Cureus Journal of Computer Science

Open Access Original Article

Lung Infection Detection for an Internet of Medical Things Application Using Chest CT Images Through a Deep Ensemble Convolutional Neural Network Model for Smart Healthcare

Received 12/26/2024
Review began 12/27/2024
Review ended 06/20/2025
Published 06/20/2025

DOI:
https://doi.org/10.7759/s44389-024-00757-8

Subhadarshini Das [1] , Goutami Das [2] , Gyana R. Patra [2] , Bibhuprasad Mohanty [2] , Mihir N. Mohanty [1]

1. Department of ECE, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, IND 2. Applied Signal Processing Laboratory, ITER, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, IND

Corresponding author: Mihir N. Mohanty, mihir.n.mohanty@gmail.com

Abstract

Lung infections, including pneumonia and tuberculosis, are major health concerns worldwide, and, hence, the diagnosis and detection of these diseases are vital components for management and treatment. Lung infection may cause the diseases related to this particular organ, including fever, tumor, tuberculosis, and cancer. The present work presents an internet of medical things framework for detection of lung infection from chest computer tomography (CT) images, aiming to provide timely and accessible healthcare solutions. Internet of things devices capture chest CT images from patients and securely upload it to a cloud-hosted pre-trained ensemble convolutional neural network (CNN) model to detect the presence of lung infections. The employed model has been trained with a dataset that contains 2,482 images of COVID and non-COVID type, collected for post-COVID cases. This work focuses on utilizing an ensemble-based deep CNN architecture, for lung infection detection. Results are verified on a web application interface, allowing healthcare professionals to visualize and interpret the findings. The proposed model has an accuracy of approximately 98.99% and achieves improved performance than several recent models.

Categories: Image Processing and Analysis, IoT Applications, Machine Learning (ML)
Keywords: lung infection, lung ct, machine learning, cnn, iomt, ensemble models

Introduction

Human life is heavily reliant on the lungs, which facilitate intake of oxygen and extraction of carbon dioxide from the body. Different types of lung diseases affect the working of organs and tissues associated with breathing, resulting in infections in airways and lung tissues, thereby limiting air circulation in the lungs. Types of lung diseases include mild discomforting ones such as common cold and influenza, whereas more severe and life-threatening ones include pneumonia, tuberculosis, and lung cancer [1]. These later types of infections, if not properly treated, result in a higher mortality rate. A comprehensive survey done by the World Health Organization in 2007 indicates that 10.4 million people suffered from mild or severe symptoms of tuberculosis, with 1.6 million of them dying [2].

In many cases, chest X-ray and computed tomography (CT) images have proven effective in detecting various types of lung infections. The use of chest X-ray and chest CT images was particularly effective during the recent COVID-19 pandemic [3].

The early detection of such lung infections can be attributed towards improved patient care and reduced treatment durations. Traditional methods of diagnosing lung infections, such as visual inspection of CT images by radiologists, can be often time-consuming and subjective [4,5]. This necessitates automated systems for accurate detection and classification of lung infections in CT images, resulting in timely intervention and quick treatment planning. “The Internet of Medical Things (IoMT)” is a platform of technology that utilizes the power of the world wide web to gather, analyze, and share immense volumes of data [6], which can be swiftly transformed into valuable information and knowledge in real-time scenarios. The advent of the IoMT has enabled seamless real-time connections between people and devices, leading to the creation of valuable services and benefits for millions worldwide and has become a cutting-edge convergence technology, effortlessly integrating various technologies from diverse domains into a unified system [7,8].

The absence of properly labeled data, small fluctuations, and strong structural similarity of structures among the background and infection make building an autonomous diagnosis system challenging for a lung cancer detection system. The timely identification and examination of illnesses have become crucial in managing the transmission of COVID-19 in recent years. Deep learning (DL) techniques, namely utilizing CT images, have been suggested to aid and simplify this analysis in the early phases of the disease and have been profoundly used by researchers currently [5].

How to cite this article
Das S, Das, Patra G R, et al. (June 20, 2025) Lung Infection Detection for an Internet of Medical Things Application Using Chest CT Images Through a Deep Ensemble Convolutional Neural Network Model for Smart Healthcare. Cureus J Comput Sci 2 : es44389-024-00757-8. DOI https://doi.org/10.7759/s44389-024-00757-8

For the purpose of identifying minute aberrations and investigating COVID-19 infections, a novel two-phase deep diagnostic technique has been proposed. The first stage is a convolutional neural network (CNN) architecture known as SB-STM-BRNet, and the second stage is known as COVID-CB-RESeg segmentation CNN. The first stage combines a novel channel called squeezed and boosted (SB) with the split-transform-merge (STM) block based on dilated convolutions [9-11]. Boundary operations and multi-path region smoothing are employed by the STM blocks of the new system, aiding in the identification of global patterns unique to COVID-19 and minute contrast changes. Furthermore, for successful identification and estimation of COVID-19 infectious zones, multiple boosted channels are built within the STM blocks using SB and transfer learning approaches. In the second step, virus-affected lung images are processed by the revolutionary COVID-CB-RESeg segmentation CNN.

A work to identify infected lung regions to validate COVID-19 patients using CT images has used a squeeze-and-excitation networks (SE Nets) along with IoMT architecture to assist with radiological tasks [12-16]. This SE block along with deep residual networks has been used to generate Seresnets based on LinkNet and U-Net. This approach integrates a P-shot N-ways Siamese network based on DL in addition to CNN classifiers for COVID identification using lung CT scan slices. Pre-trained subnetworks were used to extract weight-sharing feature vectors, and the benchmark MosMed dataset was used to measure the performance of the work.

While a substantial amount of research has gone into classifying COVID-19 using different types of medical images, such as CT scans, X-rays, and ultrasounds, none of them can effectively handle all of the different image formats in a unified manner to accurately determine whether or not a person is infected with COVID-19 [17,18].

A DL model that uses k-means clustering for segmentation before feeding it to a Visual Geometry Group-19 (VGG-16) model for classification of COVID-19 patients using lung CT scan images has been proposed [19]. The clustering step improves the efficiency of classification. A 3-layer CNN model was added after the VGG-16 model for both raw and segmented data, and the overall model was found to have improved performance.

A user interface was designed specifically for the purpose of collecting data in an interactive manner for COVID-19 [20]. This interface collects vital medical information, like pulse oxygen levels and RT-PCR test findings. The AI system utilized in this study was specifically designed for the categorization of several chest and lungs relate diseases, like COVID-19, pneumonia, or other viral illnesses. Along with this, the extent of lung infection was also obtained to provide suitable treatment to patients. In this study mostly chest X-ray images were utilized for purpose of delivering prompt and precise diagnostics. DL systems have shown remarkable proficiency in accurately diagnosing and categorizing lung illnesses.

