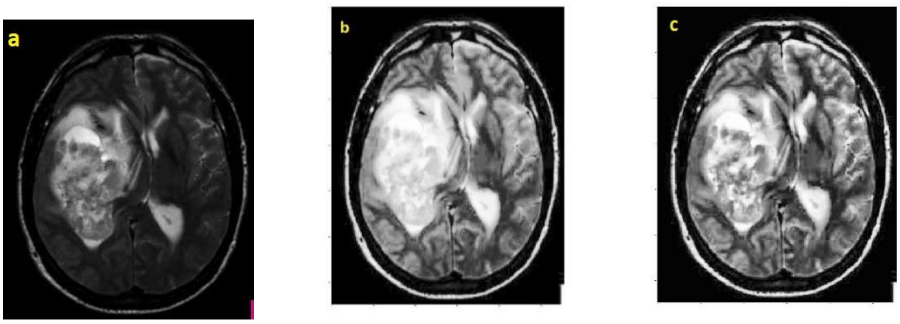

Figure 3: (a) real image (b) modified by HE, (c) modified by CLAHE

III. EXEREMENTAL

1. Classification

Transfer learning (TL) with convolutional neural networks is used to improve performance on a new task by leveraging knowledge from similar tasks learned in advance. Indeed, it has made a major contribution to medical image analysis as it overcomes the problem of data sparsity and saves time and hardware resources. However, transfer learning has been arbitrarily configured in the majority of studies. [13]

a. VGG-16

In our experiments, we first chose the pre-trained VGG-16 convolutional neural network model which indeed refined by freezing some of the layers to avoid Data overfitting as the case of our adopted image set which indeed is very small. The VGG-16 model is an architecture of 16 convolutional layers proposed in 2014 by Karen Simonyan and Andrew Zisserman [14]. Regarding the input image of network, it takes a form of dimensions (224 × 224 × 3) also it includes 16 layers of convolutional also to a fixed size filter in (3 × 3) and 5 layers of Max grouping of size (2 × 2) on the whole network. In contrast, at the top, the two layers fully connected with a softmax output layer. The VGG-16 model considers itself a large network with about 138 million parameters. It stacks many convolutional layers to create deep neural networks that improve the ability to learn hidden features. Figure 5 shows the architecture of the VGG-16 network.

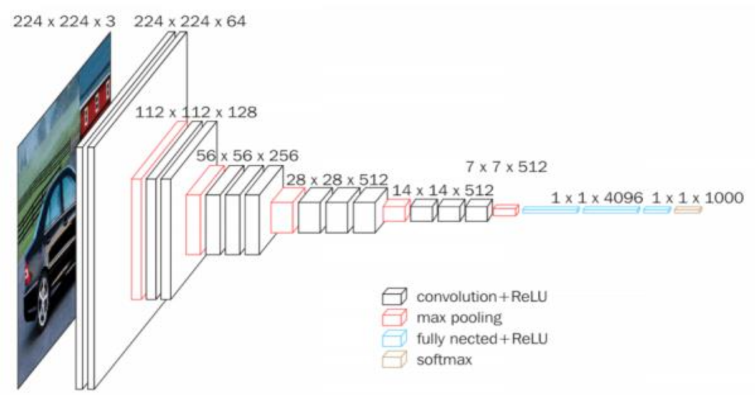

Figure 4: VGG-16 model architecture.

b. Resnet50

ResNet50 is a 50-layer residual network with 26 million parameters. Indeed, is a deep convolution neural network model introduced by Microsoft in 2015 [15]. In the residual network rather than learning features, we learn residuals which are the subtraction of learned features from the layer inputs ResNet connects the input of the nth layer directly to an (n+x)th layer, allowing additional layers to be stacked and a deep network established. We used a pre-trained ResNet50 model in our experiment and refined it. In ***Figure 8***, the architecture of ResNet50 is illustrated.

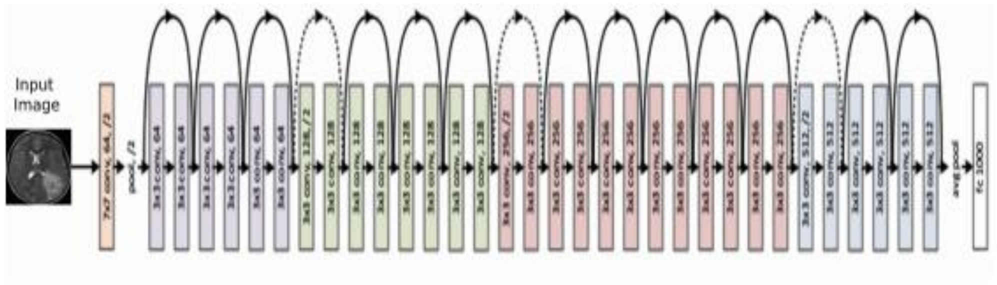

Figure 5 : ResNet-50 model architecture.

