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Coronavirus disease identification using Multi-subband feature analysis in DWT domain

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Abstract

Coronavirus disease early identification and differentiating it with other lung infections is a complex and time-consuming task. At present RT-PCR and Antigen tests are used for diagnosis, but the whole process is tedious, time exhausting and sometimes gives inaccurate results. Radiological scans like CT scan and X-rays are often considered for confirmation of infection, as it contains vital information about region of infection, disease state and severity, texture, size and opacity of infection. Automated machine learning techniques along with CXR (Chest X-ray) images can serve as alternative approach for Covid-19 diagnosis and differentiating it with other health conditions. In this work, Covid-19 disease identification is performed based on multi-subband feature extraction using 2D Discrete Wavelet Transform (DWT) on CX-Ray images. The CX-ray images are decomposed into multi-subbands of frequencies using DWT. The quarter-sized decomposed low and high frequency components are concatenated into single feature vector. In order to find suitable wavelet filter for extracting features from CX-ray images, a rigorous experimentation is carried out among various wavelet families such as Haar, Daubechies, Symlets, Biorthogonal and their respective members that have different vanishing moment and regularity properties. The feature vector is then used for training machine learning model based on support vector machine classifier. Experimental result shows that the classification model based on Haar wavelet feature extraction performs better as compared to other wavelet families with classification accuracy of 100%.

Keywords: *Covid-19; X-ray; machine learning; Discrete wavelet transform (DWT); classification; multi-subband;*

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1. Introduction and Literature review

The coronavirus disease caused by one of the most contagious and highly mutating virus SARS-CoV-2, which affects respiratory as well as other organs. Most common symptoms are high temperature, cold, throat infection, taste and smell loss, diarrhoea, difficulty in breathing, chest pain and other respiratory disorder [1]. Molecular test (also known as RT-PCR) and Antigen test are commonly used for Covid-19 detection. In some cases, radiological scans (like X-ray, CT-scans, Ultrasounds) are also performed for detailed diagnosis of infection caused by the virus. One of the reasons for wide spread and huge casualties is limited and time-consuming Covid-19 detection tools and unavailability of any treatment for Covid-19 disease. In order to contain the disease and stop further spread, it's important to detect infected patients as early as possible with the help of machine-learning based diagnosis system by analysing X-ray/CT scans images [2].

In recent years healthcare organizations have shown gradual shift towards Artificial intelligence, machine learning or deep learning-based systems to recognize medical requirements, accurate and faster diagnosis. The clinical data can be used for reviewing and analysing with the help of AI/machine learning algorithms, thus empowering radiologists and others to identify and examine critical cases more efficiently.

It is a challenging task to differentiate between viral pneumonia and Covid-19 infection using radiological scans due to their indistinguishable infection pattern. A medical expert is required for labelling and marking the radiological chest scans to differentiate between above two state. Due to increasing cases of Covid-19, it puts enormous burden on radiologists to timely diagnose each case accurately. This inconsistency between requirement and availability of human experts has encouraged to look for alternatives such as automated diagnosis systems based on ML [3]. In recent years researchers have been working towards developing efficient automated system to detect and diagnose Covid-19 from other cases.

T. Ozturk *et al*. [4] implemented DarkNet model as classifier for YOLO system based on DarkNet-19 model, the model is implemented without any feature extraction technique. S. Minaee, R. Kafieh and M. Sonka *et al.* [5] performed comparative examination of four formerly-trained deep learning networks (ResNet18, ResNet50, SqueezeNet, and DenseNet- 121) for binary classification based on CX-ray images. SqueezeNet performs comparatively better than rest of the CNN models having sensitivity of 98% and specificity of 92.9%. Ensemble method in machine learning is very useful in improving the prediction ability of the model. Many of the deep learning networks are combined for ensemble learning to provide optimal prediction. Das *et al.* [6] first individually trained three networks: DenseNet201, ResNet50V2, and Inceptionv3, then these models are combined for ensemble learning to perform Covid-19 diagnosis using five-fold cross validation giving accuracy of 91.62%.

A deep learning model called DeTraC (Decompose, Transfer and Compose) is proposed by A. Abbas *et al.* [7] for Covid-19 identification. Different pre-trained CNN networks are validated using DeTraC model, among which VGG19 obtains highest accuracy of 97.35%. The work proposed by M. Heidari *et al.* [8] is based on two-step pre-processing algorithm HE and bilateral-LPF used for enhancing and removing noise from the X-ray images. The original image and processed image combined to form pseudo colour image, which is then given to transfer learning-based CNN model for three class classification. Narin, A. *et al.* [9] performed Covid-19 classification using five different CNN models, among which ResNet50 outperforms rest of the models.

