

# AN EFFICIENT DETECTION AND CLASSIFICATION OF COVID-19 USING DEEP LEARNING APPROACH

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## ABSTRACT

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. While existing works focus on CT scans, this paper studies the application of DL techniques for the analysis of lung ultra-sonography (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 (segmentation masks). Leveraging these data, we introduce several deep models that address relevant tasks for the automatic analysis of LUS images. In particular, we present a novel deep network, derived from Spatial Transformer Networks, which simultaneously predicts the disease severity score associated to a input frame and provides localization of pathological artefacts in a weakly-supervised way. Furthermore, we introduce a new method based on uninorms for effective frame score aggregation at a video-level. Finally, we benchmark state of the art deep models for estimating pixel-level segmentations of COVID-19 imaging biomarkers. Experiments on the proposed dataset demonstrate satisfactory results on all the considered tasks, paving the way to future research on DL for the assisted diagnosis of COVID-19 from LUS data.

**Keywords:** Covid-19, Computed tomography, Image processing, Data Augmentation, Deep Learning.

## I. INTRODUCTION

The deadly coronavirus has not just devastated the lives of millions but has put the entire healthcare system under tremendous pressure. Early diagnosis of COVID-19 plays a significant role in isolating the positive cases and preventing the further spread of the disease. The medical images along with deep learning models provided faster and more accurate results in the detection of COVID-19. This article extensively reviews the recent deep learning techniques for COVID-19 diagnosis. The sensitivity of RT-PCR (real-time polymerase chainreaction) for COVID-19 depends upon various factors including the site and quality of sampling, stage of disease, gene targets and disease prevalence. While RTPCR might require as long as 24 hours and requires different tests for conclusive outcomes, analysis utilizing CT can be much speedier. Be that as it may, utilization of chest CT accompanies huge downsides:

it is expensive, opens patients to radiation, requires broad cleaning after outputs, and depends on radiologist interpretability. Of late, ultrasound imaging, an all the more broadly accessible, financially savvy, protected and continuous imaging method, is acquiring consideration. Specifically, lung ultrasound (LUS) is progressively utilized in mark-of-care settings for discovery and the executives of intense respiratory issues.

Deep Learning is realized through algorithms which are structurally composed of artificial neurons and multiple data processing layers in a deep architecture referred to as a Deep Neural Network. Chest X-ray and Chest CT are the two most common imaging studies for diagnosis and management of COVID-19 patients. In their favor, chest radiography and CT scans are readily available at most medical centers, are routinely obtained and usually interpreted with faster turnaround than the SARS-CoV-2 laboratory examination. In total, 33 studies were identified which represent a rapidly expanding evidence base for LUS in COVID-19. The quality of the included studies was relatively low; however, LUS certainly appears to be a highly sensitive and fairly specific test for COVID-19 in all ages and in pregnancy. CT (computed tomography) is highly sensitive for COVID-19 (estimated at between 97% and 98%), however LUS has several logistical advantages over CT. Ultrasound machines continue to improve in quality, affordability and portability and new technologies such as remote tele guidance have the potential to further extend the accessibility of point-of-care ultrasound. An understanding of the utility of LUS in COVID-19 is crucial for clinicians, departments and organizations to be able to determine its most suitable role based on local circumstances. The comparison made for models with and without data augmentation shows that the models performed better when the datasets are augmented. It also provides a sensible outlook for the young researchers to develop highly effective CNN models coupled with medical images in the early detection of the disease.

