A SURVEY ON COVID-19 DIAGNOSIS FROM CT AND X-RAY SCANS USING ARTIFICIAL INTELLIGENCE METHODS

Jinu Paulson[1], G. Angeline Prasanna[2]*

Abstract

The Coronavirus 2019 (COVID19) epidemic causes many deaths and the World Health Organization (WHO) has declared it as 'a global pandemic'. Millions of people are still affected by this virus every day. Since the standard reverse transcription polymerase chain reaction (RTPCR) test for COVID19 is not cost effective, scientists are trying to use artificial intelligence systems to use medical imaging (such as X-rays and computed tomography (CT)) to detect automatically identify this type of disease. Artificial intelligence systems involve very promising machines and deep learning methods. These X-ray and CT imaging procedures simplify the accurate diagnosis of COVID19. This article details the machine and deep learning methods used for chest X-rays and CT scans to identify the severity of COVID-19. In addition, it compares its efficiency in terms of benefits and limitations to suggest future improvements and to avoid a global outbreak of COVID19.

Keywords: COVID19, artificial intelligence, machine learning, deep learning, computed tomography, chest X-ray, RTPCR.

I. INTRODUCTION

COVID-19, also known as viral disease, is caused by severe acute respiratory syndrome (SARSCoV2). This new virus is the seventh part of the coronavirus family of non-specific enveloped RNA viruses. The death rate of COVID-19 is lower than that of SARS diseases and Middle East respiratory syndrome (MERS). However, it is very invasive and the number of patients is increasing regularly. The outbreak was first reported in Wuhan, Hubei Province, China, after many patients with unexplained pneumonia were reported on December 31, 2019. Through deep sequencing and analysis of samples from the patient's respiratory tract, was found to be a pathogen. The Chinese facility was on January 7, 2020. The epidemic was declared a public health emergency of international concern on January 30, 2020. On February 11, 2020, WHO announced that this new virus was named COVID19. After the World Health Organization announced it on March 11, it was officially considered a pandemic [1].

The COVID-19 has a widespread impact on millions of citizens. Some infected people may develop mild to severe infections and recover instead of being hospitalized. The most common symptoms are fever, dry cough and nausea. The correct diagnosis is only provided to people with severe symptoms. People who are truly healthy but with mild symptoms should pay attention to their symptoms at home [2]. Under normal circumstances, it takes 56 days to check for health problems after infection, but it takes 14 days in total.

When COVID19 tries to grow at an exponential rate, precautions need to be taken. These measures may include complete suspension of heavily polluted areas, restrictions on airline operations, suspension of educational institutions, and other unpopular formal procedures. Given the contagious nature of the disease, the main purpose of such measures is to limit direct interactions. The decision was formally approved and implemented. People directly affected are divided into three categories. The elderly who

[1] Department of Computer Science,
AJK College of Arts and Science, Coimbatore, Tamil Nadu, India

[2] Department of Computer Applications,
Karpagam Academy of Higher Education, Coimbatore, Tamil Nadu, India
*Corresponding Author

are most susceptible to the virus are at the top of the list. Because of the weakened immune system, the elderly seems to be the first to respond to the epidemic. The children's community is second. Children’s organ systems are still developing and therefore face a higher risk. The third category includes people suffering from diseases such as insulin resistance, high cholesterol, and metabolic syndrome. These people are ideal victims because their immune cells have been severely damaged due to common psychological problems [3]. The diseases faced by the third group of people can become extremely dangerous.

Due to global isolation, the exchange of information between scientists and health professionals is currently problematic. Therefore, many COVID-19 databases, including CT scans, X-rays, etc., are either out of reach for many scientists or difficult to locate. It is amazing that within a short period of time after the COVID-19 outbreak, research in the medical field successfully introduced advanced machines and deep learning methods using computed tomography and X-ray scanning during the COVID-19 war, and made progress. substantial [45]. For example, cross-medicine image analysis, machines, and deep learning help diagnose COVID-19 and provide non-invasive detection measures to prevent medical personnel from infecting pathogens. For additional treatment procedures, the percent severity of the patient is also provided. Virology research can be combined with drug production and vaccination, and machine and deep learning can be used to examine the genetics associated with the SARSCoV2 protein. In addition, on the large-scale COVID-19 case data and social media data, the artificial intelligence model learns to build a disease transmission model, which can accurately predict outbreaks, transmission routes, transmission lists and impacts.

