

DeepCOVID: a deep learning approach for accurate COVID-19 detection in point-of-care lung ultrasound

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ABSTRACT

Sickness still continued to spread through several countries when it first appeared in China. The number of COVID-19 cases is rising daily worldwide, posing a severe threat to the government and the populace. As a result of the virus's rapid spread, doctors are having trouble recognizing positive cases. It is obvious that computer-based diagnosis must be developed to get results at a reasonable cost. The classic convolutional neural network (CNN) is used for this, utilizing the CT dataset, and the upgraded CNN model is used with the lung ultrasound (LUS) dataset. The CT and LUS COVID imaging datasets are compared in the model. The accuracy of both deep learning models is higher. We customized ResNet50, a pre-trained deep learning architecture, for a web application paradigm. First, we suggest a method for normalizing data that addresses its variability because it is collected in hospitals using various CT scanners and ultrasound machines. Second, we identify COVID-19 patients using U-Net segmentation and classification. The CNN architecture is added for deep learning purposes, and Res-Net 50 offers incredible accuracy.

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1. INTRODUCTION

Ensuring patient isolation and effective pandemic control underscore the importance of early COVID-19 detection for both individual care and public health. Key measures include screening, rapid diagnosis, and the isolation of infected individuals from the healthy population. Clinical manifestations encompass pneumonia, fever, cough, dyspnea, and respiratory symptoms, which, though common in pneumonia, do not exclusively signify COVID-19, posing a challenge for accurate diagnosis. Since the first reported cases, COVID-19 has rapidly spread worldwide, causing a considerable number of fatalities due to acute respiratory infections. The disease's high contagion necessitates continuous efforts for detection. Nucleic acid tests from throat and nasopharyngeal swabs are currently the primary diagnostic method, yet sampling inaccuracies and low viral load can yield inaccurate results. Antigen tests offer quicker results but exhibit lower sensitivity. Pathological investigations and radiographic examinations, such as chest CT and X-ray imaging, contribute to diagnosis. Deep learning models analyzing these images aim to enhance accuracy, but limited contaminated samples for training hinder sensitivity and accuracy. The coronavirus family, including SARS-CoV-2, causes respiratory illnesses. Unlike predecessors SARS-CoV and MERS-CoV, COVID-19 symptoms may appear quickly or mildly, allowing spread through asymptomatic individuals, contributing to the pandemic. While the WHO emphasizes widespread testing, not all nations possess necessary laboratory resources, leading to delayed results and potential spread by asymptomatic

individuals. Lung ultrasound (LUS) emerges as a portable, cost-effective, and non-invasive alternative to CT and X-ray imaging. Computer-assisted analysis of LUS images holds promise for identifying pulmonary illnesses. This study delves into the effectiveness of various deep-learning approaches for detecting COVID-19 infections through lung ultrasound data, offering a novel perspective in the ongoing battle against the pandemic. The importance of COVID-19 detection by artificial intelligence (AI) lies in its potential to enhance and streamline the diagnostic process, aid healthcare professionals in timely decision-making, and contribute to effective management and control of the pandemic. Figure 1 shows the importance of using AI based detection.

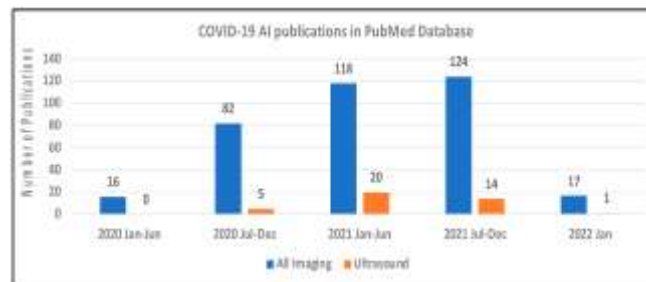


Figure 1. The number of COVID-19 AI publications based on ultrasound (orange bars) and CT, X-ray and ultrasound combined (blue bars) in PubMed database, as of 17 January 2022 [1]

