A New Deep Learning Pipeline to Detect Covid-19 on Chest X-Ray Images using Local Binary Pattern, Dual Tree Complex Wavelet Transform and Convolutional Neural Networks

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A New Deep Learning Pipeline to Detect Covid-19 on Chest X-Ray Images using Local Binary Pattern, Dual Tree Complex Wavelet Transform and Convolutional Neural Networks

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Abstract At the end of 2019, a new type of virus, belonging to the coronaviridae family has emerged and it is considered that the virus in question is of zootonic origin. The virus that emerged in China first affected this country and then spread worldwide. Pneumonia develops due to Covid-19 virus in patients having severe disease symptoms. Many literature studies have been carried out in the process where the effects of the disease-induced pneumonia in lungs have been demonstrated with the help of chest X-ray imaging. In this study, which aims at early diagnosis of Covid-19 disease by using X-Ray images, the deep-learning approach, which is a state-of-the-art artificial intelligence method, was used and automatic classification of images was performed using Convolutional Neural Networks (CNN). In the first training-test data set used in the study, there were a total of 230 abnormal and 80 normal X-Ray images, while in the second training-test data set there were 476 X-Ray images, of which 150 abnormal and 326 normal. Thus, classification results have been provided for two data sets, containing predominantly abnormal images and predominantly normal images respectively. In the study, a 23-layer CNN architecture was developed. Within the scope of the study, results were obtained by using chest X-Ray images directly in training-test procedures and the sub-band images obtained by applying Dual Tree Complex Wavelet Transform (DT-CWT) to the above-mentioned images. The same experiments were repeated using images obtained by applying Local Binary Pattern (LBP) to the chest X-Ray images. Within the scope of the study, a new result generation algorithm having been put forward additionally, it was ensured that the experimental results were combined and the success of the study was improved. In the experiments carried out in the study, the trainings were carried out using the k-fold cross validation method. Here the k value was chosen 23. Consid-

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ering the highest results of the tests performed in the study, values of sensitivity, specificity, accuracy and AUC for the first training-test data set were calculated to be 1, 1, 0,9913 and 0,9996; while for the second data set of training-test, they were 1, 0,9969, 0,9958 and 0,9996 respectively. Considering the average highest results of the experiments performed within the scope of the study, the values of sensitivity, specificity, accuracy and AUC for the first training-test data set were 0,9933, 0,9725, 0,9843 and 0,9988; while for the second training-test data set, they were 0,9813, 0,9908, 0,9857 and 0,9983 respectively.

Keywords Covid-19 · Corona 2019 · Convolutional neural networks (CNN) · Deep learning · Dual tree complex wavelet transform (DT-CWT) · Local binary pattern (LBP) · Chest X-Ray classification

1 Introduction

In the last months of 2019, a new type of virus, which is a member of the family coronaviridae, has emerged. The virus in question is considered to have a zootonic origin [1]. The virus that emerged in Wuhan city of Hubei province in China affected this region first and then spread all over the world in a short time. The virus generally affects the lower and upper respiratory tract, lungs and less frequently, the heart muscles [2]. While the virus outbreak generally affects young and middle-aged people and people who do not have any chronic diseases less, it can cause severe consequences that result in death in people suffering diseases such as hypertension, cardiovascular disease and diabetes [3]. In the epidemic, which was declared to be pandemic in March 2020 by the World Health Organization; as of the first week of May of the same year, the number of cases has approached three and a half million, while the death toll has reached two hundred and fifty thousand.

In people suffering the disease severely, it has serious adverse effects in lungs generally [3]. In this context, many literature studies have been carried out in a short time in which these effects of the disease in lungs were shown using CT scans of lungs and chest X-Ray imaging. Literature studies indicate that radiological imaging, along with clinical symptoms, blood and biochemical tests, is an effective and reliable diagnostic tool for diagnosis of Covid-19 disease.

In the study conducted by Albarello et al. [4], CT scans of lungs and chest X-Ray images of 2 Covid-19 virus-infected patients in Italy were evaluated radiologically. Within the scope of the study, it was reported that interstitial involvement and lung opacities were observed in the X-Ray images of the patients. Case reports of two Covid-19 cases detected by Hsieh et al. [5] in control scans through the Medical Center of Central Taiwan were published. Here some anomalies in the chest radiography of these 2 patients examined in the study were reported. As a result of the study performed by Zhang et al. [6] and in which clinical data of 140 Covid-19 cases were examined, in CT scans of lungs and chest X-Ray images of 89,6% of the cases, bilateral ground glass and patchy opacity were reported to have been detected.

In a study conducted by Chen et al. [7] the clinical data belonging to 99 patients who had contracted the Covid-19 virus in Taiwan were examined. In the context of the study it was stated that of all the chest X-Ray images and CT scans of

chest 25% had unilateral pneumonia, 75% had bilateral pneumonia and 14% had multiple mottling and ground-glass opacity.

In a study conducted by Lee et al. [8], the clinical status of a Covid-19 case in Taiwan was examined, and it was stated that the patient had patchy densities in the left upper and middle lung regions. A similar study was conducted by Liu et al. [9] by analyzing the X-Ray images and other clinical data of a 52-year-old woman infected locally in Taiwan. On the first day of the patient's examination, diffuse infiltrates were detected in the bilateral lower lungs. It was reported as well that, in the fifth day radiography in parallel to the course of the disease, progressive diffuse interstitial opacities had developed and consolidation in the bilateral parahilar areas and lower lung regions.

In the study conducted by Thevarajan et al. [10], clinical data related to the disease course of a non-severe Covid-19 case was published. Within the scope of the study, it was reported that bi-basal infiltrates were seen in the X-Ray images of this non-severe case, and that there was a gradual improvement in the fifth and tenth days of the disease. The data of the index patient who caused tertiary transmission of corona virus disease in 2019 in Korea and application results of the Lopinavir/Ritonavir treatment were shared by Lim et al. [11]. While in the X-Ray images taken in first, ninth and fifteenth day of the patient, there was a partial improvement in the process depending on the treatment, there was seen a clearly visible presence of ground-glass opacities.

In the study conducted by Kong and Agarwal [12], chest imaging results of Covid-19 infection were examined through 3 cases. Within the scope of the study, it was reported that patients had irregular ground glass opacities on CT scans of lungs and chest X-Ray images. In the study conducted by Yoon et al. [13], findings related to the chest X-Ray and CT scans of lungs of 9 Covid-19 patients were analyzed. According to the results of the study, parenchymal abnormalities were detected in the X-Ray images of 3 out of the 9 patients. Also, eight of the 9 patients were reported to have bilateral involvement and the other last patient unilobar reversed halo sign, with the help of CT images of lungs.

In the study conducted by Wu et al. [14], the clinical findings of 80 Covid-19 patients in total, 41 of whom were women, were analyzed. Three of the patients suffered the disease severely, while the remaining 77 had mild or moderate symptoms. Within the scope of the study, it was reported that imaging results showed abnormal intensity in 55 of 80 patients, i.e. 68,75%. In the study conducted by Zu et al. [15], radiological images of patients infected by Covid-19 virus were evaluated. In the study, it was reported that pneumonia caused by Covid-19 virus typically manifested itself as ground-glass opacity on CT scans of lungs and chest X-Ray images.

Clinical and radiology imaging data of 51 Covid-19 cases were analyzed by Song et al. [16]. Within the scope of the study, bilateral lung involvement was reported in 42 of 86 patients, i.e. in 86% of them. In the study conducted by Holshue et al. [17] again, the case report of the first Covid-19 patient in the United States was published, and it was stated that pneumonia, which developed due to the disease, could be distinguished on chest X-Ray images depending on the course of the disease.

A case report of a Covid-19 patient in Taiwan was published by Cheng et al. [18], and it was reported that abnormalities were seen in the X-Ray images taken on the tenth, thirteen, seventeen and twenty-fifth days of the disease. In

the study conducted by Ng et al. [19], radiological images of 5 Covid-19 patients were analyzed. It is stated that ground-glass opacification and consolidation in some lung sections were observed in the radiological images of the cases examined within the scope of the study. In the conclusion part of the study, an evaluation was made that glass opacities turn into consolidation depending on the course of the disease.

Some radiological images were published by Shi et al. [20] in China, by Silverstein et al. [21] in Canada, and by Phan et al. [22] and Giang et al. [23] related to Covid-19 cases, and it is understood that similar findings were found to the ones observed before.

The recent review article published by Long and Ehrenfeld [24] highlighted the importance of using artificial intelligence methods to quickly diagnose Covid-19 disease and reduce the effects of the outbreak crisis.

CT imaging generally contains more data than X-Ray imaging. However, it has some disadvantages for the follow-up of all stages of the disease due to the excess amount of radiation the patients being exposed to. For this reason, an artificial intelligence application using X-Ray images was created and tested in the study.

In this study, which aims at early diagnosis of Covid-19 disease with the help of X-Ray images, deep learning approach, which is an artificial intelligence method of latest technology, was used. In this context, automatic classification of images was carried out through the Convolutional Neural Network (CNN). In the study, experiments were carried out for the use of images directly, using Local Binary Pattern (LBP) as a pre-process and using Dual Tree Complex Wavelet Transform (DT-CWT) as a secondary operation, and the results of automatic classification were calculated separately. In the scope of the study, a new classification approach, which involves performing the experiments in together and combining the results through a result generation algorithm, has been proposed and tested. The results of the study show that in the diagnosis of Covid-19 disease, the analysis of chest X-Ray images using deep learning methods provides fast and high accuracy results.

2 Material and Method

2.1 Used Data

Chest X-Ray images of Covid-19 patients used in the study were obtained by combining metadata data sets that were made open access over Github after being created by Cohen et al. [25] and over Kaggle after being created by Dadario [26]. The images that these data sets contain in common and the clinical notes related to these images were combined and a mixed abnormal image data set consisting of 150 chest X-Ray images were created. In the study, the images obtained while patients were facing the X-Ray device directly were used. In the studies, the images taken from the same patient were obtained on different days of the course of disease and therefore they do not contain exactly the same content. The dimensions of the images in question are, vary between 255×249 and 4280×3520 and show a wide variety. Also these images have different data formats such as png, jpg, jpeg and two different bit depths such as 8 bit (gray-level) and 24 bit (RGB). Standardization of images is an essential process for use in the study. In this context, all of the images have been converted to 8 bit gray level images. Then, to

Fig. 1 a) X-Ray image of Covid-19 patient (Phan et al. [22]) b) Normal X-Ray image (Montgomery data set [27]) c) Normal X-Ray image (Shenzhen data set [27])

clarify the area of interest on the images, manual framing was performed so as to cover the chest area. After this process, all the images were rearranged to 448×448 and saved in png format.

