



Research Article

Hybridization of Convolutional Neural Networks with Wavelet Architecture for COVID-19 Detection

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Abstract: Coronavirus disease is an infectious disease caused by perilous viruses. According to the World Health Organization (WHO) updated reports, the number of people infected with Coronavirus-2019 (COVID-19) and death rate rises rapidly every day. The limited number of COVID-19 test kits available in hospitals could not meet with the demand of daily growing cases. The ability to diagnose COVID-19 suspected cases accurately and quickly is essential for prompt quarantine and medical treatment. The goal of this research is to implement a novel system called Convolution Neural Network with Wavelet Transformation (CNN-WT) to assist radiologists for the automatic COVID-19 detection through chest X-ray images to counter the outbreak of SARS-CoV-2. The proposed CNN-WT method employing X-ray imaging has the potential to be very beneficial for the medical sector in dealing with mass testing circumstances in pandemics like COVID-19. The dataset used for experimentation consists of 219 chest X-ray images with confirmed COVID-19 cases and 219 images of healthy people. The suggested model's efficacy is evaluated using 5-fold cross-validation. The CNN-WT model yielded an average accuracy of 98.63%, which is 1.36% higher than the general CNN architecture.

Keywords: COVID-19, wavelet, convolution neural network, chest X-ray, automatic identification

1. Introduction

The name 'coronavirus' coined in 1968, since the appearance of these viruses 'corona' or crowns like structure through an electron microscope [1]. A new coronavirus epidemic causes an outbreak of severe respiratory diseases in Wuhan, China. Initially, WHO identified novel virus 2019-nCoV and renamed the disease as Coronavirus-2019 (COVID-19) on February 11, 2020 [2]. Coronaviruses are large zoonotic virus populations that cause severe respiratory diseases from common cold. Zoonotic viruses transmit from animals to humans. There are many known coronaviruses present in various populations of animals that have not yet infected humans. COVID-19 is a novel animal-borne virus that was discovered at a seafood market in Wuhan City in December of 2019 and spread fast throughout the country [3].

Coronaviruses belong to Coronaviridae subfamily and nidovirus superfamily. Based on genome sequencing, Coronaviridae is classified into four classes, such as Alpha coronavirus, Gamma coronavirus, Beta coronavirus and Delta coronavirus. The human virus HCoV-229E, HCoV-NL63 and other animal spread viruses are included in the Alpha coronavirus. The Beta coronavirus genus contains the mouse hepatitis virus, the MERS with 3 human viruses

HCoV-HKU1, SARS-HCoV, HCoV-OC43, SARS viruses and other animal coronaviruses. Gamma coronavirus comprises marine mammal and bird viruses and Delta coronavirus includes bird and pig viruses [4].

Numerous coronaviruses were found in animals in the 1930s and are responsible for gastrointestinal, hepatic and neurological problems. Seven coronaviruses are responsible for human disease. Three of the seven human coronaviruses are more severe and more often lethal than other coronaviruses, resulting in large disease outbreaks in the 21st century such as MERS, SARS and COVID-19 [5].

SARS is an influenza-like disease that raises severe respiratory deficiency. SARS-CoV virus triggered severe acute respiratory syndrome outbreaks in China from 2002 to 2003. SARS-CoV was initially discovered in November 2002 in Chinese Guangdong Province and spread to over 30 countries. About 8,000 cases in which 774 deaths have occurred worldwide in this epidemic. Although no new cases have been seen since 2004, SARS cannot be said to be eradicated, as it can be produced by the causal virus with an animal reservoir [5].

MERS-CoV was originally found in Saudi Arabia in the year of September 2012 whereas its outbreak was confirmed in Jordan, April 2012. Nearly 2,500 cases of MERS-CoV infection with at least 850 deaths were recorded from 27 countries worldwide. All the cases of MERS were connected to or residing in countries in and around the Arabian Peninsula, with more than 80% involving Saudi Arabia. In 2015, the MERS outbreak in Korea is the biggest one occurred outside of the Arab Peninsula [5].

COVID-19 is a novel virus-infectious disease. It severely affects the respiratory tract. COVID-19 signs include cough, nausea, and in extreme cases cause breathing trouble. COVID-19 spreads mainly by contact with an infected person while coughing or sneezing. It also spreads to others when the person touches the surface or items containing the virus, then touching their mouth, eyes, or nose. Right now, no medications are available to combat COVID-19. Nonetheless, one can effectively defend against the virus by regularly washing hands, avoiding touching the face and near contact with infected persons [6].

