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COVID-19 classification using hybrid deep learning and standard feature extraction techniques

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ABSTRACT

There is no doubt that COVID-19 disease rapidly spread all over the world, and effected the daily lives of all of the people. Nowadays, the reverse transcription polymerase chain reaction is the most way used to detect COVID-19 infection. Due to time consumed in this method and material limitation in the hospitals, there is a need for developing a robust decision support system depending on artificial intelligence (AI) techniques to recognize the infection at an early stage from a medical images. The main contribution in this research is to develop a robust hybrid feature extraction method for recognizing the COVID-19 infection. Firstly, we train the Alexnet on the images database and extract the first feature matrix. Then we used discrete wavelet transform (DWT) and principal component analysis (PCA) to extract the second feature matrix from the same images. After that, the desired feature matrices were merged. Finally, support vector machine (SVM) was used to classify the images. Training, validating, and testing of the proposed method were performed. Experimental results gave (97.6%, 98.5%) average accuracy rate on both chest X-ray and computed tomography (CT) images databases. The proposed hybrid method outperform a lot of standard methods and deep learning neural networks like Alexnet, Googlenet and other related methods.

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1. INTRODUCTION

There is no doubt that corona virus disease rapidly dispersion all over the globe, and had an impact on everyone's day-to-day life. The infection may cause pneumonia that lead to death. COVID-19 should be diagnosed rapidly, in order to segregate affected individuals and decrease the number of mortality. Nowadays, the most way used to recognize COVID-19 infection is the reverse transcription polymerase chain reaction (RT-PCR) [1]. Due to time consumed in RT-PCR method and material limitation in the hospitals, this method does not meet the rapidly required tools to avoid and control the positive infected cases to isolate them. The medical images could be a rapid method to detect and recognize the infected peoples [2]. Image processing is a wide area in computer vision, a lot of methods and techniques are used in this point starting from preprocessing stage until classification stage. There is a need to develop a robust aided decision making support system depending on artificial intelligence (AI) to recognize and segment the area of infection at an early stage in the image. Traditional methods like PCA, 2 dimension principal component analysis (2D-PCA), discrete wavelet transform (DWT) are used in a wide range in feature extraction stage [3], [4]. Researchers [5], [6] used 1 level-DWT, 2 level-DWT, 3 level-DWT to extract image features, applied PCA and support vector machine(SVM) in different situations of image classification. In recent years, AI has seen an efficient major and rapidly growing with deep learning neural networks to solve a lot of problems like object detection, image classification,speech recognition [7], [8]. A lot of machine learning methods were used in a wide range for diagnosis detection, segmentation and classification in the medical field, recently achieved as a popular techniques by becoming an efficient tools for clinicians [9]-[13]. Deep learning (DL) techniques were applied successfully in a lot of problems like arrhythmia detection [14]-[16], breast cancer detection [17], [18], brain disease classification [19] and skin cancer classification [20], [21]. Convolution neural networks (CNNs) viewed a robust results in the field of image processing. For detection, segmentation, and classification a lot of works have been developed and achieved the impact and power of that works [22]. To detect COVID-19 infection, a review work based on CNNs was introduced in [23]. This review cover the entire pipeline of medical imaging and analysis techniques involved with COVID-19, including acquisition, segmentation, diagnosis, and follow-up on both chest X-ray images and computed tomography (CT) scans and analyzed the results.

Xu *et al.* [1] classified the CT data set images of COVID-19 to 3 classes as (COVID-19 images, healthy cases images , and viral pneumonia images). By collecting the images from a lot of hospitals in Zhejiang. The desired data set consisted of 618 cases, divided as 219 case from 110 person have COVID-19, 224 case of 224 person have influenza-A viral pneumonia, and 175 case of 175 person considered as normal cases. The introduced model gave 87.6% classification accuracy rate. Shan *et al.* [24] introduced a robust technique to segment the infected areas on CT data set. A 249 COVID-19 cases were used for training, and 300 new COVID-19 cases were used for validation at this study. The results showed a Dice similarity coefficient near by 91.6%. Ozturk *et al.* [25] developed the DarkCovidNet to segment and classify the COVID-19 images from X-ray data set. Based on the end-to-end architecture where feature extraction methods are not used. It needs only chest X-Ray patient images to detect the diagnosis. This model achieved average accuracy rate of 87.02%. An automated COVID-19 grading method with CNNs in CT images was developed in [26], it reported a 87.6% accuracy rate. Altaf *et al.* [27] provides a robust model augmentation that allows a considerable performance boost for transferring learn in the task of COVID-19 classification, they achieved average accuracy rate 82.3%. Researchers [28]-[31] reported average accuracy rate from 91.2% to 94.4%. The average accuracy rate of COVID-19 diagnose recognition still not sufficient. There is a need of a robust method for this problem.