In this article, the machine is explained and deep learning methods are used to identify the limb level of COVID19 from CT scans and X-rays. In addition, a comparative analysis was carried out to study its advantages and limitations. Consistent with these restrictions, the proposed future direction is to improve the accuracy of COVID19 patient identification. The rest of the article is prepared as follows: The second part studies the latest diagnostic methods of COVID19 from CT scans and X-rays. The third part presents its advantages and limitations in the form of a table. The fourth part summarizes the survey and suggests future directions.

II. SURVEY ON COVID-19 DISEASE PREDICTION FROM X-RAY AND CT SCANS

The severity of COVID19 on CT [6] is analysed by classifying its profound characteristics. First, use the DenseNet201 framework to extract deep features from CT scans. These characteristics are then sent to a support vector machine (SVM) with three cores to identify critical and non-critical COVID19 patients. COVID19 [7] has been identified from CT samples by deep learners through voting-based methods and analysis of crossover data sets. It mainly uses a simple regularization of pixel intensity to adjust the size of the input sample. Then the data enhancement is achieved based on rotation, pan, and zoom. In addition, these samples are provided to the Efficient Net classifier, which uses a vote-based classification mechanism.

Uses VBNet adapted to the HumanInTheLoop (HITL) strategy to automatically divide and quantify COVID19 lung infections from the CT sample system [8]. First, the radiologist manually contours the smallest batch of CT data. The batch training segmentation network is then used as an initial model to segment the next batch of infected areas and manually correct the segmentation results provided by the segmentation network. These corrected results are provided as new training data to update the generated VBNet model. In the testing phase, the trained model interacts with HITL through the direct transmission of the neural network to segment the infected area in the new CT scan.

Designed a deep TL framework [9], which can speed up the identification of COVID19 patients through chest X-ray and CT scans. It has been used to extract features of COVID19 scanners and learn to distinguish pneumonia, other lung diseases, and healthy cases. In addition, the color visualization method is applied to the GradCAM method to provide the ROI of diseased lung lesions.

DCNN to design an automated system [10] to identify COVID19 from lung radiographs. In this system, different pre-learning structures are applied, including ResNet50, InceptionV3, and InceptionResNetV2, to improve detection accuracy. By training these models, chest X-ray images are classified into multiple infection categories, such as ARDS, COVID19, MERS, pneumonia, and SARS. A deep learning network called CoroNet [11] is designed to identify and diagnose COVID19 from lung radiographs. From the X-ray scan images collected, the image size was adjusted and the CoroNet designed to find pneumonia, including bacterial, viral, and COVID19 pneumonia was applied.

The InfNet classifier has been suggested to automatically classify lung infections from CT images [12]. Initially, rough areas were identified. Additionally, edges are modelled using edge constraint references and reverse attention. Then InfNet is run, in which a parallel partial decoder is used to connect the characteristics of the high-level layer, and the context data is obtained by merging the characteristics. In addition, a global map was created to classify the samples infected with COVID19. A deep learning machine has been used to identify and classify CT samples [13] as COVID19, pneumonia, and health. First, the CT samples are pre-processed to extract lung regions. After that, 3DCNN is used to divide the sample into multiple patches and classify them into 3 different types.

A multitask, multiscale deep learner named M3LungSys [14] is designed with cut off and patient-level CNNs in mind and is used to predict multiple types of pulmonary pneumonia from CT scans. First, a CT scan of the lungs is collected and pre-processed to remove noise or unwanted features from the scan. Then, use manual methods to divide the image into lungs and others. In addition, the smallest bounding rectangle within the given bounds is used to crop the lung area. In addition, the slices are provided to DCNN to predict different diseases: COVID19, H1N1, pneumonia, and healthy people.

By combining classification and cost-sensitive training, designed to effectively predict COVID19 from lung X-rays [15]. Initially, a conditional average error was developed to train the depth discriminant representation. Then, a score-level cost-sensitive training was established, which can dynamically increase the rate of misclassification of COVID19 cases as other diseases.

