Review Article

Artificial Intelligence Approaches on X-ray-oriented Images Process for Early Detection of COVID-19

Abstract

Background: COVID-19 is a global public health problem that is crucially important to be diagnosed in the early stages. This study aimed to investigate the use of artificial intelligence (AI) to process X-ray-oriented images to diagnose COVID-19 disease. **Methods:** A systematic search was conducted in Medline (through PubMed), Scopus, ISI Web of Science, Cochrane Library, and IEEE Xplore Digital Library to identify relevant studies published until 21 September 2020. **Results:** We identified 208 papers after duplicate removal and filtered them into 60 citations based on inclusion and exclusion criteria. Direct results sufficiently indicated a noticeable increase in the number of published papers in July-2020. The most widely used datasets were, respectively, GitHub repository, hospital-oriented datasets, and Kaggle repository. The Keras library, Tensorflow, and Python had been also widely employed in articles. X-ray images were applied more in the selected articles. The most considerable value of accuracy, sensitivity, specificity, and Area under the ROC Curve was reported for ResNet18 in reviewed techniques; all the mentioned indicators for this mentioned network were equal to one (100%). **Conclusion:** This review revealed that the application of AI can accelerate the process of diagnosing COVID-19, and these methods are effective for the identification of COVID-19 cases exploiting Chest X-ray images.

Keywords: *2019-nCoV disease, artificial intelligence, computed tomography, deep learning, image processing, X-ray images*

Sorayya Rezayi[1], Marjan Ghazisaeedi[1], Sharareh Rostam Niakan Kalhori[1], Soheila Saeedi[1,2]

[1]Department of Health Information Management, School of Allied Medical Sciences, Tehran University of Medical Sciences, Tehran, Iran, [2]Clinical Research Development Unit of Farshchian Heart Center, Hamadan University of Medical Sciences, Hamadan, Iran

Submitted: 13-Apr-2021 **Revised:** 28-Oct-2021 **Accepted:** 03-Jan-2022 **Published:** 26-Jul-2022

Background

Coronavirus is a family of infectious viruses that can cause diseases typically ranging from the common cold to severe illnesses such as Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS).[1] The new coronavirus, called SARS coronavirus 2 (SARS-CoV-2), is the recently known virus in this family that causes COVID-19 disease. The number of patients around the world is increasing dramatically every day and leading to the closure of industries and the quarantine of many people.[2] This disease exerts a severe effect on people's quality of life due to its high transmission power.[2] Considering the pandemic of infectious COVID-19 disease, rapid diagnosis of this disease is enormously essential that can progressively reduce the rate of virus transmission and facilitate the control of the disease. reverse transcription-polymerase chain reaction (RT-PCR) is the gold standard for definitive diagnosis of COVID-19 infection.[3] On the other hand, not all countries have access to these diagnostic kits, and the return time for test results typically varies from 3 h to 48 h.[4] RT-PCR sensitivity may not be high range enough, and its false-negative rate is almost high.[5] According to initial reports, its sensitivity is between 37% and 71%.[6] As a result, patients may be undiagnosed and leading to further spread of the disease.

A familiar way to properly diagnose pneumonia is to employ alternative methods of chest radiography imaging, like X-rays or computed tomography (CT). These imaging techniques are easy to perform and can yield a quick and highly sensitive way to diagnose COVID-19.[7]

Radiographic images are a non-invasive diagnostic way that can identify cases of the disease and help manage and triage the COVID-19 disease.[8] CT scans may

How to cite this article: Rezayi S, Ghazisaeedi M, Kalhori SR, Saeedi S. Artificial intelligence approaches on X-ray oriented images process for early detection of COVID-19. J Med Sign Sens 2022;12:233-53.

Address for correspondence:
Soheila Saeedi, Department of Health Information Management, 3rd Floor, School of Allied Medical Sciences, Tehran University of Medical Sciences, No #17, Farredanesh Alley, Ghods St., Enghelab Ave., Postal Code: 14177-44361, Tehran, Iran.
E-mail: soheila.saeedi2021@gmail.com

Access this article online

Website: www.jmssjournal.net

DOI: 10.4103/jmss.jmss_111_21

Quick Response Code:

indicate similar features between COVID-19 disease and other types of pneumonia, which may prevent a precise diagnosis of COVID-19 disease. On the other hand, it is considered that in many medical centers, radiologists are not available 24 h per typical day.[8]

The practical applications of artificial intelligence (AI) have rapidly entered the clinical field. The increasing complexity and volume of data in healthcare attend an apparent reason why AI techniques will be used in almost every field of medicine in the advancing years.[9] In health care, AI is recommended as an indispensable tool for disease diagnosis and clinical decisions.[10] Deep learning, due to its distinctive characteristics, can provide an opportunity to expand the use of AI-oriented automated techniques in the clinical field. Deep learning represents a subset of machine learning that is becoming a significant and vital technology in the reliable detection and classification of images and video.[11] The use of deep learning in image processing is exceedingly common.[12] Deep learning possesses the considerable potential to facilitate diagnosis from medical images, longitudinal monitoring of disease progression, and determination of disease severity.[13] One of the common algorithms of machine learning comprises convolutional neural networks.[14] Convolutional neural networks are a class of deep learning techniques or deep neural networks chiefly used to analyze visual imagery and classify them. Remarkably, convolutional neural networks have been extremely successful in the classification and detection of medic.[15,16] However, AI-based methods can help reliably detect COVID-19 from radiology images in real-time with high sensitivity.[17] In this period of the global crisis, it is substantial to accelerate the development of effective AI techniques for diagnosing COVID-19 and its differentiation from pneumonia and other lung diseases in X-ray-oriented images.

Therefore, based on relevant studies, with the outbreak of COVID-19 and the lack of diagnostic kits, many medical centers used radiographic images to diagnose the disease. Simultaneously, many researchers in different countries of the world used automated detection systems based on AI to help accurately diagnose COVID-19 disease with the help of medical images. Various deep learning methods have been used to launch these automated detection tools; each of these methods delivers different accuracy. Graciously according to our best knowledge, there is no comprehensive overview of the methods used in this area to offer the readers an overview in this regard. Therefore, it seems necessary to conduct a study on the use of AI approaches to detect COVID-19 based on radiographic images and CT scans to yield a comprehensive view of this field for researchers.

This study attempts to answer the following questions: (1) Which of the AI and deep learning methods have been used for image processing? (2) Which of the methods have worked best? (3) How accurate was the method used in image processing? (4) Which of the software is most used in image processing? (5) Were most of the images used related to radiology or CT images? (6)What are the sources of the images used in the studies?

Methods

This systematic review was performed based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMAs) approach which was introduced for the first time by Moher *et al*.[18]

Design

A systematic and comprehensive search of the scientific database, Medline (through PubMed), Web of Science, Cochrane Central Register of Controlled Trials, IEEE Xplore Digital Library, and Scopus databases was conducted on 21 Sep 2020. The search strategy used in the present review comprised a combination of main keywords from Medical Subject Heading (MeSH) and Emtree (Embase Subject Headings), which were related to "Artificial Intelligence", "COVID-19 pandemic", "Diagnostic X-Ray Radiology and X-Ray Computed Tomography."

Study selection criteria

Inclusion criteria

The following inclusion criteria based on the PICO tool were considered in this systematic review.

- Population: The study population in this systematic review was patients with different COVID 19
- Intervention: Studies that used artificial intelligence techniques were operated for early detection and diagnosis
- Comparison: Not applicable
- Outcome: Articles were included in the review in which intelligent algorithms were applied, and its effectiveness was reported.

Exclusion criteria

The exclusion criteria were the following items:

(1) Retrieved studies were not about new Coronavirus disease. (2) Articles which were review, book chapters, letters, reports, and technical reports, and (3) non-English published ones, (4) Manuscripts which were in the preprint phase were excluded too.

Literature refinement

In our scientific database searching process, 208 papers were retrieved after duplicate removal. Reviewers set some exclusion and inclusion criteria for screening the citations. In the data extraction phase, two independent reviewers (SR and SS) independently determined the main classifications of selected papers and synthesized the key characteristics of selected citations. The key specifications of the papers were validated by MG and S.RNK. Based on the research questions and specific objectives, to select relevant articles, all titles and abstracts were evaluated by two reviewers under the supervision of MG and S.RNK; therefore, the titles and abstracts of the citations were carefully screened by two authors to find relevant papers independently. Another reviewer (MG) randomly reviewed a sample of papers. In total, 86 papers met our inclusion criteria, so they were selected to enter the full-text review phase. The full texts of relevant papers were screened by two reviewers thoroughly (SR and SS). So finally, 60 citations remained as relevant ones; critical characteristics were entered into a spread sheet in Excel in each paper. Two authors (SR and SS) extracted and analyzed the study characteristics independently for each paper based on the predefined classification. For ultimate extraction and for reaching an agreement, the information was re-examined again by two authors. The flow of the screening phase illustrates based on the PRISMA approach in Figure 1. The major classifications and items of reviewed citations are displayed in Table 1.

Results

Earlier comprehensive searches in scientific databases assigned 290 papers. 208 papers were remained after the duplicate removal phase. In our initial screening phase, 122 articles were eliminated because of their irrelevant titles or abstracts. So, in the last screening step, only 60 studies that met our inclusion criteria were kept. Based on the predefined classification, a summary of the results is described in Table 1.

Illustration of papers

Of all the studies reviewed, only one was a paper published in a conference, and the rest were published in reputable journals**.** However, all of the eligible papers which met our inclusion criteria are journal papers. The dating trend of publishing the reviewed articles from the outbreak of COVID-19 up to Sep-2020 is plotted in Figure 2. As we can see, the highest number of articles on our topic was published in July.

