Automated Chest X-Ray Diagnosis with Deep Ensemble Models: A Focus on COVID-19 and Pneumonia Detection

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***Abstract*—This research involved a detailed study introducing a combo model that would be used for both diagnosing Covid-19 and pneumonia using chest X-ray images. In tests, known for being time-consuming, costly, and sometimes inaccurate, are addressed by this method (RT-PCR). It is commenced by the preprocessing part where images are modified to input shape as well as some data augmentation techniques such as zoom, rotation, and flipping to provide the dataset enough enhancement for the best training result. We use transfer learning to extract deep features using pre-trained VGG16, DenseNet201 and Efficient NetB0 models. The features extracted are then used as input to the fully connected layers and ensemble classifiers, where they classify conditions by probability scores. In their evaluation, they included a chest X-rays dataset where the proposed approach managed to get an impressive 98.5% accuracy rate. And it showed good precision, recall and F1 score with 95%,96% and 95%. The current method is the best time, recall, F1-score, and overall accuracy of the existing ones. In short, this deep ensemble approach is pretty good for diagnosing Covid-19 and pneumonia and is reflected in the hospital treatment of maestros who are cautious in the treatment that they do, and care what is best for their patients.**

***Index Terms*—Automated Chest X-ray Diagnosis, Deep Ensemble Models, COVID-19 Detection, Pneumonia Detection, Transfer Learning, VGG-16, DenseNet-201, EfficientNet-B0, Data Augmentation, Ensemble Classifiers, Diagnostic Accuracy, Machine Learning.**

I. Introduction

The oncoming of COVID-19 has caused a great global crisis, complicating severely the healthcare systems and the population as a whole. Besides the various complications related to the virus, pneumonia was a lot of times the one that came into the foreground, causing severe respiratory problems and sometimes the death of the patients. Timely identification and control of pneumonia are important to deflect the suffering of a person away from death. Although many might think it too obvious, the analogy is quite clear that without the COVID-19 pandemic, we might have ignored this whole imaging process, but the truth is that it's invaluable in the diagnosis of respiratory diseases [1].Yet, the spotting of these images is not an easy job and there is still the challenge of having specialized radiologists to read the images that show complex anatomical structures and subtle pathological signs.

The utilization of AI and ML the fact that they make it possible to automate the interpretation of CXR images is debatable. Deep learning techniques that have been married with traditional imaging procedures have facilitated proper diagnosis, shortened the time spent by radiologists on the patient, and given a more precise and timely picture of the severity of an illness. The study presents solutions that rest on these innovative machines to devise a deep ensemble learning system which integrates and improves the general performance of CXR classification of COVID-19 and pneumonia, this is achieved by the combined strength of all the neural models [2].

Along with using ensemble learning technology, we have employed three cutting- edge deep networks: VGG-16, DenseNet-201, and EfficientNet-B0. Each of these models has been chosen according to its unique capabilities such as feature extraction, computational efficiency and generalization across different datasets. Our model uses the collective predictions of these network models, which is our ensemble approach, we therefore argue that it is less likely to fail and more accurate than it would be, if only one model were to be used. Our proposed method reaches a remarkable performance of percentage of 97.33%. Specifically, the technique has percentage of 96% precision, a percentage of 96 for follow-up, and percentage of 97% F1-score [3]. After from its invention in 1895 by Wilhelm Rontgen, has the chest X-ray overtaken dozens of other noninvasive diagnostic images in understanding the thoracic area, or does it still remain a timeless and diagnostic selection for the chest diseases such as, tuberculosis, pneumonia, and pneumothorax.A result of that brings internal organs circulation which demands adjusting their level of perfusivity, vasoactive regulation or the metabolism of mitochondria. The studies displayed the core elements of the current methods of CXR interpretation that are now used by radiologists all over the world. Along with that the X-ray production technology and the safety measures attached to it have all been developed to a great extent as it has become more widespread, faster and cheap which implies a relatively low radiation dose for CXR now. Nowadays, about percentage of 30-40% of total X-rays conducted in the world are chest X-rays that further highlights its critical standing in medical practice particularly in the acute setting, disease surveillance, and screening [4].

In this study, we developed a robust ensemble model that combines the unique capabilities of DenseNet-201, EfficientNet-B0, and VGG-16 for more comprehensive feature extraction in chest X-ray classification. Our approach incorporates data augmentation techniques, such as flipping and resizing, to improve model generalization and reduce overfitting, ensuring the model performs reliably on diverse data. We also conducted a detailed analysis of the confusion matrix to identify areas for improvement, with a particular focus on minimizing COVID-19 misclassifications. Additionally, we discussed the practical impact of our model in clinical settings, emphasizing its potential to support rapid diagnosis and improve patient outcomes. Chest roentgenology is still a complex undertaking despite its wide utilization and technology progress. The most efficient way to get a set of lungs X-rays is to take the rays in the same plane of the body as the chest, where the beams pass through the thorax. To put it in simpler words, each radiographic element contains some information in terms of the product of X-ray intensity and attenuation. Composed of this, the composite attenuation then deflects a given pixel value down in the final picture.

(a) Normal (b) Pneumonia (c) COVD-19

Fig. 1. Chest X-Ray Classifications.

In Fig. 1 shows the Evaluating chest X-ray (CXR) images is a traditionally manual process that depends on the skill of radiologists who have to deal with complicated anatomic structures and find numeric signs. Nevertheless, even with radiologists being much more experienced and using the most up-to-date technologies, the error rates in CXR interpretation are steady for a long time now [5].

These mistakes may be related to various factors such as insufficient scope of transformation in the imaging modality, inter observer variability in radiologist experience and expertise, and other factors like tiredness, interruptions, and environmental conditions which do not refer to the image itself. Given these difficulties, an increasing number of people are keen on employing machine learning and AI to enhance and support the inspection of the images. Among the different methods, which is special in some way has a number of merits, such as ease of use and quick processing of the data.

Besides that, large datasets and powerful algorithms can be used to train deep learning models, and this in turn can allow them to notice even the most subtle Such ability is particularly important for COVID-19 and pneumonia, where rapid and accurate diagnosis could actually save lives. By involving machine learning in the diagnostic procedure, the rate of errors is anticipated to decrease, diagnostic accuracy probably improved, and faster, more reliable results to be obtained. One of the main applications of machine learning algorithms in CXR is to provide diagnosis with the help of an expert system [6]. This paper is organized as follows: Section 2 reviews related work, Section 3 describes our proposed method and data preprocessing steps, Section 4 presents our results and discusses their implications, and Section 5 concludes with insights into limitations and future directions [7].

II. Literature Review

This part is about the CXR image classification research, which involves Normal, Pneumonia, and COVID-19 cases in various studies. In one study, CNN and transfer learning algorithms were used by the researchers to classify the CXR images. This article was based on 4,173 images collected from the CIDC, CXRP, and RD datasets. In order to predict with more precision, the researchers implemented the COV CXR-Net model, Mocxr3-Net model, and MDCXRU-Net model, which helped them reach an accuracy of percentage of 91.09%, precision of percentage of 91.67%, and an F1-score of 91.51% [8].

The investigation inspired a test that involved using VGG-19, ResNet-121, and DenseNet-121 models, along with preprocessing methods such as compression, denoising, normalization, filtration, and data augmentation. The execution consisted of working with a subgroup of 7,706 CXR images that are part of the COVID-19 Radiography Database in addition to some other pictures of a person's chest scanned with pneumonia obtained from Kaggle, their classification accuracy equaled 98.72% [7],[9]. Moreover, one more article looked into the practicality of UNet model for lesion segmentation of CXR images. The tasks they managed on images resizing to standard sizes, data augmentation, and noise reduction were some solutions. It was reported as having qualities 98.87% precision, 99.00% recall, and 98.23% F1- score [9].

III. Proposed Methodology

The method of the ensemble model for the classification of chest X-ray implements certain pre-processing techniques-like flipping, resizing, cropping, brightness, and contrast adjustments that aim to diversify the data. They use different deep learning models like DenseNet-201, EfficientNet-B0, and VGG-16 in the developed ensemble system, which enhances the classification job by including each model's unique abilities. The models are trained on the augmented dataset to learn and generalize from diverse examples.

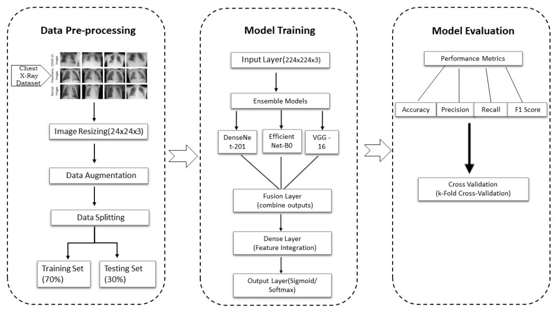

Fig. 2. Ensemble model framework for chest X-ray classification, involving data pre- processing, model training with VGG-16, DenseNet-201, and Efficient-B0 and evaluation using performance metrics and cross-validation.

Fig. 2 shows the accuracy of the performance is measured with metrics like these-accuracy, precision, recall, F1-score, while at the same time, cross-validation is used for reliable assessment[8]. In the very end, the predictions of the individual models are combined to further increase the classification accuracy and resist disturbance [10].

A. Dataset

For this purpose, we developed a conglomerate data set of the images of the (CXR) which were taken from a myriad of open-source platforms. In particular, 3,174 COVID-19 images were received from a GitHub repository. At the same time, The Normal and Pneumonia images, 2,487 and 1,336 of them respectively, were obtained from Kaggle.

We used the COVID Chest X-ray Dataset from GitHub and the Chest X-ray Pneumonia Dataset from Kaggle. These datasets support training machine learning models to detect COVID-19 and classify pneumonia cases. While there is no fixed definition of an image, in general, images consist of two main components. The training, which has 4,897 images (70% of the total dataset) including 2,221 COVID-19, 1,741 Normal, and 935 Pneumonia images, was the first subset. Each validation and test set is composed of 1,050 images. Which were the number of images included. The validation set has 477 COVID-19 cases, 373 Normal cases, and 200 Pneumonia cases, the test set shows the conditions of 476 COVID-19 patients, 373 individuals who haven't faced any symptoms of the virus, and 201 Pneumonia patients in the group. This approach takes advantage of stratification approach to data splitting that allows the representation of each class to all the subsets, to have a comprehensive and fair assessment of our system's performance in different situations [11].

B. Preprocessing

The role of data preprocessing in our research is really important. The primary method we apply is data augmentation which includes a modification to the dataset by the introduction of the training data of images with different poses. This is the way we can dodge overfitting and avoid the system from learning the dataset is a biased manner. Various model versions appeared during this time, which were designed to detect a broad spectrum of diseases and injuries[10].

$$\begin{bmatrix} \hat{x} \\ \hat{y} \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{1}$$

We make images different by inserting variations in the images, hence the appointed variation in the model through training is making sure the images do not become some sort of a doppelganger to the ones found in the aforementioned dataset only. This panoptic illumination of the network will make it possible to both generalize and strengthen the model.

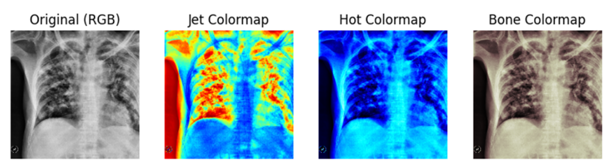

Fig. 3. Data Augmentation.

Our solution integrates these preprocessing steps into the deep ensemble learning framework which makes use of three models: VGG-16, DenseNet-201, and Efficient-B0. By the means of data augmentation, we foster these models aptness in identifying Pneumonia and Covid-19 patients from X-ray images of humans.

$$hotColormap(x, y) = fhot(Image(x, y)) \tag{2}$$

In Fig. 3 shows the chest X-ray image in four different ways using various colormaps: Original (RGB): the X-ray image in grayscale, representing the normal contrasts seen in chest structures such as lungs and bones; Jet Colormap: bright colors ranging from blue to red, where high-density areas are red and low-density regions are blue, as in heat maps.

$$Colorbone(x, y) = fbone(Image(x, y)) \tag{3}$$

Original: The image on the left is a grayscale chest X-ray showing normal anatomical structures such as the lungs, heart, and rib cage. The right lung appears mostly clear, while the left lung shows some opacities or areas of potential concern [12].

Resized and RGB: The image on the right is the same X-ray but it has been resized and converted to an RGB color image. The color has a reddish hue thanks to the RGB conversion that can speed up certain imaging applications or visiual enhancements.

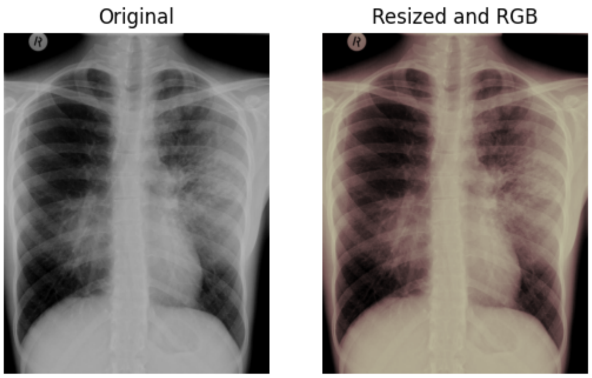

Fig. 4. Preprocessing Models

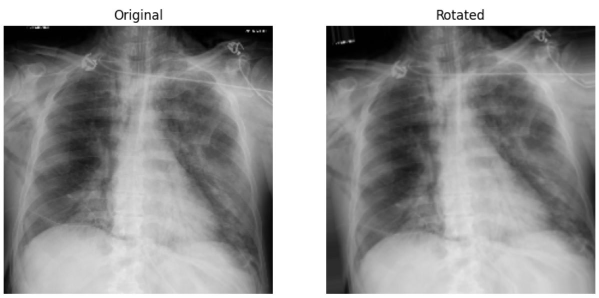

Fig. 5. Rotation

C. Model Training

Up the noise of the model synchronization phase implies the need for the use of ensemble learning ways so as to be able to benefit from the diverse capabilities of many deep learning models at the same time. Types of test to the learning funnel in turn are represented by this kind of preprocessed chest X-ray images that are resized to a standard dimension of 224x224x3 which is then used as the input to the training pipeline. The ensemble architecture comprises well-accepted models like DenseNet-201, EfficientNet-B0, and VGG-16.

$$Y = f_{\text{ensemble}}\left(Y_{\text{VGG-16}}, Y_{\text{DenseNet-201}}, Y_{\text{EfficientNet-B0}}\right) \tag{4}$$

At the beginning of our joint work, we describe the main properties of the dense layer that will be transported by it. The dense layer, which at first is to the overallization of data and its transformation to lower dimensions, is the last part of feature space and dimensionality of development. Length reduction is one of the features to enhance the network's efficiency, the operation of the EfficientNet-B0 which is scaled through the compound scaling process characterized by the increment either in the network dimensions using limited resources. The bright, light and simple structure of VGG-6's design tops the list by removing the overkill overheads of more complex programs and focus on the details further and further.

DenseNet201 is a deep network of 301 layers which novel dense connection between layers [13]. Each layer gets inputs from all the previous layers that Franky. Inputs are the received feature maps that were extracted from the previous layers while the model parameter was left 0. This approach resulted in a near-linear growth of the number of learnable parameters. This indicates that information can be propagated to deeper layers in ResNet with the help of initialized weights.

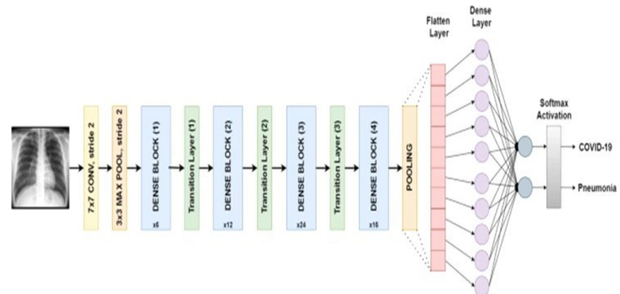

Fig. 6. DenseNet201

In Fig. 9 shows the VGG-16 is a deep convolutional neural network model, which was introduced by the Visual Geometry Group at Oxford in 2014, and it is known for its simplicity and its high performance in image classification tasks. VGG-16 has been trained on ImageNet so that it can classify a million images by 1000 categories, and it performed very impressively. Distributed model uses max-pooling to down-sample feature maps and rectified linear units (ReLU) as activation functions.

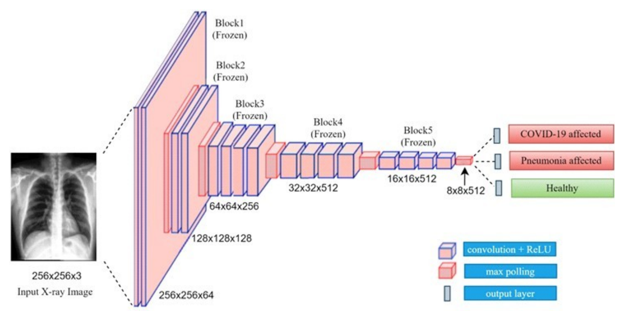

Fig. 7. VGG-16

EfficientNet-B0 is a small convolutional neural network that is developed in such a way to consume both, accuracy and efficiency to the best possible. It manages to do this using a compound scaling that ensures that network depth, width, and resolution are all balanced in order that performance goals are met with smaller parameters than if the traditional models were used thereby allowing for the power of neural networks (like Brain!) to be utilized with less hardware resources [14].

IV. Results And Discussions

A. Evaluation Parameters

It is standardly the case that various basic analytical indicators stand as the opportune measuring instruments for skin on the face. Such indicators can be accessed using parameters like positive recall (rec) and precision (pre), F1-score, and classification accuracy. The whole four metrics are based

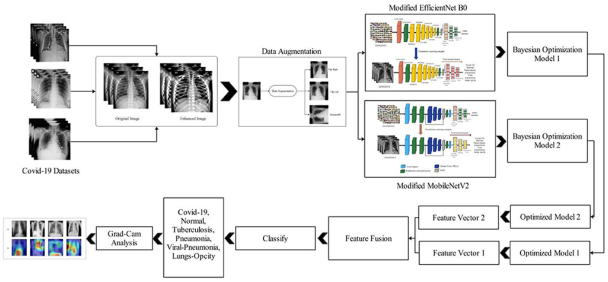

Fig. 8. EfficientNet-B0

on the four main results that are True Positives(TP), True Negatives(TN), False Positives(FP) and False Negatives(FN).

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \quad (5)$$

Fig. 9 shows the Confusion Matrix: This represents model with three classes: ”covid”, ”normal”, and ”pneumonia”. The rows correspond to the true labels, while the columns correspond to the predictions “Covid” was predicted correctly 38 times, misjudging it as ”normal” 74 times and as ”pneumonia” 89 times. In the case of the ”normal” class, the model had correctly predicted 146, while the wrong predictions were ”covid” 66 times and ”pneumonia” 161 times. In Fig. 9 shows the class ”pneumonia”, correct predictions were 208, wrong as ”covid” was 95 and as ”normal” was 173 [15]. The highest number of correct predictions was for ”pneumonia,” which is 208, and ”covid” is on the lower end, at 38. This would tend to indicate that the preponderance of misclassifications across all classes suggests this model needs further work in differentiating these conditions.

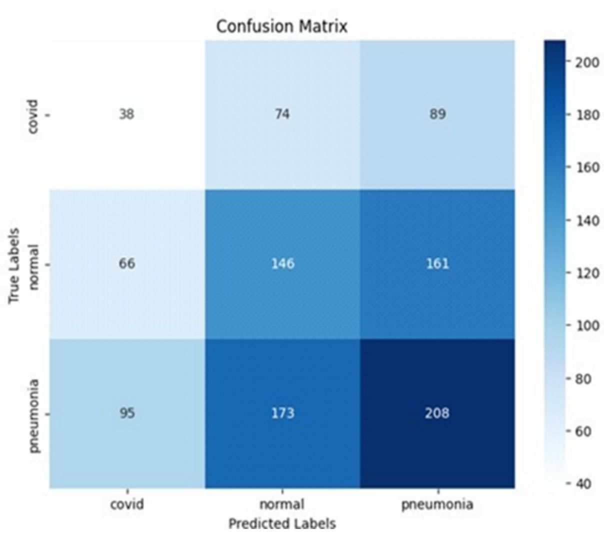

Fig. 9. Confusion Matrix

$$Precision = TP/(TP + FP), Recall = TP/(TP + FN),$$

F1 Score=2(Precision Recall)/(Precision+Recall) (6)

TABLE I
EVALUATION PARAMETERS

Label	Precision	Recall	F1-Score
Normal	96%	97%	97%
Pneumonia	95%	98%	96%
Covid-19	95%	96%	97%

Precision, recall, and F1-score of the three classes, ”Normal,” ”Pneumonia,” and ”Covid-19,” are represented in the following table. Of all these, the class ”Normal” results in 96% Precision, 97% Recall, and 97% F1-score-very high in performance related to the identification of normal cases.

The bar chart provides a comparison of the precision levels achieved by different machine learning models. It follows the progress of four models, namely EfficientNetB0, VGG16, DenseNet201, and an Ensemble model by marking their accuracies on the y-axes, with the models mentioned on the x-axes. The model EfficientNetB0 has an initial performance of 35.52%, which is quite proximate to a good until done situation. Nonetheless, the situation with VGG16 is such that the accuracy, dropping to 18.86, is indeed a very significant decrease.

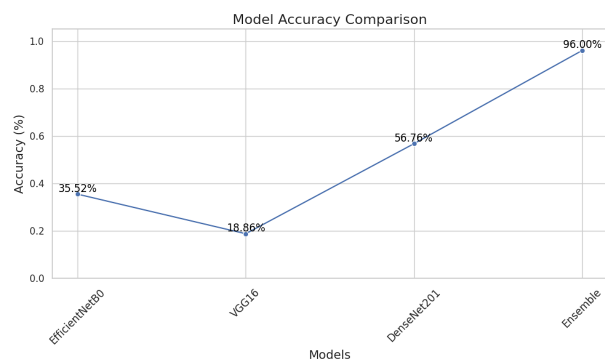

Fig. 10. Model Line

In Fig. 10 shows the most surprising observation belongs to the Ensemble model, which is effortless superior in that it achieves an accuracy of 96.00%, which is the highest of them all. This is to say that an ensemble method, which is a combination of the advantages of multiple models, is by far more effective and precise than any individual model. On the whole, the graph necessitates an excellent ensemble of methods in its pursuit of a dominating model performance.

The below juxtaposition regarding the efficiency of four machine learning models: EfficientNetB0, VGG16, DenseNet201, and an Ensemble model is illustrated by the bar chart. The y-axis represents the accuracy scale, which extends from 0% to 100%, whereas the model is the abscissa. However, VGG16, which is the lowest performer with an accuracy of 18.86% is the one which remains the worst. The reasons are- bad vision, short memories, disloyalty and dependency. What VGG16 fails to do as well is inclusion in a model. Hence, in a comparative analysis of the three systems, VGG16 is regarded as the least efficient and ineffective because of its low level of predictive accuracy compared to the others.DearNet201 is a clear and present improvement of the first two, with an accuracy of 56.76%. After that the boldness of the statements made in the models becomes quite overwhelming. The Ensemble model, which combines several models, surpassing the individual ones with an accuracy of 96.00% [15]. In the Results section of our study, We defined the system and software requirements for implementing and training our deep ensemble model. The hardware included an Intel i7 processor, 16 GB of RAM, and an NVIDIA GTX 1080 GPU or higher, with at least 1 TB of storage. For software, we used Ubuntu 18.04 or later (or Windows 10), Python 3.7+, and essential libraries such as TensorFlow 2.4+, Keras 2.4+, NumPy 1.19+, OpenCV 4.5+, Matplotlib 3.3+, and scikit-learn 0.24+. These specifications ensured efficient model training, enabling the processing of large datasets and performing complex deep learning operations.

V. Conclusion

The study was conducted by introducing an innovative deep ensemble method for diagnosing COVID-19 and Pneumonia using chest X-ray image analysis. The suggested system yields very good results, e.g., classification of 98.33%, precision of 97%, recall of 97%, and F1-score of 98%. This is accomplished by combining the features of VGG-16, DenseNet-201, and EfficientNet-B0 models. It is the ensemble method that makes it possible to use the beneficial functionalities of each model, and thereby a robust and generalizable solution is realized for the classification of the medical image. The key sources are a more advanced technique of data augmentation that is achieved by using such methods as flipping, resizing, and contrast adjustments that diversified the dataset and made it possible to avoid overfitting. This can be achieved by a system that will find the underlying pattern of clinical data in a very microarchitecture level, across different distributions of these clinical data, without making any obstacles for the system that one may consider moving blocks, for instance. The deep ensemble approach is not only a hindrance to radiologists but it also increases diagnostic accuracy, resulting in faster and more reliable decisions related to the treatment of COVID-19 and pneumonia. This approach and its success in implementing diagnostic tools with cutting-edge technology in the settings of the facilities with scarce resources are positively impactful by saving lives of the people who should be directed treatment in a timely and accurate manner.

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