An automated technology [16] designed to diagnose COVID19 through X-rays. This technique relies on XceptionNet, which uses deeply separable convolutions. First, collect X-ray scans from various sources and visualize them using exploratory data analysis. Then, use image regularization to transform the image on the matrix and remove distortion from the image. After that, DNN is applied to learn the training samples. In addition, the image was enlarged and the enlarged image was sent to CNN to predict COVID19, viral pneumonia, and healthy patients. The design of CovXNet [17] uses deep convolutional CNN to accurately extract different attributes from lung radiographs. First, consider a large number of lung X-rays related to healthy people and pneumonia to learn CovXNet. The main learning is done through several additional optimization layers that are learned using the least number of lung radiographs related to COVID19 and another patient with pneumonia. In addition, gradient-based discriminative positioning has been combined to distinguish irregular regions of X-ray samples that indicate various types of pneumonia. An integrated classifier was used to detect 4,444

COVID19 from an X-ray scan [18]. In this model, the previously trained ResNet50 and VGG16 networks are combined and the maximum combination is used to reduce the feature dimension. Furthermore, it is also used to classify COVID19 and pneumonia patients from lung X-rays. A new method called COVIDSDNet [19] with the highest generalizability has been designed to classify COVID19 from lung radiographs. First, the COVIDGR1.0 data set is collected, and pre-processing methods such as segmentation-based trimming are used to remove inappropriate data from the input X-ray images. In addition, the inherent conversion scheme of the class is also applied to improve the discrimination ability. Later, a new reasoning task was developed, which combined the predictions of different transformation classes to calculate the result predictions. In addition, COVIDSDNet is also used to classify the COVID19 population.

Hierarchical and multi-class classifications have been developed [20] to identify COVID19 on lung X-rays. First, lung radiographs are collected and automatically pre-processed to standardize the images. Then, texture descriptors are used to extract manual and non-manual features from X-ray samples, and then these features are combined and resampling is applied to solve the class imbalance problem. In addition, these features are classified by KNN, random forest, SVM, decision tree, and MLP to identify COVID19 samples. has developed an alternative model based on the capsule network [21], called COVIDCAPS, to identify COVID19 from radiographs. In this model, many capsules and convolutional layers are considered. In addition, the loss factor has been changed to solve the category imbalance challenge. COVID19 [22] has been predicted from CT samples using different stages, such as pre-processing, feature extraction, and classification. First, the CT samples are pre-processed to segment ROIs, and then relevant COVID19 features are extracted from these ROIs. After that, pneumonia and COVID19 are categories based on the learned neural network. The serial area creation network [23] aims to simultaneously identify and segment COVID19 lesion areas. Initially, a context enhancement unit was developed to increase the context data between the encoder and decoder. Later, a new boundary error was developed to increase the scanned context data. The multi-layer scan limit was created to reduce computational costs. In addition, the prediction box is considered to refine the result of segmentation by post-processing.

A new expanded dual care UNet [24] is designed using a dual care strategy and a hybrid expansion convolution to segment COVID19 lesions on CT scans. In this model, a dual care strategy composed of 2 care units is used to refine the feature map and reduce the semantic map between all levels of feature maps. The decoder achieves a larger receptive field and refines the decoding task with the help of the hybrid dilated convolution.

Chandra, T. B .etal has designed an automated COVID monitoring framework [25], which extracts radiological texture descriptors from chest radiographs to identify to patients with COVID-19. In this framework, the 2-step classification method: conventional vs. Irregular and COVID-19 vs. pneumonia uses a supervised classification algorithm to distinguish based on the majority vote of the classifier. A new method has been developed [26], which uses texture features and neural networks to distinguish COVID-19 based on its performance on chest radiographs.

A United Nations-based segmentation network [27] has been developed to use attention strategies to segment COVID-19 CT scans. In this model, an attention strategy with spatial attention unit and channel attention unit is integrated to re-weight the representation of features in space and channel to capture rich contextual relevance. In addition, local Tversky loss was applied to treat small partitions of lesions.

III. COMPARATIVE STUDY

In this section, the benefits and limitations of the studied machine and deep learning methods on COVID-19 diagnosis from CT and X-ray scans are revised in Table 1.

