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Deep Learning for COVID-19 Marker Classification and Localization in Point-of-care Lung Ultrasonography

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ABSTRACT

In light of the current COVID19 epidemic, some studies have begun to look into DL-based solutions for the aided detection of lung disorders. Deep learning (DL) has demonstrated effectiveness in medical imaging. This research investigates the use of DL approaches for the analysis of lung ultrasonography (LUS) images, whereas previous efforts have concentrated on CT scans. With labels identifying the severity of the illness at a frame-level, video-level, and pixel-level, we provide a brand-new fully-annotated collection of LUS pictures acquired from multiple Italian hospitals (segmentation masks). We offer a number of deep models using this data that address pertinent problems for the autonomous processing of LUS pictures. We introduce a brand-new deep network in particular, formed from spatial transformer networks, which, in a weakly-supervised manner, both locates pathological artefacts and predicts the illness severity score related to an input frame. We also provide a novel approach for efficient frame score aggregation at the video-level based on uniforms. Finally, we evaluate cutting-edge deep models for calculating COVID-19 imaging biomarker pixel-level segmentations. Research on DL for the aided diagnosis of COVID-19 using LUS data is now possible thanks to experiments on the suggested dataset demonstrating good results on all the tasks taken into consideration.

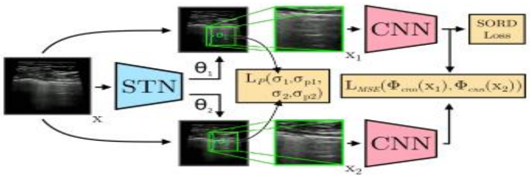
Keywords : Deep learning, Covid_19, Classification, Localization.

I. INTRODUCTION

A COVID-19 pneumonia infection can develop quickly into a potentially serious illness. Numerous acute respiratory distress syndrome (ARDS)-like symptoms, such as bilateral and multi-lobar glass ground pacifications (mostly posteriorly and/or peripherally dispersed), were observed when radiological images from more than 1,000 COVID-19 patients were examined. In order to diagnose COVID-19 patients, chest computed tomography (CT) has been suggested as a suitable substitute. CT diagnosis may often be made much more quickly than RTPCR, which can take up to 24 hours and require numerous tests to get conclusive findings. However, using chest CT has several serious drawbacks: it is expensive, exposes patients to radiation, necessitates thorough cleaning after images, and depends on the interpretability of the radiologist.Ultrasound imaging, a more accessible, affordable, secure, and in-the-moment imaging technology, is gaining popularity lately. For the identification and treatment of acute respiratory diseases, point-of-care settings increasingly employ lung ultrasonography (LUS). When identifying pneumonia, it occasionally showed more sensitivity than a chest X-ray. LUS imaging has recently been used in the emergency room to diagnose COVID-19, according to clinicians. Findings point to particular LUS traits and imaging biomarkers for COVID-19 patients that might be utilised to both identify these individuals and control how well mechanical ventilation is managing their respiratory needs. When the number of patients exceeds the capacity of the standard hospital imaging infrastructure, ultrasonic imaging is a very helpful method due to its wide range of applications and very inexpensive cost. It is also affordable for low- and middle-income nations because of this. However, because there is a high learning curve, it can be difficult and error-prone to interpret ultrasound pictures.

With the use of ultrasound pictures, automatic image analysis employing machine learning and deep learning (DL) techniques has recently demonstrated promise for the reconstruction, classification, regression, and segmentation of tissues. We discuss how DL can help doctors identify COVID-19-related imaging abnormalities on point-of-care LUS in this publication. In specifically, we focus on three distinct tasks on pathological artefact segmentation, video-level grading, and frame-based classification for LUS imaging.The first step entails categorising each individual frame of a LUS picture sequence into one of the four degrees of disease severity that the scoring system has established. The goal of video-level grading is to forecast a grade for each frame in a video using the same grading system. Instead, segmentation involves categorising the pathological abnormalities in each frame at the pixel level.

