Virtual Reality & Intelligent Hardware

• Article •

August 2022 Vol. 4 No. 4: 292–305
10.1016/j.vrih.2022.03.002

Integrating digital twins and deep learning for medical image analysis in the era of COVID-19

Imran AHMED[1], Misbah AHMAD[2], Gwanggil JEON[3*]

1. *School of Computing and Information Science, Faculty of Science and Engineering, Anglia Ruskin University, East Road, Cambridge, England, UK;*
2. *Center of Excellence in IT, Institute of Management Sciences, Hayatabad, Peshawar, Pakistan;*
3. *Department of Embedded Systems Engineering, Incheon National University, Incheon, Korea*

Received 30 January 2022; **Revised** 13 March 2022; **Accepted** 31 March 2022

Abstract: Background Digital twins are virtual representations of devices and processes that capture the physical properties of the environment and operational algorithms/techniques in the context of medical devices and technologies. Digital twins may allow healthcare organizations to determine methods of improving medical processes, enhancing patient experience, lowering operating expenses, and extending the value of care. During the present COVID-19 pandemic, various medical devices, such as X-rays and CT scan machines and processes, are constantly being used to collect and analyze medical images. When collecting and processing an extensive volume of data in the form of images, machines and processes sometimes suffer from system failures, creating critical issues for hospitals and patients. **Methods** To address this, we introduce a digital-twin-based smart healthcare system integrated with medical devices to collect information regarding the current health condition, configuration, and maintenance history of the device/machine/system. Furthermore, medical images, that is, X-rays, are analyzed by using a deep-learning model to detect the infection of COVID-19. The designed system is based on the cascade recurrent convolution neural network (RCNN) architecture. In this architecture, the detector stages are deeper and more sequentially selective against small and close false positives. This architecture is a multi-stage extension of the RCNN model and sequentially trained using the output of one stage for training the other. At each stage, the bounding boxes are adjusted to locate a suitable value of the nearest false positives during the training of the different stages. In this manner, the arrangement of detectors is adjusted to increase the intersection over union, overcoming the problem of overfitting. We train the model by using X-ray images as the model was previously trained on another dataset. **Results** The developed system achieves good accuracy during the detection phase of COVID-19. The experimental outcomes reveal the efficiency of the detection architecture, which yields a mean average precision rate of 0.94.

Keywords: Digital twins; Deep learning; Healthcare; COVID-19; Chest X-rays; Artificial intelligence

Citation: Imran AHMED, Misbah AHMAD, Gwanggil JEON. Integrating digital twins and deep learning for medical image analysis in the era of COVID-19. Virtual Reality & Intelligent Hardware, 2022, 4(4): 292–305

*Corresponding author, gjeon@inu.ac.kr

1 Introduction

Driven by Industry 4.0/5.0, the idea of "Digital Twins" has given rise to new industrial simulation models. Digital twins are virtual representations of physical objects or processes used to analyze, simulate, verify, test, adjust and optimize real products or processes and increase their value in real-life settings. This indicates that digital twins involve both up-to-date and historical data regarding the state of real-world products or processes. Healthcare organizations can employ digital twins to achieve better insights into product/device/equipment performance, enhance client service, and make more suitable operating and strategic decisions for various applications, including automobile, aerospace, manufacturing, production, cargo shipping, smart cities, and the industrial Internet of Things (IoT), particularly smart healthcare[1].

The healthcare sector is rapidly embracing digital twin technology, as shown in Figure 1. This technology acts as a digital replica for the physical devices/machines/systems used in the healthcare sector and facilitates evaluation and monitoring without being in close proximity. Integrating dynamic data into a virtual representation for different medical applications enables proactive decision-making, process optimization, and complete lifecycle management in healthcare. Digital twins can provide a secure environment for testing the changes that affect the performance of devices/machines/systems[2]. The reality of system dynamics can be interpreted by using machines, processes, or living bodies to identify problems on time if and when they occur and execute necessary changes or procedures. This will allow optimal solutions and threat reductions, essential in the healthcare sector. Intelligent machines are more likely to develop similar to humans and collect and communicate data consistently and accurately.

Digital twins play an essential role in patient care, equipment maintenance, and hospital design. For

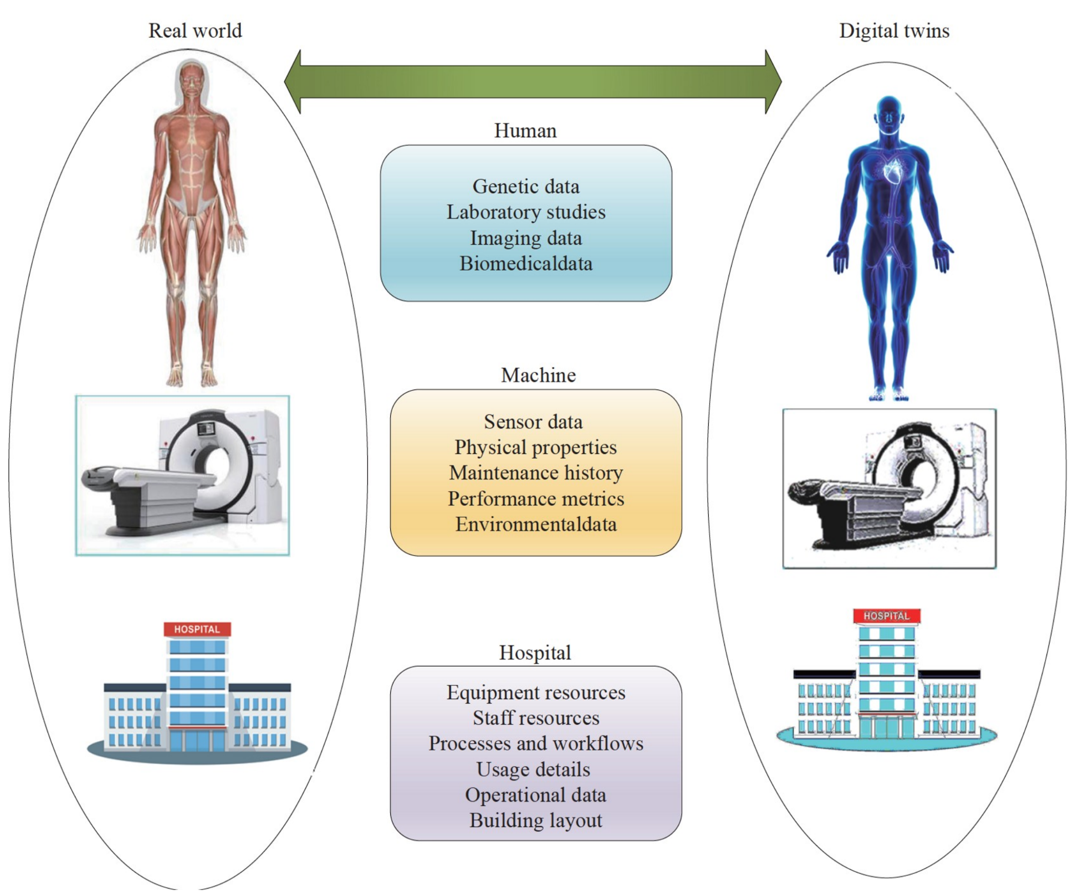


Figure 1 **Digital twins in the healthcare sector: digital twins can be used to virtually collect, process, and analyze the data related to the human body, equipment, and hospital.**

example, as shown in Figure 1, when an image of a patient or human organ virtually reproduced, and a digital twin based system is developed using important data collected from different biomedical sensors and ubiquitous wearable sensors. Similar to a smartwatch, real-time information on the blood pressure, pulse rate, body temperature, sleep patterns, and general physical activities of a patient or human can be obtained. A virtual model can be created during clinic or hospital visits by using laboratory testing data, and diagnostic imaging investigations can be conducted. Furthermore, genetic data can be coded as digital twins. When all these data are combined into a single virtual model, all the details of the patient's medical history are available to support decision-making.

