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A Hybrid Deep Learning Approach for COVID-19 Diagnosis via CT and X-Ray Medical Images

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Abstract: COVID-19 pandemic is a global health problem since December 2019. Up to date, the total number of confirmed, recovered and deaths has exponentially increased on daily basis worldwide. In this paper, a hybrid deep learning approach is proposed to directly classify the COVID-19 disease from both chest X-ray (CXR) and CT images. Two AI-based deep learning models, namely ResNet50 and EfficientNetB0, are adopted and trained using both chest X-ray and CT images. The public datasets consist of 7,863 and 2,613 chest X-ray and CT images are respectively used to deploy, train, and evaluate the proposed deep learning models. The deep learning model of EfficientNet always performed a better classification result achieving overall diagnosis accuracies of 99.36% and 99.23% using CXR and CT images, respectively. For the hybrid AI-based model, the overall classification accuracy of 99.58% is achieved. The proposed hybrid deep learning system seems to be trust worth and reliable for assisting health care systems, patients, and physicians.

Keywords: COVID-19 pandemic; Hybrid Deep learning Model;

1. Introduction

The outbreak of COVID-19 is considered as epidemic and pandemic affecting people around the world in a short period. It is rapidly transmitted among people in different local and global communities due to the traveling issues [1]. Up to date, the number of confirmed and death cases reaches to 226M and 4M worldwide, respectively. COVID- 19 is a novel coronavirus coined as Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) and it targets the human respiratory system. The confirmed biological symptoms of COVID-19 are fever, shortness of breath, dizziness, cough, headache, sore throat, fatigue, and muscle pain. Accurate and rapid classification technique become necessary to automatically diagnose the COVID-19 disease especially in a pandemic situation. Recently, AI techniques (deep learning and machine learning) were employed and to build a robust decision-making system against COVID disease [2][3][4]. Traditionally, the COVID screening involves RT-PCR (Reverse Transcription Polymerase Chain Reaction) carried out at the Pathogen laboratory. Due to its higher time consumption and lower sensitivity, medical imaging techniques such as computed tomography (CT) as well as Chest X-Ray (Radiological Image) Images are being used to fight and classify the COVID-19 respiratory disease [5][6][7]. The Lungs are the major target of the COVID-19 virus. RT-PCR is useful for the diagnosis of disease whereas, CT and CXR images are useful to assess the damage caused to the lungs due to COVID-19 at various stages of the disease. Inflammation of lung tissues can be identified based size and shape of attacked tissues with the help of X-Ray and CT images [6][3]. Deep ConvNets are extensively utilized in the fields of hyperspectral images, microscopic images, and medical image analysis, In current trending coronavirus-related diagnostic studies also used deep learning-based architectures, were proposed namely COVID-SDNet, DL-CRC, and EDL-COVID [6][8][1]. Machine learning-based techniques like SOM-LWL, PB-OCSVM, and one-shot cluster-based approaches for COVID CXR images have also introduced the diagnosis of COVID detection and classification [9][10][11]. Also, there were other techniques like transfer and learning methods were implemented using MobileNet, VGG, ResNet, Alexnet, and Densenet architectures as a base module for training for the task of COVID image classification [12][13]. Computer-Aided Diagnosis systems have been proposed for several medical image analysis tasks like Breast cancer, Brain Tumor, kidney and Lung disorders using deep learning methods [14][15][12][5].

In this proposed work, a hybrid deep learning system is deployed to perform classification task of COVID-19 using two CXR and CT datasets. Indeed, DeepConvNet's have a promising feature extraction way to automatically identify a huge deep features directly from the input images. Thus, overall classification accuracy could be improved. The objective of this study is to provide a unified deep learning model using both medical CXR and CT images. The main contributions in this hybrid system are summarized as follows. First, build a novel hybrid deep learning model in unified architecture to automatically and rapidly classify COVID-19 disease using both CXR and CT images. Second, deep learning regularizations of data balancing, transfer learning-based approaches, and data augmentation are used for improving the overall diagnostic performance. Such these experiments will help to understand COVID-19 disease and diagnose it using different medical imaging modalities [32][33][34][35][36][37].

The objective of this work is to provide an AI-based robust and feasible system for medical institutions, health care service providers, physicians, and patients by providing practical solutions for COVID-19 diagnosis.

The rest of this paper is organized as follows. A review of the relevant literature is presented in Section 2. The technical aspects of the deep learning methods for classification systems are detailed in Section 3. The results of the experiment with COVID-19 are reported and discussed in Sections 4 and 5. Finally, the most important findings of this work are summarized in conclusion Section 6.