c. VGG19

The VGG19 model has 19 layers with weights (see Figure 4), formed by 16 convolutions and 3 fully connected layers (fc) and its input is a 224 × 224 size, 3-channel image with its average RGB value subtracted. The convolutional layers have a small 3 × 3 slot size with 1 pixel padding and stride. The array has 5 max-pooling layers with 2×2 core size and 2 pixel stride. *[16]*

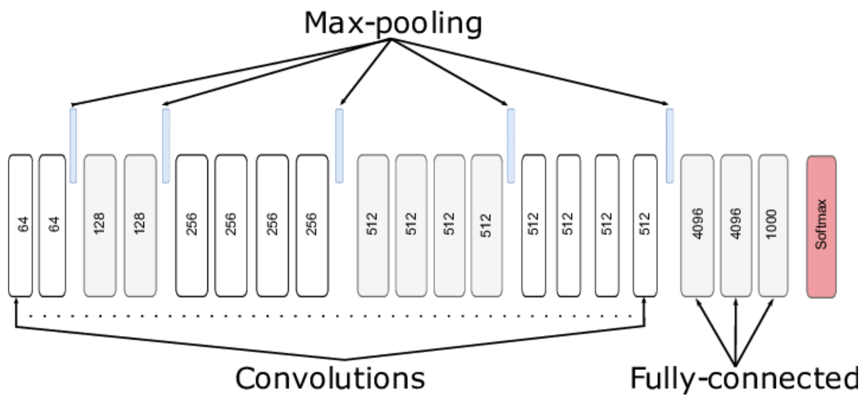

Figure 6 : VGG-19 model architecture.

2. Hyper Parametre

The choice of parameter values to set the classification task was not easy at the beginning, because the results often change depending on the values entered. Indeed, we performed several experiments with particular values chosen until we obtained the best final performances, the values recorded in the following table present the best performances. *[17,18]*

Data	Batch size	Nb of iterations	Nb of Epoches	Type of optimizer	Early stoping	Type of metrics
Train : 70% **Val : 10%** **Test : 20%**	Train : 16 Val : 4 Test : 8	11	100	Adam (0.0001)	10	accuracy

Table 2 : Hyperparameters adopted to our models for classification

3. Performances Metrics

To evaluate the performance of three models, we adopted the confusion matrix as the determinant, in fact, the parameters conferred are : TP that displays the cancerous image data that correctly classified, TN displays the normal image data that correctly classified, FP displays the cancerous image data that incorrectly classified, FN displays the normal image data that incorrectly classified *[19]*.

a. Accuracy

Accuracy is a decisive parameter used to measure the accuracy of a model or an architecture by doing the classification correctly. The formula can be seen in the following equation :

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}} \qquad (1)$$

b. Precision

Is a parameter used to estimate the ability of a model or an architecture to correctly classify positive cases (yes/yes).

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \qquad (2)$$

c. Sensitivity (Recall)

Sensitivity or Recall is a parameter that estimates the ability of a model or architecture to correctly classify all positive and negative cases.

$$\mathrm{sensitivity} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \qquad (3)$$

d. Specificity

It is indicated (the rate of true negatives), it is used to measure the accuracy of the data that are classified as correctly negative or really identified.

$$specificity = \frac{\mathrm{TN}}{\mathrm{TP+FP}} \qquad (4)$$

e. F1 Score

Is an essential parameter to measure the accuracy of a classification system, in fact, it evaluates the effectiveness of two parameters accuracy and precision, and it varied between the interval 0 and 1.

$$F1\ score = \frac{\mathrm{2.TP}}{\mathrm{2TP+FP+FN}} \qquad (5)$$

II. Results

1. With augmentation data

	Metric	N°1	N°2	N°3	N°4	N°5	N°6	N°7	N°8	N°9	N°10	Moyenne
Resnet50	Accuracy	0.70	0.62	0.70	0.64	0.66	0.64	**0.64**	0.70	0.79	0.81	**0.69**
	Recal	0.63	0.49	0.61	0.50	0.59	0.53	0.47	0.63	0.77	0.78	**0.60**
	F1 Score	0.73	0.61	0.77	0.69	0.68	0.65	0.81	0.73	0.81	0.85	**0.73**
VGG16	Accuracy	0.77	0.81	0.77	0.81	0.79	0.79	**0.79**	0.77	0.77	0.77	**0.78**
	Recal	0.75	0.78	0.74	0.79	0.76	0.77	0.76	0.73	0.73	0.73	**0.75**

	F1 Score	0.77	0.85	0.80	0.83	0.84	0.81	0.84	0.82	0.82	0.82	**0.82**
VGG19	**Accuracy**	0.70	0.64	0.62	0.62	0.68	0.68	**0.74**	0.68	0.66	0.62	**0.66**
	Recal	0.73	0.69	0.64	0.64	0.71	0.71	0.77	0.58	0.68	0.61	**0.68**
	F1 Score	0.63	0.50	0.46	0.46	0.60	0.60	0.69	0.75	0.56	0.49	**0.58**

