



**IJIRCCCE**

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

**Volume 10, Issue 6, June 2022**

**ISSN** INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA

**Impact Factor: 8.165**



9940 572 462



6381 907 438



ijircce@gmail.com



www.ijircce.com

# Classification of Covid-19 Markers in Lung Ultrasound Using Deep Learning

**Bharath Kumar B, Anwesh K, Rubesh P, Muthusundar S, Ms.Deepa**

U.G Scholar, Department of CSE, Velammal Institute of Technology, Chennai, Tamil Nadu, India

U.G Scholar, Department of CSE, Velammal Institute of Technology, Chennai, Tamil Nadu, India

U.G Scholar, Department of CSE, Velammal Institute of Technology, Chennai, Tamil Nadu, India

U.G Scholar, Department of CSE, Velammal Institute of Technology, Chennai, Tamil Nadu, India

Assistant Professor, Department of CSE, Velammal Institute of Technology, Chennai, Tamil Nadu, India

**ABSTRACT:** The COVID-19 pandemic has exposed the vulnerability of healthcare services worldwide, especially in underdeveloped countries. There is a clear need to develop novel computer-assisted diagnosis tools to provide rapid and cost-effective screening in places where massive traditional testing is not feasible. Deep learning (DL) has proved successful in medical imaging and, in the wake of the recent COVID-19 pandemic, some works have started to investigate DL-based solutions for the assisted diagnosis of lung diseases. (Chennakeshava, 2020) While existing works focus on CT scans, this paper studies the application of DL techniques for the analysis of lung ultrasonography (LUS) images. Specifically, we present a novel fully-annotated dataset of LUS images collected from several Italian hospitals, with labels indicating the degree of disease severity at a frame level, video level, and pixel level which are segmentation masks. Leveraging these data, we introduce several deep models that address relevant tasks for the automatic analysis of LUS images.

## I. INTRODUCTION

In December 2019, a novel coronavirus, named SARS-CoV-2, emerged in Wuhan, China, which caused the COVID-19 disease when infecting humans. COVID-19 is a serious illness that can lead to the death of the infected host. The threat posed by COVID-19 led the World Health Organization (WHO) to declare the COVID-19 pandemic by March 2020. (Demi, 2020) Coronaviruses are a group of highly diverse, enveloped, positive-sense, single-stranded RNA viruses and are widely spread in birds and mammals. Sometimes these viruses infect humans, causing mild to moderate respiratory diseases. Before SARS-CoV-2, two coronaviruses were known to cause severe human disease: SARS-CoV, which causes severe acute respiratory syndrome (SARS); and MERS-CoV, which causes Middle East Respiratory Syndrome (MERS). However, in contrast to SARS and MERS, the symptom onset for COVID-19 is significantly larger, or it may appear in a mild form, allowing infection to spread by asymptomatic patients, which in turn has led to the current pandemic.

### Aim of the Project

To evaluate and compare the performance of deep-learning techniques for detecting COVID-19 infections from lung ultrasound imagery. CNN models for computer-assisted analysis of LUS imaging with the aim of helping with the screening and follow-up of Covid-19 related pathologies. These works were aimed at the segmentation (identification) of artifacts in LUS images.

### Objectives

- We propose, implement, and evaluate the use of InceptionV3-, ResNet50-, VGG19-, and Xception-based deep learning (DL) models for COVID-19 screening in LUS imaging.
- We show that these DL-based models improve the COVID-19, pneumonia, and healthy classification performance on LUS imaging compared with the state-of-the-art classifiers.
- The proposed models are capable of providing the basis for further development of an LUS imaging-based COVID-19 computer-assisted screening tool.

- The provided results show that LUS is a viable alternative for the development of computer-assisted COVID-19 screening tools based on medical imaging in scenarios where screening based on CT or X-ray is not readily available.

