Improved Convolutional Neural Multi-Resolution Wavelet Network for COVID-19 Pneumonia Classification

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***Abstract*—Fast and early detection of infected patient is the most paramount step necessary to curb the spread of the COVID-19 disease. Radiographs have perhaps presented the fastest means of diagnosing COVID-19 in patients. The well-known standard for COVID-19 test requires a standard procedure and usually has low sensitivity. Previous studies have adopted various AI-based methods in detecting COVID-19 using both chest tomography and chest x-ray. In this study, the goal is to propose an enhanced convolutional neural multi-resolution wavelet network for COVID-19 pneumonia diagnosis. Our proposed model is a convolutional neural network integrated discrete wavelet transform of four level decomposition multi-resolution analysis robust to handle few dataset which is very paramount due to the fast emergence of COVID-19. We evaluated our model based on three categories of public dataset of chest x-ray and chest tomography images. Our proposed model achieves 98.5% accuracy, 99.8% sensitivity, 98.2% specificity, and 99.6% AUC for multiple class categories with less training parameters. The results of this study show that our method achieves state-of-the-art result.**

Keywords—COVID-19, wavelet network, pneumonia, multi resolution analysis, convolutional neural network

I. Introduction

COVID-19 pneumonia is a contagious respiratory disease abruptly changing the whole world. The number of transmission case is on the increase as well as the death toll leading to high volume of Intensive Care Unit admission (ICU) resulting in a demanding attention for speedy and accurate screening solution [1]. The recommended strategy to flatten transmission curve and halt epidemic transmission rate is early detection and isolation of patients with COVID-19 as soon as identification is confirm [2]. The World Health Organization has recommended Reverse Transcription Polymerase Chain Reaction (RT-PCR) as a laboratory gold standard for COVID-19 diagnosis [1]. However, RT-PCR has a drawback of low sensitivity and prolonged time of result which is undesirable for fast identification and tracking [1]. Image-based COVID-19 diagnosis have shown promising potentials in fast and accurate identification [3]. Convolutional neural network has widely been used by researchers to diagnose COVID-19 from Chest X-Ray (CXR) and Chest Tomography (CT).

Literature Review: There have been various research centered on the use of CXR and CT scans for screening COVID-19 and the bottlenecks associated with expert-centered diagnosis [4], [5], [6], [7]. A method to extract regions of infected lungs from chest tomography exams using 3D Convolutional Neural Network (CNN) transfer learning model was implemented in [1]. This method actually uses a second CNN to which the candidates are fed in order to classify the candidates into COVID-19, viral pneumonia and Influenza-A achieving a total accuracy of 86.67%. A threshold method was proposed in [2] to extract candidates where two or more regions are selected at random to build the dataset. Using this dataset to fine-tuned transfer model in order to extract features fed to the ensemble classifiers for predicting COVID-19 achieves 88.4 % accuracy. Aggregating the output of CT slices from a CNN model using max pooling technique to predict COVID-19 instances achieving 90% sensitivity was suggested in [2]. According to [8], fine-tuning a pre-trained ImageNet CNN model on CXR images achieves 84% accuracy on multi-task classification; COVID-19, non-COVID-19, normal and bacterial. A close study by the authors in [9] suggested different CNN algorithms with support victor machine classifier to recognize COVID-19 cases, achieving 95.4%

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accuracy. The authors in [10] utilize discrete wavelet transform as down-sampling operation to output the average value of coefficients of wavelet transform with classification accuracy of 71.99%. In [11], the authors adopts a method of concatenating all the component output from the discrete wavelet transform and processed them. The author reported 70.50% classification accuracy. As presented by the authors in [12] discrete wavelet transform and inverse discrete wavelet transform are integrated into CNNs for image classification by suppressing data noise during inference with 71.62% classification accuracy.

