Covid-19 detection: a Deep Learning Approach based on Wavelet Transform

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Abstract: While being considered one of the most accurate and reliable techniques for detecting the Corona virus cases, the Reverse Transcription-Polymerase Chain Reaction (RT-PCR) remains quite expensive and requires advanced infrastructure and qualified manpower that are not always available in developing countries, fact that delays the diagnosis and increases the risks of mortality. Motivated by this concern and believing that applying AI techniques on X-Ray or Computed Tomography (CT) images can help detecting Covid 19 cases in a cheaper, faster, and accurate manner, a Wavelet Transform Enhanced deep learning Model (WTEM) is proposed to detect Covid-19 cases. More particularly, this paper presents a solution based on the combination of the wavelet transform technique with deep learning (DL) models. WTEM is compared to the DarkCovidNet model proposed by Ozturk et al. in (Ozturk et al., 2020) and to the VGG-19 model (Hansen, 2020). This solution outperforms both models in terms of accuracy, recall, and F1-Score in addition to significant reduction of the processing time and memory which makes it suited for resource-constrained embedded systems.

Keywords: Covid-19, X-Ray CT Images, Wavelet Transform, AI, Deep Learning, CNN.

1. Introduction

The coronavirus continues to infect people and to cause deaths all over the world. It is affecting 219 countries and causing more than 5 million deaths (Worldometer, 2020). Reverse Transcription-Polymerase Chain Reaction (RT-PCR) has been identified as one of the most accurate and reliable techniques for detecting the Coronavirus. Nevertheless, this technique remains quite expensive and requires facilities and qualified staff that are not always available, particularly in developing countries. Indeed, in Tunisia, for instance, the PCR test kit costs 209 Tunisian dinars, which is equivalent to 77 USD, in a country where the guaranteed minimum industrial wage (SMIG) is less than 150 USD. Moreover, for a population of more a than 11,5 million people, only 20 labs have been accredited by the Tunisian Ministry of Health to perform this test. This small number of accredited labs and the high cost of the test, increase the risk of mortality and make it more difficult for developing and poor countries to face the pandemic. The World Health Organization (WHO) recommends testing all the patients that meet the suspect case definition as well as people who have had contact with a COVID-19 case (World Health Organization, 2020). However, as the number of infected people grows exponentially, countries that suffer from lack of resources and facilities struggle in containing the spread of the virus. Moreover, while being known as a "real-time" technique, the RT-PCR takes on average between 6 to 8 hours to deliver a diagnosis. Note that we should add to this time the time it takes to deliver the result to the patient and to transport the sample from the patient to the lab. In Tunisia for example, the process lasts on average 2 days. These delays increase the risk of contamination in the population and delay identifying and taking care of COVID-19 cases. Motivated by the lack of resources in facing the Coronavirus pandemic in many countries and believing that advances in Artificial Intelligence (AI) can help identify patterns in X-ray images of positive cases, the potential of deep learning techniques in diagnosing Covid-19 was investigated through this work. More particularly, this work consists in coupling the wavelet transform technique with a deep learning model to enhance and accelerate the identification of covid-19 cases. The results found in this research are very encouraging and confirm that further investigation of AI-based techniques can help identify positive cases and accelerate the diagnosis process. Relying on X-Ray or Computed Tomography (CT) images in the testing protocol, can facilitate the diagnosis process for areas and regions where accredited labs and/or qualified manpower are not available to perform the RT-PCR test. Indeed, as the proposed model needs only an X-Ray image of the patient and an Internet connection to upload it, this makes the process available and more affordable to radiologists in rural areas and to medical structures that lack adequate health care facilities to perform the PCR tests.