The distribution of articles based on sample size and data sources of articles

Out of 60 published citations, three papers did not report their applied sample size. The sufficient sample size was varied tremendously from 100 images up to 110,000, and in one paper, the sample size was reported based on recruited cases, not images. The data sources and datasets applied in the reviewed citations were varied considerably. The name of these datasets and their frequency are illustrated in Figure 3. It is noteworthy that the most widely used datasets are respectively GitHub repository, hospital-oriented

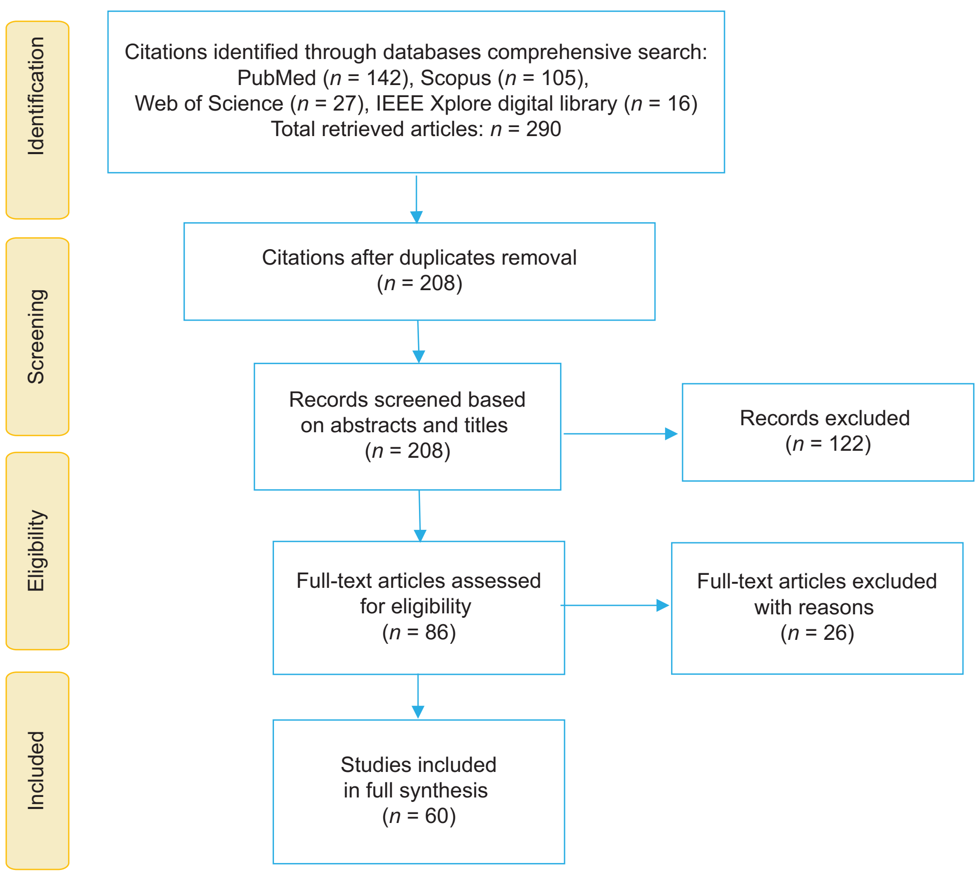

Figure 1: The PRISMA diagram for the records search and study selection

Table 1: The extracted characteristics of reviewed papers

Author	Country	Month of 2020	Applied methods	Best performance of applied model
Apostolopoulos *et al*.[19]	Greece	May 6, 2020	Mobile Net v2	Accuracy=99.18% Sensitivity=97.36% Specificity=99.42%
Albahli[20]	Saudi Arabia	May 5, 2020	ResNet InceptionV3 GAN	Accuracy=87.00%
Nour *et al*.[21]	Saudi Arabia	July 22, 2020	CNN combined with KNN SVM C4.5	Accuracy=98.97% Sensitivity=89.39% Specificity=99.75% F-score=96.72%
Öztürk *et al*.[22]	Turkey	July 11, 2020	The (SMOTE) algorithm with SVM	Accuracy=94.23% Sensitivity=91.88% Specificity=98.54% F-score=93.99%
Pathak *et al*.[23]	India	May 15, 2020	DTL technique	Accuracy=93.00% Sensitivity=91.00% Specificity=94.00%
Yan *et al*.[24]	China	July 23, 2020	MSCNN	Accuracy=87.50% Sensitivity=89.10% Specificity=85.70%
Rajaraman[25]	USA	May 30, 2020	VGG-16 Inception-V3 Xception DenseNet-121 NasNet-mobile	Accuracy=93.00% Sensitivity=97.00% Specifity=86.00% F-score=94.00%
Cohen *et al*.[26]	Canada	July 28, 2020	DenseNet model	MAE=1.14
Dey *et al*.[27]	UK	June 29, 2020	Social group optimization–based Kapur's entropy thresholding combined with RF KNN SVM DT	Accuracy=96.28% Sensitivity=75.06% Specificity=99.42% F-score=83.88%
Toraman *et al*.[28]	Turkey	July 10, 2020	Capsule network	Accuracy=97.24% Sensitivity=97.42% Specificity=97.04% F-score=97.24%
Hassantabar Sh *et al*.[29]	Iran	July 29, 2020	DNN on the fractal and CNN	Accuracy=93.20% Sensitivity=96.10% Specificity=99.70%
Islam *et al*.[30]	Bangladesh	August 7, 2020	A CNN combined with LSTM	Accuracy=99.40% Specificity=99.20% Sensitivity=99.30% F-score=98.90%
Che Azemin *et al*.[31]	Malaysia	August 18, 2020	ResNet-101	Aaccuracy=71.90% Sensitivity=77.30% Specificity=71.80%

Contd...

Table 1: Contd...

Author	Country	Month of 2020	Applied methods	Best performance of applied model
Bridge *et al*.[32]	UK	July 28, 2020	Inception V3 with a new activation function based on the GEV distribution	AUC=0.731 Sensitivity=72.60% Specificity=66.90%
Jaiswal *et al*.[33]	India	July 3, 2020	DenseNet201 VGG16 Inception ResNet ResNet152V2	Accuracy=96.25% Specificity=96.21%
Sun *et al*.[34]	China	August 26, 2020	AFS-DF	Accuracy=91.79% Sensitivity=93.05% Specificity=89.95% F-score=93.10%
Shiri *et al*.[35]	Switzerland	August 21, 2020	ResNet	RMSE decreased to 0.09
Mishra *et al*.[36]	India	July 30, 2020	CNN based decision fusion model combine with VGG16 InceptionV3 ResNet50 DenseNet	Accuracy=89.00% Sensitivity=89.00% Specificity=92.00% F-score=86.70%
Albahli[37]	Saudi Arabia	May 22, 2020	GAN	Accuracy=89.00%
Ardakani *et al*.[38]	Iran	July 20, 2020	DT KNN NB SVM Ensemble	Accuracy=93.85% Sensitivity=94.67% Specificity=93.03%
Duran-Lopez *et al*.[39]	Spain	August 13, 2020	COVID-Xnet	Accuracy=94.43% Sensitivity=92.53% Specificity=96.33% F-score=93.14%
Pathak *et al*.[40]	India	July 20, 2020	LSTM combined with mixture density network and MADE	Accuracy=98.37% F-score=98.14%
Tuncer *et al*.[41]	Turkey	May 12, 2020	ResExLBP and feature selection with (IRF) combined with DT LD SVM KNN SD	Accuracy=100.0% Sensitivity=98.29% Specificity=100.0%
Wang *et al*.[42]	China	September 10, 2020	COVID-Net	Accuracy=90.83% F-score=90.87% AUC=0.96
Zamzami *et al*.[43]	Saudi Arabia	September 11, 2020	A novel regression model based on the shifted-scaled Dirichlet distribution	Accuracy=97.10% MSE=1.24e+17
Wang *et al*.[44]	China	January 1, 2020	Combined DenseNet121-FPN and COVID-19Net	Accuracy=81.24% Sensitivity=78.93% Specificity=89.93% AUC=0.90
Oh *et al*.[45]	Republic of Korea	May 10, 2020	Patch-based method with convolutional neural network FC-DenseNet103 and ResNet-18	Accuracy=88.90% Specificity=96.40% F-score=84.40%

Contd...

Table 1: Contd...

Author	Country	Month of 2020	Applied methods	Best performance of applied model
Das *et al.*[46]	India	June 11, 2020	Truncated inception net	Accuracy=99.96% AUC=1.00 Sensitivity=88.00% Specificity=1.00%
Mahmud *et al.*[47]	Bangladesh	June 18, 2020	CovXNet	Accuracy=97.40% Specificity=94.70% AUC=0.96
Abraham and Nair[48]	India	August 5, 2020	Combination of multi-CNN with CFS and bayesnet classifier	Accuracy=97.43% F-score=98.6% AUC=0.93
Jain *et al.*[1]	Germany	August 30, 2020	ResNet50 ResNet101	Accuracy=97.77%
Xu *et al.*[49]	China	June 27, 2020	Classical ResNet-1 with and without the location attention mechanism	Accuracy=86.7%
Rahimzadeh and Attar[2]	Iran	May 21, 2020	ResNet50V2 Xception Concatenation of Xception ResNet50V2 neural networks	Accuracy=99.69% Specificity=99.76% Sensitivity=87.09%
Rajaraman *et al.*[50]	USA	June 22, 2020	VGG-16 VGG-19 Inception-V3 Xception InceptionResNet-V2 MobileNet-V2 DenseNet-201 NasNet-mobile	Accuracy=98.41% Sensitivity=98.41% F-score=98.41%
Minaee *et al.*[51]	USA	July 21, 2020	ResNet18 ResNet50 SqueezeNet DenseNet-121	AUC=0.992 Sensitivity=98% Specificity=92.9%
Ouyang *et al.*[52]	China	May 12, 2020	Attention RN34 + SS AttentionRN34 + US AttentionRN34 + DS RN34 + US	Accuracy=87.9% Sencitivity=87.2% Specificity=90.7% F1-score=82.5% AUC=0.948
Apostolopoulos and Mpesiana[53]	Greece	March 30, 2020	VGG19 MobileNet v2 Inception Xception Inception ResNet v2	Accuracy=96.78% Sensitivity=98.66% Specificity=96.46%
Yang *et al.*[54]	China	March 9, 2020	DenseNet	Accuracy=92% Sensitivity=97% Specificity=87% F-score=93% AUC=0.98
Dansana *et al.*[55]	India	August 28, 2020	VGG-16 Inception_V2 With DT	Accuracy=91% F-score=97%

Contd...

Table 1: Contd...