Contributions: Most literatures on image-based COVID-19 classification have adopted traditional convolutional neural networks which are considered to be a powerful technique for image processing [2], [13], [14], [15], [16], [17]. Although, there are some bottlenecks associated to CNN performance. They seem to perform poorly when it comes to extracting spatial information between images. This drawback makes it impossible for CNN to identify same image when rotated [14]. One possible solution to this bottleneck is to utilize huge dataset and different transformations. However, there are no large enough medical dataset especially for new diseases such as COVID-19 which has just been discovered. Wavelet integrated models present alternative option capable of extracting spatial details using wavelet multi resolution decomposition analysis by means of filter banks. From several literatures regarding the potential of wavelet [11], [18], [19], [20], we will illustrate the capability of wavelet transform for medical imaging tasks.

In this paper, we proposed a wavelet-based framework called Enhanced Convolutional Neural Multi Resolution Wavelet Network for COVID-19 Pneumonia Classification (COVID-WaveletCNN) using CT and CXR images. To further enhance the diagnosis ability of the wavelet-based framework, we considered increasing the level of multi-resolution decomposition. It is important to mention that further decomposition of wavelet multi-resolution gave better result as compare to the previous levels using different datasets [11], [21]. In summary, the 4th level decomposition further improved the accuracy of the proposed wavelet integrated model. As much as we can tell, this is the first study that investigates the application of wavelet multi resolution decomposition for COVID-19 diagnosis. The subsequent sequence of the study is as follows: Section 2 gives an overview of wavelet transform multi resolution. The wavelet integrated model is presented in section 3. Evaluation details and datasets utilized are presented in section 4 and finally, we conclude our study in section 5.

II. Wavelet Transform Multi Resolution

Multi Resolution Analysis (MRA) is the core of discrete wavelet transform where images are sub sampled into components of detail and approximate coefficients using scaling and wavelet functions of low and high pass filters respectively [22]. The detail coefficient consists of low frequency components and the approximate coefficient consists of high frequency components. For simplicity, the reconstructed signal which is exactly the same as the original image is illustrated in equation (1).

$$f(t) = cA_4 + cD_4 + cD_3 + cD_2 + cD_1 \quad (1)$$

where $f(t)$ is the real image, cA_4 is the approximate component derived from the 4th level decomposition. cD_4, cD_3, cD_2, and cD_1 are the detailed components derived from the 4th 3rd, 2nd, and 1st level decompositions. There are two important functions in MRA which are scaling and wavelet functions. The low frequency component denoted as detail component (cD) is generated by the wavelet function whereas the high frequency components denoted as approximate component (cA) is generated by the scaling function. It is worth noting that these frequencies are generated using high and low pass filter banks. Equation (2) presents the mathematical expression of signal decomposition of wavelet transform.

$$f(t) = \sum_k A_j(k)\phi(t-k) + \sum_k \sum_{j=0}^{j=1} D_j(k) 2^{j/2} \psi(2^j t - k) \quad (2)$$

where $\psi(2^j t - k)$ represents the wavelet function and $\phi(t-k)$ denotes the scaling function. The projection of $f(t)$ both in the scaling and wavelet spaces are denotes by $A_j(k)$ and $D_j(k)$ respectively. $D_j(k)$ is the discrete informative image features of the wavelet function with the wavelet space and $A_j(k)$ is the smoothing approximation within the scaling space. The down sampling of the wavelet is achieved by a scale factor of $2^{j/2}$.