The following parts of this paper is divided as follows. Section 2 introduce the main standard methods used in for feature extraction, classification and the Alexnet deep learning method. Sections 3 shows the data sets used to train, validate and evaluate the proposed method. Section 4 view the proposed method and its results. Finally, conclusion and future work are presented in section 5.

2. MAIN METHODS

In this section, a lot of previous related methods is reported. These methods will be used to create a hybrid technique. The standard methods like DWT, PCA, and SVM will be discussed. Also, the deep learning techniques will be reported. The proposed method will be based on the standard feature extraction methods merged with deep leaning techniques.

2.1. Discrete wavelet transform

Wavelets are best described as a good mathematical methods used to convert the original data to the frequency components. These coefficients are given a resolution based on their size. Wavelets considered to be developed in the electrical engineering, mathematics branch, and quantum physics [32]. Few decades ago, many robust applications of wavelet were developed like image compression, prediction of earthquake, radar and computer vision. In image processing, a wavelet and Kernel functions could be introduced as it shown in (1) and (2) respectively.

$$\Psi_{V,U(t)} = \sum_{s=0}^{M-1} \sum_{z=0}^{M-1} g(s,z) \exp^{-j\pi \frac{(Vs+Uz)}{M}}, \tag{1}$$

$$\exp^{-j\pi \frac{(Vs+Uz)}{M}} \tag{2}$$

The image is denoted as $g(s,z)$ and M is the total count of points in the used image.

Wavelet transform could be used as an efficient tool for both image and signal manipulation. DWT is utilized in a variety of applications in the computer vision field [6], [4], [33]. DWT creates 4 subbands in each decomposition stage. Horizontal, approximation, diagonal and vertical coefficient. Due to high information showed in approximation subband of the 1st level, it could be considered like the main image. Figure 1 view the 4 coefficients of a 1 level DWT on X-ray images.

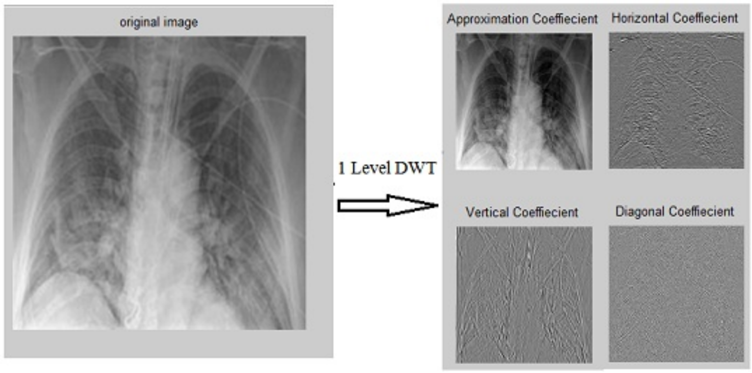


Figure 1. 1 level DWT

2.2. Principal component analysis

The PCA is defined to be a robust statistical method which is very effected in a wide range in image processing for feature extraction. The main reason to use PCA is to reduce the original data space form a wide dimension to a new smaller space. The reduction based on (3).

$$T = AX. \tag{3}$$

A, X, T are defined as (transformation, original) and the feature matrices. PCA could be used to remove redundant data, extract features, compression, and for prediction [3]. If you have a data set of M images $X_1, X_2, ..., X_M$. Assume, each X_i in the data set is 2-dimensional image of scale n by m. By converting the 2-dimensional matrix to 1-dimensional vector of scale $n \times m$ as viewed in 4.

$$X_i = \begin{pmatrix} x_1 \\ x_2 \\ . \\ . \\ . \\ x_{nm} \end{pmatrix} \tag{4}$$

The images set will be initiated as the matrix in (5),

$$X = [X_1, X_2, ...X_M] \tag{5}$$

then, compute the mean image X$_m$ as shown in (6).

$$X_m = \frac{1}{M}\sum_{i=1}^{M} X_i. \tag{6}$$

The formula in (7) is used to define the covariance for the data set,

$$C = \frac{1}{M}\sum_{i=1}^{M}(X_i - X_m)(X_i - X_m)^T. \tag{7}$$

let $N_i = (X_i - X_m)$, defined as the centered image. The covariance matrix is established in (8). The main issue is to compute eigenvectors e_i and the eigenvalues λ_i of the following covariance matrix.