## II. LITERATURE SURVEY

K. Stefanidis et al "Lung sonography and recruitment in patients with early acute respiratory distress syndrome." Acute respiratory distress syndrome (ARDS) is a clinical syndrome that often occurs in critically ill patients. It is a nonspecific response of the lung to injury due to a pulmonary or extrapulmonary insult. Specifically, it is characterized by the presence of diffuse lung inflammation, high permeability-type pulmonary oedema and massive loss of lung aeration in dependent lung regions and is associated with severe hypoxemia and a high mortality rate. Patients with ARDS invariably require mechanical ventilation to decrease the work of breathing and to improve oxygen transport. An improvement in oxygenation can be obtained in many patients by an increase in positive end-expiratory pressure (PEEP), a strategy that was initially proposed in the first description of ARDS about 40 years ago. PEEP is applied in patients with ARDS to avoid end-expiratory lung derecruitment and to improve

oxygenation by increasing lung aeration. CT is considered the reference test for assessing lung parenchyma in patients with ARDS, but it involves high irradiation and requires transportation of the critically ill patient to the department of radiology. These limitations make lung ultrasound (US) an attractive alternative to CT to assess lung morphology. US is a noninvasive, radiation-free technique that is widely used in the ICU setting. In patients on mechanical ventilation, US can be considered a reliable method to detect nonaerated lung regions. Previous studies have shown the utility of US in the detection and quantification of lung recruitment via a transesophageal approach and only recently via a transthoracic approach.

Hwang EJ, Kim KB, Kim JY, Lim J-K, NamJG, Choi H. "COVID-19 pneumonia on chest X-rays: Performance of deep learning based computeraided detection system". The primary diagnostic test for COVID-19 is a reverse transcriptase-polymerase chain reaction(RT-PCR) on nasopharyngeal swabs for virus detection. Radiologic examinations including chest X-ray (CXR) and chest CT may show findings of pneumonia, including consolidations and ground-glass opacities [8–10], however, since considerable proportion of patients may show normal radiologic finding (up to 40% in CXR) especially in early phase of the disease, CXRs and chest CTs are currently not recommended for screening or diagnosis of COVID-19. However, the massive COVID-19 outbreak has resulted in a shortage of medical resources, limiting timely testing of RT-PCR. Recent international consensus statements suggested that radiologic examinations can be used as a triage tool in resource-constrained environments. CXR has been the primary radiologic examination for pneumonia. Especially for highly contagious diseases such as COVID-19, CXR has an advantage over chest CT in preventing transmission, since transportation of patients can be minimized with portable radiography units, and disinfection of the scanners and environment is relatively easy.

M.D.KamrulHasan, Sakil Ahmed, Ekram Abdullah "Deep Learning approaches for detecting pneumonia in covid-19 patients by analyzing Chest X-ray images". Pneumonia induced by COVID-19 can be diagnosed through genetic and imaging tests. And through a rapid detection mechanism, the spread of COVID-19 can be controlled. In this research, we considered X-ray images for detecting COVID-19 patients [4]. The image dataset contained both healthy and COVID19 patients. This study primarily focuses on the pretrained VGG16 model for predicting pneumonia using chest X-ray images of coronavirus-infected patients. This study proposed a deep learning-based model to predict pneumonia in COVID-19 patients using chest X-ray images. Pneumonia is a virus-related disease and in many cases results in patient's death. COVID-19 patients with pneumonia also face various health-related complications. This research helps to detect pneumonia in COVID-19 patients so that they could be separated from other less severe patients and given appropriate life-saving treatment. Here, some deep learning features such as Average Pooling 2D, flatten, dense, Image-Data Generator, and dropout are used to preprocess the data, and a CNN-based VGG16 model is used to classify chest X-ray images of COVID-19 patients and pneumonia patients and predict COVID-19 patients with pneumonia.