Digital twins can be a virtual representation of medical devices and technology that can be used to collect information related to the device's health condition, configuration, and maintenance. For example, the chillers in X-ray machines and MRI scanners are used as refrigeration units to cool down the machines. The information obtained through these imaging machines can provide data regarding the recorded operation device temperatures, which can instantly affect the life of the remaining functional parts. Moreover, various other signals, including fluid levels, vibrations, pressures, electrical voltages, environmental parameters, and device implementation metrics, can be collected to construct an up-to-date virtual model of a medical device. As illustrated in Figure 1, digital twins can be considered on a large scale, where dynamic operations and processes of the entire medical building or organization can be simulated virtually. For instance, the digital twin of a hospital can be used to model departments and resources that can optimize their everyday operations. These facilities and structures could be, for instance, a radiology department, an intensive care unit, a patient waiting area, or an operating room. A digital schematic design can simulate floor designs, equipment logistics, and locations. In addition, operational information from hospital databases, such as staff timetables, organizational assignments, and economic transactions, can be included in a virtually constructed layout.

This discussion indicates that if all these strategies are combined in a virtual representation model, diagnostics and treatment processes can be improved. Furthermore, Digital twins can produce a safe environment for examining the effects of modifications in system performance without hazards. In December 2019, severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2; also named coronavirus or COVID-19) emerged, and it affected and still affects millions of people around the world0F[1]. It has several effects that make it highly contagious, thus enforcing people to adapt government safety and prevention measures, such as social distancing[3,4]. Medical imaging facilities are in high demand, and CT scans and X-ray machines are widely used for diagnosing the infection in patients[5–7]. The immense demand for diagnostic medical imaging has become a logistical challenge for health organizations and providers worldwide. Researchers are trying to provide solutions for the best use of space, types of equipment, and medical staff to deliver the best potential care for patients. In this case, an effective, robust, and high-fidelity simulation is necessary. Thus, we present a smart digital-twin-enabled healthcare system for diagnosing and detecting COVID-19 infection by using medical images. The developed system is combined with medical machines/devices to utilize and collect information regarding the device's current health condition, configuration, and maintenance history. The medical images, (chest X-rays) are further analyzed using the cascade recurrent convolution neural network (RCNN) architecture for detection purposes. The possible contributions of the present study are as follows:

- A digital-twin-enabled healthcare system is enabled for diagnosing and detecting COVID-19 infections by using medical images.
- Transfer learning is applied for training the model using X-ray images of COVID-19 and for a new dataset. Data augmentation is performed to enhance the detection results of COVID-19.
- A deep-learning-based architecture is utilized to apply different confidence threshold values so that the

[1] //covid19.who.int/

bounding boxes are adjusted effectively for locating a suitable set of nearest false positives during training.
- The system's effectiveness is validated by employing other techniques in terms of accuracy.

The remainder of the paper is structured as follows. Different methods suggested for detecting SARS-CoV-2 by using medical images are summarized in Section 2. Section 3 describes the developed system that uses a digital twin for analyzing and detecting infected areas in the X-ray images. The dataset used to evaluate the system is presented in Section 4. This section also provides the details of the experimental results and the evaluation parameters. The final section concludes the paper with some future guidelines.

2 Related work

Digital twin technology has become an emerging concept in the healthcare sector in recent years. Researchers have utilized this technology in various healthcare applications involving artificial intelligence, deep learning, IoT, and big data[5,6,8]. Ahmed et al. used a faster RCNN model to monitor the COVID-19 virus by employing X-ray images[5]. An IoT-enabled deep-learning model was recently presented for screening COVID-19 by using X-ray images[6].

The concept of digital twins for various applications of tools and methodologies was described in multiple studies to improve the workflows, processes, and operations of operating rooms in the healthcare sector[9]. An intelligent context-aware healthcare system utilizing a digital twin framework was proposed[10]. Researchers have also studied and utilized digital twin technology during the current pandemic[11]. Pilati et al. developed a digital twin by combining the physical and virtual devices and systems and performed real-time monitoring of patient flow to build a dynamic and sustainable center for vaccination[11].The role of digital twins during the COVID-19 outbreak was presented in[12].

Researchers have applied different deep-learning architectures and models for the classification, detection, and segmentation of the coronavirus infection; for example, biomedical image data have been used[13–20], including chest/lung X-rays and CT scans[14,21,22]. Various neural network models have also been compared to classify X-ray images as coronavirus images[23]. Wang et al. presented a convolutional neural network (CNN)-based system for classifying X-ray images into SARS-CoV-2, pneumonia, and normal images[24]. The residual neural network (RNN) model was studied for analyzing X-rays of viral and infected pneumonia[25]. Pathak et al. introduced a deep-learning model using transfer learning to classify infected cases using CT scans[26]. A CNN-based differential model was proposed to discriminate SARS-CoV-2 cases using chest CT scan data[27]. Hossain et al. proposed a healthcare system based on artificial intelligence to detect coronavirus, using images captured from CT scans and X-ray machines[28]. Muhammad et al. presented a multi-layer fusion-based model for SARS-CoV-2 and non-SARS-CoV-2 classification[29], by using images recorded from an ultrasound machine.

Shorfuzzaman et al. proposed a neural network system that used contrastive loss to recognize SARS-COV-2 in X-ray images[30]. A detection system based on transfer learning and neural networks was introduced for analyzing X-ray images[31]. COVID-19 was identified by using a developed dataset that included 1,144 X-rays of a virus, pneumonia, and normal images[32]. Some researchers have also used big data analytics; for example, a smart neural network and big-data-analytics-based framework was presented for pandemic prediction[33]. A 2D CNN model was trained[34,35] for a dataset collected from[36]. Different pre-trained designs were combined with the regularization of support vector machines[34]. A network was proposed by leveraging the power of capsule networks with different architectures to increase classification accuracy[37]. A deep-learning-based diagnosis framework was introduced to assist medical experts in identifying patients with symptoms of COVID-19 and pneumonia in CT scan data[38].

A 3D deep network was studied[39], and a model comprising a pretrained U-Net and two 3D residual blocks was proposed. Furthermore, 3D deep networks were employed for the segmentation of CT images[40]. GAN-incorporated data were used to enhance the learning of a discriminating paradigm for the segmentation of diseased lungs[41]. A deep neural network was proposed for tumor segmentation in lung CT slices by combining various residual layers of modifying resolutions[42]. An explainable method was developed for diagnosing viral infections by using a shared segmentation and classification approach[43]. An automated system that segments viruses caused by COVID-19 was presented in[44]. This method provides a quantitative measure of the infection to medical experts. The technique involves the segmentation of lung infections based on the U-Net architecture. A small network was presented for the effective segmentation of deadly viral diseases by using CT scans[45]. A U-Net-based computerized model was introduced for infection segmentation in lung CT images[46]. A deep-learning model was proposed for the segmentation of lung infections, and it was named Inf-Net[47]. The model automatically recognized infected regions in the CT scan data. An identical partial decoder was used to combine distinctive features and produce a global map. Reverse and specific edge attention were applied to enhance the representations and boundaries. Five CNN pre-trained models were investigated for the classification and analysis of patients using a chest X-ray dataset[47]. At present, researchers utilize IoT for smart healthcare frameworks; for example, monitoring systems for patients were introduced by using deep learning, time frame rules, and pairwise keypoint distance features[48–50].