The wavelet-based CNN model proposed by A.K. Verma *et al.* [10] uses two-level decomposition of different wavelet families for feature extraction. The feature vectors extracted using DWT is then fed as input to CNN model. The accuracy achieved using Symlet-7 level-2 approximation component (98.87%) is higher among other wavelet families. P. Gaur *et al.* [11] implemented Covid-19 classification model using Empirical wavelet transform and deep learning network. A.M Ismael *et al.* [12] performed two-class categorization using formerly-trained CNN models. The classifier used is Support vector machine, and experiments are conducted using different SVM kernel functions. E. Hussain *et al.* [13] developed a state-of-art technique named as CoroDet. The model is trained using large dataset, prepared by combining four publically available Covid-19 dataset. The model used for two-class and multi-class classification.

Chaudhary, P. K. *et al*. [14] introduced technique based on FBD method for CX-ray image decomposition into sub-images. The sub-images are then given input to ResNet50 network. Deep feature concatenation-based model is developed by W. Saad *et al.* [15]. Features are extracted using CNN from different X-ray and CT images and combined into single descriptor which is utilized in classification. D. Sharifrazi *et al.* [16] presented a fusion based model for distinguishing Coronavirus cases using CNN, SVM and Sobel filter together. This combined model achieves an accuracy of 99.02% using ten-fold cross validation system. Dilip Kumar Sharma, M. Subramanian, Pacha. Malyadri *et al.* [22] developed binary classification model using SVM classifier, in order to optimize the data a modified cuckoo search algorithm is adapted. The data dimension is reduced to eliminate redundant features, minimum redundancy maximum relevance algorithm is used for feature selection. This binary system achieves an accuracy of 96.73%. The machine learning model combined with fuzzy inference system is adapted by Aggarwal, A. *et al.* [23] to predict level of risk associated with diabetic patients due to Covid-19 infection. It achieved 76% accuracy using CatBoost classifer.

In the proposed work machine learning model using SVM classifier is utilized for creating a binary classification model for differentiating Coronavirus cases from non-infected healthy cases. The feature extraction is performed using DWT, which is fed to classification model as input. This work can be outlined as follows:

- The chest X-ray images are processed using Contrast Limited AHE (CLAHE) technique.
- To eliminate false positives and detect Covid-19 more precisely by the fusion of DWT multi-subband feature concatenation technique and Support Vector Machine (SVM).
- The experimental analysis carried out using different wavelet families (like Haar, Daubechies, Symlets, and Biorthogonal) for feature extraction.

The remaining part of the paper is organized as follows: Preliminaries explained in section 2, algorithm of proposed technique laid out in section 3, details of dataset, performance metrics and experimental result analysis discussed in section 4, and finally in section 5 the entire work is concluded.

2. Preliminaries

2.1. Contrast Limited Adaptive Histogram Equalization (CLAHE)

Histogram equalization (HE) is most commonly applied technique for contrast enhancement. The processed output image is produced using global intensity transformation in which input image pixels are mapped to corresponding output pixel, so that resultant image histogram is approximated to uniform distribution. This histogram approximation to uniform distribution may work where only overall enhancement is required, but fails to enhance details of specific regions in an image (specially in case of medical image enhancement) [20]. The solution to above said problem is intensity transformation based on neighbouring pixels distribution. One such technique is Contrast Limited adaptive-HE (AHE) technique.

Contrast limited-AHE has given better results in case of biomedical image enhancements. CLAHE is local histogram processing technique, in which image is divided into several contextual regions. A clip limit based on desired contrast limit expansion is set for obtaining clipped histogram of each region. Redistribution of each histogram is carried to keep the values within clip range. Finally for performing grayscale mapping the cumulative distribution function of resultant histogram is determined [21].

2.2. Discrete wavelet transform

Fourier analysis used in expansion of periodic, time-invariant or stationary signals/functions in terms of sinusoids. Whereas, wavelet is applicable in analysing transient, non-stationary, time-varying signals/functions [17]. Wavelet based signal expansion allows simultaneous analysis in time and frequency domain. In wavelet single function and its dilation and translation is used to generate orthonormal basis function set which is used to represent any signal [24-25]. Thus, wavelet function and scaling function together act as orthonormal basis of discrete wavelet transform [18]. The equation of wavelet expansion series expansion of function $f(x)$ with respect to wavelet function $\psi(x)$ and scaling function $\varphi(x)$ is given as:

$$f(x) = \sum_{k} c_{j_0}(k)\varphi_{j_0,k}(x) + \sum_{j=j_0}^{\infty}\sum_{k} d_j(k)\,\psi_{j,k}(x) \tag{1}$$

where, c_{j_0} and d_j for $j \geq j_0$ are called approximation and detail coefficients respectively.