#### **Novelty**

- The studies are aimed at detecting artifacts in LUS frames to aid in the identification of different lung pathologies.
- The deep learning architecture produces a disease severity score from LUS imaging with the aim of assisting practitioners in the diagnosis of lung pathologies related to COVID-19.
- The work aims to classify LUS frames obtained from healthy, bacterial pneumonia and COVID-19 patients.

## **II. EXISTING METHODS**

Currently, the reverse transcriptase quantitative polymerase chain reaction (RT-qPCR) test is considered a gold standard for diagnosing COVID-19. Although the test is overall deemed accurate, it is time-consuming and may take more than 24 hours to obtain results. Alternatives to RT-qPCR tests include imaging techniques such as chest computed tomography (CT) and chest X-ray (CXR) which have each shown potential for the diagnosis of the COVID-19. Chest CT has been recommended for hospitalized, symptomatic COVID-19 patients with specific clinical indications.

#### **Limitations of the Existing System**

- One limitation of CT is that it requires patient relocation because most fever clinics are relatively simple and do not include CT equipment.
- Moreover, to decrease the contagion risk for physicians and other patients, disinfection is essential after each examination.
- A large-scale study showed that for 636 CXRs from COVID-19 patients, 58.3% were reread as normal, and 41.7% were reread as abnormal.
- With the relatively low sensitivity of CXR, the American College of Radiology (ACR) recommends performing CXR with portable units in ambulatory care facilities only if medically necessary.

## **III. PROPOSED METHOD**

Lung ultrasound (LUS) is an imaging technique deployed by clinicians at the point of care to aid in the diagnosis and management of acute respiratory failure. With accuracy matching or exceeding chest X-ray (CXR) for most acute respiratory illnesses, LUS additionally lacks the radiation and laborious workflow of computed tomography (CT). (Huijben, 2020) As a lowcost, battery-operated modality, LUS can be delivered at a large scale in any environment and is ideally suited for pandemic conditions. B lines are the characteristic pathological feature on LUS, created by either pulmonary edema or non-cardiac causes of interstitial syndromes.

#### **Advantages of Proposed System**

- Lung ultrasound (LUS) is a portable, easy to disinfect, low cost and non-invasive medical imaging tool that can be used to identify lung diseases.
- Compared with CT and X-ray, ultrasound does not produce ionizing radiation.
- It has better diagnostic accuracy to detect pleural effusions, interstitial syndrome, alveolar-interstitial disorders, and consolidations when compared to CT.
- Due to the portability of ultrasound devices, LUS does not require relocating the patient and thus can minimize the potential risk of further infection.
- A frame-based predictor provides the disease severity score and a video-based score predictor is based on uni-norms that perform aggregation of the frame-based scores to provide localization.



IV. METHODOLOGY

Deep Learning-Based Analysis of LUS Images

This paper tackles several challenges towards the development of automatic approaches for supporting medical personnel in the diagnosis of COVID-19 related pathologies. In particular, following the COVID-19 LUS scoring system in we present a novel deep architecture that automatically predicts the pathological scores associated with all frames of an LUS image sequence and optimally fuses them to produce a disease severity score at the video level. Let the problem can be formalized as follows. Let  $X$  denote the input space (i.e., the image space) and  $S$  the set of possible scores. During training, we are given a training set  $T = \{(x_n, s_n)\} N n=1$  where  $x_n \in X$  and  $s_n \in S$ . 2) Model Definition: We are interested in learning a mapping:

$X \rightarrow S$ , which given an input LUS image outputs the associated pathological score label (Luijten, 2020). The mapping CNN is composed of a convolutional feature extractor and a linear layer with  $|S|$ -dimensional output logits.