Author	Country	Month of 2020	Applied methods	Best performance of applied model
Xiao *et al*.[56]	China	July 13, 2020	ResNet34 AlexNet VGGNet DenseNet	Accuracy=97.4% AUC=0.987
Yoo *et al*.[57]	Hong Kong	July 2, 2020	ResNet18	Accuracy=100% Sensitivity=100% Specificity=100% AUC=1.00
Zhu *et al*.[13]	USA	July 10, 2020	Traditional CNN model and VGG16	R2=0.90
Ni *et al*.[58]	China	June 22, 2020	MVP-Net	Accuracy=95% Sensitivity=100% Specificity=100% F-score=97%
Ko *et al*.[8]	Republic of Korea	June 29, 2020	VGG16 ResNet-50 Inception-V3 Xception	Accuracy=99.87% Sensitivity=99.58% Specificity=100.00%
Bai HX *et al*.[59]	China	April 27, 2020	EfficientNet B4	Accuracy=96% Sensitivity=95% Specificity=96%
Lessmann *et al*.[60]	The Netherlands	July 30, 2020	Deep learning model based on a 3D inflated Inception V1 architecture (I3D)	AUC=0.95 Sensitivity=99.9%
Liu *et al*.[61]	China	August 19, 2020	Machine learning algorithms DT LR SVM KNN EBT	Accuracy=94.16% Specificity=100.00%
Sakagianni *et al*.[9]	Greece	June 26, 2020	A deep learning model	AUC=0.94 F-score=85%
Sharma[62]	India	July 14, 2020	ResNet	Accuracy=91% Sensitivity=92.1%
Singh *et al*.[63]	India	April 7, 2020	MODE–based CNN ANFIS	Accuracy=93.4% Sencitivity=90.8% Specificity=90.7%
Loey *et al*.[64]	Egypt	April 16, 2020	GAN/DTL model Alexnet Googlenet Restnet18	Accuracy=100% F-score=100%
Vaid *et al*.[65]	Canada	May 6, 2020	VGG-19	Accuracy=96.3%
Albahli and Albattah[66]	Saudi Arabia	July 17, 2020	Inception ResNetV2 InceptionNetV3 NASNetLarge	Accuracy=99.02%

Contd...

Table 1: Contd...

Author	Country	Month of 2020	Applied methods	Best performance of applied model
Rahaman *et al.*[67]	China	July 11, 2020	VGG series Xception ResNetV1 ResNetV2 series Inception series DenseNet series MobileNet	Accuracy=89.3% F-score=95%
Pereira *et al.*[68]	Brazil	May 6, 2020	Inception-V3 KNN SVM MLP DT RF	F-score=83.33%
Harmon *et al.*[69]	USA	July 13, 2020	The hybrid 3D and full 3D models based on Densnet-121 architecture	Accuracy=90.80% Sensitivity=84.00% Specificity=93.00% AUC=94.70%
Wu *et al.*[70]	China	April 27, 2020	The multi-view fusion based on ResNet50	Accuracy=76.00% Sensitivity=81.10% Specificity=61.50% AUC=81.90%
Ozturk *et al.*[71]	Turkey	April 26, 2020	DarkCovidNet	Accuracy=87.02% Sensitivity=85.35% Specificity=92.18% F-score=87.37%
Khan *et al.*[72]	India	May 30, 2020	CoroNet	Accuracy=89.60% Specificity=96.40% F-score=89.80%
Brunese *et al.*[73]	Italy	June 9, 2020	VGG-16	Accuracy=98.00% Sensitivity=87.00% Specificity=94.00% F-score=89.00%

Author	Sample size	Type of input image (X-ray or CT)	Software (environment)	Data source	Outcome
Apostolopoulos *et al.*[19]	10-fold-cross-validation: 3905 images	CXR images	Keras library Tensorflow	RSNA CXR Radiopaedia encyclopedia The Italian Society of Medical CXR images SIRM	The results suggest that training CNNs from scratch may reveal vital biomarkers related to the COVID-19 disease
Albahli[20]	108,948 images	CXR images	Not mentioned	Kaggle repository GitHub	A deep neural network model provides a significant contribution in terms of detecting COVID-19 and provide effective analysis of chest related diseases
Nour *et al.*[21]	5-fold-cross-validation: 2905 images	CXR images	MatLab	The Italian Society of Medical CXR images SIRM	Based on the proposed tool, the misdiagnosis rates can be reduced, and the proposed model can be used as a retrospective evaluation tool to validate positive COVID-19 infection cases

Contd...

Table 1: Contd...

Author	Sample size	Type of input image (X-ray or CT)	Software (environment)	Data source	Outcome
Pathak *et al*.[23]	10-fold-cross-validation: 852 images	CXR images	Not mentioned	Open online databases of chest CT/X-ray	Experimental results reveal that the proposed DTL -based COVID-19 classification model provides efficient results
Yan *et al*.[24]	828 images	Chest CT images	Python Sklearn	Open online databases of chest CT	The proposed model has great potential to assist radiologists and physicians in performing a quick diagnosis and mitigate the heavy workload of them
Rajaraman[25]	5294 images	CXR images	Keras library Tensorflow	Pediatric CXR RSNA CXR CheXpert CXR NIH	Interestingly, adding COVID-19 CXRs to simple weakly labeled augmented training data significantly improves the performance, suggesting that COVID-19, though viral in origin
Cohen *et al*.[26]	153 images	CXR images	Not mentioned	RSNA CXR CheXpert CXR MIMIC CXR PadChest OpenI	The results indicate that model's ability to gauge severity of COVID-19 lung infections could be used for escalation or de-escalation of care as well as monitoring treatment efficacy
Dey *et al*.[27]	5-fold-cross-validation: 400 images	Chest CT images	MatLab	LIDC-IDRI RIDER-TCIA	Experimental results using benchmark datasets show a high accuracy for the morphology-based segmentation task
Toraman *et al*.[28]	10-fold-cross-validation: 231 images	CXR images	Not mentioned	GitHub	It is thought that the proposed method may help physicians to diagnose COVID-19 disease and increase the diagnostic performance
Hassantabar Sh *et al*.[29]	682 images	Chest CT images	Not mentioned	GitHub	Results show that the presented method can almost detect infected regions with high accuracy
Islam *et al*.[30]	5-fold-cross-validation: 4575 images	CXR images	Python Keras library Tensorflow	GitHub Radiopaedia encyclopedia RIDER-TCIA SIRM Kaggle repository NIH	The proposed system can help doctors to diagnose and treat COVID-19 patients easily
Che Azemin *et al*.[31]	10,358 images	CXR images	Not mentioned	Chest X-ray 14 NIH The University of Montreal dataset	The strength of this study lies in the use of adjudicated labels which have strong clinical association with COVID-19 cases
Bridge *et al*.[32]	1993 images	CXR images Chest CT images	Keras library Tensorflow	SIRM Chest X-ray 8 Shenzhen	The proposed GEV activation function significantly improves upon the previously used sigmoid activation for binary classification
Jaiswal *et al*.[33]	2492 images	Chest CT images	Not mentioned	Kaggle repository	Comparative analyses reveal that the proposed DTL based COVID-19 classification model outperforms the competitive approaches
Sun *et al*.[34]	5-fold-cross-validation: 2522 images	Chest CT images	Not mentioned	Datasets were collected by several universities and hospitals	Proposed AFS-DF approach can achieve superior performance on COVID-19 classification with chest CT images in comparison with several existing methods

Contd...

Table 1: Contd...

Author	Sample size	Type of input image (X-ray or CT)	Software (environment)	Data source	Outcome
Shiri *et al.*[35]	1141 images	Chest CT images	Not mentioned	Not mentioned	The results demonstrated that the deep learning algorithm is capable of predicting standard full-dose CT images with acceptable quality for the clinical diagnosis of COVID-19
Mishra *et al.*[36]	757 images	Chest CT images	Python Keras library Tensorflow	COVID-19 chest CT images dataset	The experimental observations suggest the potential applicability of such deep CNN based approach in real diagnostic scenarios, which could be of very high utility in terms of achieving fast testing for COVID19
Albahli[37]	108,948 images	CXR images	Not mentioned	Kaggle repository GitHub	It is exceptionally infectious and may prompt intense respiratory misery or numerous organ disappointments in serious cases
Ardakani *et al.*[38]	20-fold-cross-validation: 612 images	Chest CT images	MatLab SPSS	Not mentioned	The proposed model can be considered an adjunct tool by the radiologists during the current COVID-19 pandemic to make an accurate diagnosis
Duran-Lopez *et al.*[39]	5-fold-cross-validation: 2589 image	CXR images	Keras library Tensorflow	BIMCV-COVID19 dataset PadChest GitHub	Results indicate that COVID-XNet could be used as a tool to aid radiologists and contribute to the fight against COVID-19
Pathak *et al.*[40]	20-fold-cross-validation: 2482 images	Chest CT images	MatLab	COVID-19 chest CT images dataset	Comparative analysis reveals that the proposed MADE-DBM model outperforms the competitive COVID-19 classification approaches
Tuncer *et al.*[41]	10-fold-cross-validation: 321 images	CXR images	MatLab	Kaggle repository GitHub	The proposed ResExLBP and IRF based method is also cognitive, lightweight, and highly accurate
Wang *et al.*[42]	4-fold-cross-validation: 3228 images	Chest CT images	PyTorch	COVID-19 chest CT images dataset SARS-CoV-2 CT-scan datasets	Experiments on two large-scale public datasets demonstrates the effectiveness and clinical significance of their approach
Zamzami *et al.*[43]	Not mentioned	CXR images Chest CT images	Not mentioned	GitHub	The experimental results demonstrate that our approach is highly effective for detecting COVID-19 cases and understand the infection on a real-time basis with high accuracy
Wang *et al.*[44]	5372 patients	Chest CT images	Keras library Python	Datasets were collected by research team from cities or provinces	Deep learning provides a convenient tool for fast screening COVID-19 and finding potential high-risk patients, which may be helpful for medical resource optimization and early prevention
Oh *et al.*[45]	15,545 images	CXR images	MatLab	Open online databases of chest CT/X-ray USNLM JSRT	Experimental results show that method achieves state-of-the-art performance and provides clinically interpretable saliency maps, which are useful for COVID-19 diagnosis and patient triage
Das *et al.*[46]	10-fold-cross-validation: 6545 images	CXR images	Not mentioned	GitHub Kaggle repository Two publicly available tuberculosis collections	The truncated inception net can serve as a milestone for screening COVID-19 under active-learning framework on latitudinal/multimodal data

Contd...