AI techniques have been explored in (Saba et al., 2021) for the classification of Covid and Non-Covid CT lung scans. Six models have been compared by the authors. The results show that the strong presence of contrasting features in the CT images allow a successful classification. Yet, a better accuracy has been observed with the DL models (Convolutional Neural Networks CNN and iCNN) when compared to the considered Machine Learning (ML) and Transfer Learning models. Authors in (Loey, Manogaran & Khalifa 2020) have focused on overcoming the lack of chest CT images datasets for Covid-19 cases by exploring classical data augmentation techniques combined with Conditional Generative Adversarial Nets (CGAN). They have proved that the use of this approach improves the performance of the classification with the five deep CNN considered models. Other works in the literature have investigated the AI techniques for early stage Covid-19 cases detection based on chest CT (Ozturk et al., 2020), (Apostolopoulos & Mpesiana, 2020), (Harmon, et al. 2020). More details on the models used in (Ozturk et al., 2020), (Apostolopoulos & Mpesiana, 2020), (Harmon, et al. 2020) will be provided in Section 2.2. To the best of the authors' knowledge, this is the first work that explores the coupling of the Wavelet Transform (WT) with a DL technique to identify Covid-19 positive cases. The main advantage of coupling both techniques resides in the enhancement brought by the WT on the model performance in terms of accuracy, recall, F1-score, but also from a complexity and resource allocation perspective.

The remainder of this paper is organised as follows. In Section 2, the methods and materials used in this work are presented. The used dataset is described, and the proposed DL model is explained. The obtained results are presented in Section 3. Finally, conclusion and future work are given in Section 4.

2. Materials and methods

2.1. The X-ray images dataset

This work uses an open public dataset of X-ray and CT chest images available in a GitHub repository (Cohen, Morrison & Dao, 2020). The dataset consists of images of positive Covid-19 cases, patients suffering from bacterial pneumonia and people with normal conditions. Figure 1 shows a sample of each group of the dataset: a Covid-19 positive case, a negative case and the chest X-ray image of a person suffering from a bacterial pneumonia.

Figure 1. Samples of the X-Ray CT images dataset

2.2. The Wavelet Transform-Enhanced Model (WTEM)

2.2.1. Wavelet Transform (WT)

Also called Wavelet decomposition, it is a mathematical tool that is used to extract information from different audio signals, images, and other forms of data. It is based on a combination of lowpass and highpass horizontal and vertical filtering of the original image. In the studied case, the Wavelet decomposition was applied to each image of the dataset. For each sample, the results were: (i) an "approximation" image, (ii) a "horizontal detail" image, (iii) a "vertical detail" image and (iv) a "diagonal detail" image (cf. Figure 2). Once the decomposition is performed, only the "approximation image" is considered in the remaining of the process. This "approximation image", when compared to the original one, requires much less memory for storage while maintaining and even enhancing the image quality thanks to the denoising step. As a result,

the processing time is optimised since noise is eliminated. Seven different wavelets have been explored in this work to perform the wavelet analysis on each image; Daubechies (db2) and Bi-Orthogonal (bior3.1) are selected due to their good performances.
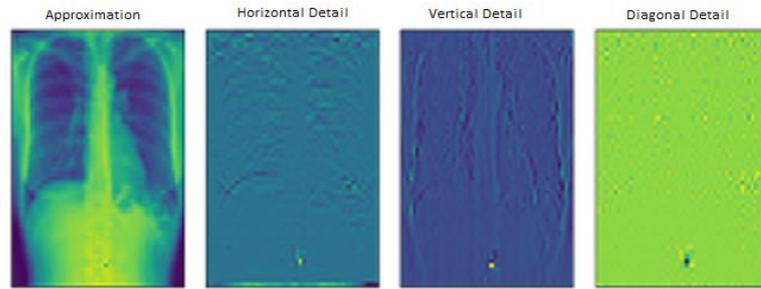
Figure 2. Samples of the X-Ray CT images dataset

Wavelet Daubechies 2 (db2) has a non-linear phase. The response to impulse is maximally flat. This wavelet is quite compact in time, but within the frequency domain, it has a high degree of spectrum superposition between scales (Burrus & Gopinath, 1998). These wavelets were the first to make discrete analysis practical. Ingrid Daubechies constructed these models with a maximum orthogonal relationship in the frequency response and half of the sampling rate, imposing a restriction on the amount of decay in a certain range, thereby obtaining a better resolution in the time domain; 2*n filter coefficients are produced.

Wavelet Biorthogonal 3.1 (bior3.1) has a linear phase. This family uses two wavelets: one for decomposition and another one for reconstruction. The Bi-Orthogonal wavelet family has compact support and is symmetric (Burrus & Gopinath, 1998).