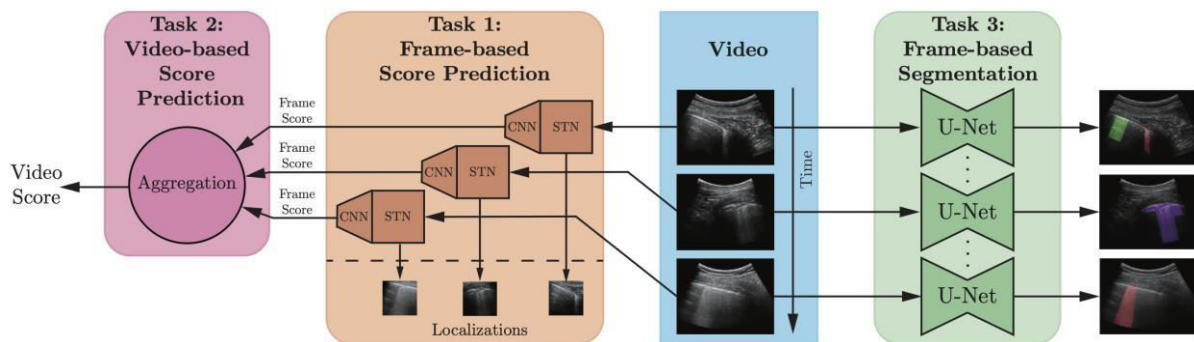


Figure 1 - Architecture Diagram

The model stn is implemented as a deep neural network derived from STN. This shows an overview of the proposed deep architecture. In the context of deep learning the generalization capability of a network is of critical importance

Evaluation

Frame-Based Prediction

The contribution of the building blocks of our model for frame-based prediction. The replacement of the traditional cross-entropy (CE) with the SORD loss for ordinal regression clearly improves the performance. On the other hand, we found that the addition of STN leads to a drop in the F1 score because of the additional trainable parameters (as many as the CNN) introduced by the STN and the absence of a regularisation. (Passerini, 2020) However, STN comes with two positive side effects: it provides weakly supervised localizations without using fine-grained supervision; and enables the use of consistency-based regularization, which is very beneficial in terms of performance but only useful when the crops cover the area of the artifact.

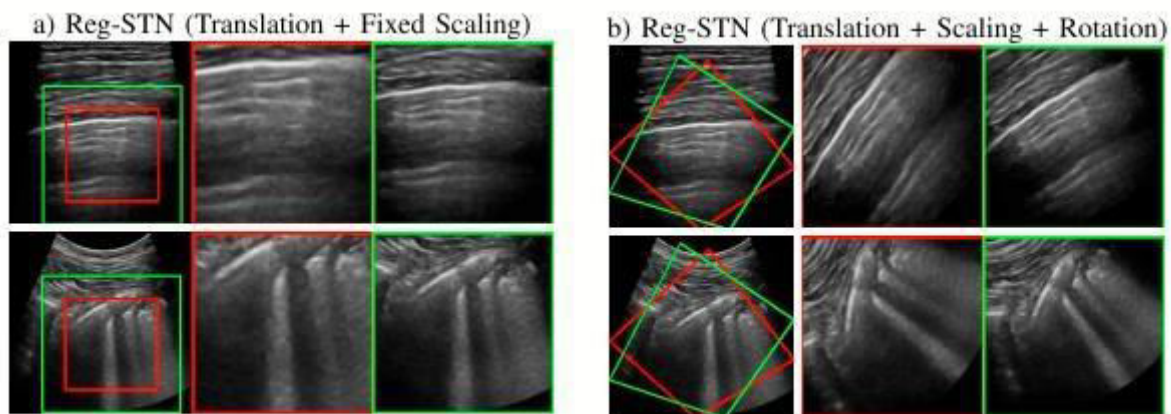


Figure 2 - Frame Based Output

In contrast to the previous work, we found that the use of more complex architectures like ResNet18 does not bring any positive improvement in performance. We reason that this is due to the low intrinsic complexity of the task. Conversely, we suggest that most of the confusion in the model is caused by the noise in both frames and labels. In turn, we believe that this noisiness is due to the subjectivity of the annotation and the presence of ambiguous frames.

**Video-Based Score Prediction**

When trained on the annotations by the most expert clinician, video-based classification achieves an F1 score of 61%, a precision of 70%, and a recall of 60%. It is noticeable that these values are in line with the low inter-annotator agreement reported in Section III, which together with the small number of samples with video-level annotations can explain the high variance of the scores across folds. We expect that extending our relatively small set of video-level annotations will help counteract the labeling noise, increase the model performance and reduce its variance.