Some key points highlighting the significance of AI in COVID-19 detection are:

- Medical professionals have a new tool at their disposal: AI algorithms capable of assessing large amounts of medical information at remarkable speed while maintaining accuracy in diagnosis through advanced machine learning and deep learning techniques. These models can assist in identifying COVID 19 cases by evaluating lab results, clinical records, and radiological images.
- Traditional testing methods like rapid test (RT) polymerase chain reaction (PCR) tests could experience delays with lengthy turnaround times or even produce false negative results for COVID 19 diagnosis alone; therefore an alternative method like analyzing chest X-rays or CT scans becomes valuable especially given limited resources during periods of low testing capacities.
- Optimizing patient management strategies through the allocation of resources is possible utilizing any information gathered that involves symptoms along with imaging from healthcare providers which allows them to differentiate high risk COVID 19 cases or any other type of medical issue that requires attention.
- Identifying potential cases in groups like high risk populations has increased accuracy due to AI powered screening systems which can identify individuals with travel history or known close contact with infected people. By leveraging AI for early detection of COVID-19 cases, public health authorities can implement prompt containment measures, including isolation, contact tracing, and targeted testing. By identification and isolation of infected individuals can help break the chains of transmission and reduce the spread of the virus.
- Insights for research and public health planning: AI-driven analytics can aid researchers and policymakers in gaining insights into disease patterns, transmission dynamics, and the effectiveness of interventions. By analyzing large-scale data, AI can contribute to the development of predictive models, epidemiological studies, and evidence-based decision-making.
- Remote healthcare and telemedicine: AI-enabled tools can facilitate remote healthcare delivery, telemedicine consultations, and remote monitoring of COVID-19 patients. This minimizes the risk of exposure for healthcare providers and patients while ensuring timely access to medical expertise and necessary care. The collaboration between AI experts, healthcare professionals, and regulatory bodies is crucial for the responsible and effective deployment of AI in COVID-19 detection and management.

Our key contributions can be outlined as follows:

- Utilizing ResNet50 deep learning (DL) models to implement and evaluate COVID-19 screening in LUS imaging.
- Demonstrating that these DL models surpass the latest classifiers in categorizing COVID-19, pneumonia, and healthy cases on CT images.
- Proposing that the developed models could serve as a fundamental basis for the future development of computer-assisted COVID-19 screening tools using LUS imaging.

- Highlighting the potential of LUS as a viable alternative for creating computer-assisted COVID-19 screening tools when CT or X-ray screening is not readily accessible.
- Emphasizing the application of DL methods in the LUS-based computer-assisted analysis of lung diseases, a research area with distinctive advantages over CT imaging, particularly in the context of deploying e-Health applications.

2. METHODS

Deep learning in medical image-based diagnosis, particularly using convolutional neural networks (CNNs), has seen significant growth. CNNs outperform traditional models in tasks such as breast cancer detection, lung disease analysis, endoscopy image interpretation, chest radiography Computer aided diagnosis (CAD), skin cancer diagnosis, and diverse chest disease diagnosis through X-ray classification. The success of CNNs highlights their versatility in medical image processing. The emergence of COVID-19 has further spurred research using deep learning to address diagnostic and management challenges, showcasing the ongoing commitment of the scientific community in this field. Weinstock *et al.* [2] analyzed 636 chest X-rays (CXR) from confirmed COVID-19 patients, with a gender distribution of 57.1% male and 42.9% female. Patients, aged 18 to 90 years, predominantly fell within the 30-70 years age group (77.5%). Of all CXRs, 58.3% were normal, while 41.7% exhibited abnormalities, categorized as mild (29.1%), moderate (10.2%), and severe (0.8%). Common findings in abnormal cases were interstitial changes (23.7%) and ground glass opacities (18.9%). Abnormalities were mainly in the lower lobe (33.8%), with bilateral involvement (20.9%) and multifocal abnormalities (24.2%). Effusions and lymphadenopathy were less frequent. These patterns highlight predominantly mild to moderate disease with specific radiological manifestations, contributing valuable insights into the characterization of COVID-19 on chest X-rays. In China and Italy, chest X-rays and RT-PCR and CT scans have been utilized to screen and monitor COVID-19 patients [3]. Similarly, British hospitals have started incorporating chest X-rays as a primary tool for triaging COVID-19 patients due to the extended turnaround times associated with RT-PCR testing. Chest radiographs and CT scans often exhibit similar abnormalities in COVID-19 patients, typically presenting with bilateral, peripheral consolidation, and ground-glass opacities. The severity of chest radiograph abnormalities tends to peak around 10-12 days from symptom onset, aligning with the peak seen in CT findings at 6-11 days. However, studies have shown chest X-rays have lower sensitivity than CT scans. Wong *et al.* [4] reported a sensitivity of 69% for baseline chest X-rays, significantly lower than the 97 to 98% sensitivity reported for CT scans.