2.2.2. Architecture of the Wavelet Transform-Enhanced Model

The architecture of the Wavelet-Transform Enhanced Model (WTEM) that is proposed in this work is illustrated by Figure 3. It consists of 4 phases:

- Data Acquisition: as input for the model, Chest X-Ray CT images have been used from the dataset. The original size of the input images is 256x256x3;

- Data Denoising and Dimensionality Reduction: Once the images acquisition is per-formed, a wavelet transform is applied. Either bior3.1 or db2 technique is used at Level 1 or Level 2. As a result of this phase and as explained in Section 2.2.1, four images are generated. Only the approximation image is used for the remaining of the process. Note that the size of the approximation image is smaller than the original size of the acquired image. If level 1 WT is applied, the size of the image is reduced i.e., 128x128x3 in this case as shown in Figure 3. If level 2 WT is performed, the size decreases to 64x64x3;

- DL Model Training and Deployment: During this phase, a classification deep learning model is applied to the approximation images. The DL models used in this paper are the DarkCovidNet model proposed by (Ozturk et al., 2020) in and the VGG19 used in (Hansen, 2020) and (Apostolopoulos & Mpesiana, 2020). Both models are based on Convolutional Neural Networks (CNN). More details about the used models are provided in the next paragraphs;

- Classification: the last phase of the proposed WTEM consists in classifying the images either into 2 classes (binary classification): whether it is a covid-19 case or not (No Findings), or into 3 classes where the difference is made between (i) normal cases (No Findings), (ii) pneumonia cases and (iii) potential Covid-19 cases. Both classifiers are investigated in this work and compared to the DL model when WT is not applied.
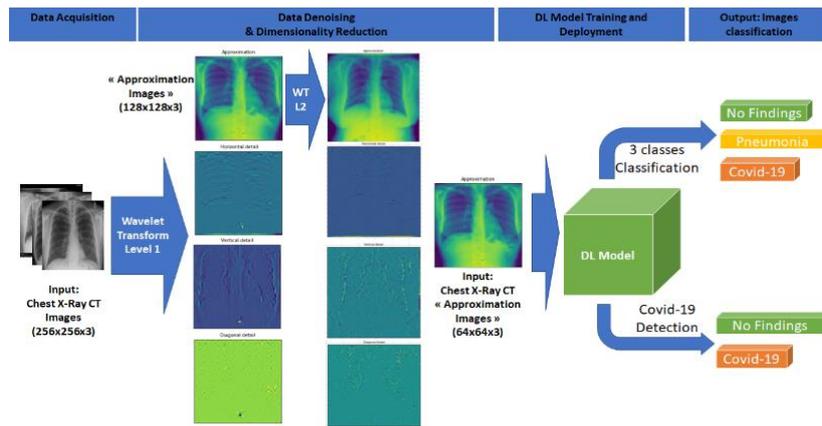
Figure 3. Architecture of the Wavelet Transform Enhanced Model (WTEM)
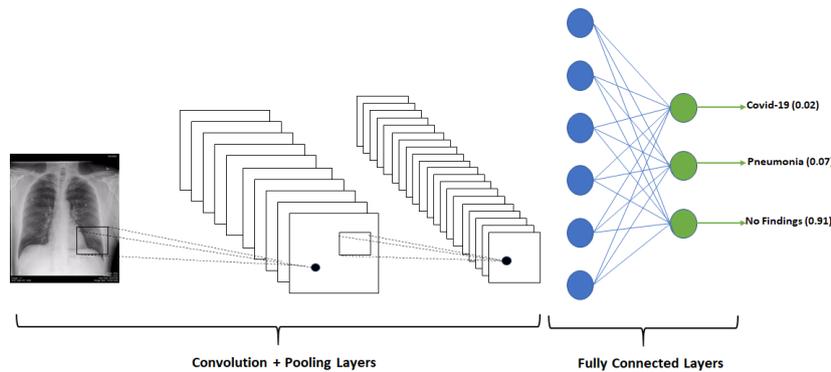
Figure 4. The ConvNet Architecture