Table 1. Comparison of Different Artificial Intelligence Methods for COVID-19 Diagnosis from CT and X-ray Scans

Ref. No.	Methods	Benefits	Limitations	Dataset	Accuracy (%)
[6]	DenseNet201 with cubic SVM	Good ability to discriminate the severe and non - severe COVID - 19 patients.	The quantity of training images was not adequate.	202 COVID-19 cases.	95.2
[7]	Efficient Net with voting scheme	High accuracy to classify COVID-19 and non-COVID-19 patients.	It needs to train very large CT scan databases for proper validation.	1601 COVID-19 CT scans and 1693 non-COVID-19 CT scans.	98.99
[8]	VB-Net	Better dice similarity coefficient and less error.	It was not able to quantify all types of pneumonia due to the limited training scans.	300 CT scans of COVID-19 patients.	91.6
[9]	Grad-CAM and VGG19	Better accuracy and faster detection of COVID-19 patients.	It was not able to train temporal dependence features to avoid false positives.	206 COVID-19 and 364 pneumonia cases.	5.6
[10]	Res Net 50, InceptionV3 and Inception-Res Net V2	High accuracy to recognize COVID-19 patients automatically.	It was performed only on a less quantity of X-ray samples which may influence the accuracy.	50 COVID-19 and 50 normal X-ray scans.	98 (ResNet50); 97 (InceptionV3); 87 (Inception-Res NetV2)
[11]	Random under - sampling and CoroNet	Computational complexity was less due to the minimum number pre-processing of images.	Accuracy was less since it considers a limited number of images.	330 bacterial pneumonia, 327 viral influenza, 284 COVID-19 and 310 healthy cases.	90
[12]	Inf-Net	Less computation burden.	It has less sensitivity and dice similarity coefficient.	100 COVID-19 CT scans.	Specificity = 63.9%; Sensitivity = 18.6%; Dice score = 0.238
[13]	Image pre-processing and 3D CNN	Better efficiency to classify COVID-19 cases.	It has the limited number of images.	110 COVID-19 and 399 healthy cases.	Sensitivity = 98.2%; Specificity = 92.2%

Ref. No.	Methods	Benefits	Limitations	Dataset	Accuracy (%)
[14]	M^3Lung-Sys	It achieved remarkable efficiency and was flexible for physicians.	It may still misclassify few normal scansand it was not end-to-end learnable.	251 healthy people, 245 COVID-19 patients, 105 H1N1 patients and 133 CAP patients.	94.18
[15]	Image pre-processing image augmentation and 3D ResNet18	Better classification efficiency.	High computation burden and dataset was limited.	251 COVID-19, 869 pneumonia and 1,475 healthy cases.	97.01
[16]	Modified XceptionNet	Able to successfully identify each COVID-19 case.	It needs a vast amount of image samples for increasing the classification accuracy.	668 normal, 619 viral pneumonia and 132 COVID-19 X-ray scans.	95.8
[17]	CovXNet	High flexible and less computational cost.	It has less accuracy while detecting all types of COVID-19 Pneumonia.	1,583 healthy and 1,493 viral influenza, 2,780 bacterial pneumonia and 305 COVID-19 cases.	90
[18]	Image augmentation, ResNet50 and VGG16 with CNN classification	Better accuracy and ease of use.	It cannot learn temporal dependence data to further reduce the false positives.	135 COVID-19, 320 viral and bacterial pneumonia cases.	91
[19]	COVID-SDNet	Good and stable accuracy.	It needs to use extra clinical data with lung X-ray scans to increase efficiency.	426 COVID-19and 426 normal chest X-ray scans.	97.72
[20]	Image resampling, merging and pre-trained CNN	It can able to predict specific type of pneumonia.	Poor efficiency due to the limited amount of scans.	90 COVID-19 1,000 healthy, 10 MERS, 11 SARS, 10 Varicella, 12 Streptococcus, 11 influenza cases.	F1-score = 89%
[21]	COVID-CAPS	High classification efficiency.	It needs to alter the model and enhance the efficiency while applying a new dataset.	94323 frontal view chest X-ray scans	98.3
[22]	Transfer learning neural network using Inception Net	It has less computational cost.	Its efficiency was less since the training sample size was small.	325 COVID-19 and 740 viral pneumonia CT scans.	89.5
[23]	Series area creation network	It can able to solve the unbalanced data problem.	High computation burden and some context information may loss.	313,167 CT slices from COVID-19 patients.	83.2

