AUTOMATIC DETECTION OF COVID-19 FROM LUNGS CT SCAN IMAGES USING TRANSFER LEARNING

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Abstract—Corona virus Disease (COVID19) may be a fast-spreading communicable disease. it's necessary to detect the COVID-19 early may help in devising an appropriate treatment plan and disease containment decisions. during this our proposed work, COVID-19 is detected using transfer learning combined with Deep learning Models from CT scan images to detect the early stages of covid-19 patients . The three-phase detection model is proposed to enhance the detection accuracy and therefore the procedures are as follows; Phase1- data augmentation using stationary wavelets, Phase2- COVID-19 detection using pre-trained CNN model and Phase3-abnormality localization in CT scan images. We also propose a picture preprocessing stage to make a trustworthy image dataset for developing and testing the deep learning models. The new approach is aimed to scale back unwanted noise from the pictures in order that deep learning models can focus on detecting diseases with specific features from them. The deep learning model, which is then extensively tuned with appropriate parameters, performs in considerable levels of COVID-19 detection. Our results indicate that provide superior detection accuracy for CT scan images.

Keywords—Deep learning, Transfer learning, residual neural network, covid-19,wavelets.

I. INTRODUCTION

He covid-19 is one in every of the fast spreading disease suffering from sizable amount of people no P through medical imaging. radiography is found to be useful for rapid COVID-19 detection. The imaging features of the chest could also be obtained severe impact on the respiratory additionally as other systems of the shape. Thus, medical imaging features of chest production of probes, primers, and physical equipment (swab, containers, etc.) COVID-19 pandemic features a really follows: a) conventional PCR test kits take longer duration for diagnosis of disease, b) longer time within the quantitative reverse transcription PCR [8]. the foremost challenges within the COVID-19 rapid detection are like a nasopharyngeal swab, storage of the swab, sending the samples to the laboratories for extraction of RNA, and polymerase chain reaction (PCR). The steps involved within the PCR test are the gathering of a clinical specimen the majority of antigen tests being produced to detect the COVID-19 disease are termed as PCR tests because they use a patients and b) antibody tests- detect the antibodies within the blood of somebody previously infected with the virus. The COVID-19 pandemic testing kits are divided into two categories: a) antigen tests- detect currently infected to the young cohort. it's been shown that old populations with other medical complications are more vulnerable to infections compared cancer are more likely to develop serious illness. Affected

People having medical problems like diabetes, chronic respiratory disease, cardiovascular diseases, and therefore the nose and/or mouth, that's expelled when a private with COVID-19 sneezes, coughs and even speaks. of from a private infected with COVID-19 to a special person through the transmission micron size droplets from dry cough, tiredness, mild to moderate respiratory disease, loss of sensation to fever. The disease spreads virus 2 (SARS-CoV-2) and WHO declared the name â€œCOVID-19â€•. The symptoms of COVID-19 ranges from Taxonomy of Viruses (ICTV) announced the new name of the virus as â severe acute respiratory syndrome corona initially discovered in Wuhan, China during December 2019. On February 11, 2020, the International Committee on creates a layer of the lesion on the lungs; which affects the normal functioning of the lungs. The COVID-19 is matter their gender and race. The infection caused because of COVID-19 severely affects the respiratory tracts and patients and b) antibody tests-detectthe antibodies within the blood of an individual previously infected with the virus. the bulk of antigen tests being produced to detect the COVID-19 disease are termed as PCR tests because they use a polymerase chain reaction (PCR). The steps involved within the PCR test are the gathering of a clinical specimen with a nasopharyngeal swab, storage of the swab, sending the samples to the laboratories for extraction of RNA, and quantitative reverse transcription PCR [8]. the main challenges within the COVID-19 rapid detection are as follows: a) conventional PCR test kits take longer duration for diagnosis of disease, b) longer time within the production of probes, primers, and physical equipment (swab, containers, etc.) COVID-19 pandemic features a very severe impact on the respiratory also as other systems of the physical body. Thus, medical imaging features of chest radiography is found to be useful for rapid COVID-19 detection. The imaging features of the chest are often obtained through medical imaging.