Akram *et al.* [5] preprocessed CT data by proposing extraction and selection schemes of relevant features to classify COVID-19 and normal scans. They tested several classifiers obtaining an accuracy of 92.6% with a Naive Bayes classifier. The most prominent work based on X-ray images was developed by Wang *et al.* [6]. They devised COVID-Net, a convolutional architecture trained with a dataset comprising 13,975 X-ray images. COVID-net attained an accuracy of 93.3% and sensitivities of 95%, 94%, and 91%, for normal, non-COVID, and COVID-19 infection, respectively. Islam *et al.* [7] discovered that the data's uncertainty is the primary obstacle to COVID19 diagnosis based on symptoms. The majority of COVID-19-infected individuals were hospitalized because to a high temperature, a coughing up of phlegm, and shortness of breath, according to the study's findings. Once infected with COVID-19, patients with hypertension, cardiovascular disease, and rapid pulse rates quickly advance to the next stage. Respiratory failure, septic shock, and multiple organ failure could occur after the infection develops into acute respiratory disease syndrome (ARDS). It is feasible to determine an infection status based on the symptoms. There are three categories for the result, or infected status: not infected, mildly infected, and severely infected.

Khaleel *et al.* [8] explores the utilization of Hive on a Hadoop cluster for querying and analyzing COVID-19 datasets, presenting a comparative analysis with traditional relational database management system (RDBMS). Various Hive properties and parameters, including compression, MapReduce strict mode, parallel reduce tasks, cost-based optimization, and optimized record columnar, were fine-tuned to enhance the proposed approach. The study conducted multiple experiments on a cluster of eight virtual machines to evaluate performance. Results demonstrate the superiority of the proposed approach over RDBMS in terms of query processing time and scalability. The findings also reveal improved performance in data load, input/output (I/O) operations, network data transfer, query execution time, and data read and write through the optimization of key Hive parameters. The application [9] of the Bradley thresholding method in segmenting thorax X-ray images successfully delineated the thoracic area and identified white patches. This segmentation technique proves effective in simplifying the analysis of X-ray images for individuals with COVID-19, yielding more accurate and precise image information. A significant distinction was observed in the average percentage of white patches between thorax X-ray images of COVID-19 patients and those of normal patients, with a notable 5.75956% difference and testing success rates of 73.33% and 54%, respectively. Future research endeavors will focus on further classification of COVID-19 severity,

incorporating additional diagnostic features to enhance the diagnostic process. Early diagnosis of COVID-19 is challenging due to its rapid spread.

