Review of Artificial Intelligence Techniques in Imaging Data Acquisition, Segmentation and Diagnosis for COVID-19

Assistant Professor Noushin Taj[1], Nishvitha N.R[2], Rajeshwari M Savalagi[3], Sharda Jha[4], Sushmitha sarraf[5]

Department of CSE,
SIT, Tumakuru, Karnataka, India

Abstract: **The pandemic of coronavirus disease 2019 (COVID-19) is spreading all over the world. Medical imaging such as X-ray and computed tomography (CT) plays an essential role in the global fight against COVID-19, whereas the recently emerging artificial intelligence (AI) technologies further strengthen the power of the imaging tools and help medical specialists. We hereby review the rapid responses in the community of medical imaging (empowered by AI) toward COVID-19. For example, AI-empowered image acquisition can significantly help automate the scanning procedure and also reshape the workflow with minimal contact to patients, providing the best protection to the imaging technicians. Also, AI can improve work efficiency by accurate delineation of infections in X-ray and CT images, facilitating subsequent quantification. Moreover, the computer-aided platforms help radiologists make clinical decisions, i.e., for disease diagnosis, tracking, and prognosis. In this review paper, we thus cover the entire pipeline of medical imaging and analysis techniques involved with COVID-19, including image acquisition, segmentation, diagnosis, and follow-up.**

Index Terms: Artificial Intelligence Techniques in Imaging Data Acquisition, Segmentation, Diagnosis for COVID-19, Prediction Model and classification Algorithm

I. INTRODUCTION

The coronavirus disease 2019 (COVID-19), caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), is an ongoing pandemic. The number of people infected by the virus is increasing rapidly. Up to April 9, 2020, 1,436,198 cases of COVID-19 have been reported in over 200 countries and territories, resulting in approximately 85,521 deaths (with a fatal rate of 5.95%) . This has led to great public health concern in the international community, as the World Health Organization (WHO) declared the outbreak to be a Public Health Emergency of International Concern (PHEIC) on January 30, 2020 and recognized it as a pandemic on March 11, 2020.

The workflow of imaging-based diagnosis for COVID-19, taking thoracic CT as an example, includes three stages in general, i.e., 1) pre-scan preparation, 2) image acquisition, and 3) disease diagnosis. In the pre-scan preparation stage, each subject is instructed and assisted by a technician to pose on the patient bed according to a given protocol. In the image acquisition stage, CT images are acquired during a single breath-hold. The scan ranges from the apex to the lung base. Scans are done from the level of the upper thoracic inlet to the inferior level of the costophrenic angle with the optimized parameters set by the radiologist(s), based on the patient's body shape. From the acquired raw data, CT images are reconstructed and then transmitted through picture archiving and communication systems (PACS) for subsequent reading and diagnosis.

Artificial intelligence (AI), an emerging technology in the field of medical imaging, has contributed actively to fight COVID-19 [13]. Compared to the traditional imaging workflow that heavily relies on human labors, AI enables more safe, accurate and efficient imaging solutions. Recent. AI-empowered applications in COVID-19 mainly include the dedicated imaging platform, the lung and infection region segmentation, the clinical assessment and diagnosis, as well as the pioneering basic and clinical research. Moreover, many commercial products have been developed, which successfully integrate AI to combat COVID-19 and clearly demonstrate the capability of the technology. The Medical Imaging Computing Seminar (MICS) 1 , a China's leading alliance of medical imaging scholars and start-up companies, organized this first online seminar on COVID-19 on February 18, 2020, which attracted more than ten thousands of visits. All the above examples show the tremendous enthusiasm cast by the public or AI-empowered progress in the medical imaging field, especially during the ongoing pandemic.

