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CONVID-19 diagnosis and detection based on deep learning models

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Abstract. The COVID-19 pandemic has caused widespread illness and death since its emergence in 2019. This study examines various Artificial Intelligence (AI) techniques for diagnosing and predicting COVID-19. One such method is the Hust 19 model, which employs a hybrid learning architecture of CNN and DNN models. The model divides CT scans into three types that identify COVID-19-related imaging features and implements a deep learning framework based on the VGG16 architecture. Another group of researchers developed a deep learning-based COVID-19 diagnostic system using multi-class and multi-center data, segmenting lungs and identifying COVID-19 infection slices. They evaluated the model's accuracy using Receiver Operating Characteristic (ROC) curves. A third group developed a deep neural network based on DenseNet121, standardizing input CXR images through anatomical landmark detection and registration, and segmenting lung lesions to diagnose pneumonia. A final group developed a three-dimensional deep learning model called COVNet, which takes CT images as input, extracts features from each slice using the ResNet50 backbone, merges the maximum features obtained by the AI model, and generates classification predictions for the entire CT scan. They also proposed a multi-decoder split network to improve the model's accuracy and efficiency. Experimental results show that the Deep learning AI system model and COVNet model are relatively good, with average sensitivity and specificity. The remaining models, particularly Hust-19, show prominent specificity, but high specificity leads to low sensitivity, making the overall model imbalanced. These AI diagnostic models are just the beginning, and there may be more inventions and creations in the future.

Keywords: CONVID-19 Diagnosis, deep learning, computer vision.

1. Introduction

The emergence and rapid spread of COVID-19 has posed an unparalleled challenge to global public health. With profound implications for human well-being, it has resulted in a significant loss of lives worldwide. As of 2019, the number of diagnosed cases and fatalities has reached millions on a global scale [1]. In this case, people have to pay attention to the problem of epidemic prevention and treatment. Researchers have also contributed a lot to this. However, it remains a challenging task. The main problem they face in medical diagnosis of COVID-19 is the huge workload. As the key diagnostic basis, Computerized tomography (CT) image reading workload is large, nucleic acid reagent detection effect is unstable, viral gene sequencing cycle is long, and production capacity is insufficient. In addition, the novel coronavirus has a long incubation period (latency) and complex

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transmission routes, so doctors need to comprehensively analyze clinical symptoms, test results and epidemiological history when diagnosing cases. In this case, artificial intelligence algorithms can be considered since the effectiveness of them has been demonstrated in many tasks.

Through the hard work of many researchers, different Artificial Intelligence (AI) models have been developed, but most of the methods are very similar, mainly by collecting various clinical data, building the deep learning-based models, then testing, and finally deploy them in the real application. For example, a group of researchers collaborated to integrate heterogeneous CT and CF datasets and developed an engineering framework termed as Hybrid Learning Unbiased Prediction of Patients with COVID-19 (HUST19). The purpose of this framework is to predict clinical outcomes with minimal bias in patients diagnosed with COVID-19, then used different algorithms to verify the performance of Hust 19 and determine its accuracy, so that the model can be better used for COVID-19 diagnosis [2]. Another group of researchers is directly using CT data as input and built model, hoping that the AI system's diagnosis results can be interpreted in the raw images to mitigate the shortcomings of interpretability in the model [3]. They divided CT volumes into different cohorts and, after section-level training, were able to distinguish four different cases for diagnosis. Additionally, another group of researchers developed a deep neural network based on DenseNet121 to construct a model utilizing Chest X-ray (CXR) images to distinguish viral pneumonia from alternative forms of pneumonia as well as non-pneumonic ailments [4]. The AI system's architecture involves initial standardization of input CXR images through anatomic landmark detection and registration, followed by pulmonary lesion segmentation and pneumonia diagnosis. To evaluate the accuracy of the diagnostic AI system, the researchers utilized the ROC curve, similar to the aforementioned group of researchers. The difference, however, is that they use a modular pipeline approach in the AI system that allows the system to categorize different conditions. Furthermore, a group of researchers conducted an investigation to assess the utility of pooled chest CT data in comparison to separate clinical metadata for predicting COVID-19 prognosis. To this end, they developed a novel patient-level algorithm that integrates chest CT volumes into 2D representations that can be seamlessly merged with clinical metadata. The algorithm is designed to differentiate chest CT volumes of COVID-19 pneumonia from those of healthy individuals and individuals with other viral pneumonias. Additionally, the researchers proposed a multi-tasking model capable of jointly segmenting various categories of lung lesions present in COVID-19 infected lungs. These methods leverage deep learning techniques to automatically extract clinically significant features from chest CT volumes, enabling risk stratification in COVID-19 patients [5].