For normal X-Ray images in the study, two data sets, Montgomery data set [27] and Shenzhen data set [27], were used separately. These databases contain 80 and 326 normal X-Ray images, respectively. The first training-test data set contains a total of 230 abnormal and 80 normal X-Ray images, while the second training-test data set contains a total of 476 X-Ray images, of which 150 abnormal and 326 normal. Thus, it was ensured that classification results were obtained for two data sets containing predominantly abnormal images and predominantly normal images respectively. The processes applied to abnormal images were applied to normal images likewise. In Figure 1, there are original and edited versions of the X-Ray images, one belonging to a single Covid-19 patient and two to normal person.

2.2 Local Binary Pattern (LBP)

Local Binary Pattern (LBP) is an approach which was proposed by Ojala et al. [28] to reveal local features. The method is basically based on comparing a pixel on the image to the neighboring pixels one by one in terms of size. In this way, the local binary pattern code of this center pixel is calculated and then this code is

converted to a local number, that is, the new pixel value of the center. Although this comparison can be made for various distance radius values, 3×3 square operators are most preferred in processes. In Equality (1), there is a mathematical representation of this operation.

$$LBP_{p,r} = \sum_{n=0}^{p-1} s(x_{r,n} - x_{0,0})2^n \quad (1)$$

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

In Figure 2, the images obtained by applying LBP operation to the X-Ray images given in Figure 1 are included.

When LBP is applied to the images, since the square operator can not complete the pixels lying in a distance of the radius value across the start and end rows and columns, these pixels are excluded from the operations. This means that the size of the image obtained as a result of the LBP operation is lower than the size of the original image. For example, when an LBP operation with a radius of 2 is applied to an image of a size of 448×448 size used in the study, an image of a size of 444×444 is obtained. The size of the image obtained after LBP operations has been rearranged as 448×448 so that this size reduction does not cause problems in advanced operations and the experiments can be compared with each other accurately. The purpose of benefiting from LBP operation within the scope of the study is to observe the effects of using LBP images, apart from the original images, which reflect local features, in CNN input on study results. In addition, the aim of the study is to increase the image feature depth used in the new result generation algorithm.

2.3 Dual Tree Complex Wavelet Transform (DT-CWT)

Dual Tree Complex Wavelet Transform (DT-CWT) was first introduced by Kingsbury [29]-[31]. This method is generally similar to the Gabor Wavelet Transform. Unlike this conversion, instead of a single filter, it uses two filters that work in parallel. These two trees contain real and imaginary parts of complex numbers. That is, as a result of the DT-CWT process, the sub-band containing more directions than the Gabor Wavelet Transform is obtained. When DT-CWT is applied to an image, processes are performed for six different directions, $+15^\circ$, -15° , $+45^\circ$, -45° , $+75^\circ$ and -75° degree. Three of these directions represent real and other three represent imaginary sub-bands. Figure 3 shows the DT-CWT decomposition tree. In Figure 4, real and imaginary sub-band images obtained by applying DT-CWT process (scale=1) to X-Ray images given in Figure 1 are shown. Within the scope of the study, DT-CWT process was used with a scale (level) value of 1, and the dimensions of the sub-band images obtained were half the size of the original image. Since the complex wavelet transform has been successful in many studies [32]-[34] where medical images were used before, this conversion was preferred in the study.

Fig. 2 Images created by applying LBP and resizing the images in Figure 1

Fig. 3 Structure of the DT-CWT decomposition tree

Fig. 4 Real and imaginary sub-band images obtained by applying DT-CWT to X-Ray Image (scale=1)

2.4 Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is the most preferred deep learning model in image processing applications in recent years. CNN's convolution layer provides the feature patterns of images. Convolution layers placed one after another reveal the visual properties from low to high level. Activation functions, on the other hand, produce outputs by passing inputs to it through its own function. Since the data subjected to convolution operations and passed through the activation function have large size, their sizes need to be reduced in order to facilitate and speed up advanced operations. In CNN architecture, this is done by sampling at the pooling layer. Property matrices obtained after size reduction are flattened and converted to feature vectors. At the last stage, these feature vectors are subjected to classification in the fully connected layer. This process is essentially a classification process using a standard neural network. In this context, Figure 5 describes the general operation of the CNN classifier.

Within the scope of the study, a CNN architecture with a total of 23 layers was designed. An effective design was aimed at, since increasing the number of layers in the CNN architecture leads to increased processing time in training and classification processes. Table 1 contains details of the CNN architecture used in the study. In the context of the study, Matlab 2019a program was preferred as software. Layer name and parameters in Table 1 are the names and parameters used directly in the software. In the study, more than one experiment were done and the sizes of the input image used in the experiments differ. For this reason, there are different sizes in the input layer in Table 1. This CNN architecture was used in all experiments carried out within the scope of the study.

Table 1 CNN architecture designed within the scope of the study

Layer	Layer Name	Layer Parameters (Matlab)
1	imageInputLayer	[448 448 1], [224 224 1], [224 224 2], [224 224 3], [224 224 6]
2	convolution2dLayer	(3,4,'Padding','same')
3	batchNormalizationLayer	default
4	reluLayer	default
5	maxPooling2dLayer	(2,'Stride',2)
6	convolution2dLayer	(3,8,'Padding','same')
7	batchNormalizationLayer	default
8	reluLayer	default
9	maxPooling2dLayer	(2,'Stride',2)
10	convolution2dLayer	(3,16,'Padding','same')
11	batchNormalizationLayer	default
12	reluLayer	default
13	maxPooling2dLayer	(2,'Stride',2)
14	convolution2dLayer	(3,32,'Padding','same')
15	batchNormalizationLayer	default
16	reluLayer	default
17	maxPooling2dLayer	(2,'Stride',2)
18	convolution2dLayer	(3,64,'Padding','same')
19	batchNormalizationLayer	default
20	reluLayer	default
21	fullyConnectedLayer	2
22	softmaxLayer	default
23	classificationLayer	default

Fig. 5 General operation of the Convolutional Neural Network classifier

2.5 The Evaluation Criterias For The Classification Results

Within the scope of the study, confusion matrix and statistical parameters obtained from this matrix were used to evaluate the results. A sample confusion matrix is given in Table 2.

Table 2 An example confusion matrix

		Actual	
		Class-1	Class-2
Predicted Class	Class-1	TP	FP
	Class-2	FN	TN

If Class 1 is considered patient (abnormal) and Class 2 normal in Table 2, TP is the number of times that the patient data are considered as patients and FP on the other side is actually the number of times that normal data are considered as patients, as a result of classification. Similarly, according to the same acceptance, TN is the number of labeling actually normal data as normal and FN is on the other side, normally the number of labeling actually sick data as normal, as a result of classification.

Sensitivity (SEN), specificity (SPE) and accuracy (ACC) values calculated using these parameters are defined mathematically between Equation (2)-(4). In the study, SEN, SPE and ACC values were calculated for the distinction of patient (target assigned as 0) and normal (target assigned as 1), for the case of the threshold value being accepted as 0,5.

$$SEN = TP/(TP + FN) \quad (2)$$

$$SPE = TN/(TN + FP) \quad (3)$$

$$ACC = (TP + TN)/(TP + TN + FP + FN) \quad (4)$$

Receiver Operating Characteristic (ROC) analysis was also used to evaluate the results. In addition, the sizes of the areas under the ROC curve (Area Under Curve-AUC) were calculated. ROC analysis basically reflects graphically, the variation of sensitivity (SEN) (y-axis) relative to 1-SPE (x-axis) for the case that the threshold value is gradually changed with a certain precision between the minimum and maximum output predicted for classification. Equal Error Rate (EER) on the other side is the point where the SEN and SPE values are equal on the ROC curve. At this point, since the SEN and SPE values are equal, the complement of the value of EER to 1 is also equal to the ACC value at the intersection point where this equation is achieved.

2.6 Pipeline Methodology

First of all in the proposed pipeline algorithm, training and test procedures for images of size of 448×448 were performed and results were obtained.

Before the experiments coming after the first experiment were conducted, DT-CWT was applied to the images of size of 448×448 (scale=1) and 224×224 sub-band images were obtained.

- In the second experiment, results were obtained for the case of giving the real part of the LL sub-band image obtained by applying DT-CWT, as input to CNN.
- In the third experiment, training and testing procedures were carried out and results were obtained for the case of giving the imaginary part of the LL sub-band image obtained by applying DT-CWT, as input to CNN.

- In the fourth experiment, training and testing procedures were carried out and results were obtained for the case of giving the real parts of LL, LH and HL sub-band images obtained by applying DT-CWT as input to CNN together.
- In the fifth experiment, training and test procedures were carried out and results were obtained for the case of giving the imaginary parts of the LL, LH and HL sub-band images obtained by applying DT-CWT as input to CNN together.
- In the sixth experiment, results were obtained for the case of giving the real and imaginary parts of the LL sub-band image obtained by applying DT-CWT as input to CNN together.
- In the seventh experiment, results were obtained for the case of giving the real and imaginary parts of the LL, LH, HL sub-band images obtained by applying DT-CWT, as input to CNN together.

The first seven experiments conducted were repeated using new images obtained by applying LBP to X-Ray images and the first stage experiments were completed. As explained earlier in this context, since the image sizes decreases after LBP processing, these images were rearranged as 448×448 in size.

In the ongoing part of the study, a pipeline classification algorithm was designed using the principle of parallel operation. This algorithm is based on combining the results of previous experiments to obtain new results. This pipeline classification algorithm mentioned above works as follows:

- If the number of labeling (threshold value for 0,5) obtained in the experiments (with and without LBP) for an image is not equal to each other, the labeling result obtained in more than half of the experiments is considered to be the algorithm labeling result (abnormal or normal). In this case, if the algorithm labeling result is abnormal, the real experiment result closest to the number 0, if the algorithm labeling result is normal, the closest to the number 1 respectively is assigned as the algorithm result.
- If the number of labeling (for threshold value 0,5) obtained in the experiments (with and without LBP) for an image is equal to each other, the actual test results obtained in the experiments conducted for the image are averaged and the result is accepted as the algorithm result. After that, the labeling of the image is realized as abnormally or normally (for the threshold value 0,5) according to this result obtained.