2.2.3. Image classification using CNNs

Over the last decade, deep neural networks (NN) and particularly Convolutional Neural Networks (CNN or ConvNets) have shown a tremendous potential in developing machine intelligence to learn and recognise complex patterns in the domain of computer vision. Inspired by the visual cortex, CNNs are based on a multi-layer structure that aims at extracting high-level features from the input image with minimal preprocessing. As illustrated by Figure 4, CNNs are based on three main concepts (Sarkar, Bali & Sharma 2018):

- Multiple convolutional layers: The convolution consists in applying a filter across the two dimensions of the image (height and width). The dot product between the convolutional layer and raw pixels of the input image results in a feature map indicating the location and the strength of the identified feature. The objective of the convolution operation is to extract features such as edges, colors, orientation, etc. from the input image. To cover the depth of the image, the convolution operation is applied several times through different layers (filters) to capture multiple features of the input data;

- Pooling layers: pooling (also called *down sampling*) aims at reducing the spatial size of the convolved feature by decreasing the size of the input and eliminating some parameters from the convolutional layer output. Pooling prevents overfitting and simplifies the deep learning process. Typical pooling techniques are max pooling and average pooling;

- Fully connected layers: after extracting high level features, thanks to convolutional and pooling layers, the fully connected layers are applied to use these features for classifying the input image into different classes based on the training dataset.

2.2.4. The DarkCovidNet Model

Darknet-19 is a classification model that has been proposed by (Redmon & Farhadi 2017) as a base for one of the most powerful real-time object detection systems: YOLOv2 (You Look Only Once). It has 19 convolutional layers and 5 max pooling layers. The model proposed by Ozturk et al. in (Ozturk et al., 2020) is based on DrakNet, yet it has 17 convolution layers. As illustrated by Figure 5, each DarkNet – DN layer consists of a combination of (i) one convolutional layer a (ii) batch normalisation operation to standardise the input and increase the stability of the model and (iii) a LeakyReLU activation function to avoid that some neurons die and remain inactive in the neural network. Like in Darknet-19, the Dark-CovidNet model proposed in (Ozturk et al., 2020) uses 5 Max pooling layers to reduce the input size and the computation complexity.

2.2.5. The VGG model

The main idea behind proposing VGGNet in 2014 was accelerating the learning process by reducing the size of the filters at each conv layer (e.g., 3x3), thus reducing the number of trainable variables. While being simple, the Conv Network is deep as it uses many filters per layer (64 to 512 filters/layer). Five Max pooling layers are used in this architecture. VGGNet has several variants that differ from each other in the number of layers in the network (16 for the VGG-16, 19 for the VGG-19, etc.). VGG ends up being a large network with about 138 million parameters.
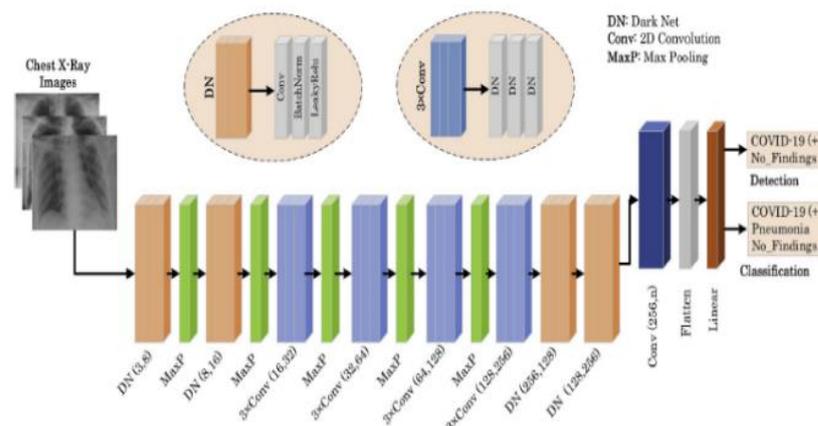
Figure 5. Architecture of the DarkCovidNet Model (Ozturk et al., 2020)

3. Results

3.1. Metrics

To evaluate the performance of the proposed model and to figure out how well it performs, several metrics can be used. This section is started by defining these metrics and highlighting the main differences between them.