In the medicine field, image processing technology visualizes the interior portions of the body that helps the specialists for easy diagnosis. It also allowed specialists to make keyhole medical surgery to reach the inside parts without an opening body. The wide usage of computerized imaging in the medical field requires sharp, clear and noise-free medical images to diagnose the diseases accurately. Even though technological advancement produces digital medical images with higher resolution, the reduction of noise in digital images remains one of the primary issues in medical imaging research [7].

Chest X-ray requires a very low dose of ionizing radiation to create internal chest images. It is used to measure the liver, heart and chest wall to treat shortness of breath, constant cough, fever, chest pain or injury. This can also aid in detecting and tracking treatment for a variety of lung diseases, including emphysema, pneumonia and cancer. Because chest X-rays are quick and easy to perform, they are very valuable for emergency diagnosis and treatment [8].

While dealing with a large amount of work and a lack of time during the current epidemic, frontline expert physicians are experiencing increased physical and psychological strain, which may have a negative impact on the diagnostic efficiency. Medical image processing technologies may have the potential for fast and reliable diagnosis of COVID-19, reducing the strain on experts, because modern hospitals have advanced digital imaging technology. Physicians spend more time to investigate the X-ray images of COVID-19 patients. The major goal of the proposed approach is to develop an intelligent approach to support radiologists to analyse COVID-19 images quickly. This paper proposes Convolutional Neural Networks (CNN) architecture with wavelet transformed chest X-ray images (CNN-WT) to identify COVID-19. The proposed algorithm's performance is evaluated in comparison to the CNN architecture. The wavelet transformed chest X-ray images with CNN architecture yielded highest accuracy compared to the traditional CNN architecture. The proposed model's architecture is shown in Figure 1. The wavelet transformation minimizes the signal-to-noise ratio of chest X-ray images to enhance the classification efficiency of the CNN method.

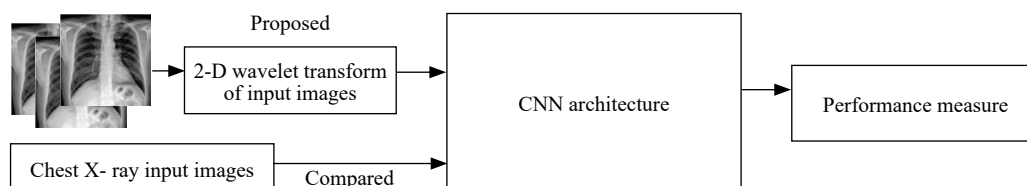


Figure 1. General architecture of proposed method

2. Materials and methods

Deep learning is a subclass of machine learning approaches that focuses on artificial neural networks that learn representations. It is based on brain structure and function. It uses multiple layers to extract higher-level features from the raw images to identify relevant classes. Departments of Radiology have been continuously working since the COVID-19 outbreak. During the COVID-19 pandemic, the researchers are in a panic to answer the questions, such as how to diagnose the suspected COVID-19 outbreak. Deep learning frameworks is a remarkable recent success in many fields such as medical data classification, segmentation and lesion detection.

2.1 Wavelet decomposition of X-ray chest images

A unique type of image, medical images are utilised for diagnosis and accurate interpretation in various applications. Generally, X-ray images may be blurry, low contrast, poor resolution, or even skewed by noise during acquisition and transmission. In these cases, decision-making would be challenging for the radiologist. Wavelets are a type of mathematical function that divides a function or continuous-time signal into scale components.

Wavelets transform is an effective tool for analysing time-frequency and represents the scale and location features of the image. It is also possible to use wavelet transforms in feature extraction, image compression, image denoising, and other medical image technology. The Discrete Wavelet Transform (DWT) divides a waveform into signal components correlating to specific spectral units or sub-bands. DWT is basically a band-pass filter collection. The DWT decomposition and reconstruction is performed recursively and effectively using in the combination of high pass and low pass filters [9]. Figure 2 shows a general decomposition process using 2-D wavelet transformation.