Method	F1 (%)	Precision (%)	Recall (%)
<i>max_argmax</i>	46 ± 21	55 ± 27	49 ± 18
<i>argmax_mean</i>	51 ± 12	56 ± 19	53 ± 09
<i>uninorms</i>	<b>61 ± 12</b>	<b>70 ± 19</b>	<b>60 ± 07</b>

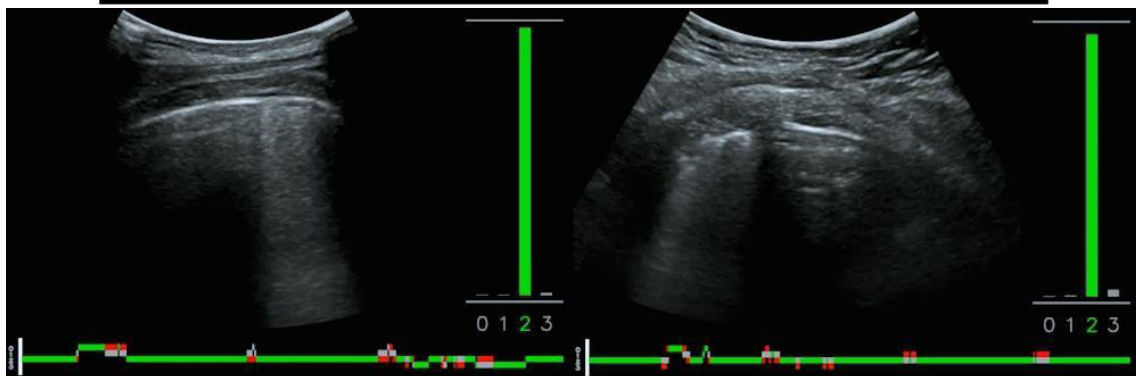
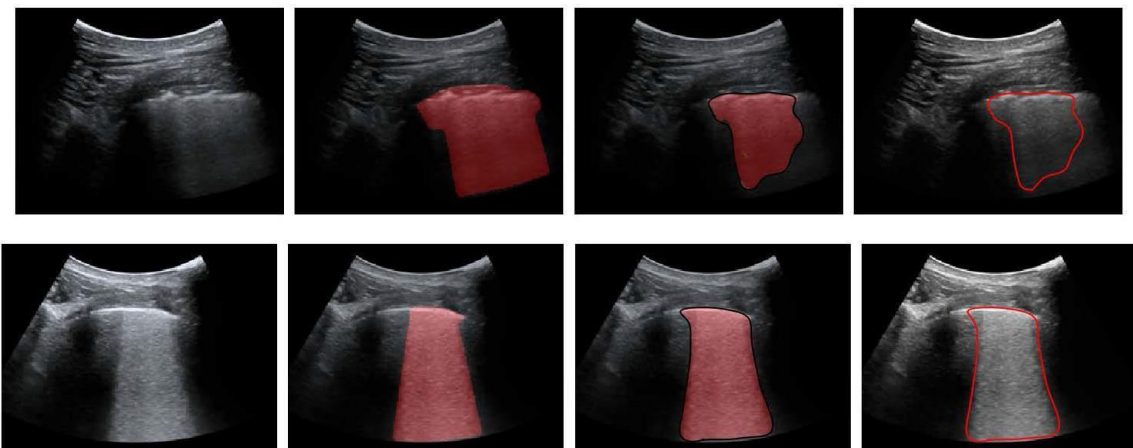


Figure 3 - Video Based Output

**Segmentation**

Our segmentation model is able to segment and discriminate between areas in B-mode LUS images that contain background, healthy markers, and (different stages of) COVID-19 biomarkers at a pixel level, reaching a pixel-wise accuracy of 96% and a binary Dice score of 0.75. (Peschiera, 2020) Alongside these segmentations, we provide spatial uncertainty estimates that may be used to interpret model predictions. Interestingly, and importantly, none of the highest (and most severe) score index annotations in the test set were missed by our model, judged by visual assessment of the resulting segmentation, and by analyzing the relative image-level intersections among the corresponding predicted and annotated regions.