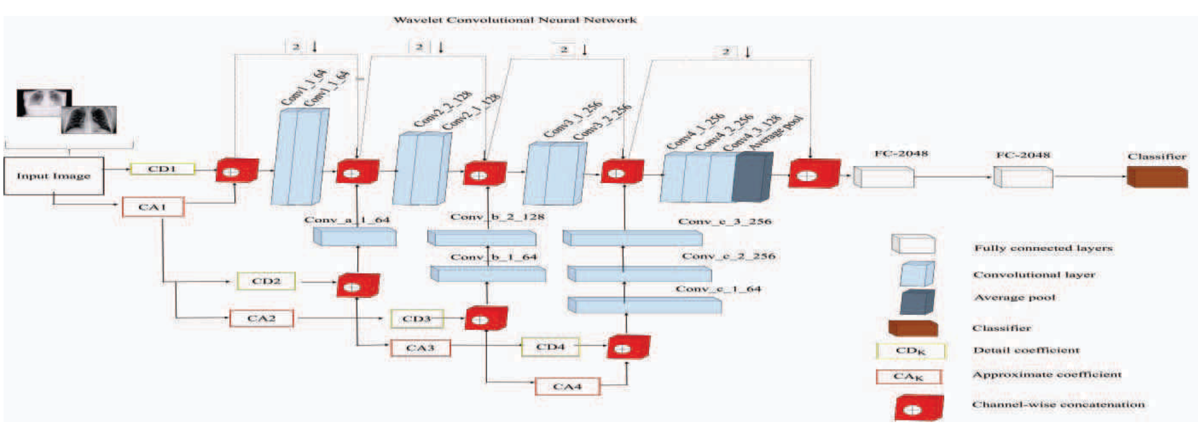


Fig. 1. Proposed COVID wavelet convolutional neural network.

III. THE PROPOSED COVID-WAVELETCNN

The proposed architecture of COVID-WaveletCNN is a wavelet integrated convolutional neural network for COVID-19 diagnosis as presented in Figure 1, which consists of 9 convolutional layers grouped in blocks and 4 level decomposition of multi-resolution wavelet transform with each level of the decomposition fed as input to each block of the convolution layers. The inputs to the proposed network are wavelet decomposed three channel X-ray images. The first block consists of two convolutional layers; the generated detail coefficient of the first level decomposition is fed as input to the first convolutional block. The approximate coefficient of the first decomposition level is further down-sampled to generate detail and approximate coefficients of the second decomposition level from which the detail coefficient is fed as input to the second convolutional block which consists of two convolutional layers. It is important to mention that before the detail coefficient is fed to the second convolutional block, it is concatenated channel-wise through $1x1$ convolutional layer of 64 kernel size for the purpose of achieving a dimensionality match with the output of the first convolutional block. Similarly, this technique is applied to the third and fourth convolutional blocks. However, at the third decomposition level, the channel-wise concatenation to the third convolutional block is via two $1x1$ convolutional layers of kernel size 64 and 128 respectively.

The final decomposition level is concatenated to the fourth convolutional block which consists of three convolutional layers followed by global average pooling. The channel-wise concatenation is achieved via three $1x1$ convolutional layers of 64, 128 and 256 respectively. It is important to mention that during the process of wavelet decomposition, the images are down-sampled by a scale factor of 2. The fifth convolutional block consists of three fully connected layers with the final fully connected layer corresponding to the number of classes. We used a learning rate of 10^4 with batch size of 16 and Adam optimizer training with 20 epochs. The dataset is split into training, validation and test as described in section 4. During the training phase of the model, the model is equally validated for performance. The proposed model is tested with the test dataset to obtain the final performance. The evaluation metrics adopted to evaluate the performance of our model is as follows; Accuracy, sensitivity, specificity, recall, precision and area under curve (AUC).

TABLE I. DESCRIPTION OF CHEST X-RAY DATASET FOR BACTERIA AND VIRUS PNEUMONIA CASES COLLECTED FROM RSNA KAGGLE PNEUMONIA CHALLENGE AND COVID-19 EXAMS COLLECTED FROM COVID-CXR

Dataset	COVID-19	Bacteria pneumonia	Virus pneumonia	Healthy
COVID-CXR	180	22	20	234
RSNA	0	3,029	2,983	8,851