3.1.1. Confusion Matrix

It is one of the most popular techniques to evaluate the performance of a classification model. As shown in Figure 6, the confusion matrix is a combination of predicted and actual values.

- True Positives (TP): These are the events (in this case images) that were correctly predicted by the model as "Yes" – a Covid-19 case.

- True Negatives (TN): These are the images that were correctly predicted by the model as "No Findings".

- False Positives (FP): These are the images that were predicted as "Covid-19" while the

actual class is "No Findings".

- • False Negatives (FN): This is the opposite of FP, i.e., images are predicted by the model as "No Findings" while they belong to the "Yes" – "Covid-19" class.

Predicted class

		P	N
Actual Class	P	True Positives (TP)	False Negatives (FN)
	N	False Positives (FP)	True Negatives (TN)

Figure 6. Confusion Matrix

3.1.2. Accuracy

It is the most intuitive metric to measure performance. It says how often the model predicts correctly. As expressed by (1), it is the ratio of correctly predicted images to the total images.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

3.1.3. Precision

It indicates how often the model performs wrong. As expressed by (2), it is the ratio of correctly predicted positive images to the total predicted positive images.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

3.1.4. Recall

Also called sensitivity; as expressed by (3), recall is the ratio of correctly predicted positive images (Covid-19) to all the images in actual class – Covid-19. It should be as high as possible. In the case of a pandemic such as Covid-19, recall is a very important metric. Imagine that a patient is informed that his test is negative while it is positive; this "false negative" case would be propagating the virus in his environment and could contaminate other people because of this wrong diagnosis. Therefore, when discussing the results, a special emphasis will be placed on recall for performance measurement.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

3.1.5. F1-Score

As it is difficult to compare two models with a high accuracy and low recall or vice versa, the use of F1-Score helps combining these two metrics. As expressed by (4), it uses Harmonic Mean of precision and recall.

$$F_1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

3.2. Experimental results

To evaluate the performances of the proposed Wavelet, Transform Enhanced Model (WTEM), the Wavelet Transform technique is first coupled with the DarkCovidNet model

proposed in (Ozturk et al., 2020) then with the VGG-19 model used in (Hansen, 2020) and (Apostolopoulos & Mpesiana, 2020). The proposed model shows a real improvement in accuracy, recall and processing time when compared to the models proposed in (Ozturk et al., 2020) and (Hansen, 2020). During the experiments, two different scenarios are considered:

- A binary classifier that identifies (i) Covid-19 cases from (ii) No Findings cases. In this scenario, No Findings correspond to all negative cases regarding the Coronavirus;

- A 3 classes classifier: where X-ray and CT images are classified by the model into one of the three classes: (i) Covid-19, (ii) No Findings, and (iii) Pneumonia cases.

As stated before, the dataset consists of X-ray and CT images from the database available in (Cohen, Morrison & Dao, 2020). More precisely, it consists of 1125 images split as follows: 125 Covid-19 images, 500 Pneumonia and 500 Normal (No Finding) images. For the binary classifier, only the Covid-19 and normal images are considered (i.e., 625 images in total). The pneumonia X-Rays and CT are introduced in the dataset of the 3-class classifier. In this work, 80% percent of the dataset was used for training and 20% for validation. All the experiments have been carried out on IBM Watson Platform (IBM, 2021) in the free execution context composed of 2 virtual central processing unit (vCPU) and 8 GB of RAM. For the sake of ensuring the same conditions when comparing the results with those of other works, all the experiments have been conducted in the same execution context which explains why the performances might be slightly different from the original sources.