An approach for the automatic identification of lung nodule images utilizing VGG-SegNet has been proposed and implemented for mining and identifying lung nodules using pre-trained DL models [21]. This method integrates generated features such as the Grey Level Co-Occurrence Matrix, Local Binary Pattern, and Pyramid Histogram of Oriented Gradients, resulting in improved precision in disease identification in pulmonary nodules.

The Internet of Things (IoT) has undergone a lot of advancements for applications in healthcare systems for successful processing and evaluation of patient data. The processing of data generated by IoT medical devices is accomplished via a cloud-based platform, rather than depending on large amounts of storage and computational resources. One of the studies introduces a framework that utilizes DL and IoT connection to automatically identify problematic spots in lung imaging [22]. A CNN model has been developed for extraction of all features from radiological lung image dataset consisting of a collection of various stages of infections. The trained CNN model has displayed excellent performance in classification of healthy and sick lung tissue. The integration of IoT has enabled the capture of data in real-time and thus has allowed seamless connectivity between the diagnostic system and the treatment environment. This study facilitates the comparison of accuracy outcomes among the Resnet model, VGG19 model, VGG16 model, and long short-term memory. Continuous monitoring of patient health is facilitated by employing IoT, which ensures prompt intervention and individualized treatment programs.

A work on related to pulmonary infections by using multi-modal medical images has been proposed for identification, diagnosis, and classification of different types of lung infections using DL models [23]. This study also included a thorough account of the application of these strategies in the treatment of lung nodules, tuberculosis, pneumonia, lung cancer, COVID-19, and interstitial lung disease. This work has examined the utilization of various ML/DL algorithms and transfer learning, envisioning future obstacles and potential prospects in the early detection of various lung infections for investigation, identification, and classification in the context of medical image analysis [24].

A method for identifying and segmenting chronic obstructive pulmonary disease has been developed using pretrained DL models with Parzen's probability density [25]. This study has introduced a model employed with IoMT-based application programming interface for the purpose of classifying lung images and utilizes the mask region-based CNN network to segment the lungs, creating a map of the pulmonary region. Furthermore, fine-tuning was introduced for accurate identification of the boundaries of the lungs on the CT image.

The use of IoT technology in e-healthcare, including remote healthcare for in-hospital patients, has improved the affordability and accessibility of healthcare services [26]. This technique has potential, especially in developing nations where there is a scarcity of healthcare services relative to the demands of the people. Contemporary medical imaging methods have greatly enhanced the precision of illness diagnosis. These technologies have significant advantages in enhancing homecare, particularly for patients with chronic illnesses and the elderly. This results in decreased healthcare expenses and relieves the burden on hospital systems and healthcare personnel. IoT devices in healthcare environments provide huge quantities of data. A work has been introduced that employed the VGG16 model to extract features and devised the SDD300 model for classification. ResNet50 model has been utilized for feature extraction and support vector machine for classification. In addition, they utilized ResNet-101 with five cross-validations [27-29].

A study using the nCOVnet method to detect individuals with COVID-19 is based on transfer learning for identification of the disease utilizing chest X-ray images [28]. In a separate investigation, both image classification and image segmentation methods were utilized to identify lung infections. Edge detection and segmentation algorithms were applied in image processing for detection, identification, and classification purposes. Prior to training, a comprehensive investigation of various edge detection techniques for identifying colloidal crystals was conducted. The study also introduced morphological segmentation as a tool for detecting tumors in brain MR images, which demonstrated the lowest mean square error compared to other segmentation methods investigated. DL models, specifically SqueezeNet and GoogleNet, were used for infection identification, with GoogleNet achieving superior accuracy. CNN models are employed for the classification of complex images, such as breast histopathology images, gene data-generated images, and chest X-ray images [28-32]. A 16-layer CNN model was proposed by Hammad et al. [31] for COVID-19 detection using chest X-ray images. CNNs have shown remarkable performance in handling and analyzing large datasets, particularly when combined with Wavelet Transforms and Metaheuristic Algorithms. Furthermore, the mobility of lung infection patients can be monitored via the Internet of Things (IoT) using sensor-based systems. According to a survey, CNN models demonstrate performance in medical image processing that is comparable to that of human experts in several domains. Several studies have also employed DL models to detect lung infections [33,34].

The IoMT has been utilized in various applications related to bioanalysis with the use of software programs and networked biomedical devices that support many critical healthcare tasks. IoMT refers to the collection and transmission of medical data via a network of interconnected devices, allowing for remote monitoring and analysis. It is believed that IoMT will enable early detection of potential health concerns to individuals and enable proper intervention. Since it enables real-time analysis and continuous data collection, IoMT is a suitable platform for earlier diagnosis of the illness especially for patients staying in remote and rural locations. Additionally, IoMT can help with the management of massive amounts of data from multiple sources, like patient monitors and imaging devices, which is necessary for precise diagnosis. The accuracy and efficacy of DL models in lung cancer prediction have improved with the integration of DL techniques with IoMT devices, a development that has shown encouraging results. Consequently, IoMT is not only significant but also a revolutionary approach to healthcare, especially for oncology.

The suggested framework involves capturing images through IoT devices, analyzing them on a cloud-based infrastructure, and enabling user interaction through a web-based interface. These devices, such as CT scanners, capture lung CT images and transmit them securely to the cloud server where a machine learning model has been deployed to process them, identifying regions indicative of lung infections. These findings are then accessible to users through a web-based interface, allowing healthcare professionals to remotely review and interpret them. A DL model, like CNN, undergoes training to classify lung CT images into infected and non-infected categories. The training utilizes a labeled dataset of CT images annotated to indicate the presence of lung infections. The pre-trained models can employ transfer learning techniques to address the specific task of detecting lung infections, thereby mitigating the requirement for extensive annotated datasets.

An IoT module, presented along with the imaging device, allows for real-time information exchange, diagnosis, and data retrieval while avoiding data loss issues. The key points of this work are:

1) An IoT-based architecture with an e-Health web application has been developed for classification of lung CT images that is both low-cost and scalable.

2) The VGG19 model has been chosen for classification and trained for lung CT image classification via

transfer learning. This model is proposed and hosted on a cloud-based server for online access.

Materials And Methods

In recent literature, many ML models have been utilized for effective analysis and identification of cancer-affected regions in lung images using different types of medical images, such as CT scans and X-ray images. Such systems many a times help the radiologists to address the concern immediately and effectively by means of reduction in interpretation errors, resulting in improvement of diagnostic accuracy. DL algorithms like the CNN have been successfully used in the extraction of features from various medical images connected with and detection of benign and malignant cancer nodules based on the patterns and characteristics in the images.