TABLE II. DESCRIPTION OF CHEST TOMOGRAPHY DATASET

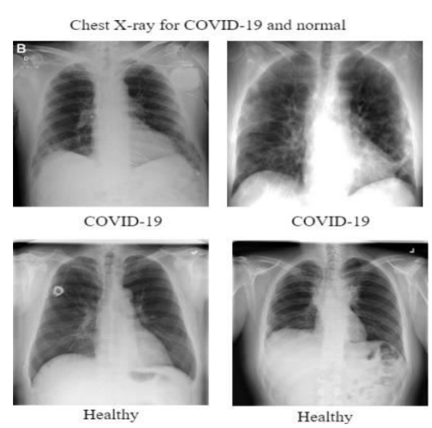
Dataset	COVID-19	Non-COVID-19
COVID-CT	349	397

TABLE III. DESCRIPTION OF CHEST X-RAY DATASET FOR OTHER PNEUMONIA CASES COLLECTED FROM NIH

Dataset	Data count
Atelectasis	4,999
Cardiomegaly	10,000
Consolidation	10,000
Effusion	10,000
Infiltration	10,000
Mass	10,000
Nodule	10,000
Pneumothorax	10,000
Healthy	10,000

IV. EXPERIMENTAL RESULTS

The dataset utilized to evaluate the performance of our model are obtained from four public domains [23], [24], [25], and [26]. Since it is challenging to collect all datasets belonging to different diseases related to pneumonia from one data source especially COVID-19 cases, therefore we put together dataset from different open sources depending on what classes of pneumonia related illnesses are available. Figure 2 depict the binary class distribution of our dataset whereas Table I shows a description of CXR dataset collected from Radiological Society of North America (RSNA) [26] and COVID-CXR. COVID-CXR is an open repository of COVID-19 dataset released by the authors in [24]. More so, Table II gives a description of CT datasets collected from [25]. From the standpoint of multi-classification task, we collected a wide range of pneumonia related illnesses from a dataset repository of the National Institute of Health (NIH) [23] and [27] as described in Table III. We group our classification task in two categories; binary classification task and multi-classification task. The binary classification task consists of COVID-19 and Healthy classes whereas the multi-classification task consists of COVID-19 and other pneumonia related cases as illustrated in Table III. In this study, the objective is to identify COVID-19 instances whether in binary or multi-classification. Evaluating the performance of the proposed wavelet integrated framework based on the aforementioned dataset, COVID-WaveletCNN achieved 95.5% accuracy, 99.8% sensitivity, 98.2% specificity and 99.6% AUC for multi-class classification.



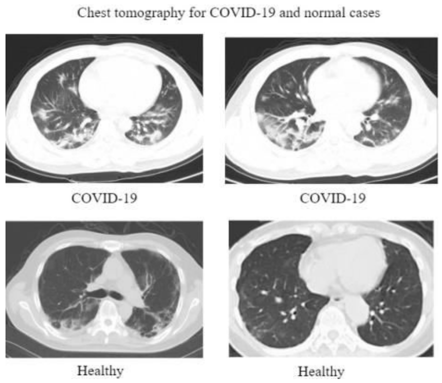


Fig. 2. Dataset of chest x-ray and chest tomographyscans of COVID-19 and healthy cases.

More insightful details are provided to further understand the classes that are more prone to misclassification by COVID-19. We compare our results with previous state-of-the-art models that used CXR and CT images. COVID-WaveletCNN performs better than its counterparts both on CXR and CT images in terms of accuracy, sensitivity, AUC and specificity. It is worth mentioning that COVID-WaveletCNN is computationally effective and timely-centered due to its fewer trainable parameters and low model complexity compared to previous state-of-the-art models.

Binary classification: we trained our model on two class identification task of COVID-19 and Healthy instances. The datasets are derived from [24], [25]. In order to clean up the data and balance the dataset for each class, we select 162 images for each class in CXR dataset and 345 images for each class in CT dataset. The distribution of our dataset is presented in Table I and II. The obtained results by our model is presented in Table IV which shows that our model performs better than previous state-of-the-art model on the bases of binary classification achieving accuracy of 98.1%, sensitivity of 98.8%, specificity of 97.8%, and AUC of 98.9%.