$$C = MM^T. \tag{8}$$

Let d_i, μ_i are eigenvalues and eigenvectors of $N^T N$. We find in (9) that,

$$N^T N d_i = \mu_i d_i. \tag{9}$$

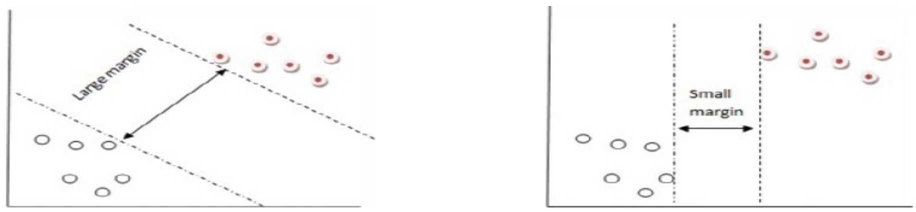
we shall multiply (9) two sides by N, to get (10).

$$(NN^T)Nd_i = \mu_i(Nd_i). \tag{10}$$

The first $M - 1$ from λ_i and e_i of the computed covariance $C = NN^T$ are defined as Nd_i and μ_i. Nd_i will be normalized to equal the e_i. The eigenvectors related to largest k eigenvalues of the covariance matrix C will be used to get the transformation matrix T.

2.3. Support vector machine

SVM is considered to be a statistical machine learning method used for data classification. This could be done based on Shaping a group of support vectors [34]. SVM construct a hyperplanes among two classes of row data to classify them [35]. SVM trying to find an optimal hyperplane, which have the large distance between the components of training tuples. Assume we have two groups of data, founding two hyperplanes like Figure 2. It is clear that, Figure 2(a) with the larger margin could give us a great accuracy than Figure 2(b).



(a) (b)

Figure 2. Two hyperplanes: (a) large and (b) small margins

2.4. Deep learning

A new branch in AI is called DL, used to develop methods that enable computers learning in complex tasks, like hearing and seeing to get a efficient accuracy rate. It provides high performance level in image classification, object detection, speech recognition, language processing, and vehicle detection. Ad-hoc methods are used to extract specific features from a picture in classical classification algorithms. These feature extraction techniques' outputs are then sent into a classification function, which decides if a certain object was detected. Low and false-alarm detectors result from this strategy. A lot of problems appeared like:

- It's difficult to come up with general, dependable qualities that correspond to specific object kinds.
- Determining the optimal combination of attributes for each object type to identify is a difficult task.
- It's tough to come up with ways for translating, rotating, and scaling objects that are both sufficient and efficient.

The above mentioned problems effect the segmentation, classification and detection processes. DL methods, extract a large amount of labeled data to determine the correct features and combinations of characteristics that best describe each class of objects to be categorized. Then provide a hybrid feature extraction and classification model. The previous model is developed to classify a lot of a related unseen objects, not only the one which was trained on it. CNN, is depending on a large set of hidden layers, to make a huge computations on the inputs data. The output of the previous layer is fed as an input to the following layer as shown in Figure 3. The final layer have the classes labels, which have been trained on. When completing the training stage, the prediction level will start to measure the efficiency of the proposed network [36].

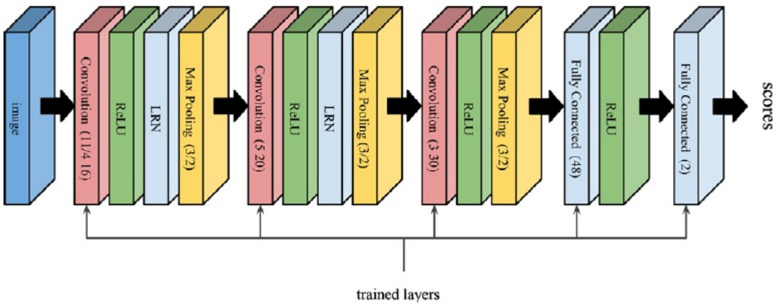


Figure 3. CNN architecture

2.4.1. Alexnet deep learning neural network

Alexnet is treated as a CNN , had a huge performance on the DL and computer vision applications [22]. Figure 4 views the main structure of Alexnet DL neural networks layers. It has eight layers, five of them are convolution layers and the rest are of them are fully_connected. In order to speed the training process, Rectified linear unit (ReLU) is applied after every convolution and fully_connected. Dropout is applied before 1^{st} and 2^{nd} fully_connected layer. For training stage, the images were resized to $256 * 256$. 1.2 million images used for in the training stage, 150,000 image in the testing, and 50,000 images were used to validate the network.