This discussion reveals that researchers have presented various methods and techniques for the classification and detection of the viral COVID-19 infection by utilizing medical images captured using X-rays and CT scan machines. Researchers have adopted state-of-the-art deep-learning techniques to detect and identify infectious diseases by combining their frameworks with IoT and big data. However, to the best of our knowledge, digital twin technology that combines advanced machines/equipment and deep-learning models has not been explored to analyze medical images for the detection of COVID-19 infected regions and areas in patients' images. Thus, in this work, we present an advanced digital-twin-enabled model to analyze COVID-19 X-ray images.

3 Methodology

In this study, we introduce a digital-twin-enabled smart healthcare system. The developed system is based on deep learning used to detect the COVID-19 virus in the infected lungs of patients. A schematic illustration of the developed system is shown in Figure 2. The lungs of patients are analyzed using X-ray machines. Several images are collected to analyze the infection. The collected data in conventional systems are subjected to an artificial-intelligence-based deep-learning model, where the necessary classification and detection are performed after data pre-processing. In such cases, inspection revocations and unpredictable workflow disruptions are crucial problems for healthcare organizations. Moreover, all medical equipment should be prepared and be functional when needed in critical situations. Failure of the system can also generate unexpected downtime, which is expensive and uncomfortable for the patient. These situations negatively affect clinical outcomes. However, stopping the demand for maintenance is impossible, and recognizing potential problems before they occur is challenging.

When the same system is combined with the developed digital twin concept, where the same devices, systems, and environment are virtual, created, analyzed, tested, and validated, handling the aforementioned issues becomes easy. Using the data collected from the same device sensors in a virtual environment, we can track and analyze early indications of upcoming technical issues.

In digital twins, the potential problems can be analyzed before they occur, so scheduling equipment maintenance at a time is possible. Although the system data are analyzed in advance, the engineer knows exactly what type of maintenance is required. Moreover, because continuity of care is very important for

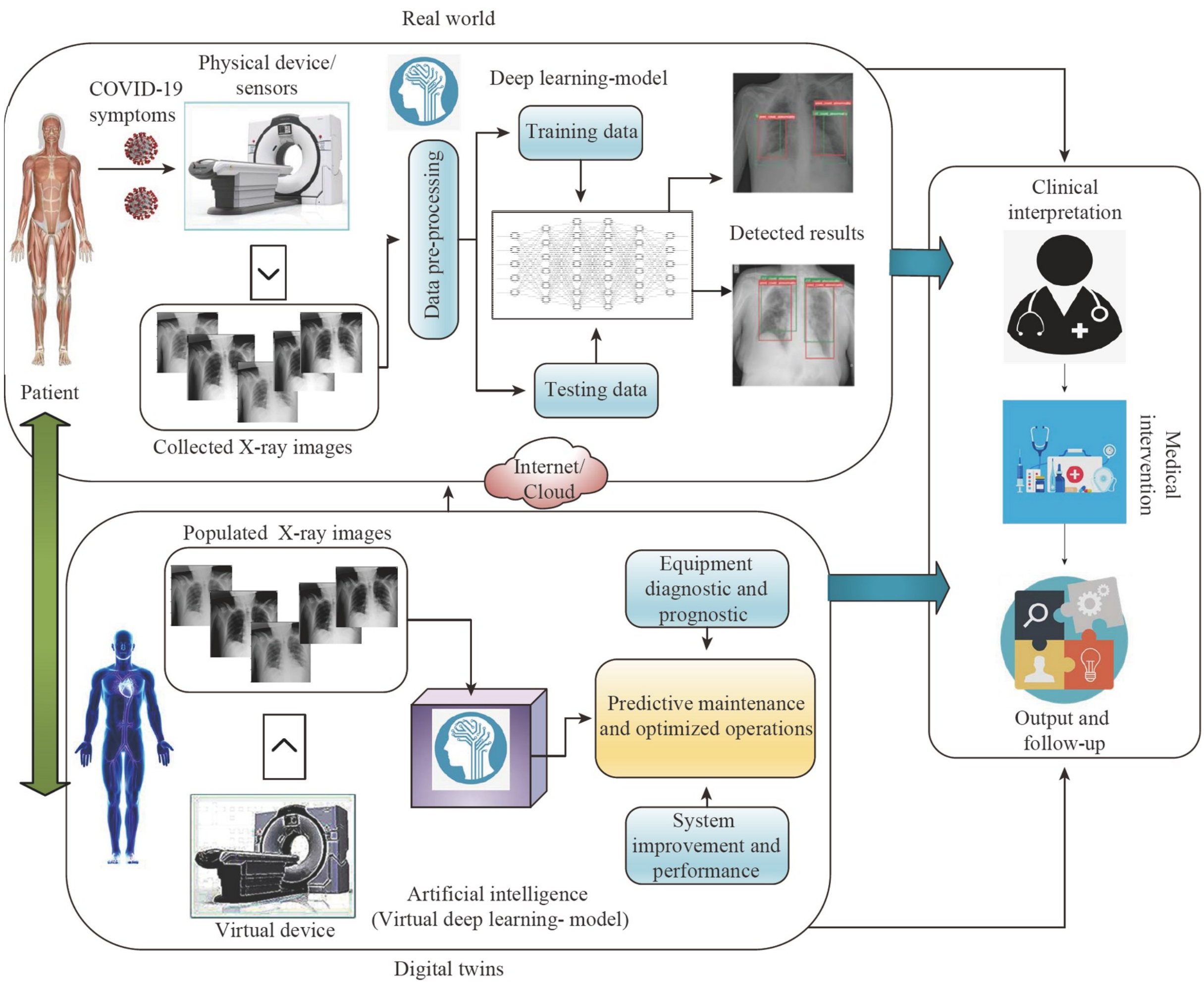


Figure 2 Envisioned workflow utilizing the fully developed digital twin concept for analyzing and detecting COVID-19/SARS-CoV-2 in X-ray images. The collected data from X-rays machines are analyzed using deep learning. In the digital twin, the number or population data is increased and collected for preceding patients; this information is used to create and validate the mechanical model. Finally, the digital twin model is analyzed and integrated with conventional data to assist medical facilities in decision-making.

healthcare organizations and patients, there is notable value in identifying potential technical problems in medical systems and devices and solving them before they occur. Figure 2 shows that the population collected data are virtually increased from the foregoing patients. The dataset was utilized to design and validate mechanistic and statistical models and develop a population-based digital twin. The new patient data were analyzed using the existing model—the assessment and interaction between digital twins and the real world. According to the follow-up data, the digital twins were designed in line with the condition of the patients, that is, adjusting and improving the results. The resultant outcomes were added to alter the data and improve the follow-up medical data. We developed this system for the analysis of COVID-19 infection using X-ray images.