Block diagram of experiments and the pipeline algorithm proposed in the study are shown in Figure 6 and Figure 7.

Fig. 6 Block diagram representation of the study of experiments

Fig. 7 Block diagram of the pipeline algorithm proposed in the study

3 Experiments and Results

3.1 Experiments

In this study, which aims to detect the early diagnosis of Covid-19 disease by using X-Ray images, the deep learning approach, which is the artificial intelligence method utilizing the latest technology, was used and automatic classification of the images was performed using CNN. In the first training-test data set used in the study, there were a total of 230 abnormal and 80 normal X-Ray images, while in the second training-test data set there were 476 X-Ray images, of which 150 abnormal and 326 normal. Thus, it was ensured that classification results obtained from two data sets containing predominantly abnormal images and predominantly normal images separately. The information of the training-test data sets are given in Table 3.

Table 3 Information about the images used in the study

Data set	Covid-19 Image	Normal Image	Total
1. Data set	150 ([25] and [26])	80 (Montgomery [27])	230
2. Data set	150 ([25] and [26])	326 (Shenzhen [27])	476

Within the scope of the study, chest X-ray images were manually framed to cover the lung region, primarily to determine the areas of interest on the image. Then, standardization was carried out since the images used were of very different sizes, formats and bit depths. The areas of interest on the image were resized and the image sizes were arranged as 448×448 . After that, the images in question were saved in png format so as to be as gray-scale and 8 bit depth. These operations were applied to all abnormal and normal images used in the study.

In the ongoing part of the study, a 23-layer CNN architecture has been designed, the details of which have been previously described. This CNN architecture was used in all experiments. Due to the fact that more than one experiment is performed within the scope of the study, only the images given to the CNN input differ in size.

In the experiments conducted in the study, the trainings were carried out with the k-fold cross validation method. In this context, k value was chosen 23. Since the first training-test data set consists of 230 images in total, 220 images, except for 10 images at each stage (fold), were used for training operations, and the remaining 10 images were used for testing operations. The second training-test data set consists of a total of 476 images, and in the same way, except 20/21 (16 groups consisting of 21 images and 7 groups of 20 images) images, 456/455 images were used in training operations, and the remaining 20/21 images were used in test operations. The test procedures were repeated 23 times and classification results were obtained for all images.

In this part of the study, a total of fourteen experiments were carried out. Some initial weights and parameters in the CNN are randomly assigned. In order to make the study results stable, each experiment was repeated 5 times in itself and all results were shown in the study.

Within the scope of the study, the time taken for an experiment to be completed as a whole, including training and testing, was divided by the total number of images processed, and the processing time per image was measured. The experiments of this study were carried out using MATLAB 2019 (a) software running on a computer with 4 GB RAM and Intel i5-2430M 2.4 GHz, and this data should be taken into consideration during the interpretation of these times.

3.2 Results

In the first experimental group within the scope of the study, training and testing procedures were performed using the chest X-Ray images firstly, and the results were obtained. LBP operation was then applied to the images in question, then the training and testing procedures were repeated and the results were calculated. Finally, the results were calculated using the pipeline classification algorithm, the details of which were previously described and proposed within the scope of the study. Due to the random assignment of some initial variables used in the internal structure of CNN, each experiment group was repeated 5 times in order to make the results more stable. The image sizes given to the CNN as input for this experiment were $448 \times 448 \times 1$. The results obtained from the experimental group are given in Table 4 and Table 6. As can be seen from Table 4-6, the highest sensitivity for the first training test set was 0,9907, while the highest average specificity was calculated to be 0,9600. The average highest accuracy was 0,9774 and the highest average for the area under the ROC curve was calculated to be 0,9968. For the second set of training-tests, the average highest sensitivity was 0,9733, while the highest average specificity was calculated to be 0,9877. The average highest accuracy was 0,9832 and the highest average for the area under the ROC curve was calculated to be 0,9982.

Table 4 Results obtained using directly chest X-Ray images

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	145	5	77	3	0,9667	0,9625	0,9652	0,0371	0,9927	50,2374
2	147	3	77	3	0,9800	0,9625	0,9739	0,0210	0,9988	47,9187
3	145	5	77	3	0,9667	0,9625	0,9652	0,0371	0,9927	48,9727
4	147	3	77	3	0,9800	0,9625	0,9739	0,0210	0,9988	45,2314
5	147	3	76	4	0,9800	0,9500	0,9696	0,0306	0,9977	44,8296
Average	146,2	3,8	76,8	3,2	0,9747	0,9600	0,9696	0,0294	0,9961	47,4380
1	145	5	321	5	0,9667	0,9847	0,9790	0,0160	0,9976	88,7600
2	146	4	324	2	0,9733	0,9939	0,9874	0,0136	0,9979	92,6095
3	142	8	322	4	0,9467	0,9877	0,9748	0,0160	0,9981	95,8276
4	144	6	322	4	0,9600	0,9877	0,9790	0,0216	0,9965	94,0016
5	145	5	321	5	0,9667	0,9847	0,9790	0,0160	0,9976	98,3115
Average	144,4	5,6	322,0	4,0	0,9627	0,9877	0,9798	0,0166	0,9975	93,9021

Table 5 Results obtained by applying LBP to chest X-Ray images

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	148	2	67	13	0,9867	0,8375	0,9348	0,0565	0,9902	47,3856
2	148	2	76	4	0,9867	0,9500	0,9739	0,0160	0,9979	56,5030
3	148	2	74	6	0,9867	0,9250	0,9652	0,0160	0,9985	43,0535
4	146	4	71	9	0,9733	0,8875	0,9435	0,0500	0,9904	42,7633
5	149	1	70	10	0,9933	0,8750	0,9522	0,0371	0,9926	47,8648
Average	147,8	2,2	71,6	8,4	0,9853	0,8950	0,9539	0,0351	0,9939	47,5140
1	138	12	316	10	0,9200	0,9693	0,9538	0,0503	0,9891	95,1551
2	136	14	316	10	0,9067	0,9693	0,9496	0,0511	0,9872	97,3104
3	138	12	315	11	0,9200	0,9663	0,9517	0,0424	0,9906	96,8410
4	138	12	315	11	0,9200	0,9663	0,9517	0,0424	0,9906	96,8410
5	136	14	320	6	0,9067	0,9816	0,9580	0,0488	0,9921	99,6471
Average	137,2	12,8	316,4	9,6	0,9147	0,9706	0,9529	0,0470	0,9899	97,1589

Table 6 New results using pipeline classification algorithm

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	148	2	75	5	0,9867	0,9375	0,9696	0,0290	0,9940	97,6230
2	149	1	78	2	0,9933	0,9750	0,9870	0,0210	0,9994	104,4216
3	149	1	77	3	0,9933	0,9625	0,9826	0,0242	0,9941	92,0262
4	148	2	75	5	0,9867	0,9375	0,9696	0,0242	0,9979	87,9947
5	149	1	76	4	0,9933	0,9500	0,9783	0,0242	0,9988	92,6944
Average	148,6	1,4	76,2	3,8	0,9907	0,9525	0,9774	0,0245	0,9968	94,9520
1	147	3	321	5	0,9800	0,9847	0,9832	0,0152	0,9987	183,9150
2	145	5	322	4	0,9667	0,9877	0,9811	0,0111	0,9987	189,9200
3	146	4	322	4	0,9733	0,9877	0,9832	0,0152	0,9978	192,6686
4	145	5	322	4	0,9667	0,9877	0,9811	0,0264	0,9968	190,8427
5	147	3	323	3	0,9800	0,9908	0,9874	0,0096	0,9992	197,9587
Average	146,0	4,0	322,0	4,0	0,9733	0,9877	0,9832	0,0155	0,9982	191,0610

In the second experimental group within the scope of the study, training and testing procedures were performed using the real part of the LL sub-image obtained by applying DT-CWT to the chest X-Ray images, and the results were obtained. Then, training and testing procedures were performed using the real part of the LL sub-image obtained by applying LBP and DT-CWT operation to X-Ray images, respectively. Finally, the results were calculated using the pipeline classification algorithm, the details of which were previously described and proposed within the scope of the study. The image sizes given to the CNN as input for this experiment were $224 \times 224 \times 1$. The results obtained from the experimental group are given in Table 7 and Table 9. As can be seen from Table 7-9, the highest sensitivity for the first training test set was 0,9933, while the highest average specificity was calculated to be 0,9675. The average highest accuracy was 0,9843 and the highest average for the area under the ROC curve was calculated to be 0,9988. For the second set of training-tests, the average highest sensitivity was 0,9760, while the highest average specificity was calculated to be 0,9883. The average highest accuracy was 0,9845 and the highest average for the area under the ROC curve was calculated to be 0,9978.

