Identification of COVID-19 patients using an intelligent technique

التعرف على مرضى كوفد -١٩ باستخدام تقنية ذكية

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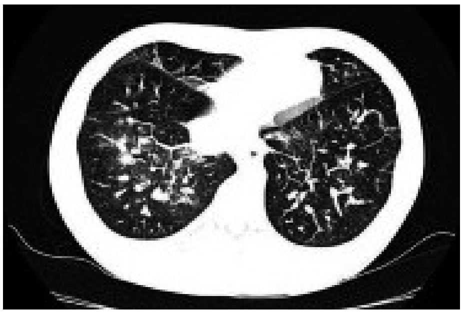
Abstract
Coronavirus disease is considered a serious disease because of its devastating impact on the health and life of the world and its significant impact on the deterioration of the economic and commercial situation in the world. In this paper, we presented a technique for diagnosing the Coronavirus disease based on deep learning and discrete wavelet transform. The discrete wavelet transform used in the pre-processing stage to reduce the complexity witch led to increasing the speed of the proposed technique while the deep learning used in the feature extraction and classification stage. Unlike the other methods in this domain, the proposed technique evaluates the noise impact on the accuracy of the proposed technique by considering two type of the noise namely: pepper & Salt noise and Gaussian Noise. Furthermore, the proposed technique evaluates the effect of the rotation on the accuracy by taken different rotation angles. The analysis of the extensive experiments that carried out on the dataset refer that the proposed technique achieve high accuracy (99%) with less computation time, as well as it robust against the noise and rotation variations.
Keywords: Coronavirus (COVID-19), deep learning, discrete wavelet transformation (DWT), Pepper & Salt noise, Gaussian Noise

المستخلص
يعتبر مرض فايروس كورونا مرض خطير لما له تأثير مدمر على صحة وحياة العالم وتأثيره الكبير على الوضع الاقتصادي والتجاري في العالم. في هذا البحث قدمنا تقنية لتشخيص مرض كرونا فيروس اعتمادا على التعلم العميق وتحويل المويجات المتقطع . تحويل المويجات المتقطع استخدم في مرحلة المعالجة الاولية لتقليل درجة التعقيد الذي يقود الى زيادة سرعة التقنية المقترحة , بينما التعلم العميق استخدم في مرحلة استخلاص وتصنيف الصفات. على خلاف الطرق الخرى في هذا المجال فان التقنية المقترحة قيمت تاثير الضوضا على الدقة من خلال اعتماد نوعين من الضوضاء وهما ضوضا الملح والفلفل وكذالك ضوضاء كاوسين. اضافة لذالك فان التقنية المقترحة قيمت تاثير الدوران على الدقة باخذ زوايا دوران مختلفة. ان تحليل نتائج التجارب المكثفة التي اجريت على قواعد البيانات اشارت الى ان التقنية المقترحة تحقق دقة عالية (٩٩٪) مع وقت تنفيذ قليل, اضافة الى انها رصينة ضد تاثيرات الضوضا والدوران.

1.Introduction

Corona virus(Covid-19) is disease that first appeared in the Chinese city of Wuhan in late 2019 and then spread throughout the world. COVID-19 has spread in China and around the world. It is caused by SARS-CoV-2 infection, which is a group of acute respiratory diseases. Where the infection is transmitted from one person to another through contact and drops of hands, as well as contaminated surfaces. Corona virus is not limited to respiratory diseases only, but it also affects the central nervous system, symptoms may range from one person to another, and sometimes no symptoms or signs appear on the patient, and the incubation period for the virus is from 1-14 days, and one of the most important symptoms of this disease is high fever Coughing, shortness of breath, joint and muscle pain, and stomatitis. The disease can be diagnosed by a sample from the nose or through a blood analysis for the purpose of diagnosing the disease. Since the disease is modern, the techniques used are very few to measure some of the effects that previous studies did not address, such as noise and rotation. In this research, we presented a new technique and tested it on a set of medical images and it gave accurate results after the test.

(a)



(b)

Fig.1 (a) picture of Covid-19 , and (b) picture of non Covid-19

2. Related studies

Luca Brunese, Francesco Mercaldo[1] using adeep learning methodology proposed a three-stage approach: the first stage to detect whether there is pneumonia, the researchers proposed the adoption of deep learning to detect the disease by extracting features by automatic diagnosis, where he used a database consisting of 375 images of people infected with the virus and 390 images For pneumonia and 963 infection-related images, the proposed approach achieved an accuracy of 96% for people with pneumonia and an accuracy of 98% for people with the virus with a time of 5.2 seconds.