2. Related work

In early 2020 while the world was under a pandemic situation due to the COVID-19 outbreak, Some Computer-Aided Diagnosis systems have been proposed based on deep learning were introduced to predict COVID-19 on digital X-Ray and CT-Images.

In [18], Yang et al. Presented diagnosis of COVID-19 with the help of CT images and proposed an AI-based diagnosis system based on DensNet and ResNet pre-trained models with transfer and learning technique to classify and reported accuracy of 89%, AUC of 98%, and F1-score 90% and dataset have made opensource. Madallah Alruwaili et al. in [19] used an improved Inception-ResNetV2 to Diagnosis COVID-19 in x-Ray images which have got high accuracy in Radiography Dataset to detect COVID-19. Mundher et al. In [13] designed a model to Detect COVID-19 from X-Ray Images Using Convolutional Neural Networks with transfer learning-based techniques with VGG16 and MobileNet modules reported the highest accuracy of 98.28%. with VGG16 as a base model. In [19] Madallah Alruwaili et al. used an improved Inception-ResNetV2 to Diagnosis COVID-19 in X-Ray images. Xception, VGG16, InceptionV3, ResNet50V2, MobileNetV2, ResNet101V2, and DenseNet121 models were used for experimentation and with CXR images with Inception-ResNetV2 model achieved of 99.8%. In [20] Fareed Ahmad et al. design a deep learning model for detecting Coronavirus using Chest X-Ray Images. They use different CNN models such as MobileNet, InceptionV3 and, ResNet50. The best was model is InceptionV3 which ash 95.75% and 91.47%, accuracy and F-Score respectively. In [5] Boran Sekeroglu et al. CNN model to detect COVID-19 from Chest X-Ray Images Using available dataset. They used CNN without pre-processing and a decreasing number of layers is capable of detecting COVID-19 in a limited number of data and imbalanced, chest X-ray images with an accuracy of 98.50%. In [21] Pramit Brata Chanda et al. implemented a new model to diagnose COVID-19 using Chest X-ray. They used CNN Based Transfer Learning Framework for the Classification task and reported an accuracy of 96.13%. In [22] Mubashir Rehman et al. deign a platform Monitoring System to detect and Diagnosis of COVID-19 using breathe rate measurement. In [8] S. Tabik et al. contributed a new open-source dataset, called COVIDGR-1.0. In their experiment, they designed a new model to detect COVID-19 using X-Ray Images also helped in measuring severity. And they reported the classification as Moderate and Severe 86.90% and 97.72% respectively on the basis CXR database. In [12] Wentao et al. presented a new model based on deep learning for the diagnosis COVID-19 using CT images. The transfer learning technique was achieved good accuracy of 98%. In [6] Sadman et al. proposed a deep learning-based chest radiograph classification (DL-CRC) framework to distinguish COVID-19 cases with high accuracy from two classes abnormal and normal. They Presented a deep learning model called the DL-CRC framework with two-part the first is the DARI algorithm and generic data augmentation accuracy of 93.94%. In [23] Khalid M. Hosny et al. designed a hybrid model to detecting COVID-19 using two types of CT scans and chest X-ray images. Their work combined two types of images to fit memory and computational time. They proposed the framework for CXR and CT images with 99.3% and 93.2% respectively. In [7] presented transfer learning to detect COVID-19 using X-ray and CT Scan Images. It is because, in COVID-19, initial screening of chest X-ray (CXR) may provide significant information in the detection of suspected COVID-19 cases. In [24] Ravi et al. presented the model to detect COVID-19 using both CT and CXR datasets. In [25] Elmehdi Benmalek et al. aimed to make a comparison for the performances of CT scan and chest X-ray image to detect COVID-19 pandemic utilizing CNN and they got accuracy equal to 98.5% and 98.6%, respectively. In [16] Muhammad E. H. et al. Presented a strong model to detect COVID-19 pneumonia using l chest X-ray images utilizing the pre-trained deep-learning technique. They have created a database by merging data that has been created by previous work. They have got classification accuracy of 99.77%.