Due to the importance of AI in all the spectrum of the imaging-based analysis of COVID-19, this review aims to extensively discuss the role of medical imaging, especially empowered by AI, in fighting the COVID-19, which will inspire future practical applications and methodological research. In the following, we first introduce intelligent imaging platforms for COVID-19, and then summarize popular machine learning methods in the imaging workflow, including segmentation, diagnosis and prognosis. Several publicly available datasets are also introduced. Finally, we discuss several open problems and challenges. We expect to provide guidance for researchers and radiologists through this review. Note that we review the most related medical-imaging-based COVID-19 studies up to March 31, 2020.

Healthcare practitioners are particularly vulnerable concerning the high risk of occupational viral exposure. Imaging specialists and technicians are of high priority, such that any potential contact with the virus could be under control. In addition to the personal protective equipment (PPE), one may consider dedicated imaging facilities and workflows, which are significantly important to reduce the risks and save lives.

II. LITERATURE SURVEY

[1] J. P. Kanne, "Chest CT findings in 2019 novel coronavirus (2019-nCoV) infections from Wuhan, China: key points for the radiologist," *Radiology*, p. 200241, 2020.

In clinical practice, easily accessible imaging equipment, such as chest X-ray and thoracic CT, provide huge assistance to clinicians. Particularly in China, many cases were identified as suspected of COVID-19, if characteristic manifestations in CT scans were observed. The suspected patients, even without clinical symptoms (e.g. Fever and coughing), were also hospitalized or quarantined for further lab tests. Given the current sensitivity of the nucleic acid tests, many suspected patients have to be tested multiple times several days apart before reaching a confident diagnosis. Hence, the imaging findings play a critical role in constraining the viral transmission and also fighting against COVID-19.

[2] I. D. Apostolopoulos and T. Bessiana, "Covid-19: Automatic detection from X-Ray images utilizing transfer Learning with convolutional neural networks," *arXiv:2003.11617*, 2020.

Chest X-ray and CT are widely used in the screening and diagnosis of COVID-19. It is important to employ a contactless and automated image acquisition workflow to avoid the severe risks of infection during COVID-19 pandemic. However, the conventional imaging workflow includes inevitable contact between technicians and patients. Especially, in patient positioning, technicians first assist in posing the patient according to a given protocol, such as head-first versus feet-first, and supine versus prone in CT, followed by visually identifying the target body part location on the patient and manually adjusting the relative position and pose between the patient and the X-ray tube. This process puts the technician's in close contact with the patients, which leads to high risks of viral exposure. Thus, a contactless and automated imaging workflow is needed to minimize the contact.

[3] S. Scheib, "Dosimetric end-to-end verification devices, systems, and methods," ed: Google Patents, 2019.

Many modern X-ray and CT systems are equipped with cameras for patient monitoring purposes. During the outbreak of COVID-19, those devices facilitate the implementation of a contactless scanning workflow. Technicians can monitor the patient from the control room via a live video stream from the camera. However, from only the overhead view of the camera, it is still challenging for the technician to determine the scanning parameters such as scan range. In this case, AI is able to automate the process by identifying the pose and shape of the patient from the data acquired with visual sensors such as RGB, Time-of-Flight (TOF) pressure imaging or thermal (FIR) cameras. Thus, the optimal scanning parameters can be determined.

[4]. Y. Wang, X. Lu, J. Liu, X. Li, R. Hu, X. Meng, *et al.*, "Precise pulmonary scanning and reducing medical radiation exposure by developing a clinically applicable intelligent CT system: Towards improving patient care," *Preprints with The EBioMedicine*, 2020.

One typical scanning parameter that can be estimated with AI-empowered visual sensors is the scan range that defines the starting and ending positions of the CT scan. Scan range can be identified by detecting anatomical joints of the subject from the images. Much recent work has focused on estimating the 2D or 3D key point locations on the patient body. These key point locations usually include major joints such as the neck, shoulders, elbows, ankles, wrists, and knees. Wang *et al.* have shown that such an automated workflow can significantly improve scanning efficiency and reduce unnecessary radiation exposure. However, such key points usually represent only a very sparse sampling of the full 3D mesh in the 3D space (that defines the digital human body).