Table 3 : simulation by using *normal* contrast images

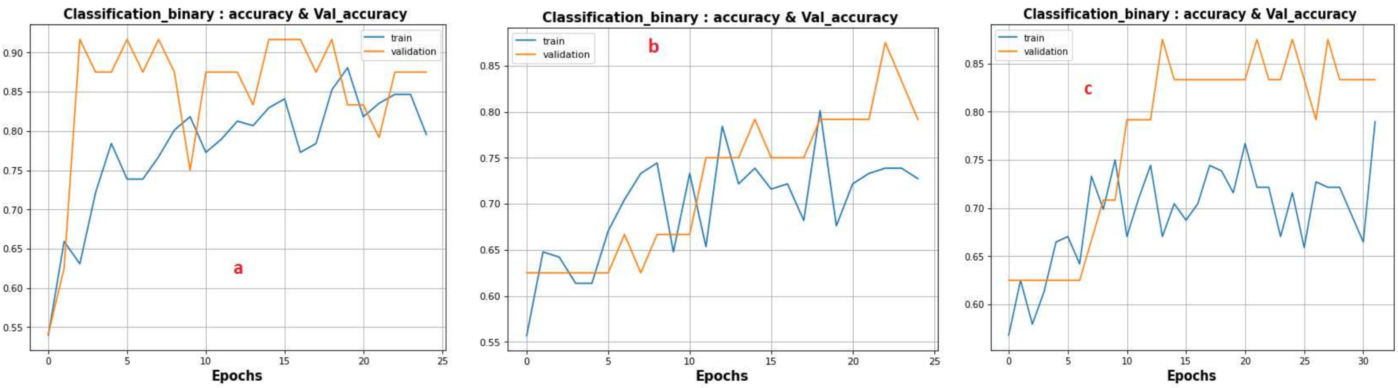

Figure 7: Accuracy evolution of the models (a: VGG16, b: Resnet50, c: VGG19)

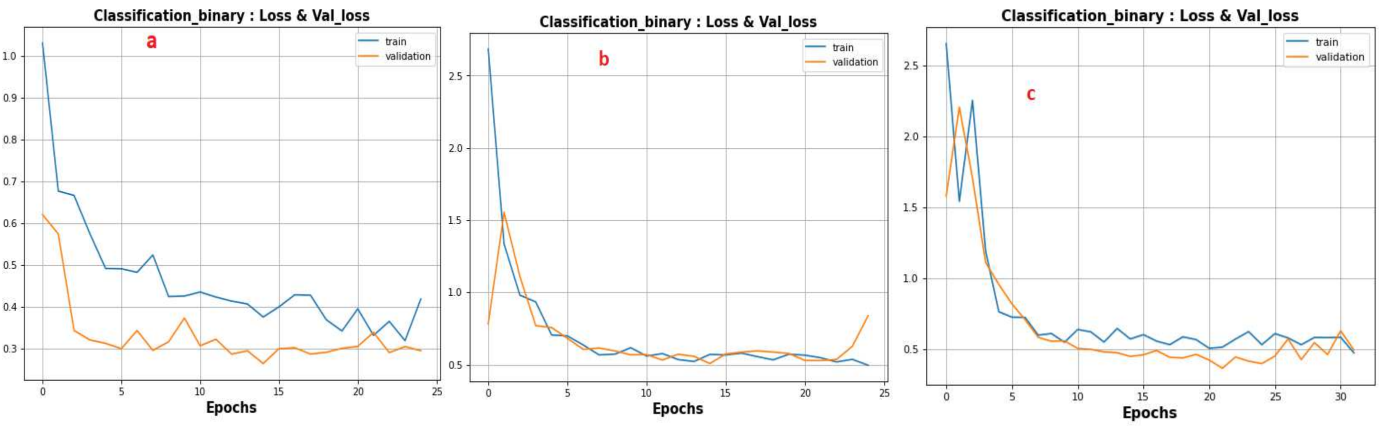

Figure 8 : Loss evolution of the models (a: VGG16, b: Resnet50, c: VGG19)