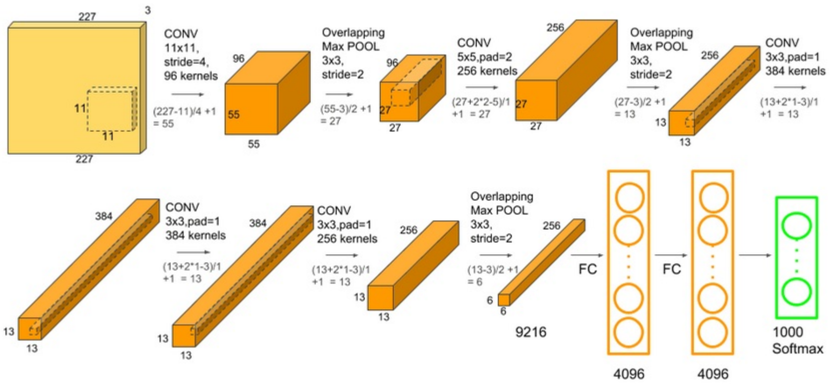


Figure 4. Alexnet architecture

3. DATABASES DESCRIPTION

To view the effectiveness of the proposed work, two data sets will be introduced and referenced in this section. Data sets features, number of images, number of classes, number of images in each class and class type will be mentioned. Chest X-ray and CT databases will be mentioned as well as sample of images of the described data sets. These data sets were used in a lot of research for COVID-19 classification.

3.1. X-ray database

Covid-19 Chest X-RAY database, A group of researchers from Qatar, Bangladesh, Pakistan and Malaysia, have created a database of chest X-ray pictures for COVID-19 positive cases, as well as normal and viral pneumonia pictures, in collaboration with medical doctors. The data set for COVID-19, normal, and other lung infections is being released in stages. They shared 219 COVID-19, 1,341 normal, and 1,345 viral pneumonia chest X-ray (CXR) images in the first release. In the most recent update, they included 3,616 COVID-19 positive cases to the database, as well as 10,192 normal, 6,012 lung opacity (non-COVID lung infection), and 1,345 viral pneumonia pictures. [28], [37]. Figure 5 shows a sample of different images from the X-ray database.

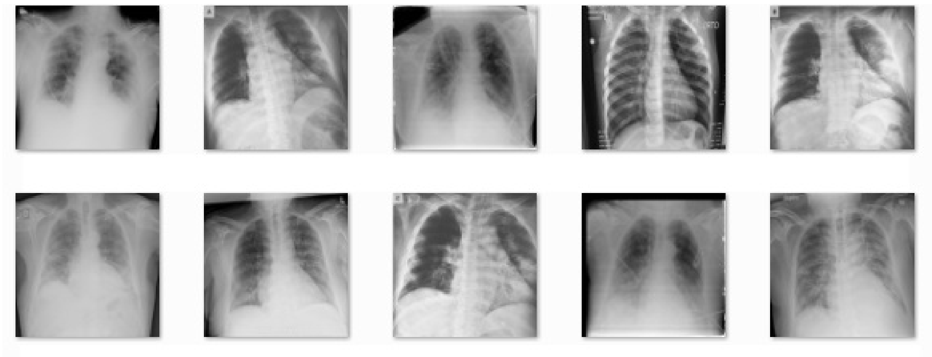


Figure 5. Sample of X-ray chest images

3.2. CT database

CT database is a new data set consists of 2,500 pictures. Unlike the X-ray database, the CT database is divided to two classes. Positive COVID-19 class have 1,252 different images, non-COVID class have 1,229 different images [38], [39]. It is used to identify if a person is infected by COVID-19 through the analysis of his/her CT image. Figure 6 shows a sample of different images from the CT database.