ML algorithms can develop more comprehensive models for detection of lung cancer with enhanced diagnostic accuracy and improved risk assessment by integrating data from various sources, which include imaging data, clinical data, and genetic information, which help in the capture of more meaningful information about the disease.

The architecture for infected lungs classification is shown in Figure *1*.

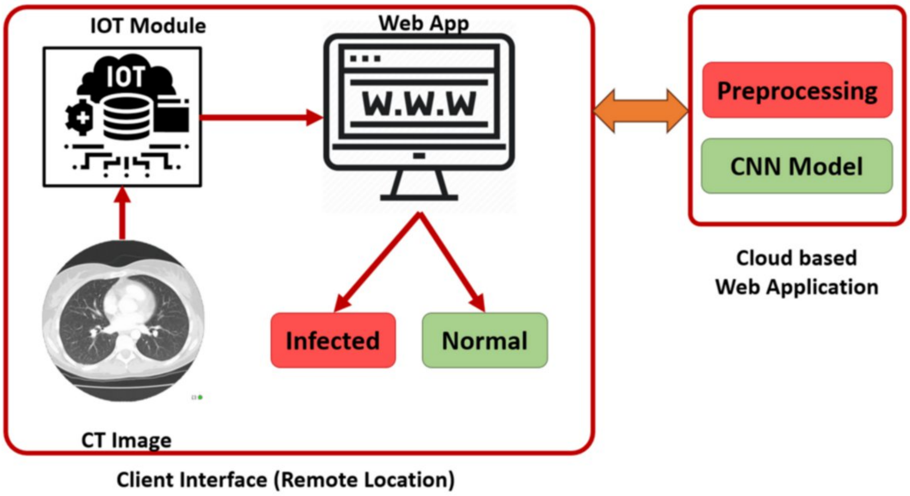

FIGURE 1: Proposed scalable and low-cost architecture for smart healthcare

IoT, Internet of Things; CNN, Convolutional Neural Network

There are two functional units, and they are described as follows.

A. User End

In the client side, the CT scan of the patient is performed by a technician, and then these images are uploaded to the web-based interface by using the IoT module. The IoT module contains a Raspberry Pi 4. The CT images are generated by a CT scan machine, and then processed by a python script running in a Raspberry Pi and is then uploaded to a secure web server with a 256-bit encrypted connection.

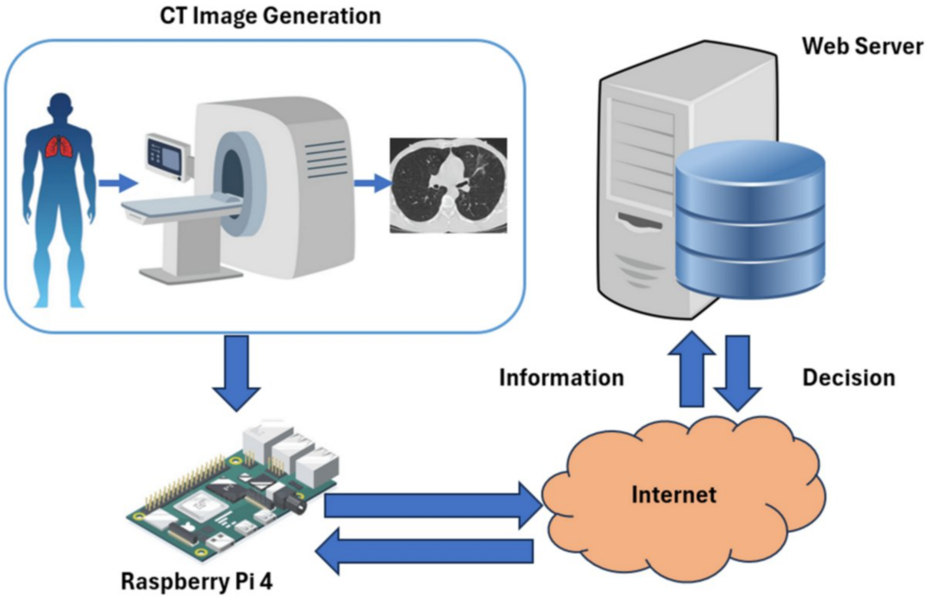

FIGURE 2: Architecture of the IoMT system

IoMT, Internet of Medical Things

The web application running in the web server present in the cloud is responsible for classification of the images as normal or abnormal. This classification information is transmitted back to the client side where the result gets displayed in the web-based interface in the Raspberry Pi. The system architecture utilized in this work has been presented in Figure *2*.

B. Web Architecture

A web application is developed and hosted in the cloud, which performs the classification and detection of lung cancer from the uploaded CT image. This cloud-based application performs necessary preprocessing and then applies the same to a CNN model. Figure *3* represents the algorithm of the proposed framework

Algorithm 1: Proposed Framework

1. Open the Web application using the IOT Module.
2. Enter a CT scan image.
3. IOT module sends the image to the cloud.
4. Image preprocessing is performed.
5. Classification is performed by using the VGG19 model.
6. Result of the classification sent back to the client machine for displaying.

FIGURE 3: Algorithm for the proposed framework

Dataset description

This work utilizes a publicly available chest CT dataset containing 2,482 images (1,252 COVID and 1,230 non-COVID images). These images have been obtained from patients in Sao Paulo, Brazil [35]. The COVID-positive images comprise irregular ground glass opacities (GGOs) that might blend with the dense and consolidative lesions under the pleura and along the bronchovascular networks. These lesions get increased in number and size for higher levels of infections. Additionally, other than the GGOs patterns such as interstitial widening, crazy-paving pattern, halo and reversed halo patterns, airway and vascular variations are also found in CT for COVID-19 cases. The dataset is an almost balanced one; hence, there is no need for balancing the same. The images have been resized to 224 × 224 pixels in accordance with the CNN model employed here, which has been trained for images of the same dimensions. The training and test image sets have been obtained by dividing the original dataset with 80-20% ratio.

Some of the CT scan images of both classes have been shown in Figure 4.