[5] R. Booij, R. P. Budde, M. L. Dijkshoorn, and M. van Straten, "Accuracy of automated patient positioning in CT using a 3D camera for body contour detection," *European Radiology*, vol. 29, pp. 2079-2088, 2019.

Other important scanning parameters can be inferred by AI, including ISO-centering. ISO-centering refers to aligning the target body region of the subject, so that the center of the target body region overlaps with the scanner ISO center and thus the overall imaging quality is optimal. Studies have shown that, with better ISO-centering, radiation dosage can be reduced while maintaining similar imaging quality.

[6] G. Georgakis, R. Li, S. Karanam, T. Chen, J. Kosecka, and Z. Wu, "Hierarchical hinematic human mesh recovery," *arXiv:2003.04232*, 2020.

In order to align the target body region to the ISO center, and given that anatomical keypoints usually represent only a very sparse sampling of the full 3D mesh in the 3D space (defining the digital human body), Georgakis *et al.* [44] propose to recover human mesh from a single monocular RGB image using a parametric human model SMPL [45]. Unlike other related studies [46], they employ a hierarchical kinematic reasoning for each kinematic chain of the patient to iteratively refine the estimation of each anatomical keypoint to improve the system robustness to clutters and partial occlusions around the joints of the patient

III. IMPLEMENTATION

Architecture:

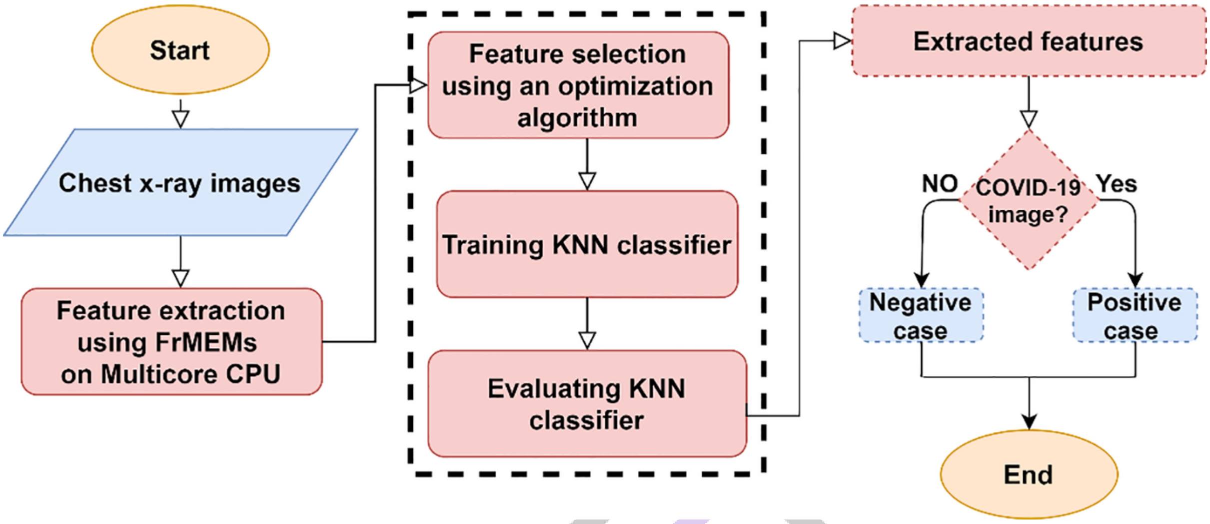

Fig 1: Architecture of Civid-19 Model

During the outbreak of COVID-19, several essential contactless imaging workflows were established from the utilization of monitoring cameras in the scan room, or on the device, to mobile CT platforms with better access to patients and flexible installation. A notable example is an automated scanning workflow based on a mobile CT platform empowered by visual AI technologies. The mobile platform is fully self-contained with an AI-based pre-scan and diagnosis system. It was redesigned into a fully isolated scan room and control room. Each room has its own entrance to avoid any unnecessary interaction between technicians and patients.
After entering the scan room, the patient is instructed, by visual and audio prompts, to pose on the patient bed. Technicians can observe through the window and also the live video transmitted from the ceiling mounted AI camera in the scan room, and correct the pose of the patient if necessary. Once the patient is deemed ready, either by the technician or the motion analysis algorithm, the patient positioning algorithm will automatically recover the 3D pose and fully-reconstructed mesh of the patient from the images captured with the camera [42]. Based on the 3D mesh, both the scan range and the 3D centerline of the target body part of the patient are estimated and converted into control signals and optimized scanning parameters for the technician to verify. If necessary, the technician can make adjustments. Once verified, the patient bed will be automatically aligned to ISO center and moved into CT gantry for scanning. After CT images are acquired, they will be processed and analyzed for screening and diagnosis purposes.

Segmentation can be used in various COVID-19 applications, among which diagnosis is frequently reported. For example, it uses U-Net for lung segmentation in a multi-center study for distinguishing COVID-19 from community-acquired pneumonia on propose an AI system for fast COVID-19 diagnosis. The input to the classification model is the CT slices that have been segmented by a segmentation network. Another application of image segmentation is quantification which further serves for many medical applications. For example, they propose a VB-Net for segmentation of lung, lung lobes and lung infection, which provide accurate quantification data for medical studies, including quantitative assessment of progression in the follow-up, comprehensive prediction of severity in the enrolment, and visualization of lesion distribution using percentage of infection (POI). It assesses longitudinal progression of COVID-19 by using voxel-level deep learning-based CT segmentation of pulmonary opacities. Huang *et al.* segment lung region and GGO for quantitative evaluation, which is further used for monitoring the progression of COVID-19. Qi *et al.* segment lung lesions of COVID-19 patients using a U-Net based algorithm, and extract radionics features for predicting hospital stay.
In summary, image segmentation plays an important role in COVID-19 applications, i.e., in lung delineation and lesion measurement. It facilitates radiologists in accurately identification of lung infection and prompting quantitative analysis and diagnosis of COVID-19.

Data collection is the first step to develop machine learning methods for COVID-19 applications. Although there exist large public CT or X-ray datasets for lung diseases, both X-ray and CT scans for COVID-19 applications are not widely available at present, which greatly hinders the research and development of AI methods. Recently, several works on COVID-19 data collection have been reported. Cohen *et al.* creates COVID-19 Image Data Collection by assembling medical images from websites and publications, and it currently contains 123 frontal view X-rays. The COVID-CT dataset includes 288 CT slices for COVID-19 confirmed cases thus far. It is collected from over 700 pre-printed literature on COVID-19 from media and bioRxiv. The Corona cases Initiative also shares confirmed cases of COVID-19 on the website (https://coronacases.org). Currently, it includes 3D CT images of 10 confirmed COVID-19 cases. Also, the COVID-19 CT segmentation dataset (http://medicalsegmentation.com/covid19/) contains 100 axial CT slices from 60 patients with manual segmentations, in the form of JPG images. It is worth noting that the current public datasets still have a very limited number of images for training and testing of AI algorithms, and the quality of datasets is not sufficient.

Tool & Technologies

Hardware Requirements

Processor	Intel Core i5 or AMD FX 8 core series with clock speed of 2.4 GHz or above
RAM	2GB or above
Hard disk	120 GB or above
Input device	Keyboard or mouse or compatible pointing devices
Display	XGA (1024*768 pixels) or higher resolution monitor with 32 bit color settings
Miscellaneous	USB Interface, Power adapter, etc

Software Requirements

Operating System	Linux
Programming Language – Backend	Core Java, Advanced Java, J2EE, MVC Framework
Programming language - Frontend	Bootstrap Framework, HTML, CSS, JavaScript, Ajax, JQuery
Development environment	Eclipse Oxygen IDE
Application Server	Apache Tomcat v9.0
Database	MySQL