Sahib H. Abiyev and Abdullahi Ismail "COVID-19 and Pneumonia Diagnosis in X-Ray

Images Using Convolutional Neural Network” We present a Convolutional Neural Network (CNN) model, which was developed to help in detecting COVID-19 and pneumonia cases in X-ray images with the aim of facilitating early diagnosis and preventing transmission of the virus to other people. main contributions of this paper include the following: the structure of CNN for detecting COVID-19 and pneumonia cases is proposed; the training of CNN with imbalanced data is demonstrated using random sampling of data with data augmentation; the effect of transfer learning on construction of the final model has been demonstrated; a CNN was designed to diagnose COVID-19; accuracy precision and recall evaluation metrics were used to tackle the imbalance problem. To diagnose COVID-19, two different datasets were utilized, where one contained only pneumonia and normal chest X-ray images, and the other one contained COVID-19, pneumonia, and normal chest X-ray images. Two models were proposed: the first model was trained on pneumonia and normal cases chest X-ray images, while the second model made use of the knowledge that was learned from the first model and trained on COVID-19, pneumonia, and normal cases chest X-ray images. Transfer learning approach was utilized to transfer the weight/knowledge of the first model to the second model for COVID-19, pneumonia, and normal class classification.

H. Mary Shyni “X-ray and CT images in covid-19 detection using image processing and deep learning techniques” RT-PCR (Reverse Transcription – Polymerase Chain Reaction) is the initial laboratory testing procedure for COVID-19 diagnosis. Coronavirus contains only RNA (Ribonucleic acid) which needs to be converted to DNA (Deoxyribonucleic acid) for amplification which is done by RT-PCR for virus detection. Apart from its advantages, it is time-consuming which may lead to further spread of the disease from the infected person and the deep nasal swabs are troublesome. Early diagnosis of the disease plays a pivotal role in isolating the positive cases in advance and preventing community spread. Since the lung region is the primarily infected area by the virus, medical imaging modalities like X-ray and Computed Tomography (CT) are generally considered in examining the severity of the infection. X-ray imaging techniques are often employed in the diagnosis of COVID-19 due to their wide availability, quick processing time and low cost. But CT imaging techniques are preferred as it carries detailed information of the infected region.

L. Tutino, G. Cianchi, F. barbani, S. Batacchi. R. Cammelli, and A. Peris “Time needed to achieve completeness and accuracy in bedside lung ultrasound reporting in Intensive Care Unit”. Bedside lung ultrasound can provide accurate information on lung status in critically ill patients in Intensive Care Unit (ICU) and the important role of defining standards in critical care ultrasonography has been recently discussed. Before April 2008, in the ICU of Emergency Department beside Lung Ultrasound (LUS) was only performed as support of invasive device positioning (central venous catheter, chest drainage), and for quantification of pleural effusions. After April 2008, trained intensivists started to use bedside LUS on a daily basis in order to make diagnosis, to monitor chest pathologies and to improve pulmonary patterns interpretation. The present study describes the accuracy and quality curve of the LUS reporting during method implementation.

R.J.van Sloun, R. Cohen and Y.C.Eldar “Deep learning in Ultrasound Imaging” We consider deep learning strategies in ultrasound systems, from the front-end to advanced applications. Our goal is to provide the reader with a broad understanding of the possible impact

of deep learning methodologies on many aspects of ultrasound imaging. In particular, we discuss methods that lie at the interface of signal acquisition and machine learning, exploiting both data structure and data dimensionality (big data) already at the raw radio-frequency channel stage. As some examples, we outline efficient and effective deep learning solutions for adaptive beam forming and adaptive spectral Doppler through artificial agents, learn compressive encodings for colour Doppler, and provide a framework for structured signal recovery by learning fast approximations of iterative minimization problems, with applications to clutter suppression and super-resolution ultrasound. These emerging technologies may have considerable impact on ultrasound imaging, showing promise across key components in the receive processing chain. Deep learning; ultrasound imaging; image reconstruction; beamforming, Doppler, compression, deep unfolding, super resolution.