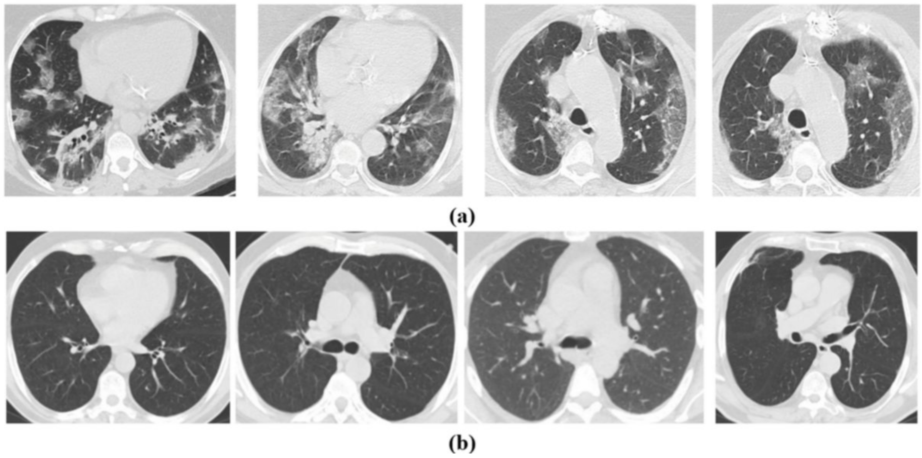

FIGURE 4: Sample images of infected lungs of each category: (a) COVID class and (b) non-COVID class

Data augmentation

The problem of data deficiency has been addressed in the work by using a data augmentation method where new image-label pairs have been generated using the existing images. The augmentation is performed by implementing random transformation like translation and rotation of the images, random crop, and random flip operations. The process of data augmentation has been explained in Figure 5 and Algorithm 2 shown in Figure 6 where the batch size of 40 images has been maintained.

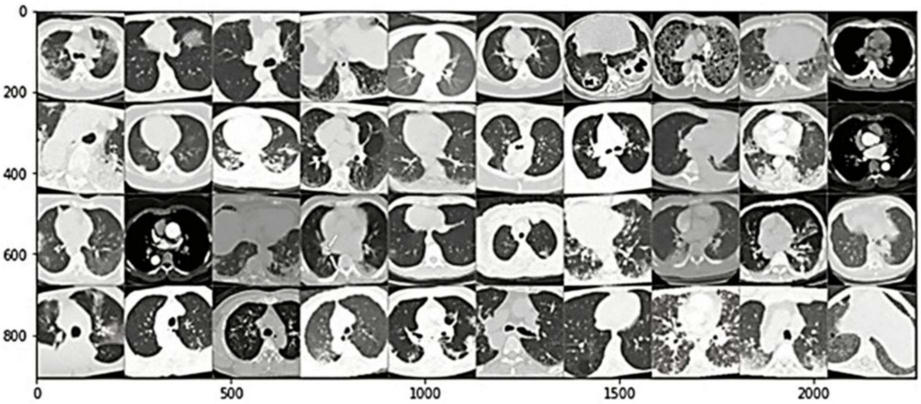

FIGURE 5: Augmented images with batch size = 40

Algorithm 2: Data Augmentation

```
Input: CT Image Dataset
Initialization: Load the Data Transformer model
Training:
train_transform=transformsCompose(transforms)
{
      transforms.RandomRotation=value;
      transforms.RandomHorizontalFlip=probability_value;
      transforms.Resize=imgSize
      transforms.CenterCrop=cropSize
      transforms.ToTensor=a NumPy array or PIL image
      transforms.Normalize=( [meanOfChannel1,meanOfChannel2,meanOfChannel3],
                             [stdOfChannel1, stdOfChannel2, stdOfChannel3]);
                             Return transforms;
                             ] )
      train_data=images. train_transform;
}
Output: Augmented dataset
```

FIGURE 6: The data augmentation algorithm

Different CNN models used in this study

In this study, five widely used CNN models, namely, VGG19, VGG16, ResNet50, InceptionV3, and Xception, were employed for the detection of COVID-19-infected cases from chest CT scan images.

The VGG19 is a deep CNN with 19 layers is a DL model with simple and uniform architecture since it uses small 3 × 3 filters across the network. The VGG16 model is similar to VGG19 but has only 16 layers. Both these models are widely used for image classification applications and are appreciated for their straightforward and consistent design.

The ResNet50 is a 50-layer deep residual network developed by researchers at Microsoft that employs skip connections, or residual connections, which in turn results the gradients to flow without any complications during training, resulting in training very deep networks without encountering the vanishing gradient problem.

The InceptionV3 was introduced in 2015. It employs a combination of convolutions of different sizes within the same module to capture various features at different scales. InceptionV3 is known for its efficiency and high performance specifically in image classification applications, making it a popular alternative in such tasks.

Xception model was introduced in 2016 and stands for “Extreme Inception” since is an extension of the Inception architecture, where the standard Inception modules are replaced with depth wise separable convolutions. This change leads to better performance and efficiency, resulting in the Xception model to be well suited for various image recognition tasks.

Table *1* provides a general comparison of all the models undertaken in this study.

Parameter	VGG19	VGG16	ResNet50	InceptionV3	Xception
Input Size	224 × 224	224 × 224	224 × 224	224 × 224	299 × 299
No. of Layers	19	16	50	42	71
No. of Parameters	143.67M	135M	24M	23.8M	22.9M
Year	2014	2014	2015	2015	2017

TABLE 1: Comparison of different CNN models used in this study

CNN, Convolutional Neural Network

Methodology for transfer learning

The five pre-trained base models are fine-tuned by using the transfer learning method. The base models are created with the same weights used for the 'ImageNet' dataset. The last stages of the base models are modified as per Figure *7*. Then, further transfer learning trains the weights of the last few layers only as the first layers are mostly associated with feature extraction, while the later layers are responsible for the classification action. During the model training process, a dropout rate of 0.3 has been chosen to avoid over-fitting cases. Additionally, the "Categorical Cross Entropy Loss" function has been used as the loss function and the model is trained with the "Adam" optimizer. The training is conducted for 65 epochs with a batch size of 40.

FIGURE 7: Proposed modification of the base architecture

The hyperparameters of the all the base models have been chosen as per Table *2*.

Hyperparameter	Value
Optimizer	Adam
Learning rate	0.001
Loss function	Categorical cross-entropy
Dropout probability	0.3
Batch size	40
Number of epochs	65

TABLE 2: Hyperparameter tuning of the proposed model

Proposed deep ensemble model for COVID-19 detection from chest CT images

The ensemble model combines different models into a single predictive model for effective classification applications. In this work, a deep ensemble model containing five state-of-the-art deep CNN networks has been utilized. They are VGG19, VGG16, ResNet50, InceptionV3, and Xception models. These networks were pretrained on the ImageNet dataset, and their weight were retrained on the chest CT dataset. The corresponding diagram has been presented in Figure 8.

The ensemble model employs a majority voting classifier which takes a number of classifier models to predict the correct label of data based on which option will receive maximum number of votes. Algorithm 3 presented in Figure 9 presents the working of the proposed algorithm.