$$c_{j_0} = \langle f(x), \varphi_{j_0,k}(x)\rangle \tag{2}$$

$$d_j = \langle f(x), \psi_{j,k}(x)\rangle \tag{3}$$

For discrete signal $s(n)$ sampled at $n = 0,1, \dots . M - 1$, the discrete wavelet transform in one dimension can be represented by following equation:

$$W_\varphi(j_0, k) = \frac{1}{\sqrt{M}} \sum_n s(n)\varphi_{j_0,k}(n) \tag{4}$$

$$W_\psi(j, k) = \frac{1}{\sqrt{M}} \sum_n s(n)\psi_{j,k}(n) \tag{5}$$

where, $W_\varphi(j_0, k), W_\psi(j, k)$ are scaling and wavelet function coefficients, for $j > j_0$ $j = 0,1, \dots . . J - 1$ and $M = 2^j$ called normalizing term. The equations (4) and (5) are called forward DWT, and the inverse DWT is given by equation (6) below:

$$s(n) = \frac{1}{\sqrt{M}}\left[\sum_k W_\varphi(j_0, k)\varphi_{j_0,k}(n) + \sum_{j=j_0}^{\infty}\sum_k W_\psi(j, k)\psi_{j,k}(n)\right] \tag{6}$$

The expansion coefficient of DWT can be computed as:

$$W_\varphi(j, k) = \sum_m h_\varphi(m - 2k)W_\varphi(j + 1, m) \tag{7}$$

$$W_\psi(j, k) = \sum_m h_\psi(m - 2k)W_\varphi\,(j + 1, m) \tag{8}$$

$$W_\varphi(j, k) = W_\varphi(j + 1, m) * h_\varphi(-m) \tag{9}$$

$$W_\psi(j, k) = W_\varphi(j + 1, m)) * h_\psi(-m) \tag{10}$$

In order to understand 2D wavelet analysis, let's take an example of a 2D image function $f(x, y)$, which is our X-ray image of chest. One dimensional low and high frequency wavelet filter is applied on rows of image and then downsampling its output column by two producing two subimages. Again 1D low and high frequency wavelet filters are applied on columns of subimages, and again the output rows are downsampled by two. Finally four quarter-sized decomposed wavelet subbands – approximation $W_\varphi(j, k, l)$, horizontal $W_\psi^H(j, k, l)$, vertical $W_\psi^V(j, k, l)$, and diagonal W_ψ^D are obtained as shown in figure 1.

2.3. Supervised machine learning classifier based on Support vector machine

Support vector machine based classifier is widely used in ML algorithms which find its application in recognition, categorization, regression and other tasks related to supervised learning. SVM is a useful technique when dealing with high dimensional data because it allows for the creation of a hyperplane to separate classes. The SVM model separates the classes by creating the optimal hyperplane which maximizes the distance between them. In a feature space of n-dimensions, the hyperplane is a subset of $n - 1$ dimensions dividing the space into distinct classes. For example, when the data is in two dimensions, the hyperplane is of one dimension [19].

Most of the SVMs have a component called the Kernel Function which are used as parameters for determining the hyperplane. Some of the most common kernel functions are:

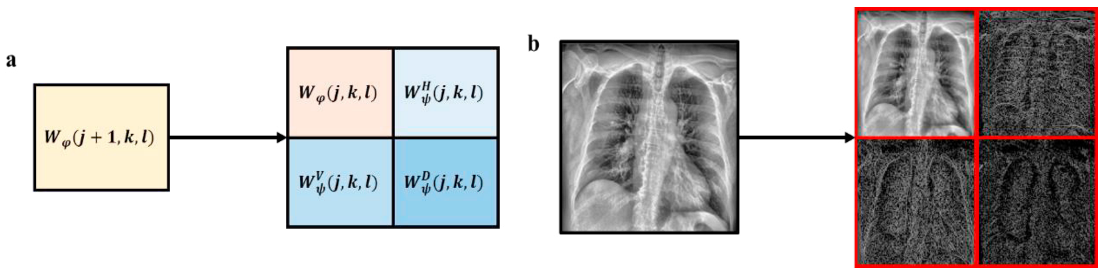

Fig. 1. Two dimensional wavelet transform (a) Resultant wavelet decomposed quarter-sized multi-subbands (b) X-ray image decomposition into four wavelet subbands.