The automated interpretation of LUS images for aiding healthcare professionals in the identification of COVID-19-related illnesses is one area where this study advances the state of the art. We suggest extending and completely annotating the ICLUS-DB database.Both at the frame and video levels, the collection includes labels on the suggested 4-level scale. Additionally, it contains a portion of pixel-level annotated LUS pictures that may be used to create and access semantic segmentation techniques. We present a unique deep architecture that enables weakly supervised detection of areas containing pathological artefacts and score prediction for a single LUS picture. In order to localize illness patterns, our network uses the Spatial Transformers Network (STN) and consistency losses, and it derives its robust score estimate from a soft ordinal regression loss. We present a straightforward and light-weight method based on uniforms to combine frame-level predictions and calculate the score for a video sequence. We evaluate the efficacy of cutting-edge semantic segmentation techniques built from fully convolutional architectures in order to solve the issue of automated localization of pathological artefacts. Finally, we perform a thorough analysis of our approaches across all tasks, demonstrating that the suggested solutions can successfully predict and localize COVID-19 imaging biomarkers. Dataset and code may be found at many computer vision tasks, from object identification and detection to semantic segmentation, have shown that DL is effective in them. These achievements have spurred further recent growth in the use of deep learning (DL) in medical applications, such as the segmentation of biological images or the diagnosis of pneumonia from chest X-rays.These groundbreaking studies show that DL may help with and automate preliminary diagnosis, which are extremely important in the medical field, when data is available.



Recent studies have concentrated on the detection of COVID-19 from chest CT in the wake of the current pandemic. A quadrant-based filtering is used to minimize potential false positive detections, and a U-Net type network is used to regress a bounding box for each suspicious COVID-19 pneumonia region on subsequent CT scans. In contrast, the input scan's region of interest is first retrieved using a threshold-based region proposal, and each suggested RoI is then classified using the Inception network. Similar to in, RoIs are proposed in the input CT using a VNET-IR-RPN model pre-trained for pulmonary TB detection, and a 3D version of Resnet-18 is utilised to categories each RoI.However, there aren't many publications that use DL on LUS photos. For lung pathology, a classification and loosely guided localization approach is given in. In order to find patterns associated to COVID-19, a frame-based classification and weakly-supervised segmentation approach is performed to LUS pictures. Here, class activation mappings (CAMs) are used to create a weakly-supervised segmentation map of the input picture after Efficient net is trained to detect COVID-19 in LUS images. Comparing our work to all the earlier efforts, there are a number of discrepancies. In this study, we employ STN to develop a weakly-supervised localization policy from the data, as opposed to the traditional localization methods of CAMs (That is, instead of using plain, frame-based categorization labels to infer it from explicitly marked places.) Second, when a classification issue has been resolved, we concentrate on ordinal regression, which forecasts both the existence of COVID-19-associated artefacts and a score linked to the severity of the disease. Third, by suggesting a video-level prediction model built on top of the frame-based technique, we advance relative to all prior methods. Finally, utilizing an ensemble of several cutting-edge neural network architectures for image segmentation, we provide a straightforward yet efficient way to predict segmentation masks. To make it easier to comprehend the findings, the model's predictions are also accompanied by uncertainty estimates.

II. RELATED WORKS

Quantifying bias of COVID-19 prevalence and severity estimates in Wuhan, China that depend on reported cases in international travelers: Using imported case numbers of overseas passengers, and frequently on the supposition that all cases in travellers are confirmed, the risk of COVID-19 infection in Wuhan has been assessed. Recent research suggests that the ability of governments to detect imported cases varies. With a long history of excellent epidemiological monitoring and contact tracing, Singapore has demonstrated a high sensitivity of case discovery in the COVID-19 pandemic. In order to determine how well other nations can detect imported cases compared to Singapore, we employed a Bayesian modelling technique.

According to our calculations, the capability of Singapore is 38% (95% HPDI 22% - 64%) of the capacity of the world to identify imported cases. If all nations had the same capacity for detection as Singapore, an estimated 2.8 (95% HPDI 1.5-4.4) times the present number of imported cases may have been found. The ability to detect imported cases relative to Singapore is 40% (95% HPDI 22% - 67%) among high surveillance locations, 37% (95% HPDI 18% - 68%) among intermediate surveillance locations, and 11% (95% HPDI 0% - 42%) among low surveillance locations, according to our analysis of the second component of the Global Health Security Index.We also show that considering all visitors as if they were locals (rather than taking into account some of these visitors' brief stays in Wuhan) can somewhat understate prevalence. This is supported by a straightforward mathematical model. We come to the conclusion that estimates of case counts in Wuhan based on the assumption of 100% detection in travellers may be several fold underestimated, and severity may be several fold inflated. Unreported cases are probable in all nations, with the danger being higher in those with weaker detection systems and closer ties to the outbreak's hub.