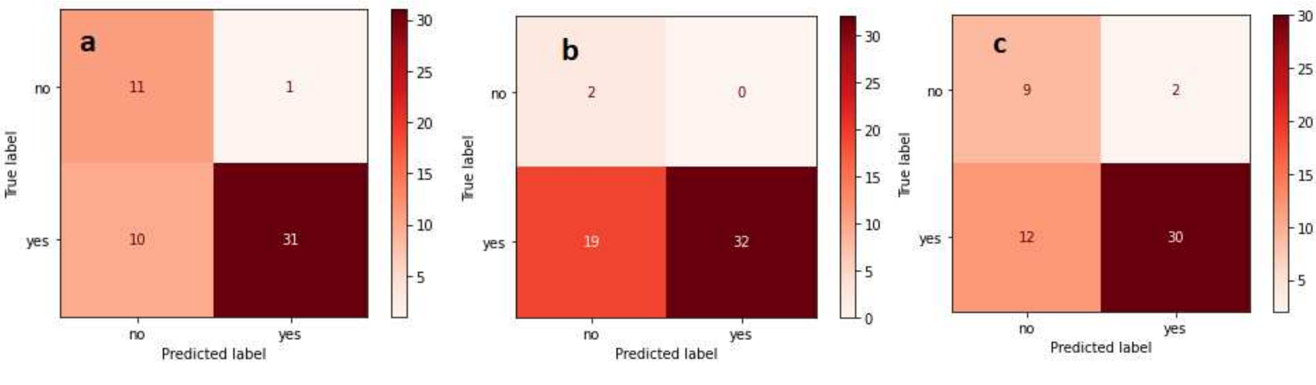

Figure 9 : Confusion matrices for models (a: VGG16, b: Resnet50, c: VGG19).

	Metric	N°1	N°2	N°3	N°4	N°5	N°6	N°7	N°8	N°9	N°10	moyenne
Resnet50	**Accuracy**	0.72	0.72	0.77	0.66	0.75	0.72	0.70	0.74	0.66	0.77	**0.72**
	Recal	0.70	0.64	0.76	0.66	0.73	0.69	0.69	0.72	0.66	0.75	0.70
	F1 Score	0.70	0.78	0.76	0.68	0.75	0.71	0.69	0.72	0.74	0.77	0.73
VGG16	**Accuracy**	0.83	0.81	0.77	0.77	0.79	0.77	0.81	0.79	0.74	0.77	**0.78**
	Recal	0.81	0.78	0.73	0.74	0.77	0.73	0.78	0.77	0.67	0.73	0.75
	F1 Score	0.86	0.85	0.82	0.80	0.81	0.82	0.85	0.81	0.80	0.82	0.82
VGG19	**Accuracy**	0.77	0.75	0.77	0.77	0.75	0.77	0.77	0.75	0.77	0.77	**0.76**
	Recal	0.82	0.81	0.82	0.82	0.81	0.82	0.82	0.81	0.82	0.82	0.82
	F1 Score	0.73	0.70	0.73	0.73	0.70	0.73	0.73	0.70	0.73	0.73	0.72

Table 4 : simulation using contrast images modified by CLAHE

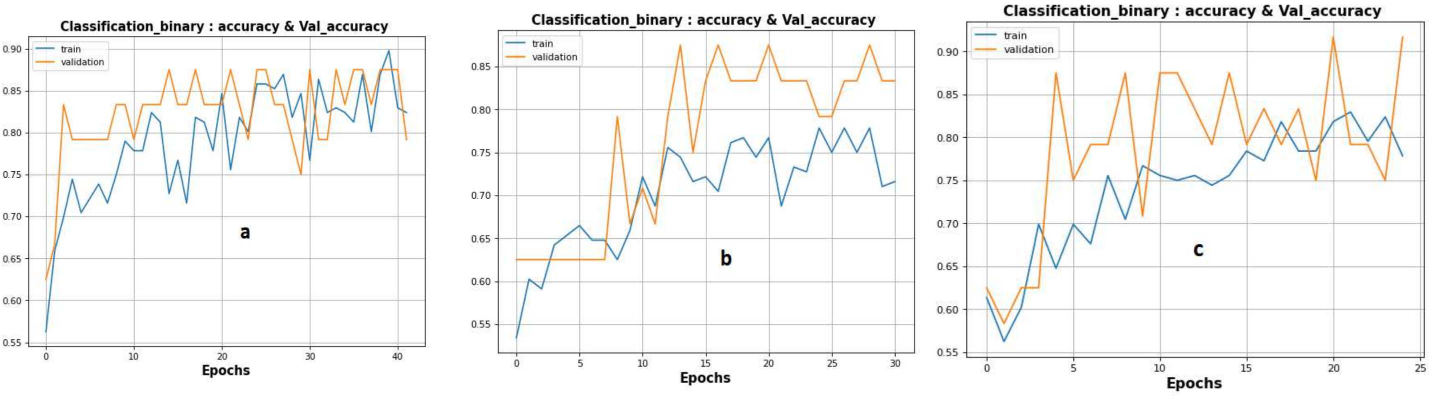

Figure 10 : Accuracy evolution of the models (a: VGG16, b: Resnet50, c: VGG19)