R. Raheja, m. Brahmavar, D.Joshi, and D.raman, "Application of Lung Ultrasound in Critical Care Setting", The introduction of lung ultrasound has revolutionized the care of patients in a modern ICU. It has also shown an impact in non-ICU settings such as in pulmonology and thoracic surgery ambulatory clinics. Historically, lung ultra sonography (LUS) has been a neglected area given perceived notions about the utility of this modality in air-filled structures. However, in the last two decades, significant progress has been made in using ultrasonography as a valuable tool in evaluating lung pathologies. This article reviews the use of thoracic ultrasound in the intensive care unit (ICU). The focus of this article is to review the basic terminology and clinical applications of thoracic ultrasound. The diagnostic approach to a breathless patient, the blue protocol, is presented in a simplified flow chart. The diagnostic application of thoracic ultrasound in lung parenchymal and pleural diseases, role in bedside procedures, diaphragmatic assessment, and lung recruitment are described. Recent updates discussed in this review help support its increasingly indispensable role in the emergent and critical care setting.

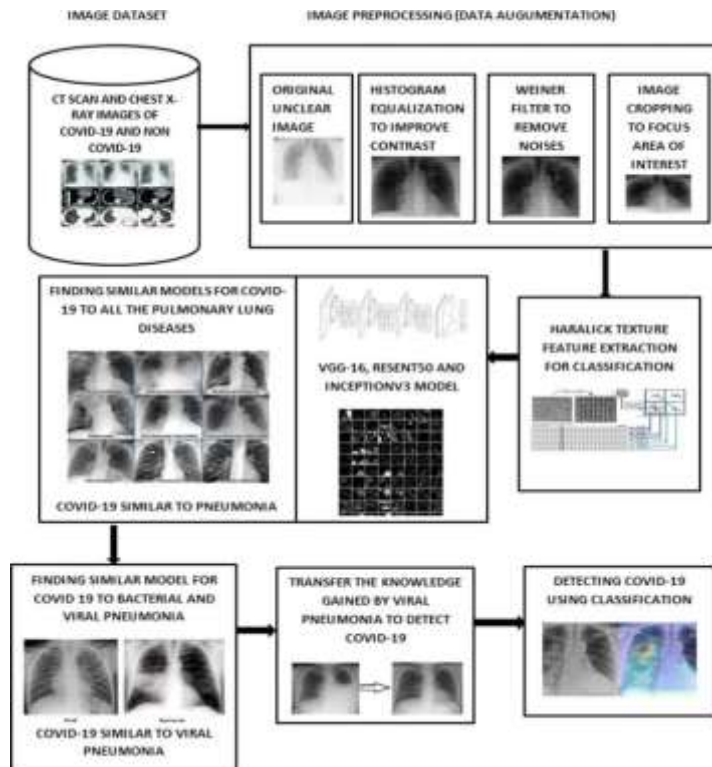
G.Recinella "Proposal for international standardization of the use of lung ultrasound for COVID-19 patients". A decade of clinical and physical studies clearly showed that lung ultrasound (LUS) is able to detect interstitial lung disease, subpleural consolidations and acute respiratory distress syndrome from any etiological cause. New evidences from published studies, national and international organization statements, and informal case discussions with internationally recognized experts are showing the usefulness of LUS for the management of patients with COVID-19 pneumonia, from diagnosis to monitoring and follow-up. To date, available medical treatments for COVID-19 pneumonia include anti-HIV drugs, idrossicloroquine; ventilatory support, prone positioning and extracorporeal membrane therapy represent the supports for critical patients. However, recent findings suggest that anti interleukin-6 monoclonal antibodies can be useful in blocking the inflammatory cascade involved in lung inflammation during COVID-19 infection. Evidences also suggest that the earlier we treat the better patients improve with treatment. Therefore, this global emergency need a global unified approach, speaking all researchers the same language. For this reason, we propose a standardization for the international use of LUS for the management of COVID-19 patients.

M.Jaderberget “Spatial Transformer Networks”, In this work we introduce the Spatial Transformer module, that can be included into a standard neural network architecture to provide spatial transformation capabilities. The action of the spatial transformer is conditioned on individual data samples, with the appropriate behaviour learnt during training for the task in question (without extra supervision). Unlike pooling layers, where the receptive fields are fixed and local, the spatial transformer module is a dynamic mechanism that can actively spatially transform an image (or a feature map) by producing an appropriate transformation for each input sample. The transformation is then performed on the entire feature map (non locally) and can include scaling, cropping, rotations, as well as non-rigid deformations. This allows networks which include spatial transformers to not only select regions of an image that are most relevant (attention), but also to transform those regions to a canonical, expected pose to simplify inference in the subsequent layers. Notably, spatial transformers can be trained with standard back-propagation, allowing for end-to-end training of the models they are injected in.