Table 1: Contd...

Author	Sample size	Type of input image (X-ray or CT)	Software (environment)	Data source	Outcome
Mahmud *et al*.[47]	6161 images	CXR images	Not mentioned	Datasets were collected by several universities and hospitals	The proposed schemes can serve as an efficient tool in the current state of COVID-19 pandemic
Abraham and Nair[48]	1028 images	CXR images	MatLab Weka	Kaggle repository	The experiments performed in this study proved the effectiveness of pretrained multi-CNN over single CNN in the detection of COVID-19
Jain *et al*.[1]	5-fold-cross-validation: 1832 images	CXR images	Python	Kaggle repository GitHub	Proposed method can be used as an alternative diagnostic tool with potential candidature in detection of COVID-19 cases
Xu *et al*.[49]	618 images	Chest CT images	Not mentioned	Datasets were collected from hospitals	The deep learning models were effective for the early screening of COVID-19 patients and were demonstrated to be a promising supplementary diagnostic method for frontline clinical doctors
Rahimzadeh and Attar[2]	3783 images	CXR images	Keras library	GitHub Kaggle repository	Proposed model can be helpful for medical diagnosis
Rajaraman *et al*.[50]	Not mentioned	CXR images	Not mentioned	GitHub Twitter COVID-19 CXR RSNA CXR Pediatric CXR	This model can be quickly adopted for COVID-19 screening using chest radiographs
Minaee *et al*.[51]	5184 images	CXR images	PyTorch	Research paper datasets	The achieved performance was very encouraging
Ouyang *et al*.[52]	5-fold-cross-validation: 4982 images	Chest CT images	PyTorch	Datasets were collected from hospitals	The proposed algorithm could potentially aid radiologists with COVID-19 diagnosis, especially in the early stage of the COVID-19 outbreak
Apostolopoulos and Mpesiana[53]	10-fold-cross-validation: 2869 images	CXR images	Not mentioned	Open online databases of CXR	The present work contributes to the possibility of a low-cost, rapid, and automatic diagnosis of the coronavirus disease
Yang *et al*.[54]	295 images	Chest CT images	PyTorch Python Sklearn	Datasets were collected from hospitals	The proposed model can reduce the miss diagnosis rate and radiologists' workload
Dansana *et al*.[55]	360 images	CXR images Chest CT images	Not mentioned	GitHub	It can help in finding and providing early diagnosis to diseases and gives both quick and precise outcomes
Xiao *et al*.[56]	23,812 images	Chest CT images	PyTorch	Datasets were collected from hospitals	Deep learning-based model can accurately predict disease severity as well as disease progression in COVID-19 patients
Yoo *et al*.[57]	1170 images	CXR images	PyTorch	Eastern Asia Hospital dataset NIH Shehnzen GitHub	The proposed deep learning-based decision-tree classifier may be used in prescreening patients to conduct triage and fast-track decision making before RT-PCR results are available

Contd...

Table 1: Contd...

Author	Sample size	Type of input image (X-ray or CT)	Software (environment)	Data source	Outcome
Zhu *et al*.[13]	5-fold-cross-validation: 131 images	CXR images	Not mentioned	GitHub	This approach may prove useful to stage lung disease severity, prognosticate, and predict treatment response and survival, thereby informing risk management and resource allocation
Ni *et al*.[58]	19,291 images	Chest CT images	Not mentioned	Datasets were collected from hospitals	The algorithm showed excellent performance in detecting COVID-19 pneumonia on chest CT images compared with resident radiologists
Ko *et al*.[8]	5-fold-cross-validation: 3993 images	Chest CT images	Tensorflow Keras library Python MatLab	Datasets were collected from hospitals SIRM Interventional Radiology public database	The proposed method provides excellent diagnostic performance in detecting COVID-19 pneumonia
Bai HX *et al*.[59]	1186 images	Chest CT images	Keras library Tensorflow R	Datasets were collected from hospitals	Artificial intelligence assistance improved radiologists' performance in distinguishing coronavirus disease 2019 pneumonia from noncoronavirus disease 2019 pneumonia at chest CT
Lessmann *et al*.[60]	5-fold-cross-validation: 887 images	Chest CT images	R Python	Datasets were collected from hospitals	With high diagnostic performance, the CO-RADS AI system correctly identified patients with COVID-19 using chest CT scans
Liu *et al*.[61]	10-fold-cross-validation: 88 cases	Chest CT images	Not mentioned	Datasets were collected from hospitals	The experimental results show that, as compared to other state of-the-art works, the proposed method achieved pronouncedly superior performance with a small amount of CT images
Sakagianni *et al*.[9]	746 images	Chest CT images	Google automl cloud vision	Research paper datasets	These methods could deliver significant potential benefits for patients in the future by allowing for earlier disease detection and care
Sharma[62]	2200 images	Chest CT images	Microsoft azure	Datasets were collected from hospitals	Machine learning techniques can be used for early detection of coronavirus
Singh *et al*.[63]	20-fold cross-validation: Not mentioned	Chest CT images	MatLab	COVID-19 X-ray image database	The proposed model is useful for real-time COVID-19 disease classification from chest CT images
Loey *et al*.[64]	306 images	CXR images	MatLab	Research paper datasets	The detection of coronavirus with AI in early stages will help in fast recovery
Vaid *et al*.[65]	545 images	CXR images	Not mentioned	Research paper datasets NIH	COVID-19 detection model minimizes manual interaction dependent on radiologists as it automates identification of structural abnormalities in patient's CXRs
Albahli and Albattah[66]	2265 images	CXR images	Not mentioned	COVID-19 X-ray image database	DTL is feasible to detect COVID-19 disease automatically from CXR
Rahaman *et al*.[67]	860 images	CXR images	Google Colab notebooks	Kaggle repository GitHub	This study demonstrates the effectiveness of DTL techniques for the identification of COVID-19 cases using CXR images

Contd...

Table 1: Contd...

Author	Sample size	Type of input image (X-ray or CT)	Software (environment)	Data source	Outcome
Pereira *et al*.[68]	1144 images	CXR images	Not mentioned	GitHub Radiopedia encyclopedia NIH	The good identification rate achieved for COVID-19 can be quite useful to help the screening of patients in the emergency medical support services
Harmon *et al*.[69]	2724 images	Chest CT images	Tensorflow	Datasets were collected fron a multinational cohort LIDC-IDRI	AI-based algorithms can readily identify CT scans with COVID-19 associated pneumonia, as well as distinguish non-COVID related pneumonias with high specificity in diverse patient populations
Wu *et al*.[70]	495 three-view images	Chest CT images	Python Keras library R	Dataset was collected from three hospitals in China	The model showed great potential to improve the efficacy of diagnosis and mitigate the heavy workload of radiologists for the initial screening of COVID-19 pneumonia
Ozturk *et al*.[71]	5-fold-cross-validation: 1125 images	CXR images	Not mentioned	COVID-19 X-ray image database	The proposed method can be employed to assist radiologists in validating their initial screening, and can also be employed via cloud to immediately screen patients
Khan *et al*.[72]	4-fold cross-validation: 1300 images	CXR images	Keras library Tensorflow	ImageNet dataset GitHub RSNA	The proposed method can be very helpful tool for clinical practitioners and radiologists to aid them in diagnosis, quantification and follow-up of COVID-19 cases
Brunese *et al*.[73]	6523 images	CXR images	Not mentioned	GitHub Kaggle repository Research paper datasets	Experimental analysis on CXRs belonging to different institutions demonstrated the effectiveness of the proposed approach

AFS-DF – Adaptive feature selection guided deep forest; AI – Artificial intelligence; ANFIS – Adaptive neuro-fuzzy inference system; AUC – Area under the ROC Curve; CFS – Correlation-based feature selection; CNN – Convolutional neural network; CT – Computed tomography; CXR – Chest X-ray; DNN – Deep neural network; DT – Decision tree; DTL – Deep transfer learning; EBT – Ensemble of bagged Tree; GAN – Generative adversarial network; GEV – Generalized extreme value; IRF – Iterative relief; JSRT – Japanese Society of Radiological Technology; KNN – K-nearest neighbor; LD – Linear discriminant; LIDC-IDRI – The Lung image database consortium-Image database resource initiative; LSTM – Long short-term memory; MADE – Memetic adaptive differential evolution; MAE – Mean absolute error; MODE – Multi-objective differential evolution; MSCNN – Multi-Scale convolutional neural network; NB – Naïve bayes; NIH – National Institutes of Health; ResExLBP – Residual exemplar local binary pattern; RF – Random forest; RIDER-TCIA – The Reference image database to evaluate therapy response-the cancer imaging archive; RMSE – Root-mean-square error; RSNA – Radiological Society of North America; RT-PCR – Reverse transcription polymerase-chain-reaction; SARS – Severe Acute Respiratory Syndrome; SARS-CoV-2 – Severe acute respiratory syndrome coronavirus 2; SD – Subspace discriminant; SIRM – Italian Society of Radiology; SMOTE – Synthetic minority over-sampling technique; SVM – Support vector machine; TCIA – The cancer imaging archive; USNLM – U.S. National Library of Medicine; MERS – Middle East Respiratory Syndrome; MeSH – Medical subject heading; PRISMA – Preferred reporting items for systematic reviews and meta-analyses; VGG: Visual Geometry Group; DCNN: Deep Convolution Neural Network; DBM: deep bidirectional long short-term memory network with mixture density network; MSE: Mean Squared Error; FPN: Feature Pyramid Network; LR: Linear regression; MVP: Multi-View FPN with Position-aware attention; FC: Fully Connected; ROC: receiver operating characteristic curve; MLP: Multilayer perceptron; MIMIC CXR: MIMIC Chest X-ray; BIMCV: Medical Imaging Databank of the Valencia Region; CO-RADS: COVID-19 Reporting and Data system

datasets, Kaggle repository, COVID-19 chest CT/X-ray datasets.

The distribution of reviewed citations based on applied software

In this part, we illustrate applied software, technical environments, and tools in reviewed studies. Out of 60 selected papers, 26 citations did not report their applied software and tools, but in the remaining ones, variable tools for deep and machine learning approaches were particularly mentioned. It is remarkable that in the selected studies, several tools have repeatedly been used to conduct research. The reported tools based on their frequency of use are shown in Figure 4. As it turns out, tools like The Keras library, Tensorflow, and Python have been in addition widely used in articles.