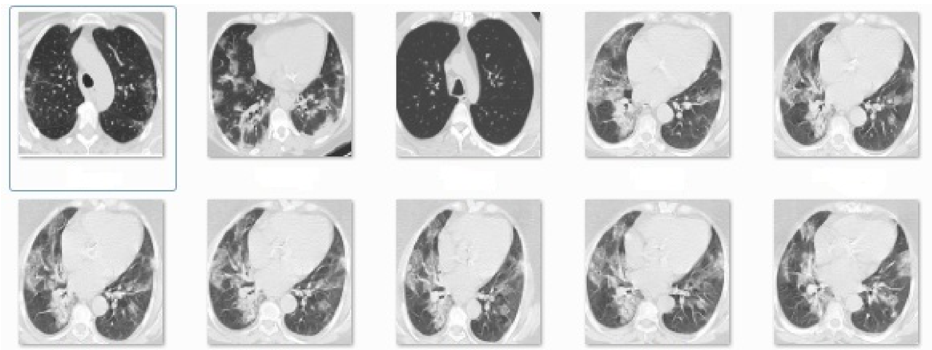


Figure 6. Sample of CT images

4. PROPOSED METHOD

In this paper, we introduce a hybrid feature extraction method. The proposed method depend on both DL techniques and traditional methods. Figure 7 shows a flow chart of the proposed hybrid method. Firstly in the training stage, the input image is decomposed to its coefficients using 1 level 2D-DWT. DWT generate 4 coefficients, LL, LH, HL ,HH. It is shown that the LL coefficient has more information about the input image, so it will be used as an input to the next stage. Now we construct the covariance matrix to extract features using PCA, which will produce the projection matrix. Using Alexnet DL neural network, after a pre-processing stage where images converted from gray to rgb and resized to 227*227. Alexnet is trained using the training images. we divided the databases to 70% images for training stage and 30% for testing stage. Learning rate was reduced to $1 * 10^-5$, no of epohs equal 20. The second feature matrix is extracted from layer 20 using the activations() function. Now, the first and second feature matrices are concatenated to perform the new feature matrix. In this stage, the MultiSvmTrain() function will be used to models the new feature matrix with a corresponding group vector. In the testing stage, a test image is decomposed using 1 level 2D-DWT, get the first feature vector using the PCA projection matrix. Using the activations() function, to extact the second feature vector. After concatenating the extracted feature vectors, the MultiSvmClassify() function is used to classify the input image. Using different Kernel functions, results showed that the Gaussian radial basis function (RBF) is the best SVMs kernel function for this study. The RBF kernel is defined in (11).

$$k_{RBF}(x, x') = \exp[-\gamma \|x - x'\|^2] \tag{11}$$

Where γ is considered to be a scale parameter, γ default value equal to 1.

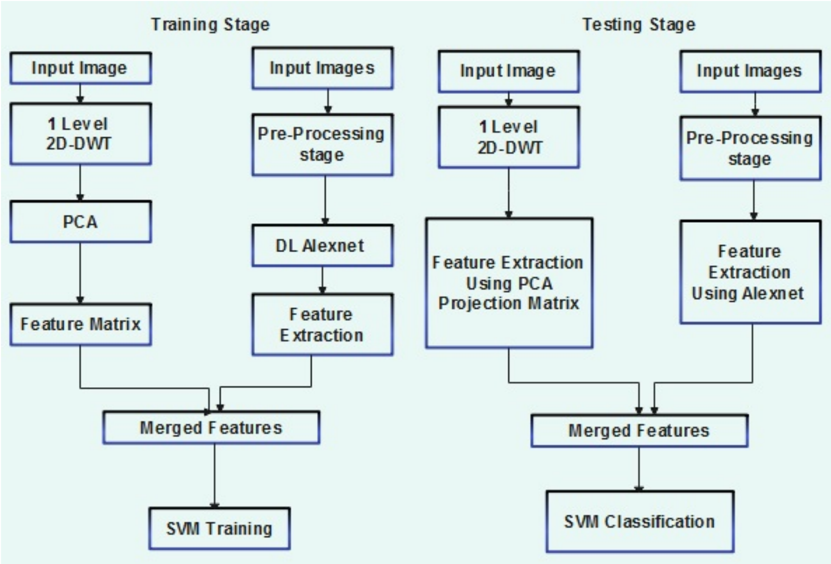


Figure 7. Proposed hybrid method

4.1. Performance metrics

To evaluate the proposed method, a lot of performance parameters were used. True positive (TP), false positive (FP), true negative (TN) and false negative (FN) are the main component used for computing the performance metrics. T_P is defined as the number of images classified as class1 and they are located already in class1. T_N is defined as the number of images classified as class1 and they are not located already in class1. F_P is defined as the number of images not classified as class1 and the are located already in class1. F_N is defined as the number of images not classified as class1 and they are not located already in class1. recall, precision, specificity, sensitivity, accuracy, and Fscore are defined in (12) to (17) respectively.