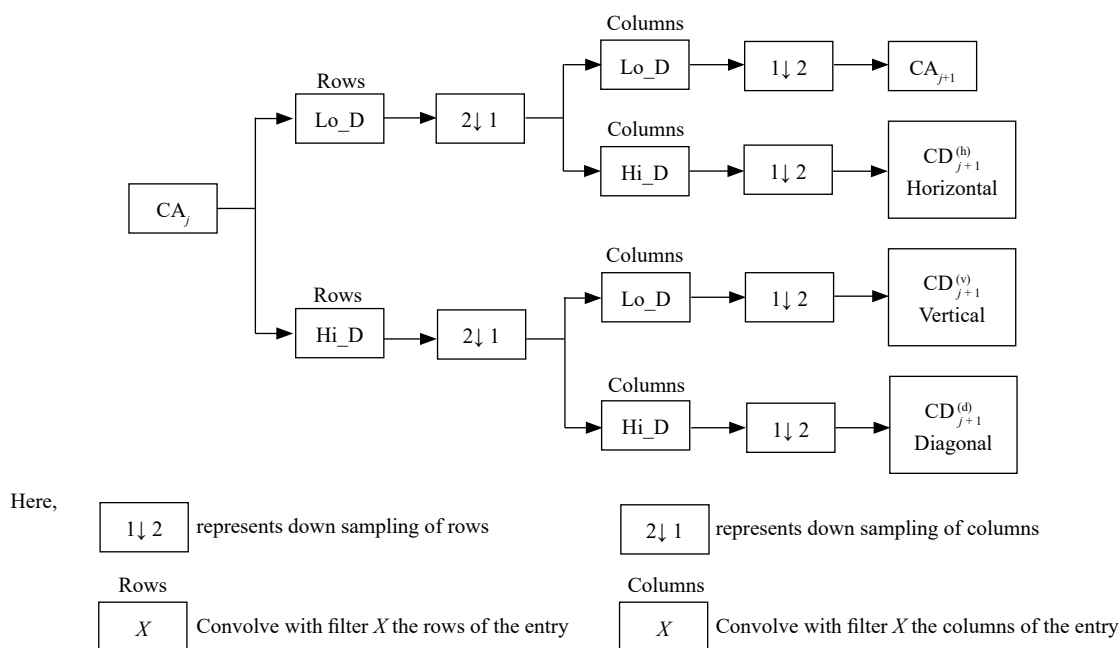


Figure 2. Two-dimensional wavelet decomposition of images

The 2-D wavelet and scaling functions are implemented with the tensor product of the 1-D wavelet and scaling function. This type of 2-D DWT decomposes approximation coefficients at level j into four components: level $j + 1$ approximation, horizontal, vertical, and diagonal information. Figure 3 depicts the fundamental stages of image decomposition. DWT decomposes the image pixels into four wavelet sub-bands, such as LL or cA, HL or cH, LH or cV, and HH or cD. LL is the approximate image coefficient, HL is horizontal, LH is the vertical and HH is the diagonal features of the image [10].

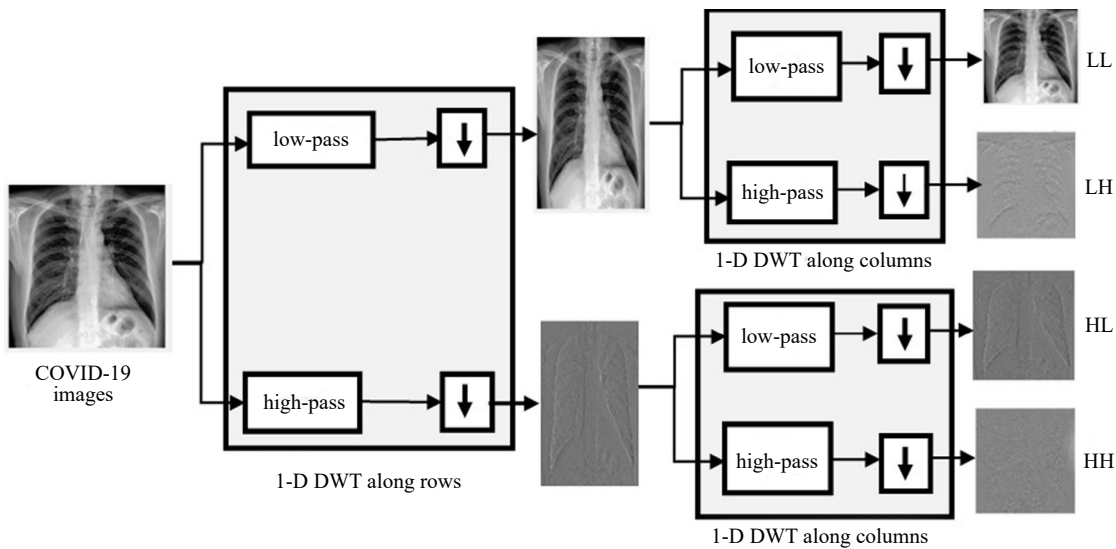


Figure 3. 2-D Wavelet procedure of COVID-19 X-ray image

The X-ray image inputs are subjected to 2-D DWT and decomposed into approximate coefficients and detailed coefficients (horizontal, vertical, diagonal). Initially, 1-D DWT along with the rows of the X-ray image is determined. Next, 1-D DWT has been calculated from the first step along with the columns of the transformed X-ray images. The result of the 1-D wavelet is transformed with four discrete bands, such as LL, LH, HL and HH. L accounts for low-pass filtering, H refers to high-pass filtering. The LL band corresponds roughly to a down-sampled (two-factor) version of the original X-ray image. LH band tends to preserve localized horizontal features, while the HL band tends to preserve localized vertical features in the original X-ray image. Finally, the HH band appears to separate localized high-frequency image features. This can be better visualized in Figure 3. The LL component of the decomposed X-ray image has been considered as input to deep learning neural network. The wavelet transformation applied in the chest X-ray images reduces the signal to noise ratio while simultaneously enhancing CNN classifier efficiency. The following section explains the CNN model with wavelet transformation for X-ray images to automatically identify COVID-19 cases.