The distribution of included papers by their publishers

Our selected scientific citations (n = 60) were retrieved from 45 reputable journals and one international conference. The frequency of reviewed papers is displayed in Table 2. As it is apparent, "Chaos, Solitons and Fractals," "Computer Methods and Programs in Biomedicine," "European Radiology" and "IEEE Journal of Biomedical and Health Informatics" have the highest rank with three papers between the journals.

The distribution of papers by their conducted countries

The selected papers are presented in Figure 5 based on their conducted countries. As it is clear that 22% of all citations were set in China, and 17% of them were performed in India. In the United States and Saudi Arabia, 16% of the articles were compiled equally.

The distribution of selected articles based on input types

In the reviewed articles, two types of inputs have been utilized to train, test, and validate machine learning techniques and deep neural networks. Figure 6 shows what kind of images (CT or simple X-ray images) were used in the selected articles. As it turns out, in some cases, both types of images were applied.

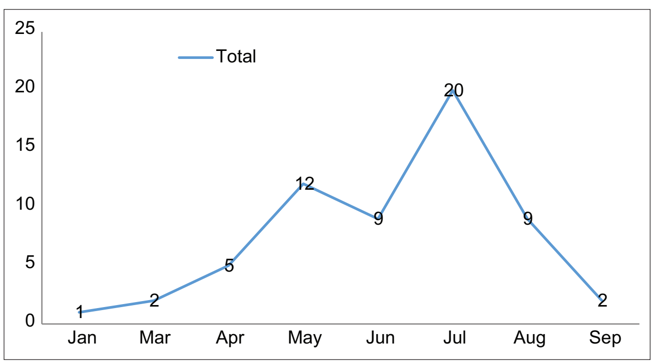

Figure 2: The distribution of papers by their date of publications

The distribution of selected papers based on applied best algorithms

In this section, we examined the best-applied techniques in the reviewed articles. Figure 7 shows an overview of the distribution of applied image processing methods in reviewed articles. It is apparent that the most favorite method was employed in reviewed articles is combined methods, VGG-19, and VGG-16 networks. Accordingly, such pretrained networks have a high volume of computations but at the same time have better diagnostic accuracy and classification due to their complex structures. In four of the reviewed articles, combined networks have been used to identify and classify images, which adds to the complexity and execution time of the work and highlights the need to provide complex systems.

The distribution of reviewed citations based on their artificial intelligence oriented approaches and reported effectiveness

The effectiveness of applied AI-oriented methods is displayed in Table 1. The outstanding results showed that these deep learning and machine learning approaches have the potential and power to early diagnose, detect, and classify COVID-19 disease. The effectiveness and performance of these techniques were reported and assessed by valid criteria such as accuracy, sensitivity, specificity, AUC, F-score, and mean average error. The highest value of accuracy, sensitivity, specificity, and AUC is reported for ResNet18 in reviewed techniques; all the mentioned indicators for this mentioned network are equal to one (100%). On the other hand, some of the applied methods provide the most excellent accuracy (100%), like ResExLBP with Iterative ReliefF (IRF) by Support Vector Machine (SVM) classifier and Googlenet. As an accomplished result of the studies, various designed deep convolutional networks such as Mobile Net V2, DenseNet, ResNet, COVID-Xnet, VGG-16, VGG-19, etc., have been used to analyze the chest radiographic images and correctly classify patients with pneumonia and COVID-19.

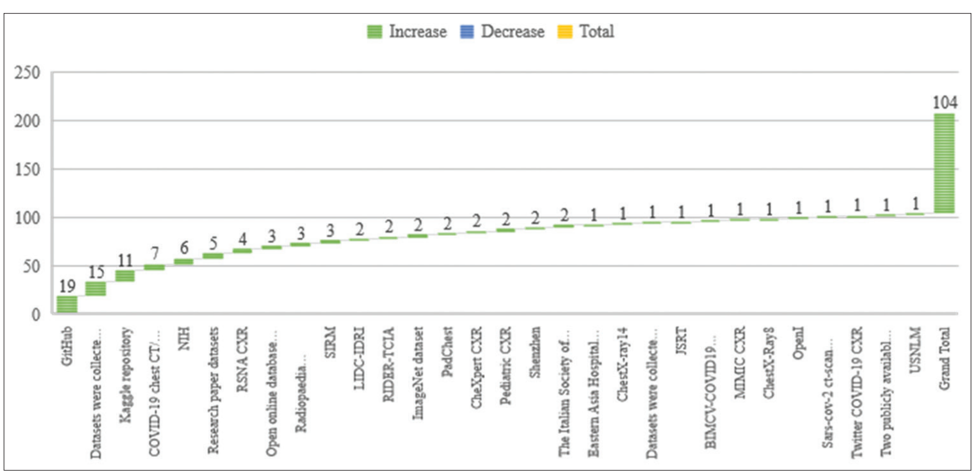

Figure 3: The distribution of papers based on data sources

Table 2: Distribution of papers based on their publishers

Frequency of Journal/conference Journal/Conference name	Column labels		Quartile
	Conference	Journal	
2020 IEEE 21st International Conference on IRI for Data Science	1		-
Chaos, solitons and fractals		3	Q1
Computer Methods and Programs in Biomedicine		3	Q1
IEEE Journal of Biomedical and Health Informatics		3	Q1
European Radiology		3	Q1
Biocybernetics and Biomedical Engineering		2	Q2
Computers in Biology and Medicine		2	Q1
IEEE Transactions on Medical Imaging		2	Q1
Informatics in Medicine Unlocked		2	Q2
Journal of X-ray Science and Technology		2	Q3
Physical and Engineering Sciences in Medicine		2	Q2
Radiology		2	Q1
Annals of Translational Medicine		1	-
Applied Sciences		1	Q1
Applied Soft Computing		1	Q1
BioMedical Engineering OnLine		1	Q1
Chemometrics and Intelligent Laboratory Systems		1	Q1
Cognitive Computation		1	Q1
Cureus		1	-
Current medical imaging		1	Q3
Diagnostics		1	Q4
Engineering		1	Q1
Environmental Science and Pollution Research		1	Q1
European Journal of Clinical Microbiology and Infectious Diseases		1	Q2
European Journal of Radiology		1	Q1
European Respiratory Journal		1	Q1
Frontiers in Bioengineering and Biotechnology		1	Q3
Frontiers in Medicine		1	Q1
IEEE Access journal		1	Q1
IEEE/ACM Transactions on Computational Biology and Bioinformatics		1	Q1
International Journal of Biomedical Imaging		1	Q1
International Journal of Imaging Systems and Technology		1	Q2
International Journal of Medical Sciences		1	Q1
International Orthopaedics		1	Q1
IRBM		1	Q3
Journal of Biomolecular Structure and Dynamics		1	Q3
Journal of Healthcare Engineering		1	Q1
Journal of Medical and Biological Engineering		1	Q3
Journal of Medical Internet Research		1	Q1
Medical Image Analysis		1	Q1
Nature Communications		1	Q1
PLOS ONE		1	Q1
Soft Computing		1	Q1
Studies in health technology and informatics		1	Q3
Symmetry		1	Q1
Grand total	1	59	

IRI – Information Reuse and Integration; IEEE: The Institute of Electrical and Electronics Engineers; ACM: Association for Computing Machinery; IRBM: Innovation and Research in BioMedical engineering; PLOS: Public Library of Science; IRBM: Innovation and Research in BioMedical engineering

In most studies, feature extraction methods have been properly used to recognize attributes that will be useful in the recognition and categorization of images to optimize learning. However, in some reviewed articles, combined methods, convolutional networks, and supervised machine learning classification models like SVM, DT, KNN, etc., have been utilized likewise. Consequently, it can be considered that the combined use of two numerous

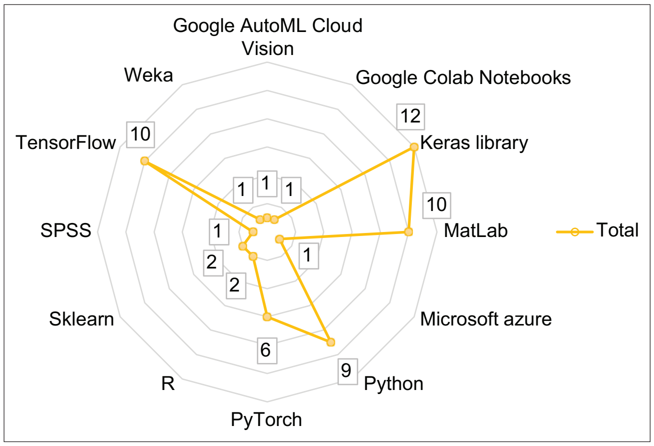

Figure 4: The frequency of applied software in selected citations

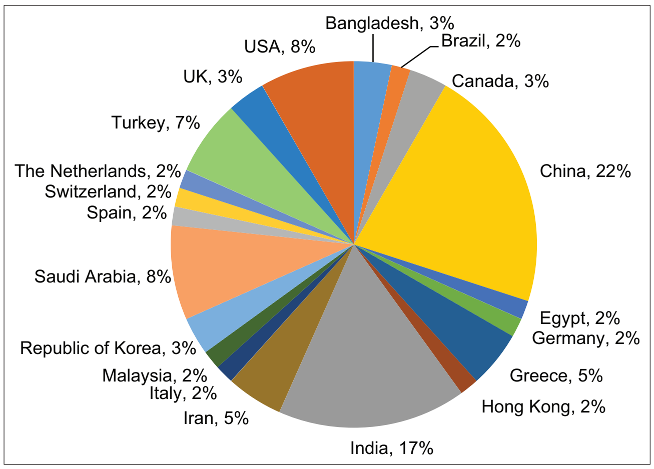

Figure 5: The distribution of papers based on countries

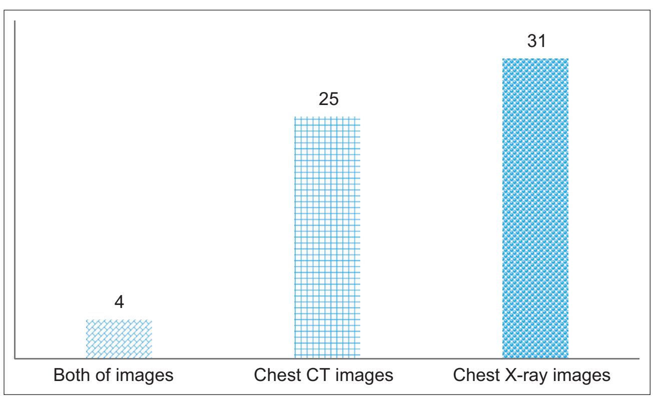

Figure 6: The distribution of papers based on applied inputs

approaches of artificial intelligence, i.e., the unique combination of the deep convolution neural networks with classification models, can optimize the approach of accurate patient identification. It is comprehensible that usage of these innovative and efficient methods in medical science, especially in the current coronavirus pandemic, reduces the workload of physicians and medical staff in early diagnosis.