$$Recall = \frac{T\_P}{T\_P + F\_N}. \tag{12}$$

$$Precision = \frac{T\_P}{T\_P + F\_P}. \tag{13}$$

$$Specificity = \frac{T\_N}{T\_N + F\_P}. \tag{14}$$

$$Sensitivity = \frac{T\_P}{T\_P + F\_N}. \tag{15}$$

$$Accuracy = \frac{T\_P + T\_N}{T\_P + T\_N + F\_P + F\_N}. \tag{16}$$

$$Fscore = \frac{2 * T\_P}{(2 * T\_P) + (F\_P + F\_N)}. \tag{17}$$

5. EXPERIMENTAL RESULTS AND DISCUSSION

To view the effectiveness of the proposed hybrid method, chest X-ray and CT images databases were used for training, validating and testing the proposed method. Confusion matrix were computed as shown bellow. Figure 8 shows the confusion matrix of the Alexnet, Googlenet deep learning techniques applied on the chest X-Ray database.The Alexnet gave average accuracy rate 90.5%

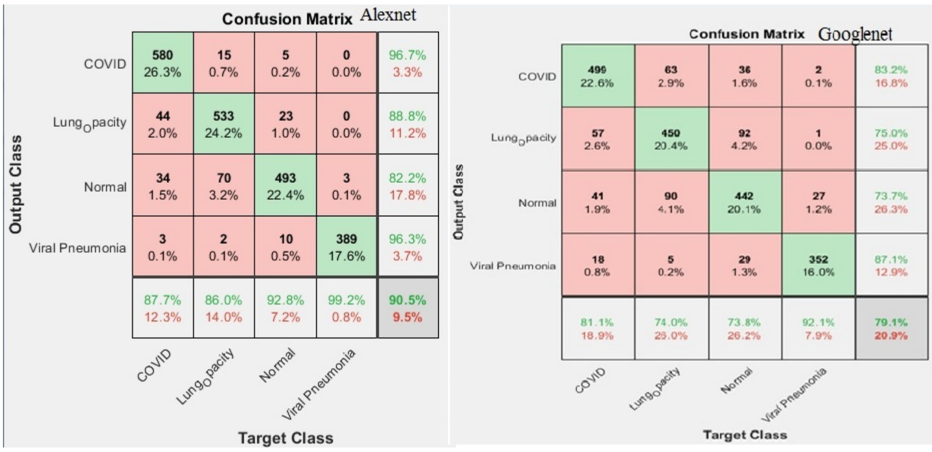


Figure 8. Confusion matrix of Alexnet and Googlenet on chest X-ray images database

Figure 9 shows the confusion matrix of the proposed method applied on both the chest X-ray and CT databases. It is shown that the new hybrid method greater than Alexnet and Googlenet methods. It gave average accuracy rate 95.2 % and 98.5% on Chest X-ray and CT databases respectively.

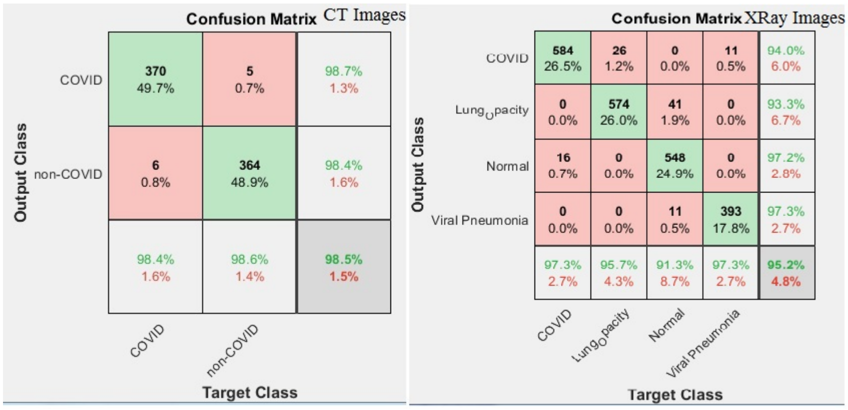


Figure 9. Confusion matrix of the proposed method on chest X-ray and CT databases

Table 1 shows a comparative analysis on the X-ray data set results for Alexnet, Googlenet, other reported articles, and the proposed hybrid method. It is shown that the proposed method outperform the mentioned methods. Not only in the accuracy metric, but also in the specificity, sensitivity and Fscore metrics.

Table 1. Comparative results on X-ray data set proposed method VS related literature

Method	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Alexnet	91	91.4	95.3	96.7	91	91.1
Googlenet	79.7	80.4	79.1	92	79.7	80
Cavallo *et al.* [29]	93	-	91.8	90	93	
Echtioui *et al.* [31]	88	91	91.34	-	-	89.66
Rajpal *et al.* [30]	94.50	-	94.4	-	94	95
Proposed	95.5	95.4	97.6	98.4	95.5	95.4

Table 2 shows the performance metrics results on the X-ray data set. Classifying the images to 4 classes (COVID, lung_opacity, normal and viral pneumonia). The COVID class has accuracy rate 97.6% and 95.7% Fscore rate. The proposed method outperform the related literature methods in the accuracy and Fscore metrics.