2.2 Wavelet transformed chest X-ray images with deep learning model (CNN-WT) for COVID-19 diagnosis

Deep learning can be characterized as neural network systems with an oversized range of parameters and layers inside one amongst four elementary network architectures, such as unsupervised pre-prepared networks, CNN, Recurrent Neural Networks (RNN) and Recursive Neural Networks (RNN). In this research, CNN architecture is adopted. Since, CNN is a standard neural network extended over space with shared weights. Here, CNN is designed to recognize COVID-19 in X-ray images by having convolutions inside. The parameters learning rate, batch size, optimizer and number of epoch are set to CNN for training. One of the configurable parameters is the learning rate whose range is between 0.0 and 1.0. Initially, the weights of a CNN can be computed via optimization procedure instead of an analytical method and the same is used for updating weight during the network training phase. The optimization algorithms performed robustly, no single best algorithm has emerged. Currently, most optimization algorithms such as SGD, SGD with momentum, RMSProp, RMSProp with momentum, Ada Delta, and Adam are actively used in CNN. Adam is used to training CNN in this research. Adam is a combination of Stochastic Gradient Descent with momentum and RMSprop. It uses the squared gradients to scale the learning rate like RMSprop and it takes advantage of momentum by shifting gradient average instead of the gradient itself. Image classification is the process of producing a class label for each input image. The application of CNNs provides a great breakthrough in image classification and recognition [11].

Figure 4 shows COVID-19 detection using chest X-ray images and the suggested CNN model with wavelet transformation.