Elayaraja *et al.* (2022) a GA-based CNN classification algorithm was developed for segmenting the tumor section in cervical pictures, and it achieved 99.37 percent mean sensitivity, 98.9 percent mean specificity, and 95.21 percent mean accuracy [11]. Thiyaneswaran et al. (2020) utilized k-mean clustering approach for the detection and segmentation of cancer portions in skin pictures and obtained 90.0% of mean accuracy [12]. Kumarganesh et.al. (2018) suggested an ANFIS classifier process for the classification of cancers from the foundation imageries and attained 96.0% of classification precision [13]. Kumarganesh et.al. (2016) advised an Adaptive Neuro Fuzzy Inference System (ANFIS) classifier system for the classification of cancers from the source imageries and attained 93.07% of sensitivity, 98.79% of specificity, and 97.63% of tumor segmentation accuracy [14].

### III. PROPOSED SYSTEM

We propose a casing based model that accurately recognizes COVID-19 LUS Images from sound and bacterial pneumonia information with a responsiveness of 0.90 0.08 and a particularity of 0.96 0.04 utilizing CNN Algorithm. To examine the utility of the proposed CNN technique, we utilize interpretability strategies for the spatiotemporal confinement of pneumonic biomarkers, which are considered helpful for human-in the know situations in a dazed report with clinical specialists. Holding back nothing, perform vulnerability assessment and exhibit the model to perceive low-certainty circumstances which additionally further develops execution. Ultimately, we approved our model on a free test dataset and report promising execution (responsiveness 0.806, explicitness 0.962). The gave dataset works with the approval of related technique locally and the proposed structure could help the improvement of a quick, open evaluating strategy for Covid-19 illnesses.



**Fig 3.1:** Data flow diagram

*a. IMAGE DATASET*

A dataset in computer vision is a curated set of digital photographs that developers use to test, train and evaluate the performance of their algorithms. The algorithm is said to learn from the examples contained in the dataset.

*b. IMAGE PREPROCESSING*

Image processing is the process of transforming an image into a digital form and performing certain operations to get some useful information from it. The image processing system usually treats all images as 2D signals when applying certain predetermined signal processing methods.

*c. DATA AUGMENTATION*

Data augmentation is a set of techniques to artificially increase the amount of data by generating new data points from existing data. Data augmentation is a process of artificially increasing the amount of data by generating new data points from existing data. This includes adding minor alterations to data or using machine learning models to generate new data points in the latent space of original data to amplify the dataset.

*d. VGG-16*

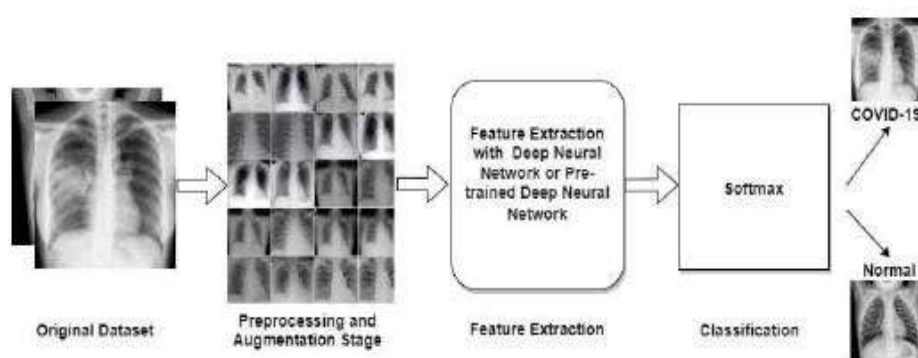
VGG-16 is a convolutional neural network that is 16 layers deep. You can load a pre-trained version of the network trained on more than a million images from the ImageNet database. The pre-trained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

### e. INCEPTIONV3

The Inception V3 is a deep learning model based on Convolutional Neural Networks, which is used for image classification. The inception V3 is a superior version of the basic model Inception V1 which was introduced as GoogleNet in 2014. As the name suggests it was developed by a team at Google.