Table 7 Results obtained by using LL real sub-band obtained by applying DT-CWT to chest X-Ray images

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	146	4	79	1	0,9733	0,9875	0,9783	0,0113	0,9993	11,3456
2	148	2	76	4	0,9867	0,9500	0,9739	0,0194	0,9987	10,9008
3	147	3	76	4	0,9800	0,9500	0,9696	0,0194	0,9983	10,8512
4	145	5	77	3	0,9667	0,9625	0,9652	0,0340	0,9960	10,8887
5	147	3	79	1	0,9800	0,9875	0,9826	0,0144	0,9994	10,8402
Average	146,6	3,4	77,4	2,6	0,9773	0,9675	0,9739	0,0197	0,9983	10,9653
1	146	4	320	6	0,9733	0,9816	0,9790	0,0175	0,9982	15,3129
2	146	4	320	6	0,9733	0,9816	0,9790	0,0264	0,9959	15,1743
3	142	8	321	5	0,9467	0,9847	0,9727	0,0296	0,9973	15,1492
4	139	11	321	5	0,9267	0,9847	0,9664	0,0175	0,9963	15,3329
5	145	5	322	4	0,9667	0,9877	0,9811	0,0152	0,9987	16,2744
Average	143,6	6,4	320,8	5,2	0,9573	0,9840	0,9756	0,0212	0,9973	15,4487

Table 8 Results obtained by using LL real sub-band obtained by applying LBP and DT-CWT to chest X-Ray images, respectively

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	143	7	77	3	0,9533	0,9625	0,9565	0,0402	0,9893	11,5224
2	145	5	70	10	0,9667	0,8750	0,9348	0,0500	0,9771	11,3245
3	147	3	71	9	0,9800	0,8875	0,9478	0,0419	0,9954	11,4449
4	149	1	74	6	0,9933	0,9250	0,9696	0,0371	0,9960	11,5952
5	146	4	71	9	0,9733	0,8875	0,9435	0,0402	0,9871	11,3552
Average	146,0	4,0	72,6	7,4	0,9733	0,9075	0,9504	0,0419	0,9890	11,4484
1	132	18	308	18	0,8800	0,9448	0,9244	0,0639	0,9845	16,5153
2	135	15	312	14	0,9000	0,9571	0,9391	0,0616	0,9856	16,7774
3	142	8	316	10	0,9467	0,9693	0,9622	0,0535	0,9923	16,7099
4	132	18	308	18	0,8800	0,9448	0,9244	0,0639	0,9845	15,8507
5	135	15	312	14	0,9000	0,9571	0,9391	0,0616	0,9856	18,8465
Average	135,2	14,8	311,2	14,8	0,9013	0,9546	0,9378	0,0609	0,9865	16,9399

Table 9 New results using pipeline classification algorithm

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	149	1	79	1	0,9933	0,9875	0,9913	0,0113	0,9992	22,8680
2	149	1	75	5	0,9933	0,9375	0,9739	0,0273	0,9978	22,2252
3	149	1	78	2	0,9933	0,9750	0,9870	0,0144	0,9991	22,2962
4	149	1	77	3	0,9933	0,9625	0,9826	0,0242	0,9985	22,4839
5	149	1	78	2	0,9933	0,9750	0,9870	0,0177	0,9992	22,1954
Average	149,0	1,0	77,4	2,6	0,9933	0,9675	0,9843	0,0190	0,9988	22,4137
1	147	3	323	3	0,9800	0,9908	0,9874	0,0136	0,9980	31,8282
2	147	3	322	4	0,9800	0,9877	0,9853	0,0168	0,9979	31,9517
3	146	4	321	5	0,9733	0,9847	0,9811	0,0160	0,9985	31,8590
4	144	6	322	4	0,9600	0,9877	0,9790	0,0216	0,9958	31,1835
5	148	2	323	3	0,9867	0,9908	0,9895	0,0104	0,9989	35,1209
Average	146,4	3,6	322,2	3,8	0,9760	0,9883	0,9845	0,0157	0,9978	32,3887

In the third experimental group within the scope of the study, training and testing procedures were performed using the imaginary part of the LL sub-image obtained by applying DT-CWT to the chest X-Ray images, and the results were obtained. Then, training and testing procedures were performed using the imaginary part of the LL sub-image obtained by applying LBP and DT-CWT operation to X-Ray images, respectively. Finally, the results were calculated using the pipeline classification algorithm, the details of which were previously described and pro-

posed within the scope of the study. The image sizes given to the CNN as input for this experiment were $224 \times 224 \times 1$. The results obtained from the experimental group are given in Table 10 and Table 12. As can be seen from Table 10-12, the highest sensitivity for the first training test set was 0,9853, while the highest average specificity was calculated to be 0,9675. The average highest accuracy was 0,9774 and the highest average for the area under the ROC curve was calculated to be 0,9980. For the second set of training-tests, the average highest sensitivity was 0,9813, while the highest average specificity was calculated to be 0,9877. The average highest accuracy was 0,9857 and the highest average for the area under the ROC curve was calculated to be 0,9981.

Table 10 Results obtained by using LL imaginary sub-band obtained by applying DT-CWT to chest X-Ray images

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	146	4	78	2	0,9733	0,9750	0,9739	0,0290	0,9965	10,7806
2	148	2	77	3	0,9867	0,9625	0,9783	0,0242	0,9978	10,7265
3	147	3	77	3	0,9800	0,9625	0,9739	0,0273	0,9987	10,7930
4	144	6	78	2	0,9600	0,9750	0,9652	0,0306	0,9969	10,8289
5	147	3	77	3	0,9800	0,9625	0,9739	0,0306	0,9961	10,8242
Average	146,4	3,6	77,4	2,6	0,9760	0,9675	0,9730	0,0283	0,9972	10,7906
1	147	3	324	2	0,9800	0,9939	0,9895	0,0072	0,9990	16,6464
2	147	3	321	5	0,9800	0,9847	0,9832	0,0160	0,9986	16,3507
3	142	8	320	6	0,9467	0,9816	0,9706	0,0224	0,9927	16,4984
4	144	6	322	4	0,9600	0,9877	0,9790	0,0216	0,9983	15,3405
5	145	5	323	3	0,9667	0,9908	0,9832	0,0247	0,9965	15,1365
Average	145,0	5,0	322,0	4,0	0,9667	0,9877	0,9811	0,0184	0,9970	15,9945

Table 11 Results obtained by using LL imaginary sub-band obtained by applying LBP and DT-CWT to chest X-Ray images, respectively

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	147	3	76	4	0,9800	0,9500	0,9696	0,0273	0,9946	11,9483
2	145	5	69	11	0,9667	0,8625	0,9304	0,0629	0,9741	13,7095
3	146	4	73	7	0,9733	0,9125	0,9522	0,0500	0,9938	13,4324
4	146	4	77	3	0,9733	0,9625	0,9696	0,0290	0,9956	11,3019
5	144	6	73	7	0,9600	0,9125	0,9435	0,0452	0,9863	10,8861
Average	145,6	4,4	73,6	6,4	0,9707	0,9200	0,9530	0,0429	0,9889	12,2556
1	137	13	316	10	0,9133	0,9693	0,9517	0,0503	0,9910	16,4081
2	131	19	310	16	0,8733	0,9509	0,9265	0,0663	0,9801	15,7047
3	133	17	311	15	0,8867	0,9540	0,9328	0,0687	0,9872	15,4837
4	139	11	313	13	0,9267	0,9601	0,9496	0,0471	0,9869	15,5339
5	134	16	310	16	0,8933	0,9509	0,9328	0,0695	0,9852	15,8380
Average	134,8	15,2	312,0	14,0	0,8987	0,9571	0,9387	0,0604	0,9861	15,7937

Table 12 New results using pipeline classification algorithm

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	148	2	77	3	0,9867	0,9625	0,9783	0,0306	0,9975	22,7289
2	147	3	76	4	0,9800	0,9500	0,9696	0,0290	0,9968	24,4361
3	149	1	77	3	0,9933	0,9625	0,9826	0,0242	0,9987	24,2254
4	147	3	78	2	0,9800	0,9750	0,9783	0,0210	0,9988	22,1308
5	148	2	77	3	0,9867	0,9625	0,9783	0,0242	0,9983	21,7102
Average	147,8	2,2	77,0	3,0	0,9853	0,9625	0,9774	0,0258	0,9980	23,0463
1	150	0	324	2	1,0000	0,9939	0,9958	0,0047	0,9989	33,0545
2	148	2	321	5	0,9867	0,9847	0,9853	0,0160	0,9976	32,0554
3	146	4	321	5	0,9733	0,9847	0,9811	0,0168	0,9977	31,9821
4	146	4	322	4	0,9733	0,9877	0,9832	0,0183	0,9986	30,8744
5	146	4	322	4	0,9733	0,9877	0,9832	0,0200	0,9977	30,9744
Average	147,2	2,8	322,0	4,0	0,9813	0,9877	0,9857	0,0152	0,9981	31,7882

In the fourth experimental group within the scope of the study, training and testing procedures were performed using the real part of the LL, LH and HL sub-images obtained by applying DT-CWT to the chest X-Ray images, and the results were obtained. Then, training and testing procedures were performed using the real part of the LL, LH and HL sub-images obtained by applying LBP and DT-CWT operation to X-Ray images, respectively. Finally, the results were calculated using the pipeline classification algorithm, the details of which were previously described and proposed within the scope of the study. The image sizes given to the CNN as input for this experiment were $224 \times 224 \times 3$. The results obtained from the experimental group are given in Table 13 and Table 15. As can be seen from Table 13-15, the highest sensitivity for the first training test set was 0,9893, while the highest average specificity was calculated to be 0,9725. The average highest accuracy was 0,9817 and the highest average for the area under the ROC curve was calculated to be 0,9984. For the second set of training-tests, the average highest sensitivity was 0,9773, while the highest average specificity was calculated to be 0,9902. The average highest accuracy was 0,9836 and the highest average for the area under the ROC curve was calculated to be 0,9979.