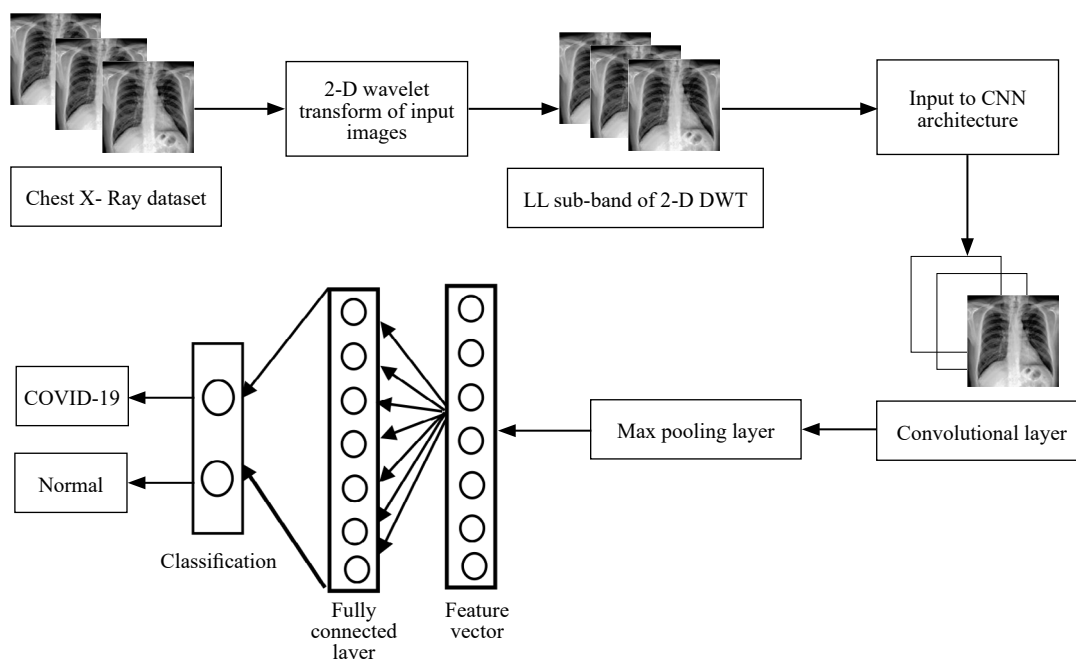


Figure 4. Proposed architecture of COVID-19 automatic detection using CNN-WT

The general architecture of the CNN model consisted of convolutional layers, Rectified Linear Unit (ReLU) layers, max pooling layers and a fully connected layer. The wavelet transformed chest X-ray images are given to the convolutional layer as input and subsequently processed by a max pooling layer (sub-sampling layers) on the output of the convolutional layer until a fully connected layer is eventually processed. The LL sub-bands of 2D-DWT images are given as input to CNN architecture. The 2D-DWT converted images reduce noise and LL sub-bands provides fine details of the images and the performance of the proposed model increases substantially. The feature extraction module is constructed with initial convolution and sub sampling layers, whereas the classification module is formed only by fully connected layers. A fully connected layer is the last processing layer of a standard CNN and is also called an output layer. Convolution involves shifting, multiplying and summing operations. The key processing feature of this layer is to calculate the weight matrix filter or mask. The computational step of the proposed system is presented in Figure 5.

Wavelet Transformed Input Chest X-Ray Images trained using CNN
<p>Input: Chest X-ray dataset with COVID-19 patients and normal images.</p> <p>Output: Classification of chest X-ray images with performance validation.</p>
<p>Step 1. The given X-ray image dataset is transformed into discrete wavelet coefficients and obtain LL sub-bands of 2D-DWT for all the chest X-ray images.</p> <p>Step 2. The LL sub-bands of 2D-DWT images are given as input to CNN architecture.</p> <p>Step 3. CNN architecture applies many different filters to the given set of X-ray images to create a feature map.</p> <p>Step 4. The max pooling layer is applied to each feature map and extracts the pooled images into a single vector.</p> <p>Step 6. CNN trains with many epochs by forward propagation and backpropagation techniques. It is repeated until a well-defined neural network (NN) with training weights and features are obtained.</p> <p>Step 7. The final fully connected layer classify the chest X-ray images as COVID-19 or normal based on voting of the classes.</p>

Figure 5. Computational steps for CNN-WT for COVID-19 detection

3. Experimental results and discussions

The success of the proposed CNN-WT approach is evaluated using chest X-ray images. The proposed algorithms are implemented in a single CPU system using MATLAB R2018(b). The description of the dataset, outcome and analysis are exposed hereunder.

3.1 Dataset

The chest X-ray images of COVID-19 patients are downloaded from the Kaggle dataset [12]. The archives comprise 219 X-ray images of COVID-19, as well as 1,345 images of patients who had viral pneumonia and 1,340 photographs of controls. The representativeness of these datasets is unknown. The dataset taken for analysis consisted of 219 COVID-19 patients and 219 normal chest X-ray images. All of the images have been scaled to 224×224 pixels. The 5-fold cross-validation techniques are used to measure the method's efficiency.

3.2 Performance metrics

Statistical measures such as accuracy, F1-score, sensitivity, and specificity are measured to evaluate the suggested classifier CNN-WT. The following are brief summaries of evaluation parameters.

Confusion matrix (CM) is also referred to as a contingency table, used to express the classifier's outcome. It consists of 2 rows and 2 columns for binary classification. The general format of a confusion matrix is projected in Table 1.

Table 1. General format of confusion matrix

	Actual Positive	Actual Negative
Predicted Positive	True Positive (TP)	False Positive (FP)
Predicted Negative	False Negative (FN)	True Negative (TN)

Sensitivity measures the classifier's ability to accurately identify positive COVID-19 cases. Specificity indicates the numbers of negative (normal) instances are correctly recognized. Accuracy shows how accurately the classifier distinguishes or forecasts COVID-19 and normal cases correctly. Sensitivity and specificity are frequently employed to represent positive and negative occurrences, respectively, whilst the accuracy is used to describe the stability of a classifier's performance. Precision quantifies the number of predictions of positive class that actually corresponds to the positive observations. F1-score is also known as a weighted average of precision and recall. A successful F1-score results in low false positives and negatives cases, so the model correctly identifies COVID-19 cases and not interrupt by false alarms. A F1-score proves that the model is perfect when it reaches 1, while the model is a total failure when it is 0. The assessment metrics and associated formulae are presented in Table 2.

Table 2. Performance metrics

Metrics	Formula
Accuracy	$(TP + TN) / (TP + FP + FN + TN)$
Sensitivity	$TP / (TP + FN)$
Specificity	$TN / (FP + TN)$
Precision	$TP / (TP + FP)$
F1-score	$2 \times ((Precision \times Recall) / (Precision + Recall))$

3.3 Results and discussion

The wavelet transformed chest X-ray images are given as input to the general CNN architecture. By evaluating chest X-ray images for the recognition of COVID-19, the CNN-WT model's outcomes are compared to that of the CNN model. To achieve the desired convergence in this limited X-ray image data set with a few iterations, and to prevent the degradation problem, the initial learning rate, minimum batch size, the maximum number of epochs is set to $1e-5$, 2 and 30, respectively. The 5-fold cross-validation is applied to measure the performance.