### f. HARALICK TEXTURE

Haralick texture features are calculated from a Gray Level Co-occurrence Matrix, (GLCM), a matrix that counts the co-occurrence of neighboring gray levels in the image. The GLCM is a square matrix that has the dimension of the number of gray levels  $N$  in the region of interest (ROI).



**Fig 3.2: System Architecture**

### g. ORIGINAL DATASET

A dataset (also spelled 'data set') is a collection of raw statistics and information generated by a research study. Several resources may be consulted and strategies applied in order to locate the actual datasets used in a research article. Locating Datasets in ACM Digital Library database

### h. DATA AUGMENTATION

Data augmentation is a set of techniques to artificially increase the amount of data by generating new data points from existing data. Data augmentation is a process of artificially increasing the amount of data by generating new data points from existing data. This includes adding minor alterations to data or using machine learning models to generate new data points in the latent space of original data to amplify the dataset.

### i. DATA PREPROCESSING

Data preprocessing is the process of transforming raw data into an understandable format. It is also an important step in data mining as we cannot work with raw data. The quality

of the data should be checked before applying machine learning or data mining algorithms.

*j. DEEP NEURAL NETWORK*

A deep neural network is a neural network with a certain level of complexity, a neural network with more than two layers. Deep neural networks use sophisticated mathematical modeling to process data in complex ways.

*k. SOFTMAX*

The softmax function is a function that turns a vector of  $K$  real values into a vector of  $K$  real values that sum to 1. The input values can be positive, negative, zero, or greater than one, but the softmax transforms them into values between 0 and 1, so that they can be interpreted as probabilities. If one of the inputs is small or negative, the softmax turns it into a small probability, and if an input is large, then it turns it into a large probability, but it will always remain between 0 and 1.

## IV. RESULT AND DISCUSSIONS

### a. DATABASE 1

In this section, we present our research test results, which include the model input image of Covid-19 detected patient. Before training, all images were resized to. We have used data augmentation technique to deal with training problem and simple image processing techniques.

Figure (4.1) and (4.5) shows the X-ray images obtained from two different sources were used for the diagnosis of covid-19. This model ends with Avgpool and Softmax layer that produce the output eventually the deep model with large number of layers is essential for the feature extraction of real time object detection system. When the deep model examines all x-ray images over and over again for each epoch during training these rapid ups and downs are slowly reduced in the later part of the training.

The proposed model has achieved an average accuracy of 98.08% in detecting covid-19 and the obtained macro average, weighted average and F1 score values of 98%,97%,97% respectively.