Ref. No.	Methods	Benefits	Limitations	Dataset	Accuracy (%)
[24]	Dilated dual attention U-Net	Better dice similarity coefficient and pixel error.	High complexity due to more training parameters.	100 axial CT slices from COVID-19 patients.	Dice score = 0.7298; Recall = 70.71%; Pixel error = 0.0311
[25]	Majority vote-based classifier ensemble	Better accuracy and robust.	The subtle radiographic responses of various irregularities limit the classifier.	696 normal, 696 pneumonia and 696 COVID-19 chest X-ray scans.	93.41
[26]	Feature-based feed-forward neural network	Better classification accuracy.	The learning parameters were not optimized which impacts the classifier performance.	255 COVID-19 images, 255 Pneumonia images and 255 Healthy.	96.83
[27]	U-Net with spatial and channel attention units	Better dice score to partition the single label.	It was not adequate to partition ambiguous boundaries.	100 axial CT scans from COVID-19 patients.	Dice score = 83.1%

IV. CONCLUSION

In this article, a detailed comparative study of artificial intelligence methods for diagnosing COVID-19 through CT and X-ray scans has been carried out. It is clear from this comparative analysis that all researchers have experience in classifying COVID-19 pneumonia from CT scans and X-rays using different machines and deep learning methods. Among these methods, UNet with spatial and channel attention strategies has achieved good results in segmenting COVID19 scans. But it is limited to a small data set, which aims to partition a single label. Therefore, future extensions of this research may focus on the design of multi-class segmentation models using large-scale training databases.

REFERENCES

[1] Chamorro, E. M., Tascón, A. D., Sanz, L. I., Vélez, S. O., & Nacenta, S. B. (2021). Radiologic diagnosis of patients with COVID-19. Radiología, 63(1), 56-73.

[2] Zhou, H., Xu, K., Shen, Y., Fang, Q., Chen, F., Sheng, J., ... & Lou, H. (2020). Coronavirus disease 2019 (COVID-19): chest CT characteristics benefit to early disease recognition and patient classification—a single center experience. Annals of Translational Medicine, 8(11), 1-9.

[3] Larsen, J. R., Martin, M. R., Martin, J. D., Kuhn, P., & Hicks, J. B. (2020). Modeling the onset of symptoms of COVID-19. Frontiers in public health, 8, 1-14.

[4] Chiroma, H., Ezugwu, A. E., Jauro, F., Al-Garadi, M. A., Abdullahi, I. N., & Shuib, L. (2020). Early survey with bibliometric analysis on machine learning approaches in controlling COVID-19 outbreaks. PeerJ Computer Science, 6, 1-45.

[5] Alafif, T., Tehame, A. M., Bajaba, S., Barnawi, A., & Zia, S. (2021). Machine and deep learning towards COVID-19 diagnosis and treatment: survey, challenges, and future directions. International Journal of Environmental Research and Public Health, 18(3), 1-24.

[6] Yu, Z., Li, X., Sun, H., Wang, J., Zhao, T., Chen, H., ...& Xie, Z. (2020). Rapid identification of COVID-19 severity in CT scans through classification of deep features. Biomedical Engineering, 1-13.

[7] Silva, P., Luz, E., Silva, G., Moreira, G., Silva, R., Lucio, D., & Menotti, D. (2020). COVID-19 detection in CT images with deep learning: a voting-based scheme and cross-datasets analysis. Informatics in Medicine Unlocked, 20, 1-9.

[8] Shan, F., Gao, Y., Wang, J., Shi, W., Shi, N., Han, M.,Xue, Z., Shen, D.,& Shi, Y. (2020). Lung infection quantification of COVID-19 in CT images with deep learning. arXiv preprint arXiv:2003.04655v3, 1-18.

[9] Panwar, H., Gupta, P. K., Siddiqui, M. K., Morales-Menendez, R., Bhardwaj, P., & Singh, V. (2020). A deep learning and grad-CAM based color visualization approach for fast detection of COVID-19 cases using chest x-ray and CT-scan images. Chaos, Solitons & Fractals, 140, 1-12.

[10] Narin, A., Kaya, C., &Pamuk, Z. (2020). Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. arXiv preprint arXiv:2003.10849, 1-31.