- *Linear Kernel*: It is the elementary type of kernel, usually one dimensional in nature. It is considered to be the best function in case of high dimensional feature vectors.

$$f(X, X_i) = sum\ (X.X_i) \tag{11}$$

- *Polynomial kernel*: It is a more generic representation of the linear kernel. It is less preferred over other functions owing to its low efficiency and accuracy.

$$f(X, X_i) = (X.X_i + 1)^d \tag{12}$$

- *Radial basis function*: It is most popular kernel function in SVM. It is primarily chosen for non-linear data. It is preferred due to its efficiency in classification when there is no prior knowledge of data.

$$f(X, X_i) = \exp(-gamma * ||X - X_i||^2) \tag{13}$$

3. Proposed methodology for Covid-19 disease identification using multi-subband feature extraction in DWT domain

In the proposed work, a classification model is developed using SVM classifier and discrete-WT for feature extraction. The CX-ray images are decomposed into four wavelet feature coefficients: approximation, horizontal, vertical and diagonal. These subbands are then concatenated into single feature descriptor which is then used for training the SVM based machine learning model. The above mentioned one-level decomposition using DWT carried out using available wavelet families such as Haar, Daubechies, Symlets, and Biorthogonal. The analysis made by varying the percentage of data distribution in training and testing set for balanced and unbalanced data. The proposed approach of DWT and machine learning fusion based classification model is represented in figure 2.

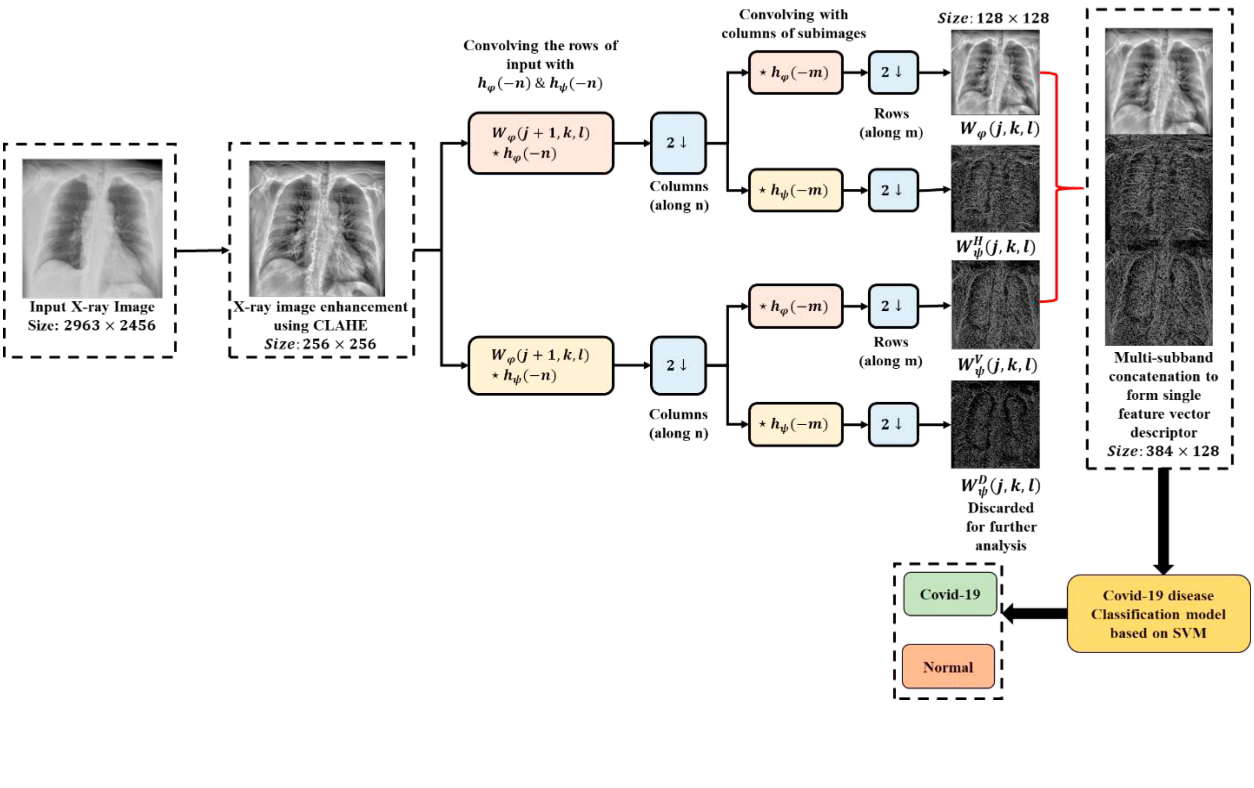

Fig. 2. Block diagram illustration of Covid-19 classification model using DWT and machine learning approach

The algorithm for proposed model for Covid-19 disease identification based on multi-subband feature analysis in DWT domain is described as follows:

Step 1: The CX-ray images are enhanced during the pre-processing phase, it is accomplished using contrast limited adaptive histogram equalization method.

