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

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

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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 (PRISMA) 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
| 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%                 |
|                   |            |               |                                  | Accuracy=87.00%                   |
| Albahli[20]       | Saudi Arabia | May 5, 2020   | ResNet, InceptionV3, GAN          | Accuracy=98.97%                   |
|                   |            |               |                                  | Sensitivity=89.39%                 |
|                   |            |               |                                  | Specificity=99.75%                 |
| Nour *et al.*[21] | Saudi Arabia | July 22, 2020 | CNN combined with KNN, SVM, C4.5 | Accuracy=94.23%                   |
|                   |            |               |                                  | Sensitivity=91.88%                 |
|                   |            |               |                                  | Specificity=98.54%                 |
|                   |            |               |                                  | 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%                 |
| Rajaraman[25]     | USA        | May 30, 2020   | VGG-16, Inception-V3, Xception, DenseNet-121, NasNet-mobile | Specificity=85.70%                |
|                   |            |               |                                  | Accuracy=93.00%                   |
|                   |            |               |                                  | Sensitivity=97.00%                 |
|                   |            |               |                                  | Specificity=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%                   |
|                   |            |               |                                  | Sensitivity=99.40%                 |
|                   |            |               |                                  | Specificity=99.30%                 |
|                   |            |               |                                  | F-score=98.90%                    |
| Che Azemin *et al.*[31] | Malaysia | August 18, 2020 | ResNet-101                       | Accuracy=71.90%                   |
|                   |            |               |                                  | Sensitivity=77.30%                 |
|                   |            |               |                                  | Specificity=71.80%                 |

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| Author          | Country     | Month of 2020 | Applied methods                               | Best performance of applied model            |
|-----------------|-------------|---------------|-----------------------------------------------|---------------------------------------------|
| Bridge et al.   | 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%                          |
|                 |             |               |                                               | Accuracy=96.25%                             |
|                 |             |               |                                               | Specificity=96.21%                          |
| Jaiswal et al.  | India       | July 3, 2020  | DenseNet201, VGG16, Inception ResNet, ResNet152V2 |                                              |
|                 |             |               |                                               |                                               |
| Sun et al.      | China       | August 26, 2020| AFS-DF                                        | Accuracy=91.79%                             |
|                 |             |               |                                               | Sensitivity=93.05%                          |
|                 |             |               |                                               | Specificity=89.95%                          |
| Shiri et al.    | Switzerland | August 21, 2020| ResNet, CNN based decision fusion model combine with VGG16, InceptionV3, ResNet50, DenseNet | Accuracy=93.10%                             |
| Mishra et al.   | India       | July 30, 2020 |                                               | RMSE decreased to 0.09                       |
|                 |             |               |                                               |                                               |
| Albahli         | Saudi Arabia| May 22, 2020  | GAN, DT, KNN, NB, SVM, Ensemble, COVID-Xnet    | Accuracy=98.35%                             |
| Ardakani et al. | Iran        | July 20, 2020 |                                               | Sensitivity=94.67%                          |
|                 |             |               |                                               | Specificity=93.03%                          |
| Duran-Lopez et al. | Spain   | August 13, 2020| COVID-Xnet                                   | Accuracy=94.43%                             |
|                 |             |               |                                               | Sensitivity=92.53%                          |
|                 |             |               |                                               | Specificity=96.33%                          |
|                 |             |               |                                               | F-score=93.14%                              |
| Pathak et al.   | India       | July 20, 2020 | LSTM combined with mixture density network and MADE | Accuracy=98.37%                             |
|                 |             |               |                                               | F-score=98.14%                              |
| Tuncer et al.   | Turkey      | May 12, 2020  | ResExLBP and feature selection with (IRF) combined with DT, LD, SVM, KNN, SD, Ensemble, COVID-Xnet | Accuracy=98.29%                             |
|                 |             |               |                                               | Specificity=100.0%                          |
| Wang et al.     | China       | September 10, 2020 | COVID-Net                                    | Accuracy=90.83%                             |
|                 |             |               |                                               | F-score=90.87%                              |
|                 |             |               |                                               | AUC=0.96                                    |
| Zanzami et al.  | 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.     | 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.       | Republic of Korea | May 10, 2020 | Patch-based method with convolutional neural network FC-DenseNet103 and ResNet-18 | Accuracy=88.90%                             |
|                 |             |               |                                               | Sensitivity=96.40%                          |
|                 |             |               |                                               | Specificity=84.40%                          |

