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The Diagnostic Accuracy of Artificial Intelligence-Assisted CT Imaging in COVID-19 Disease: A Systematic Review and Meta-Analysis

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Abstract
Artificial intelligence (AI) systems have become critical in support of decision-making. This systematic review summarizes all the data currently available on the AI-assisted CT-Scan prediction accuracy for COVID-19. The ISI Web of Science, Cochrane Library, PubMed, Scopus, CINAHL, Science Direct, PROSPERO, and EMBASE were systematically searched. We used the revised Quality Assessment of Diagnostic Accuracy Studies (QUADAS-2) tool to assess all included studies’ quality and potential bias. A hierarchical receiver-operating characteristic summary (HSROC) curve and a summary receiver operating characteristic (SROC) curve have been implemented. The area under the curve (AUC) was computed to determine the diagnostic accuracy. Finally, 36 studies (a total of 39,246 image data) were selected for inclusion into the final meta-analysis. The pooled sensitivity for AI was 0.90 (95% CI, 0.90-0.91), specificity was 0.91 (95% CI, 0.90-0.92) and the AUC was 0.96 (95% CI, 0.91-0.98). For deep learning (DL) method, the pooled sensitivity was 0.90 (95% CI, 0.90 - 0.91), specificity was 0.88 (95% CI, 0.87 - 0.88) and the AUC was 0.96 (95% CI, 0.93 - 0.97). In case of machine learning (ML), the pooled sensitivity was 0.90 (95% CI, 0.90 - 0.91), specificity was 0.95 (95% CI, 0.94 - 0.95) and the AUC was 0.97 (95% CI, 0.96-0.99). AI in COVID-19 patients is useful in identifying symptoms of lung involvement. More prospective real-time trials are required to confirm AI’s role for high and quick COVID-19 diagnosis due to the possible selection bias and retrospective existence of currently available studies.

Keywords: Artificial Intelligence; Machine Learning; Deep Learning; Respiratory Tract Infections; Coronavirus Infections; COVID-19; Computed Tomography; CT-Scan.

Abbreviations:
2019-nCoVs: New Coronaviruses-2019
SARS-CoV-2: Severe Acute Respiratory Syndrome Coronavirus 2
COVID-19: Coronavirus Disease-2019
ALI: Acute Lung injury
ARDS: Acute Respiratory Distress Syndrome
HA: Hyaluronic Acid
ACE2: Angiotensin-Converting Enzyme 2
CXR: Chest X-ray Radiography
CT-Scans: Computed Tomography-Scans
GGO: Ground-Glass Opacity
AI: Artificial Intelligence
ML: Machine Learning
DL: Deep Learning
AUC: Area Under the Curve
CI: Confidence Interval
FN: False Negative
FP: False Positive
TN: True Negative
TP: True Positive
QUADAS-2: Quality Assessment of Diagnostic Accuracy Studies 2
HSROC: Hierarchical Summary Receiver-Operating Characteristic
MOOSE: Meta-analyses Of Observational Studies in Epidemiology
PRISMA: Preferred Reporting Items for Systematic reviews and Meta-Analyses
**Introduction**

The 2019-new coronavirus (2019-nCoV, causing COVID-19 disease) was reported as the cause of the outbreak of pneumonia in Wuhan, Hubei province of China, at the end of 2019 [1]. This virus is associated with the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), a group of beta viruses that cause respiratory, gastrointestinal, neurological diseases in humans. The virus transmission appears to be done via respiratory droplets mainly [2].

COVID-19 patients usually present with trouble breathing, cough, and fever. The COVID-19-associated cytokine storms and innate immune system over-activation can lead to Acute Lung Injury (ALI) and induction of Acute Respiratory Distress Syndrome (ARDS), especially in patients with hypertension [3]. The cytokine storm induces the production of Hyaluronic Acid (HA) molecules in lung tissue, with consequent progressive fibrosis, tissue stiffness, and impaired lung function [4]. SARS-CoV-2 enters the cell by binding to spike (S) glycoproteins of the enzyme Angiotensin-Converting Enzyme 2 (ACE2) receptor [5, 6]. Thus, pulmonary involvement is common in patients, and imaging techniques such as Chest X-ray Radiography (CXR) or Computed Tomography (CT-scans) are recommended as the first-line diagnostic tools [7].