3.2.1. Optimization of the learning rate

The learning rate is one of the most important hyperparameters in deep neural networks. It scales the magnitude of the weights used in the NN. Optimising the learning rate helps reaching a tradeoff between the quality of the proposed solution and the speed of the training process. Therefore, instead of setting it randomly, the loss value was evaluated while varying the learning rate. As shown in Figure 7, the optimal value is 1e-3.
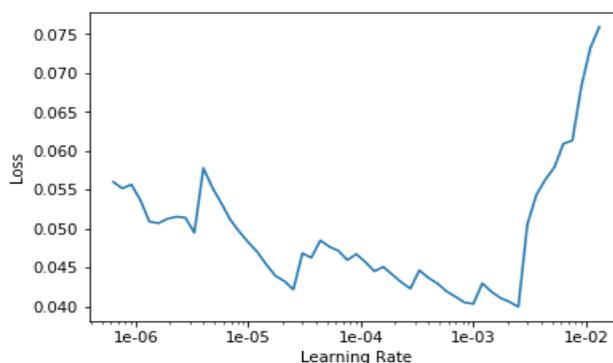
Figure 7. Optimisation of the learning rate

Table 1. VGG-19 DL model (with/without WT): Performance metrics

	F1-Score		Accuracy	Processing Time
	No Findings	Covid-19		
VGG-19 [4]	0.8	0.84	0.82	14 s/step
VGG-19 + WT	0.88	0.95	0.93	8 s/step

Table 2. Performance metrics with WTEM (db2 L1)

	precision	recall	F1-score	support
Covid-19	1.00	1.00	1.00	13
No_Findings	1.00	1.00	1.00	112
micro avg	1.00	1.00	1.00	125

macro avg	1.00	1.00	1.00	125
weighted avg	1.00	1.00	1.00	125

Table 3. Performance metrics with DarkCovidNet

	precision	recall	F1-score	support
Covid-19	1.00	0.88	0.93	24
No_Findings	0.97	1.00	0.99	101
micro avg	0.98	0.98	0.98	125
macro avg	0.99	0.94	0.96	125
weighted avg	0.98	0.98	0.98	125

3.2.2. The enhanced 2 classes classifier

This section is dedicated to the performance evaluation of the binary classification of CT and X-ray images into Covid-19 or No Finding classes. More precisely, the results of the WTEM model are compared to DarkNetCovid (Ozturk et al., 2020, then to the VGG19 model (Hansen, 2020).

WTEM vs VGG-19: To investigate the impact of using the Wavelet Transform combined with a DL model, a series of measurements have been carried out comparing the VGG-19 model, whose results have been reported by Hansen in (Hansen, 2020), with the WTEM binary classifier combining VGG-19 with db2 Level 1 WT. The obtained results are reported in Table 1. As it can be seen, a substantial improvement is noticed on both F1-score and accuracy. Moreover, the processing time is significantly reduced with the mix VGG+WT thanks to the denoising and dimensionality reduction insured by the WT process.

WTEM vs DarkCovidNet: Table 2. shows the excellent results obtained with the WTEM thanks to the combination of the Level 1 of Daubechies 2 (db2) Wavelet Transform with the DarkCovidNet model. The DarkCovidNet (Ozturk et al., 2020) performance metrics are illustrated by Table 3. Note that there is an improvement of the recall from 0.88 with DarkCovidNet to 1.00 with the used model. Moreover, the confusion matrix in Figure 8.(a) shows that neither false positive nor false negatives are predicted by the prosposed model for the binary classification. Figure 8.(b) depicts the confusion matrix obtained when using Biorthogonal 3.1 (bior) WT with DarkCovidNet model. While results are slightly worse than when using Daubechies WT (Figure 8.(a)), they reach better performance when compared to the DarCovidNet model (cf. Figure 8.(c)).