Multi-classification: In another experiment, our model was trained on 12 classes of pneumonia related CXR exams including COVID-19 using the dataset extracted from [23] in which we selected 162 CXR images for each class. The distribution of the dataset is presented in Table III. For fair comparison, we compared our proposed model with selected famous deep learning transfer models trained on ImageNet. We ran the selected pre-trained models on our dataset of 12 classes as shown in Table III. The result of our model outperforms some famous transfer learning models adopted in this work base on the multi-classification task of 12 classes as presented in Table V.

V. Discussion

In this section, we will report the performance of our proposed model in comparison with other well-known pre-trained model adopted in this study for the diagnosis of COVID-19 based on three different categories of dataset class. We compared our model with some transfer learning models using 12 classes which include COVID-19 and other pneumonia related illnesses. Our model obtained a specificity of 98.2% as shown in Figure 5, sensitivity of 99.8% as shown in Figure 3, accuracy of 98.5% as seen in Figure 4 and AUC of 99.6% as illustrated in Figure 8. In each category of metric, our model outperformed all the pre-trained models. It is evident that our model outperformed the other transfer learning models on the same datasets.

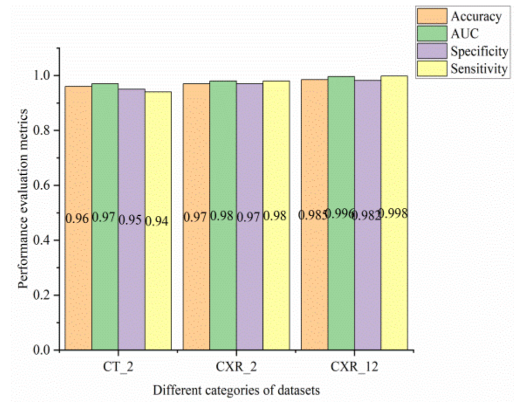


Fig. 3. Performance evaluation of our model for the three catagories of datasets. The best results was obtained using CXR_12 dataset.

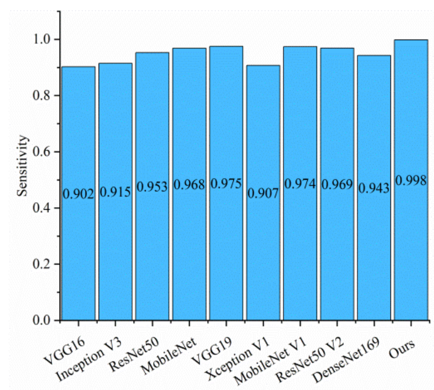


Fig. 4. Sensitivity report for the selected deep transfer models and our proposed model for 12 classes.

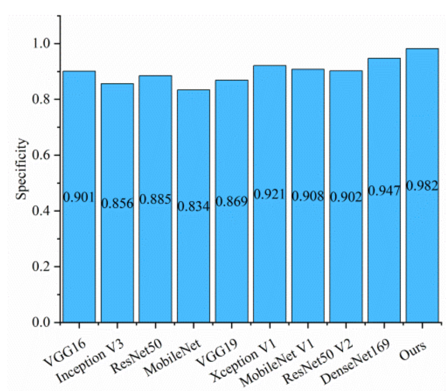


Fig. 5. Specificity report for the selected deep transfer models and our proposed model for 12 classes.

Several literatures have reported that different deep learning models behave differently with different datasets. So for fair comparison, we evaluated our proposed model on the bases of dataset in the following order; binary class of chest tomography (CT_2), binary class of chest x-ray (CXR_2) and 12 classes of chest x-ray (CXR_12). From Figure 6, it is obvious how the model behaves with respect to dataset where we obtained the best result using CXR_12. More so, the loss and accuracy curves in Figure 7 and 9 shows that our model is stable for the three different data categories. We went further to show the effectiveness of our proposed model by presenting the ROC graph on the three categories of datasets. The ROC offers clarity for experts to balance between sensitivity and specificity in order to reduce reported cases of false positive. The effectiveness of our proposed model is simply attributed to the robustness of wavelet transform to extract spatial features and offers better filtering operation.