Discussion

The main objective of our literature review was to critically analyze studies conducted in the chosen field of X-ray-oriented image processing approaches in fierce COVID-19 outbreaks. Hence, broadly 60 citations were selected and reviewed from 208 retrieved irrelevant papers. It is noteworthy that medical images like X-rays and CTs accurately represent a vast source of valuable data in potential patients with COVID-19.[74] In this problematic and challenging situation, medical technologies can effectively use artificial intelligence methods for image processing. The direct results showed that using convolutional deep learning methods for X-rays and CT scans processing can provide an accurate and quick diagnostic tool for unknown Coronavirus disease;[75] the latest deep learning algorithms are currently enabling automated analysis for adequately providing sensitive diagnosis results for this ambiguous unknown disease.[76] These mentioned automated systems are already pervasive in the medical industry, so we expect these intelligent methods are to be able to help in the COVID-19 era and meaningfully improve preliminary treatments and the quality of proper care for patients.[77] Consequently, these AI-based approaches demonstrate considerable potential and analysis benefits to altering the way of specialists work and yielded satisfaction to health organizations and their patients.[78,79] The results and key findings of our study are eagerly discussed in specific detail in this section.

Due to the favorable review of datasets applied in the selected papers, some main and frequent datasets were widely employed in these studies; these provided datasets in the citations are freely available to the public. For instance, data sources of chest X-rays and CT scans in GitHub repository, Kaggle repository, and NIH Clinical Centers were utilized in a large number of the reviewed articles. These data sources permit researcher teams across diverse countries and around the world to attain them freely, and they promote researchers 's ability to train computers with intelligent algorithms to diagnose and detect disease properly.[80] By applying the open-access datasets reported in the reviewed studies, researchers hope that research and academic institutions around the world will be able to appropriately train computers and familiar deep learning algorithms can process a significant maximum number of medical images carefully.[81] All the desired results obtained from medical imaging processing (like radiographic X-rays and CTs) can promptly confirm the empirical findings reported by radiologists and potentially ignored and obscure findings can be identified and made available to specialists.[82] It can also be acknowledged that according to our direct results, in a significant number of studies, multinational or local datasets collected from various hospitals in countries and universities have been used. Most local datasets are collected from Chinese hospitals.

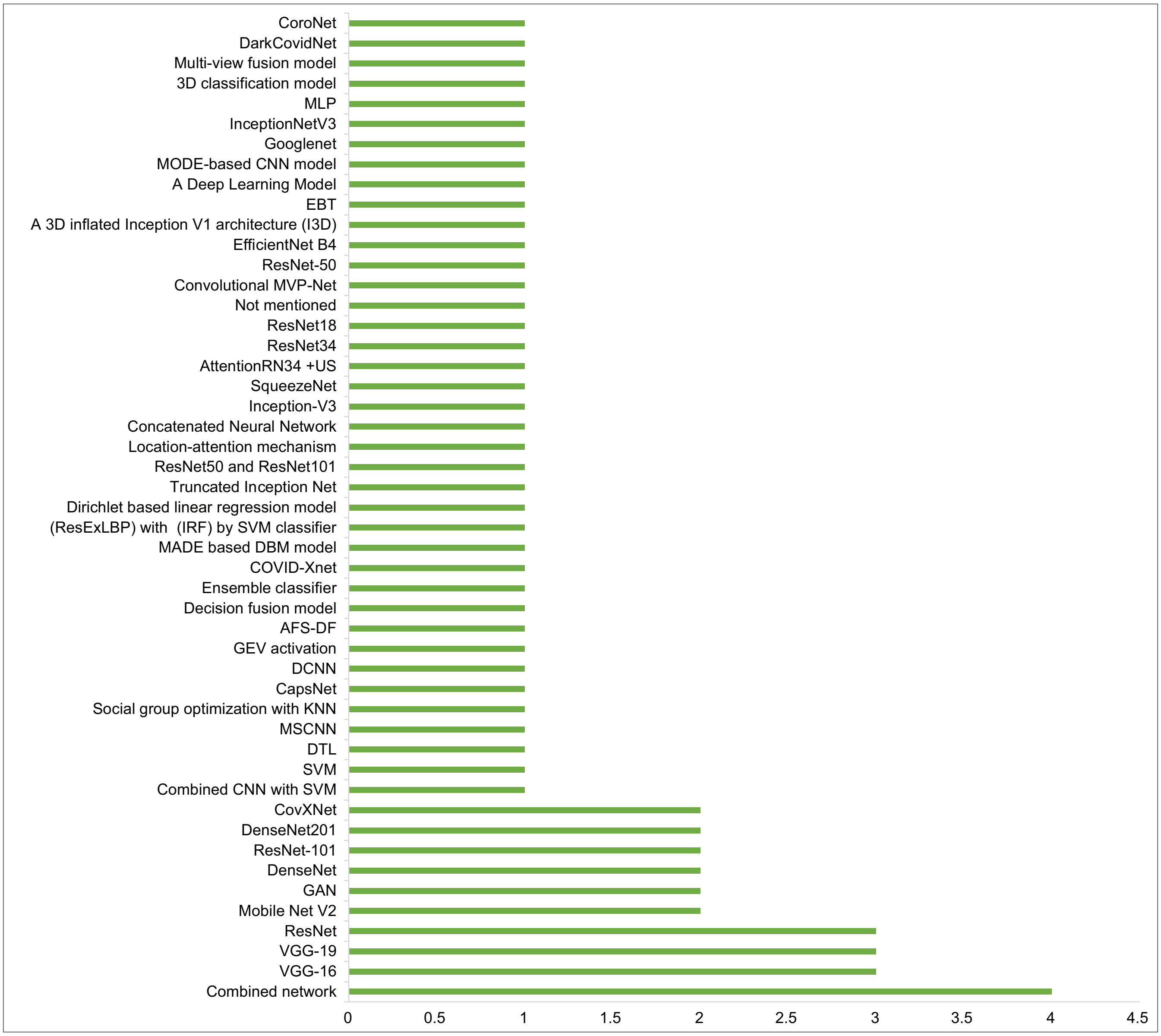

Figure 7: The distribution of the best deep learning techniques

Besides, 22% of the surveyed studies have been conducted in this country. The reason for this can be attributed to the fact that the first country where the new Coronavirus pandemic appeared was China.

RT-PCR in common is the gold standard to detect the COVID-19,[83] but this standard method contains several limitations, including low sensitivity, lack of diagnostic kit, insufficient laboratory, and time-consuming.[67] Other screening methods that can be used to diagnose this infectious disease are radiographic images such as CT and chest X-rays. According to studies, chest X-rays have been used to image processing more than CT scans. Imaging tools remain rapid screening tools to identify suspected patients promptly. There can be several apparent reasons why CT images have been used sparsely in studies. These include the fact that CT scanners are not widely available.[67] On the other hand, to interpret CT scan images, a radiologist must be involved, which due to the lack of this specialty in medical centers, the use of chest X-rays is more common.[50] In many medical centers, chest X-rays are the first effective tool to diagnose COVID-19. Reasons for the widespread use of this manner to diagnose the disease can be mentioned as follows: Chest X-ray is cheaper than a CT scan, so this factor leads to more use of this method. Also, by imaging with this approach, the patient is exposed to radiation for a shorter time, and for other reasons, we can point out that this method is more rapid.[84]

The results showed that different convolutional neural network techniques were used to process radiographic images (CT and chest X-rays). Our most impressive results showed that utilized AI-based methods had good accuracy. Several contributing factors undoubtedly affect the performance of these systems, including the following: Image content, image quantity, imaging modality, distribution of the dataset, model complexity, the structure of the model, loss function, number of epochs, optimizer, and so on.[67] Various methods can be employed to process images, including VGG series (VGG16, VGG19), Xception, ResNetV1 (ResNet50, ResNet101, ResNet152) and ResNetV2 series (ResNet50V2, ResNet101V2, ResNet152V2), Inception series (InceptionV3, InceptionResNetV2), DenseNet series (DenseNet121, DenseNet169, DenseNet201), and MobileNet.[85-87] VGG16 and VGG19 can provide extremely impressive results in a specific task.[11] ResNetV1 introduced skip reconnections and the Residual layer that can be progressively expanded to hundreds or thousands of active layers in these algorithms.[88] ResNetV2 accepts numerous arrangements in the residual block, and the batch normalization and ReLU activation function are placed before the convolution layer. The InceptionResNetV2 technique is capable to reliably producing higher accuracy at the lower epochs.[67] The Xception represents the expansion of the Inception model, which follows the inception modules with deeply separable convolutions.[89] The MobileNet model is less complex and the size of the model is small.[90] DenseNet series is one of the models that radically reduces the vanishing gradient problem.[91]

Most studies used deep neural networks to analyze images in this review, but these methods vary in simplicity and cost-effectiveness. Artificial intelligence comprises powerful techniques such as VGG 19, DenseNet, VGG 16, ResNet101, and SVM to automate cost estimates with high precision based on collected image data. Nevertheless, the accuracy of cost prediction is a significant criterion in the success of any construction project, where cost overruns are a critical unknown risk, especially with the current emphasis on tight budgets. Applied pre-trained networks are robust and have unique architecture, so it is expected to obtain better results. Also, running time is an important criterion to evaluate neural networks. Pretrained networks often take a long time to run, so they are slow, but our proposed network was fast, and despite its simple architecture, obtained results were promising. However, there is a trade-off between high-performance accuracy and longer execution times, simplicity, and low computational point of view that can be chosen. The studies show that deep learning performance is relatively more when compared with machine learning techniques for extensive data set like images; pretrained models such as MobileNet, MobileNetV2, VGG16, VGG19, and ResNet have been used for image classification and prediction despite their high computational volume and execution time.