Shamrat *et al.* [10] explores the potential of deep learning methods and soft computing for precise and expedited diagnostics. Eight deep learning models were evaluated, revealing that the MobileNetV2 model outperformed others in terms of accuracy, average data loss, and compilation time. While VGG19 exhibited the lowest data loss rate, its longer completion time and lower accuracy compared to MobileNetV2 were noted. The study suggests future research should focus on developing a hybrid deep learning method capable of efficiently assessing a large volume of images and quantifying the extent of lung infection for enhanced diagnostic capabilities. The proposed [11] system integrates heat and hygrometer sensors to monitor patients' conditions and create an optimal environment. A microcontroller forms the core of a smart monitoring system, remotely alerting healthcare professionals through lights and alarm signals in emergency situations. The system prioritizes privacy and confidentiality through the use of a medical application, safeguarding against data breaches and sabotage attempts. With a focus on easy implementation, the system ensures high accuracy, enhanced security, and cost-effectiveness, making it a practical solution for healthcare monitoring. A comprehensive review [12] of deep learning and machine learning approaches applied to the diagnosis of the COVID-19 outbreak in Malaysia. The aim is to synthesize existing research and applications related to COVID-19. The selected studies, sourced from reputable databases, are categorized into machine learning and deep learning approaches. Notably, support vector machines (SVM) and CNN emerge as the most popular algorithms for COVID-19 diagnosis. Moreover, a limited number of researchers have employed machine learning or deep learning for forecasting the COVID-19 outbreak in Malaysia. Machine learning algorithms such as SVM [13], linear discriminant analysis (LDA) [14], adaptive neuro-fuzzy inference system (ANFIS) [15], and Naive Bayes, along with deep learning algorithms like long short term memory (LSTM), deep neural network (DNN), recurrent neural networks (RNN), NN-TF and NN-Keras [16], are employed for both COVID-19 diagnosis and epidemic prediction. SVM is identified as the most commonly used machine learning mechanism, while LSTM stands out as the predominant deep learning mechanism in this context. A deep learning model with two stages of computation training and inference is employed in [17]. To create a model using training data, stochastic computation is utilized in an iterative training process. Before training, a variety of factors, including learning rate, epoch number, and batch size, must be established. Depending on the configuration, the accuracy of the resulting models will vary. A deep learning model that has been trained uses inference as a prediction method. There are certain well-known deep learning architectures, such as CNNs and RNN.

A hybrid learning paradigm [18] capable of intelligently mixing various machine learning models to deliver more reliable and accurate prediction outcomes than a single model. A multilayer neural network that can provide predictions based on higher level properties that are gradually extracted from unprocessed data, such photos. COVIDNet, a cutting-edge open-sourced deep CNN for COVID-19 case recognition from CXR pictures, is the foundation of EDL-COVID. Using cooperative training methods [19] that do not require a single pool of centralized data, FL is an ML architecture to address the data privacy problem. A good example of FL deployment in a medical scenario FL is an iterative process. AI and blockchain technology [20] can offer workable solutions to address many facts of the coronavirus epidemic. In reality, blockchain has been used in the context of other contagious epidemics, such as the Ebola virus, to conduct real-time contact tracing, monitor transmission patterns, and administer vaccines. It also demonstrates how the blockchain's cryptography capabilities can assist avoid insecure data sharing between patients and healthcare entities like providers. Blockchain can actively simplify the process of accelerating medication trials, recording and tracking all fundraising actions and donations in an immutable manner, and supporting the management of outbreaks and treatments in the fight against the coronavirus. In response to the urgent need for reliable COVID-19 diagnostic tools during the 2020 outbreak, research [21] addresses the limitations of traditional computed tomography (CT) scans by focusing on LUS imaging. Collaborating with the emergency department at fondazione IRCCS Policlinico San Matteo in Pavia, the study develops an advanced deep learning system to enhance the accuracy and reliability of LUS [22]–[26]. The goal is to provide a cost-effective and accessible alternative to expensive and contamination-prone CT scans. By emphasizing the potential of radiation-free LUS in early detection and monitoring of pulmonary conditions, the study aims to contribute valuable insights into the role of deep learning in COVID-19 diagnosis. The findings aspire to support healthcare workers with practical tools for prompt identification and management of Covid 19 cases, marking significant advancement in diagnostic capabilities during outbreaks.