Figure 6 depicts the training progress and loss values of the proposed architecture for fold-2. To avoid overfitting, the maximum epochs is set to 30. Each epoch requires 176 iterations. The whole training progress up to 5,280 iterations. As illustrated in Figure 6, the training accuracy remains stable after 800 iterations. The training loss value declines from iteration 1,000 and the loss value reach 0 from the 1,500 iterations. The minimum training time required for a fold is 8 minutes. The overall running time for training CNN-WT architecture required 40 minutes in a single CPU system. The training efficiency will further be increased if we train through the GPU system. Hence, the overall training accuracy of the proposed CNN-WT architecture is 100%.

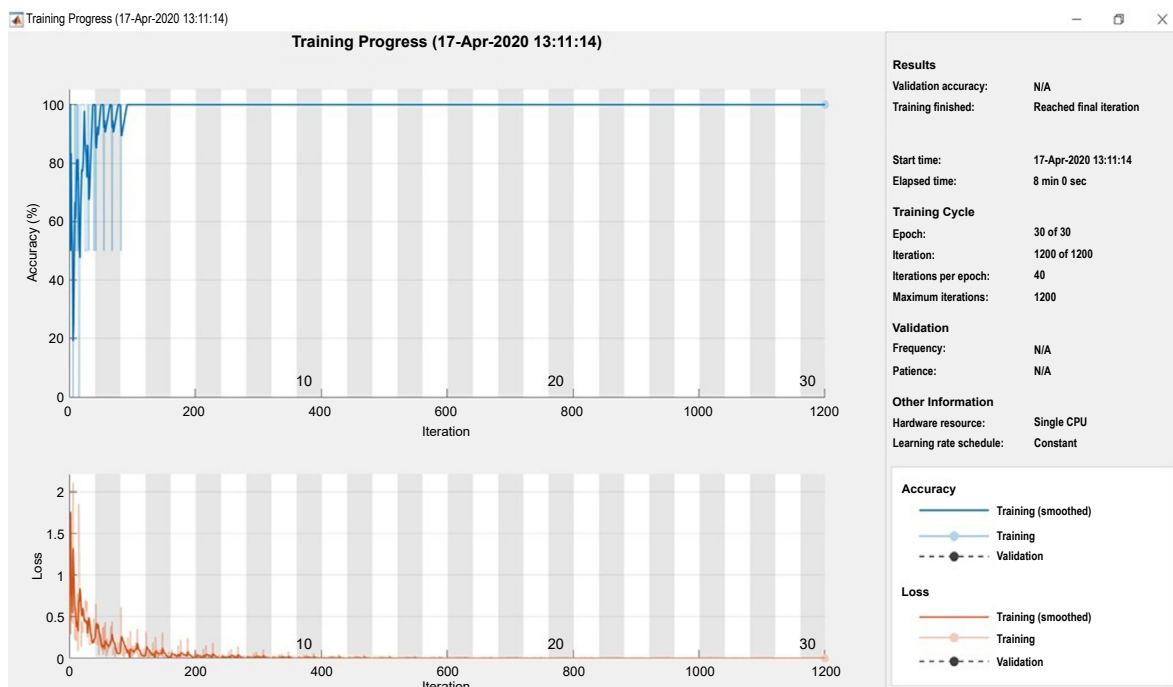


Figure 6. Training accuracy and loss evaluation of CNN-WT architecture for fold-2

The confusion matrices of the proposed CNN-WT model and CNN for 5 folds are shown in Figure 7. The proposed CNN-WT architecture classified 44 of the COVID-19 cases as true positive and 44 of the healthy patients as true negative without a false positive and false negative in fold-1 and fold-5. In fold-3 and fold-4, the proposed architecture accurately identified 43 normal and 42 COVID-19 cases. For fold-2, the architecture perfectly recognized 42 COVID-19 cases and 42 normal cases recognized accurately and 2 cases misclassified as normal, similarly 42 normal cases, whereas 2 cases in each class are misclassified.

In the general CNN architecture, 43 COVID-19 cases and 43 normal cases are identified accurately in fold-2 and fold-5. In fold-1 and fold-4, the method correctly classified 43 normal cases and 41 COVID-19 cases, whereas the technique misclassified a normal case and 3 COVID-19 cases in each fold. For fold-3, the method recognized 42 normal and 42 COVID-19 cases accurately, whereas a case in each class is misclassified. The average F1-score, precision, accuracy, specificity, and sensitivity are estimated from CM.