Rahimzadeh [2] trained several deep convolutional networks using advanced techniques to classify X-ray images into three categories: normal, pneumonia, and COVID-19 based on two data sets containing 180 images of infected people. This network has the best accuracy through the use of multiple features extracted from the two networks and they tested it on 11302 images, where the accuracy of the proposed network for detecting the virus reached 99.55%, and the total average accuracy for all groups was 91.41%.

Pedro Mises de Sousa[3] and others tested and trained CNN-COVID19 (Convolutional Neural Networks) randomly on two different bases containing X-ray images of people infected with the virus and consisting of 434 images. This rule was used at the beginning of the spread of the virus and in October, 4030 images of infected people were used The researchers relied on the classification of pictures of patients to distinguish the infected person from the uninfected person. The experiment showed that the proposed method achieved the best results with an accuracy equal to 97.22% for the first rule and 98.84% for the second rule.

Saddam Hussien Khan[4] and others have proposed a new deep technique based on CNN to classify COVID-19 in x-ray images consisting of 6,448 images of 3,224 people infected with the virus and 3,224 people who are not infected. Two new CNN-specific architectures, COVID-RENet-1 and COVID-RENet-2, have been developed to analyze COVID-19 pneumonia The proposed idea feature is validated by running a series of experiments and comparing the results with two core CNNs, The discrimination ability of the proposed technique is evaluated by measuring it against the CNNS on the X-ray dataset. The results showed that the proposed classification method achieved an accuracy of 98%. The F-score degree of freedom is 0.98.

Zonguldak Bulent Ecevit [5]used 50 x-ray images of a person infected with the virus and 50 x-ray images of people who mainly suffer from respiratory distress and pneumonia. Experiments were conducted on 50 images of a normal patient and 50 images of a patient infected with the virus by extracting features. Train and test popular pre-trained models like ResNet50, InceptionV3, Inception ResNetV2, and ResNet Inceptionv3

The researcher proposed a deep learning-based approach using chest x-ray images obtained from COVID19 patients, and the results showed that the pre-trained ResNet50 model had a 98% higher accuracy for detecting the disease at an early stage.

Researcher Shuai Wang et al[6]. collected 1,065 cross-sectional images of confirmed COVID-19 cases along with those diagnosed with viral pneumonia. The researchers modified a deep learning model using artificial intelligence methods by extracting features to diagnose the virus and achieved an overall accuracy of 89.5%.

Using 54 COVID-19 images, the researcher predicted 46 positive COVID-19 test results, with an accuracy of 85.2%.

Faizan Ahmed[7] and others applied deep learning technology to a group of X-ray images using convolutional neural networks, where the image consists of three groups, the first group is 289 for people infected with Corona virus, and the second group is 550 images for people with pneumonia, and the third group consists of 550 images For uninfected people, the model proposed by the researchers achieved an average accuracy of 90.64% for the three categories.

3. Proposed technique

In this paper we presented an intelligent technique for covid-19 patient identification based on DWT and Deep learning. The DWT utilized in the preprocessing stage to reduce the training time with preserving the accuracy while the deep learning used to in features extraction and classification stage and the VGG16 model is utilized , figure 2 presented the block diagram of the proposed technique.