This study had several strengths and methodological limitations. Strengths include searching four important databases with comprehensive keywords, which led to the maximum number of accompanying articles and a review of papers presented at the conference. The first restriction of this study was that articles in non-English language are not included. The second limitation of this review was that some conference papers did not have full text and were unincluded in the study. The third limitation of this study was that the performance of applied methods in the various articles was different, making it difficult to compare the performance carefully.

Implications for practice

As a practical plan, considering that some of the designed algorithms, especially convolutional neural networks such as Resnet 18, DenseNet, or Mobile net-V2, maintain extraordinarily high accuracy, sensitivity and specificity settled that the implementation and development of such intelligent techniques in the therapeutic environments can substantially decrease the workload of physicians and radiologists and progressively improve care outcomes. Therefore, most of the networks used in the reviewed studies have high computational dimensions, although for a large volume of data such as medical images are highly useful and can provide optimal diagnostic accuracy.

Conclusion

The present review analysis can help researchers and health informaticians to properly select the most effective machine learning methods for carefully designing automated COVID-19 disease diagnosis systems. According to the studies reviewed by the research team, this study obtains the first systematic review that examines applied techniques based on artificial intelligence for image processing in the new Coronavirus disease pandemic era. This completed survey revealed that the use of intelligent methods in the field of machine learning could accelerate the process of identifying and diagnosing COVID-19 ambiguous disease, and significant findings extracted from these algorithms can be applied by physicians as an auxiliary diagnostic tool.

Financial support and sponsorship

None.

Conflicts of interest

There are no conflicts of interest.

References

1. Jain G, Mittal D, Thakur D, Mittal MK. A deep learning approach to detect Covid-19 coronavirus with X-ray images. Biocybern Biomed Eng 2020;40:1391-405.
2. Rahimzadeh M, Attar A. A modified deep convolutional neural network for detecting COVID-19 and pneumonia from chest X-ray images based on the concatenation of Xception and ResNet50V2. Inform Med Unlocked 2020;19:100360.
3. Zu ZY, Jiang MD, Xu PP, Chen W, Ni QQ, Lu GM, *et al.* Coronavirus disease 2019 (COVID-19): A perspective from China. Radiology 2020;296:E15-25.
4. Sekeroglu B, Ozsahin I. <? covid19?> Detection of COVID-19

from Chest X-ray Images Using Convolutional Neural Networks. SLAS TECHNOLOGY: Translating Life Sciences Innovation. 2020;25:553-65.

5. Li J, Yu X, Hu S, Lin Z, Xiong N, Gao Y. COVID-19 targets the right lung. Crit Care 2020;24:339.
6. Rubin GD, Ryerson CJ, Haramati LB, Sverzellati N, Kanne JP, Raoof S, *et al*. The role of chest imaging in patient management during the COVID-19 pandemic: A multinational consensus statement from the Fleischner Society. Chest 2020;158:106-16.
7. Ai T, Yang Z, Hou H, Zhan C, Chen C, Lv W, *et al.* Correlation of chest CT and RT-PCR testing for coronavirus disease 2019 (COVID-19) in China: A report of 1014 cases. Radiology 2020;296:E32-40.
8. Ko H, Chung H, Kang WS, Kim KW, Shin Y, Kang SJ, *et al.* COVID-19 pneumonia diagnosis using a simple 2D deep learning framework with a single chest CT image: Model development and validation. J Med Internet Res 2020;22:e19569.
9. Sakagianni A, Feretzakis G, Kalles D, Koufopoulou C, Kaldis V. Setting up an easy-to-use machine learning pipeline for medical decision support: A case study for COVID-19 diagnosis based on deep learning with CT scans. Stud Health Technol Inform 2020;272:13-6.
10. Topol EJ. High-performance medicine: The convergence of human and artificial intelligence. Nat Med 2019;25:44-56.
11. Simonyan K, Zisserman A. Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv Preprint arXiv: 14091556; 2014.
12. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature 2015;521:436-44.
13. Zhu J, Shen B, Abbasi A, Hoshmand-Kochi M, Li H, Duong TQ. Deep transfer learning artificial intelligence accurately stages COVID-19 lung disease severity on portable chest radiographs. PLoS One 2020;15:e0236621.
14. Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems. 2012;25.
15. Wang D, Khosla A, Gargeya R, Irshad H, Beck AH. Deep Learning for Identifying Metastatic Breast Cancer. arXiv Preprint arXiv: 160605718;2016.
16. Cheng JZ, Ni D, Chou YH, Qin J, Tiu CM, Chang YC, *et al.* Computer-aided diagnosis with deep learning architecture: Applications to breast lesions in US images and pulmonary nodules in CT scans. Sci Rep 2016;6:24454.
17. Li L, Qin L, Xu Z, Yin Y, Wang X, Kong B, *et al*. Artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT. Radiology 2020;E65-E71.
18. Moher D, Liberati A, Tetzlaff J, Altman DG. Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA statement. PLoS Med 2009;6:e1000097.
19. Apostolopoulos ID, Aznaouridis SI, Tzani MA. Extracting possibly representative COVID-19 biomarkers from X-ray images with deep learning approach and image data related to pulmonary diseases. J Med Biol Eng 2020;40:462-9.
20. Albahli S. A deep neural network to distinguish COVID-19 from other chest diseases using X-ray images. Curr Med Imaging 2021;17:109-19.
21. Nour M, Cömert Z, Polat K. A Novel Medical Diagnosis model for COVID-19 infection detection based on Deep Features and Bayesian Optimization. Appl Soft Comput 2020;97:106580.
22. Öztürk Ş, Özkaya U, Barstuğan M. Classification of coronavirus (COVID-19) from X-ray and CT images using shrunken features. Int J Imaging Syst Technol 2020;31:5-15.
23. Pathak Y, Shukla PK, Tiwari A, Stalin S, Singh S, Shukla PK. Deep transfer learning based classification model for COVID-19 disease. Ing Rech Biomed 2020. In press.
24. Yan T, Wong PK, Ren H, Wang H, Wang J, Li Y. Automatic distinction between COVID-19 and common pneumonia using multi-scale convolutional neural network on chest CT scans. Chaos Solitons Fractals 2020;140:110153.
25. Rajaraman S, Antani S. Weakly labeled data augmentation for deep learning: A study on COVID-19 detection in chest X-rays. Diagnostics (Basel) 2020;10:358.
26. Cohen JP, Dao L, Roth K, Morrison P, Bengio Y, Abbasi AF, *et al.* Predicting COVID-19 pneumonia severity on chest X-ray with deep learning. Cureus 2020;12:e9448.
27. Dey N, Rajinikanth V, Fong SJ, Kaiser MS, Mahmud M. Social Group Optimization-Assisted Kapur's entropy and morphological segmentation for automated detection of COVID-19 infection from computed tomography images. Cognit Comput 2020;12:1-13.
28. Toraman S, Alakus TB, Turkoglu I. Convolutional capsnet: A novel artificial neural network approach to detect COVID-19 disease from X-ray images using capsule networks. Chaos Solitons Fractals 2020;140:110122.
29. Hassantabar S, Ahmadi M, Sharifi A. Diagnosis and detection of infected tissue of COVID-19 patients based on lung x-ray image using convolutional neural network approaches. Chaos Solitons Fractals 2020;140:110170.
30. Islam MZ, Islam MM, Asraf A. A combined deep CNN-LSTM network for the detection of novel coronavirus (COVID-19) using X-ray images. Inform Med Unlocked 2020;20:100412.
31. Che Azemin MZ, Hassan R, Mohd Tamrin MI, Md Ali MA. COVID-19 deep learning prediction model using publicly available radiologist-adjudicated chest X-ray images as training data: Preliminary findings. Int J Biomed Imaging 2020;2020:8828855.
32. Bridge J, Meng Y, Zhao Y, Du Y, Zhao M, Sun R, *et al.* Introducing the GEV activation function for highly unbalanced data to develop COVID-19 diagnostic models. IEEE J Biomed Health Inform 2020;24:2776-86.
33. Jaiswal A, Gianchandani N, Singh D, Kumar V, Kaur M. Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning. J Biomol Struct Dyn 2021;39:5682-9.
34. Sun L, Mo Z, Yan F, Xia L, Shan F, Ding Z, *et al.* Adaptive feature selection guided deep forest for COVID-19 classification with chest CT. IEEE J Biomed Health Inform 2020;24:2798-805.
35. Shiri I, Akhavanallaf A, Sanaat A, Salimi Y, Askari D, Mansouri Z, *et al*. Ultra-low-dose chest CT imaging of COVID-19 patients using a deep residual neural network. Eur Radiol 2020;31:1-12.
36. Mishra AK, Das SK, Roy P, Bandyopadhyay S. Identifying COVID19 from chest CT images: A deep convolutional neural networks based approach. J Healthc Eng 2020;2020:8843664.
37. Albahli S. Efficient GAN-based Chest Radiographs (CXR) augmentation to diagnose coronavirus disease pneumonia. Int J Med Sci 2020;17:1439-48.
38. Ardakani AA, Kanafi AR, Acharya UR, Khadem N, Mohammadi A. Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks. Comput Biol Med 2020;121:103795.
39. Duran-Lopez L, Dominguez-Morales JP, Corral-Jaime J, Vicente-Diaz S, Linares-Barranco A. COVID-XNet: A custom deep learning system to diagnose and locate COVID-19 in chest X-ray images. Appl Sci (Switzerland) 2020;10:5683.