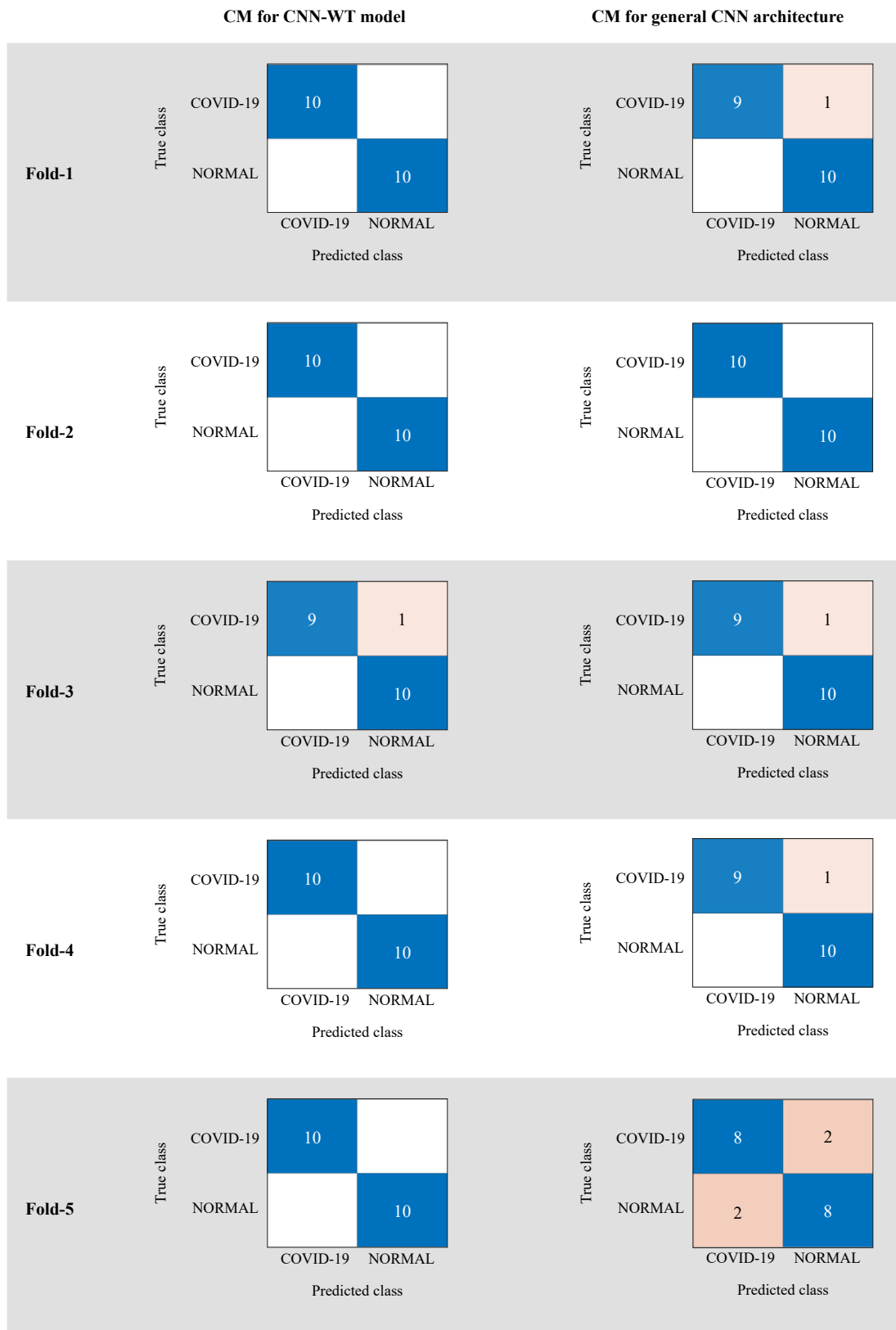


Figure 7. CM for CNN-WT model and general CNN architecture for 5 folds

Table 3 shows the outcome of the CNN-WT model and the general CNN architecture. The evaluation results of each fold clearly stated that the proposed architecture identified 44 normal and 44 COVID-19 images accurately without false positive and false negative in fold-1 and fold-5. Hence, the precision, accuracy, specificity, sensitivity, and F1-Score are 100% for fold-1 and fold-5. For fold-3 and fold-4, CNN-WT architecture identified 43 normal cases accurately. Among the 43 COVID-19 cases, 42 cases are recognized correctly. Hence, F1-score, precision, accuracy, specificity and sensitivity are 98.82%, 97.67%, 98.83%, 97.72%, and 100% respectively. For fold-2, CNN-WT recognized 42 normal and COVID-19 cases accurately and achieved F1-score, precision, accuracy, specificity, and sensitivity of 95.45%. The general CNN architecture identified 43 normal and 43 COVID-19 images accurately without false positive and false negative in fold-2 and fold-5. Hence the precision, accuracy, specificity, sensitivity, and F1-score are 100%. For fold-2, general CNN achieved F1-score, precision, accuracy, specificity, and sensitivity of 95.45% in fold-2, since 42 normal and COVID-19 cases are recognized accurately. In fold-1 and fold-4, general CNN architecture identified 43 normal cases and 41 COVID-19 cases accurately. Hence, F1-score, precision, accuracy, specificity and sensitivity are 95.34%, 93.18%, 95.45%, 93.47%, and 97.61% respectively.