A deep learning algorithm using ct images to screen for corona virus disease (covid-19): Background More than 2.5 million cases of Corona Virus Disease (COVID-19) have been reported worldwide as a result of the SARS-COV-2 outbreak, and that figure is steadily rising. Large numbers of suspected patients must be screened for proper quarantine and treatment in order to stop the disease's spread. The gold standard is pathogenic laboratory testing, but it takes a long time and frequently yields false negatives. As a result, the need for alternate diagnostic techniques to tackle the disease is critical.Based on COVID-19 radiographic alterations in CT scans, we postulated that Artificial Intelligence's deep learning techniques could be able to extract COVID-19's unique graphical characteristics and offer a clinical diagnosis before the pathogenic test, saving crucial time for disease treatment.

Techniques and Results We gathered 1,065 CT pictures of COVID-19 patients (325 images) with pathogen confirmation and those who had previously been diagnosed with normal viral pneumonia (740 images). To create the method, we modified the Inception transfer-learning model, This was subsequently verified both internally and internationally. The specificity and sensitivity of the internal validation were 0.88 and 0.87, respectively, yielding a total accuracy of 89.5%. A overall accuracy of 79.3%, a specificity of 0.83, and a sensitivity of 0.67 were shown in the external testing dataset. Additionally, out of 54 COVID-19 pictures for which the first two nucleic acid test results were negative, 46 were correctly predicted by the algorithm as COVID-19 positive with an accuracy of 85.2%.

Conclusion. These findings offer a proof-of-concept for the use of AI to extract radiological characteristics for prompt and precise COVID-19 diagnosis.

Author synopsis Screening several suspected cases for necessary quarantine and treatment measures is a priority in order to stop the spread of the COVID-19. The gold standard is pathogenic laboratory testing, but it takes a long time and frequently yields false negatives. Alternative diagnostic techniques are so urgently required to fight the illness. We postulated that deep learning techniques in artificial intelligence could be able to extract the unique graphical characteristics of COVID-19 and offer a clinical diagnosis prior to the pathogenic test, saving crucial time. We gathered 1,065 CT scans of COVID-19 patients with pathogen confirmation and those who had previously been identified as having normal viral pneumonia. To create the method, we tweaked the Inception transfer-learning model. The specificity and sensitivity of the internal validation were 0.88 and 0.87, respectively, yielding a total accuracy of 89.5%. A overall accuracy of 79.3%, a specificity of 0.83, and a sensitivity of 0.67 were shown in the external testing dataset. Additionally, out of 54 COVID-19 pictures for which the first two nucleic acid test results were negative, 46 were correctly predicted by the algorithm as COVID-19 positive with an accuracy of 85.2%. Our work is the first to successfully screen for COVID-19 using CT scans and artificial intelligence.

Deep learning in medical ultrasound analysis: a review: One of the most frequently used imaging modalities in clinical practise is ultrasound (US). It is a quickly developing technology with some benefits and some difficulties, such as poor image quality and considerable variability. To aid in US diagnosis and/or to improve the objectivity and accuracy of such evaluation, sophisticated automatic US image analysis methods must be developed from the standpoint of image analysis. Particularly in computer vision and general imaging analysis, deep learning has lately emerged as the most effective machine learning technology. Additionally, deep learning has enormous promise for several autonomous US image processing applications. This paper begins by briefly introducing a few well-known deep learning architectures before summarizing and in-depth discussing how they were applied to several particular US image analysis tasks such segmentation, detection, and classification. The remaining issues and prospective directions for the future use of deep learning in US medical image processing are highlighted.

Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography: a prospective study: Background The best imaging technique for identifying pneumonia caused by the 2019 new coronavirus (COVID19) is computed tomography (CT). Our research aims to develop a deep learning-based method for identifying COVID-19 pneumonia on high resolution CT, lessen the workload of radiologists, and aid in the epidemic's containment.