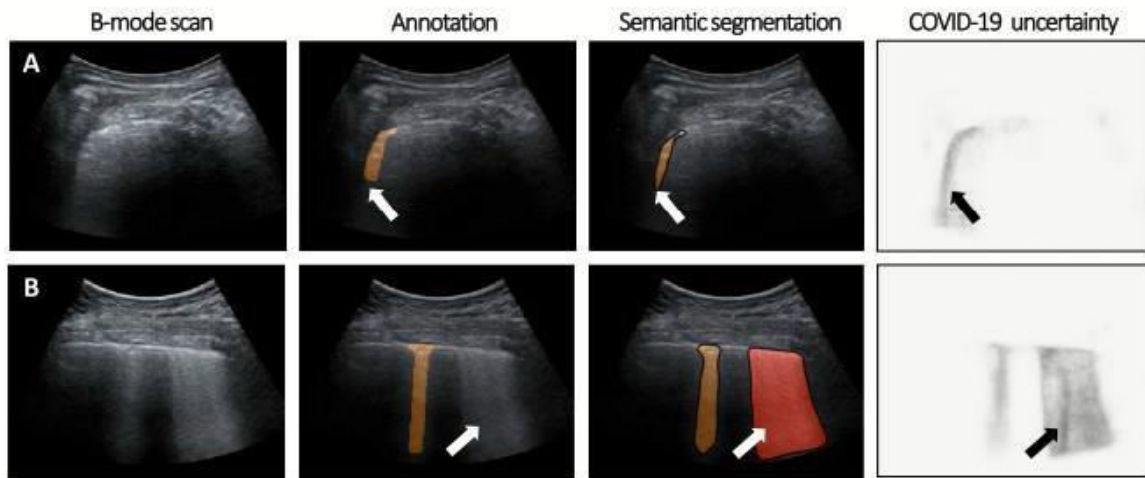


Figure 4 - Segmentation Output

Moreover, we observed model predictions of COVID-19-positive regions, that had however not been annotated as such. shows a representative example of such a case. After reevaluating some of such examples from the test set, together with the annotators, we learned that the annotators were sometimes unsure whether to annotate a region e.g., score 2 or 3, and therefore decided that the marker was not clear enough to annotate the region at all, leading to the aforementioned discrepancy.

**Overall Performance Results**

Model	Classes	Precision	Recall	F1-score
<b>InceptionV3</b> ACC 89.1(±2.3) BACC 89.3(±2.2) AUC-ROC 97.1(±1.0)	COVID-19	90.1(±3.1)	86.4(±3.6)	88.0(±3.0)
	Pneumonia	84.2(±3.7)	90.8(±2.5)	87.1(±2.5)
	Healthy	91.8(±2.1)	90.7(±2.6)	91.1(±2.1)
<b>Xception</b> ACC 88.6(±2.3) BACC 88.7(±2.3) AUC-ROC 97.0(±0.9)	COVID-19	91.4(±2.7)	85.1(±3.5)	88.0(±2.8)
	Pneumonia	84.1(±3.8)	90.0(±3.3)	86.6(±3.0)
	Healthy	89.0(±2.3)	91.1(±2.5)	89.9(±2.1)
<b>POCOVID-net</b> ACC 86.5(±1.8) BACC 86.3(±1.8) AUC-ROC 95.4(±0.9)	COVID-19	86.9(±2.8)	87.9(±3.0)	87.2(±2.3)
	Pneumonia	83.7(±3.4)	85.9(±3.9)	84.3(±2.5)
	Healthy	88.9(±2.0)	85.1(±2.6)	86.8(±1.8)
<b>VGG19</b> ACC 85.8(±2.0) BACC 85.8(±2.0) AUC 95.2(±1.0)	COVID-19	86.2(±3.2)	86.6(±3.1)	86.2(±2.7)
	Pneumonia	82.4(±4.0)	85.9(±3.8)	83.5(±2.6)
	Healthy	88.8(±2.3)	85.0(±2.7)	86.6(±1.9)
<b>ResNet50</b> ACC 78.3(±2.0) BACC 78.1(±2.1) AUC-ROC 90.2(±1.3)	COVID-19	80.0(±4.1)	73.5(±5.5)	75.6(±3.2)
	Pneumonia	77.8(±4.9)	77.4(±4.9)	76.6(±3.3)
	Healthy	79.6(±2.8)	83.5(±2.9)	81.1(±1.7)