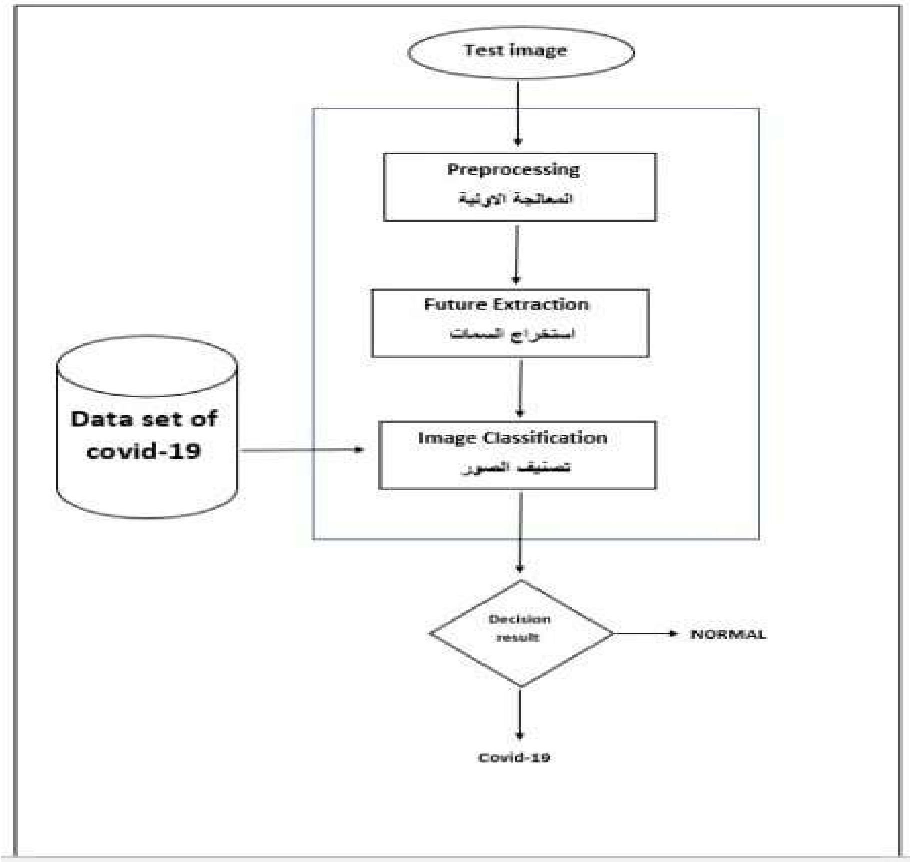


Fig. 2. Block diagram of the suggested technique .

3.1 The used dataset

The dataset that used in the proposed technique provided by GitHub repository shared by a postdoctoral fellow at University of Montreal Dr. J. Cohen consist of 1580 images. These images are mixed of normal (negative) and not normal (positive) related to covid-19 patients. The size of these images is 300×320 pixel as mention in figure 1.

3.2 pre-processing stage

This stage included two steps: the first one is noise removal using Fourier filter. The second step is complexity reduction by implementing DWT. The Fourier filter is a type of filter function that processes the frequency components, that is, it works by Fourier transform of the signal and then attenuating or amplifying different frequencies and is used in many scientific measurements such as spectroscopy and chromatography, This filter is used to remove noise, gradually reduce higher harmonics, and rebuild the signal, It is an important tool used for image processing and is also used in wide applications such as analyzing, filtering, rebuilding and compressing images [9].

3.3 Noise In image

The noise is a deterioration in the image signal due to external sources, and images with double noise have the advantage that the brighter the area the more. Noise in images, in other words, is any undesirable signal present in the image. It has different types that the image may be exposed to and affect it, and this depends mainly on the way we obtain the image. One of the most important causes of distortions, for example, when electronic transmission of digital data[10].

3.3.1 pepper & Salt Noise

Salt and pepper noise is added to an image by adding both random brightness (255 pixels) and random darkness (0 pixels) throughout the image. This model is also known as data projection noise. Because it statistically drops the original data values[17]. Figure 3 shows an example of this type of noise. This noise given by

$$P(z) = p(a) \quad \text{for } z=a \quad (1)$$

$$P(z) = P(b) \quad \text{for } z=b \quad (2)$$

$$P(z) = 0 \quad \text{otherwise} \quad (3)$$

If b>a, intensity ‘b’ will appear as light dot in the image. Otherwise intensity ‘a’ appears like a dark dot.

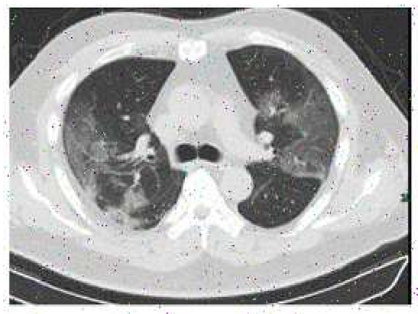


Fig.3. pepper & Salt Noise

3.3.2 Gaussian Noise

Intensity at different frequencies, which gives it a fixed spectral density, and it is sometimes called white noise. It is called white noise because it is similar to white light [13] .They are discrete noises that are not sequentially correlated or, when normally distributed, are sequential in time, or arranged along one or more spatial dimensions. In digital image processing, pixels in a white noise image are typically arranged in a rectangular grid, and are assumed to be independent random variables with a uniform probability distribution over a given time interval[14][15]. The concept can also be defined for signals scattered over more complex spheres, such as a sphere or a ring [17]. Figure 4 presented an example of Gaussian noise. The Gaussian random variable given by

$$F(g) = 1/\sqrt{2\pi\sigma^2} \quad e^{-(g-m)^2 \;/2\sigma 2} \qquad (٤)$$

F(g) = Gaussian distribution noise in image where
σ = stander deviation
m = mean value