Table 13 Results obtained by using LL, LH, HL real sub-bands obtained by applying DT-CWT to chest X-Ray images

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	144	6	79	1	0,9600	0,9875	0,9696	0,0290	0,9968	14,6870
2	144	6	78	2	0,9600	0,9750	0,9652	0,0340	0,9967	14,9660
3	147	3	79	1	0,9800	0,9875	0,9826	0,0113	0,9986	15,2863
4	148	2	75	5	0,9867	0,9375	0,9696	0,0273	0,9963	13,9943
5	148	2	78	2	0,9867	0,9750	0,9826	0,0144	0,9996	14,0232
Average	146,2	3,8	77,8	2,2	0,9747	0,9725	0,9739	0,0232	0,9976	14,5914
1	145	5	323	3	0,9667	0,9908	0,9832	0,0136	0,9974	19,3784
2	145	5	323	3	0,9667	0,9908	0,9832	0,0168	0,9976	19,8620
3	146	4	323	3	0,9733	0,9908	0,9853	0,0152	0,9954	19,7493
4	145	5	321	5	0,9667	0,9847	0,9790	0,0183	0,9972	20,3641
5	146	4	324	2	0,9733	0,9939	0,9874	0,0136	0,9993	20,0191
Average	145,4	4,6	322,8	3,2	0,9693	0,9902	0,9836	0,0155	0,9974	19,8746

Table 14 Results obtained by using LL, LH, HL real sub-bands obtained by applying LBP and DT-CWT to chest X-Ray images, respectively

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	147	3	66	14	0,9800	0,8250	0,9261	0,0598	0,9803	13,8983
2	147	3	76	4	0,9800	0,9500	0,9696	0,0340	0,9952	13,7918
3	148	2	70	10	0,9867	0,8750	0,9478	0,0419	0,9940	13,7221
4	147	3	70	10	0,9800	0,8750	0,9435	0,0306	0,9953	13,6808
5	148	2	76	4	0,9867	0,9500	0,9739	0,0290	0,9980	13,7128
Average	147,4	2,6	71,6	8,4	0,9827	0,8950	0,9522	0,0390	0,9926	13,7611
1	135	15	311	15	0,9000	0,9540	0,9370	0,0616	0,9874	20,3436
2	136	14	309	17	0,9067	0,9479	0,9349	0,0663	0,9800	20,1501
3	130	20	310	16	0,8667	0,9509	0,9244	0,0806	0,9780	20,1194
4	125	25	315	11	0,8333	0,9663	0,9244	0,0663	0,9829	19,9814
5	134	16	304	22	0,8933	0,9325	0,9202	0,0870	0,9750	22,0309
Average	132,0	18,0	309,8	16,2	0,8800	0,9503	0,9282	0,0724	0,9807	20,5251

Table 15 New results using pipeline classification algorithm

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	147	3	77	3	0,9800	0,9625	0,9739	0,0273	0,9964	28,5852
2	148	2	78	2	0,9867	0,9750	0,9826	0,0242	0,9983	28,7578
3	150	0	78	2	1,0000	0,9750	0,9913	0,0113	0,9995	29,0085
4	148	2	76	4	0,9867	0,9500	0,9739	0,0210	0,9981	27,6750
5	149	1	78	2	0,9933	0,9750	0,9870	0,0065	0,9995	27,7360
Average	148,4	1,6	77,4	2,6	0,9893	0,9675	0,9817	0,0180	0,9984	28,3525
1	149	1	321	5	0,9933	0,9847	0,9874	0,0096	0,9985	39,7221
2	148	2	321	5	0,9867	0,9847	0,9853	0,0136	0,9982	40,0121
3	146	4	321	5	0,9733	0,9847	0,9811	0,0168	0,9975	39,8687
4	143	7	320	6	0,9533	0,9816	0,9727	0,0224	0,9973	40,3454
5	147	3	321	5	0,9800	0,9847	0,9832	0,0168	0,9981	42,0500
Average	146,6	3,4	320,8	5,2	0,9773	0,9840	0,9819	0,0158	0,9979	40,3996

In the fifth experimental group within the scope of the study, training and testing procedures were performed using the imaginary part of the LL, LH and HL sub-images obtained by applying DT-CWT to the chest X-Ray images, and the results were obtained. Then, training and testing procedures were performed using the imaginary part of the LL, LH and HL sub-images obtained by applying LBP and DT-CWT operation to X-Ray images, respectively. Finally, the results were calculated using the pipeline classification algorithm, the details of which were previously described and proposed within the scope of the study. The image sizes given to the CNN as input for this experiment were $224 \times 224 \times 3$. The results obtained from the experimental group are given in Table 16 and Table 18. As can be seen from Table 16-18, the highest sensitivity for the first training test set was 0,9893, while the highest average specificity was calculated to be 0,9675. The average highest accuracy was 0,9817 and the highest average for the area under the ROC curve was calculated to be 0,9982. For the second set of training-tests, the average highest sensitivity was 0,9747, while the highest average specificity was calculated to be 0,9902. The average highest accuracy was 0,9845 and the highest average for the area under the ROC curve was calculated to be 0,9982.

Table 16 Results obtained by using LL, LH, HL imaginary sub-bands obtained by applying DT-CWT to chest X-Ray images

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	146	4	77	3	0,9733	0,9625	0,9696	0,0306	0,9978	14,0655
2	146	4	77	3	0,9733	0,9625	0,9696	0,0306	0,9982	14,3875
3	144	6	77	3	0,9600	0,9625	0,9609	0,0402	0,9965	14,0948
4	145	5	78	2	0,9667	0,9750	0,9696	0,0323	0,9944	14,1031
5	145	5	78	2	0,9667	0,9750	0,9696	0,0242	0,9968	14,0892
Average	145,2	4,8	77,4	2,6	0,9680	0,9675	0,9678	0,0316	0,9967	14,1480
1	144	6	322	4	0,9600	0,9877	0,9790	0,0183	0,9985	20,2871
2	147	3	322	4	0,9800	0,9877	0,9853	0,0136	0,9988	19,7666
3	144	6	323	3	0,9600	0,9908	0,9811	0,0232	0,9972	19,4721
4	147	3	324	2	0,9800	0,9939	0,9895	0,0136	0,9973	19,5145
5	147	3	323	3	0,9800	0,9908	0,9874	0,0136	0,9981	21,0419
Average	145,8	4,2	322,8	3,2	0,9720	0,9902	0,9845	0,0164	0,9980	20,0165

Table 17 Results obtained by using LL, LH, HL imaginary sub-bands obtained by applying LBP and DT-CWT to chest X-Ray images, respectively

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	146	4	70	10	0,9733	0,8750	0,9391	0,0500	0,9866	14,8405
2	145	5	76	4	0,9667	0,9500	0,9609	0,0371	0,9867	14,8694
3	147	3	76	4	0,9800	0,9500	0,9696	0,0242	0,9963	15,2968
4	149	1	71	9	0,9933	0,8875	0,9565	0,0323	0,9972	14,1579
5	147	3	66	14	0,9800	0,8250	0,9261	0,0435	0,9911	13,3012
Average	146,8	3,2	71,8	8,2	0,9787	0,8975	0,9504	0,0374	0,9916	14,4932
1	135	15	314	12	0,9000	0,9632	0,9433	0,0582	0,9840	20,0881
2	138	12	310	16	0,9200	0,9509	0,9412	0,0559	0,9865	19,7368
3	139	11	314	12	0,9267	0,9632	0,9517	0,0488	0,9877	19,7934
4	128	22	306	20	0,8533	0,9387	0,9118	0,0870	0,9791	20,0165
5	134	16	313	13	0,8933	0,9601	0,9391	0,0663	0,9819	20,1128
Average	134,8	15,2	311,4	14,6	0,8987	0,9552	0,9374	0,0633	0,9839	19,9495

Table 18 New results using pipeline classification algorithm

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	149	1	76	4	0,9933	0,9500	0,9783	0,0306	0,9977	28,9060
2	148	2	78	2	0,9867	0,9750	0,9826	0,0177	0,9988	29,2569
3	149	1	77	3	0,9933	0,9625	0,9826	0,0242	0,9983	29,3915
4	148	2	78	2	0,9867	0,9750	0,9826	0,0242	0,9988	28,2609
5	148	2	78	2	0,9867	0,9750	0,9826	0,0242	0,9976	27,3904
Average	148,4	1,6	77,4	2,6	0,9893	0,9675	0,9817	0,0242	0,9982	28,6412
1	145	5	322	4	0,9667	0,9877	0,9811	0,0183	0,9979	40,3751
2	149	1	321	5	0,9933	0,9847	0,9874	0,0111	0,9987	39,5034
3	145	5	321	5	0,9667	0,9847	0,9790	0,0232	0,9985	39,2656
4	147	3	324	2	0,9800	0,9939	0,9895	0,0119	0,9986	39,5310
5	145	5	322	4	0,9667	0,9877	0,9811	0,0200	0,9972	41,1547
Average	146,2	3,8	322,0	4,0	0,9747	0,9877	0,9836	0,0169	0,9982	39,9660

In the sixth experimental group within the scope of the study, training and testing procedures were performed using the real and imaginary parts of the LL sub-image obtained by applying DT-CWT to the chest X-Ray images, and the results were obtained. Then, training and testing procedures were performed using the real and imaginary parts of the LL sub-image obtained by applying LBP and DT-CWT operation to X-Ray images, respectively. Finally, the results were calculated using the pipeline classification algorithm, the details of which were

previously described and proposed within the scope of the study. The image sizes given to the CNN as input for this experiment were $224 \times 224 \times 2$. The results obtained from the experimental group are given in Table 19 and Table 21. As can be seen from Table 19-21, the highest sensitivity for the first training test set was 0,9880, while the highest average specificity was calculated to be 0,9700. The average highest accuracy was 0,9800 and the highest average for the area under the ROC curve was calculated to be 0,9982. For the second set of training-tests, the average highest sensitivity was 0,9787, while the highest average specificity was calculated to be 0,9908. The average highest accuracy was 0,9845 and the highest average for the area under the ROC curve was calculated to be 0,9983.