**Fig 4.1:** Input Xray image

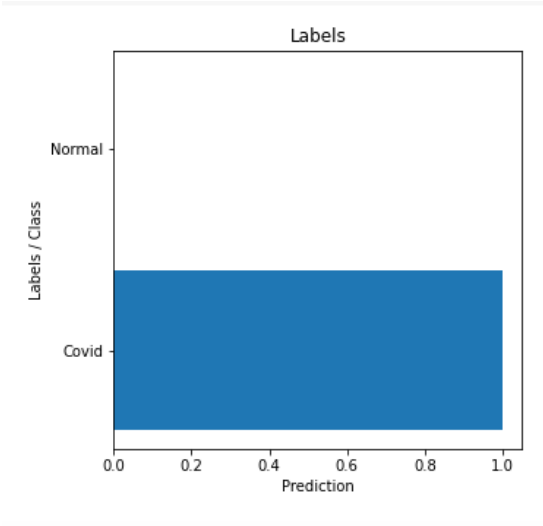


Fig 4.2: Prediction of Covid-19 level

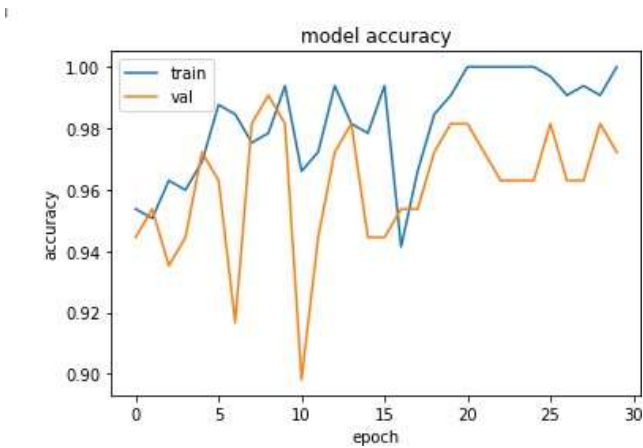


Fig 5.3: First model accuracy per epoch

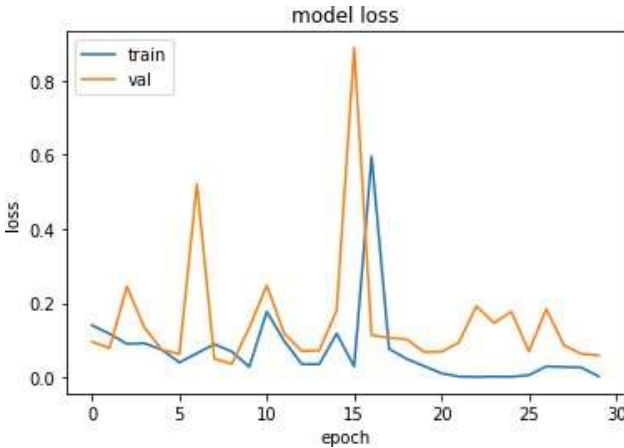


Fig 5.4: First model loss per epoch

Figure (4.3) and (4.7) shows the training and validation plots of model accuracy and loss against each plot. As shown on the plot, the model achieved high performance. It can be clearly seen that the model accuracy was high, and the model loss was very low. This is because of our first model transfer learning method, which helped to reduce the training time and also attain high performance with the small amount of training data and number of epoch.

**Table 4.1:** Prediction values of Patient 1

Precision	Recall	f1-score	Support	Epoch
0	0.98	0.96	0.97	52
1	0.96	0.98	0.97	56
Accuracy	98.15%	97.51%	98.25%	97.45%
Macro avg	0.97	0.97	0.97	108
Weighted avg	0.97	0.97	0.97	108