The developed system assists medical experts in analyzing the severity of infection using the confidence score of the detection results. We performed the necessary preprocessing, data augmentation, and virus detection for detection purposes. The datasets used for the experimentation were collected from different available online resources. To detect the virus in X-ray images, we trained the deep-learning model, cascade-RCNN[51]. The processing job was performed on the Internet using cloud computing at a high computation speed. After training, the deep-learning-model results were forwarded to medical experts for further analysis. The details of the deep-learning system shown in Figure 3 are as follows.

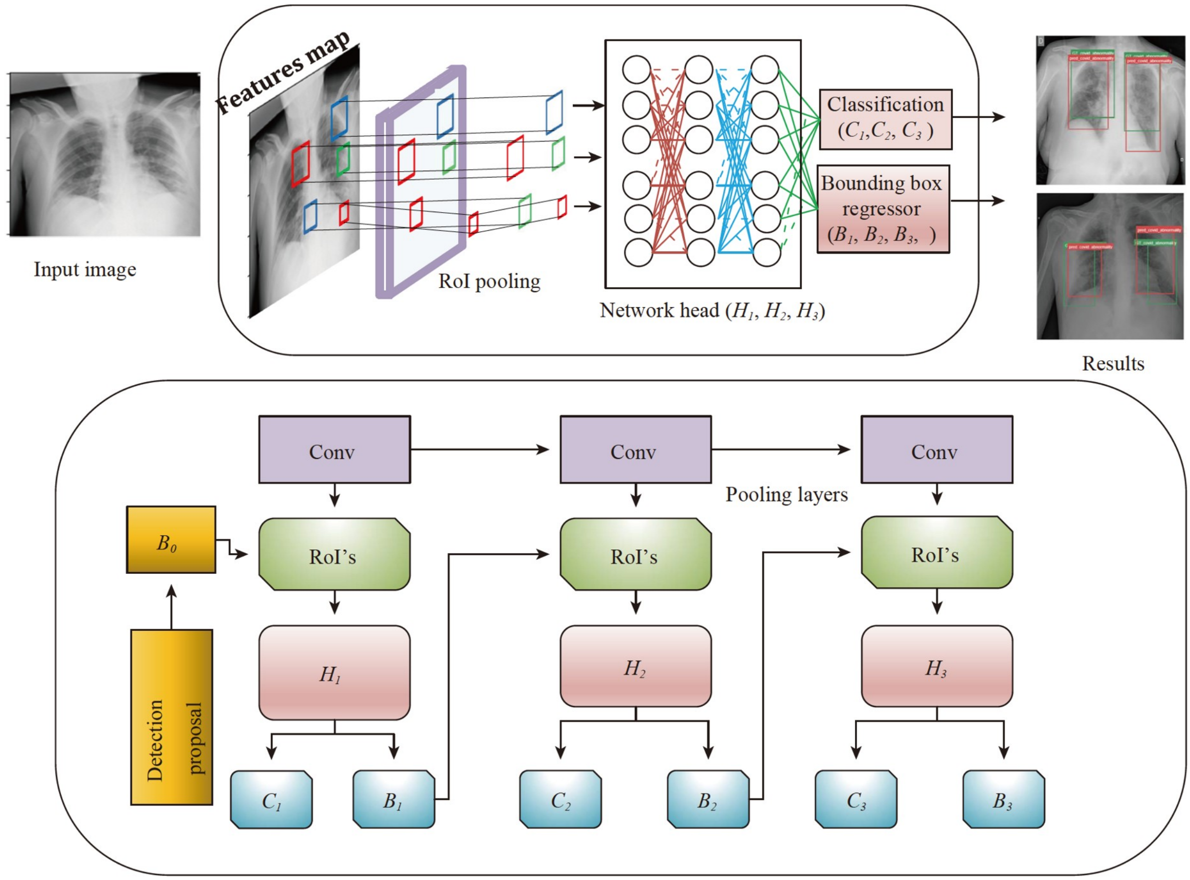


Figure 3 Deep-learning model used to detect SARS-CovV2/ COVID-19 infection, the feature pyramid network output is given to Cascade RCNN as input. The obtained feature maps are forwarded using the RoI pool layer. The Region Proposal Network (RPN) is used to extract region proposals. Different colors represent different anchors, whereas similar anchors are specified with one color. To categorize anchors into negative and positive samples, the network used RPN, while the regression is applied for fine-tuning of the extracted bounding boxes. The input medical image is processed using backbone convolutional layers "Conv" here, we used Resnet101, and then extracted features or proposals are passed within the polling layer.

The primary stage network, also called the proposal sub-network (H_0), is an extended version of the Faster-CNN, applied to the complete input image to produce initial detection proposals, also called hypotheses. In the next stage, these detected proposals are treated by the detection head, denoted as the region-of-interest (RoI) and detection subnetwork (H_1). The bounding box (B_1) and classification score (C_1) were assigned to each hypothesis. The first stage's detected bounding box (B_1) was not sufficiently accurate. Therefore, (B_1) is regressed the same as the input into (H_1) again to obtain the bounding box (B_2), and so on. This iterative process attempts to slowly fine-tune the bounding box to obtain precisely detected boxes. The equation for iterative bounding box regression is defined as

$$f'(x,b) = f,f,\cdots,f(x,b) \tag{1}$$

In this equation, all heads, f or (H_1), in the figure are the same. It is used repeatedly to enhance performance. For all bounding boxes, the four coordinates, $b=(b_x, b_y, b_w, b_h)$, are obtained using image x. The regressor function primarily reverts a selected/ and obtains bounding box b using a single function, $f(x, b)$. Usually, there is no progression beyond twice. Furthermore, during training, there is a single H1, whereas multiple H1 during inference generates a mismatch between the training and testing. This is similar to the post-processing step. The integral loss of the different heads was used as follows:

$$L_{cls}(h(x), y)) = \sum_{u'U} L_{cls}(h(x), y_u)) \tag{2}$$

The cross-entropy loss function is presented as $L_{cls}(h(x), y))$, where y denotes the label of classes for x, and the intersection over union (IoU) threshold is identified as u. The quality of the detector model is defined using U ranging from 0.2 to 0.7. This was also applied to determine the negative and positive samples. In this work, we used high and low threshold values of 0.5 and 0.7. During the inference, the classifiers were assembled. However, high-quality classifiers are also prone to overfitting. Furthermore, these classifiers must process low-quality detected proposals for which they are not optimized. Thus, additional heads, (H_1, H_2, H_3), are used at different stages, as shown in Figure 3 and in the following equation.

$$f'(x,b) = f_T, f_{T-1}, \cdots, f_1(x,b) \tag{3}$$

T indicates the cumulative number of stages, and f_T is optimized for a similar (b_T) obtained from the corresponding stage. A cascade network is progressively used to enhance object proposals. A precisely defined threshold is given to all the detection heads of the network, starting from small to large, as shown in Figure 3. Regression in the cascade network is usually denoted as the resampling scheme rather than post-processing. This provides positive samples for the other stages. Furthermore, no difference was found between the inference of the training and testing because the model and IoU thresholds were identical. Consequently, cascade regression resamples the distributions successively for higher $IoUs$. All cascade stages were designed for one distinct IoU threshold, from small to large.