II . PROBLEM STATEMENT

In covid-19 pandemic situation it is important to detect covid 19 early and quick. Because if the corona affect lungs too much its goes to death rate. For doing this purpose we are going to detect the covid-19 from lungs Ct scan images. Proposing a deep learning method to identify the ct scan images. The following problems may occur while we are developing deep learning models are:In conventional PCR test kits take longer duration for diagnosis of disease, longer time in the production of probes, primers, and physical equipment (swab, containers, etc.) COVID-19 pandemic has a very severe impact on the respiratory as well as other systems of the human body. If the corona affect the lungs too much, risk factor is higher and its goes to death rate.

I. ARCHITECTURE

In this section complete architecture of this paper is explained below:

A.PRE-PROCESSING

In this section we are divided in to 3 steps. Those steps are explained below:

1) Image to PNG:

In this step we are changing the any image format to PNG format. Because in our dataset there are various image are here. Those image are various format. So to take care of the uniformity are often change the format to PNG format.

2)Resizing:

The CT scan images within the input dataset are of various sizes, thus to take care of the uniformity the input images are resized to 256x256x3. These images are compatible with stationary wavelet decomposition up to 3 levels because the dimensions of all the pictures in three levels remains an equivalent, i.e., 256x256x3. Further, 4 different transfer learning models (ResNets-18, 50,-101, and Squeezenet) used for the binary classification, have different input size requirements. So, during the transfer learning process, images sizes are again adjusted but the uniformity in size of input CT scan employed by the pre trained layers is retained thanks to pre-processing step.

3)Normalization (Linear Normalization):

Then resized CT scan images are normalized within the confined range [0 1] using (1).

$$I\_norm = (In - \min(In)) / (\max(In) - \min(In)) \ldots(1)$$

Here, ‘In’ represents the input CT scan images from binary classes (COVID and non-COVID). allow us to assume the generalized size of ‘In’ has a size p x q x 3, and therefore the normalized image is represented by ‘I_norm’. during this work, we'll perform a function that produces a normalization of an input image (grayscale or RGB). Then, we understand a representation of the range of values of the size of the image represented between 0 and 255, during this way we get, for instance, that very dark images become clearer. The linear normalization of a digital image is performed consistent with the above formula. Over fitting may be a major challenge with a transfer-learning based model trained on a limited set of datasets. Thus data augmentation technique is applied to the training.

B.THREE LEVEL STATIONARY WAVELET DECOMPOSITION:

The wavelet transforms are wont to extract useful information from data. This makes wavelets compatible with image processing applications. The input image I_norm is fed to stationary wavelet decomposition up-to k levels. The dimension of output decomposed image depends on dimensions of I_norm and level (k).

Suppose, I norm may be a 2-D matrix and level k greater than 1, the outputs are 3-D arrays with following stationary wavelet coefficients:

SWC 2D =[H(:,:,1: k);V(:,:,1: k); D(:,:,1: k);A(:,:,k)]

Here, ‘A’ symbolizes approximation, ‘D’ diagonal, ‘V’: vertical, and ‘H’: Horizontal. For n but adequate to k in (2),the output matrix. SWC 2D contains approximation coefficient= A(:,:,n) of level i; H(:,:,n), V(:,:,n), and D(:,:,n) contain the coefficients details of level n (horizontal, vertical, and diagonal). allow us to consider I norm may be a 3-D matrix of dimension p x q x 3, and k greater than 1, then the coefficients of the output are 4-D arrays of dimension p x q x 3 x k with following output matrix and coefficients:

SWC 3D =[H(:,:,1:3,1: k);V(:,:,1:3,1: k); D(:,:,1:3,1: k);A(:,:,1:3,k)] …….(3)