Step 2: To analyse the effect of varying size of training and test image dataset on classification accuracy, the number of images in dataset is split into two subsets by varying the partition percentage into ratio of 40%-60%, 60%-40%, 70%-30%, and 80%-20% respectively.

Step 3: The images are decomposed by applying wavelet filter on processed image dataset to obtained multi-subband features.

Step 4: In order to obtain most suitable wavelet function for extracting relevant features from CXR images, experiments are conducted by selecting various wavelet families and their members in step 3.

Step 5: Among the four wavelet multi-subbands: low frequency (approximation $W_{\varphi}(j,k,l)$), and two high frequency (horizontal $W_{\psi}^{H}(j,k,l)$, vertical $W_{\psi}^{V}(j,k,l)$) subbands are selected, as it contain most appropriate features to form single feature vector by applying feature concatenation scheme, for further classification.

Step 6: The concatenated robust training and testing multi-subband feature vector based on DWT is then utilized for Covid-19 classification using SVM, and various performance parameters analysed using Equations (14) to (18).

4. Experimental Benchmarks and Result discussion

The proposed system experimentation performed using MATLAB R2022a software installed on system having processor Intel i5 core, CPU speed of 2.4 GHz and 16 GB random access memory. The dataset obtained from [4], consists 1125 X-ray images of lung cavity in which 125 images are of Coronavirus disease, 500 Pneumonia images and 500 are of Healthy. The model is designed for binary classification, so pneumonia images are excluded and only Covid-19 and normal images are selected.

The performance metrics used for evaluating the classification model using the confusion matrix output are:

$$Classification\ Accuracy = \frac{TP + TN}{TN + TP + FN + FP} \tag{14}$$

$$Sensitivity\ or\ Recall = \frac{TP}{TP + FN} \tag{15}$$

$$Specificity = \frac{TN}{TN + FP} \tag{16}$$

$$Precision = \frac{TP}{TP + FP} \tag{17}$$

$$F1\ Score = \frac{2 \times Sensitivity \times Precision}{Sensitivity + Precision} \tag{18}$$

The model is trained for binary classification. The COVID-19 diagnosis system consists of three phases: data pre-processing, feature extraction and disease recognition. In the first stage, the images dataset is prepared by converting RGB X-ray images to grayscale format. That way, every image was reduced to a single channel instead of the three RGB channels. The images were then reduced to a size of 256×256 pixels and then CLAHE is applied to enhance the image further. The pre-processed CXR images of normal and Covid-19 infected lung cavity is shown in figure 3.

The experiments are performed in three stages: (i) X-ray image decomposition into four DWT subbands approximation, horizontal, vertical and diagonal. Different wavelet families are used for feature extraction using level-1 wavelet decomposition method. (ii) The DWT subbands are then concatenated into single feature descriptor vector. This feature vector is then used for training the machine learning model using SVM classifier. (iii) The model is trained using balanced and unbalanced dataset and the results are compared.