Radiological manifestations clinically confirmed, such as unilateral or bilateral multilobar infiltration, Ground-Glass Opacity (GGO), and peripheral infiltration in chest CT-scan, have essential roles in the diagnosis of COVID-19 disease [8, 9]. There is often no sign of lung involvement on a CT-scan in the early stages of the infection. In some cases, minimal involvement of up to two pulmonary lobes in the form of GGO, consolidation, or nodules less than one-third the volume of each lobe, especially in the peripheral areas [7, 10].
to the removal and a high number of CT images of the lungs and its complex and uneven structure, it is challenging to diagnose vessels' nodules in patients' images [11]. Therefore, using computer-assisted techniques, especially Artificial Intelligence (AI) systems, has become more significant in supporting decision-making [12]. AI has great potential to improve clinical decisions; however, such systems' successful implementation requires careful attention to each information system's principles[13]. Due to the abundance and interference of variables in medical decisions, physicians can make faster and more efficient decisions using AI systems and spend more time evaluating decisions.

So far only two systematic reviews and meta-analyses have been performed on AI in the COVID-19 field. Li et al. conducted a systematic review and meta-analysis of 151 published studies to generate a more accurate diagnostic model of COVID-19 using correlations between clinical variables, clustering COVID-19 patients into subtypes, and generating a computational classification model for discriminating between COVID-19 patients and influenza patients based on clinical variables alone [14]. Michelson et al. proposed an approach to answer clinical queries, termed rapid meta-analysis (RMA). Unlike traditional meta-analysis, it is an AI-based method with rapid time to production and reasonable data quality assurances. They performed a RMA on 11 studies and estimated the incidence of ocular toxicity as a side effect of hydroxychloroquine in COVID-19 patients [15]. Thus, the purpose of this meta-analysis was to systematically assess and summarize all of the data currently available on the prediction accuracy of AI-assisted CT-Scanning for COVID-19.

**Materials and Methods**

*Protocol and registration*
This study was done according to Meta-analyses Of Observational Studies in Epidemiology (MOOSE) [16] and Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) [17], and Synthesizing Evidence from Diagnostic Accuracy Tests (SEDATE) [18] guidelines.

**Eligibility criteria**

Studies suggest that lung involvement in the confirmed cases of COVID-19 patients based on RT-PCR results without language limits were included. We excluded papers that did not fit into the study's conceptual framework focused on other types of infectious diseases.

**Information sources**

We systematically searched the ISI Web of Science, Cochrane Library, PubMed, Scopus, CINAHL, Science Direct, PROSPERO, and EMBASE for studies that evaluated the diagnostic accuracy of different models of AI-assisted CT-Scan for predict COVID-19 published between 2020-2021 years.

**Search**

two reviewers (K.SH and F.R) performed the search using medical subject headings (MeSh) terms included “artificial neural network” OR “Artificial Intelligence” OR “Machine Learning” OR “expert system” OR “Deep Learning” OR “Supervised Machine Learning” OR “computer-aided” AND “Respiratory Tract Infections” OR “Respiratory System” OR “Coronavirus Infections” OR “COVID-19” OR “SARS COV 2 Infection” AND “Computed Tomography” OR “CT-Scan” and all possible combinations.

**Summary measures**
Our desired outcomes were sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV); studies that did not provide sufficient information to calculate true positive (TP, true COVID-19 predicted to be COVID-19 by AI), false positive (FP, non-COVID-19 predicted to be COVID-19), true negative (TN, non-COVID-19 predicted to be non-COVID-19 by AI) and false negative (FN, COVID-19 predicted to be non-COVID-19) values of AI on detection of COVID-19 in the patients, versus healthy control (HC). When the sensitivity and specificity were directly unavailable, we calculated them according to the following formulas: sensitivity = TP / (TP + FN) and specificity = TN / (FP + TN).

**Risk of bias across studies**

Data extraction for meta-analysis on detection of COVID-19 was based on the definition of criterion standard in the original study. Information including the year of publication, the country where the study was conducted, type of study, number of patients also retrieved. We used the revised Quality Assessment of Diagnostic Accuracy Studies (QUADAS-2) tool to assess the quality and potential bias of all studies by two independent reviewers (K.SH., F.R.)

Any disagreements were resolved with discussion and involvement of the third reviewer (B.A.), and reviewers [K.SH., F.R.] assessed the first included articles independently. Four domains, namely patient selection, index test, reference standard, and flow and timing, were assessed. Two categories, including the risk of bias and applicability, were assessed under the domain of patient selection, index test, and reference standard. The risk of bias was assessed in the domain of flow and timing.