Figure 5 - Performance Results

**V. CONCLUSION**

In the context of the current COVID-19 pandemic, where health services are often saturated, the use of automated image diagnosing tools could importantly help to alleviate the burden of health systems with a limited number of specialized clinicians. In this paper, we do not compete with AI-based solutions previously proposed for computer-assisted COVID-19 screening based on CT or X-ray imaging. Instead, we seek to lay the foundations to develop an AI-based COVID-19 screening tool that uses LUS imaging as an alternative when there is limited or no access to CT or X-ray equipment. In this sense, the advantages offered by LUS (e.g., portability, cost, ease of disinfection, etc.) combined with the feasibility of readily implementing and deploying already trained AI-based solutions in a wide variety of

portable devices (e.g., laptops, smartphones, etc.), has the potential of providing an accessible and mobile COVID-19 screening tool for medical staff.

## VI. FUTURE SCOPE

A benefit of using ultrasound is the low risk of cross-infection when using a plastic disposable cover and individually packaged ultrasound gel on a portable handheld machine. This is in contrast with the use of CT, for which rooms and systems need to be rigorously cleaned to prevent contamination (and preferably reserved for patients with a high COVID-19 suspicion).

(Saltori, 2020) LUS can be performed inside the patient's room without the need for transportation, making it a superior method for the point-of-care assessment of patients. Moreover, ultrasound renders real-time images and, combined with our DL methods, provides results instantly. It may also directly assist in the triage of patients; first-look estimation of the disease's severity and the urgency at which a patient needs to be addressed.