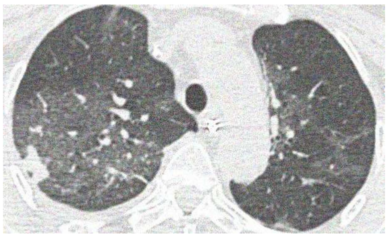


Fig.4.Gaussian Noise

3.4 Complexity reduction using DWT

In order to reduce the image dimension and consequence increase the speed of the proposed technique we utilized DWT. The two-dimensional discrete wavelet transform (DWT) coefficients are calculated using digital filters (low frequency and high frequency pass filters) and low sampling. A one-dimensional DWT is executed on the rows of the resulting image resulting in two sub-images. Both sub-images are then subjected to a one-dimensional DWT to create four sub-images, which are an approximate sub-image and three detailed sub-images. Each of these four sub-images bears different characteristics from the original image. The following is an explanation of these sub-images:

• The sub-zoom image represents low-frequency components in both the horizontal and vertical (LL) directions and contains the most important characteristics of the original image. It is a smooth copy of the original image.

• The sub-image corresponds to the low-frequency components in the horizontal direction and the high-frequency components in the vertical direction. (HL) Therefore, it represents the high variations of the image along the vertical direction and the low variations along the horizontal direction. Hence, it represents the horizontal edges.

• The sub picture is associated with the high frequency components in the horizontal direction and the low frequency components in the vertical direction. (LH) Therefore, it shows the high

variations of the image along the horizontal direction and the low variations along the vertical direction, it represents the vertical edges
• The sub-image corresponds to the higher frequency components in the vertical and horizontal (HH) directions, since they represent high image differences in the diagonal direction [11]

3.5 Image Rotation

Rotation is a geometric transformation that determines the location of the pixels in the image, where x1 and y1 are represented in the image from input x2,y2 to output through an angle θ that is rotated by the user, usually the rotation factor is used for the purpose of improving the image, and it can also be used as a processor. In some cases, elements that are set outside the image are ignored because they do not fit within the borders of the image[16] .The rotation operator performs a transformation given by:

$$x2 = \cos(\theta)(x1 - x0) - \sin(\theta)(y1 - y0) + x0 \quad (٥)$$

$$x2 = \sin(\theta)(x1 - x0) + \cos(\theta)(y1 - y0) + y0 \quad (٦)$$

where (x0, y0) are the coordinates of center of rotation (input image),and θ is the angle of rotation with clockwise rotations having positive angles. Figure 5 shows image under 60 rotation angle.

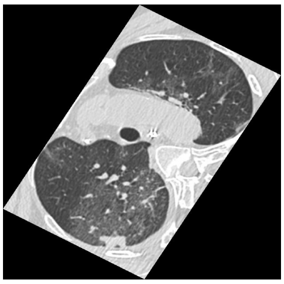


Fig.5.image rotation used 60 ·

3.6 Deep Learning for feature extraction and classification

In this stage, the deep learning is considered for feature extraction and classification. the convolution CNN has been utilized in VGG16. The VGG16 model is a convolutional neural network model proposed by K. Simonyan and A. Zisserman This architecture achieved the top 5 accuracy tests with 92.7% accuracy in ImageNet, which includes more than 14 million images belonging to 1000 categories. It is one of the most famous architectures in the field of deep learning. The input to the convolutional neural network is a 224 x 224 RGB fixed size image. The only preprocessing it does is subtract the average RGB values, which are computed on the training dataset, from each pixel. Next, the image passes through the convolutional layers (Conv.), where there are filters with a very small receiving field of 3 x 3, the smallest image capture size from left , right, top , bottom, and center part [12]. Figure 6 shows GG16 model architecture. The training, and testing sets are formed from the database as follows 80% of the database is set aside for training and 20% is set aside for testing. The parameters are grouped in the validation set with the parameters that have the lowest error rate, where the error that occurs in each stage of training is calculated in the softmax classifier to validate the current structure, and also the value of the error cost is calculated to see how accurate the results are. Then the learning rate was reset, and the dropout process was used to avoid repetition at each stage of training and to measure training performance, and thus the best model was obtained.