**Additional analyses**
We used a bivariate model of random effects to estimate sensitivity, accuracy, and 95% confidence intervals (CI). A hierarchical summary receiver operating characteristic (HSROC) curve and a summary receiver operating characteristic (SROC) curve have been mounted. All experiments were viewed with the HSROC curve as a circle and plotted. The overview point was depicted by a dot surrounded by a 95% trust area (95 percent CI). The area under the curve (AUC) was computed to determine the diagnostic accuracy. Approaches 1.0 to the AUC would mean outstanding results, and impaired performance would be suggested if it approaches 0.5. Among numerous subgroups, we compared the 95% CI of the AUC. We used non-overlapping 95% CI between two subgroups to identify statistically relevant variations. The variability and threshold effects of the studies included were also measured. Generally, the Chi-Square test of p<0.1 reveals substantial heterogeneity performed was Cochran’s Q statistics and I2 test. Spearman’s correlation coefficient with r≥0.6 between sensitivity and FP rate typically suggests a substantial threshold influence. We conducted both statistical studies using version 1.4 of the MetaDiSc software [19] and the quality and potential bias of all studies by using Review Manager 5.4 (RevMan 5.4) [20].

**Results**

**Study selection and characteristics**

Finally, 886 studies were retrieved on the initial search, and 223 duplicates were removed. After reviewing the title, abstract and full article, finally, 36 studies were selected for inclusion into the meta-analysis [21-57] (Figure 1). All included studies were retrospective, and all the studies were based on record images.
Based on the number of enrolled images, 32,857 images (19,623 COVID-19 images and 13,234 Healthy images) classified by analysis were included. The AI algorithm based on the neural network was established in a number of research articles [21-23, 25-27, 29-31, 33-37, 41-43, 47, 48, 50-55, 57]. Among the included studies, twenty-nine models were selected for meta-analysis on DL assisted detection for predict COVID-19 [21, 22, 25-27, 30, 33-37, 40-42, 46, 47, 50-54, 56, 57] and fourteen models on ML assisted detection for predict COVID-19 [21, 24, 28, 31, 38, 43, 45, 46, 48, 49] (Table 1).

Risk of bias within studies

In the final part, 31 studies had a low risk of bias in patient selection, while 5 studies had a high risk of bias (Supplementary Figures 1). In terms of the patient selection, two studies [21, 46] used multiple tests, including (DL, and ML). Overall, studies with high risk [39, 44, 48, 55, 58] in at least one of the seven domains were rated as low methodological quality in the subgroup analysis.

Diagnostic Test Accuracy (DTA)

Results of AI

Among the 37 studies [21-57] of image-based analysis, the pooled sensitivity was 0.90 (95% CI, 0.90 - 0.91), specificity was 0.90 (95% CI, 0.90 - 0.91), the AUC was 0.96 (95% CI, 0.91 - 0.98), and diagnostic odds ratio (DOR) was 88.98 (95% CI, 56.38 – 140.44) as shown in (Figure 2) (Supplementary Figures 2-8).

Results of DL

Among the 23 studies [21, 22, 25-27, 30, 31, 33-37, 40-42, 46, 47, 50-54, 56, 57] of image-based analysis, the pooled sensitivity was 0.91 (95% CI, 0.90 - 0.91), specificity was 0.88
(95% CI, 0.87 - 0.89), the AUC was 0.96 (95% CI, 0.93 - 0.97), and DOR was 99.04 (95% CI, 54.68 – 179.36) as shown in (Figure 3) (Supplementary Figures 3-8).

**Results of ML**

Among the 9 studies [21, 24, 28, 38, 43, 45, 46, 48, 49] of image-based analysis, the pooled sensitivity was 0.91 (95% CI, 0.90 - 0.91), specificity was 0.95 (95% CI, 0.94 - 0.95), the AUC was 0.97 (95% CI, 0.96-0.99), and DOR was 88.27 (95% CI, 29.52 – 263.96) as shown in (Figure 4) (Supplementary Figures 4-8).

**Discussion**

This meta-analysis study exhibited a satisfactory performance using the AI algorithm for AI assisted CT-Scan identification of COVID-19 vs. healthy samples. We showed that AI was accurate on the lung involvement in the COVID-19 with a pooled sensitivity was 0.90 (95% CI, 0.90-0.91), specificity was 0.90 (95% CI, 0.90-0.91) and the AUC was 0.96 (95% CI, 0.91-0.98). According to the **Table 2**, ResNet-50, ResNet101, ensemble of bagged tree (EBT), Tree-based pipeline optimization tool (TPOT), Gaussian Naive Bayes (GNB), random forest (RF), and convolution neural network (CNN) algorithms had performed good on the CT-based COVID-19 detection.