3. PROPOSED METHOD

3.1. Module description

This project requires deep learning techniques. It is implemented in Windows 10, Pycharm, Xampp and Google Colaboratory. It uses Keras, TensorFlow, NumPy, flask, and tqdm libraries. It is implemented in Python 3. It requires deep learning techniques of CNN, ResNet50.

3.1.1. Steps for executing

To execute the process, initially, one needs to undertake several steps. These include installing the required packages, loading the datasets, and combining them into a unified dataset. Subsequently, the data needs to be pre-processed, followed by the crucial step of splitting the dataset into training and testing sets. Then, utilizing the training dataset, the DCNN model with five layers is trained. Finally, the model's performance is assessed by using the test data to make predictions and generate accuracy metrics.

3.1.2. Data preprocessing

Data preprocessing: before start exploring preprocessing techniques, first explore the RGB channels of our original image. Process of shifting image pixels horizontally or vertically. Flipping: this reverses the rows or columns of pixels in vertical or horizontal cases. Rotation: this process involves rotating an image by a specified degree. Cropping is the process of selecting a random portion of an original image and resizing it to match the original image's dimensions. Scaling: scaling an image can be done both inward and outward. An image becomes more significant than the original as it is scaled outward, and vice versa. Standardizing images, standardization is a technique that preprocesses and scales photographs to give them comparable heights and widths. Data is rescaled to have a mean of 0 and a standard deviation of 1 (unit variance). Data consistency and quality are enhanced through standardization.

3.1.3. Feature extraction

Feature extraction: using CNN It is a transfer learning method. It uses a pre-trained model already trained on massive datasets. Using the model, the features are extracted and used further. The pre-trained model ResNet50 is trained on the LUS dataset that can classify 2 different classes. The model is directly imported from Keras applications. The ResNet50 model takes image size input as $299 \times 299 \times 3$. Since ResNet50 model is used to extract the feature vector, the last classification layer is removed. Thus will obtain a 2,048 feature vector. From the images, the features are extracted and the respective feature array is created by extracting features corresponding to the images.

3.2. Discussion

Developing a unique CNN model from scratch is a key aspect of our approach, utilizing a distinctive image dataset designed for both training and testing purposes. The proposed model, as illustrated in Figure 2, undergoes training, validation, and testing phases through a strategic division of the dataset. Leveraging the validation-set strategy, we carefully train the model in Google Colab, assessing its performance through classification reports and confusion matrices on both testing and validation datasets.