Algorithms:

1. ResNet50 ResNet-50 is a convolutional neural network that is 50 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. Unlike traditional sequential network architectures such as AlexNet, OverFeat, and VGG, ResNet is instead a form of “exotic architecture” that relies on micro-architecture modules.

```
net = resnet50
net = resnet50('Weights','imagenet')
lgraph = resnet50('Weights','none')
```

2. **VGG16** is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper “Very Deep Convolutional Networks for Large-Scale Image Recognition”. The model achieves 92.7% top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes.

```
net = vgg16
net = vgg16('Weights','imagenet')
layers = vgg16('Weights','none')
```

3. Inception-V3 is a convolutional neural network that is 48 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 299-by-299.

```
net = inceptionv3
net = inceptionv3('Weights','imagenet')
lgraph = inceptionv3('Weights','none')
```

4. Xception is a convolutional neural network that is 71 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 299-by-299.

```
net =  xception
net =  xception('Weights','imagenet')
lgraph =  xception('Weights','none')
```

IV. RESULTS

With proposed system we can successfully detect, segementation and diagnosis the images for COVID 19 Pandemic.

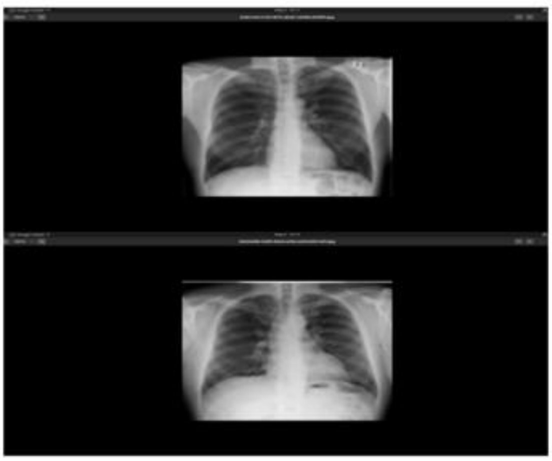

Fig 2:Normal Chest_X_Ray

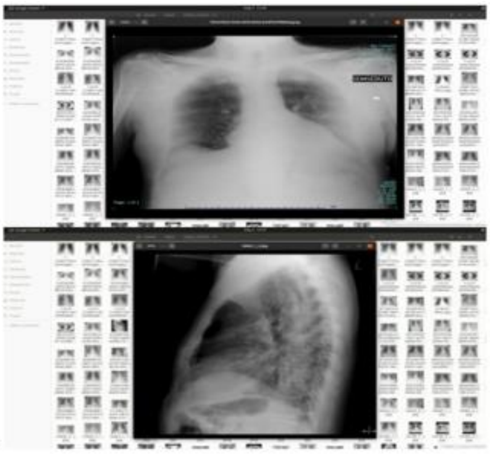

Fig 3:Affected From Covid_19

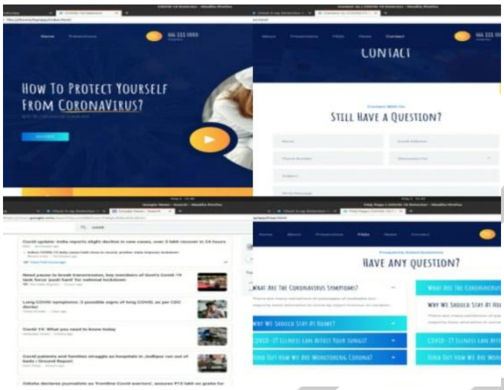

Fig 4:Interface

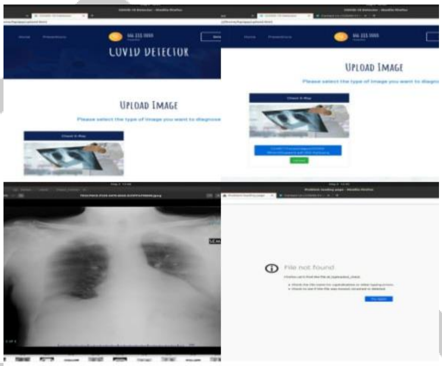

Fig 5:Process Of Detecting Of Covid_19

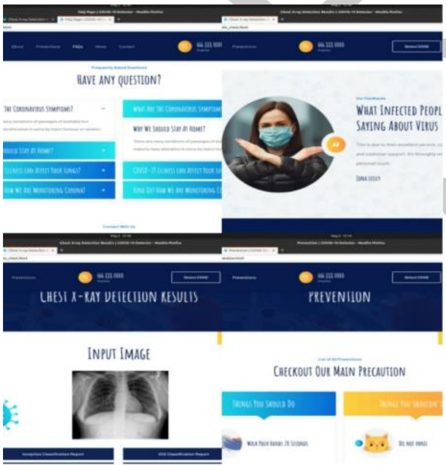

Fig 6:Interface

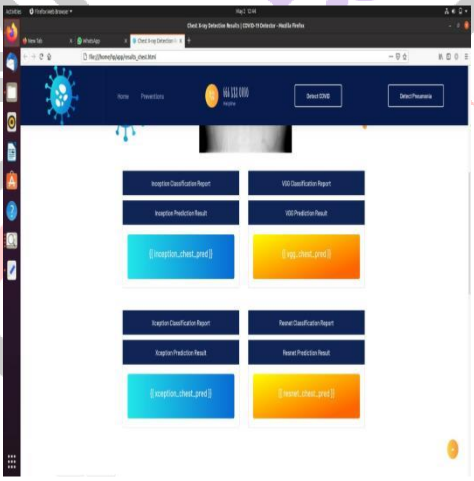

Fig 7:Final Result

V. CONCLUSION