## b. DATABASE 2



**Fig 4.5:** Input Xray image

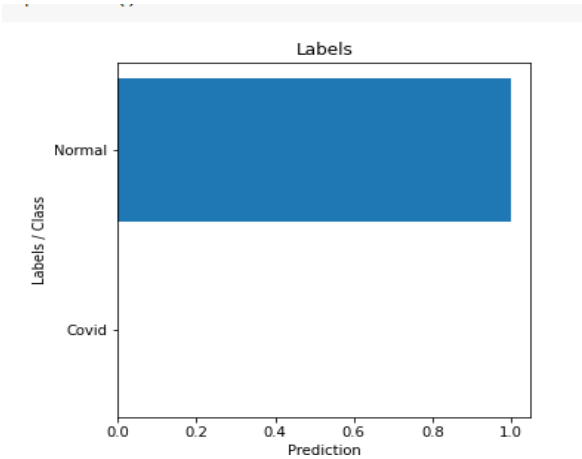


Fig 4.6: Prediction of normal level

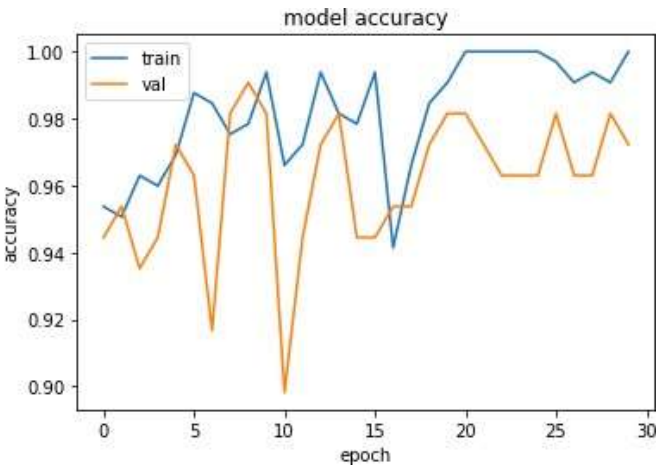


Fig 4.7: Second model accuracy per epoch

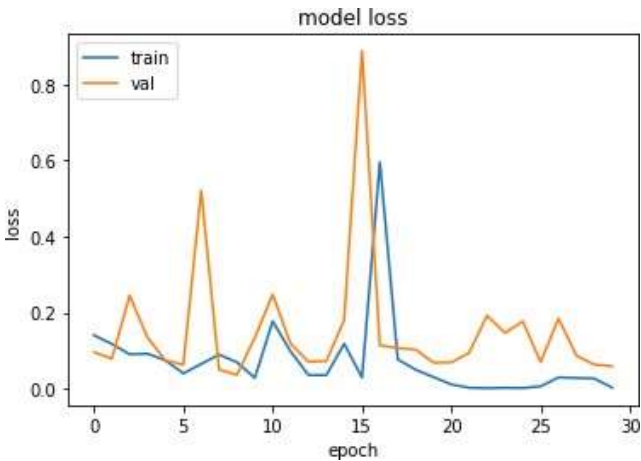


Fig 4.8: Second model loss per epoch

Figure (4.4) and (4.8) shows the training accuracy and loss for the first model. The model is trained to extent that it can learn the important basic x-ray image features. However, the model plot below shows signs of model underfitting and this is because the first dataset used in model training was small. Therefore, this issues can be resolved by adding the training data.

**Table 4.2:** Prediction values of Patient 2

Precision	Recall	f1-score	Support	Epoch
0	0.98	0.96	0.97	52
1	0.96	0.98	0.97	56
Accuracy	97.15%	98.51%	97.25%	98.45%
Macro avg	0.97	0.97	0.97	108
Weighted avg	0.97	0.97	0.97	108

Table 4.3 Compares the proposed Deep learning (DL) based diagnose COVID-19 classification methodology with state of sculptures systems.

**Table 4.3** Comparisons of proposed methodology with state of arts methods

S.No	Methodology	Classification Accuracy (%)
1	<b>Proposed work (2022)</b>	<b>98.08</b>
2	Elayaraja <i>et al.</i> (2022)	95.21
3	Thiyaneswaran et al (2020)	90.0
4	Kumarganesh et al (2018)	96.0

## V. CONCLUSION AND FUTURE ENHANCEMENT

In this work, an automated COVID-19 are finding and classification methodology is proposed to classify the affected area in the images. The low quality pixels are highlighted in the upgraded low resolution X ray images. This high resolution X ray images is then used to extract the texture features, which are subsequently trained and classed using the Deep Learning classification method. It is Evaluated using Recall, f1-score, Support, Epoch and accuracy of the methods suggested in this research are 97.0%, 97.0%, 97.0%, 108 and 98.08% respectively. LUS is almost certainly more sensitive than chest radiograph for COVID-19 and has several advantages over computed tomography and real-time polymerase chain reaction. High-quality research is needed into various aspects of LUS including: diagnostic accuracy in undifferentiated patients; triage and prognostication; monitoring

progression and guiding interventions. In the future, this technology will be paired with a convolutional neural network and a genetic algorithm to increase classification precision.

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