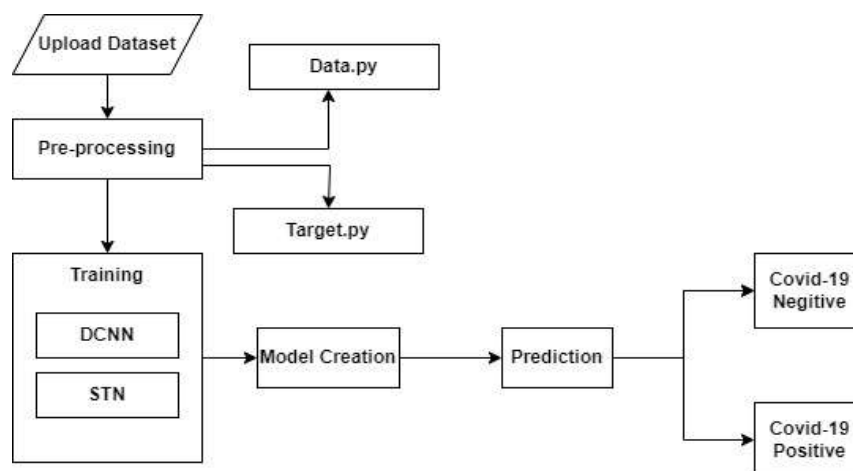


Figure 2. Overall proposed model

Our focus is on building a CNN model for COVID-19 using TensorFlow, specifically on a multiclass dataset comprising CT scans. The aim is to train the CNN model to distinguish CT scans belonging to COVID patients, those with other pulmonary disorders excluding COVID, and scans of healthy patients. The problem encompasses three classes: COVID, healthy, and other pulmonary disorders (referred to as 'others'). Image pre-processing is initiated by reshaping all images to the desired size (100×100) and normalizing them by dividing pixel values by 255. The dataset is systematically divided into training, testing, and validation sets. A total of 3,002 images belong to the training set, 751 to the validation set, and 418 to the test set. In constructing the CNN model, Conv2D layers are added to extract features, MaxPooling2D layers for downsampling, and batch normalization layers to enhance training and validation accuracies. The CNN architecture incorporates four Conv2D and MaxPooling layers. The convolutional layer parameters are fine-tuned for optimal model performance. Following the convolution and maxpooling layers, batch normalization is applied, and the input layer is introduced using the Flatten () function. There are no hidden layers, as they did not contribute to improving model performance during training. The output layer is then added, utilizing the Dense () function with three parameters to correspond to the three categories: COVID, healthy, and others. The softmax function is employed as the activation function, given the multi-class nature of the problem. The common Adam optimizer is used, and due to the categorical nature of the labels, sparse categorical cross-entropy loss function is chosen. To mitigate overfitting, early stopping is implemented, terminating training when a sudden increase in validation loss is detected. Our custom CNN model undergoes training for 30 epochs, but early stopping intervenes at the 16th epoch. Consequently, the model achieves a training accuracy of 85% and a validation accuracy of 80%. The test dataset exhibits an accuracy of 75%, demonstrating consistent performance comparable to the validation dataset. In the second model, LUS images of the covid dataset is used. The dataset is randomly divided for training and testing. After preprocessing, the ResNet50 model is used for train the model. The prediction of this model is COVID-19 positive and negative. It provides 98% accuracy and it is better than other methods

Dataset include the image data of the COVID-19 patient. Here using two dataset for comparison of two different methods. One dataset which contains LUS images of COVID-19 patients of two classes are positive, negative. Another dataset which contains CT images of COVID patient having 3 classes are Normal, COVID and other. LUS dataset uses the ResNet50 method for detection and CT images using the traditional CNN for prediction. Both dataset are collected from Kaggle. LUS contain 2435 total images and 3002 images are in the CT image dataset.

4. RESULTS AND DISCUSSION

To enhance the context and substantiate the novelty of our findings, a comparison with results from other published articles is strongly recommended. Our custom CNN model underwent training for 30 epochs, but early stopping occurred at the 16th epoch. Consequently, the model was trained only for 16 epochs, concluding with a training accuracy of 85% and a validation accuracy of 80%. Subsequently, the model demonstrated an accuracy of 75% on the test dataset, exhibiting a performance consistent with that of the validation dataset. The graphical representation of these results is depicted in Figure 3. In the second model, LUS images from the COVID dataset were utilized, introducing a novel dimension to our investigation. This approach broadens the scope of our analysis and contributes to a more comprehensive understanding of the performance of CNN models in the context of COVID detection. The dataset is randomly divided for training and testing. After preprocessing, the ResNet50 model is used for train the model. The prediction of this model is COVID-19 positive and negative. It provides 98% accuracy and it is better than other method. Result is shown in Figure 4. The system is implemented and is able to detecting the COVID-19. The health information of each patient is in the form of image data. There are two module namely system and user, and treated as different entities. Using CNN in CT dataset find the performance of the method. The classification report and evaluation metrics are created