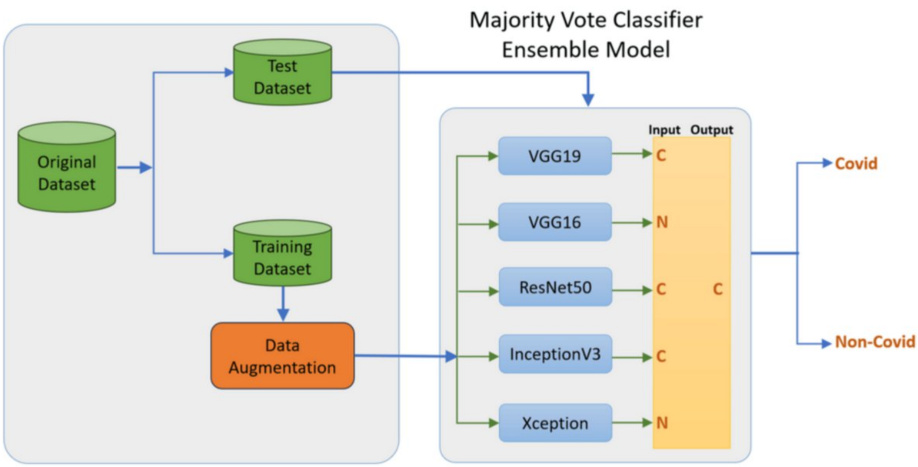

FIGURE 8: Workflow of the proposed deep ensemble CNN model for detecting COVID-19 using chest CT scan images

CNN, Convolutional Neural Network

Algorithm 3 The Proposed Deep Ensemble CNN Algorithm

Input: Chest-X-ray images

Output: The trained model that classifies the Chest CT images

Steps

1. Import a set of pre-trained models
   E = {VGG19, VGG16, Resnet50, InceptionV3, Xception}.
2. For each model in E
3. Replace the last fully connected layer of each model by the structure shown in Figure 6.
4. for epochs = 1 to 20
5. model.fit (train_data, validation_data)
6. Return Class (COVID/non-COVID)

FIGURE 9: The proposed deep ensemble CNN algorithm

CNN, Convolutional Neural Network

Results

This work utilizes a publicly available chest CT dataset containing 2,482 images (1,252 COVID and 1,230 non-COVID images). These images have been obtained from patients in Sao Paulo, Brazil [35].

The training and validation accuracy plots for each of the base models with respect to the epochs are presented in Figures 10-14.

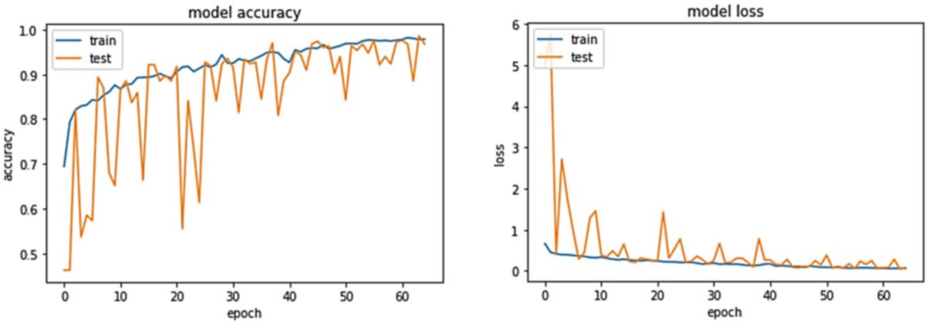

FIGURE 10: Performance of VGG19 model: (a) accuracy curve and (b) loss curve

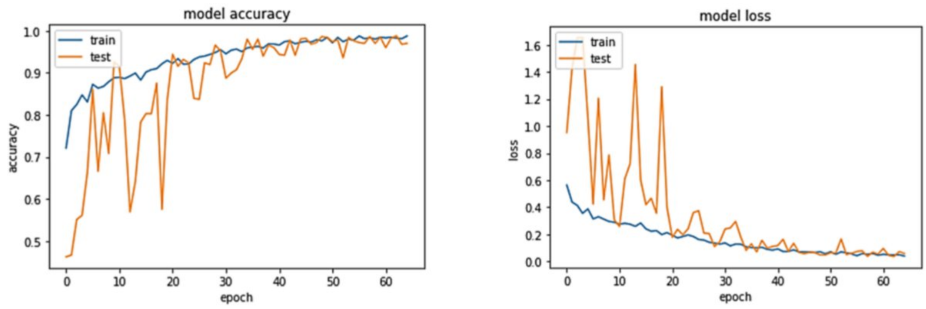

FIGURE 11: Performance of VGG16 model: (a) accuracy curve and (b) loss curve

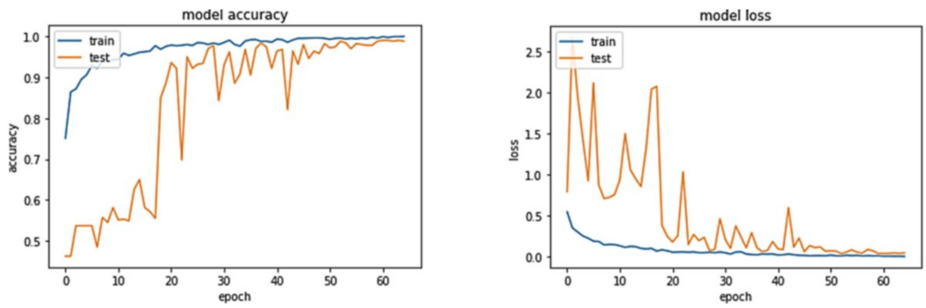

FIGURE 12: Performance of ResNet50 model: (a) accuracy curve and (b) loss curve

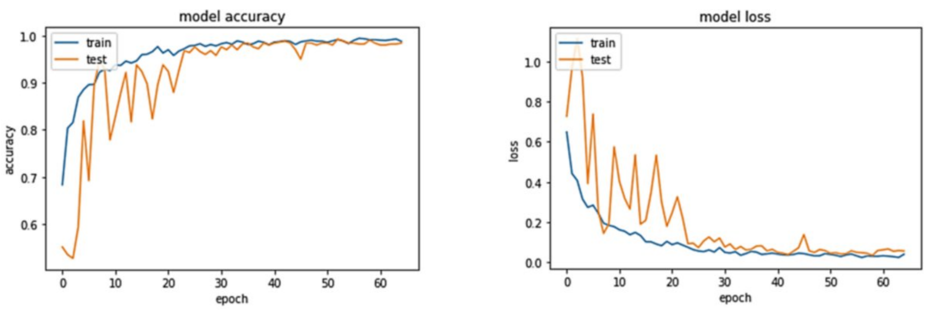

FIGURE 13: Performance of Inception V3 model: (a) accuracy curve and (b) loss curve