To provide the comprehensive view of the AI-based COVID-19 detection, this paper will summarize different AI diagnostic model systems, explain in depth the different methods used by different researchers to develop systems, compare and evaluate them, and show the advantages of different AI diagnostic systems and areas to be improved. In the form of pictures, this study will help to understand the construction and components of different AI models, and fully explain their help in medical diagnosis. In addition, the advantages and promise of AI diagnostics and its contribution to humanity so far will be also provided.

2. Methodology

2.1. Overview of the deep learning-based methods

The deployment of artificial intelligence (AI) for diagnostic purposes has garnered considerable attention in recent years [6, 7]. Deep learning methodology, employing neural networks to facilitate machine learning, has emerged as a widely favored approach in this domain [8-10]. Researchers typically leverage neural networks to train AI algorithms to recognize and identify the distinct characteristics of various diagnostic cases, enabling them to read and memorize such features for more accurate judgment and differentiation of case data.

To this end, researchers usually begin by manually annotating and segmenting lung computed tomography (CT) data collected from leading hospitals, following which they construct deep neural

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networks for machine learning. They subsequently establish an experimental cohort, enabling the AI algorithm to diagnose the experimental data and subsequently compare the diagnosis results with those of radiologists. The feasibility of the model is then assessed using different algorithms. Ultimately, the AI diagnostic model is applied to actual cases.

2.2. HUST 19 model for Convid-19 diagnosis

In one of the AI diagnostic models, researchers built a hybrid learning architecture called Hust 19, which consists of four components such as the individual CT section classification and integration of CT and cf predictions (see Figure 1) [2]. It includes 13 Convolutional Neural networks for predicting individual CT slices, and a 7-layer Deep Neural Network framework for predicting clinical outcomes of COVID-19 patients from CFs.

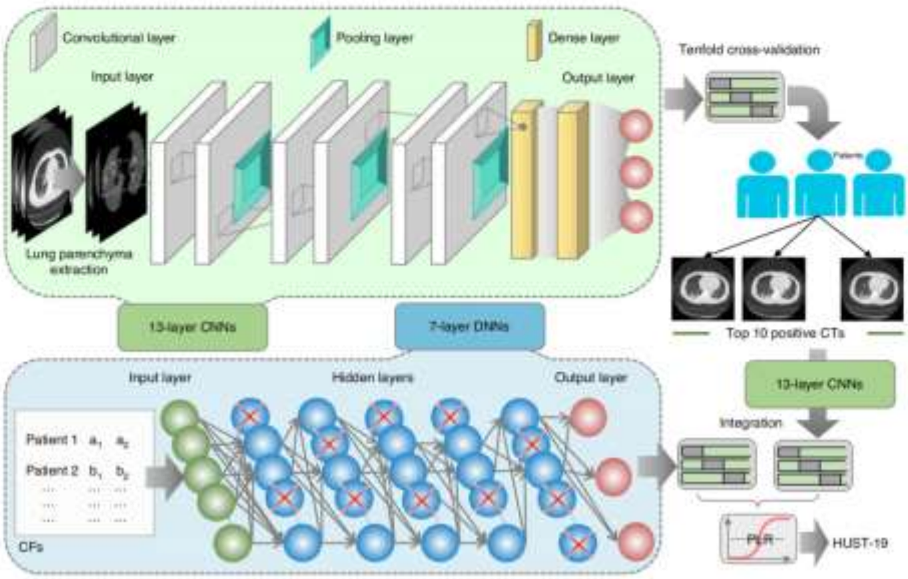

Figure 1. The designing of HUST-19 [2].

The researchers initially categorized individual computed tomography (CT) sections into three distinct types. Then, a deep learning framework based on VGG16 which is a famous convolutional neural network model) is implemented and simplified to reduce the complexity of the model and achieve faster training.