At detection stage t, the model contains classifier h_t and regressor f_t, augmented for IoU thresholds, and the cost of the threshold differs from $u_t > u_{t-1}$. The minimized loss function is given as

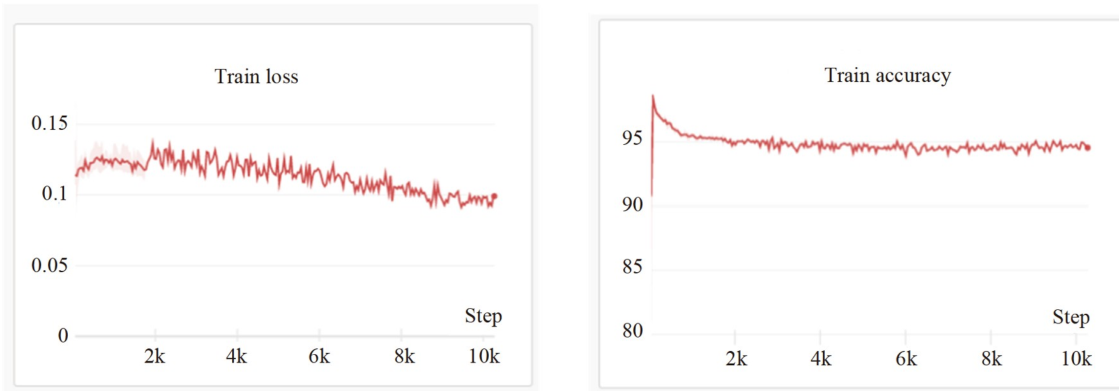
$$L(x^t, g) = L_{cls}(h(x), y)) + \lambda(y_t \geq 1) L_{loc} f((x,b), g) \tag{4}$$

In Equation (4), ground truth g is for object x^t, λ is the trade-off coefficient equal to 1, and the label of the detected object is represented as y_t. It does not eliminate negative samples but attempts to obtain a good collection of false positives, which are closed and used for further training so that bounding boxes are adjusted. The series of detectors decreases the overfitting problem by using higher IoUs during the training. Moreover, a similar cascade approach was applied for the inference. After training, testing samples are used to evaluate the developed system at the output, as shown in Figure 3. We obtained the desired results when an infected area was detected. In the developed system, by producing a digital-twin-enabled system, the operational strategies, staffing, capacities, and care models can be observed to regulate the actions on time when needed. This identifies any inefficiencies and problems to be speckled rapidly to save time, expenses, and lives.

4 Experiments and results

An experiment conducted by employing the aforementioned model is presented in this section. First, we discuss training and validation observations, and second, the output results of the detection model used for screening COVID-19 or SARA-CoV-2 infection in X-ray images. Finally, the model evaluation results were discussed to illustrate the model's performance. The proposed system was implemented using a Python programming language OpenCV 3.6 on an NVIDIA-SMI GPU. We used different threshold values for bounding box regression: the low and high threshold values, ranging between 0.2 and 0.7. The results for all IoU threshold values are discussed in detail. The datasets utilized in the experiments were collected from online repositories[52]. The dataset comprised 6334 chest scans for training, re-identified to maintain patient privacy. All images were in DICOM format and labeled for the existence of opacities and complete appearance by experienced radiologists. The dataset was randomly split at a ratio of 70% to 30% for training and testing sample purposes.

The aforementioned model's training accuracy and loss curves are presented in Figure 4a and Figure 4b, respectively. The model was trained in 1.5k steps. As shown in Figure 4a, after the 20th step, the loss values are reduced for training. Figure 4b displays that the training accuracy is improved, and the overfitting problem



(a) (b)

Figure 4 Training loss and accuracy curve for the aforementioned model plotted for 10k steps. Both curves are improved with training data. (a) shows the training loss curve, and (b) shows the accuracy curve. The x-axis shows the total steps (epochs) used for training, whereas the y-axis shows the loss and accuracy values during training.

is reduced.

The validation performance of the bounding box is shown using the mean average precision (mAP) value in Figure 5. The model's performance is enhanced during training, and the mAP nearly equals 0.54.

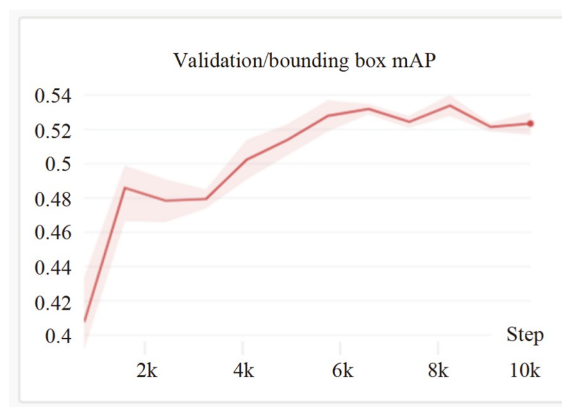
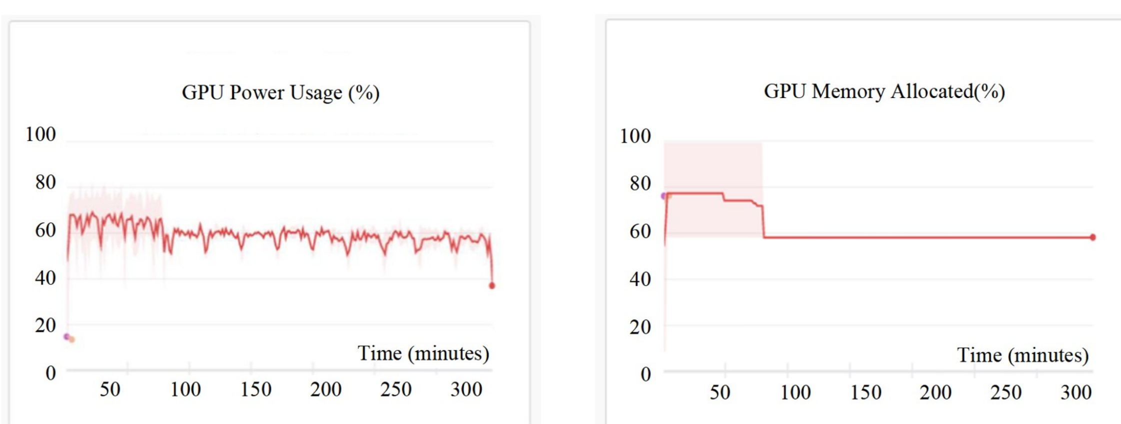


Figure 5 Validation performance of the model for 10k steps.

The GPU power usage and memory allocation are shown in Figure 6. The total time utilized during training was 300min, power usage ranged between 60 and 40V, memory utilization was 80GBs, and power usage decreased from 80V to 60V after 180min.

The detection results are depicted in Figure 7. To analyze the results, we used two different colored bounding boxes to show the ground truth labeled as gt_covid-19_abnormality and predicted bounding boxes labeled as pred_covid-19_abnormality. Different threshold values of the IoU were used to extract accurate bounding boxes for COVID-19 detection in chest X-ray images. Thus, we show the visualization results for four threshold values ranging from 0.2 and 0.7. When



(a) (b)

Figure 6 GPU utilization in terms of power, time, and memory. (a) Time is 300min; power usage ranges between 60 and 40V. (b) Memory utilization is 80 GBs; power usage decreases from 80 V to 60 V after 180min.