Table 2. Proposed method performance metrics results on X-ray data set 4 classes

Class	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
COVID	94	97.3	97.6	99	94	95.7
Lung_opacity	93.3	95.7	97	98.4	93.3	94.5
Normal	97.2	91.3	96.9	96.8	97.2	94.2
Viral pneumonia	97.3	97.3	99	99.4	97.3	97.3

Figure 10 shows a visual representation of the proposed method. Recall, precision, accuracy, specificity, sensitivity and FScore metrics are represented in this chart for the 4 classes. For the COVID class, the proposed method report a 97.6%, 95.7% for both Accuracy and Fscore metrics respectively. The Viral Pneumonia results were high than 97.3% for all of the mentioned metrics.

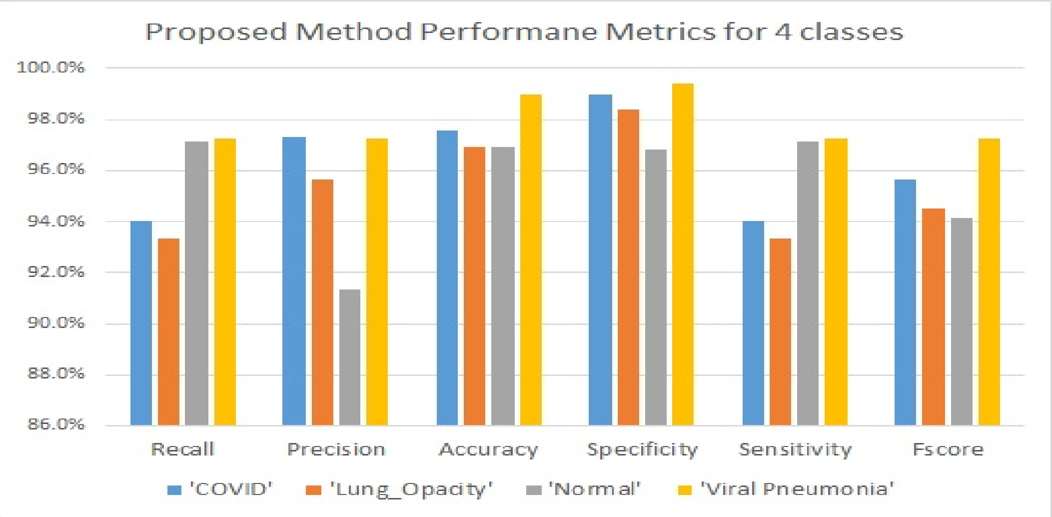


Figure 10. Proposed method performance metrics for 4 classes on X-ray data set

In Figure 11, a visual representation of the proposed methods versus reported articles results were analyzed. The Alexnet gave 95.3% accuracy rate. Also, the Googlenet Fscore was 80%. It is clear from the graphical representation that the proposed method gave high accuracy rate. Also, it reported high Fscore rate greater than the mentioned methods.

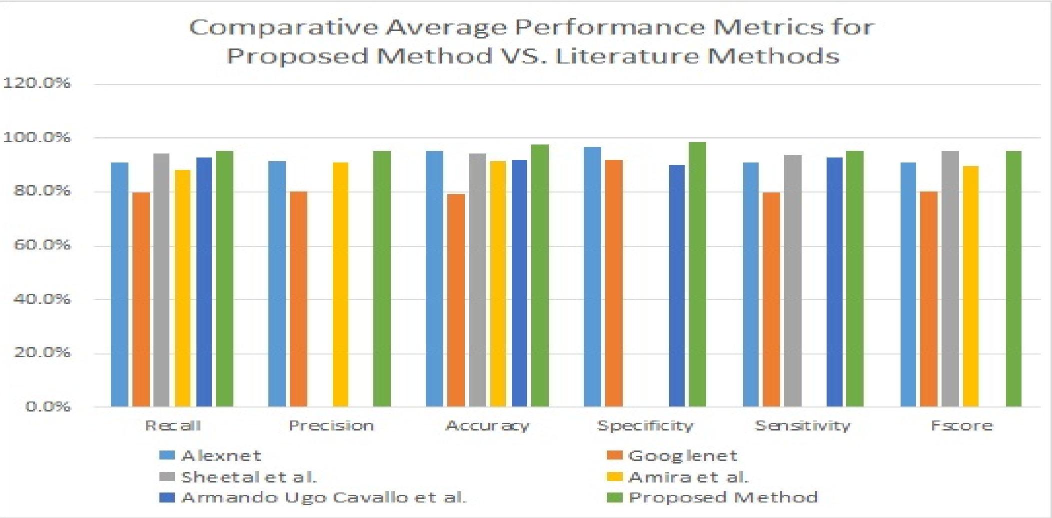


Figure 11. Comparative analysis of the proposed method VS literature methods on X-ray data set