2.3. Deep learning AI system for Convid-19 diagnosis

Another study introduced a novel deep learning-based artificial intelligence (AI) system for the diagnosis of COVID-19 using computed tomography (CT) data as input for lung segmentation, COVID-19 diagnosis, and localization of infected areas. The proposed system encompasses five principal components: (1) a lung segmentation network, (2) a biopsy diagnostic network, (3) a COVID-19 biopsy localization network, (4) a visualization module for the interpretation of the deep network's attention area, and (5) an image phenotype analysis module for the interpretation of attention area features (the workflow depicted in Figure 2 [3]). CT volumes are segregated into different queues, and the model can categorize input slices into four groups: non-pneumonia, community-acquired pneumonia (CAP), influenza A or B, and COVID-19 after section-level training. Following this, a fusion module specialized for the given task is employed to combine the results of individual image slices to form case-level diagnoses for various diagnostic tasks. This allows the network to be used for

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multiple tasks without the need for additional training. As CT scans inherently possess a three-dimensional quality, the researchers trained and evaluated their segmentation models on such volumetric data.

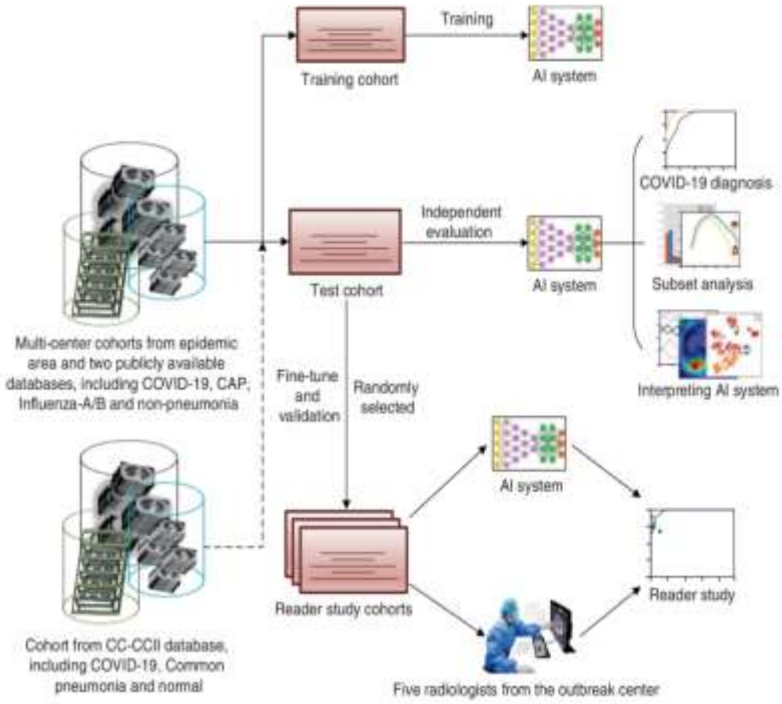

Figure 2. The architecture of the proposed system [3].

2.4. DenseNet121 model for Convid-19 diagnosis

Another group of researchers built a deep neural network based on DenseNet121 in order to build a model based on CXR images to distinguish viral pneumonia from other types of pneumonia and the absence of pneumonia (see Figure 3). The artificial intelligence (AI) system employed in this study initially standardized the input chest X-ray (CXR) images by detecting and registering anatomical landmarks. Subsequently, it performed pulmonary lesion segmentation and pneumonia diagnosis. The researchers implemented and compared the performance of landmark detection, including systematic generalization to different populations or new three-group deep learning models. Additionally, they compared the AI model's results with those of radiologists' notes. For training the model, the researchers initially used gold standard tags to train the AI system on a subset of 13,158 images from CC-CXRI (which includes data from confirmed cases in all CXR images) and then tested it on a separate test set of 1,519 CXR images from CC-CXRI. This was followed by a second training session. Furthermore, to evaluate the impact of standardized modules on diagnostic performance, the researchers also tested the AI system's test set by skipping entire modules or parts of modules.