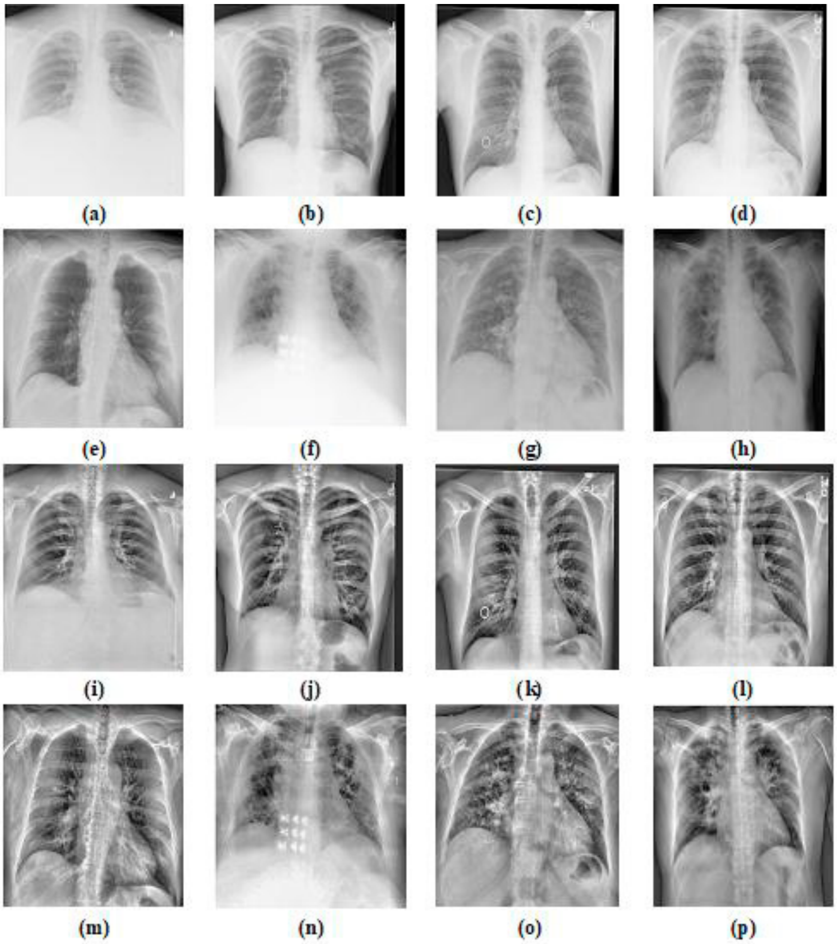

Fig. 3. (a)-(d) Normal chest X-ray (CXR) images. (e)-(h) Chest X-rays images with Covid-19 infection; (i)-(l) and (m)-(p) Pre-processed images of normal CXR images (a)-(d) and Covid-19 infected images (e)-(h) using CLAHE respectively.

4.1. Experimental results on selecting different wavelet families for feature extraction

In this section rigorous experiments are performed to determine which wavelet family has substantial influence on classification accuracy and other parameters. There are various wavelet families available, within which individual member differ in number of vanishing moments. For carrying out the examination, four wavelet families Haar, Daubechies, Symlets, and Biorthogonal are selected. The image is disintegrated into multi-subbands using DWT filters. The model is separately trained using individual wavelet subband features, and it was observed that model trained with high frequency diagonal features produces lowest classification accuracy in comparison with other subbands. When wavelet coefficients are used for training Covid-19 classification model, low frequency approximation component performs better in discriminating between normal and Covid-19 disease. Sometimes it is required to emphasize borders, edges and shapes in an image, especially in case of medical images for diagnosis purposes. High frequency horizontal and vertical components provide the abovementioned details, diagonal component provides too much details which in turn becomes insignificant. Thus out of four subbands only three (approximation, horizontal, vertical) are selected to form a single feature vector excluding diagonal component.

Table 1. Classification accuracy comparison of listed wavelet families based on varying training dataset (for balanced sequential distribution of image data)

Wavelet Families	Accuracy (40% training data)	Accuracy (60% training data)	Accuracy (70% training data)	Accuracy (80% training data)
haar	94.6667	95	98.6486	100
db2	93.3333	93	97.2973	98
db4	92	92	91.8919	92
db6	94	90	87.8378	88
db8	94	91	87.8378	86
db10	93.3333	92	91.8919	92
sym2	93.3333	93	97.2973	98
sym4	94	94	93.2432	98
sym6	94.6667	93	93.2432	96
sym8	95.3333	93	89.1892	92
bior1.3	94	94	95.9459	98
bior1.5	94	94	97.2973	90
bior2.2	93.3333	92	91.8919	92
bior2.4	92.6667	92	93.2432	92
bior2.6	92.6667	93	93.2432	92
bior3.1	91.3333	91	93.2432	96
bior3.3	92.6667	92	91.8919	92
bior4.4	94.6667	93	93.2432	92

The comparison analysis of various wavelet families based on accuracy is presented in Table 1, from the experimental analysis it was observed that among various wavelet families for 40% training set sym8 produced accuracy of 95.33%, Haar gave 95% accuracy for 60% training set, 98.67% for 70% of training images and 100% when taking 80% of images in training set. The classification model is evaluated based on confusion matrix and classifier characteristics plotted using ROC curve, as shown in figure 4. The performance of various wavelet families is depicted in figure 5 using parameters accuracy, precision, sensitivity, specificity and F-1 score.

4.2. Experimental results based on balanced and unbalanced dataset

In medical image analysis application the major challenge faced is due to discrepancy and availability of dataset. Since it has been only two years in Covid-19 outbreak, number of radiological scans of the disease is limited. The dataset used in this paper consists of only 125 CXR images of Covid-19 infections and 500 images of non-infected cases. The experiment is performed in two parts, one in which the dataset is balanced using under sampling and other in which dataset is used as it is in unbalanced for. The comparative analysis using above two dataset is presented in table 2 and table 3.