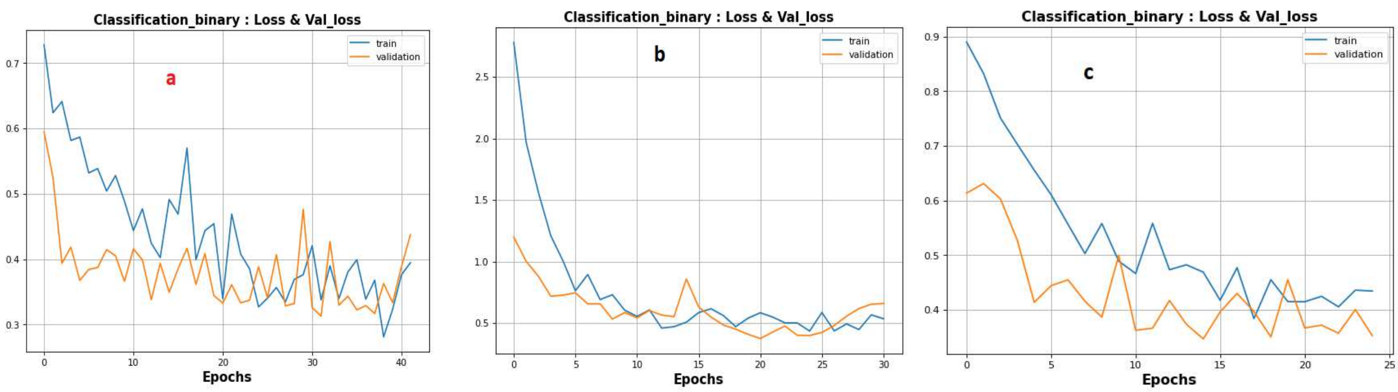

Figure 11: Loss evolution of the models (a: VGG16, b: Resnet50, c: VGG19)

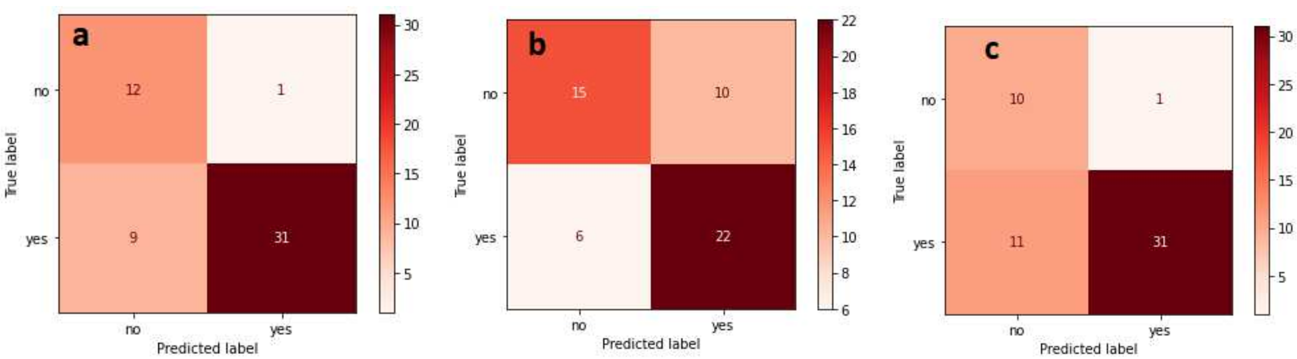

Figure 12 : Confusion matrices for models (a: VGG16, b: Resnet50, c: VGG19).

1. Cases without Augmentation data

	Metric	N°1	N°2	N°3	N°4	N°5	N°6	N°7	N°8	N°9	N°10	MOYENNE
Resnet50	**Accuracy**	0.77	0.72	0.72	0.70	0.75	0.72	0.79	0.79	0.77	0.77	**0.75**
	Recal	0.75	0.67	0.66	0.63	0.74	0.67	0.77	0.77	0.75	0.75	0.72
	F1 Score	0.78	0.73	0.75	0.73	0.75	0.72	0.80	0.80	0.78	0.78	0.76
VGG16	**Accuracy**	0.85	0.89	0.89	0.87	0.87	0.89	0.89	0.89	0.87	0.85	**0.88**
	Recal	0.84	0.88	0.88	0.86	0.86	0.88	0.88	0.88	0.86	0.84	0.87
	F1 Score	0.84	0.88	0.88	0.86	0.87	0.87	0.88	0.88	0.86	0.84	0.87
VGG16	**Accuracy**	0.77	0.79	0.77	0.79	0.77	0.82	0.79	0.83	0.79	0.77	**0.79**
	Recal	0.76	0.78	0.76	0.78	0.76	0.83	0.78	0.82	0.78	0.76	0.78
	F1 Score	0.77	0.78	0.77	0.78	0.77	0.82	0.78	0.82	0.78	0.77	0.78