Table 19 Results obtained by using LL real and imaginary sub-bands obtained by applying DT-CWT to chest X-Ray images

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	147	3	78	2	0,9800	0,9750	0,9783	0,0242	0,9983	13,1864
2	145	5	76	4	0,9667	0,9500	0,9609	0,0323	0,9972	13,1463
3	146	4	78	2	0,9733	0,9750	0,9739	0,0210	0,9988	13,2251
4	145	5	80	0	0,9667	1,0000	0,9783	0,0194	0,9987	13,3918
5	146	4	76	4	0,9733	0,9500	0,9652	0,0323	0,9920	13,9956
Average	145,8	4,2	77,6	2,4	0,9720	0,9700	0,9713	0,0258	0,9970	13,3890
1	144	6	323	3	0,9600	0,9908	0,9811	0,0200	0,9980	19,2930
2	143	7	321	5	0,9533	0,9847	0,9748	0,0175	0,9976	19,0530
3	142	8	323	3	0,9467	0,9908	0,9769	0,0136	0,9977	17,8987
4	141	9	324	2	0,9400	0,9939	0,9769	0,0200	0,9983	17,5171
5	145	5	324	2	0,9667	0,9939	0,9853	0,0136	0,9983	18,3077
Average	143,0	7,0	323,0	3,0	0,9533	0,9908	0,9790	0,0169	0,9980	18,4139

Table 20 Results obtained by using LL real and imaginary sub-bands obtained by applying LBP and DT-CWT to chest X-Ray images, respectively

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	146	4	66	14	0,9733	0,8250	0,9217	0,0598	0,9877	12,1207
2	145	5	65	15	0,9667	0,8125	0,9130	0,0500	0,9857	12,1283
3	146	4	73	7	0,9733	0,9125	0,9522	0,0402	0,9949	12,1344
4	146	4	73	7	0,9733	0,9125	0,9522	0,0531	0,9903	12,1688
5	146	4	67	13	0,9733	0,8375	0,9261	0,0581	0,9830	11,9928
Average	145,8	4,2	68,8	11,2	0,9720	0,8600	0,9330	0,0523	0,9883	12,1090
1	139	11	317	9	0,9267	0,9724	0,9580	0,0567	0,9888	18,3826
2	136	14	313	13	0,9067	0,9601	0,9433	0,0559	0,9875	17,9891
3	132	18	315	11	0,8800	0,9663	0,9391	0,0631	0,9847	17,7745
4	135	15	308	18	0,9000	0,9448	0,9307	0,0623	0,9830	18,2332
5	134	16	315	11	0,8933	0,9663	0,9433	0,0518	0,9877	18,1780
Average	135,2	14,8	313,6	12,4	0,9013	0,9620	0,9429	0,0580	0,9863	18,1115

Table 21 New results using pipeline classification algorithm

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	149	1	77	3	0,9933	0,9625	0,9826	0,0242	0,9978	25,3070
2	149	1	77	3	0,9933	0,9625	0,9826	0,0242	0,9980	25,2745
3	148	2	78	2	0,9867	0,9750	0,9826	0,0144	0,9991	25,3595
4	148	2	78	2	0,9867	0,9750	0,9826	0,0242	0,9989	25,5606
5	147	3	76	4	0,9800	0,9500	0,9696	0,0306	0,9970	25,9885
Average	148,2	1,8	77,2	2,8	0,9880	0,9650	0,9800	0,0235	0,9982	25,4980
1	146	4	322	4	0,9733	0,9877	0,9832	0,0160	0,9984	37,6756
2	148	2	321	5	0,9867	0,9847	0,9853	0,0119	0,9979	37,0421
3	147	3	321	5	0,9800	0,9847	0,9832	0,0152	0,9984	35,6732
4	146	4	322	4	0,9733	0,9877	0,9832	0,0247	0,9981	35,7502
5	147	3	323	3	0,9800	0,9908	0,9874	0,0111	0,9986	36,4857
Average	146,8	3,2	321,8	4,2	0,9787	0,9871	0,9845	0,0158	0,9983	36,5254

In the seventh experimental group within the scope of the study, training and testing procedures were performed using the real and imaginary parts of the LL, LH, HL sub-images obtained by applying DT-CWT to the chest X-Ray images, and the results were obtained. Then, training and testing procedures were performed using the real and imaginary parts of the LL, LH, HL sub-images obtained by applying LBP and DT-CWT operation to X-Ray images, respectively. Finally, the results were calculated using the pipeline classification algorithm, the details of which were previously described and proposed within the scope of the study. The image sizes given to the CNN as input for this experiment were $224 \times 224 \times 6$. The results obtained from the experimental group are given in Table 22 and Table 24. As can be seen from Table 22-24, the highest sensitivity for the first training test set was 0,9880, while the highest average specificity was calculated to be 0,9700. The average highest accuracy was 0,9809 and the highest average for the area under the ROC curve was calculated to be 0,9984. For the second set of training-tests, the average highest sensitivity was 0,9800, while the highest average specificity was calculated to be 0,9908. The average highest accuracy was 0,9845 and the highest average for the area under the ROC curve was calculated to be 0,9982.

Table 22 Results obtained by using LL, LH, HL real and imaginary sub-bands obtained by applying DT-CWT to chest X-Ray images

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	147	3	78	2	0,9800	0,9750	0,9783	0,0194	0,9988	15,9677
2	146	4	77	3	0,9733	0,9625	0,9696	0,0340	0,9975	15,7080
3	149	1	78	2	0,9933	0,9750	0,9870	0,0242	0,9980	15,7554
4	149	1	77	3	0,9933	0,9625	0,9826	0,0242	0,9972	16,1321
5	144	6	78	2	0,9600	0,9750	0,9652	0,0290	0,9961	17,4210
Average	147,0	3,0	77,6	2,4	0,9800	0,9700	0,9765	0,0261	0,9975	16,1968
1	143	7	322	4	0,9533	0,9877	0,9769	0,0175	0,9989	41,4175
2	143	7	322	4	0,9533	0,9877	0,9769	0,0247	0,9964	36,0668
3	147	3	323	3	0,9800	0,9908	0,9874	0,0111	0,9989	41,3384
4	144	6	323	3	0,9600	0,9908	0,9811	0,0175	0,9972	38,9158
5	147	3	325	1	0,9800	0,9969	0,9916	0,0072	0,9996	37,3788
Average	144,8	5,2	323,0	3,0	0,9653	0,9908	0,9828	0,0156	0,9982	39,0235

Table 23 Results obtained by using LL, LH, HL real and imaginary sub-bands obtained by applying LBP and DT-CWT to chest X-Ray images, respectively

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	146	4	75	5	0,9733	0,9375	0,9609	0,0419	0,9938	18,1903
2	146	4	76	4	0,9733	0,9500	0,9652	0,0402	0,9933	17,5809
3	145	5	75	5	0,9667	0,9375	0,9565	0,0323	0,9910	17,8466
4	143	7	72	8	0,9533	0,9000	0,9348	0,0660	0,9854	18,6340
5	147	3	73	7	0,9800	0,9125	0,9565	0,0435	0,9879	17,9964
Average	145,4	4,6	74,2	5,8	0,9693	0,9275	0,9548	0,0448	0,9902	18,0496
1	123	27	304	22	0,8200	0,9325	0,8971	0,0951	0,9693	34,1810
2	138	12	307	19	0,9200	0,9417	0,9349	0,0680	0,9822	35,1865
3	125	25	316	10	0,8333	0,9693	0,9265	0,0680	0,9823	35,8496
4	128	22	308	18	0,8533	0,9448	0,9160	0,0774	0,9790	36,7996
5	132	18	308	18	0,8800	0,9448	0,9244	0,0751	0,9803	32,6469
Average	129,2	20,8	308,6	17,4	0,8613	0,9466	0,9197	0,0767	0,9786	34,9327

Table 24 New results using pipeline classification algorithm

Test	TP	FN	TN	TP	SEN	SPE	ACC	EER	AUC	Time
1	147	3	79	1	0,9800	0,9875	0,9826	0,0144	0,9993	34,1580
2	148	2	76	4	0,9867	0,9500	0,9739	0,0242	0,9977	33,2889
3	150	0	77	3	1,0000	0,9625	0,9870	0,0144	0,9990	33,6021
4	148	2	77	3	0,9867	0,9625	0,9783	0,0242	0,9986	34,7660
5	148	2	78	2	0,9867	0,9750	0,9826	0,0242	0,9975	35,4174
Average	148,2	1,8	77,4	2,6	0,9880	0,9675	0,9809	0,0203	0,9984	34,2465
1	147	3	320	6	0,9800	0,9816	0,9811	0,0200	0,9967	75,5985
2	145	5	320	6	0,9667	0,9816	0,9769	0,0264	0,9965	71,2533
3	148	2	322	4	0,9867	0,9877	0,9874	0,0119	0,9978	77,1880
4	147	3	323	3	0,9800	0,9908	0,9874	0,0200	0,9972	75,7154
5	148	2	323	3	0,9867	0,9908	0,9895	0,0119	0,9989	70,0258
Average	147,0	3,0	321,6	4,4	0,9800	0,9865	0,9845	0,0180	0,9974	73,9562

The summary of the results obtained from the study and given between Table 4 and Table 24 is given in Table 25 for the first training-test data set and in Table 26 for the second training-test data set.

Table 25 The summary of the results for first training-test data set

Input Type	Input Size	SEN	SPE	ACC	EER	AUC	Time
Original image	448×448×1	0,9747	0,9600	0,9696	0,0294	0,9961	47,4380
LBP image	448×448×1	0,9853	0,8950	0,9539	0,0351	0,9939	47,5140
Pipeline Algorithm	448×448×1	0,9907	0,9525	0,9774	0,0245	0,9968	94,9520
Original image-DT-CWT (LL-Real Part)	224×224×1	0,9773	0,9675	0,9739	0,0197	0,9983	10,9653
LBP image-DT-CWT (LL-Real Part)	224×224×1	0,9733	0,9075	0,9504	0,0419	0,9890	11,4484
Pipeline Algorithm	224×224×1	0,9933	0,9675	0,9843	0,0190	0,9988	22,4137
Original image-DT-CWT (LL-Imaginary Part)	224×224×1	0,9760	0,9675	0,9730	0,0283	0,9972	10,7906
LBP image-DT-CWT (LL-Imaginary Part)	224×224×1	0,9707	0,9200	0,9530	0,0429	0,9889	12,2556
Parallel Operation	224×224×1	0,9853	0,9625	0,9774	0,0258	0,9980	23,0463
Original image-DT-CWT (LL, LH, HL-Real Parts)	224×224×3	0,9747	0,9725	0,9739	0,0232	0,9976	14,5914
LBP image-DT-CWT (LL, LH, HL-Real Parts)	224×224×3	0,9827	0,8950	0,9522	0,0390	0,9926	13,7611
Pipeline Algorithm	224×224×3	0,9893	0,9675	0,9817	0,0180	0,9984	28,3525
Original image-DT-CWT (LL, LH, HL-Imaginary Parts)	224×224×3	0,9680	0,9675	0,9678	0,0316	0,9967	14,1480
LBP image-DT-CWT (LL, LH, HL-Imaginary Parts)	224×224×3	0,9787	0,8975	0,9504	0,0374	0,9916	14,4932
Pipeline Algorithm	224×224×3	0,9893	0,9675	0,9817	0,0242	0,9982	28,6412
Original image-DT-CWT (LL-Real and Imaginary Parts)	224×224×2	0,9720	0,9700	0,9713	0,0258	0,9970	13,3890
LBP image-DT-CWT (LL-Real and Imaginary Parts)	224×224×2	0,9720	0,8600	0,9330	0,0523	0,9883	12,1090
Pipeline Algorithm	224×224×2	0,9880	0,9650	0,9800	0,0235	0,9982	25,4980
Original image-DT-CWT (LL, LH, HL-Real and Imaginary Parts)	224×224×6	0,9800	0,9700	0,9765	0,0261	0,9975	16,1968
LBP image-DT-CWT (LL, LH, HL-Real and Imaginary Parts)	224×224×6	0,9783	0,9425	0,9658	0,0316	0,9954	17,7822
Pipeline Algorithm	224×224×6	0,9880	0,9675	0,9809	0,0203	0,9984	34,2465