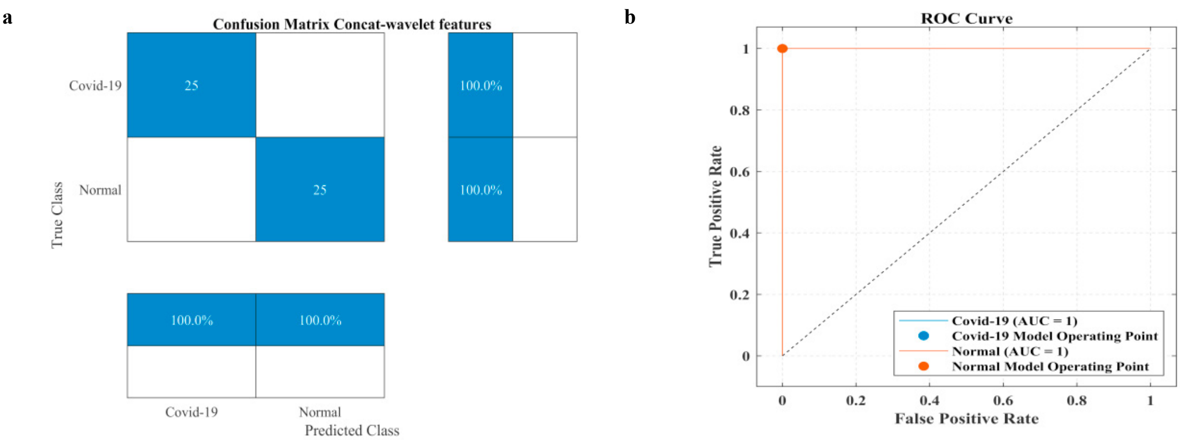

Fig. 4. (a) Confusion matrix and (b) corresponding ROC curve for machine learning model trained with 80% of training dataset

Table 2. Performance metric evaluated for Covid-19 binary classification using Haar wavelet function for feature extraction (Balanced dataset)

Training set percentage	Accuracy (%)	Sensitivity/ Recall (%)	Specificity (%)	Precision (%)	F-1 score (%)
60%	95	95.918	94.118	94	94.949
70%	98.6486	97.368	100	100	98.667
80%	100	100	100	100	100

Table 3. Performance metric evaluated for Covid-19 binary classification using Haar wavelet function for feature extraction (Unbalanced dataset)

Training set percentage	Accuracy (%)	Sensitivity/ Recall (%)	Specificity (%)	Precision (%)	F-1 score (%)
60%	96.4	95.556	96.585	86	90.526
70%	97.861	97.143	98.026	91.892	94.444
80%	98.4	96	99	96	96