Table 5 : simulation by using *normal* contrast images

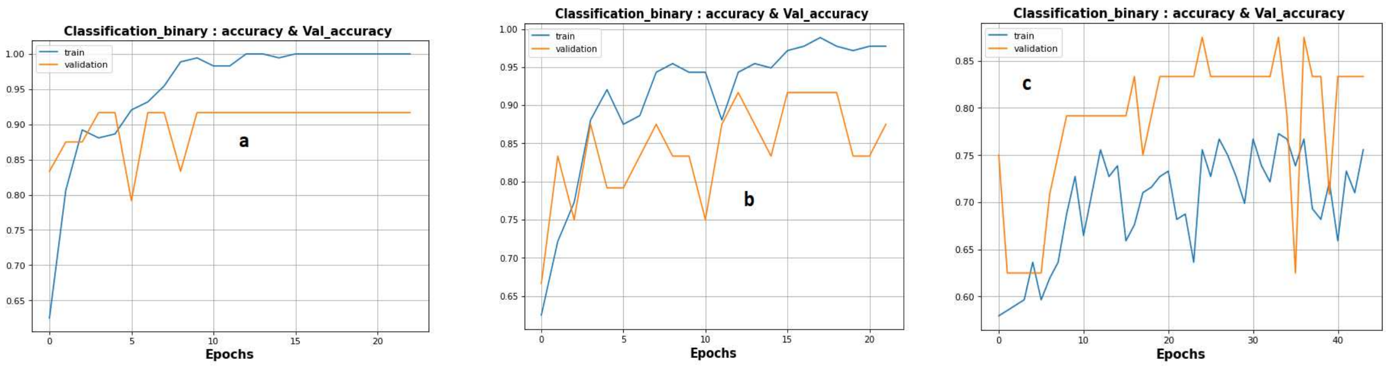

Figure 13: Accuracy evolution of the models (a: VGG16, b: Resnet50, c: VGG19)

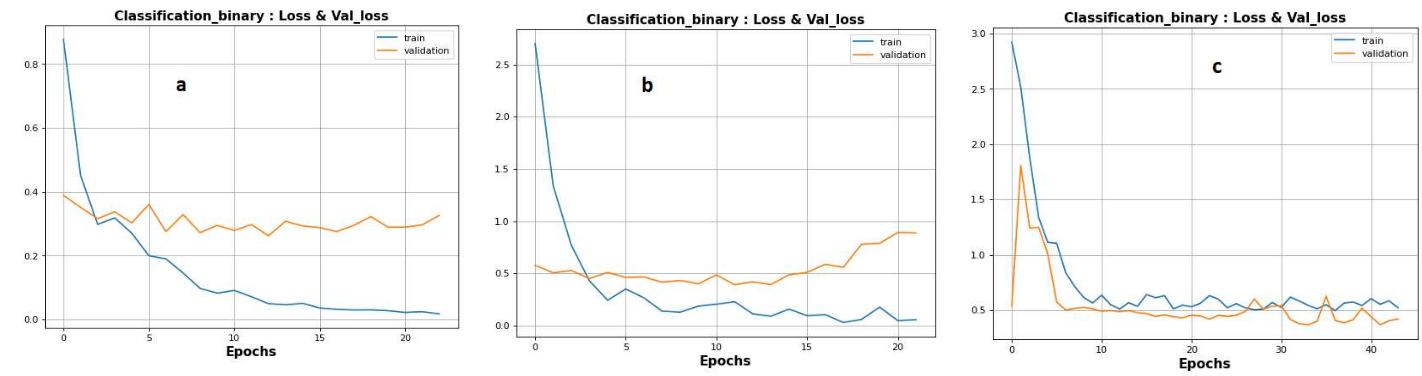

Figure 14: Loss evolution of the models (a: VGG16, b: Resnet50, c: VGG19)

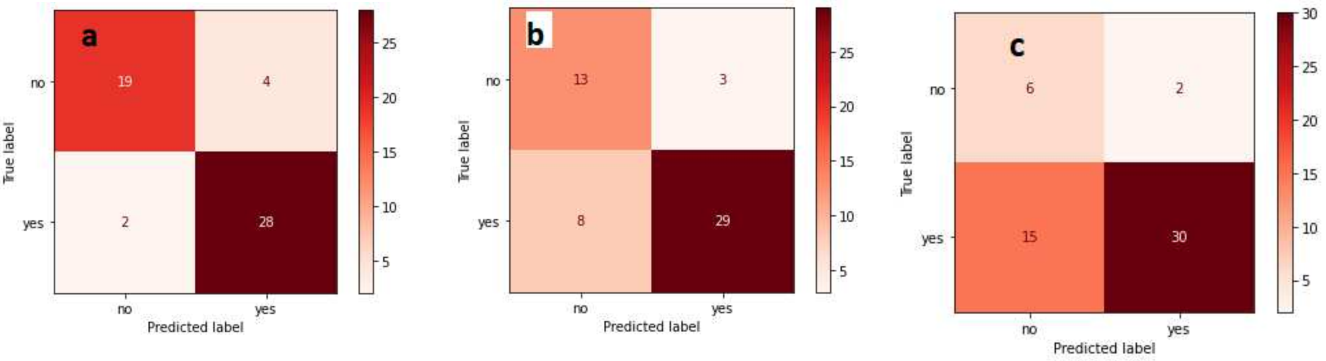

Figure 15 : Confusion matrices for models (a: VGG16, b: Resnet50, c: VGG19).