In Equation 3, For n but adequate to k and t= 1, 2, 3, the output matrix H(:,:,t,n), V(:,:,t,n) and D(:,:,t,n) contain the coefficients of details of level n(horizontal, vertical, and diagonal) and A(:,:,t,n) is coefficients of approximation of level n. In the our proposed work, stationary wavelet transform performs 3 levels of the wavelet decomposition. The 2D stationary wavelet is orthogonal (Haar; Daubechies: db1, db2,..., db10, etc.), and a biorthogonal wavelet (bior1.1, bior1.3, and bior1.5, etc.). within the proposed work, a 2-D stationary wavelet is decomposed employing a db2 orthogonal filter.

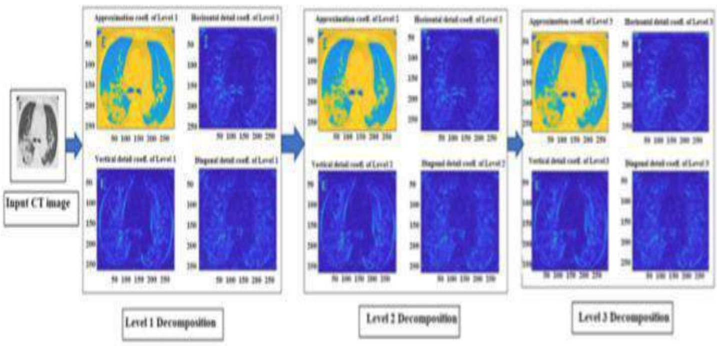
In 2-D stationary wavelet decomposition, the normalized input image I norm passes through a group of the Low Pass Filters (LPF) and High Pass Filters (HPF). In level 1 decomposition using wavelets, I norm is down-sampled by an element of two and output obtained is: level 1 approximate coefficient (A1) of low frequency and detail coefficients (H1, V1, and D1) of high frequency. In second level decomposition, the output coefficient is level 2 approximate coefficient (A2) and detail coefficients of level 2 (H2, V2, and D2). Similarly, output coefficients from level 3 are Approximation coefficient A3, and detailed coefficients V3,H3 and D3.The detailed hierarchy of normalized input CT scan images decomposed up to 3 levels is shown in Figure 3.

TYPE	TRAINING DATA WITHOUT AUGMENTATION	TRAINING DATA WITH AUGMENTATION	VALIDATION DATA	TESTING DATA
COVID	178	1602	76	95
NON-COVID	228	2052	97	72

The A1, A2, and A3 images obtained from wavelet decomposition up to three levels contain the foremost useful information and therefore the size of the image remains unaltered.

within the proposed methodology, data augmentation is completed as follows: a) decompose the training images up to three levels using stationary wavelets, b) shear operation within the range [-30, 30], c) random rotation of

Fig:1 –3 level Wavelet decomposition of training images



Thus, to enhance the training data, these wavelet decomposed images further undergone through random rotation, shear, and translation operation under a specific range.

DATASET	TRAINING(%)	VALIDATION (%)	TESTING (%)
WITH AUGMENTATION	96.32%	95.24%	97.15%
WITHOUT AUGMENTTATION	99.87%	97.32%	99.1%