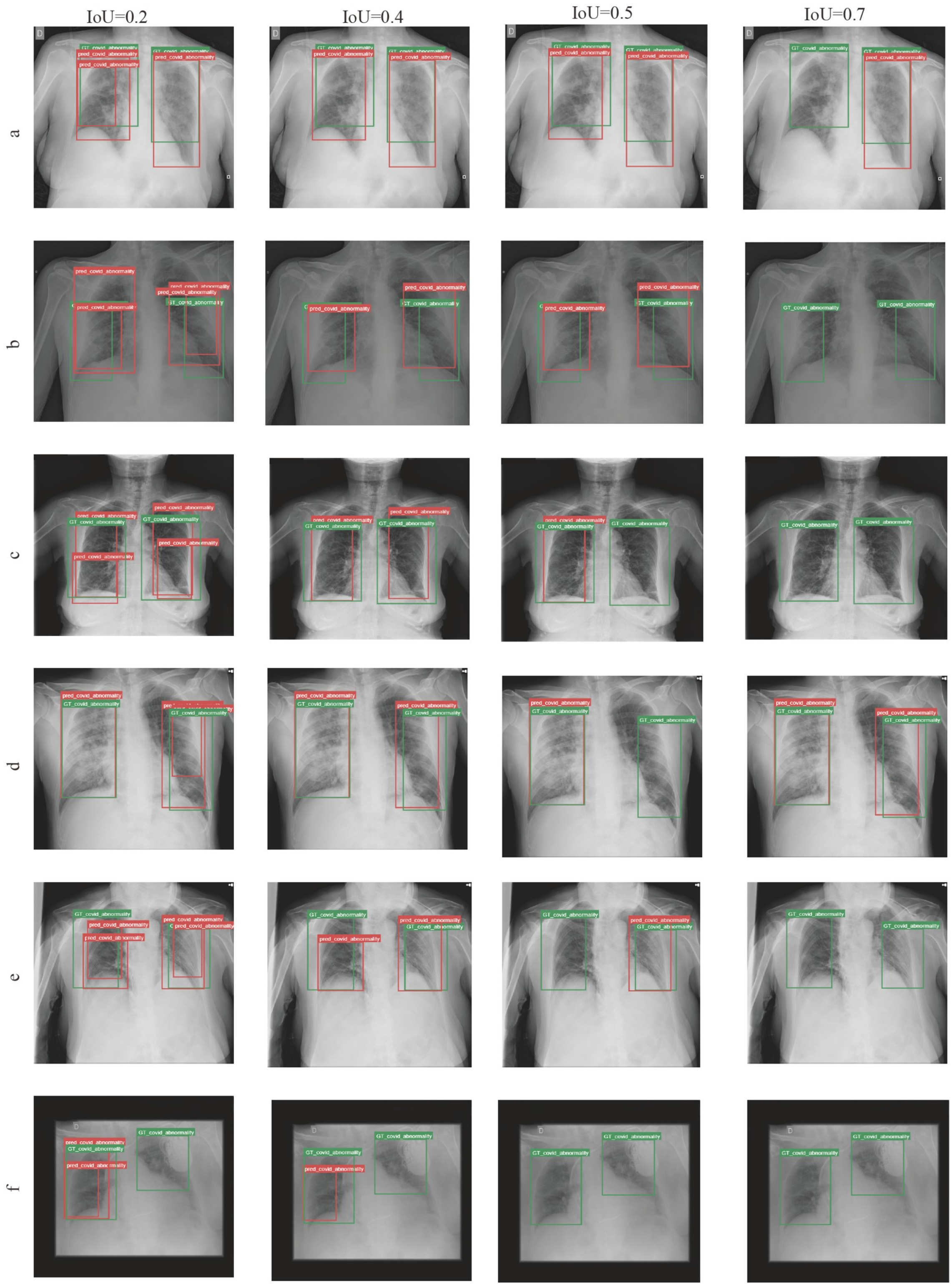


Figure 7 **Detection results of the deep-learning architecture used for detecting COVID-19 infection; the green color bounding boxes show the ground truth, and the red color shows the predicted bounding boxes. The column-wise results are provided for different IoU threshold values.**

the threshold value is small, the noise is created, and numerous bounding boxes are extracted. When the value is high (0.7), no predicted bounding box is obtained as the model searches for higher values that are not possible in our cases. We also visualized the results for a threshold value of 0.5 and observed that only a few bounding boxes were predicted to detect COVID-19 infection. By adjusting the values of the bounding boxes, we finally obtained the best threshold value of 0.4. In this case, we obtained the best detection bounding boxes for almost all the cases. The visualization results revealed that the deep-learning model accurately and effectively detect the region where lungs are affected by the virus; even in some sample cases, very small regions are also detected.

The testing samples provide the results for various cases (Figure 7a); the infected region is very small and is missed by the higher threshold values. Even though some false positives are obtained when the value is set for a small threshold, as depicted in Figure 7b and Figure 7d, accurate results are obtained, and infection is detected in both lungs; predicted bounding boxes are identical to the ground truth bounding boxes. In Figure 7e, we show the results for another sample image, where the deep-learning model effectively detected the infected area. Because of the noise, the results presented in Figure 7f are not as good as those in the others. Overall, the results indicated that the performance of the detection model was improved by adjusting its threshold values.

The results of the detection model are also compared with those of other state-of-the-art methods. The Cascade RCNN outperforms the Fast RCNN, Faster RCNN, FPN, and Mask R-CNN by a large margin. The comparison results are presented in Table 1 and Figure 8. The results of the models are improved when IoU thresholds are adjusted for the bounding boxes.

5 Conclusion and future works

A digital-twin-based smart healthcare system is introduced and integrated with medical devices to collect information regarding medical devices' health condition and maintenance history. We analyzed medical images of patients with COVID-19 or SARS-CoV-2 captured by using X-ray machines. Using X-ray images, we presented a deep-learning-based system to detect and localize COVID-19 infection. The designed system is

Table 1 Comparison results with state-of-the-art models

S.No	Model	Accuracy			
	Threshold	IoU=0.2	IoU=0.4	IoU=0.5	IoU=0.7
1	Fast RCNN	0.7	0.8	0.6	0.4
2	Faster RCNN	0.7	0.85	0.65	0.5
3	FPN	0.6	0.8	0.6	0.5
4	Mask RCNN	0.7	0.85	0.6	0.6
5	Cascade RCNN	0.7	0.94	0.65	0.6

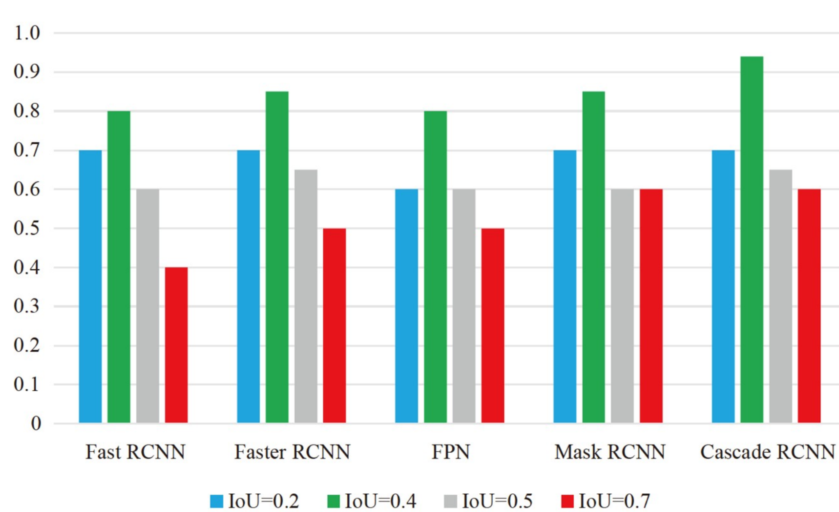


Figure 8 Comparison results with state-of-the-art models.

based on the Cascade RCNN architecture. We evaluated the system by conducting experiments using different threshold values and reduced false positives by adjusting the IoU value during the training. In addition, we trained the model for chest X-ray images as it was pre-trained on the COCO dataset. The experimental results revealed the efficiency of the detection architecture, yielding an mAP rate of 0.94. In the future, we might aim to extend the developed system to other explainable artificial-intelligence-based methods and techniques. More effective solutions can be developed for healthcare organizations to help obtain in-depth information that might enhance patient experiences and raise the value of care.