3. Methods and Materials

The proposed hybrid deep learning system for COVID-19 diagnosis is demonstrated in Figure 1. Two different deep learning models, namely ResNet50 and EfficientNetB, are used for CXR and CT images, respectively. Both deep learning models are trained using 100 epochs. The last layers from both deep learning models are concatenated together to merge the derived deep features and generate most single robust deep feature set. This set carries a promising features generated from both CXR and CT images in the same time. This is a key to improve the overall accuracy performance of the proposed deep learning system. Then, the concatenated deep features are scaled in 1D form using a global average pooling (GAP). This is to make the derived feature maps suitable for the following two fully connected layers. Finally, Softmax layer is used to make the final decision regarding the output is a positive COVID-19 disease or a normal negative case. To reduce the overfitting that may occur during training phase, the 0.5 dropout strategy is used. For pre-training, transfer leering strategy is used with ImageNet database.

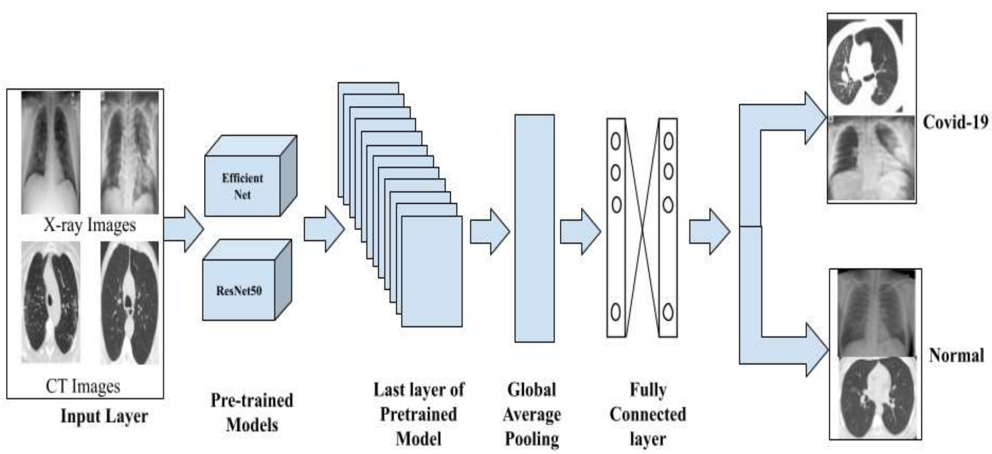

Figure 1. Schematic Hybrid deep learning diagram of the COVID-19 classification system.

3.1. Preprocessing

The pre-processing technique is the most significant step of the model. Here, we consider raw data and transform it into specific input data format and dimension

[3][28][31]. We inculcate the data augmentation and class balancing strategy to reduce the overfitting and this acts as a catalyst for the training process [15][31]. Later, we divide both data into 70% for training, 20% for testing, 10% for validation. For each class, the dataset is selected in a randomized manner. For hyper parameters initialization, transfer earning strategy is applied using the dataset of imageNet [3][15][31].

3.2. Feature extraction

Deep CNN has shown improved performance regardless of domain namely medical imaging, and generalization of the model has been observed. Transfer learning is being explored to provide an efficient solution [6]. In our experimental analysis, we employ ResNet50 [27] and EfficientNet [24][26] models for the task of feature generation, Deep features are later passed to custom layers user-specific, in our work we push to global average pooling followed by fully connected layer [24] we use 2 FC layers and improve efficiency and to generalize learning also introduced Dropout in middle of FC layers. These extracted features passed for the classification layer to assign the appropriate class label of the given input data instance.

3.3. Classification

The pipeline of extracted deep features through feed-forward models ResNet and Efficintnets for feature extraction passed to SoftMax layer for classification. The results were generated for both CT and CXR databases separately and results were discussed in table 2 and table 3. The results were promising in contrast to existing works.

4. Experimental analysis

4.1. Dataset

To quantify our work, two datasets of chest X-ray and CT are used. These datasets are publically available at Kaggle databases [16][17][18]. The datasets are described as shown in Table 1.

Table 1. Chest X-ray and CT datasets distribution per class.

Type of Images	COVID	**Normal**
CT	1,323	1,290
X-Ray	3,923	3,960

4.2. Implementation Environment

To perform all experiments in this study, we use a PC with the following specifications: Intel R © Core(TM) i7-6850 K processor with 32 GB RAM, 3.360 GHz frequency GPUs NVIDIA GeForce GTX1050Ti. Deep learning algorithms are implemented herein using Python 3.8.0 programming with Anaconda [Jupyter notebook]. The Python-based ML libraries such as Torch, TensorFlow, OpenCV, pandas, and Scikitlearn are utilized to investigate the performance metrics by the proposed methods at the same time TensorFlow and Keras in Colab have been used to implement Transfer learning. The results and discussions concerning various techniques incorporated are highlighted in the subsequent sections. The source codes were made available at GitHub[1].