The lesions could explain AI’s excellent performance in detecting COVID-19 with the handle, bronchial vascularization, or lower extremities in bilateral lungs [59]. In contrast, AUC of ML detecting COVID-19 patients was 0.97 (95% CI, 0.96-0.99). However, the AUC of DL on detecting of COVID-19 patients was 0.96 (95% CI, 0.93 - 0.97). Thus, it may increase the AI, ML, and DL models’ close diagnosis to detect COVID-19.
The AI system demonstrated performance comparable to senior practicing radiologists and can help to diagnose COVID-19 patients rapidly with 0.97 and 0.95 AUC [23, 55]. Consequently, AI software expressing objective evaluations of the percentage of ventilated lung parenchyma compared to the affected one and can readily identify CT-scans with COVID-19 associated pneumonia [58, 60]. Ilker Ozsahin et al., 2020, in the review study, showed that AI to be used in the clinic as a supportive system for physicians in detecting COVID-19 [61]. Also, pooled AUC in this study was 0.96 (95% CI, 0.91-0.98).

Lin Li et al., 2020, showed that the DL model with 0.96 AUC could accurately detect COVID-19 and differentiate it from Community-Acquired Pneumonia (CAP) and other lung conditions [35]. In contrast, Xiangjun Wu et al., 2020, Xueyan Mei et al., 2020, and Shuo Wang et al., 2020, showed that DL model with 0.732, 0.86, and 0.87 AUC could accurately detect COVID-19, respectively [51, 53, 62]. However, one study was showed that chest CT-Scan with AI could not replace molecular diagnostic tests with a nasopharyngeal swab (RT-PCR) or suspected for COVID-19 patients [63]. Overall, analysis shows that the DL model can classify the chest CT-Scan at a high accuracy rate and AUC values ranging from 0.90 to 1.00 [33, 52, 64, 65]. At the same time, this study showed that the AUC of DL on detecting COVID-19 patients was 0.96 (95% CI, 0.93 - 0.97), which was near the same results with the research studies.

Daowei Li et al., 2020, showed that the AUR score of ML was 0.93 [34]. However, in our study, pooled AUC in ML was higher, 0.97 (95% CI, 0.96-0.99). Overall, ML’s accuracy is almost achieved over 0.90 for COVID-19 classification [66], and Chenglong Liu et al., 2020, showed that AUC was 0.99 [38].
This meta-analysis has several limitations. 1. All studies were retrospective based on static images. 2. The selection bias of studies cannot be eliminated (shown in the QUADAS-2). 3. There were some heterogeneities in the CT-Scans equipment, images, and algorithm of AI, DL, and ML used. 4. Also, two studies used some algorithms and methods for AI, which was effect bias for this analysis.

**Conclusion**

Our findings revealed that AI-platforms based on the ResNet-50, ResNet101, an ensemble of the bagged tree, Tree-based pipeline optimization tool, Gaussian Naive Bayes, random forest, and convolution neural network algorithms perform well for CT-based COVID-19 detection. To confirm AI’s role for rapid and accurate COVID-19 diagnosis, more prospective real-time trials are required due to reduce the possibility of selection bias and to compare with currently available studies.
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Figure 1. PRISMA 2009 Flow Diagram.

Figure 2. The summary receiver-operating characteristic (SROC) curves of the diagnostic performance of AI and CT-Scan on detection. Significant difference was present when the 95% confidence regions.

Figure 3. The summary receiver-operating characteristic (SROC) curves of the diagnostic performance of DL and CT-Scan on detection. Significant difference was present when the 95% confidence regions.

Figure 4. The summary receiver-operating characteristic (SROC) curves of the diagnostic performance of ML and CT-Scan on detection. Significant difference was present when the 95% confidence regions.

Table 1. Characteristics of included studies on various models in patients with COVID-19.

Table 2. A detailed information of used AI-models to detect and Classified COVID-19 by Compressed Chest CT Image.
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Table 1. Characteristics of included studies on various models in patients with COVID-19.