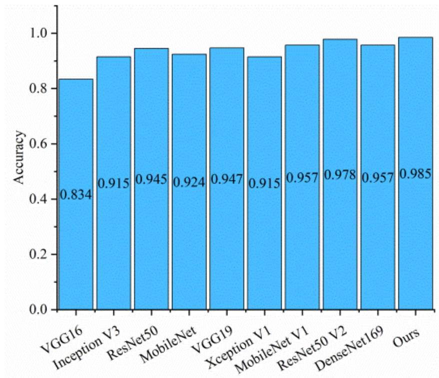


Fig. 6. Accuracy report for the selected deep transfer models and our proposed model for 12 clsses.

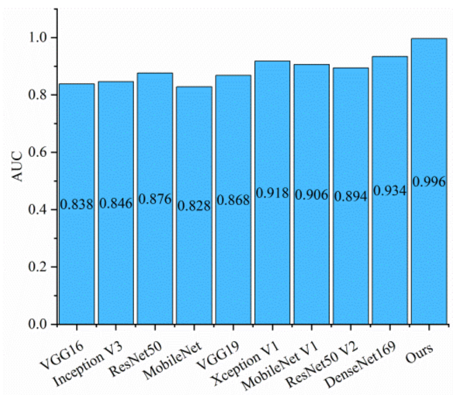


Fig. 7. AUC report for the selected deep transfer models and our proposed model for 12 classes.

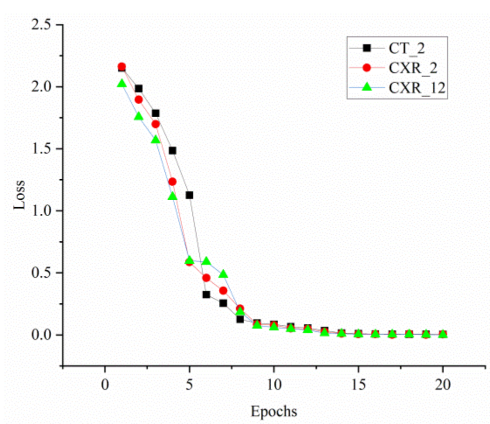


Fig. 8. Loss curves reported for our proposed model using the three dataset categories. It is evident that our model is stable.

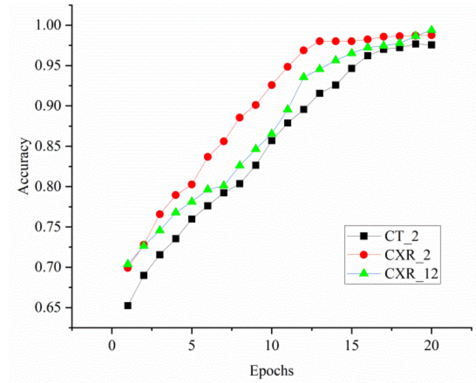


Fig. 9. Accuracy curves reported for our proposed model usig the three dataset categories. Our model maintains smooth and steady progression with fast convergence.

Comparison: A lot of research has been carried out to diagnose COVID-19 from CT and CXR exams. We compare the findings of proposed wavelet integrated CNN model with previous recognized literatures. Chen et al. [5] utilized U-Net to capture high-resolution details from CT. Wang et al. [27] uses a CNN method to detect COVID-19 from CT exams. Shi et al. [28] uses a random forest based technique to classify COVID-19. Jin et al. [7] adopted a logistic regression algorithm to detect COVID-19. Jin et al. [15] developed an AI-based system to detect COVID-19. Xu et al. [1] and Wang et al. [2] report an impressive works, however, only few indicator were reported. Song et al. [16] uses a deep learning model to detect COVID-19 from CT scans. Barstugan et al. [17] suggested a machine learning algorithm to classify COVID-19 from CT exams. Table IV summarizes the findings of the aforementioned methods. Our proposed model shows a competitive efficiency for COVID-19 diagnosis as shown in Table IV. Our model is capable of handling small-scale dataset with far less computing cost compare to deeper neural networks.