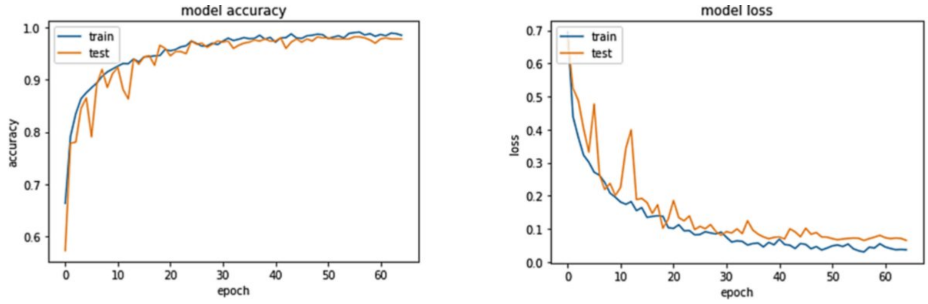

FIGURE 14: Performance of Xception model: (a) accuracy curve and (b) loss curve

The proposed ensemble model's performance is assessed by measuring variables such as Sensitivity, Specificity, Precision, Accuracy, F1-Score, and Mathew's Correlation Coefficient (MCC). Eq. (1) through Eq. (6) provide the mathematical relation of the performance parameters.

$$Accuracy = \frac{(TP)+(TN)}{(TP)+(TN)+(FP)+(FN)} \quad (1)$$

$$Specificity = \frac{(TN)}{(TN)+(FP)} \quad (2)$$

$$Recall = \frac{(TP)}{(TP)+(FN)} \quad (3)$$

$$Precision = \frac{(TP)}{(TP)+(FP)} \quad (4)$$

$$F - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

$$MCC = \frac{(TP)\times(TN)-(FP)\times(FN))}{\sqrt{((TN)+(FN))((TP)+(FP))((TN)+(FP))((TP)+(FN))}}$$

(6)

where, true positives = TP, false positives = FP, true negatives = TN, and false negatives = FN.

The sensitivity is a measure of the model's capability of identifying positive cases. Specificity of true negative rate indicates how well the model identifies negative cases. The recall value is an indicator of how well a classifier is able to find the relevant cases in the dataset. The precision of a model has an inverse relationship with the false positive rate. The accuracy of a model is an indicator of overall correctness of the model, although it might not provide meaningful insights for highly imbalanced datasets. Similarly, a high F1-score indicates that the model has high values of both precision and recall. MCC produces values in [-1, +1], where +1 indicates perfect prediction, 0 indicates similar results to random prediction, and -1 represents total disagreement between prediction and observation.

The training of the proposed model is carried out with Kaggle platform with NVIDIA P100 GPU. The confusion matrix of the classification for the five base models and the proposed ensemble model is presented in Tables *3*-*8*.

	Predicted Label		
True Label		COVID	Non-COVID
	COVID	262	5
	Non-COVID	14	216

TABLE 3: Confusion matrix for VGG19 Model

	Predicted Label		
True Label		COVID	Non-COVID
	COVID	254	13
	Non-COVID	4	226

TABLE 4: Confusion matrix for VGG16 Model

	Predicted Label		
True Label		COVID	Non-COVID
	COVID	258	9
	Non-COVID	6	224

TABLE 5: Confusion matrix for ResNet50 Model

	Predicted Label		
True Label		COVID	Non-COVID
	COVID	256	11
	Non-COVID	5	225

TABLE 6: Confusion matrix for InceptionV3 Model

	Predicted Label		
True Label		COVID	Non-COVID
	COVID	257	10
	Non-COVID	7	223

TABLE 7: Confusion matrix for Xception Model

	Predicted Label		
True Label		COVID	Non-COVID
	COVID	254	2
	Non-COVID	3	227

TABLE 8: Confusion matrix for the proposed deep ensemble CNN model

Table 9 shows the performance parameters such as Sensitivity, Specificity, Precision, Accuracy, F1-Score, and MCC for the base models and the proposed deep ensemble CNN model.

Measure	VGG19	VGG16	ResNet50	InceptionV3	Xception	Deep Ensemble CNN
Sensitivity	0.9493	0.9845	0.9773	0.9808	0.9735	**0.9887**
Specificity	0.9774	0.9456	0.9614	0.9534	0.9571	**0.9913**
Precision	0.9813	0.9513	0.9663	0.9588	0.9625	**0.9924**
Accuracy	0.9618	0.9568	0.9698	0.9678	0.9568	**0.9899**
F1 Score	0.9650	0.9676	0.9718	0.9697	0.9680	**0.9905**
MCC	0.9235	0.9320	0.9394	0.9356	0.9313	**0.9797**

TABLE 9: Performance comparison of the deep ensemble CNN model with the base models

MCC, Matthews Correlation Coefficient; CNN, Convolutional Neural Network

From the confusion matrices presented in Tables 3-8 and Table 9, it can be observed that the proposed deep ensemble CNN model has a Sensitivity value of 0.9887, Specificity of 0.9913, Precision of 0.9924, Accuracy of 0.9899, F1-Score of 0.9905, and MCC of 0.9797. The accuracy of the VGG19, VGG16, ResNet50, InceptionV3, and Xception models is found to be 0.9618, 0.9568, 09698, 0.9678, and 0.9568, respectively.

Table 10 provides a comprehensive comparison of the deep ensemble CNN model with similar works for detection of chest infections. It can be seen that the proposed method achieves an accuracy score of 98.99%.

Authors	Image Type	Classification Model	Accuracy (%)
Ismael and Şengür [14]	X-Ray	ResNet50	94.70
Panwar et al. [15]	X-Ray	nCOVnet	88.00
Alshmrani et al. [17]	X-Ray	VGG19+CNN	96.48
Yang et al. [21]	Chest CT	DenseNet	84.70
Jain et al. [29]	X-Ray	ResNet-101	94.04
Saiz and Barandiaran [32]	X-Ray	SDD300	94.92
Minaee et al. [33]	X-Ray	ResNet18	89.00
Proposed Model	Lungs CT	Deep Ensemble CNN	98.99

TABLE 10: Comparison of performance of the proposed model with similar works

CNN, Convolutional Neural Network

Figures 15 and 16 represent the images of the infected lung and non-infected lung obtained by uploading them via the web application running in the Raspberry Pi.