| Country/ID | Country | Expert Radiologists involved as control | AI model | Reference standard | Chest CT images | Diagnosis factors |
|------------|---------|----------------------------------------|----------|--------------------|-----------------|-------------------|
|            |         |                                        |          |                    | Positive | Healthy samples | Accuracy, % | AUROC | PPV | NPV | Sen. | Spec. |
| Kelei He et al., 2021 [1] | China     | Yes                                    | DL       | RT-PCR             | 666      | NA              | 0.985      | 0.991 | 0.799 | NA   | 0.783 | NA   |
| Ziwei Zhu et al., 2021[2] | China     | Yes                                    | DL       | RT-PCR             | 687      | 395             | 0.93       | 0.93  | NA   | NA   | 0.93  | 0.92  |
| Vruddhi Shah et al., 2021 [3] | India     | Yes                                    | DL       | RT-PCR             | 738      | NA              | 0.821      | NA   | NA   | NA   | NA   | NA   |
| Carlos Quiroz et al., 2021 [4] | Australia | Yes                                    | ML       | RT-PCR             | 346      | NA              | NA         | 0.926 | NA   | NA   | 0.818 | 0.901 |
| H Alshazly et al., 2021 [5] | Germany   | Yes                                    | DL       | RT-PCR             | 1252     | 1230            | 0.994      | NA   | NA   | NA   | 0.998 | 0.996 |
| Mohit Agarwal et al., 2021 [6] | India     | Yes                                    | DL       | RT-PCR             | 705      | 990             | 0.994      | 0.991 | NA   | NA   | 0.99  | 0.985 |
| Xi Fang et al., 2021 [7] | USA       | Yes                                    | DL       | RT-PCR             | 193      | NA              | 0.994      | 0.988 | NA   | NA   | 0.99  | 0.985 |
| Kumar Mishra et al., 2020 [8] | India     | Yes                                    | DL       | RT-PCR             | 360      | 397             | 0.8834     | 0.8832 | NA   | NA   | 0.8813 | 0.9051 |
| Jun Chen et al., 2020 [9] | China     | Yes                                    | DL       | RT-PCR             | 636      | 691             | 0.9524     | NA   | NA   | NA   | 1     | 0.9355 |
| Liang Sun et al., 2020 [10] | China     | Yes                                    | DL       | RT-PCR             | 1495     | 1027            | 0.9179     | 0.9635 | NA   | NA   | 0.9305 | 0.8995 |
| S Carvalho et al., 2020 [11] | Portugal  | Yes                                    | DL       | RT-PCR             | 130      | NA              | 0.82       | 0.90  | NA   | NA   | 0.80  | 0.86  |
| Lu-Shan Xiao et al., 2020 [12] | China     | Yes                                    | DL       | RT-PCR             | 408      | NA              | 0.974      | 0.987 | NA   | NA   | NA   | NA   |
| Kimura-Sandoval et al., 2020 [13] | Mexico    | Yes                                    | AI       | RT-PCR             | 166      | NA              | NA         | 0.88  | NA   | NA   | 0.74  | 0.91  |
| Hui-Bin Tan et | China     | Yes                                    | ML       | RT-PCR             | NA       | NA              | NA         | 0.95  | NA   | NA   | 0.987 | 0.984 |
| Study                  | Country | Method | Test Method | Sensitivity | Specificity |conciliation | PPV | NPV |
|------------------------|---------|--------|-------------|-------------|-------------|--------------|------|------|
| al., 2020 [14]         |         |        |             |             |             |              |      |      |
| Liping Fu et al., 2020 [15] | China   | Yes    | ML          | RT-PCR      | 64          | NA            | NA   | 0.833 NA NA 0.8095 0.7442 |
| Kang Zhang et al., 2020 [16] | China   | Yes    | AI          | RT-PCR      | 752         | 697           | 0.8411 0.9050 NA NA 0.8667 0.8226 |
| Quan Cai et al., 2020 [17] | China   | Yes    | ML          | RT-PCR      | 81          | 122           | 0.709 0.811 NA NA 0.765 0.625 |
| D Javor et al., 2020 [18] | Austria | Yes    | DL          | RT-PCR      | 3102        | NA            | NA   | 0.956 NA NA 0.844 0.933 |
| Daowei Li et al., 2020 [19] | China   | Yes    | DL          | RT-PCR      | 10          | 36            | NA   | 0.68 NA NA NA NA |
| Hoon Ko et al., 2020 [20] | Korea   | Yes    | DL          | RT-PCR      | 337         | 998           | 0.9987 1 NA NA 0.9958 1 |
| Xueyan Mei et al., 2020 [21] | USA     | Yes    | DL          | RT-PCR      | 419         | 486           | 0.796 0.86 NA NA 0.836 0.759 |
| Xinggang Wang et al., 2020 [22] | China   | Yes    | DL          | RT-PCR      | 313         | 229           | 0.901 0.959 NA NA 0.95 0.95 |
| Xiangjun Wu et al., 2020 [23] | China   | Yes    | DL          | RT-PCR      | 294         | 101           | 0.819 0.76 NA NA 0.811 0.615 |
| Shuo Wang et al., 2020 [24] | China   | Yes    | DL          | RT-PCR      | 560         | 149           | 0.8124 0.90 NA NA 0.7893 0.8993 |
| Lin Li et al., 2020 [25] | China   | Yes    | DL          | RT-PCR      | 1296        | 1325          | NA   | 0.96 NA NA 0.90 0.96 |
| A. Harmon et al., 2020 [26] | USA     | Yes    | AI          | RT-PCR      | 1029        | 1695          | 0.908 0.949 NA NA 0.84 0.93 |
| Chenglong Liu et al., 2020 [27] | China   | Yes    | ML          | RT-PCR      | 73          | 27            | 0.9416 0.99 NA NA 0.8862 1 |
| Harrison X. Bai et al., 2020 [28] | China   | Yes    | AI          | RT-PCR      | 521         | 665           | 0.96 0.95 NA NA 0.95 0.96 |
| A. Sakagianni et al., 2020 [29] | Greece  | Yes    | ML          | RT-PCR      | 349         | 397           | 0.932 0.94 NA NA 0.8831 0.8831 |
| Deepika Selvaraj et al., 2020 [30] | India   | Yes    | ML          | RT-PCR      | 50          | NA            | 0.886 0.8723 NA NA 0.5549 0.8988 |
| Yuehua Li et al., 2020 [31] | China   | Yes    | DL          | RT-PCR      | 148         | NA            | 0.626 0.660 NA NA 0.5897 0.6429 |
| Fei Shan et al., 2020 [32] | China   | Yes    | ML          | RT-PCR      | 249         | NA            | 0.916 NA NA NA NA |