Reference [13] reported that manually detection of COVID-19 by expert using CXR could lead to high sensitivity but with very low specificity of 25%. This low specificity gives rise to false positive prediction which eventually leads to wrongly administered treatment and expense. It is obvious that our proposed model, COVID-WaveletCNN achieves a very high specificity of 98.2% which can be adopted to assist expert radiologist to reduce the reported cases of false positive. More so, the reported result in terms of Receiver Operating Characteristic (ROC) can assists expert radiologist form a balance between sensitivity and specificity.

Conclusively, it is important to make some remarks on COVID-WaveletCNN computational cost and model complexity. By introducing wavelet transform, we eliminated the use of max pooling at each convolutional blocks thereby reducing model complexity and computational time. Another interesting advantage of our COVID-WaveletCNN is the ability to reduce noise in the input images as we concatenated the generated detail coefficient at each level of decomposition with the output feature of the previous block to every convolutional block via $1x1$convolutional layer. Talking about computational cost, our model was trained for 15 minutes on

NVIDIA GTX 1080. We adopted Keras framework for implementing our architecture. The model complexity of the proposed model is far reduced due to less training parameters compared to previous state-of-the-art models.

TABLE IV. WE COMPARED OUR PROPOSED MODEL WITH STATE-OF-THE-ART IMAGE-BASED COVID-19 DIAGNOSIS MODELS

Literature	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC (%)
Chen et al. [5]	95.2	88.7	92.1	90.2
Wang et al. [27]	92.3	90.4	89.5	91.5
Shi et al. [28]	87.9	90.7	83.3	89.5
Jin et al. [7]	96.5	94.5	92.8	89.4
Jin et al. [15]	95.7	94.1	95.5	94.7
Xu et al. [1]	86.7	87.9	90.7	91.5
Wang et al. [2]	82.9	85.9	89.4	88.7
Song et al. [16]	86.0	87.4	85.9	87.8
Barstugan et al. [17]	90.7	91.8	92.3	95.7
Ours	**98.5**	**99.8**	**98.2**	**99.6**

TABLE V. PERFORMANCE COMPARISON OF SELECTED DEEP LEARNING MODELS. FROM ALL INDICATIONS OUR PROPOSED WAVELET INTEGRATED NEURAL NETWORK EXIBITED THE HIGHEST SCORE WITH THE BOLD VALUE INDICATING THE BEST PERFORMAMCES

Famous Network	Accuracy (%)	AUC (%)	Specificity (%)	Sensitivity (%)
VGG16	83.4	83.8	90.1	90.2
Inception V3	91.5	84.6	85.6	91.5
ResNet50	94.5	87.5	88.5	95.3
MobileNet	92.4	82.8	83.4	96.8
VGG19	94.7	86.8	86.9	97.5
Xception V1	91.5	91.8	92.1	90.7
MobileNet V1	95.7	90.6	90.8	97.4
ResNet50 V2	97.8	89.4	90.2	96.9
DensNet169	95.7	93.4	94.7	94.3
Ours	**98.5**	**99.6**	**98.2**	**99.8**

VI. CONCLUSION

We proposed a wavelet integrated framework called COVID-WaveletCNN for the diagnosis of COVID-19 from radiographs. The model consists of several convolutional layers in blocks and channel-wise convolutional layers for the purpose of concatenating the generated detail coefficient from the multi-resolution decomposition of the images at every decomposition level with the output features of the previous convolutional block. We adopted binary cross entropy and categorical cross entropy loss functions for each respective classification task problem. The results attained by our model show that COVID-WaveletCNN provides a reliable performance considering the low training weight and less complex model with few training datasets. We intend to further develop our model as we hope to have access to high power computational GPU workstation as more cases of COVID-19 are being detected globally which will give rise to large dataset in the near future..

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