Methods 46,096 anonymous images from 106 admitted patients at Renmin Hospital of Wuhan University (Wuhan, Hubei Province, China), including 51 patients with laboratory-confirmed COVID-19 pneumonia and 55 control patients with other diseases, were retrospectively collected and processed for model development and validation. To assess and compare radiologists' effectiveness against 2019-CoV pneumonia with that of the model, data on 27 consecutive patients who underwent CT scans on February 5, 2020, at Renmin Hospital of Wuhan University were prospectively gathered.

Findings For each patient, the model achieved 100% sensitivity, 93.55% specificity, 95.24% accuracy, 84.62% positive predictive value (PPV), and 100% negative predictive value (NPV). For each image, the model achieved 94.34% sensitivity, 99.16% specificity, 98.85% accuracy, 88.37% PPV, and 99.61% NPV in a retrospective dataset. The model's performance for 27 potential patients was on par with an experienced radiologist's. The approach helped radiologists significantly cut down their reading time by 65%.

Conclusion The deep learning model performed on par with professional radiologists and significantly increased the effectiveness of radiologists in clinical settings. It has a great chance of relieving the strain on front-line radiologists, enhancing early diagnosis, isolation, and treatment, and assisting in epidemic management.

Encoder decoder with atrous separable convolution for semantic image segmentation: Deep neural networks utilise spatial pyramid pooling modules or encode-decoder structures for semantic segmentation tasks. While the latter networks can capture sharper object boundaries by gradually recovering the spatial information, the former networks can encode multi-scale contextual information by probing the incoming features with filters or pooling operations at multiple rates and multiple effective fields-of-view. In this paper, we suggest combining the benefits of both approaches. Our suggested model, DeepLabv3+, specifically expands DeepLabv3 by including a straightforward yet efficient decoder module to improve the segmentation results, particularly at object borders. In order to create a quicker and more effective encoder-decoder network, we further investigate the Exception model and apply the depth wise separable convolution to both the Atrous Spatial Pyramid Pooling and the decoder modules. We use the PASCAL VOC 2012 and Cityscapes datasets to show the usefulness of the suggested model, attaining test set performance of 89% and 82.1% respectively without any post-processing. A publicly accessible reference implementation of the suggested models is provided with our study.

III. Methodology

Proposed system:

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 uniforms 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.

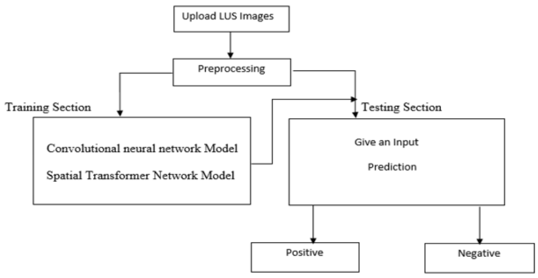


Figure 1: Block diagram

IV. Implementation

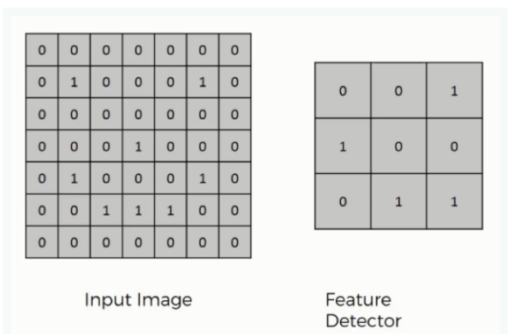
The project has implemented by using below listed algorithm.

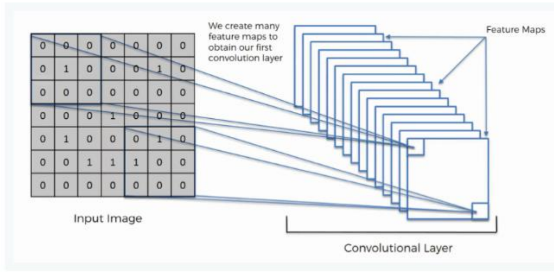
1. Convolutional Neural Network

Step1: convolutional operation

The convolution operation is the first component of our strategy. We will discuss feature detectors in this phase since they essentially act as filters for neural networks. Additionally, we'll talk about feature maps, their parameters, how patterns are found, the detection layers, and how the results are laid out.