The table above lists studies that have been referenced in the text. The columns represent the study authors, publication year, country, method of testing, test method, sensitivity, specificity, concordance, PPV, and NPV. The sensitivity and specificity values are provided for each study, along with the corresponding PPV and NPV values. The table also includes the method of testing, which can be ML, DL, or AI, and the test method, which can be RT-PCR. The concordance values are also provided for each study.
| Study                        | Country | Application | Methodology | Samples | Controls | FP  | FN  | TN  | TP  | AUC | C | RF |
|------------------------------|---------|-------------|-------------|---------|----------|-----|-----|-----|-----|-----|---|----|
| Minghuan Wang et al., 2020 [33] | China   | Yes         | DL          | RT-PCR  | 1647     | 800 | NA  | 0.953| 0.790| 0.948| 0.923| 0.851 |
| H-W Ren et al., 2020 [34]   | China   | Yes         | AI          | RT-PCR  | 58       | NA  | NA  | 0.740| NA   | NA   | NA  | 0.912 | 0.588 |
| Zhang Li et al., 2020 [35]   | China   | Yes         | DL          | RT-PCR  | 204      | 164 | NA  | 0.97 | NA   | NA   | NA  | NA   |
| Jiantao Pu et al., 2020 [36] | USA     | Yes         | DL          | RT-PCR  | 151      | 498 | NA  | 0.70 | NA   | NA   | NA  | NA   |
| Fengjun Liu et al., 2020 [37] | USA     | Yes         | AI          | RT-PCR  | 134      | 115 | NA  | 0.84 | NA   | NA   | NA  | NA   |

False Positive (FP), False Negative (FN), True Negative (TN), True Positive (TP), Area Under the Curve (AUC), Deep Learning (DL), Machine Learning (ML), convolution neural network (CNN), artificial neural network (ANN), Decision tree (DT), and random forest (RF), artificial neural network (ANN), Tree-based pipeline optimization tool (TPOT), ensemble of bagged tree (EBT), support vector machine (SVM), Gaussian Naive Bayes (GNB), Logistic Regression (LR), Deep Neural Network (DNN),
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Table 2. A detailed information of used AI-models to detect and Classified COVID-19 by Compressed Chest CT Image.