Declaration of competing interest

We declare that we have no conflict of interest.

References

1 Fuller A, Fan Z, Day C, Barlow C. Digital twin: enabling technologies, challenges and open research. IEEE Access, 2020, 8108952–108971
DOI: 10.1109/access.2020.2998358

2 Angulo C, Ortega J A, Gonzalez-Abril L. Towards a healthcare digital twin 1. In Artificial Intelligence Research and Development. IOS Press, 2019
DOI: 10.3233/FAIA190139

3 Ahmed I, Ahmad M, Jeon G. Social distance monitoring framework using deep learning architecture to control infection transmission of COVID-19 pandemic. Sustainable Cities and Society, 2021, 69102777
DOI: 10.1016/j.scs.2021.102777

4 Ahmed I, Ahmad M, Rodrigues J J P C, Jeon G, Din S. A deep learning-based social distance monitoring framework for COVID-19. Sustainable Cities and Society, 2021, 65102571
DOI: 10.1016/j.scs.2020.102571

5 Ahmed I, Ahmad A, Jeon G. An IoT-based deep learning framework for early assessment of COVID-19. IEEE Internet of Things Journal, 2021, 8(21): 15855–15862
DOI: 10.1109/jiot.2020.3034074

6 Ahmed I, Jeon G, Chehri A. An IoT-enabled smart health care system for screening of COVID-19 with multi layers features fusion and selection. Computing 2022, 1
DOI: 10.1007/s00607-021-00992-0

7 Ahmed I, Jeon G. Enabling artificial intelligence for genome sequence analysis of COVID-19 and alike viruses. Interdisciplinary Sciences: Computational Life Sciences 2021, 1
DOI: 10.1007/s12539-021-00465-0

8 Pires F, Cachada A, Barbosa J, Moreira A P, Leitão P. Digital twin in industry 4.0: technologies, applications and challenges. In: 2019 IEEE 17th International Conference on Industrial Informatics. Helsinki, Finland, IEEE, 2019, 721–726
DOI: 10.1109/INDIN41052.2019.8972134

9 Patrone C, Lattuada M, Galli G, Revetria R. The role of internet of things and digital twin in healthcare digitalization process. Transactions on Engineering Technologies, 2020, 30–37
DOI: 10.1007/978-981-15-6848-0_3

10 Elayan H, Aloqaily M, Guizani M. Digital twin for intelligent context-aware IoT healthcare systems. IEEE Internet of Things Journal, 2021, 8(23): 16749–16757
DOI: 10.1109/jiot.2021.3051158

11 Pilati F, Tronconi R, Nollo G, Heragu S S, Zerzer F. Digital twin of COVID-19 mass vaccination centers. Sustainability, 2021, 13(13): 7396
DOI: 10.3390/su13137396

12 Alrashed S, Min-Allah N, Ali I, Mehmood R. COVID-19 outbreak and the role of digital twin. Multimedia Tools and Applications2022, 1
DOI: 10.1007/s11042-021-11664-8

13 Ahmad M, Ahmed I, Khan F A, Qayum F, Aljuaid H. Convolutional neural network–based person tracking using overhead views. International Journal of Distributed Sensor Networks, 2020, 16(6): 155014772093473
DOI: 10.1177/1550147720934738

14 Shi F, Wang J, Shi J, Wu Z, Wang Q, Tang Z, He K, Shi Y, Shen D. Review of artificial intelligence techniques in imaging data acquisition, segmentation, and diagnosis for COVID-19. IEEE Reviews in Biomedical Engineering, 2021, 144–115
DOI: 10.1109/rbme.2020.2987975

15 Wynants L, Van Calster B, Collins G S, Riley R D, Heinze G, Schuit E, Bonten M M J, Dahly D L, Damen J A, Debray T P A, de Jong V M

T, De Vos M, Dhiman P, Haller M C, Harhay M O, Henckaerts L, Heus P, Kammer M, Kreuzberger N, Lohmann A, Luijken K, Ma J, Martin G P, McLernon D J, Andaur Navarro C L, Reitsma J B, Sergeant J C, Shi C, Skoetz N, Smits L J M, Snell K I E, Sperrin M, Spijker R, Steyerberg E W, Takada T, Tzoulaki I, van Kuijk S M J, van Bussel B C T, van der Horst I C C, van Royen F S, Verbakel J Y, Wallisch C, Wilkinson J, Wolff R, Hooft L, Moons K G M, van Smeden M. Prediction models for diagnosis and prognosis of COVID-19: systematic review and critical appraisal. BMJ2020, m1328
DOI: 10.1136/bmj.m1328

16 Ahmad M, Ahmed I, Jeon G. An IoT-enabled real-time overhead view person detection system based on Cascade-RCNN and transfer learning. Journal of Real-Time Image Processing, 2021, 18(4): 1129–1139
DOI: 10.1007/s11554-021-01103-0

17 Ahmed I, Jeon G. A real-time person tracking system based on SiamMask network for intelligent video surveillance. Journal of Real-Time Image Processing, 2021, 18(5): 1803–1814
DOI: 10.1007/s11554-021-01144-5

18 Shah F M, Joy S K S, Ahmed F, Hossain T, Humaira M, Ami A S, Paul S, Jim M A R K, Ahmed S. A comprehensive survey of COVID-19 detection using medical images. SN Computer Science, 2021, 2(6): 434
DOI: 10.1007/s42979-021-00823-1

19 Ahmed I, Din S, Jeon G, Piccialli F. Exploring deep learning models for overhead view multiple object detection. IEEE Internet of Things Journal, 2020, 7(7): 5737–5744
DOI: 10.1109/jiot.2019.2951365

20 Wang S, Kang B, Ma J, Zeng X, Xiao M, Guo J, Cai M, Yang J, Li Y, Meng X, Xu B. A deep learning algorithm using CT images to screen for Corona virus disease (COVID-19). European Radiology, 2021, 31(8): 6096–6104
DOI: 10.1007/s00330-021-07715-1

21 Hassanien A E, Mahdy L N, Ezzat K A, Elmousalami H H, Ella H A. Automatic X-ray COVID-19 lung image classification system based on multi-level thresholding and support vector machine, 2020
DOI: 10.1101/2020.03.30.20047787

22 Kadry S, Rajinikanth V, Rho S, Raja N S M, Rao V S, Thanaraj K P. Development of a machine-learning system to classify lung CT scan images into normal/COVID-19 class. 2020 //www.researchgate.net/publication/340997443

23 Hemdan E E D, Shouman M A, Karar M E. COVIDX-net: a framework of deep learning classifiers to diagnose COVID-19 in X-ray images, 2020
DOI: 10.48550/arXiv.2003.11055

24 Wang L, Lin Z Q, Wong A. COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images. Scientific Reports, 2020, 10(1): 19549
DOI: 10.1038/s41598-020-76550-z