40. Pathak Y, Shukla PK, Arya KV. Deep bidirectional classification model for COVID-19 disease infected patients. IEEE/ACM Trans Comput Biol Bioinform 2020;18:1234-41.
41. Tuncer T, Dogan S, Ozyurt F. An automated Residual Exemplar Local Binary Pattern and iterative ReliefF based corona detection method using lung X-ray image. Chemometr Intell Lab Syst 2020;203:104054.
42. Wang Z, Liu Q, Dou Q. Contrastive cross-site learning with redesigned net for COVID-19 CT classification. IEEE J Biomed Health Inform 2020;24:2806-13.
43. Zamzami N, Koochemeshkian P, Bouguila N, editors. A Distribution-Based Regression for Real-Time COVID-19 Cases Detection from Chest X-ray and CT Images. 2020 IEEE 21st International Conference on Information Reuse and Integration for Data Science (IRI); 11-13 August, 2020.
44. Wang S, Zha YF, Li WM, Wu QX, Li XH, Niu M, *et al.* A fully automatic deep learning system for COVID-19 diagnostic and prognostic analysis. Eur Respir J 2020;56:2000775.
45. Oh Y, Park S, Ye JC. Deep learning COVID-19 features on CXR using limited training data sets. IEEE Trans Med Imaging 2020;39:2688-700.
46. Das D, Santosh KC, Pal U. Truncated inception net: COVID-19 outbreak screening using chest X-rays. Phys Eng Sci Med 2020;43:915-25.
47. Mahmud T, Rahman MA, Fattah SA. 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. Comput Biol Med 2020;122:103869.
48. Abraham B, Nair MS. Computer-aided detection of COVID-19 from X-ray images using multi-CNN and Bayesnet classifier. Biocybern Biomed Eng 2020;40:1436-45.
49. Xu X, Jiang X, Ma C, Du P, Li X, Lv S, *et al.* A deep learning system to screen novel coronavirus disease 2019 pneumonia. Engineering (Beijing, China) 2020;6:1122-9.
50. Rajaraman S, Siegelman J, Alderson PO, Folio LS, Folio LR, Antani SK. Iteratively pruned deep learning ensembles for COVID-19 detection in chest X-rays. IEEE Access 2020;8:115041-50.
51. Minaee S, Kafieh R, Sonka M, Yazdani S, Jamalipour Soufi G. Deep-COVID: Predicting COVID-19 from chest X-ray images using deep transfer learning. Med Image Anal 2020;65:101794.
52. Ouyang X, Huo J, Xia L, Shan F, Liu J, Mo Z, *et al.* Dual-sampling attention network for diagnosis of COVID-19 from community acquired pneumonia. IEEE Trans Med Imaging 2020;39:2595-605.
53. Apostolopoulos ID, Mpesiana TA. Covid-19: Automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. Phys Eng Sci Med 2020;43:635-40.
54. Yang S, Jiang L, Cao Z, Wang L, Cao J, Feng R, *et al.* Deep learning for detecting corona virus disease 2019 (COVID-19) on high-resolution computed tomography: A pilot study. Ann Transl Med 2020;8:450.
55. Dansana D, Kumar R, Bhattacharjee A, Hemanth DJ, Gupta D, Khanna A, *et al.* Early diagnosis of COVID-19-affected patients based on X-ray and computed tomography images using deep learning algorithm. Soft Computing 2020. p. 1-9.
56. Xiao LS, Li P, Sun F, Zhang Y, Xu C, Zhu H, *et al.* Development and validation of a deep learning-based model using computed tomography imaging for predicting disease severity of coronavirus disease 2019. Front Bioeng Biotechnol 2020;8:898.
57. Yoo SH, Geng H, Chiu TL, Yu SK, Cho DC, Heo J, *et al.* Deep learning-based decision-tree classifier for COVID-19 diagnosis from chest X-ray imaging. Front Med (Lausanne) 2020;7:427.
58. Ni Q, Sun ZY, Qi L, Chen W, Yang Y, Wang L, *et al.* A deep learning approach to characterize 2019 coronavirus disease (COVID-19) pneumonia in chest CT images. Eur Radiol 2020;30:6517-27.
59. Bai HX, Wang R, Xiong Z, Hsieh B, Chang K, Halsey K, *et al*. Artificial intelligence augmentation of radiologist performance in distinguishing COVID-19 from pneumonia of other origin at chest CT. Radiology 2020;296:E156-65.
60. Lessmann N, Sánchez CI, Beenen L, Boulogne LH, Brink M, Calli E, *et al.* Automated assessment of CO-RADS and chest CT severity scores in patients with suspected COVID-19 using artificial intelligence. Radiology 2020;1:202439.
61. Liu C, Wang X, Liu C, Sun Q, Peng W. Differentiating novel coronavirus pneumonia from general pneumonia based on machine learning. Biomed Eng Online 2020;19:66.
62. Sharma S. Drawing insights from COVID-19-infected patients using CT scan images and machine learning techniques: A study on 200 patients. Environ Sci Pollut Res Int 2020;27:37155-63.
63. Singh D, Kumar V, Vaishali, Kaur M. Classification of COVID-19 patients from chest CT images using multi-objective differential evolution-based convolutional neural networks. Eur J Clin Microbiol Infect Dis 2020;39:1379-89.
64. Loey M, Smarandache F, Khalifa NE. Within the lack of chest COVID-19 X-ray dataset: A novel detection model based on GAN and deep transfer learning. Symmetry 2020;12:651.
65. Vaid S, Kalantar R, Bhandari M. Deep learning COVID-19 detection bias: Accuracy through artificial intelligence. Int Orthop 2020;44:1539-42.
66. Albahli S, Albattah W. Detection of coronavirus disease from X-ray images using deep learning and transfer learning algorithms. J Xray Sci Technol 2020;28:841-50.
67. Rahaman MM, Li C, Yao Y, Kulwa F, Rahman MA, Wang Q, *et al.* Identification of COVID-19 samples from chest X-Ray images using deep learning: A comparison of transfer learning approaches. J Xray Sci Technol 2020;28:821-39.
68. Pereira RM, Bertolini D, Teixeira LO, Silla CN Jr., Costa YM. COVID-19 identification in chest X-ray images on flat and hierarchical classification scenarios. Comput Methods Programs Biomed 2020;194:105532.
69. Harmon SA, Sanford TH, Xu S, Turkbey EB, Roth H, Xu Z, *et al.* Artificial intelligence for the detection of COVID-19 pneumonia on chest CT using multinational datasets. Nat Commun 2020;11:4080.
70. Wu X, Hui H, Niu M, Li L, Wang L, He B, *et al.* Deep learning-based multi-view fusion model for screening 2019 novel coronavirus pneumonia: A multicentre study. Eur J Radiol 2020;128:109041.
71. Ozturk T, Talo M, Yildirim EA, Baloglu UB, Yildirim O, Rajendra Acharya U. Automated detection of COVID-19 cases using deep neural networks with X-ray images. Comput Biol Med 2020;121:103792.
72. Khan AI, Shah JL, Bhat MM. CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. Comput Methods Programs Biomed 2020;196:105581.
73. Brunese L, Mercaldo F, Reginelli A, Santone A. Explainable deep learning for pulmonary disease and coronavirus COVID-19 detection from X-rays. Comput Methods Programs Biomed 2020;196:105608.
74. Jalaber C, Lapotre T, Morcet-Delattre T, Ribet F, Jouneau S, Lederlin M. Chest CT in COVID-19 pneumonia: A review of current knowledge. Diagn Interv Imaging 2020;101:431-7.
75. Manigandan S, Wu MT, Ponnusamy VK, Raghavendra VB,

Pugazhendhi A, Brindhadevi K. A systematic review on recent trends in transmission, diagnosis, prevention and imaging features of COVID-19. Process Biochem 2020;98:233-40.
76. Mertz L. AI-Driven COVID-19 tools to interpret, quantify lung images. IEEE Pulse 2020;11:2-7.
77. Zhou L, Li Z, Zhou J, Li H, Chen Y, Huang Y, *et al*. A rapid, accurate and machine-agnostic segmentation and quantification method for CT-based COVID-19 diagnosis. IEEE Trans Med Imaging 2020;39:2638-52.
78. Zhang K, Liu X, Shen J, Li Z, Sang Y, Wu X, *et al*. Clinically applicable AI system for accurate diagnosis, quantitative measurements, and prognosis of COVID-19 pneumonia using computed tomography. Cell 2020;181:1423-33.e11.
79. Kerkech M, Hafiane A, Canals R, Ros F, editors. Vine Disease Detection by Deep Learning Method Combined with 3D Depth Information. International Conference on Image and Signal Processing: Springer; 2020.
80. Singh D, Jain N, Jain P, Kayal P, Kumawat S, Batra N. PlantDoc: A Dataset for Visual Plant Disease Detection. Proceedings of the 7th ACM IKDD CoDS and 25th COMAD; 2020. p. 249-53.
81. Oakden-Rayner L. Exploring large-scale public medical image datasets. Acad Radiol 2020;27:106-12.
82. Lu Y, Young S. A survey of public datasets for computer vision tasks in precision agriculture. Comput Electron Agric 2020;178:105760.
83. Li X, Geng M, Peng Y, Meng L, Lu S. Molecular immune pathogenesis and diagnosis of COVID-19. J Pharm Anal 2020;10:102-8.
84. Self WH, Courtney DM, McNaughton CD, Wunderink RG, Kline JA. High discordance of chest X-ray and computed tomography for detection of pulmonary opacities in ED patients: Implications for diagnosing pneumonia. Am J Emerg Med 2013;31:401-5.
85. Zhang W, Li C, Peng G, Chen Y, Zhang Z. A deep convolutional neural network with new training methods for bearing fault diagnosis under noisy environment and different working load. Mech Syst Signal Process 2018;100:439-53.
86. Wang J, Deng G, Li W, Chen Y, Gao F, Liu H, *et al.* Deep learning for quality assessment of retinal OCT images. Biomed Opt Express 2019;10:6057-72.
87. Alashhab S, Gallego AJ, Lozano MÁ, editors. Hand Gesture Detection with Convolutional Neural Networks. International Symposium on Distributed Computing and Artificial Intelligence, Springer; 2018.
88. He K, Zhang X, Ren S, Sun J, editors. Deep Residual Learning for Image Recognition. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2016.
89. Chollet F, editor Xception: Deep Learning with Depthwise Separable Convolutions. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2017.
90. Howard AG, Zhu M, Chen B, Kalenichenko D, Wang W, Weyand T, *et al.* Mobilenets: Efficient Convolutional Neural Networks for Mobile Vision Applications. arXiv Preprint arXiv: 170404861; 2017.
91. Huang G, Liu Z, Van Der Maaten L, Weinberger KQ, editors. Densely Connected Convolutional Networks. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2017.