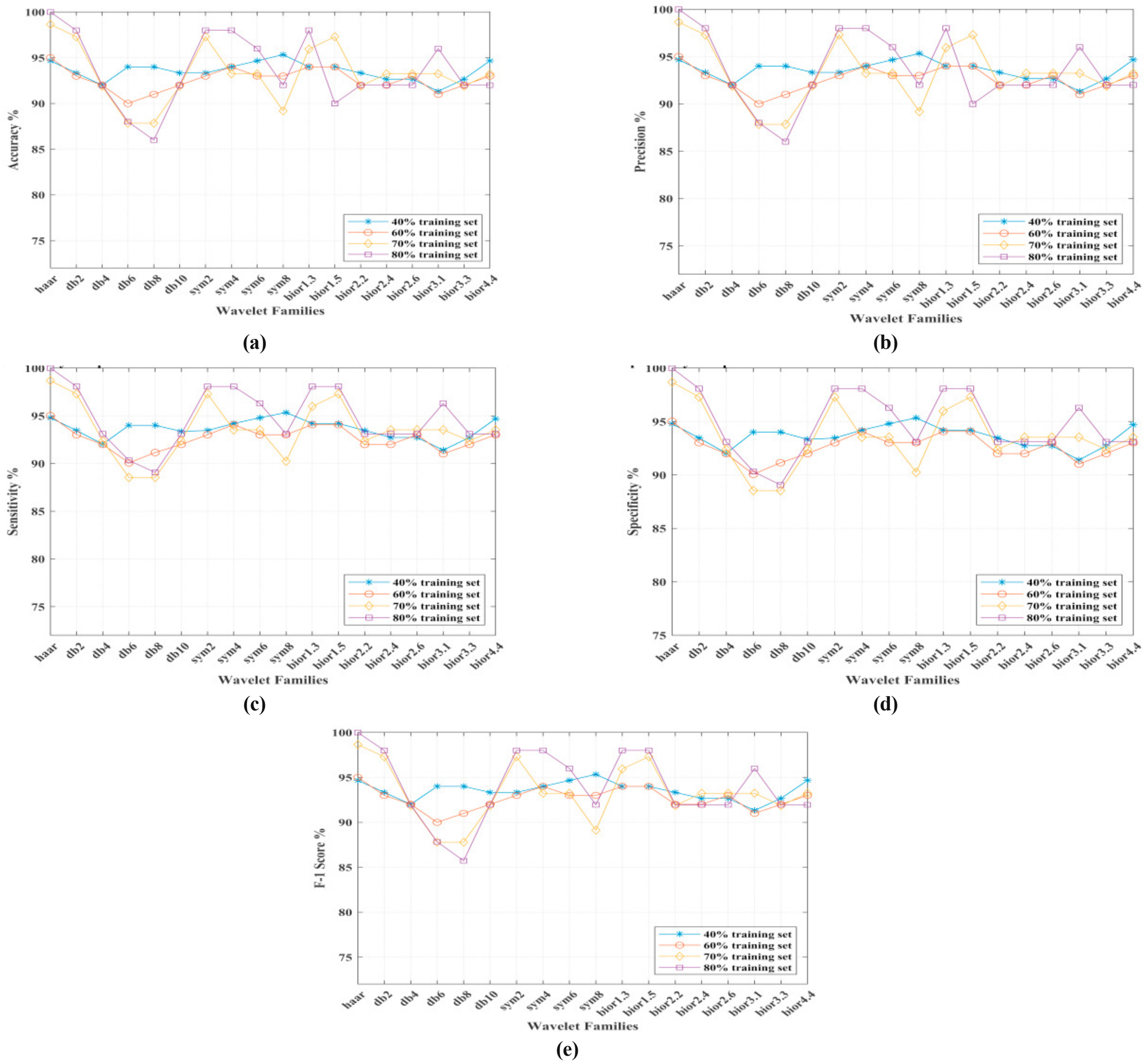

Fig. 5. Covid-19 classification model performance graphs (a) Accuracy (b) Precision (c) Sensitivity (d) Specificity (d) F-1 score

4.3. Comparative study of presented method with recent state-of-art techniques

The application of ML based systems in medical field has grown recently. In last two years the same trend has followed in identification and diagnosis of COVID-19 cases. In Table 4, the proposed model's performance is compared with various state-of-art models developed for detection and classification of COVID-19. T. Ozturk *et al.* [4] DarkNet model predicted output with an accuracy of 98.08%, whereas S. Minaee *et al.* [5] model based on SqueezeNet performs comparatively better than rest of the CNN models having sensitivity of 98% and specificity of 92.9%. The wavelet-based CNN model proposed by A.K. Verma *et al.* [10] accomplished an accuracy of 98.87% using Symlet-7 level-2 approximation component. D. Sharifrazi *et al.* [16] fusion based model for distinguishing Coronavirus cases using CNN, SVM and Sobel filter together achieves an accuracy of 99.02%. Dilip K.S. *et al.* [22] binary classification model using SVM classifier achieves an accuracy of 96.73%. Whereas, the proposed model attains classification accuracy of 100% at level-1 decomposition using Haar wavelet.

Table 4. Performance assessment of proposed technique with various prevailing state-of-art Covid-19 disease identification models

Methods	Accuracy (%)
Ozturk T *et al.* [4], 2020	98.08
Verma A.K. *et al*. [10], 2021	98.87
Gaur P *et al*. [11], 2022	85.50
Chaudhary P.K. *et al*. [14], 2020	98.66
Saad W. *et al*. [15], 2021	96.13
Sharifrazi D. *et al*. [16], 2021	99.02
Ye Y. *et al*. [19], 2020	98
Dilip K.S. *et al*. [22], 2022	96.73
Aggarwal, A. *et al*. [23], 2022	76
Proposed work	100

5. Conclusion

Efficient detection of Coronavirus infection and differentiating it with other lung conditions is a complex and time-consuming task. The ML model using CX-ray images is developed for Covid-19 classification using SVM and DWT based feature extraction technique. In this work, DWT muti-subband feature concatenation approach for Covid-19 disease identification has been discussed. Rigorous experiment performed to select most suitable wavelet function among various wavelet families for feature extraction purpose. From the experiments it was observed that, feature extracted using Haar wavelet outperformed other wavelet families with classification accuracy of 100% for balanced dataset. The higher decomposition scale did not seem to have any significant effect in disease recognition, thus level-1 decomposition is applied using DWT. As for future work, the model can be extended for multi-class classification and performance can be evaluated for a larger dataset.

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