4.3. Evaluation metrics

To assess our proposed system, we use the evaluation metrics of Recall/ Sensitivity (Re), Specificity (Sp), F1-measure (F-M), and overall accuracy (Az). The mathematical formula for these evaluation metrics are defined as follows,

$$\text{Recall/Sensitivity (Re)} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{1}$$

$$\text{Specificity (Sp)} = \frac{\text{TN}}{\text{TN} + \text{FP}}, \tag{2}$$

$$\text{F1} - \text{score (F} - \text{M)} = \frac{2 \cdot \text{TP}}{2 \cdot \text{TP} + \text{FP} + \text{FN}}, \tag{3}$$

$$\text{Overall accuracy (Az)} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{TN} + \text{FP}}, \tag{4}$$

where TP, TN, FP, and FN are defined to represent the number of true positive, true negative, false positive, and false negative detections, respectively. The confusion matrix is used to derive all of these parameters.

5. Results and discussion

This section shows our experimental results as in the following two different scenarios: single straight forward scenario and hybrid scenario. Former scenario means both deep learning models (i.e., ResNet50 and EfficientNetB) are separately used and tested to investigate which model could provide the best overall classification accuracy for a single dataset; chest X-ray or CT images. The later scenario means both deep learning models are concatenated to produce the proposed hybridization model as shown in Figure 1. This is to check which hybridization combination could achieve the best performance when both chest medical images are used.

5.1. Single Straight Forward Scenario

For each medical chest dataset (i.e., chest X-ray or CT images), two different experiments are performed. One experiment is done using the deep convolutional ResNet50 model and another one is perforemed using the EfficientNetB deep learning model. By other words, the single deep learning model (i.e., ResNet50 or EfficientNetB) is trained twice: on time for chest X-ray and another time for CT images. In both training styles, same deep learning architecture as well as training/testing settings are used.

[1] https://github.com/IIITK-AI-LAB/Hybrid-covid-model

5.1.1. COVID-19 Classification based on Chest X-Ray Images

In this case, the input dataset is only X-ray images for deep learning ResNet50 or EfficientNetB. The overall classification evaluation results are summarized in Table 2. Although it is obviously shown that both deep learning models achieve almost the same results, the EfficientNetB deep learning model achieves a slightly better overall accuracy by 99.36%.

Table 2: Classification evaluation results (%) using chest X-Ray images

Model	Az	Sp	Re	F-M
ResNet50	98.47	99.0	100	99.0
EfficientNet	99.36	98.0	99.0	99.0

5.1.2. COVID-19 Classification based on Chest CT Images

Chest CT dataset is only used to separately train the deep learning models of ResNet50 and EfficientNetB. The overall classification evaluation results are reported in Table 3. The EfficientNetB deep learning model achieves a slightly better overall accuracy by 99.23%, while other evaluation metrics show the consist and stable performance.

Table 3: Classification evaluation results using chest CT images

Model	Az	Sp	Re	F-M
ResNet50	98.85	99.0	98.0	99.0
EfficientNet	99.23	99.0	99.0	99.0

5.2. Hybrid scenario: COVID-19 classification using Chest and X-Ray Images

In the proposed hybrid deep learning model, both chest X-ray and CT datasets are used as input as shown in Figure 1. The evaluation classification results for the best combination hybrid model are demonstrated in Table 4. Each row in Table 4 presents the classification assessment results by using a single deep learning model in a hybrid style for both chest X-Ray and CT images as well.

Table 4: Classification evaluation results (%) for the proposed hybrid deep learning model using both chest X-Ray and CT medical images

Model	Az	Sp	Re	F-M
ResNet50	98.01	99.0	99.0	99.0
EfficientNet	99.58	99.0	99.0	99.0

6. Conclusion

A hybrid deep learning model is proposed to automatically detect COVID-19 respiratory disease from both chest X-ray and CT images. The proposed hybrid model uses two deep convolutional networks namely ResNet and EffiecientNet to generate promising deep hierarchical features. The proposed hybrid deep learning approach could achieve classification accuracies of 99.58% using chest X-ray and CT images. Further improvements could be achieved by including ultrasound images as well. This is to construct and build much robust and reliable diagnosis system to fight COVID-19 in early stages. The promising results seem to be helpful to provide a better real-time diagnosis system for health care service providers, physicians, and patients.

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