Table 26 The summary of the results for second training-test data set

Input Type	Input Size	SEN	SPE	ACC	EER	AUC	Time
Original image	448×448×1	0,9627	0,9877	0,9798	0,0166	0,9975	93,9021
LBP image	448×448×1	0,9147	0,9706	0,9529	0,0470	0,9899	97,1589
Pipeline Algorithm	448×448×1	0,9733	0,9877	0,9832	0,0155	0,9982	191,0610
Original image-DT-CWT (LL-Real Part)	224×224×1	0,9573	0,9840	0,9756	0,0212	0,9973	15,4487
LBP image-DT-CWT (LL-Real Part)	224×224×1	0,9013	0,9546	0,9378	0,0609	0,9865	16,9399
Pipeline Algorithm	224×224×1	0,9760	0,9883	0,9845	0,0157	0,9978	32,3887
Original image-DT-CWT (LL-Imaginary Part)	224×224×1	0,9667	0,9877	0,9811	0,0184	0,9970	15,9945
LBP image-DT-CWT (LL-Imaginary Part)	224×224×1	0,8987	0,9571	0,9387	0,0604	0,9861	15,7937
Pipeline Algorithm	224×224×1	0,9813	0,9877	0,9857	0,0152	0,9981	31,7882
Original image-DT-CWT (LL, LH, HL-Real Parts)	224×224×3	0,9693	0,9902	0,9836	0,0155	0,9974	19,8746
LBP image-DT-CWT (LL, LH, HL-Real Parts)	224×224×3	0,8800	0,9503	0,9282	0,0724	0,9807	20,5251
Pipeline Algorithm	224×224×3	0,9773	0,9840	0,9819	0,0158	0,9979	40,3996
Original image-DT-CWT (LL, LH, HL-Imaginary Parts)	224×224×3	0,9720	0,9902	0,9845	0,0164	0,9980	20,0165
LBP image-DT-CWT (LL, LH, HL-Imaginary Parts)	224×224×3	0,8987	0,9552	0,9374	0,0633	0,9839	19,9495
Pipeline Algorithm	224×224×3	0,9747	0,9877	0,9836	0,0169	0,9982	39,9660
Original image-DT-CWT (LL-Real and Imaginary Parts)	224×224×2	0,9533	0,9908	0,9790	0,0169	0,9980	18,4139
LBP image-DT-CWT (LL-Real and Imaginary Parts)	224×224×2	0,9013	0,9620	0,9429	0,0580	0,9863	18,1115
Pipeline Algorithm	224×224×2	0,9787	0,9871	0,9845	0,0158	0,9983	36,5254
Original image-DT-CWT (LL, LH, HL-Real and Imaginary Parts)	224×224×6	0,9653	0,9908	0,9828	0,0156	0,9982	39,0235
LBP image-DT-CWT (LL, LH, HL-Real and Imaginary Parts)	224×224×6	0,8613	0,9466	0,9197	0,0767	0,9786	34,9327
Pipeline Algorithm	224×224×6	0,9800	0,9865	0,9845	0,0180	0,9974	73,9562

4 Discussion

As a result of our study on the automatic classification of chest X-Ray images and using one of the deep learning methods, Convolutional Neural Network, some important and comprehensive test results were obtained for early diagnosis of Covid-19 disease. In the experimental tests carried out in the study, the highest sensitivity (Table 15/Test 3) and specificity (Table 19/Test 4) value was 1 for the first training-test set consisting of 230 images in total, of which 150 abnormal and 80 normal images. The highest accuracy was calculated to be 0,9913 (Table 9/Test 1 and Table 15/Test 3) and the largest area under the ROC curve was calculated to be 0,9996 (Table 13/Test 5). While the highest sensitivity was 1 (Table 12/Test 1) for the second training-test set consisting of 476 images in total, of which 150

abnormal and 326 normal images, the highest average specificity was calculated to be 0,9969 (Table 22/Test 5). The highest accuracy was 0.9958 (Table 12/Test 1) and the largest area under the ROC curve was 0.9996 (Table 22/Test 5).

Considering the average results obtained in the experiments conducted in the study, the average highest sensitivity, specificity, accuracy and AUC values for the first set of training-tests were calculated to be 0,9933; 0.9725; 0,9843 and 0,9988 respectively. On the other side, the average highest sensitivity, specificity, accuracy and AUC values for the second training-test set were calculated to be 0.99813; 0.9908; 0.9857 and 0.9993 respectively.

In the context of the study, if an evaluation should be based on the differentiation made between giving the images to CNN as input directly and after the LBP was applied, it is seen that the images obtained by applying the LBP produced worse results than the original images. However, the pipeline classification algorithm presented in the context of this study, enabled the results obtained to improve by combining the original and LBP-applied images. In this context, a significant part of the best results obtained in the study was provided by using pipeline classification algorithm. In this sense, it is seen that the results of the study support some other literature studies [35]-[39] where CNN and LBP methods are used together and use of LBP was shown to increase the success of the relevant study.

It is also evaluated that another important factor in achieving successful results in the study is that, framing process including the chest region to clarify the area of interest is realized before the training and test procedures start. Hence, thanks to this pre-process carried out in this context, the parts lacking medical diagnostic information were removed from the images and only the relevant areas on the images were used in the procedures.

As the size of the inputs given to CNN increases, the time taken for training and testing increases. The DT-CWT transformation used in the study reduces the sizes of image by half. Although the image sizes are reduced by half, there is no serious adverse effect on the study results. On the contrary, the best results achieved in the study were obtained using the DT-CWT. In this context, although the pipeline classification algorithm proposed in the study increases the time to produce results for the image, the times in question are less than half the time required for the images to be used directly without applying LBP and DT-CWT. Also, all the training and test procedures provided in the study reflect the amount per image. However, approximately 98% of these periods are spent in training procedures. In this context, in case the results obtained by the transfer learning approach are used with the pipeline classification algorithm proposed in the study, the periods mentioned will decrease accordingly.

The results of the study show that analyzing the chest X-Ray images in the diagnosis of Covid-19 disease using deep learning methods will speed up the diagnosis and significantly reduce the burden on healthcare personnel. In order to further improve the results of the study, increasing the number of images in the training set, that is, the creation of databases in which clinical data of Covid-19 patients are accessible to the public is of prime importance.

After this stage, it is aimed to realize applications using CT images of lung, an important diagnostic tool such as chest X-Ray images, in Covid-19 disease diagnosis. In addition, it is planned to analyze the effects of using the results obtained through direct transfer learning in pipeline classification algorithm, on

the study results. It is evaluated as well that another important application is to classify the complex-valued sub-bands of images obtained by applying DT-CWT, with the help of using complex-valued CNN directly.

Compliance with Ethical Standards

Conflict of Interest: Dr. Ceylan declares that he has no conflict of interest. Mr. Yasar declares that he has no conflict of interest.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

References

1. Zhu N, Zhang D, Wang W, Li X, Yang B, Song J, Zhao X, Huang B, Shi W, Lu R, Niu P, Zhan F, Ma X, Wang D, Xu W, Wu G, Gao GF, Tan W (2020) A novel coronavirus from patients with pneumonia in China, 2019. *New England Journal of Medicine* 382:727-733. <https://doi.org/10.1056/NEJMoa2001017>
2. Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, Zhang L, Fan G, Xu J, Gu X, Cheng Z, Yu T, Xia J, Wei Y, Wu W, Xie X, Yin W, Li H, Liu M, Xiao Y, Gao H, Guo L, Xie J, Wang G, Jiang R, Gao Z, Jin Q, Wang J, Cao B (2020) Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *The Lancet* 395(10223):497-506. [https://doi.org/10.1016/S0140-6736\(20\)30183-5](https://doi.org/10.1016/S0140-6736(20)30183-5)
3. Singhal T (2020) A review of coronavirus disease-2019 (COVID-19). *The Indian Journal of Pediatrics* 87(4):281-286. <https://doi.org/10.1007/s12098-020-03263-6>
4. Albarello F, Pianura E, Stefano FD, Cristofaro M, Petrone A, Marchioni L, Palazzolo C, Schinina V, Nicastri E, Petrosillo N, Campioni P, Eskild P, Zumla A, Ippolito G (2020) 2019-novel Coronavirus severe adult respiratory distress syndrome in two cases in Italy: An uncommon radiological presentation. *International Journal of Infectious Diseases* 93:192-197. <https://doi.org/10.1016/j.ijid.2020.02.043>
5. Hsieh WH, Cheng MY, Ho MW, Chou CH, Lin PC, Chi CY, Liao WC, Chen CY, Leong LY, Tien N, Lai HC, Lai YC, Lu MC (2020) Featuring COVID-19 cases via screening symptomatic patients with epidemiologic link during flu season in a medical center of central Taiwan. *Journal of Microbiology, Immunology and Infection*. <https://doi.org/10.1016/j.jmii.2020.03.008>
6. Zhang JJ, Dong X, Cao YY, Yuan YD, Yang YB, Yan YQ, Akdis CA, Gao YD (2020) Clinical characteristics of 140 patients infected with SARS-CoV-2 in Wuhan, China. *Allergy*. <https://doi.org/10.1111/all.14238>
7. Chen N, Zhou M, Dong X, Qu J, Gong F, Han Y, Qiu Y, Wang J, Liu Y, Wei Y, Xia J, Yu T, Zhang X, Zhang L (2020) Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study. *The Lancet* 395(10223):507-513. [https://doi.org/10.1016/S0140-6736\(20\)30211-7](https://doi.org/10.1016/S0140-6736(20)30211-7)
8. Lee NY, Li CW, Tsai HP, Chen PL, Syue LS, Li MC, Tsai CS, Lo CL, Hsueh PR, Ko WC (2020) A case of COVID-19 and pneumonia returning from Macau in Taiwan: Clinical course and anti-SARS-CoV-2 IgG dynamic. *Journal of Microbiology, Immunology and Infection*. <https://doi.org/10.1016/j.jmii.2020.03.003>
9. Liu YC, Liao CH, Chang CF, Chou CC, Lin YR (2020) A locally transmitted case of SARS-CoV-2 infection in Taiwan. *New England Journal of Medicine* 382(11):1070-1072. <https://doi.org/10.1056/NEJMc2001573>
10. Thevarajan I, Nguyen TH, Koutsakos M, Druce J, Caly L, van de Sandt CE, Jia X, Nicholson S, Catton M, Cowie B, Tong SYC, Lewin SR, Kedzierska K (2020) Breadth of concomitant immune responses prior to patient recovery: a case report of non-severe COVID-19. *Nature Medicine* 26:450-455. <https://doi.org/10.1038/s41591-020-0819-2>
11. Lim J, Jeon S, Shin HY, Kim MJ, Seong YM, Lee WJ, Choe KW, Kang YM, Lee B, Park SJ (2020) Case of the index patient who caused tertiary transmission of COVID-19 infection in Korea: the application of lopinavir/ritonavir for the treatment of COVID-19 infected pneumonia monitored by quantitative RT-PCR. *Journal of Korean medical science* 35(6):e79. <https://doi.org/10.3346/jkms.2020.35.e79>