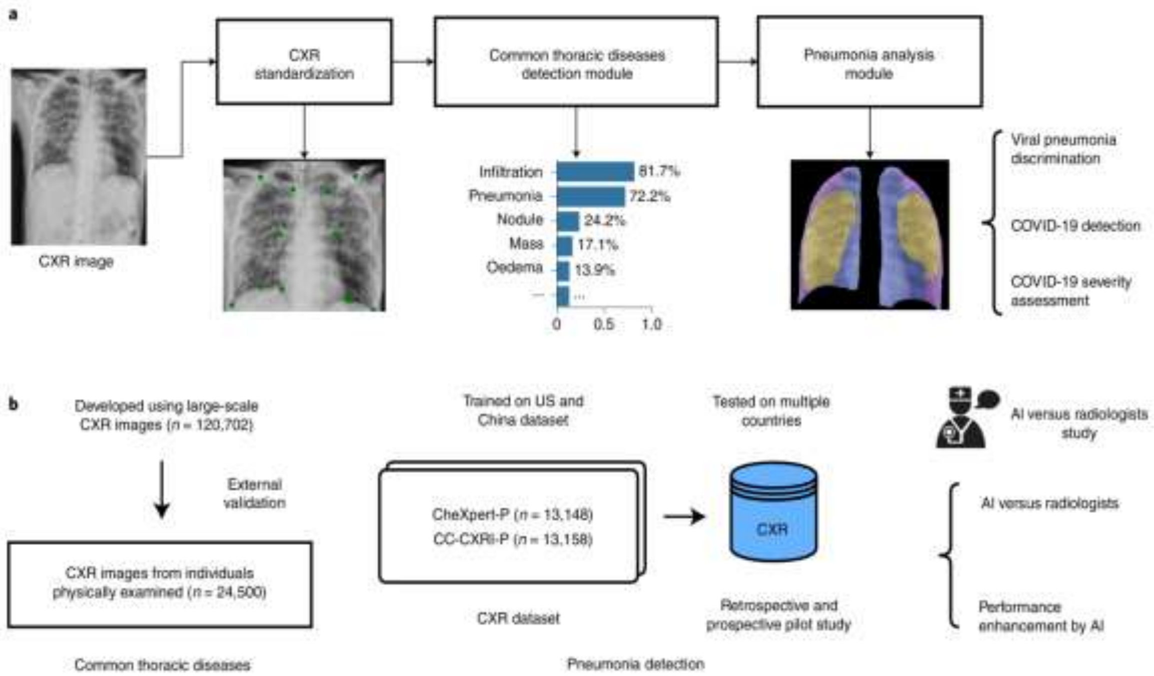

Figure 3. The artificial intelligence (AI) system developed for the identification of viral pneumonia [4].

2.5. COVNet model for Convid-19 diagnosis

The final group of researchers used chest CT volume to predict COVID-19. They developed a 3D model for diagnosing COVID-19, called COVNet. The COVNet architecture is designed to receive a sequence of CT slices as input and extract features from each slice using the ResNet50 backbone. These features are then merged through the maximum pool operation (depicted in Figure 4), and the resulting merged features are employed to generate classification predictions for the entire CT scan. They used the categorical data set, the CC-CCII pulmonary lesion segmentation data set, the CCSabur-CCII prognostic data set, and the Stony Brook University (SBU) prognostic data set, and combined 241 of these patients with complete CT volumes with available demographic information (age and sex only) to create an experimental prognostic data set. The authors of this study also developed a novel methodology for extracting global features, which can be utilized to create a two-dimensional global representation of a boundary's size for any three-dimensional CT volume. The proposed approach involves leveraging the intensity histogram of a single CT slice as a horizontal input to extract these features. In addition, a "multitask multidecoder" network architecture was proposed, which was designed to split the network into 21 coding parts that were shared across various lung variable tasks, leading to a novel approach termed "multitask segmentation". To train the segmentation models, the authors utilized PyTorch, a widely-used open-source machine learning framework, and executed the training process on a computational system comprised of four Graphics Processing Units (GPUs).