On CT data set, Table 3 shows a comparison analysis of the proposed method and the related literature methods. To view the performance of the proposed method, a lot of metrics were used. The proposed method outperform the reported methods in terms of recall, precision, accuracy, specificity, sensitivity and Fscore. The proposed method gave high than 98% rate for all of the used metrics.

Table 3. Comparative analysis on CT data set proposed method VS related literature

Method	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Alexnet	97.33	97.34	97.32	97.33	97.33	97.32
Googlenet	66.03	66.05	66.04	66.03	66.03	66.02
de Vente *et al*. [26]	66.0	74.0	87.6			69.8
Altaf *et al*. [27]			82.3	97.2	67.6	84.0
Proposed	98.53	98.52	98.52	98.53	98.53	98.53

Figure 12 shows a visual representation of the comparative analysis for the proposed method against the literature methods on CT data set. CT data set is divided into two classes. The graphical representation shows that the proposed method outperform all of the mention methods in all of the used metrics. The Fscore and accuracy metrics were 98.53%.

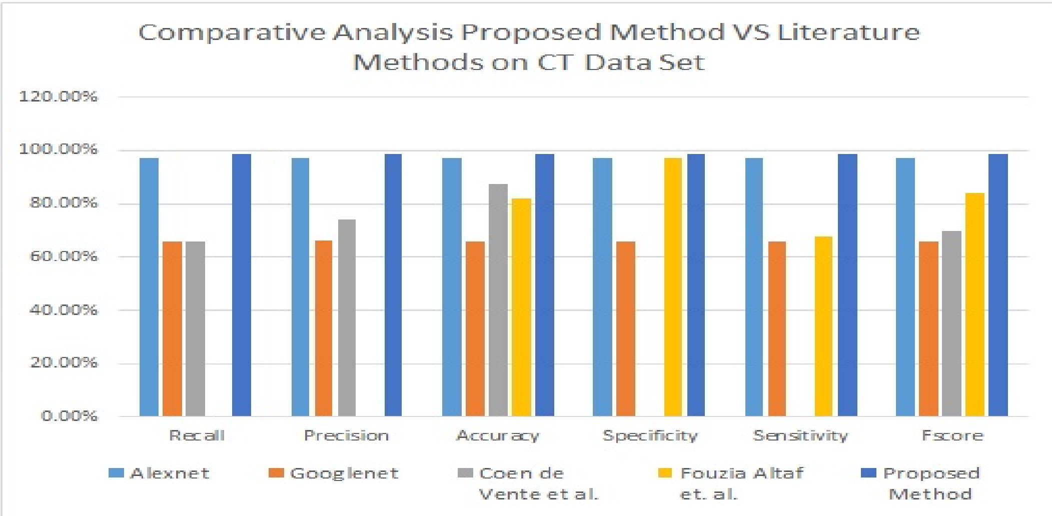


Figure 12. Comparative analysis of the proposed method VS literature methods on CT data set

6. CONCLUSION

In this paper, we present a hybrid feature extraction methods for COVID-19 image classification. The proposed method depends on both traditional feature extraction methods and DL neural networks. The proposed method was trained and tested on two COVID-19 image data sets. Experimental results showed that the proposed method gave accuracy rate 97.6% and Fscore 95.4% on the chest X-ray database. Also, results show a 98.5% accuracy rate and 98.53% Fscore on CT image database. It was shown that the proposed method outperform the Alexnet and Googlnet DL neural networks on both databases. On X-ray database, the classification rate increased with 6% from the Alexnet DL method and 20% from the Googlenet DL method. On CT database, the classification rate increased with 1.2% from the Alexnet DL method and 47% from the Googlenet DL method. The proposed method outperform the related literature methods on a lot of used performance metrics on the same data sets. Our Future work will be for trying to testing other CNN models and using data augmentation techniques to increase the classification performance. Also for trying to extract and segment the infected area using segmentation methods. After segmentation, we will not only classify the image if infected or not. The images will be classified to level of infection. Applying some hyperparameter optimization and combining classifications techniques to increase the accuracy rate.

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