(**a**)   (**b**)   (**c**)
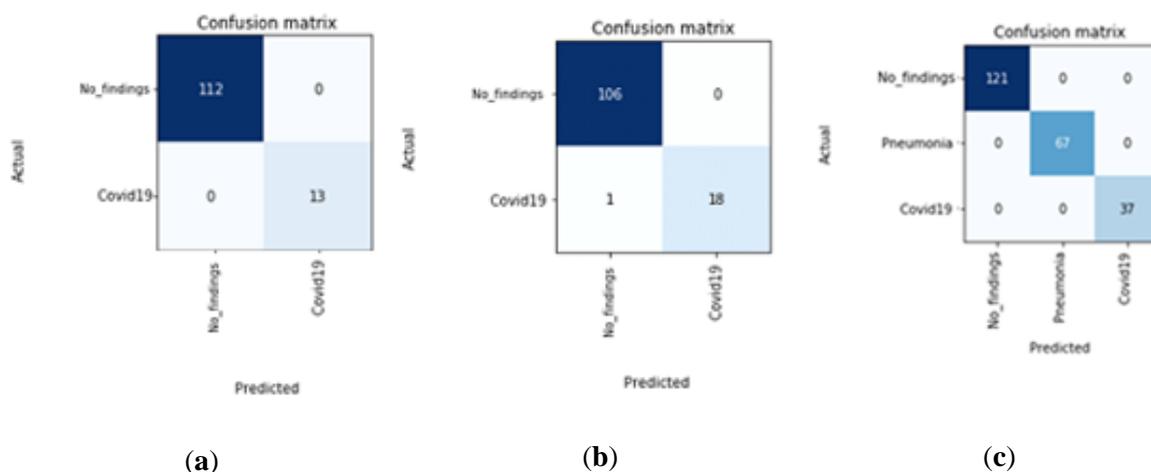
Figure 8. The confusion matrix of the binary classification for: (**a**) WTEM using db2 L1 Wavelet Transform; (**b**) WTEM using bior L1 Wavelet Trânsform; (**c**) DarkCovidNet (Ozturk et al., 2020)

(a)   (b)
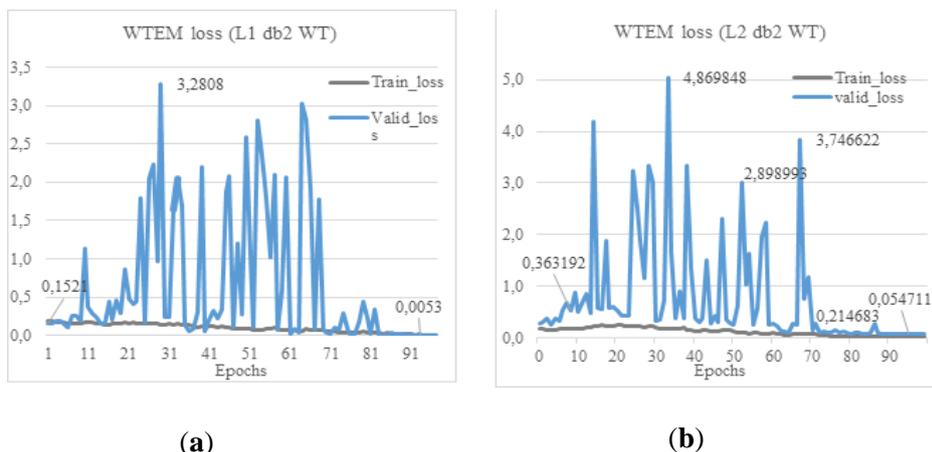
Figure 9. Validation and Training Losses for the Wavelet Enhanced DarkCovidNet Model using:
(a) L1 db2 WT; (b) L2 db2 WT

(a)   (b)   (c)
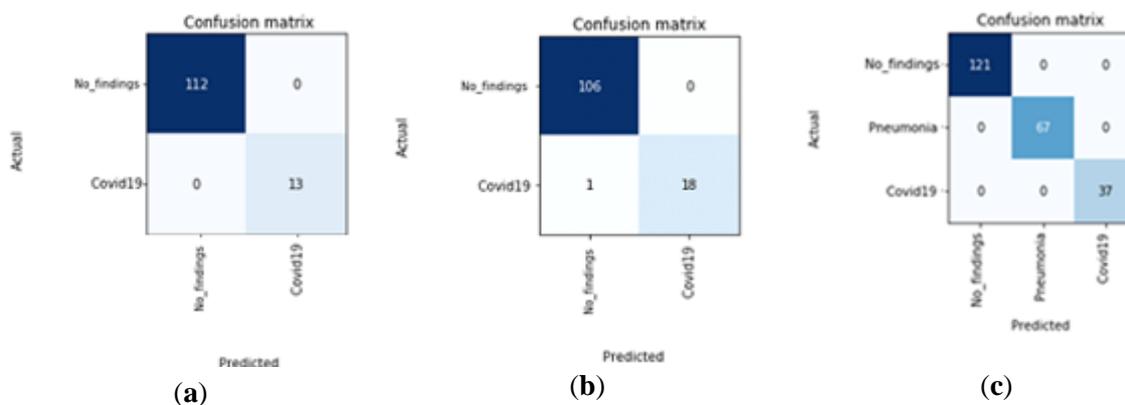
Figure 10. Confusion Matrix of the three-classes classifiers for: (a) WTEM using L1 db2 WT; (b)
WTEM using L2 db2 WT; (c) DarkCovidNet (Ozturk et al., 2020)