## REFERENCES

1. Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, et al. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *The lancet*. 2020;395(10223):497–506.
2. World Health Organization. Coronavirus disease (COVID-19) pandemic. [cited 2021 July 8]. Available from: <https://www.who.int/emergencies/diseases/novel-coronavirus-2019>
3. Zumla A, Chan JF, Azhar EI, Hui DS, Yuen KY. Coronaviruses—drug discovery and therapeutic options. *Nature reviews Drug discovery*. 2016;15(5):327–347. pmid:26868298
4. Cheng VC, Lau SK, Woo PC, Yuen KY. Severe acute respiratory syndrome coronavirus as an agent of emerging and reemerging infection. *Clinical microbiology reviews*. 2007;20(4):660–694. pmid:17934078
5. Chan JF, Lau SK, To KK, Cheng VC, Woo PC, Yuen KY. Middle East respiratory syndrome coronavirus: another zoonotic betacoronavirus causing SARS-like disease. *Clinical microbiology reviews*. 2015;28(2):465–522. pmid:25810418
6. Munster VJ, Koopmans M, van Doremalen N, van Riel D, de Wit E. A novel coronavirus emerging in China—key questions for impact assessment. *New England Journal of Medicine*. 2020;382(8):692–694.
7. Meraj T, Hassan A, Zahoor S, Rauf HT, Lali MI, Ali L, et al. Lungs nodule detection using semantic segmentation and classification with optimal features. 2019. Available from: <https://www.preprints.org/manuscript/201909.0139/v1>
8. Sahlol AT, Abd Elaziz M, Tariq Jamal A, Damašević R, Farouk Hassan O. A novel method for detection of tuberculosis in chest radiographs using artificial ecosystem-based optimisation of deep neural network features. *Symmetry*. 2020;12(7):1146.
9. Albahli S, Rauf HT, Arif M, Nafis MT, Algosaibi A. Identification of thoracic diseases by exploiting deep neural networks. *neural networks*. 2021;5:6.
10. Albahli S, Rauf HT, Algosaibi A, Balas VE. AI-driven deep CNN approach for multi-label pathology classification using chest X-Rays. *PeerJ Computer Science*. 2021;7:e495. pmid:33977135
11. Jian-ya G, et al. Clinical characteristics of 51 patients discharged from hospital with
12. COVID-19 in Chongqing, China. medRxiv: 20025536v1 [Preprint]. 2020 [Posted 2020 Feb
13. 23; cited 2021 July 8]. Available
14. from: <https://www.medrxiv.org/content/10.1101/2020.02.20.20025536v1>
15. Akram T, Attique M, Gul S, Shahzad A, Altaf M, Naqvi SSR, et al. A novel framework for rapid diagnosis of COVID-19 on computed tomography scans. *Pattern analysis and applications*. 2021; p. 1–14.
16. Albahli S. A deep neural network to distinguish covid-19 from other chest diseases using x-ray images. *Current medical imaging*. 2021;17(1):109–119. pmid:32496988
17. Narin A, Kaya C, Pamuk Z. Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. *Pattern Analysis and Applications*. 2021; p. 1–14. pmid:33994847
18. Wang L, Lin ZQ, Wong A. Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images. *Scientific Reports*. 2020;10(1):1–
19. 12. pmid:33177550
20. Shi F, Wang J, Shi J, Wu Z, Wang Q, Tang Z, et al. Review of artificial intelligence techniques in imaging data acquisition, segmentation and diagnosis for covid-19. *IEEE reviews in biomedical engineering*. 2020.





21. Ulhaq A, Khan A, Gomes D, Pau M. Computer Vision for COVID-19 Control: A Survey. arXiv preprint arXiv:2004.09420v2. 2020 [Posted 2020 May 2020; cited 2021 July 8]. Available from: <https://arxiv.org/abs/2007.10785>
22. Shoeibi A, Khodatars M, Alizadehsani R, Ghassemi N, Jafari M, Moridian P, et al. Automated Detection and Forecasting of COVID-19 using Deep Learning Techniques: A
23. Review. arXiv preprint arXiv:2007.10785v3. 2020 [Posted 2020 Jul 2020; cited 2021 July 8]. Available from: <https://arxiv.org/abs/2004.09420>

### **BIOGRAPHY**

Bharath Kumar B is a B.E final year student in the department of Computer Science And Engineering from Velammal Institute of Technology, Panchetti. Her current research focuses on Classification of COVID -19 markers in lung ultrasound using deep learning .

Anwesh K is a B.E final year student in the department of Computer Science And Engineering from Velammal Institute of Technology, Panchetti. Her current research focuses on Classification of COVID -19 markers in lung ultrasound using deep learning .

Rubesh P is a B.E final year student in the department of Computer Science And Engineering from Velammal Institute of Technology, Panchetti. Her current research focuses on Classification of COVID -19 markers in lung ultrasound using deep learning .

Muthusundar S is a B.E final year student in the department of Computer Science And Engineering from Velammal Institute of Technology, Panchetti. Her current research focuses on Classification of COVID -19 markers in lung ultrasound using deep learning .

Ms.Deepa, M.E is an assistant professor of Computer Science and Engineering Department in Velammal Institute of Technology, Panchetti.





INNO  SPACE  
SJIF Scientific Journal Impact Factor

Impact Factor: 8.165

 **doi**<sup>®</sup>  
**cross** **ref**

**ISSN** INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

 9940 572 462  6381 907 438  [ijircce@gmail.com](mailto:ijircce@gmail.com)



[www.ijircce.com](http://www.ijircce.com)

Scan to save the contact details