The Convolution Operation



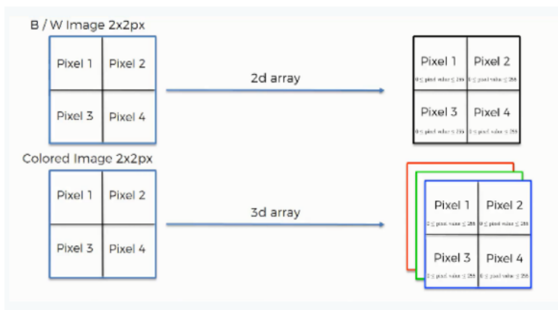


Step (1b): ReLU Layer

The Rectified Linear Unit or Relook will be used in the second portion of this process. We will discuss Relook layers and examine the role of linearity in Convolutional Neural Networks.

Although it's not required to comprehend CNN's, it wouldn't hurt to take a brief course to advance your knowledge.

Convolutional Neural Networks Scan Images



Step 2: Pooling Layer

We'll discuss pooling in this section and learn exactly how it typically operates. But max pooling will be the central concept in this situation. However, we'll discuss a variety of strategies, including mean (or total) pooling. This section will conclude with a demonstration created with a visual interactive tool that will undoubtedly clarify the entire idea for you.

Step 3: Flattening

Here's a quick explanation of the flattening procedure and how to switch between pooled and flattened layers when using convolutional neural networks.

Step 4: Full Connection

Everything we discussed in the previous section will be combined in this section. By understanding this, you'll be able to visualize Convolutional Neural Networks more clearly and understand how the "neurons" they create ultimately learn to classify pictures.

Summary

Finally, we'll put everything in perspective and provide a brief summary of the idea addressed in the section. If you think it will help you in any way (and it probably will), you should look at the additional tutorial that covers Cross-Entropy and Soft axe. Although it is not required for the course, it will benefit you greatly to be familiar with these principles since you will probably encounter them when working with convolutional neural networks.

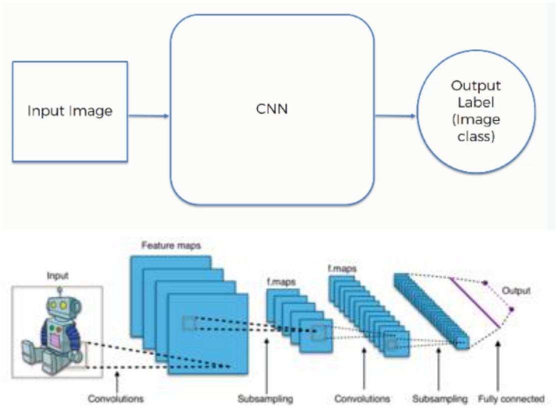


Fig. CNN Architecture

V. Results and Discussion

The following screenshots are depicted the flow and working process of project.

Home page:

User registration page:

User Login page:

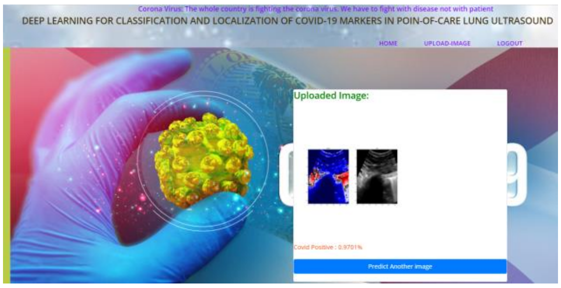
About project page:

User home page:

Upload image:

Upload an image and predict the results(as Negative)

Upload an image and predict the results(as Positive)



VI. Conclusion

In this application, LUS offers significant benefits over computed tomography and real-time polymerase chain reaction, and is probably definitely more sensitive than a chest radiograph for COVID-19. Numerous aspects of LUS, such as diagnostic precision in undifferentiated patients, triage and prognostication, monitoring progress and directing interventions, the persistence of residual LUS findings, inter-observer agreement, and the function of contrast-enhanced LUS, require high-quality research.

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