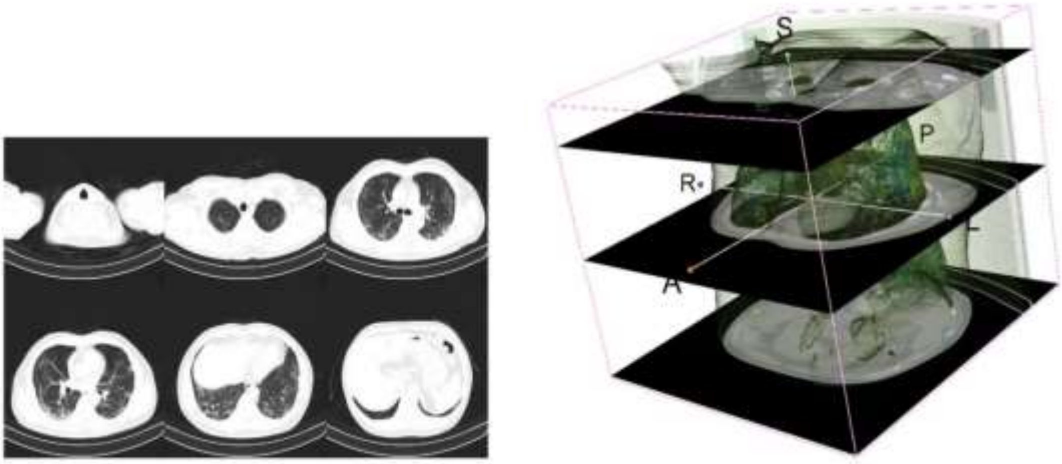

Figure 4. CT scan slices and lung volume reconstruction [5].

3. Result and discussion

Table 1. The performance of different models.

Model name	Dataset	AUC (CF)	AUC (CT)	AUC (CXR)	Sensitivity	Specificity
Hust-19 [2]	type I and type II patients	0.8820	0.9190	-	0.8501	0.9980
Deep learning AI system [3]	COVID-19, CAP, A and Non-pneumonia databases	-	0.9847	0.9527	0.9469	0.9503
DenseNet121 [4]	CC-CXRI, COVID19cxr, Other viral pneumonia	-	-	0.9660	0.9207	0.9012
COVNet [5]	CC-CCII	-	0.9249/ 0.9070	-	0.9490/ 0.9251	0.9113/ 0.8592

Table 1 presents the performance results of various models evaluated for accuracy, sensitivity, and specificity. The test data indicates that the Deep learning AI system exhibits high accuracy with a percentage of 0.9847, demonstrating its proficiency in accurately predicting the likelihood of individuals contracting a disease. Additionally, the COVNet model displays superior sensitivity,

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differing by 0.0989 from the Hust 19 data, showcasing its accuracy in diagnosing patients. Regarding specificity, the Hust 19 model outperforms the other models with a percentage of 0.9980, indicating its accuracy in diagnosing patients without the disease.

The Deep learning AI system attains an excellent average test level in performance. This achievement stems from the researchers' training, evaluation model, and hand-marked lung segmentation image assisted model learning. These researchers utilized distinct datasets and assigned unique tasks to compare the COVID-19 prediction using CT and CXR images. Furthermore, their AI systems underwent comprehensive validation on large multi-class datasets, displaying a superior diagnostic performance in COVID-19 diagnosis than human experts. The visualized AI systems can decode the effective representation of COVID-19 on CT imaging, and applied radiomic analysis can potentially uncover new biomarkers, unlike traditional black-box deep learning methods.

Of the four models for predicting COVID-19, the second best is the COVNet model, which is also the one with the most unique approach. The 3D model they adopted can better extract the features in CT images, and then use the features to generate the entire CT scan classification prediction. They used intensity mapping projection to create a two-dimensional global representation of a boundary size of any three-dimensional CT volume using the intensity histogram of a single CT slice/plane as a horizontal entry. They also used texture analysis to help describe medical images, and then proposed the use of multi-decoding segmentation network, using segmentation results to obtain the anatomical range of each lesion, making the prediction of the whole model more perfect.

4. Conclusion

In the whole paper, the models of AI diagnosis and prediction of COVID-19, including Hust 19 Model, Deep learning AI system model, DenseNet121 Model and COVNet model were investigated. This paper also looked at the learning methods of different models such as the widely used deep learning methods based on neural networks and the algorithms used in evaluation models. The experimental results show that the Deep learning AI system model and the COVNet model have good effects, and the other two models, especially the Hust 19 model, show outstanding specificity, which makes the whole model out of balance. It is hoped that in the future AI diagnostic model, researchers could combine various methods to make the AI model understand different case characteristics comprehensively, so as to make better judgments in the later diagnostic process and improve the diagnostic efficiency.

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