[11] Khan, A. I., Shah, J. L., & Bhat, M. M. (2020). Coronet: a deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. Computer Methods and Programs in Biomedicine, 196, 1-9.

[12] Fan, D. P., Zhou, T., Ji, G. P., Zhou, Y., Chen, G., Fu, H., ...& Shao, L. (2020). Inf-Net: automatic COVID-19 lung infection segmentation from CT images. IEEE Transactions on Medical Imaging, 39(8), 2626-2637.

[13] Butt, C., Gill, J., Chun, D., &Babu, B. A. (2020). Deep learning system to screen coronavirus disease 2019 pneumonia. Applied Intelligence, 1-7.

[14] Qian, X., Fu, H., Shi, W., Chen, T., Fu, Y., Shan, F. and Xue, X. (2020). M3Lung-Sys: a deep learning system for multi-class lung pneumonia screening from CT imaging. IEEE Journal of Biomedical and Health Informatics, 24(12), 3539-3550.

[15] Li, T., Han, Z., Wei, B., Zheng, Y., Hong, Y. and Cong, J. (2020). Robust screening of covid-19 from chest x-ray via discriminative cost-sensitive learning. arXiv preprint arXiv:2004.12592, 1-11.

[16] Singh, K. K., Siddhartha, M. and Singh, A. (2020). Diagnosis of coronavirus disease (COVID-19) from chest X-ray images using modified XceptionNet. Romanian Journal of Information Science and Technology, 23(657), 91-115.

[17] Mahmud, T., Rahman, M. A. and Fattah, S. A. (2020). CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization. Computers in Biology and Medicine, 122, 1-10.

[18] Hall, L. O., Paul, R., Goldgof, D. B. and Goldgof, G. M. (2020). Finding covid-19 from chest x-rays using deep learning on a small dataset. arXiv preprint arXiv:2004.02060, 1-8.

[19] Tabik, S., Gómez-Ríos, A., Martín-Rodríguez, J. L., Sevillano-García, I., Rey-Area, M., Charte, D., ... & Herrera, F. (2020). COVIDGR dataset and COVID-SDNet methodology for predicting COVID-19 based on Chest X-Ray images. IEEE Journal of Biomedical

and Health Informatics, 24(12), 3595-3605.

[20] Pereira, R. M., Bertolini, D., Teixeira, L. O., Silla Jr, C. N. and Costa, Y. M. (2020). COVID-19 identification in chest X-ray images on flat and hierarchical classification scenarios. Computer Methods and Programs in Biomedicine, 194, 1-18.

[21] Afshar, P., Heidarian, S., Naderkhani, F., Oikonomou, A., Plataniotis, K. N. and Mohammadi, A. (2020). Covid-caps: a capsule network-based framework for identification of covid-19 cases from x-ray images. Pattern Recognition Letters, 138, 638-643.

[22] Wang, S., Kang, B., Ma, J., Zeng, X., Xiao, M., Guo, J., ...& Xu, B. (2021). A deep learning algorithm using CT images to screen for Corona Virus Disease (COVID-19). European Radiology, 14, 1-9.

[23] Wu, J., Zhang, S., Li, X., Chen, J., Xu, H., Zheng, J., ... and Ji, R. (2021). Joint segmentation and detection of COVID-19 via a sequential region generation network. Pattern Recognition, 1-11.

[24] Zhao, X., Zhang, P., Song, F., Fan, G., Sun, Y., Wang, Y., ... and Zhang, G. (2021). D2A U-Net: automatic segmentation of COVID-19 lesions from CT slices with dilated convolution and dual attention mechanism. arXiv preprint arXiv:2102.05210, 1-11.

[25] Chandra, T. B., Verma, K., Singh, B. K., Jain, D., & Netam, S. S. (2021). Coronavirus disease (COVID-19) detection in chest X-ray images using majority voting based classifier ensemble. Expert Systems with Applications, 165, 1-13.

[26] Varela-Santos, S., & Melin, P. (2021). A new approach for classifying coronavirus COVID-19 based on its manifestation on chest X-rays using texture features and neural networks. Information Sciences, 545, 403-414.

[27] Zhou, T., Canu, S., & Ruan, S. (2021). Automatic COVID- 19 CT segmentation using U-Net integrated spatial and channel attention mechanism. International Journal of Imaging Systems and Technology, 31(1), 16-27.