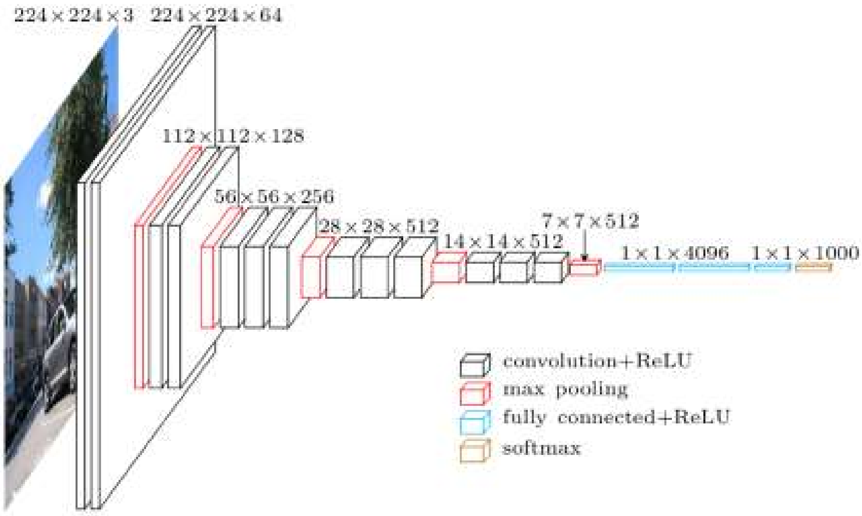


Figure 6 Architecture of VGG16

4- Experimental Result and analysis

Many experiments have carried out to evaluate the proposed technique. in all experiments the system divided dataset of image into training, by randomly taken 80% for training and 20% for testing.

In the first experiment we compute the accuracy and training time without using DWT. The results of this experiment are presented in table 1 . It can be observed that the proposed technique achieved high recognition rate (99%) with training time (3.85). In the second experiment DWT has been utilized in preprocessing stage and the accuracy is computed for different levels of DWT. The results of this experiment are provided in table 2. These results indicated that using DWT leads to increase the speed of the proposed technique with keeping the high accuracy. It can be preserved also that in the first level of DWT the accuracy are close it before using DWT with high reduction in the training time, in the second level the accuracy is slightly affected while in the third and fourth levels the accuracy is highly affected with very less training time, this is because that in the third and fourth levels of DWT the signal of image are highly attenuated.

Table 1 : The accuracy of the proposed technique

Accuracy (%)	Training time (s)
99%	3.85

Table 2 : The accuracy of the proposed technique and its training time after using DWT over different levels

Level of DWT	Accuracy (%)	Training time (s)
First level	99%	00.10.0541
Second level	98.32%	00.07.0123
Third level	81.54%	00.02.1111
Fourth level	76.71%	00.01.0002

In the third and fourth experiments the impact of noise and rotation on the accuracy of the proposed technique are evaluated respectively. The results of third experiments are presented in table 3 while the results of fourth experiments are presented in table 4. The analysis of these results refer that the prposed technique are robust against the noise and rotation variations.

Table 3. The recognition accuracy of dataset

Accuracy of noise pepper &salt	Accuracy of noise pepper &salt	Accuracy of noise pepper &salt	Accuracy of noise pepper &salt	Accuracy of noise pepper &salt	Accuracy of noise Gaussian
0.1	0.2	0.3	0.4	0.5	
99.33%	98.83%	97.99%	98.47%	98.32%	99.37%

Table 4. the accuracy over different rotation angle values

Accuracy of 60 angle rotation	Accuracy of 90 angle rotation	Accuracy of 180 angle rotation
96%	99%	98%

5.Conclusion

In this work we presented an efficient technique for covid-19 patient identification based on DWT and Deep learning. The proposed technique archived high recognition rate of 99%. The training time of the proposed technique are highly reduced with preserving the high accuracy by using DWT especially in the first and second levels of DWT. While in the third and fourth level the accuracy are affected because of the attenuation of the image signal in these levels. The evaluation of the presented technique under tow types of the noise and three rotation angle indicated that the proposed technique are robust against these variations.

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