A website application is created for the ResNet50 which gives the greater accuracy than the traditional CNN. Figure 5 shown in the home page and Figure 6 is the upload page. Home page: it is the front page shows three icon home, user and about-project. The home directed to this page. User registration page: in this page, is to register each patient into the site to check whether the patient is COVID-19 positive or negative. To register each person needs to enter some information like username, email, password, mobile number, and gender. User login page: after registration, the user can login into site predict the disease. For user login username and password is needed. If person is already registered in the hospital, then the user can easily login if the details are correct. About project page: the detailed description about the project and graphical representation. Upload image: to predict the person is covid positive or not by uploading the LUS image. The image can be jpeg, png, and tif. The comparison of accuracy of 80%, while the utilization of ResNet with LUS pictures significantly enhances accuracy to 98% as shown in Table 1.

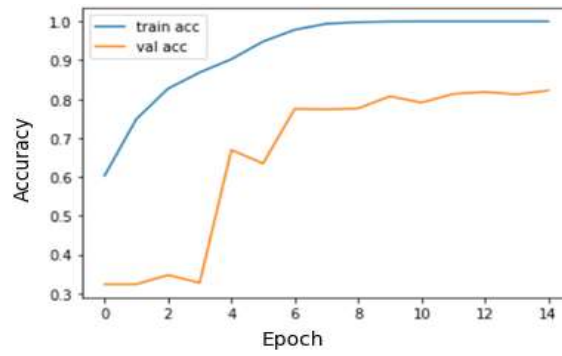


Figure 3. Accuracy graph of CNN

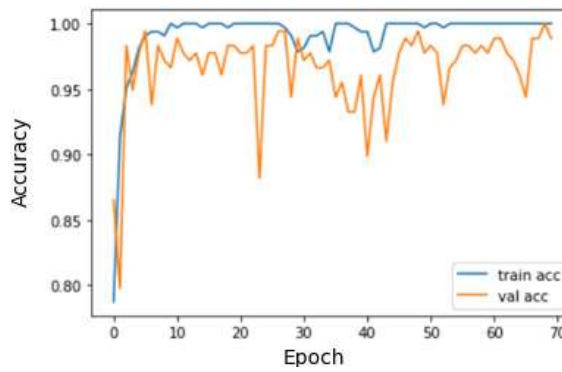


Figure 4. Accuracy graph of DCNN (ResNet50)



Figure 5. Home page



Figure 6. Upload page

Table 1. The performance analysis

Sl. No	Methods	Accuracy level
1	CNN	80%
2	ResNet50	98%

5. CONCLUSION

In this particular application, LUS emerges as a promising tool, offering notable advantages over computed tomography and real-time polymerase chain reaction methods. It is highly likely to exhibit greater sensitivity than chest radiographs in the context of COVID-19 diagnosis. There exists a substantial research gap in several aspects related to LUS, including diagnostic precision in undifferentiated patients, triage and prognostication, tracking interventional progress, guiding interventions, the persistence of residual LUS findings, inter-observer agreement, and the potential role of contrast-enhanced LUS. Addressing these topics necessitates rigorous and high-quality research efforts. One potential avenue for the detection and treatment of COVID-19 involves the utilization of deep learning techniques for computer-assisted interpretation of lung ultrasound images. The efficacy of deep learning models and neural networks in disease detection is further heightened with the availability of pertinent and high-quality medical imaging datasets. Notably, employing a classical CNN with CT scan images achieves an accuracy of 80%, while the utilization of ResNet with LUS pictures significantly enhances accuracy to 98%. Looking ahead, the integration of a real-time version of this application holds promise, allowing for the immediate generation of findings following an individual's lung ultrasound examination. This real-time functionality could be particularly beneficial in settings such as airports, aiding travelers to other countries. The incorporation of blockchain technology is proposed to bolster security in the handling of sensitive medical data. Additionally, the application of machine learning techniques facilitates the simultaneous analysis of two datasets while upholding stringent data privacy standards. These advancements underscore the potential for impactful developments in the field, aligning with the ongoing pursuit of innovative and secure healthcare technologies.





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