| Country/ID          | Method | Input                                      | Output                                                        | Algorithm names          | Performance evaluation                                      | Training/test splitting | Transfer learning/ ab initio training | Network Architecture                          |
|---------------------|--------|--------------------------------------------|---------------------------------------------------------------|--------------------------|--------------------------------------------------------------|-------------------------|---------------------------------------|---------------------------------------------|
| Kelei He et al.,   | DL     | The raw 3D CT image                        | The lung segmentation and severity assessment of COVID19 patients | multi-task multi-instance U-Net (M^2UNet) | A five-fold cross-validation strategy used                  | One subset as the testing set (20%)/ Four subsets are combined to construct the training set (70%) and validation set (10%) | Synergistic Learning                       | A bag (consisting of a set of 2D image patches) as the input data. M2UNet employs an encoding module for patch-level feature extraction |
| 2021 [1]            |        |                                            |                                                               |                          |                                                              |                         |                                       |                                                             |
| Ziwei Zhu et al.,   | DL     | The raw 3D CT image                        | The lung segmentation and severity assessment of COVID19 patients | Keras platform based on ResNet50 architecture | training set, validation set and testing set | One subset as the training set, one subset as validation set, and one subset as testing set | Transfer learning to detect the patients with COVID-19 | Imagenet dataset, Newly initialized weights, Output |
| 2021[2]             |        |                                            |                                                               |                          |                                                              |                         |                                       |                                                             |
| Vruddhi Shah et al,| DL     | The raw 3D CT image                        | The lung segmentation and severity assessment of COVID19 patients | ResNet-50                | The confusion matrix                                        | A training set, validation set, and test set with a split | A pre-trained network | VGG-19 architecture                  |
| 2021 [3]            |        |                                            |                                                               |                          |                                                              |                         |                                       |                                                             |
| Carlos Quiroz et al,| ML     | CT slices with <3 mm² of lung tissue       | The lung segmentation and severity assessment of COVID19 patients | EfficientNetB7 U-Net    | 5-fold repeated stratified cross-validation                  | -                       | -                                    | A 4-layer, fully connected architecture |
| 2021 [4]            |        |                                            |                                                               |                          |                                                              |                         |                                       |                                                             |
| H Alshazly et al.,  | DL     | Chest CT scans                             | The lung segmentation and severity                            | ResNet50 and ResNet101  | K-fold cross-validation                                     | About 600 images only, and the test fold has | Transfer learning to detect the patients with COVID-19; which | The deep CNN architectures                |
| 2021 [5]            |        |                                            |                                                               |                          |                                                              |                         |                                       |                                                             |
| Name                      | Methodology | Data Type | Data Description | Methods                          | Data Size | Data Availability |
|---------------------------|-------------|-----------|------------------|----------------------------------|-----------|-------------------|
| Mohit Agarwal et al., 2021 [6] | DL, ML      | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients | CNN, RF, VGG16, DenseNet121, DenseNet169, DenseNet201, MobileNet, ANN, DT | less than 200 images | data are scarce |
| Xi Fang et al., 2021 [7]   | DL          | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients | U-Net | Cross-dataset validation (training on Site A and testing on Site B; training on Site B and testing on Site A) | Labeled all five pulmonary lobes in 71 CT volumes from Site A using chest imaging platform | - |
| Kumar Mishra et al., 2020 [8] | DL          | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients | ResNet50 | - | Split 80% of the data is kept for training purpose (training data) and the rest for testing (testing data) | - |
| Jun Chen et al., 2020 [9]   | DL          | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients | UNet++ | - | 35,355 images were selected and split into training and retrospectively testing datasets. | - |
| Liang Sun et al., 2020[10]  | DL          | Chest CT scans | The lung segmentation | VB-Net | - | Adaptive Feature Selection guided | - |