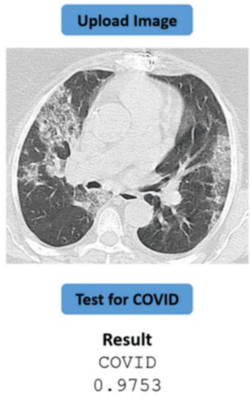

FIGURE 15: Predicted COVID image through web application

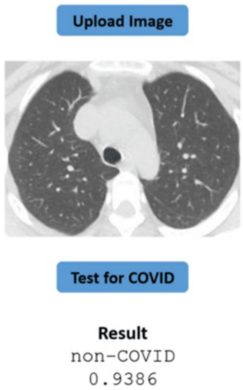

FIGURE 16: Predicted non-COVID image through web application

Discussion

The performance of the proposed deep ensemble CNN model was compared with the results of all the base models used in the study, i.e., VGG19, VGG16, ResNet50, InceptionV3, and Xception models. The results have been presented in Table 9. It has been observed that the proposed model achieves higher performance scores in the values of Sensitivity, Specificity, Precision, Accuracy, F1-Score, and MCC than all the base models. This observation can be attributed to the fact that the ensemble models combine the strengths of individual base models, resulting in an increase in the robustness and accuracy of the prediction process.

The performance of the proposed deep ensemble CNN method has also been compared with several earlier published works as shown in Table 10. The accuracy of the proposed model is found to be 98.99%, whereas other models considered in this study show accuracies between 88% and 96.48%. Thus, the proposed method has been observed to outperform all the other models. This can be credited to the fact that the rest of the models are standalone models like VGG19, ResNet50, nCOVnet etc., where as the proposed model is an ensemble model.

It can be observed that the proposed deep ensemble CNN model has better performance than the base models utilized for the ensemble, and hence it is a suitable candidate for implementation in the IoMT framework.

It can be observed that the majority of the works cited in Table 10 have been proposed for classification and detection of lung diseases only while the proposed framework integrates IoT and cloud-based web application for effective classification and remote access.

The improved performance of the proposed work can be attributed to the deep ensemble CNN model. This framework can be implemented and used via remote access in a contactless manner, which adheres to COVID 19 protocol of social distancing and can avoid additional dissemination of the disease. The data is stored in a secure server in the cloud where it can only be accessed with proper validation of credentials.

Conclusions

The proposed IoT-based web application framework offers a scalable and accessible solution for the detection and analysis of infected lung CT images. In this work, a cloud classification model using a deep ensemble CNN network has been implemented. The constituent pretrained networks have undergone transfer learning for classifying the Chest CT images. In order to improve the training dataset, a data augmentation scheme has been employed. The experimentation provides 98.99 % accuracy that surpasses the performance of many other techniques available in literature. The proposed deep ensemble CNN network, with its deep architecture and mathematical representations, offers a powerful technique using CNNs and DL techniques, for detection of COVID-19 in an earlier stage can be improved, leading to better patient treatment, care and enhanced survival rates. The use of proposed deep ensemble CNN network holds promise for accurate and efficient lung cancer detection, contributing to advancements in medical imaging and patient care. Further research could focus on fine-tuning the model using larger and more diverse datasets. The following is a list of how the current research can proceed further.

Integration of additional clinical data and advanced image preprocessing techniques may enhance the model’s performance. Also, the deployment of the trained model into clinical settings for real-time detection could be explored. Fine-tuning of the model for efficiency and reducing computational resources required for IoT deployment. The developed framework in this paper based on an IoMT web application for CT imaging of diseased lungs is a notable progress in healthcare technology. However, it may be extended for other different medical images.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Mihir N. Mohanty, Gyana R. Patra, Bibhuprasad Mohanty

Critical review of the manuscript for important intellectual content: Mihir N. Mohanty, Gyana R. Patra, Bibhuprasad Mohanty

Supervision: Mihir N. Mohanty, Bibhuprasad Mohanty

Acquisition, analysis, or interpretation of data: Subhadarshini Das, Goutami Das

Drafting of the manuscript: Subhadarshini Das, Goutami Das

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue.
Animal subjects: All authors have confirmed that this study did not involve animal subjects or tissue.
Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

References

1. Karar ME, Khan ZF, Alshahrani H, Reyad O: Smart IoMT-based segmentation of coronavirus infections using lung CT scans. Alexandria Engineering Journal. 2023, 69:571-583. 10.1016/j.aej.2023.02.020
2. World Health Organization: Global Surveillance, Prevention and Control of Chronic Respiratory Diseases: A Comprehensive Approach. Bousquet J, Khaltaev N (ed): World Health Organization, Switzerland; 2007.
3. Ahuja S, Panigrahi BK, Dey N, Taneja A, Gandhi TK: McS-Net: Multi-class Siamese network for severity of COVID-19 infection classification from lung CT scan slices. Applied Soft Computing. 2022, 131:109683. 10.1016/j.asoc.2022.109683
4. Kumari KS, Samal S, Mishra R, Madiraju G, Mahabob MN, Shivappa AB: Diagnosing COVID-19 from CT image