25 Farooq M, Hafeez A. COVID-ResNet: a deep learning framework for screening of COVID19 from radiographs. 2020

26 Pathak Y, Shukla P K, Tiwari A, Stalin S, Singh S, Shukla P K. Deep transfer learning based classification model for COVID-19 disease. IRBM, 2022, 43(2): 87–92
DOI: 10.1016/j.irbm.2020.05.003

27 Singh D, Kumar V, Vaishali V, Kaur M. Classification of COVID-19 patients from chest CT images using multi-objective differential evolution–based convolutional neural networks. European Journal of Clinical Microbiology & Infectious Diseases, 2020, 39(7): 1379–1389
DOI: 10.1007/s10096-020-03901-z

28 Hossain M S, Muhammad G, Guizani N. Explainable AI and mass surveillance system-based healthcare framework to combat COVID-I9 like pandemics. IEEE Network, 2020, 34(4): 126–132
DOI: 10.1109/mnet.011.2000458

29 Muhammad G, Shamim Hossain M. COVID-19 and non-COVID-19 classification using multi-layers fusion from lung ultrasound images. Information Fusion, 2021, 7280–88
DOI: 10.1016/j.inffus.2021.02.013

30 Shorfuzzaman M, Hossain M S. MetaCOVID: a Siamese neural network framework with contrastive loss for n-shot diagnosis of COVID-19 patients. Pattern Recognition, 2021, 113107700
DOI: 10.1016/j.patcog.2020.107700

31 Apostolopoulos I D, Mpesiana T A. Covid-19: automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. Physical and Engineering Sciences in Medicine, 2020, 43(2): 635–640
DOI: 10.1007/s13246-020-00865-4

32 Pereira R M, Bertolini D, Teixeira L O, Silla Jr. C N, Costa Y M G. COVID-19 identification in chest X-ray images on flat and hierarchical classification scenarios. Computer Methods and Programs in Biomedicine, 2020, 194105532
DOI: 10.1016/j.cmpb.2020.105532

33 Ahmed I, Ahmad M, Jeon G, Piccialli F. A framework for pandemic prediction using big data analytics. Big Data Research, 2021, 25100190
DOI: 10.1016/j.bdr.2021.100190

34 Saeedi A, Saeedi M, Maghsoudi A. A novel and reliable deep learning web-based tool to detect COVID-19 infection from chest CT-scan. 2020
DOI: 10.48550/arXiv.2006.14419
35 Mobiny A, Cicalese P A, Zare S, Yuan P Y, Nguyen H V. Radiologist-level COVID-19 detection using CT scans with detail-oriented capsule networks. 2020
DOI: 10.48550/arXiv.2004.07407
36 He K M, Zhang X Y, Ren S Q, Sun J. Deep residual learning for image recognition. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition. Las Vegas, NV, USA, IEEE, 2016, 770–778
DOI: 10.1109/cvpr.2016.90
37 Song Y, Zheng S, Li L, Zhang X, Zhang X, Huang Z, Chen J, Wang R, Zhao H, Chong Y, Shen J, Zha Y, Yang Y. Deep learning enables accurate diagnosis of novel coronavirus (COVID-19) with CT images. IEEE/ACM Transactions on Computational Biology and Bioinformatics, 2021, 18(6): 2775–2780
DOI: 10.1109/tcbb.2021.3065361
38 Zheng C S, Deng X B, Fu Q, Zhou Q, Feng J P, Ma H, Liu W Y, Wang X G. Deep learning-based detection for COVID-19 from chest CT using weak label. 2020
DOI: 10.1101/2020.03.12.20027185
39 Gozes O, Frid-Adar M, Greenspan H, Browning P, Zhang H Q, -B Ji W, Bernheim A, Siegel E. Rapid AI development cycle for the coronavirus (COVID-19) pandemic: initial results for automated detection & patient monitoring using deep learning CT image analysis. 2020
DOI: 10.48550/arXiv.2003.05037
40 Jin D K, Xu Z Y, Tang Y B, Harrison A P, Mollura D J. CT-realistic lung nodule simulation from 3D conditional generative adversarial networks for robust lung segmentation. In: Medical Image Computing and Computer Assisted Intervention – MICCAI 2018. Cham: Springer International Publishing, 2018, 732–740
DOI: 10.1007/978-3-030-00934-2_81
41 Jiang J, Hu Y C, Liu C J, Halpenny D, Hellmann M D, Deasy J O, Mageras G, Veeraraghavan H. Multiple resolution residually connected feature streams for automatic lung tumor segmentation from CT images. IEEE Transactions on Medical Imaging, 2019, 38(1): 134–144
DOI: 10.1109/tmi.2018.2857800
42 Wu Y H, Gao S H, Mei J, Xu J, Fan D P, Zhang R G, Cheng M M. JCS: an explainable COVID-19 diagnosis system by joint classification and segmentation. IEEE Transactions on Image Processing, 2021, 303113–3126
DOI: 10.1109/tip.2021.3058783
43 Diniz J O B, Quintanilha D B P, Santos Neto A C, da Silva G L F, Ferreira J L, Netto S M B, Araújo J D L, Da Cruz L B, Silva T F B, da S. Martins C M, Ferreira M M, Rego V G, Boaro J M C, Cipriano C L S, Silva A C, de Paiva A C, Junior G B, de Almeida J D S, Nunes R A, Mogami R, Gattass M. Segmentation and quantification of COVID-19 infections in CT using pulmonary vessels extraction and deep learning. Multimedia Tools and Applications, 2021, 80(19): 29367–29399
DOI: 10.1007/s11042-021-11153-y
44 Qiu Y, Liu Y, Xu J. MiniSeg: an extremely minimum network for efficient COVID-19 segmentation. 2020
DOI: 10.48550/arXiv.2004.09750
45 Müller D, Rey I S, Kramer F. Automated chest CT image segmentation of COVID-19 lung infection based on 3D U-net. 2020
DOI: 10.48550/arXiv.2007.04774
46 Narin A, Kaya C, Pamuk Z. Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks. Pattern Analysis and Applications, 2021, 24(3): 1207–1220
DOI: 10.1007/s10044-021-00984-y
47 Fan D P, Zhou T, Ji G P, Zhou Y, Chen G, Fu H, Shen J, Shao L. Inf-net: automatic COVID-19 lung infection segmentation from CT images. IEEE Transactions on Medical Imaging, 2020, 39(8): 2626–2637
DOI: 10.1109/tmi.2020.2996645
48 Ahmed I, Camacho D, Jeon G, Piccialli F. Internet of health things driven deep learning-based system for non-invasive patient discomfort detection using time frame rules and pairwise keypoints distance feature. Sustainable Cities and Society, 2022, 79103672
DOI: 10.1016/j.scs.2022.103672
49 Ahmed I, Jeon G, Piccialli F. A deep-learning-based smart healthcare system for patient's discomfort detection at the edge of internet of things. IEEE Internet of Things Journal, 2021, 8(13): 10318–10326
DOI: 10.1109/jiot.2021.3052067
50 Ahmed I, Khan I, Ahmad M, Adnan A, Aljuaid H. Automated patient discomfort detection using deep learning. Computers, Materials & Continua, 2022, 71(2): 2559–2577
DOI: 10.32604/cmc.2022.021259
51 Cai Z W, Vasconcelos N. Cascade R-CNN: delving into high quality object detection. 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2018, 6154–6162
DOI: 10.1109/cvpr.2018.00644