	Metric	N°1	N°2	N°3	N°4	N°5	N°6	N°7	N°8	N°9	N°10	Moyenne
Resnet50	**Accuracy**	0.62	0.79	0.60	0.62	0.70	0.60	0.68	0.70	0.60	0.60	**0.65**
	Recal	0.43	0.77	0.38	0.43	0.69	0.38	0.61	0.71	0.38	0.38	0.52
	F1 Score	0.81	0.80	0.30	0.81	0.69	0.30	0.69	0.69	0.30	0.30	0.57
VGG16	**Accuracy**	0.87	0.85	0.83	0.87	0.87	0.85	0.85	0.89	0.87	0.84	**0.86**
	Recal	0.86	0.84	0.82	0.85	0.86	0.84	0.84	0.88	0.86	0.82	0.85
	F1 Score	0.87	0.86	0.83	0.89	0.87	0.86	0.86	0.90	0.87	0.82	0.86
VGG19	**Accuracy**	0.87	0.87	0.89	0.87	0.87	0.87	0.89	0.87	0.87	0.87	**0.87**
	Recal	0.85	0.85	0.87	0.85	0.85	0.85	0.87	0.85	0.85	0.85	0.85
	F1 Score	0.91	0.91	0.92	0.91	0.91	0.91	0.92	0.91	0.91	0.91	0.91

Table 6 : simulation using contrast images modified by CLAHE

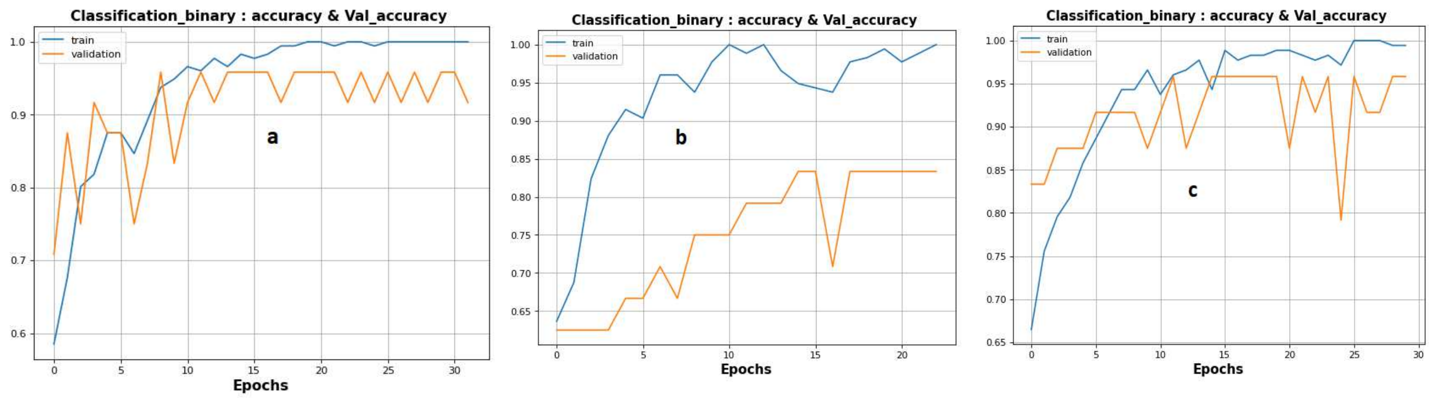

Figure 16 : Accuracy evolution of the models (a: VGG16, b: Resnet50, c: VGG19)