12. Kong W, Agarwal PP (2020) Chest imaging appearance of COVID-19 infection. *Radiology: Cardiothoracic Imaging* 2(1):e200028. <https://doi.org/10.1148/ryct.2020200028>
13. Yoon SH, Lee KH, Kim JY, Lee YK, Ko H, Kim KH, Park CM, Kim YH (2020) Chest radiographic and ct findings of the 2019 novel coronavirus disease (Covid-19): Analysis of nine patients treated in Korea. *Korean journal of radiology* 21(4):494-500. <https://doi.org/10.3348/kjr.2020.0132>
14. Wu J, Liu J, Zhao X, Liu C, Wang W, Wang D, Xu W, Zhang C, Yu J, Jiang B, Cao H, Li L (2020) Clinical Characteristics of Imported Cases of Coronavirus Disease 2019 (COVID-19) in Jiangsu Province: A Multicenter Descriptive Study. *Clinical Infectious Diseases*. <https://doi.org/10.1093/cid/ciaa199>
15. Zu ZY, Jiang MD, Xu PP, Chen W, Ni QQ, Lu GM, Zhang LJ (2020) Coronavirus disease 2019 (COVID-19): a perspective from China. *Radiology* 200490. <https://doi.org/10.1148/radiol.2020200490>
16. Song F, Shi N, Shan F, Zhang Z, Shen J, Lu H, Ling Y, Jiang Y, Shi Y (2020) Emerging 2019 novel coronavirus (2019-nCoV) pneumonia. *Radiology* 295(1):210-217. <https://doi.org/10.1148/radiol.2020200274>
17. Holshue ML, DeBolt C, Lindquist S, Lofy KH, Wiesman J, Bruce H, Spitters C, Ericson K, Wilkerson S, Tural A, Diaz G, Cohn A, Fox L, Patel A, Gerber SI, Kim L, Tong S, Lu X, Lindstrom S, Pallansch MA, Weldon WC, Biggs HM, Uyeki TM, Pillai SK (2020) First case of 2019 novel coronavirus in the United States. *New England Journal of Medicine* 382:929-936. <https://doi.org/10.1056/NEJMoa2001191>
18. Cheng SC, Chang YC, Chiang YLF, Chien YC, Cheng M, Yang CH, Huang CH, Hsu YN (2020) First case of Coronavirus Disease 2019 (COVID-19) pneumonia in Taiwan. *Journal of the Formosan Medical Association* 119(3):747-751. <https://doi.org/10.1016/j.jfma.2020.02.007>
19. Ng MY, Shi EY, Yang J, Yang F, Li X, Wang H, Lui MM, Lo CSY, Leung B, Khong PL, Hui CKM, Yuen KY, Kuo MD (2020) Imaging profile of the COVID-19 infection: radiologic findings and literature review. *Radiology: Cardiothoracic Imaging* 2(1):e200034. <https://doi.org/10.1148/ryct.2020200034>
20. Shi H, Han X, Zheng C (2020) Evolution of CT manifestations in a patient recovered from 2019 novel coronavirus (2019-nCoV) pneumonia in Wuhan, China. *Radiology* 295(1):20-20. <https://doi.org/10.1148/radiol.2020200269>
21. Silverstein WK, Stroud L, Cleghorn GE, Leis JA (2020) First imported case of 2019 novel coronavirus in Canada, presenting as mild pneumonia. *The Lancet* 395(10225), 734. [https://doi.org/10.1016/S0140-6736\(20\)30370-6](https://doi.org/10.1016/S0140-6736(20)30370-6)
22. Phan LT, Nguyen TV, Luong QC, Nguyen TV, Nguyen HT, Le HQ, Nguyen TT, Cao TM, Pham QD (2020) Importation and human-to-human transmission of a novel coronavirus in Vietnam. *New England Journal of Medicine* 382(9):872-874. <https://doi.org/10.1056/NEJMc2001272>
23. Giang HTN, Shah J, Hung TH, Reda A, Truong LN, Huy NT (2020) The first Vietnamese case of COVID-19 acquired from China. *The Lancet Infectious Diseases* 20(4):408-409. [https://doi.org/10.1016/S1473-3099\(20\)30111-0](https://doi.org/10.1016/S1473-3099(20)30111-0)
24. Long JB, Ehrenfeld JM (2020) The role of augmented intelligence (ai) in detecting and preventing the spread of novel coronavirus. *Journal of Medical Systems* 44:59. <https://doi.org/10.1007/s10916-020-1536-6>
25. Cohen JP, Morrison P, Dao L (2020) COVID-19 image data collection, arXiv. <https://github.com/ieee8023/covid-chestxray-dataset> (Access Time :11 May 2020)
26. Dadario AMV (2020) COVID-19 X rays. Kaggle. <https://doi.org/10.34740/KAGGLE/DSV/1019469>
27. Jaeger S, Candemir S, Antani S, Wang YXJ, Lu PX, Thoma G (2014) Two public chest X-ray datasets for computer-aided screening of pulmonary diseases. *Quantitative imaging in medicine and surgery* 4(6):475. <https://doi.org/10.3978/j.issn.2223-4292.2014.11.20>
28. Ojala T, Pietikäinen M, Harwood D (1996) A comparative study of texture measures with classification based on featured distributions. *Pattern recognition* 29(1):51-59. [https://doi.org/10.1016/0031-3203\(95\)00067-4](https://doi.org/10.1016/0031-3203(95)00067-4)
29. Selesnick IW, Baraniuk RG, Kingsbury NC (2005) The dual-tree complex wavelet transform. *IEEE signal processing magazine* 22(6):123-151. <https://doi.org/10.1109/MSP.2005.1550194>
30. Kingsbury N (1998, September) The dual-tree complex wavelet transform: a new efficient tool for image restoration and enhancement. In *Signal Processing Conference*:1-4.
31. Kingsbury N (1999, March) Shift invariant properties of the dual-tree complex wavelet transform. In *International Conference on Acoustics, Speech, and Signal Processing* 3:1221-1224. <https://doi.org/10.1109/ICASSP.1999.756198>

32. Iqbal MZ, Ghafoor A, Siddiqui AM, Riaz MM, Khalid U (2014) Dual-tree complex wavelet transform and SVD based medical image resolution enhancement. *Signal Processing* 105:430-437. <https://doi.org/10.1016/j.sigpro.2014.05.011>
33. Ceylan M, Ozbay Y, Ucan ON, Yildirim E (2010) A novel method for lung segmentation on chest CT images: complex-valued artificial neural network with complex wavelet transform. *Turkish Journal of Electrical Engineering and Computer Sciences* 18(4):613-624. <https://doi.org/10.3906/elk-0908-137>
34. Ceylan M, Yasar H (2013, July) Blood vessel extraction from retinal images using complex wavelet transform and complex-valued artificial neural network. In *International Conference on Telecommunications and Signal Processing* 822-825. <https://doi.org/10.1109/TSP.2013.6614053>
35. Zhang H, Qu Z, Yuan L, Li G (2017, March) A face recognition method based on LBP feature for CNN. In *Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*:544-547. <https://doi.org/10.1109/IAEAC.2017.8054074>
36. Yang X, Li M, Zhao S (2017, December) Facial expression recognition algorithm based on CNN and LBP feature fusion. In *International Conference on Robotics and Artificial Intelligence*:33-38. <https://doi.org/10.1145/3175603.3175615>
37. Juefei-Xu F, Naresh Boddeti V, Savvides M (2017) Local binary convolutional neural networks. In *Conference on Computer Vision and Pattern Recognition*:19-28.
38. Ke P, Cai M, Wang H, Chen J (2018, August) A novel face recognition algorithm based on the combination of LBP and CNN. In *International Conference on Signal Processing (ICSP)*:539-543. <https://doi.org/10.1109/ICSP.2018.8652477>
39. Touahri R, AzizI N, Hammami NE, Aldwairi M, Benaida F (2019, April) Automated breast tumor diagnosis using local binary patterns (LBP) based on deep learning classification. In *International Conference on Computer and Information Sciences (ICCIS)*:1-5. <https://doi.org/10.1109/ICCISci.2019.8716428>

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Figures

Figure 1

a) X-Ray image of Covid-19 patient (Phan et al. [22]) b) Normal X-Ray image (Montgomery data set [27])
c) Normal X-Ray image (Shenzhen data set [27])

Figure 2

Images created by applying LBP and resizing the images in Figure 1

Figure 3

Structure of the DT-CWT decomposition tree

Figure 4

Real and imaginary sub-band images obtained by applying DT-CWT to X-Ray Image (scale=1)

Figure 5

General operation of the Convolutional Neural Network classifier

Figure 6

Block diagram representation of the study of experiments

Figure 7

Block diagram of the pipeline algorithm proposed in the study