The COVID-19 is a disease that has spread all over the world. Intelligent medical imaging has played an important role in fighting against COVID-19. This paper discusses how AI provides safe, accurate and efficient imaging solutions in COVID-19 applications. The intelligent imaging platforms, clinical diagnosis, and pioneering research are reviewed in detail, which covers the entire pipeline of AI-empowered imaging applications in COVID-19. Two imaging modalities, i.e., X-ray and CT, are used to demonstrate the effectiveness of AI-empowered medical imaging for COVID-19.

It is worth noting that imaging only provides partial information about patients with COVID-19. Thus, it is important to combine imaging data with both clinical manifestations and laboratory examination results to help better screening, detection and diagnosis of COVID-19. In this case, we believe AI will demonstrate its natural capability in fusing information from these multi-source data, for performing accurate and efficient diagnosis, analysis and follow-up.

REFERENCES

[1] J. P. Kanne, "Chest CT findings in 2019 novel coronavirus (2019-nCoV) infections from Wuhan, China: key points for the radiologist," *Radiology*, p. 200241, 2020.

[2] I. D. Apostolopoulos and T. Bessiana, "Covid-19: Automatic detection from X-Ray images utilizing transfer Learning with convolutional neural networks," *arXiv:2003.11617*, 2020.

[3] World Health Organization Coronavirus disease (COVID-2019) situation reports website", available online [10.4.2020] at https://www.who.int/emergencies/diseases/novel-coronavirus- 2019/situation-reports

[4]. "SEWIO UWB Real-Time Location System (RTLS)", available online [5.4.2020] at https://www.sewio.net/real-time-location-system-rtls-onuwb/

[5]. C. Sagonas, E. Antonakos, G, Tzimiropoulos, S. Zafeiriou, M. Pantic. 300 faces In-the-wild challenge: Database and results. Image and Vision Computing (IMAVIS), Special Issue on Facial Landmark Localisation "In-The-Wild". 2016.