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| 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 ResNet18 ResNet50 SqueezeNet DenseNet-121 Attention RN34 + SS AttentionRN34 + US AttentionRN34 + DS RN34 + US | Accuracy=98.41%                  |
|                        |           |               |                                                      | Sensitivity=98.41%                |
|                        |           |               |                                                      | F-score=98.41%                   |
| Minaee et al.\[51\]    | USA       | July 21, 2020 | ResNet18 ResNet50 SqueezeNet DenseNet-121 Attention RN34 + SS AttentionRN34 + US AttentionRN34 + DS RN34 + US | 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%                   |
|                        |           |               |                                                      | Sensitivity=87.2%                |
|                        |           |               |                                                      | Specificity=90.7%                 |
|                        |           |               |                                                      | F1-score=82.5%                   |
|                       |           |               |                                                      | AUC=0.948                        |
|                       |           |               |                                                      | Accuracy=96.78%                  |
|                       |           |               |                                                      | Sensitivity=98.66%                |
|                       |           |               |                                                      | Specificity=96.46%                |
| Apostolopoulos and Mpesiana\[53\] | Greece | March 30, 2020| VGG19 MobileNet v2 Inception Xception Inception ResNet v2 DenseNet | Accuracy=92%                     |
|                        |           |               |                                                      | Sensitivity=97%                  |
|                        |           |               |                                                      | Specificity=87%                  |
|                        |           |               |                                                      | F-score=93%                      |
|                        |           |               |                                                      | AUC=0.98                         |
| Yang et al.\[54\]      | China     | March 9, 2020 | VGG19 MobileNet v2 Inception Xception Inception ResNet v2 DenseNet | Accuracy=91%                     |
| Dansana et al.\[55\]   | India     | August 28, 2020| VGG-16 Inception_V2 With DT | Accuracy=97%                     |
|                        |           |               |                                                      | F-score=97%                      |
### Table 1: Contd...

| Author          | Country         | Month of 2020 | Applied methods                          | Best performance of applied model         |
|-----------------|-----------------|---------------|------------------------------------------|------------------------------------------|
| Xiao et al.     | China           | July 13, 2020 | ResNet34                                 | Accuracy=97.4%                           |
|                 |                 |               | AlexNet                                  | AUC=0.987                                |
|                 |                 |               | VGGNet                                   |                                          |
|                 |                 |               | DenseNet                                 |                                          |
|                 |                 |               | ResNet18                                 |                                          |
| Yoo et al.      | Hong Kong       | July 2, 2020  | ResNet18                                 | Accuracy=100%                            |
|                 |                 |               | AlexNet                                  | Sensitivity=100%                         |
|                 |                 |               | VGGNet                                   | Specificity=100%                         |
|                 |                 |               | DenseNet                                 |                                          |
| Zhu et al.      | USA             | July 10, 2020 | Traditional CNN model and VGG16          | Accuracy=99.87%                          |
| Ni et al.       | China           | June 22, 2020 | MVP-Net                                  | R2=0.90                                  |
| Ko et al.       | Republic of Korea | June 29, 2020 | VGG16                                    | Accuracy=99.87%                          |
|                 |                 |               | ResNet-50                                | Sensitivity=99.58%                       |
|                 |                 |               | Inception-V3                             | Specificity=100.00%                      |
|                 |                 |               | EfficientNet B4                          |                                          |
| Bai HX et al.   | China           | April 27, 2020| Deep learning model based on a 3D inflated Inception V1 architecture (I3D) | Accuracy=99.87%                          |
|                 |                 |               | Accuracy=95%                             |
|                 |                 |               | Sensitivity=100%                         |
|                 |                 |               | Specificity=100%                         |
|                 |                 |               | F-score=97%                              |
| Lessmann et al. | The Netherlands | July 30, 2020 | Machine learning algorithms              | Accuracy=94.16%                          |
|                 |                 |               | DT                                       | Specificity=100.00%                      |
|                 |                 |               | LR                                       |                                          |
|                 |                 |               | SVM                                      |                                          |
|                 |                 |               | KNN                                      |                                          |
|                 |                 |               | EBT                                      |                                          |
| Sakagianni et al.| Greece         | June 26, 2020 | A deep learning model                    | Accuracy=91%                             |
|                 |                 |               |                                          | Specificity=92.1%                        |
| Sharma          | India           | July 14, 2020 | ResNet                                   | Accuracy=93.4%                           |
|                 |                 |               |                                          | Specificity=90.8%                        |
| Singh et al.    | India           | April 7, 2020 | MODE–based CNN                           | Accuracy=90.7%                           |
|                 |                 |               | ANFIS                                    | Specificity=99.7%                        |
| Loey et al.     | Egypt           | April 16, 2020| GAN/DTL model                            | F-score=100%                             |
|                 |                 |               | Alexnet                                  | Accuracy=96.3%                           |
|                 |                 |               | Googlenet                                | Specificity=99.02%                       |
|                 |                 |               | Restnet18                                |                                          |
| Vaid et al.     | Canada          | May 6, 2020   | VGG-19                                   | Accuracy=96.3%                           |
| Albahli and Albattah | Saudi Arabia | July 17, 2020 | Inception ResNetV2                      | Accuracy=99.2%                           |
|                 |                 |               | InceptionNetV3                           |                                          |
|                 |                 |               | NASNetLarge                              |                                          |
### Table 1: Contd...