Based CNN thus has a total of 7 layers mainly adapting for simplicity.
| Authors                          | Method | Used Data          | Task Description                                                                 | Model Details                                                                 | Validation Details                                                                 | Architecture                  |
|---------------------------------|--------|--------------------|--------------------------------------------------------------------------------|--------------------------------------------------------------------------------|---------------------------------------------------------------------------------|--------------------------------|
| S Carvalho et al., 2020 [11]    | DL     | Chest CT scans     | The lung segmentation and severity assessment of COVID19 patients                | ANN                                                                           | Minimization of the cross-entropy                                               | 60 neurons in a single-hidden-layer architecture |
| Lu-Shan Xiao et al., 2020 [12]   | DL     | Chest CT scans     | The lung segmentation and severity assessment of COVID19 patients                | ResNet34                                                                      | Five-fold cross-validation                                                       | ResNet34, AlexNet, VGGNet, and DenseNet |
| Kimura-Sandoval et al., 2020 [13]| AI     | Chest CT scans     | The lung segmentation and severity assessment of COVID19 patients                | Logistic                                                                      |                                                                                  |                                |
| Hui-Bin Tan et al., 2020 [14]   | ML     | Chest CT scans     | The lung segmentation and severity assessment of COVID19 patients                | TPOT                                                                          | Radiomics Auto-ML model in the first CT images                                  | Auto-ML, each group’s original data is imported into TPOT |
| Liping Fu et al., 2020 [15]     | ML     | Chest CT scans     | The lung segmentation and severity assessment of COVID19 patients                | K(K-1)/2 binary                                                               | One-leave-out cross-validation                                                   |                                |
| Kang Zhang et al., 2020 [16]    | AI     | Chest CT scans     | The lung segmentation and severity assessment of COVID19 patients                | ResNet-18                                                                     | A five-fold cross-validation test                                               | A computer-aided diagnosis (CAD) system for detecting COVID-19 patients |
| Authors | Methodology | Dataset | Main Task | Split of Data | Additional Details |
|---------|-------------|---------|-----------|---------------|--------------------|
| Quan Cai et al., 2020 [17] | ML | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients | 7:3 ratio to either the training cohort or the testing cohort | - |
| D Javor et al., 2020 [18] | DL | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients | Split for training the model and internal validation (20% of the samples) | More layers (ResNet-101) |
| Daowei Li et al., 2020 [19] | DL | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients | - | - |
| Hoon Ko et al., 2020 [20] | DL | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients | On one of the following four pretrained CNN | Initially used the predefined weights for each CNN architecture |
| Xueyan Mei et al., 2020 [21] | DL | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients | - | - |
| Xinggang Wang et al., 2020 [22] | DL | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients | A simple 2D UNet using the CT images in our training set | 3D deep convolutional neural Network to Detect COVID-19 (DeCoVNet) from CT volumes. |
| Authors                  | Layer | Dataset       | Description                                                                 | Architecture     | Examples                                                                 | Notes |
|-------------------------|-------|---------------|-----------------------------------------------------------------------------|-------------------|-------------------------------------------------------------------------|-------|
| Xiangjun Wu et al., 2020 [23] | DL    | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients          | ResNet50          | The layer outputs the risk value of COVID-19 pneumonia                 |       |
| Shuo Wang et al., 2020 [24] | DL    | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients          | COVID-19Net       | Train and externally validate the performance                           |       |
| Lin Li et al., 2020 [25]  | DL    | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients          | COVID-19Net       | The auxiliary training set                                              |       |
| A. Harmon et al., 2020 [26] | AI    | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients          | AH-Net            | A ratio of 9:1 into a training set and an independent testing set at the patient level. |       |
| Chenglong Liu et al., 2020 [27] | ML    | Chest CT scans | The lung segmentation and severity                                        | EBT               | SVM, LR, DT, KNN are implemented                                        |       |
| Authors | Methodology | Type | Description | Model | Parameters | Output | Architecture |
|---------|-------------|------|-------------|-------|------------|--------|--------------|
| Harrison X. Bai et al., 2020 [28] | AI | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients | EfficientNet B4 | - | - | EfficientNet B4 deep neural network architecture |
| A. Sakagianni et al., 2020 [29] | ML | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients | - | - | - | - |
| Deepika Selvaraj et al., 2020 [30] | DL, ML | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients | SVM, GNB, LR, DT, DNN | 50 images are used for testing the trained network | The dataset of training points is manually selected from the infected and background pixels from the 30 training images | The size of the input layer is 38 neurons (38 features), three hidden layers with 58 neurons per layer and binary classification output layer |
| Yuehua Li et al., 2020 [31] | DL | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients | U-Net | The Dice coefficient | - | - |
| Fei Shan et al., 2020 [32] | ML | Chest CT scans | The lung segmentation and severity assessment of COVID19 patients | VB-Net | - | - | - |
| Minghuan Wang et al., 2020 [33] | DL | Chest CT scans | The lung segmentation | U-Net | - | Randomly split into a training set | - |
| Authors               | Method | Data Type            | Task                                                                 | Details                                                                                                                                 |
|----------------------|--------|----------------------|----------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------|
| H-W Ren et al., 2020 [34] | AI     | Chest CT scans       | The lung segmentation and severity assessment of COVID19 patients      | -                                                                                                                                         |
| Zhang Li et al., 2020 [35] | DL     | Chest CT scans       | The lung segmentation and severity assessment of COVID19 patients      | U-Net                                                                                                                                 |
| Jiantao Pu et al., 2020 [36] | DL     | 3D Chest CT scans    | The lung segmentation and severity assessment of COVID19 patients      | CNN                                                                                                                                 |
| Fengjun Liu et al., 2020 [37] | AI     | Chest CT scans       | The lung segmentation and severity assessment of COVID19 patients      | -                                                                                                                                         |

False Positive (FP), False Negative (FN), True Negative (TN), True Positive (TP), Area Under the Curve (AUC), Deep Learning (DL), Machine Learning (ML), convolution neural network (CNN), artificial neural network (ANN), Decision tree (DT), and random forest (RF), artificial neural network (ANN), Tree-based pipeline optimization tool (TPOT), ensemble of bagged tree (EBT), support vector machine (SVM), Gaussian Naive Bayes (GNB), Logistic Regression (LR), Deep Neural Network (DNN),
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Figure 1. PRISMA 2009 Flow Diagram.

Records identified through database searching (n = 546)
- ISI web of science (n = 141)
- PubMed (n = 240)
- Scopus (n = 290)
- Embase (n = 132)
- Ovid (n = 78)
- Cochrane library (n = 2)

Additional records identified through other sources (n = 3)

Records after removing duplicates (n = 663)

Records screened (n = 64)

Records excluded (n = 23)

Full-text articles assessed for eligibility (n = 41)

Full-text articles excluded, with reasons (n = 5)

Studies included in qualitative synthesis (n = 36)

Studies included in quantitative synthesis (meta-analysis) (n = 36)
Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: