Automatika

Journal for Control, Measurement, Electronics, Computing and Communications

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/taut20

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To cite this article: M. Shimja & K. Kartheeban (2024) A comparative study of lung disease classification using fine-tuned CXR and chest CT images, Automatika, 65:1, 312-322, DOI: 10.1080/00051144.2023.2293274

To link to this article: https://doi.org/10.1080/00051144.2023.2293274

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Published online: 08 Jan 2024.

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AUTOMATIKA
2024, VOL. 65, NO. 1, 312–322
https://doi.org/10.1080/00051144.2023.2293274

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A comparative study of lung disease classification using fine-tuned CXR and chest CT images

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ABSTRACT

The diagnosis of lung disease is a challenging process that frequently combines clinical information, such as patient symptoms, medical history and test findings, with medical imaging, like X-rays or CT scans. The classification of lung diseases is very important in healthcare since it helps with diagnosis and treatment of many different lung diseases. A precise classification of lung conditions can aid doctors in choosing the best course of action and enhancing patient outcomes. Additionally, accurate classification can aid in evaluating the effectiveness of therapies, forecasting results and tracking the development of diseases. It is extremely important to accurately classify lung conditions. A comparison of a novel model for lung disease classification from chest CT and CXR images was presented in this paper. A modified VGG-16 model was used as the classification model. To improve the performance, a fine-tuning mechanism was added to the proposed model. The effectiveness of the suggested method is analyzed and compared on two distinct datasets in terms of performance metrics. The experimental outcomes showed that the suggested model performs better on the CXR image dataset.

ARTICLE HISTORY
Received 26 August 2023
Accepted 1 December 2023

KEYWORDS
Lung diseases; chest X-ray images; chest CT images; deep learning; VGG-16; fine-tuning

1. Introduction

Millions of people worldwide suffer from lung disease, which is a serious global health concern. The World Health Organization (WHO) estimates that respiratory disorders cause over 7.1 million fatalities annually, ranking them as the fourth highest cause of death globally [1]. Lung diseases are a set of illnesses that damage the lungs and impair their functionality. They may be acute or chronic, and they can range in severity from moderate to severe. Smoking, exposure to air pollution, hereditary factors, infections and autoimmune illnesses are only a few of the causes of lung diseases. Depending on the exact disease, lung disease symptoms can vary and comprise shortness of breath, wheezing, coughing, chest pain and exhaustion. For better results and fewer consequences, lung diseases must be identified and treated early. If lung disease is not identified at an early stage, it frequently results in patient death [2]. A variety of issues with the lungs can be caused by viruses, poor eating habits, bad habits and genetics. Prior to a diagnosis of asthma, a condition known as reactive airway disease affects the airways in the lungs, causing inflammation and narrowing that makes breathing difficult.

The lungs are sacks of tissue that are situated above the diaphragm and just below the rib cage. They play a significant role in the body's waste disposal and respiratory system. A number of conditions and drugs, as well as infections and workplace exposure, can have an impact on the lungs. Radiology is responsible for determining the pattern, location and geographical distribution of involvement in the diagnosis of lung disease. The ability of the lungs to hold, move and interchange O_2 and CO_2 can be used as a diagnostic tool by doctors to check for lung conditions [3] (Figure 1).

Asthma, pneumonia, lung cancer, tuberculosis, COVID-19 and chronic obstructive pulmonary disease are a few examples of common lung diseases. A common lung sickness called pneumonia affects the lungs' air sacs, inflaming them and leading them to become filled with fluid or pus. Inhaling specific chemicals or compounds, as well as a range of bacteria, viruses and other microbes, can also result in it. Pneumonia can range in severity from moderate to severe, and it can be especially deadly for elderly individuals, kids and persons with compromised immune systems [4]. The bacteria, Mycobacterium tuberculosis, is responsible for tuberculosis. Although it mostly harms the lungs, it can also affect the spine, brain and kidneys. TB is disseminated through the air when an infected individual coughs, sneezes, or talks and another person inhales the germ [5]. The new coronavirus "SARS-CoV-2" causes the extremely contagious respiratory disease COVID-19. When an infected individual talks, coughs, or sneezes and another person inhales those droplets, COVID-19 is mostly disseminated through respiratory

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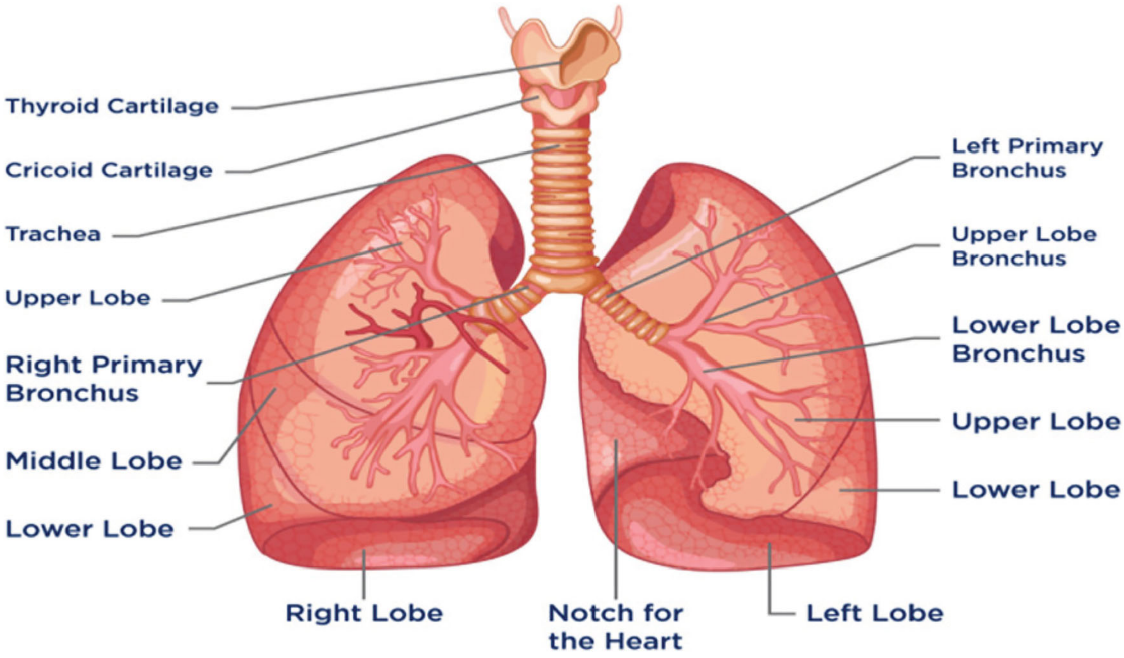

Figure 1. Lung anatomy.

droplets. A few of the mild to severe COVID-19 symptoms include coughing, muscle aches, shortness of breath, fever, exhaustion, loss of taste or smell and sore throat. Others may need to be hospitalized because of severe respiratory distress or other consequences, while other people may have no symptoms at all [6].

Finding a quick and effective lung disease diagnostic tool is a top priority for worldwide public health [7]. Timely diagnosis and treatment are crucial for the patient's morbidity and death. Chest X-ray imaging, magnetic resonance imaging, computed tomography and ultrasound imaging are the most frequently utilized medical imaging modalities for lung diseases. Due to its efficiency, quickness and affordable price, X-ray imaging is frequently used in medical diagnosis. There is a slight danger of injury, especially with repeated exposures, due to the small quantity of ionizing radiation that is exposed. Healthcare professionals employ the least amount of radiation necessary to get high-quality images in order to reduce this danger, and they only advise X-ray imaging when it is absolutely necessary [8]. Computed tomography, a medical imaging modality, may produce exact, 3-D images of the internal organs and tissues of the body with the aid of X-rays, computers and other imaging equipment. Due to their ability to give a thorough image of the lungs and adjacent tissues, CT scans can be very helpful in the diagnosis and monitoring of lung disorders [9]. Lung disorders like pneumonia, lung cancer and pulmonary embolism can all be detected and monitored with the help of CT scans. They can offer a thorough image of the size, shape and position of lung nodules or masses, as well as the degree of damage or inflammation in the lungs. The classification of lung disorders has the potential to be a useful tool for the early detection, care and management of many respiratory conditions. The classification of lung diseases can help to harmonize medical language and enhance communication between healthcare professionals. Healthcare professionals can communicate about a patient's diagnosis, treatment and prognosis more precisely and clearly with the help of a standardized classification system, which can enhance patient outcomes and lower the chance of medical mistakes. Therefore, it is crucial to develop an effective approach for classifying lung diseases. In this paper, a DL-based transfer learning model with a fine-tuning mechanism was presented for lung disease classification from CXR and CT images. The major contribution of the proposed work includes:

- The paper proposed an efficient model for lung disease classification from CXR and CT images. The performance of the proposed model for both CXR and CT images was examined and compared in this paper.
- The performance of the lung disease classification model was enhanced by the Fine-tuned Modified VGG-16 Model

The remainder of the paper is organized as follows. The literature review and research gaps are presented in section two. Section three explains the detailed methodology. Section 4 discusses the experimental findings. The fifth section provides the conclusion of the work.

2. Background

2.1. Literature review

The classification of lung diseases makes it easier to determine the underlying disease process, which can help in lung disease diagnosis. While the symptoms of various lung diseases can be similar, a thorough classification can help to direct the diagnostic process and make sure that the appropriate tests and procedures are employed to provide an accurate diagnosis. So it is crucial to have an effective classification model for lung diseases. Lung disease can be classified using a variety of techniques using CXR and CT images.

Juan Eduardo Luján-Garca et al. [10] presented an efficient and quick method to automatically classify three categories of CXR images. Two separate datasets were used to assess the proposed model. Despite the age gaps, the recommended technique showed effectiveness in spotting disease-related features. According to the experimental findings, the suggested approach performed very effectively. A deep learning system was presented by Abhir Bhandary et al. [11] for the identification of lung diseases utilizing CXR and CT data. Initially, SVM is utilized to implement the classification, and its performance is contrasted with Softmax. Additionally, the effectiveness of the method is verified using other DL models that have already been trained. The suggested approach offered superior detection performance and did well with the image dataset. Vinayakumar Ravi et al. [12] presented a large-scale learning technique for COVID-19 classification employing a "stacked ensemble meta-classifier" and DL-based feature fusion. The suggested method was assessed using CT and X-ray images. SVM and Random Forest classifiers are used to make predictions using a combination of the retrieved characteristics. For the classification of unlabelled samples, a logistic regression model was finally used. According to the experimental findings, the proposed model misclassified less frequently across both datasets. A deep TL technique was created by Harsh Panwar et al. [13] to speed up the identification of COVID-19 cases in CXR and CT-Scan images. The suggested model is evaluated using three different datasets. In order to improve reading and comprehension of the suggested deep learning model, a colour visualization methodology has also been developed using the "Grad-CAM" approach. An accuracy of 95.61% is offered by the suggested model. But there is a chance for misclassification. Shimpy Goyal and Rajiv Singh [14] implemented a novel methodology for predicting lung disorders like pneumonia and COVID-19 from patient CXR images. The suggested strategy is based on deep learning, machine learning and soft computing techniques. After the image enhancement, feature extraction and normalization were performed. In terms of performance measures, the suggested model exhibits efficient performance.

A TL approach using the Pruned Efficient Net model was created by Amit Kumar Jaiswal et al. [15] for the identification of COVID-19 cases. For the explain ability of the predictions, the suggested model is further integrated by post-hoc analysis. The effectiveness of the proposed methodology is demonstrated using two systematic computed tomography and chest radiograph datasets. The proposed strategy provides remarkable detection performance on chest CT and X-ray images. A deep unsupervised framework was presented by Pooja Yadav et al. [16] to categorize lung disorders from chest CT and X-ray images. This method offers multi-layer generative adversarial networks that may be trained on unlabelled data to discover acceptable depictions of lung disease images. It trained an SVM and a stacking classifier using the lung attributes that the model had learned. The experimental findings demonstrated that the proposed technique outperformed the most recent unsupervised models for classifying lung diseases. The framework's inability to manage samples that have been incorrectly classified is the main drawback of the suggested technique. A unique and automated method for the diagnosis of chronic pulmonary illnesses was developed by Rajat Mehrotra et al. [17]. In this study, two classification models are presented. The first model seeks to distinguish between normal and diseased CXR images. If the CXR image is discovered to be contaminated by a CPD by the first model, the second model analyzes the type of CPD in more detail. When dividing the infected images into three main groups, the second model has a classification accuracy of 96.8%. The lack of a substantial dataset is this study's main drawback. A form of dynamic CNN modification approach was created by Guangyu Jia et al. [18] for the categorization of COVID-19 from CXR image datasets and a CT image dataset. Point-wise convolution blocks are used in the proposed method to create dynamic layer combinations and connect the distinct layers of the original CNN framework. The suggested method is compared to six well-known deep learning models and two recently implemented methods developed exclusively for COVID-19 identification. The outcomes demonstrate that the suggested techniques perform better than the comparative models. Several experiments using supervised learning models were offered by Sergio Varela-Santos and Patricia Melin [19] in order to successfully complete a precise categorization on datasets made up of medical images from COVID-19 patients and medical images of numerous lung disorders. This study is an initial investigation utilizing feed-forward, CNN and image texture feature descriptors on freshly constructed datasets with COVID-19 images. According to the experimental findings, the proposed approach performed significantly well. The lack of appropriate parameter optimization approaches is the work's main shortcoming.

Varalakshmi Perumal et al. [20] used the transfer learning technique to clinical imaging of numerous lung conditions, such as COVID-19. In order to speed up the prediction process and help the medical experts, a unique transfer learning model was proposed. The proposed approach outperforms the current models. This helps radiologists complete the time-consuming process more quickly and easily, this contributes to saving lives and preventing disease transmission. An efficient technique for the early phase recognition of Coronavirus using machine learning approaches was proposed by Mucahid Barstugan et al. [21]. The abdomen CT images were used to carry out the detecting process. Patches were submitted to the feature extraction method in order to enhance classification performance. The collected characteristics were categorized using Support Vector Machines. Better detection performance was displayed by the proposed model. A novel technique to categorize ILD imaging patterns on CT images was introduced by Mingchen Gao et al. [22]. The proposed approach differs greatly from earlier image patch-based algorithms in that it takes holistic features as input. The experimental outcomes demonstrated the suggested feasibility and benefits of the suggested strategy. The proposed method cannot focus on slice-level detection with multiple labels. In order to detect and predict lung disorders in smokers, German Gonzalez et al. [23] suggested a deep learning-based technique. Computed tomography scans were used to train a CNN. COPD diagnosis and ARD prediction were evaluated using logistic regression. To calculate mortality, Cox regression was utilized. The suggested technique produced better outcomes. The main drawback of the suggested approach is the high computational and memory costs associated with model training, which restrict the quantity of data that can be used to train the models. A unique technique for the recognition of COVID-19 utilizing TL from CT scan images that have been splitted into three levels using stationary wavelets was presented by Sakshi Ahuja et al. [24]. A 3-phase recognition paradigm is recommended to enhance the accuracy. Computing the common performance measurements allows for an evaluation of the suggested architectures' performance. The outcomes of the experimental evaluation demonstrate that the pre-trained TL-based ResNet18 model provided higher classification accuracy on the analyzed image dataset when compared to the alternatives [25].

2.2. Research gap

Some of the limitations of the existing works related to lung disease classification are discussed below. One of the drawbacks of the current approach is that the framework lacks an appropriate method for dealing with samples that have been incorrectly categorized. The development of precise and trustworthy machine learning models depends on the availability of big, high-quality datasets. A lack of annotated medical images still exists for lung disorders, particularly for uncommon conditions. Some of the works need an appropriate method for parameter optimization. The amount of data that may be utilized to train the models is constrained by the high computational and memory costs of some of the existing methods. Deep learning algorithms could overlook crucial clinical aspects like patient history, symptoms and test data. This may reduce the classification of lung diseases' accuracy and usefulness. Deep learning models are significantly influenced by the training dataset that was used to develop the model. The model may not generalize effectively to new cases or groups if the dataset is not representative of the diversity of lung disease cases. Therefore, an effective method for classifying lung diseases from CXR and chest CT images is required.

3. Methodology

The primary goal of this work is to create a reliable system for categorizing lung disorders from chest CT and CXR data. Data preprocessing was done after dataset collection. The CXR and CT dataset Images were utilized to train the pretrained models, which were previously trained on the ImageNet dataset. The classification of lung disease using CXR and chest CT images was proposed using a fine-tuned framework. Finally, the effectiveness of the suggested model was assessed and compared using the two various datasets. Figure 2 is a block diagram of the suggested method.

3.1. Dataset description

The performance of the suggested method is evaluated using data from two separate datasets (chest CT and CXR images). A combination of two or more different datasets was used to create the dataset. The dataset [25] with four classifications (COVID-19, Pneumonia, Tuberculosis and Normal) and another dataset with two classes (Bacterial Pneumonia and Viral Pneumonia) are combined for CXR images. Similar steps are taken to prepare the chest CT image dataset. The two datasets consist of five classes and three subfolders (train, test, validation). Figures 3 and 4 contain examples of the images from the two datasets.

3.2. Data preprocessing and data augmentation

Image preprocessing is an essential step that helps to prepare the input data for the model. Image preprocessing techniques are used to enhance the image's quality, simplify computation, get rid of noise and normalize the data. Preprocessing operations frequently involve resizing an image to a particular size. In order to avoid distortion, it's crucial to maintain the image's aspect

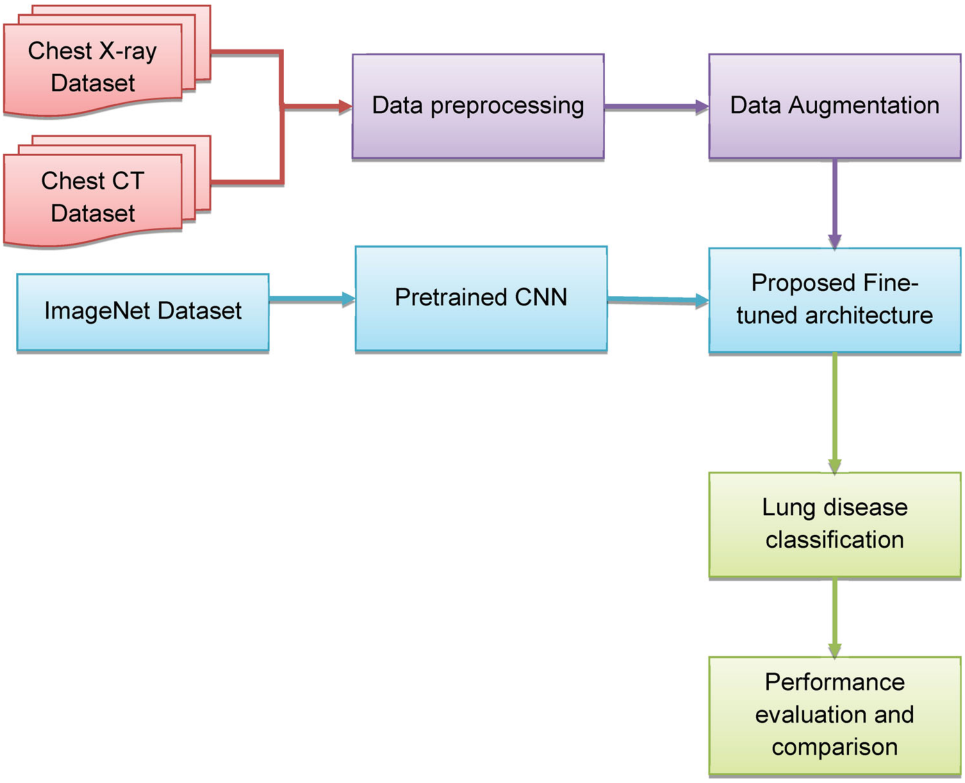

Figure 2. Block diagram of the suggested approach.

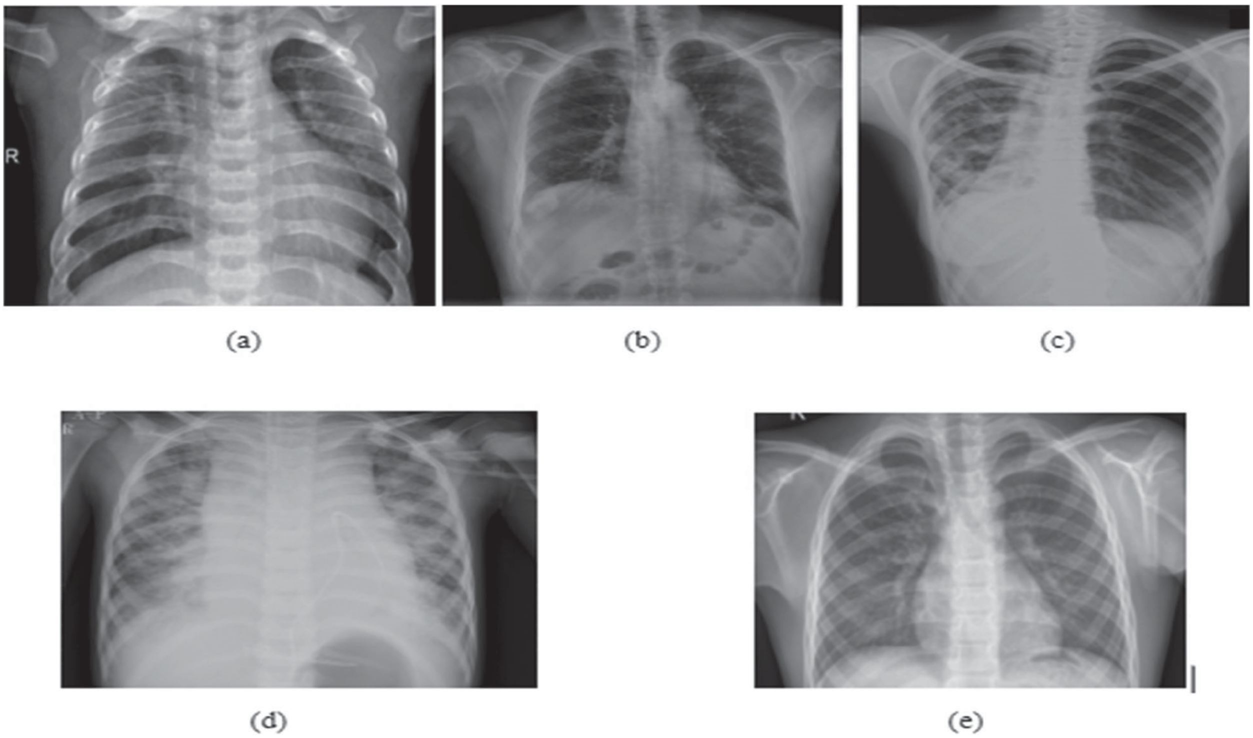

Figure 3. CXR images of (a) Bacterial Pneumonia (b) COVID-19 (c) Tuberculosis (d) Viral Pneumonia (e) Normal.

ratio when resizing. This makes the input images' sizes more uniform and lowers the processing cost. The pixel values are scaled to a predetermined range as part of the normalization of the input images. As a result, the model will converge more quickly during training because the data will have a mean value of zero and variance of one. Mean subtraction and dividing by standard deviation are two frequently used normalization methods. It is crucial to eliminate noise from an image when they are noisy or of low quality. Denoising can be done using methods including bilateral filtering, median filtering and gaussian smoothing. The training dataset is artificially enlarged using techniques for data augmentation. This is accomplished by applying random

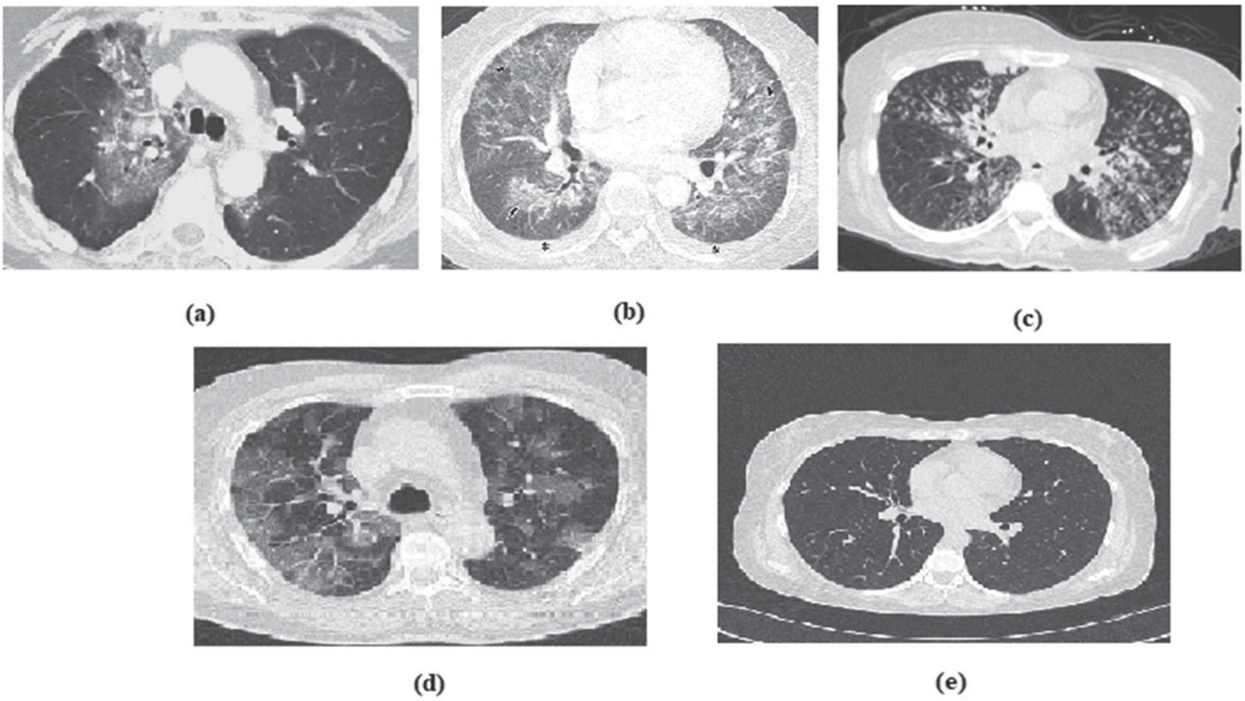

Figure 4. CT images of (a) Bacterial Pneumonia (b) Viral Pneumonia (c) Tuberculosis (d) COVID-19 (e) Normal.

image changes, such as rotation, flipping, zooming and shifting, to the input images. As a result, the model's capacity for generalization is enhanced and overfitting is reduced.

3.3. Proposed fine-tuned model

It is possible to apply the information gained from one task or area to a similar task or domain by using the fine-tuning technique. It entails taking a model that has already been trained, typically on a big dataset, and refining it on a smaller or more focused dataset. In order to enhance the pre-trained model's performance on the new task, the pre-trained model will be further trained using the new data. When the new dataset is small and similar to the initial pre-training sample, fine-tuning can be especially beneficial. The fine-tuning process can take advantage of the transfer learning effect and enhance the model's performance on the new task without requiring it to be trained from scratch.

Choose a pre-trained model: Select a "pre-trained model" that is already trained on a large dataset for a related task. Remove the last layer: The last layer of the pre-trained model, which are usually responsible for classification tasks, are removed. Add new layer: Add new layers that are specific to the new task, such as a new output layer for classification. Freeze pre-trained layers: Freeze the weights of the pre-trained layers so that they are not updated during training. Train the model: Train the new model on the new dataset using a smaller learning rate to prevent overfitting. Fine-tune the model: Gradually unfreeze some of the earlier layers in the model to allow the model to learn more task-specific attributes.

3.3.1. Fine-tuned modified VGG-16 model

VGG-16 is a deep CNN framework. It is a well-known DL model that is applied to image classification applications. The VGG-16 was trained using the "ImageNet" dataset, which consists of over a million images divided into a thousand different classes. Since then, many different computer vision tasks have used the VGG-16 architecture as a baseline, and it has influenced the creation of additional deep learning models. The VGG-16 architecture consists of sixteen layers, including thirteen convolutional layers and three fully connected layers. To maintain the spatial information of the input image, the convolutional layers employ small 3×3 filters with a stride of 1 and padding of 1. Figure 5 is a diagram illustrating the basic VGG-16 structure.

In order to avoid the problem of underfitting and overfitting during training, a modified VGG-16 model was employed in this study. A fine-tuning technique has been applied to this modified VGG-16 network. The original framework of the VGG16 convolutional network was retained by using two succeeding small convolutional kernels rather than a single large one during feature extraction. By reducing the number of parameters and retaining the VGG16 perceptual effects, this speeds up training and preserves the network depth. The input image was 224×224 pixels in size. The hidden layer contained five blocks. The image size was lowered by the pooling layers, and the feature map dimensions were shrunk by the flattened layer. The suggested model was trained using the CXR and chest

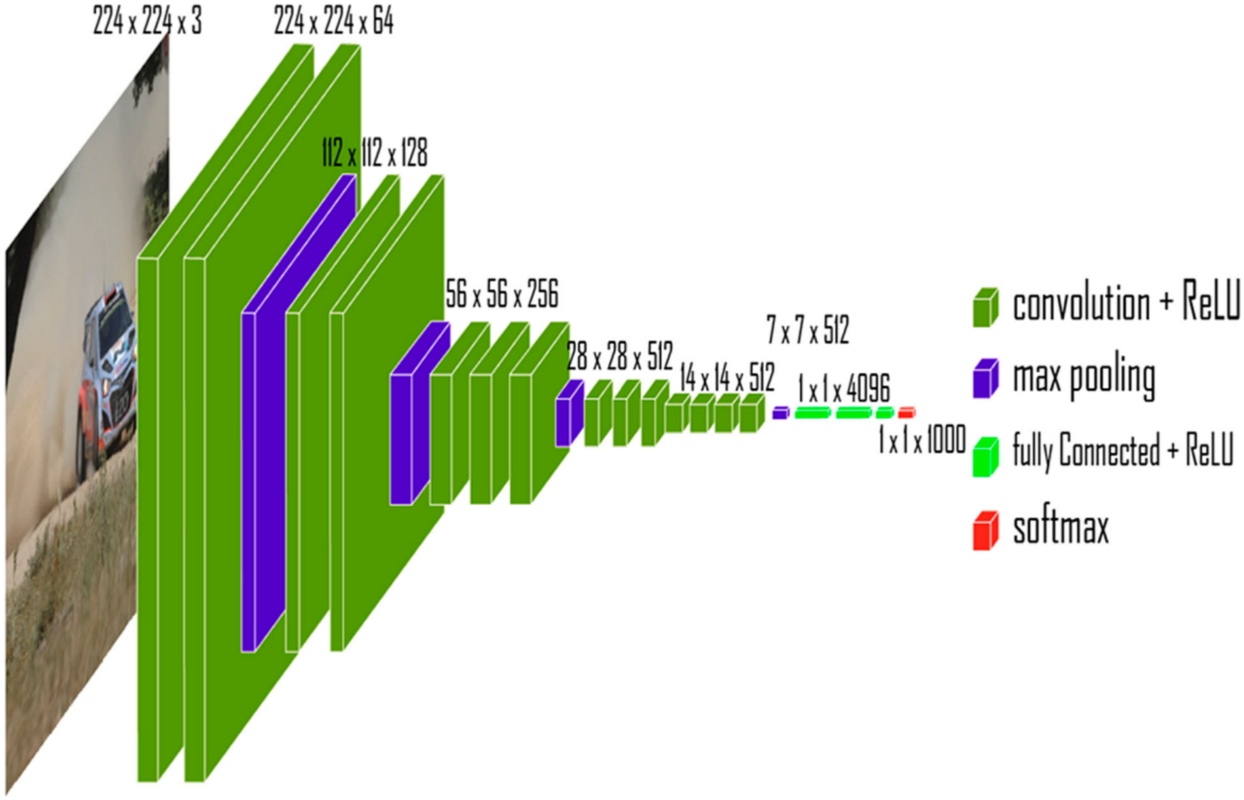

Figure 5. Basic Structure of VGG-16.

Table 1. Model review of fine-tuned modified VGG-16 model.

	Before Fine-tuning	After fine-tuning
Total parameters	39,808,693	39,808,693
Trainable parameters	25,094,005	38,073,205
Non-Trainable parameters	14,714,688	1,735,488

CT data. The modified VGG-16 model went through 50 epochs before being fine-tuned. Fine-tuning was applied at the tenth layer onwards of the base model and provided a low learning rate. The model was trained for fifty epochs after the fine-tuning. Table 1 shows a summary of the suggested modified VGG-16 model's before-and-after fine-tuning.

From the above table, it can be seen that the number of trainable parameters increases after fine-tuning. The number of trainable parameters in a model often rises when it is being fine-tuned. This is so that the model's weights can be adjusted to the new task or domain during fine-tuning. The model may perform better if there are more trainable parameters available to enable it to better adapt to the new task or area. The model can learn more intricate features that are unique to the new task or domain by fine-tuning with more trainable parameters.

3.4. Performance parameters

Performance metrics are crucial for assessing how well deep learning models perform. These variables offer perceptions of a model's effectiveness and can be used to identify areas that require development. The value of performance parameters resides in their capacity to offer an impartial assessment of a model's performance, which is necessary for making defensible choices regarding the model's application.

One of the variables that is most frequently used to assess the effectiveness of deep learning models is accuracy. Accuracy is the ratio of correct prediction to the total number of predictions. In other words, it assesses how frequently the model predicts the target variable accurately.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

When false positives are expensive or undesired, precision is very helpful. It calculates the ratio of actual positive results to all expected positive results. It measures the proportion of predictions for the positive class that the model makes that are accurate.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall evaluates the ratio of true positives to all other positive results in the dataset. In other words, it evaluates the ratio of positive cases in the sample for which the model predicts the positive class accurately.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

The F1-score is especially helpful when classes are dis-

Table 2. Classification report of proposed fine-tuned model on CXR dataset.

	Before Fine-tuning	After Fine-tuning
Accuracy	93.14%	98.00%
Precision	93.42%	98.57%
Recall	91.71%	98.28%
F1-Score	94.85%	98.57%

Table 3. Classification report of proposed fine-tuned model on chest CT dataset.

	Before Fine-tuning	After Fine-tuning
Accuracy	83.33%	91.25%
Precision	85.42%	89.34%
Recall	86.54%	90.43%
F1-Score	85.97%	89.88%

tributed unevenly or when assessing the effectiveness of the model, both precision and recall are critical. The F1-Score provides an equal emphasis on both precision and recall when assessing a model's performance, and it is determined as the harmonic mean of precision and recall.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

4. Results and discussion

4.1. Hardware and software setup

The separate datasets obtained from the Kaggle repository are combined to generate the CXR image dataset and the chest CT image dataset. The two datasets were divided into training data, testing data and validation data. This study employed the Microsoft Windows 10 and Google Colaboratory operating systems to create a stable computing environment. The chest CT image dataset and the CXR image dataset were used as the input to the fine-tuned structure. Subsequently, the model categorized the input images into five distinct groups: COVID-19, Bacterial Pneumonia, Tuberculosis, Viral Pneumonia and Normal. On both datasets, the performance of the suggested model was evaluated and compared.

4.2. Experimental results

The prepared datasets were used to run the suggested model. Python and TensorFlow were utilized for the development and training of the model on Google Colaboratory platform. The Adam optimization technique was utilized for classification. The categorical cross-entropy was used as the loss function, and the batch size was chosen as 32. The effectiveness of the suggested model was estimated on both CXR dataset and chest CT image dataset at two instances ("before fine-tuning and after fine-tuning"). The classification results of the suggested model on two independent datasets are tabulated in Tables 2 and 3.

The classification outcomes reveal that the suggested model exhibited superior performance on the CXR image dataset. The effectiveness of the suggested system can be enhanced through fine-tuning techniques. When a model is trained on a small dataset or a dataset that is highly dissimilar from the target task, overfitting can happen and fine-tuning can help to solve this issue. It is possible to prevent overfitting and improve

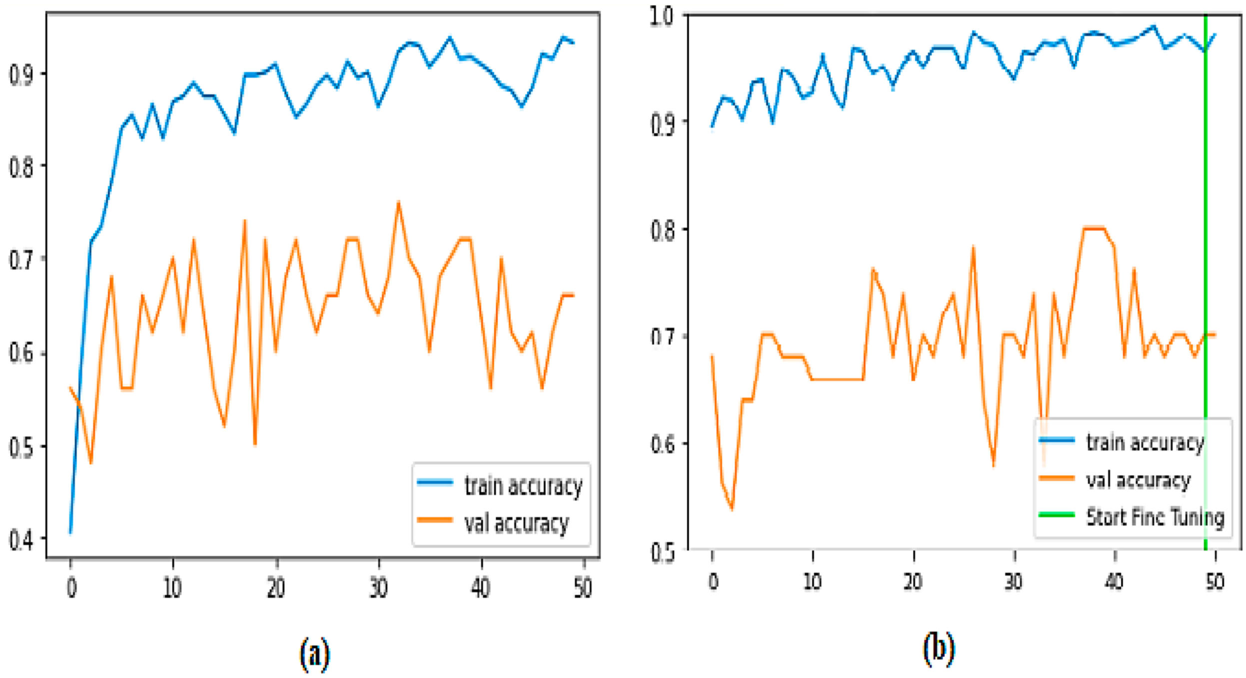

Figure 6. Accuracy plot of proposed model on CXR image "dataset (a) before fine-tuning (b) after fine tuning".

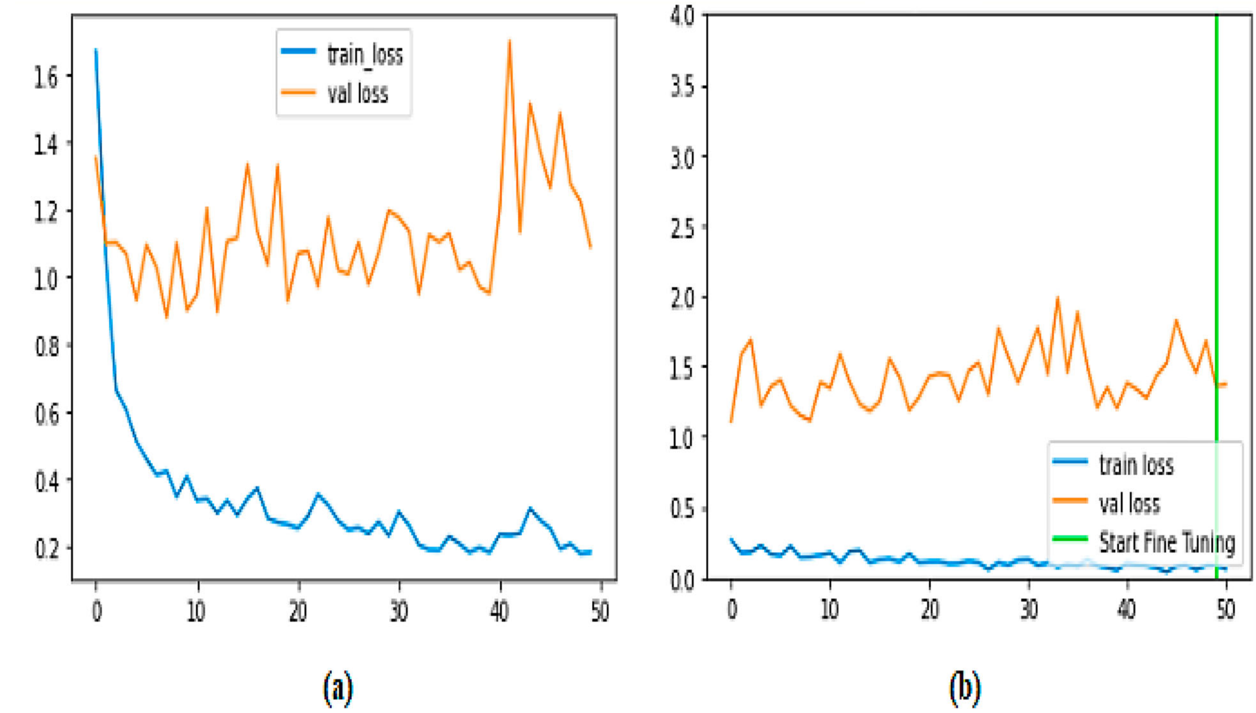

Figure 7. Loss plot of proposed model on CXR image "dataset (a) before fine-tuning (b) after fine tuning".

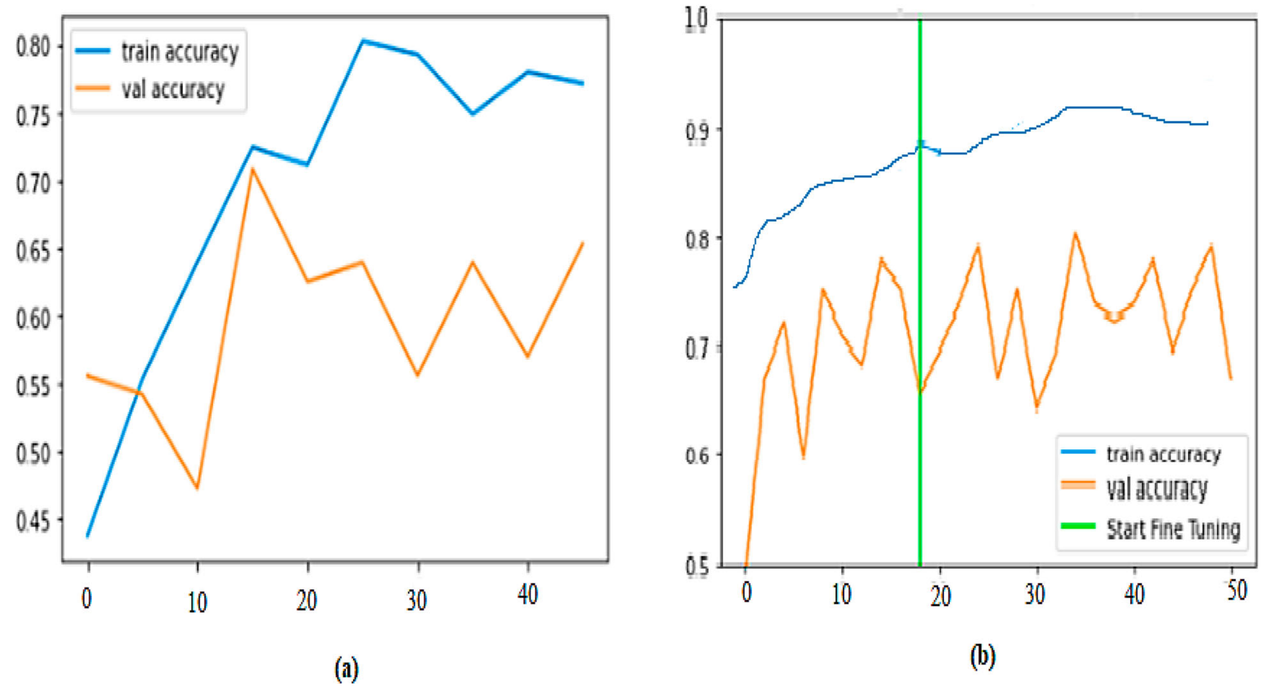

Figure 8. Accuracy plot of proposed model on Chest CT image "dataset (a) before fine-tuning (b) after fine tuning".

performance on the target task by starting with a model that has already been trained and has learnt generic features. This is especially true if the target task has minimal training data.

An accuracy plot is a graphic representation of a model's accuracy over the period of training. It typically displays the training and validation accuracy over a number of training epochs. The validation accuracy of the model indicates its accuracy on a separate validation set that was not utilized during training, whereas the training accuracy denotes the model's accuracy on the training data at each epoch. The validation accuracy should first rise and then level off or slightly decline, while the training accuracy should rise over time. A loss plot is a graphic representation of a model's loss during the period of training. The training loss and validation loss are often displayed over a number of training epoch. The validation loss displays the model's error on a unique validation set that is not used for training, whereas the training loss displays the model's error on

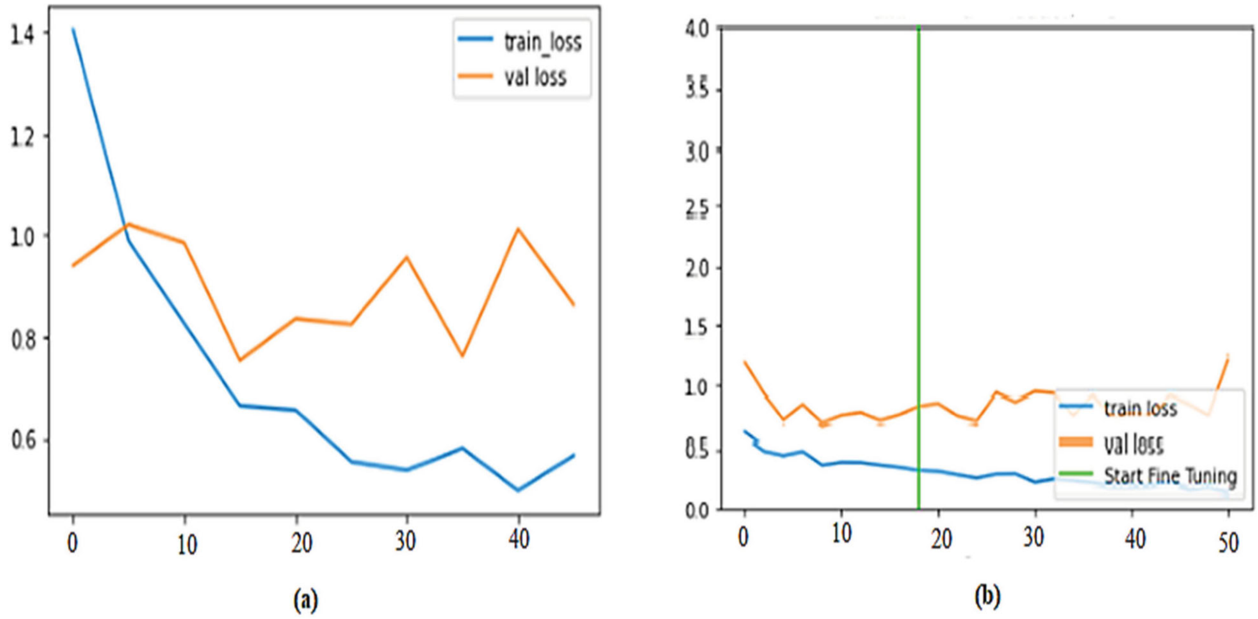

Figure 9. Loss plot of proposed model on Chest CT image "dataset (a) before fine-tuning (b) after fine tuning".

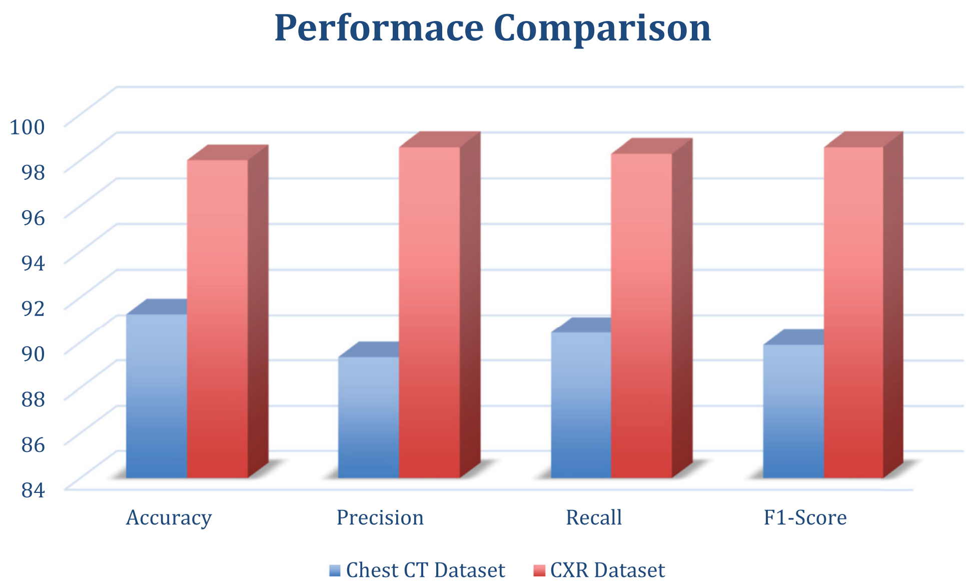

Figure 10. Performance comparison of proposed fine-tuned model on CXR dataset and chest CT dataset.

the training data at each epoch. A loss plot can be helpful in determining how well a model changes over time and whether the training set is being over- or under-fitted. The validation loss should initially decrease and then level off or slightly increase, whereas the training loss should decrease over time, which are shown from Figures 6–9.

A comparison of effectiveness of the proposed model on both datasets is shown in Table 4, and a graphical illustration of its effectiveness is given in Figure 10.

The performance comparison indicated that the proposed lung disease classification model performed well on the CXR dataset compared to the chest CT image dataset. The proposed model got 98.00% accuracy on the CXR image dataset. The process of fine-tuning can significantly enhance the suggested model's efficiency on both datasets.

Table 4. Performance comparison of proposed fine-tuned model on CXR dataset and chest CT dataset.

	CXR Image Dataset		Chest CT Image Dataset	
Performance metrics	Before Fine-tuning	After Fine-tuning	Before Fine-tuning	After Fine-tuning
Accuracy	93.14%	98.00%	83.33%	91.25%
Precision	93.42%	98.57%	85.42%	89.34%
Recall	91.71%	98.28%	86.54%	90.43%
F1-Score	94.85%	98.85%	85.88%	89.88%

5. Conclusion

A major global public health concern that affects many people is lung diseases. It affects millions of people and is a cause for great concern. To improve patient outcomes, it is crucial to encourage early diagnosis and effective care of patients' conditions and to increase public awareness of the risk factors, symptoms and prevention methods for lung disease. In order to diagnose, monitor and treat patients with respiratory disorders, healthcare professionals frequently use classifications of lung diseases. Healthcare professionals can provide individualized and efficient care to enhance patient outcomes by having a thorough awareness of the various lung disease categories. Deep learning algorithms have shown considerable potential in disease categorization and medical image analysis. Deep learning can be applied to the classification of lung diseases to precisely identify and categorize various lung diseases from diagnostic images like CXR and CT images. This paper offers a comparison of the classification of lung diseases. A fine-tuned modified VGG-16 model was used as the classification model. The suggested framework was assessed on the newly generated CXR and chest CT image dataset. The suggested model's effectiveness was ultimately assessed and compared on two distinct datasets. Based on the experimental outcome, it can be concluded that the suggested technique performed better on the CXR image dataset.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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