Table 3. Classification result of COVID-19 dataset

Model	Fold	Accuracy	Sensitivity	Specificity	Precision	F1-score
CNN-WT (Proposed method)	1	1.00	1.00	1.00	1.00	1.00
	2	1.00	1.00	1.00	1.00	1.00
	3	0.95	1.00	0.91	0.90	0.95
	4	1.00	1.00	1.00	1.00	1.00
	5	1.00	1.00	1.00	1.00	1.00
	Average	0.99	1.00	0.98	0.98	0.99
General CNN architecture	1	0.95	1.00	0.91	0.90	0.95
	2	1.00	1.00	1.00	1.00	1.00
	3	0.95	1.00	0.91	0.90	0.95
	4	0.95	1.00	0.91	0.90	0.95
	5	0.80	0.80	0.80	0.80	0.80
	Average	0.93	0.96	0.91	0.90	0.93

The proposed model produced an average accuracy of 98.63%, which is 1.36% superior to the general CNN architecture. F1-score, precision, specificity, and sensitivity of CNN is 97.23%, 96.36%, 96.48%, and 98.14%, which are 1.39%, 1.80%, 1.70%, and 1% lower than the proposed CNN-WT method. The experimental analysis clearly stated that CNN-WT architecture is superior to general CNN architecture.

The performance analysis chart of these two architectures is exposed in Figure 8. Figure 8 clearly stated that the CNN-WT model yielded an accuracy of 98.63%, the sensitivity of 99.09%, specificity of 98.18%, precision of 98.16%, and F1-score of 98.62%, whereas general CNN architecture yielded an overall accuracy of 97.27%. The precision, specificity, sensitivity, and F1-score of general CNN architecture are 96.36%, 96.48%, 98.14%, and 97.23%, respectively.

Table 4 discloses the classification results of various CNN models proposed so far to detect COVID-19 cases. From Table 4, it is clear that deep learning architecture plays an evolving role in COVID-19 cases identification using chest X-rays as well as CT images. Most of the deep learning models achieved above 90% of accuracy for the identification of COVID-19 cases. The CNN-WT architecture achieved 98.63% of accuracy. The proposed CNN-WT method is implemented in Intel Core i5-7200U @ 2.50 GHz processor with 8 GB RAM. And, its main limitation is the overhead of computational time. The processing time of the proposed CNN-WT architecture for each fold required nearly 10 minutes. The overall computational time needed for the CNN-WT method with 5-fold cross-validation required 50 minutes.



Figure 8. Performance comparison of proposed algorithms

Table 4. Classification accuracy of existing deep learning models for COVID-19

Author	Method	Dataset	Classification accuracy
[13]	Resnet50	COVID-19 chest X-ray	98%
[14]	VGG19	COVID-19 chest X-ray	90%
[15]	Deep learning architecture	CT images of COVID-19, Influenza-A viral pneumonia	86.7%
[16]	Deep learning with weak label	CT images	98.2%
[17]	Deep learning	CT images	Dice similarity coefficients: 91.6% ± 10.0%
[18]	VGG19	Chest X-ray images	98.75%
[19]	Deep learning	CT images	95.24%
[20]	Deep learning algorithm	CT images	89.5%
Proposed	CNN-WT	Chest X-ray images	99%

In summary, the proposed deep learning with the wavelet transformation based model gives always great potential results to improve diagnostic performance and treatment of COVID-19 patients, thus contributing to epidemic control.

4. Conclusion

The world is stunned by infectious COVID-19 and it still threatens the lives of billions of people. Early COVID-19 patient diagnosis and prognosis is crucial to preventing disease spread. This research work presents the automatic identification of COVID-19 cases through chest X-ray images using CNN-WT. The general CNN architecture yielded 93% of accuracy, whereas the proposed CNN-WT method yielded 99% of accuracy for COVID-19 cases recognition.

The wavelet transformation of chest X-ray images reduces the signal to noise ratio present in the images. Hence, the CNN model with wavelet transformation yielded higher accuracy compared to CNN. The scope of this research can be further expanded by using transfer learning techniques for CT pictures as well as chest X-ray images in order to identify COVID-19 instances with less computing time.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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