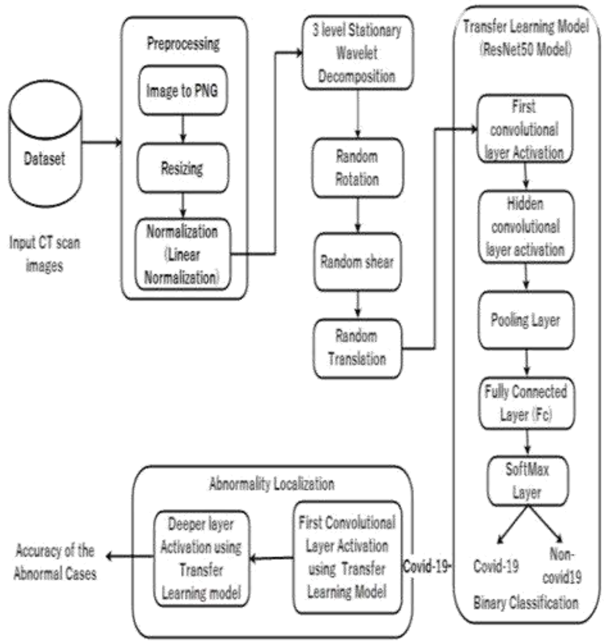


Fig2 : Architecture of the proposed system

C.TRANSFER LEARNING MODEL

The pre-trained transfer learning-based COVID-19 detection model classifies a CT scan of lungs into binary classes: a) COVID-19 and, b) Non-COVID. Different models used for the binary classification are: ResNet18, ResNet50, ResNet101, and SqueezeNet. the dimensions of the training augmented images is adjusted based upon the compatibility with numerous pre-trained CNN models. the dimensions requirement for transfer learning models are: ResNet18 (224x224x3), ResNet50 (224x224x3), ResNet101 (224x224x3) and Squeeze Net (227x227x3). The pre-trained models can classify CT scan images based upon class labels assigned to the training dataset, i.e., COVID-19 and Non-COVID. To classify new images, retrain a pre-trained model by updating fully connected layers consistent with the input augmented dataset. The training parameters opted for the transfer learning-based CNN model are: a) 'sgdm' optimizer is employed, b) mini-batch size is 64, b) the training is performed up to 50 epochs, c) validation frequency is about to value 3, and d) pre-specified initial learning rate for the training is 3e-4.

The performance of various pre-trained networks is examined supported the subsequent parameters: accuracy, precision, Negative of COVID-19 positive cases. abnormality detection in CT scan images of COVID-19 positive cases. Predictive Value (NPV), sensitivity, AUC, F1-score, and specificity. Further, the deeper layer of the simplest performing model is employed for abnormality detection in CT scan images.

Table 2: Comparison of training, validation and testing accuracy of the ResNet18

D.LOCALIZATION OF ABNORMALITY

The first convolutional layer (conv1) and therefore the deeper layer from the pre-trained transfer learning model 'ResNet18' are wont to obtain the features map. The low-level features; namely, texture, color, and edges are generally evaluated using the primary convolutional layer (conv 1). The output activation is obtained by passing the testing image (COVID19 positive CT scan image) through the simplest performing ResNet18 pre-trained network. Further, all the activations are scaled to a variety [0 1]; here '0' symbolizes minimum activation and '1' symbolizes maximum activation. the small print of the abnormality (location, and severity) in medical data are often obtained from a more complex feature of the deeper layers of the CNN model. within the proposed pre-trained ResNet18 model the deeper layers used are conv5 x and pooling layer. In these layers, feature maps symbolize the features learned by the pre-trained model on the CT scan datasets used. Further, the features useful for abnormality localization in COVID-19 positive CT scans are obtained through the strongest activation channel. Table 6 presents the brief details of the performance comparison of the proposed methodology for COVID-19 detection with the techniques available within the literature using chest radiography.

A. EXPERIMENTAL RESULTS

The system requirements are the Intel Core i7 processor, 2 GB graphic card, 64-bit operating system at 1.80 GHz, and 8 GB RAM.

