The proposed framework for efficient prediction of COVID−19 for the chest X−ray and CT images present a new CNN model, and it depends on one of the transfer learned and finetuned deep pre−trained CNNs models to extract deep features. As depicted in Fig. 1, we introduced a new CNN architecture based on a modification of the ResNet50 architecture and makes use of the pre−trained model of ResNet50. The ResNet50 model architecture is enhanced to suit the Covid19 dataset by adding some layers at its end. X−ray and CT images are taken with a low resolution which may have a variable height to width ratio. Therefore, training and testing dataset images are resized to 224×224×3 for a similar course of action in the developed model architecture. ResNet is known to be a better deep learning architecture as it is relatively easy to be optimized and can attain higher accuracy. Furthermore, there is always a problem of vanishing gradient, which is resolved using the skip connections in the network. As the number of layers in the deep network architecture increases, the time complexity of the network increases. This complexity can be reduced by utilizing a bottleneck design. As a consequence, we preferred ResNet50 pre−trained model to build up our framework and excluded other pre−trained networks that have bigger number of layers. A detailed description of the architecture is explained below.

Some modifications are applied to the ResNet50 architecture to reach efficient performance for predicting Covid19. First, we altered the last three layers (fully connected, softmax and classification layers) of the pre−trained ResNet50 architecture in order to adapt them to our classification task. The fully connected layer in the original pre−trained networks are replaced by another fully connected layer, in which the output size represents the two classes in our case, Covid and Non−Covid. Next, three layers, namely, Conv , Batch Normaliz and Activation Relu are added to the ResNet50 architecture as shown in Fig. 1, to automatically extract the robust features in chest X−ray and CT images. These layers are convolution layer followed by batch normalization layer followed by an activation layer. The addition of the three layers is done as in the following steps 1. The activation 49 relu layer is disconnected from avg pool layer and connected instead to the newly added Conv layer. 2. The newly added activation relu layer is connected to avg pool layer. 3. The avg pool layer is followed by the last three newly added layers fully connected , softmax and ClassificationLayer Figure 1a depicts the ResNet50 architecture before modifications and Fig. 1b shows the modified architecture after injecting the new layers. The input images are now passed through this modified network to obtain features for each image in the dataset and then classified either to Covid or Non−Covid using the network classifier. The proposed model was trained for the classification of Covid and Non−Covid.

We have implemented the proposed system for COVID−19 diagnosis using Matlab R2020a programming language with a processor of Intel Core i5 and RAM of 6 GB running on Windows 10. The Adam optimizer is utilized for weight updates along with 1e−4 learning rate and five epochs. The classification model’s usefulness and productivity were measured using the wellknown metrics of accuracy, sensitivity, specificity and precision. Precision is the calculation of the model’s correct predictions all over all predictions. Four major outcomes: true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) are necessary to compute the evaluation criteria according to the following equations

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A well-known evaluation measure, i.e. accuracy is used to evaluate the effectiveness of the proposed system. Table 1 shows that our proposed model scores 97.1%, 98.9%, 95.7% and 94.5% for the accuracy, Sensitivity, Specificity and Precision measures, respectively, using X−ray dataset. Table 2 shows that the proposed model achieves 97.7%, 98.7%, 95.6% and 97.9% for the accuracy, Sensitivity, Specificity and Precision measures, respectively, using the CT dataset. However, the accuracies achieved by ResNet50 and Resnet101 are 96.8%, 96.8% for X−ray dataset and 96.9%, 95.3% CT dataset, respectively. Figure 2 displays the Accuracy and loss curves for the proposed model using the X−ray and CT datasets. Figure 3 depicts the confusion matrix for the proposed model using the X−ray and CT datasets. The confusion matrix gives an understanding of the proposed methodology and its potential for detailed classification. ResNet101 is 101 layers deep, and ResNet50 is 50 layers deep, so ResNet101 consumes, approximately, twice the time of ResNet50. From the results of Tables 1 and 2, we can conclude that the proposed model accuracy superior to the accuracy of both Resnet101 and Resnet50. Therefore, the suggested scheme is not only efficient in performance, but also it has low time consumption. The proposed method used pre-trained CNN models to obtain the best performance for the detection of COVID-19. We evaluated the performance results of deep feature extraction based on the ResNet50, ReseNet101, GoogleNet, AlexNet, DenseNet201, VGG16, VGG19, InceptionV3, and (ResNet50+SVM) models. To show the superiority of our model, we compared our proposed model with the previous mentioned powerful pre−trained architectures of CNN. Utilizing these CNN models without its own classification layer enables us to extract features for our target task based on the knowledge of source task. Tables 1 and 2 show the accuracy, specificity, sensitivity and precision measures for each model. It is observed that the accuracy of our proposed model outperforms the ones of the other 8 models. In addition the proposed method increased the detection accuracy in case of CT and X-ray, from 97.5%, 95.6% to 97.7%, 97.1%, respectively, compared to the sate of the art method in [16] (ResNet50+SVM) and in [2]. According to the results, the proposed algorithm achieved the highest classification accuracy in case of X-ray and CT datasets, i.e. 97.1% and 97.7%, respectively.It is asserted that the accuracy of 97.1% for the X-ray dataset achievable from the proposed algorithm is highly encouraging compared to 88.8% presented from the VGG19 model [2]. Moreover, the proposed method increases the detection accuracy by 10.4% from 87.5% to 97.7% compared to the accuracy presented by the VGG-19 model in the CT dataset. To prove the robustness of the proposed method, the data set is divided into five folds namely, Fold1, Fold2, Fold3, Fold4 and Fold5. A five−fold cross−validation strategy is employed, i.e. five experiments are conducted, in each experiment, four folds are used for training and one for testing. Table 3 shows the results of cross-validation achieved from applying the proposed model on both the CT and X−ray datasets.

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