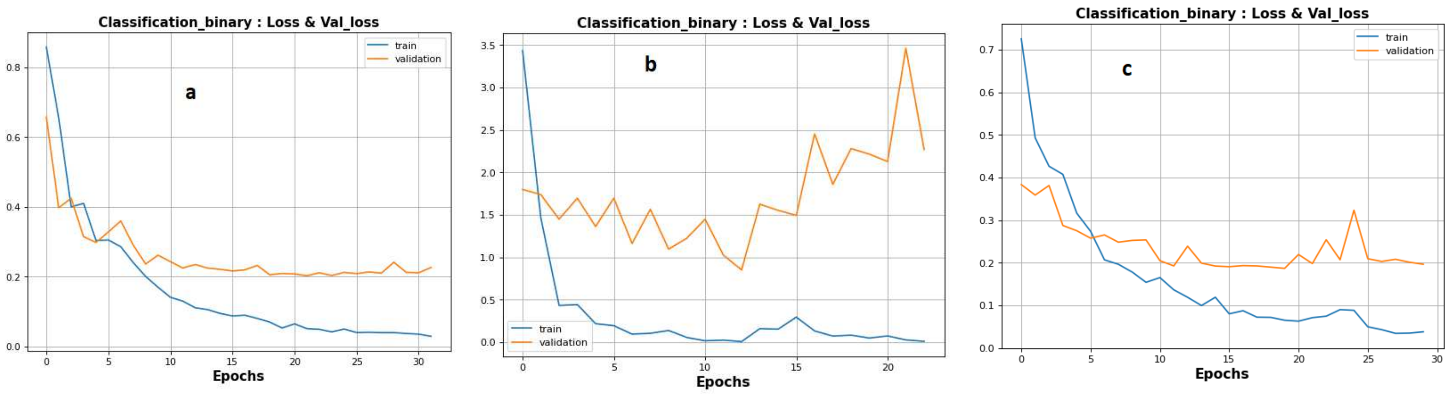

Figure 17: Loss evolution of the models (a: VGG16, b: Resnet50, c: VGG19)

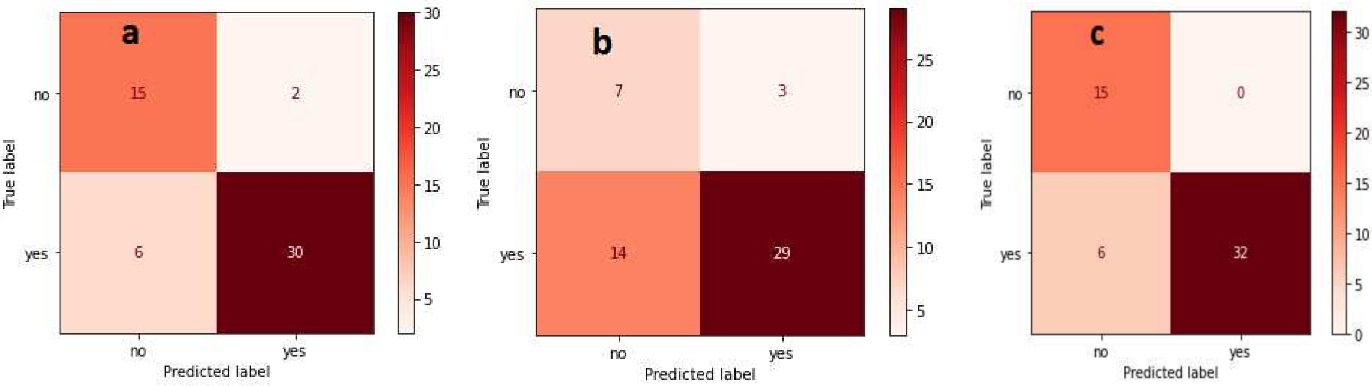

Figure 18 : Confusion matrices for models (a: VGG16, b: Resnet50, c: VGG19).

IV. Conclusion

After the obtained results, it clearly seems that this study was up to our expectations and it took us to very relevant findings, The architecture of VGG-16 is the most efficient for the medical image classification task with high performance compared to the architectures of VGG-19 and Resnet50 for the different image contrast states either normal or enhanced by the CLHAE technique, The efficiency of the VGG-16 architecture remains constant in any data situation either with the integration of data augmentation processes or without. The second findings to conclude that the CLAHE technique is an extremely effective technique to enhance the medical image contrast without losing its information, also the results demonstrate that the performance of CLAHE enhanced image cases are really high than those of normal contrast images. Third finding is that the performances of three architectures in case of integration the process of DATA augmentation are inferior to those of cases without data augmentation, we can conclude that this process is not always contributed to the accuracy increase but indeed its use depends on several simulation parameters such volume of data, architecture chosen and number of EPOCHS sectioned, The last finding that can be concluded is that the use of CHLAHE enhanced contrast medical images increases the simulation time and the number of EPOCHES as well.

Declarations

Competing Interests

Indeed the study of this article is a step of our PhD thesis project which started in 2019, the idea is to develop a system of treatment of cancerous tumors by the use of X-rays based on artificial intelligence algorithms, the idea comes to minimize the risk of irradiation of adjacent organs as well as to raise the accuracy and efficiency of irradiation of cancerous tumors. This project has divided into 4 essential studies in which we prepare our articles:

1. To highlight an effective technique to improve the contrast of medical images while maintaining the image quality (CLAHE technique)

2. Implemented a binary classification system of cancerous tumors based on CNNs using themedical images previously enhanced by the CLAHE technique.

3. Semantic segmentation of tumor found in the medical image to be enhanced by the CLAHEtechnique

4. Irradiation of cancerous tumor by X-rays using the monte carlo method.

Editorial Board Members and Editors

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