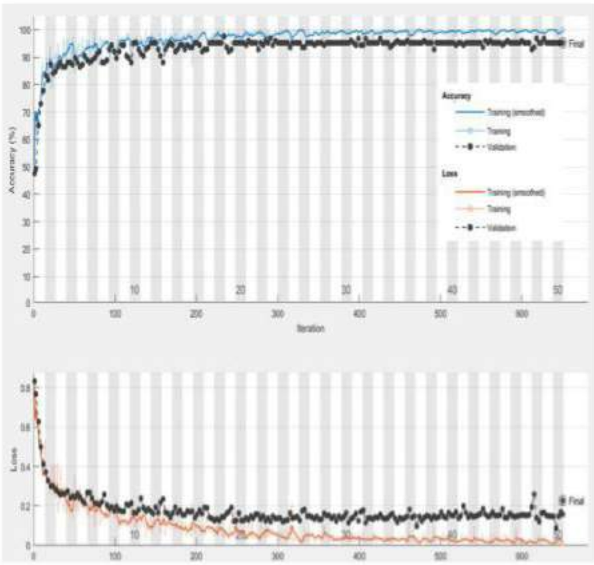
A.THE PRE_TRAINED TRANSFER LEARNING MODEL

within the proposed research, the pre-trained transfer learning model is trained and validated for binary classification of input CT scan images into COVID-19 and Non-COVID For the binary classification task, 4 different transfer learning models (ResNet18,ResNet50,ResNet101,and SqueezeNet) are examined.

The highest classification accuracy, i.e.,99.82% of coaching accuracy, and validation accuracy of 97.32% is obtained with the ResNet18 model on the used CT scan dataset. Accuracy of the ResNet18 model along-with loss function up to 50 epochs (7:3 training and validation data).The classification performance of the ResNet18 model with and without augmentation is put forth in Table2.

The performance with novel data augmentation technique is far superior to model accuracy on training done on without augmentation. Also, the info augmentation technique eliminates the overfitting issues with the transfer learning model trained on a limited COVID-19 positive CT scan dataset. However, the model robustness are often further investigated by implementing the proposed methodology on larger datasets. Classification performance of the pre-trained transfer learning model on testing data is evaluated supported following parameters: a) sensitivity defines

Fig.7 Convergence graph of Accuracy and loss function using ResNet18 model up to epoch 50



patients with a COVID-19 disease, b) specificity defines correct detection of normal patients supported CT scan images, c) accuracy is that the ratio of correct predictions to total predictions of the COVID-19 disease, d) AUC value defines the power of pre-trained transfer learning model to differentiate between binary classes, i.e., COVID and Non-COVID, and e) F1 score may be a measure of the mean of sensitivity and precision.The ResNet18 pre-trained transfer learning model obtained testing accuracy of 99.4% and major outcomes are: a) COVID and Non-COVID images are classified with 98.6% specificity and 100% sensitivity, (c) AUC of 0.9965 (shown in Figure 8). The performance parameters are summarized in Table 5 (TP- True Positive, FP-False Positive, TN-True Negative, and FN- False Negative). The performance comparison of pre-trained models utilized in the proposed work (ResNet18, ResNet50, ResNet101, and SqueezeNet) is shown in Figure 9.

B. IV CONCLUSION

This work proposes a three-phase methodology to classify the considered lung CT scan slices into COVID-19 and non-COVID-19 class. Initially, the collected images are resized supported the need, and therefore the following procedures are implemented sequentially; in phase-1, data augmentation is implemented to decompose the CT scan slices into 3 levels using stationary wavelets. Further, other operations, like random rotation, translation, and shear operations are applied to extend the dataset size. In phase2, a two-level classification is executed using four different transfer learning-based architectures, like ResNet18, ResNet50, ResNet101, and SqueezeNet, and their performances are verified. the very best classification accuracy for training (99.82%) and validation (97.32%) is achieved with the ResNet18 using the transfer learning model. The testing data yields an accuracy of 99.4%, the sensitivity of 100%, the specificity of 98.6%, and AUC with the very best value of

0.9965. In phase-3, the chosen best performing model (ResNet18) is chosen and implemented for abnormality localization within the chest CT scan slices of COVID-19 positive cases. The developed model will definitely help within the rapid and accurate detection of COVID-19 signature from lungs CT scan slices. within the future, the performance of the proposed system are often considered to look at the clinically obtained CT scan slices with COVID-19 infection. Further, the proposed methodology must be investigated on the larger set of COVID-19 positive CT scan of patients.

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