| Author        | Country   | Month of 2020 | Applied methods                                                                 | Best performance of applied model                                                                 |
|---------------|-----------|---------------|--------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------|
| Apostolopoulos et al.\(^{(19)}\) | China     | July 11, 2020 | VGG series, Xception, ResNetV1, ResNetV2 series, Inception series, DenseNet series, MobileNet, Inception-V3, KNN, SVM, MLP, DT, RF | Accuracy=89.3%, F-score=95%                                                                     |
| Percira et al.\(^{(48)}\)        | Brazil    | May 6, 2020   | The results suggest that training CNNs from scratch may reveal vital biomarkers related to the COVID-19 disease | F-score=83.33%                                                                                   |
| Harmon et al.\(^{(69)}\)         | USA       | July 13, 2020 | The hybrid 3D and full 3D models based on Densely-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%, AUC=89.60%               |
| Khan et al.\(^{(72)}\)           | India     | May 30, 2020  | CoroNet                                                                          | Accuracy=89.60%, Specificity=96.40%, F-score=89.80%, Sensitivity=87.00%, Specificity=94.00%, F-score=89.00% |
| Brunese et al.\(^{(73)}\)        | Italy     | June 9, 2020  | VGG-16                                                                           | Accuracy=76.00%, Sensitivity=81.10%, Specificity=61.50%, AUC=81.90%                              |

| 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, Radiopaedia encyclopedia, The Italian Society of Medical CXR images | RSNA CXR, SIRM | The results suggest that training CNNs from scratch may reveal vital biomarkers related to the COVID-19 disease |
| Albalhi\(^{(20)}\) | 108,948 images | CXR images | Not mentioned | SIRM, 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 |
**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                        | 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...
| 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                 | 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 COVID-19. |
| 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 images | 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                       | 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 GitHub | 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          | 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.                                                             |
| 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]        | 1832 images | CXR images                       | Python                 | Kaggle repository GitHub     | Proposed method can be used as an alternative diagnostic tool with potential candidacy 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                       | Proposed model can be helpful for medical diagnosis                                                                                                                                                   |
| Rajaraman et al. [50]  | Not mentioned | CXR images                       | Not mentioned          | 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]     | 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] | 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 Sklearm | 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...*
| 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. [18]  | 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. [18]  | 5-fold-cross-validation: 3993 images | Chest CT images                   | Tensorflow             | Keras library                | The proposed method provides excellent diagnostic performance in detecting COVID-19 pneumonia |
| Bai HX et al. [19] | 1186 images | Chest CT images                   | Keras library          | Python                       | Artificial intelligence assistance improved radiologists’ performance in distinguishing coronavirus disease 2019 pneumonia from noncoronavirus disease 2019 pneumonia at chest CT |
| Lessmann et al. [20] | 5-fold-cross-validation: 887 images | Chest CT images                   | R                      | Python                       | With high diagnostic performance, the CO-RADS AI system correctly identified patients with COVID-19 using chest CT scans |
| Liu et al. [21] | 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. [22] | 746 images | Chest CT images                   | Google automl          | cloud vision                 | These methods could deliver significant potential benefits for patients in the future by allowing for earlier disease detection and care |
| Sharma [23]     | 2200 images   | Chest CT images                   | Microsoft             | azure                        | Machine learning techniques can be used for early detection of coronavirus |
| Singh et al. [24] | 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. [25] | 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. [26] | 545 images    | CXR images                        | Not mentioned          | Research paper datasets      | COVID-19 detection model minimizes manual interaction dependent on radiologists as it automates identification of structural abnormalities in patient’s CXRs |
| Albahli and Al Battah [27] | 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. [28] | 860 images  | CXR images                        | Google Colab notebooks | GitHub                       | This study demonstrates the effectiveness of DTL techniques for the identification of COVID-19 cases using CXR images |

Contd...
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.

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.
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

| Frequency of Journal/conference | Column labels | Quartile |
|---------------------------------|--------------|----------|
| Journal/Conference name         | 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.
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’ 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.
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.[56] 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. 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. VGG16 and VGG19 can provide extremely impressive results in a specific task. ResNetV1 introduced skip reconnections and the Residual layer that can be progressively expanded to hundreds or thousands of active layers in these algorithms. 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. The Xception represents the expansion of the Inception model, which follows the inception modules with deeply separable convolutions. The MobileNet model is less complex and the size of the model is small. DenseNet series is one of the models that radically reduces the vanishing gradient problem.

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 VGG19, DenseNet, VGG16, 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 unincuded 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.

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**Conflicts of interest**

There are no conflicts of interest.

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