The enhanced WTEM 3 classes classifier: studies the results of the 3 classes classification. The model consists in identifying one of the three classes: (i) Covid19, (ii) Pneumonia and (iii) No Findings. In addition to comparing the proposed model to the one described in (Ozturk et al., 2020), the impact of the choice of Level 1 or Level 2 when using the Wavelet Transform technique is explored. Therefore, the value of the training and the validation losses for the two levels of the WT during 100 epochs are investigated. First, as seen in Figure 9.(a) and Figure 9.(b), very small values of losses are reached (~0,0048 and ~0,055 with L1 and L2, respectively) in comparison to the one obtained in (Ozturk et al., 2020) (a loss of 0.25 to 0.3). While showing similar behaviors during the two scenarios, they reach different loss values. It's clear that the scenario of WTEM with L1 db2 (cf. Figure 9.(a)) outperforms the two other scenarios. This conclusion is confirmed by the confusion matrices depicted in Figure 10.

The last metric to be evaluated in the presented experiments is the processing time. As shown in Figure 11, the impact of the WT technique is studied during the time it takes to process the input (X-ray and CT images) and classified into one of the three classes. Three scenarios are considered in this study: (i) the DarkCovidNet model (Ozturk et al., 2020), (ii) WTEM model using the db2 WT at level 1 and (iii) WTEM using the WT at level 2. The three scenarios are carried out with 2 virtual central processing unit (vCPU) and 8 GB of RAM. A significant decrease in the processing time is observed when the WT is introduced, as it falls from 2ms to 0,32ms/epoch. Moreover, the deeper the WT is, the shorter the processing time is. Indeed, with level 2 WT, the processing decreases to only 0,18ms/epoch.
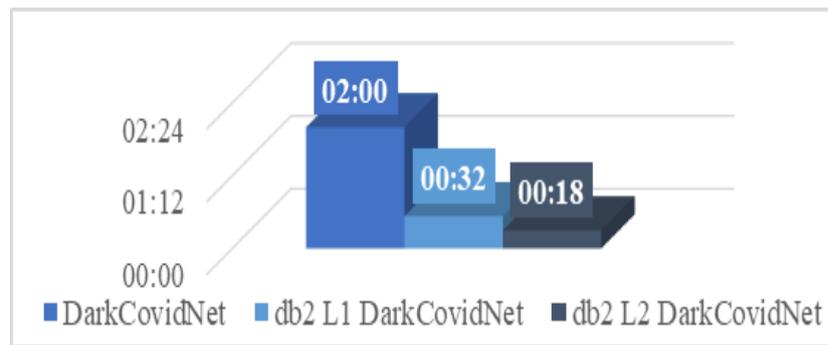
Figure 11. Impact of the Wavelet Transform on the Processing Time

4. Conclusion and future work

This paper explores the potential of using Deep Learning in detecting covid-19 cases from X-ray and CT chest images. More particularly, the Wavelet Transform technique is combined with CNN models proposed in literature to study the impact of denoising and dimensionality reduction offered by the WT on the overall performances. In this context, there have been carried out several measurements and a comparison between the presented solution and the one proposed by Ozturk et. al in (Ozturk et al., 2020) and the VGG-19 model used by Hansen (Hansen, 2020) to detect the Coronavirus.

The obtained results are very promising and show that the proposed solution outperforms the two other models by bringing a faster, lighter (in terms of memory), yet more accurate classification of X-Ray and CT chest images. Though results are very encouraging, it is important to follow up with more intensive measurements campaigns using bigger and more balanced datasets. The implication of medical professionals is also envisioned as a perspective of this work.

The conclusion is that AI offers a huge potential in medical imaging and should attract more attention from the scientific community to face pandemics such as the Covid-19.

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