of lung segmentation & classification with deep learning based on convolutional neural networks. Wireless Personal Communications. 2021, 127:2483-2499. 10.1007/s11277-021-09076-w
5. Thandapani S, Mahaboob MI, Iwendi C, Selvaraj D, Dumka A, Rashid M, Mohan S: IoMT with deep CNN: AI-based intelligent support system for pandemic diseases. Electronics. 2023, 12:424. 10.3390/electronics12020424
6. Hussain Ali Y, Chinnaperumal S, Marappan R, Raju SK, Sadiq AT, Farhan AK, Srinivasan P: Multi-layered non-local Bayes model for lung cancer early diagnosis prediction with the Internet of Medical Things. Bioengineering. 2023, 10:138. 10.3390/bioengineering10020138
7. Merabet A, Saighi A, Laboudi Z, Ferradji MA: Multiple diseases forecast through AI and IoMT techniques: systematic literature review. Intelligent Systems and Pattern Recognition. Bennour A, Bouridane A, Chaari L (ed): Springer, Cham; 2024. 1940:189-206. 10.1007/978-3-031-46335-8_15
8. Rajagopalan S, Janakiraman S, Rengarajan A, Rethinam S, Arumugham S, Saravanan G: IoT framework for secure medical image transmission. 2018 International Conference on Computer Communication and Informatics (ICCCI). 2018, 1-5. 10.1109/ICCCI.2018.8441284
9. Khan SH, Iqbal J, Hassnain SA, Owais M, Mostafa SM, Hadjouni M, Mahmoud A: COVID-19 detection and analysis from lung CT images using novel channel boosted CNNs. Expert Systems with Applications. 2023, 229:120477. 10.1016/j.eswa.2023.120477
10. Yadav S, Rizvi SAM, Agarwal P: Detection of lung diseases for pneumonia, tuberculosis, and COVID-19 with artificial intelligence tools. SN Computer Science. 2024, 5:303. 10.1007/s42979-024-02617-7
11. Elharrouss O, Subramanian N, Al-Maadeed S: An encoder-decoder-based method for segmentation of COVID-19 lung infection in CT images. SN Computer Science. 2022, 3:13. 10.1007/s42979-021-00874-4
12. Rahman MM, Nooruddin S, Azharul Hasan KM, Dey NK: HOG + CNN Net: diagnosing COVID-19 and pneumonia by deep neural network from chest X-ray images. SN Computer Science. 2021, 2:371. 10.1007/s42979-021-00762-x
13. Arias-Garzón D, Alzate-Grisales JA, Orozco-Arias S, et al.: COVID-19 detection in X-ray images using convolutional neural networks. Machine Learning with Applications. 2021, 6:100138. 10.1016/j.mlwa.2021.100138
14. Ismael AM, Şengür A: Deep learning approaches for COVID-19 detection based on chest X-ray images. Expert Systems with Applications. 2021, 164:114054. 10.1016/j.eswa.2020.114054
15. Panwar H, Gupta PK, Siddiqui MK, Morales-Menendez R, Singh V: Application of deep learning for fast detection of COVID-19 in X-rays using nCOVnet. Chaos Solitons & Fractals. 2020, 138:109944. 10.1016/j.chaos.2020.109944
16. Amyar A, Modzelewski R, Li H, Ruan S: Multi-task deep learning based CT imaging analysis for COVID-19 pneumonia: Classification and segmentation. Computers in Biology and Medicine. 2020, 126:104037. 10.1016/j.compbiomed.2020.104037
17. Alshmrani GMM, Ni Q, Jiang R, Pervaiz H, Elshennawy NM: A deep learning architecture for multi-class lung diseases classification using chest X-ray (CXR) images. Alexandria Engineering Journal. 2023, 64:923-935. 10.1016/j.aej.2022.10.053
18. Muhammad Y, Alshehri MD, Alenazy WM, Vinh Hoang T, Alturki R: Identification of pneumonia disease applying an intelligent computational framework based on deep learning and machine learning techniques. Mobile Information Systems. 2021, 2021:9989237. 10.1155/2021/9989237
19. Khan MA, Rajinikanth V, Satapathy SC, Taniar D, Mohanty JR, Tariq U, Damaševičius R: VGG19 network assisted joint segmentation and classification of lung nodules in CT images. Diagnostics. 2021, 11:2208. 10.3390/diagnostics11122208
20. Xiao AT, Tong YX, Zhang S: Profile of RT-PCR for SARS-CoV-2: A peliminary study from 56 COVID-19 patients. Clinical Infectious Diseases. 2020, 71:2249-2251. 10.1093/cid/ciaa460
21. Yang X, He X, Zhao J, Zhang Y, Zhang S, Xie P: COVID-CT-Dataset: A CT scan dataset about COVID-19. arXiv:2003.13865. 10.48550/arXiv.2003.13865
22. Prabakaran J, Selvaraj P: Advance IoT intelligent healthcare system for lung disease classification using ensemble techniques. Computer Systems Science and Engineering. 2023, 46:2141-2157. 10.32604/csse.2023.034210
23. Al-Sheikh MH, Al Dandan O, Al-Shamayleh AS, Jalab HA, Ibrahim RW: Multi-class deep learning architecture for classifying lung diseases from chest X-Ray and CT images. Scientific Reports. 2023, 13:19373. 10.1038/s41598-023-46147-3
24. Mohanty MN, Das A: Skin cancer detection from dermatoscopic images using hybrid fuzzy ensemble learning model. International Journal of Fuzzy Systems. 2024, 26:260-273. 10.1007/s40815-023-01593-z
25. Souza LFdF, Silva ICL, Marques AG, et al.: Internet of medical things: an effective and fully automatic IoT approach using deep learning and fine-tuning to lung CT segmentation. Sensors. 2020, 20:6711. 10.3390/s20236711
26. Sarangi L, Mohanty MN, Pattanayak S: Design of MLP based model for analysis of patient suffering from influenza. Procedia Computer Science. 2016, 92:396-403. 10.1016/j.procs.2016.07.396
27. Jasmine Pemeena Priyadarsini M, Kotecha K, Rajini GK: Lung diseases detection using various deep learning algorithms. Journal of Healthcare Engineering. 2023, 2023:3563696. 10.1155/2023/3563696
28. Ghosh Argho A, Maswood MMS, Mahmood MI, Mondol N: EfficientCovNet: A CNN-based approach to detect various pulmonary diseases including COVID-19 using modified EfficientNet. Intelligent Systems with Applications. 2024, 21:200315. 10.1016/j.iswa.2023.200315
29. Jain G, Mittal D, Thakur D, Mittal MK: A deep learning approach to detect Covid-19 coronavirus with X-ray images. Journal of Applied Biomedicine. 2020, 40:1391-1405. 10.1016/j.bbe.2020.08.008
30. Mallick PK, Satapathy BS, Mohanty MN, Kumar SS: Intelligent technique for CT brain image segmentation. 2015 2nd International Conference on Electronics and Communication Systems (ICECS). 2015, 1269-1277. 10.1109/ECS.2015.7124789
31. Hammad MS, Ghoneim VF, Mabrouk MS, Al-atabany WI: A hybrid deep learning approach for COVID-19 detection based on genomic image processing techniques. Scientific Reports. 2023, 13:4003. 10.1038/s41598-023-30941-0
32. Saiz FA, Barandiaran I: COVID-19 detection in chest X-ray images using a deep learning approach.

International Journal of Interactive Multimedia and Artificial Intelligence. 2020, 11-14. 10.9781/IJIMAI.2020.04.003

33. Minaee S, Kafieh R, Sonka M, Yazdani S, Jamalipour Soufi G: Deep-COVID: Predicting COVID-19 from chest X-ray images using deep transfer learning. Medical Image Analysis. 2020, 65:101794. 10.1016/j.media.2020.101794
34. Das A, Mohanty MN, Mallick PK, Tiwari P, Muhammad K, Zhu H: Breast cancer detection using an ensemble deep learning method. Biomedical Signal Processing and Control. 2021, 70:103009. 10.1016/j.bspc.2021.103009
35. Soares E, Angelov P, Biaso S, Froes MH, Abe DK: SARS-CoV-2 CT-scan dataset: A large dataset of real patients CT scans for SARS-CoV-2 identification. medRxiv. 2020, 10.1101/2020.04.24.20078584