REVIEW ARTICLE

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Rapid, Reproducible and Reliable – multimodal AI for CT, chest X-ray and clinical data integration with insights from COVID-19

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Abstract

Introduction and Objective. The COVID-19 pandemic accelerated development of multimodal artificial intelligence (AI) models that combine chest computed tomography (CT), chest X-ray (CXR) and clinical/laboratory data to support imaging-based diagnosis, triage and prognostication. This review synthesizes reported performance, clinical utility and limitations.
Review Methods. PubMed, Scopus and Google Scholar (Jan 2020–Jun 2025) were searched and included peer-reviewed English studies applying machine learning or deep learning to CT and/or CXR with reported sample sizes and performance metrics (AUC, sensitivity, specificity, F1). Preprints, case reports and studies without sample sizes or performance metrics were excluded.
Brief description of the state of knowledge. Meta-analyses report high discriminative performance for severity prediction (pooled AUC ≈ 0.89) alongside a high prevalence of study bias. Selected studies reported top accuracies up to ≈98% and multimodal F1 scores up to 0.89. Recurring limitations were dataset heterogeneity, single-centre training and scarce external validation. Some reports found automated pipelines substantially faster than manual reads (e.g. ~2.7 s vs ~6.5 min), although workflow times vary by setting.
Summary. Multimodal integration of CT, CXR and clinical data with AI is promising for rapid, reproducible assessment of COVID-19 severity. Clinical translation requires standardized acquisition and reporting, rigorous multicentre external validation, transparent methods, and formal evaluation of clinical impact and fairness.

Key words

COVID-19, chest X-ray, deep learning, chest computed tomography, multimodal artificial intelligence, clinical data, laboratory data, severity prediction, clinical decision support, algorithmic fairness

INTRODUCTION

Radiology, long allied with technological progress, has become a key field in which artificial intelligence (AI) can drive substantial change across multiple sectors, including healthcare. How exactly AI is affecting contemporary radiological practice, diagnostic efficiency, and the extent to which it can meet the challenges of real-world implementation, remains a central question. A representative example is a retrospective study assessing the performance of deep learning algorithms for the detection of pneumonia on chest radiographs. Neural network–based approaches achieved a high AUROC (0.923) and sensitivity of 95.4% [1], markedly exceeding conventional radiological interpretation in that series. Such technologies not only support diagnostic workflows but also shorten result turnaround times, which can be critical in emergency settings.

Moreover, AI is employed in lung cancer screening, where it shows substantial potential to improve nodule detection sensitivity, reduce false-positive rates and assist nodule classification; it also contributes to growth prediction and radiogenomic characterization of nodules [2]. AI tools are also increasingly appearing in pulmonary digital pathology, including multimodal data analysis, three-dimensional pathology and applications related to transplant rejection [3].

The COVID-19 pandemic, caused by SARS-CoV-2, represented one of the most serious global health challenges of the twenty-first century. Since late 2019, the disease has spread to more than 200 countries, causing millions of infections and a substantial number of deaths. Its sudden emergence and high transmissibility overwhelmed health systems and produced widespread organizational challenges – staff shortages, reduced access to routine services and delays in diagnosis and treatment for other conditions [4]. The topic of AI-augmented imaging and rapid diagnostic support therefore aligns with the stated interests of AAEM in applied clinical and public-health issues, including the health of rural communities, occupational and environmental determinants and accessibility of medical care – areas in which faster, more reproducible imaging interpretation and AI-driven decision support may directly affect patient outcomes and system resilience.

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One of the major challenges during the pandemic was accurate and timely diagnosis of COVID-19. Because of the disease's rapid course, heterogeneous clinical manifestations and the limited availability of molecular tests, imaging methods gained importance for diagnosis and monitoring. Current viral detection methods, such as molecular diagnostics, can be time-consuming and have imperfect sensitivity, while chest radiography provides faster results but is less sensitive than computed tomography (CT) [5]. CT played an important role in COVID-19 diagnosis by offering high sensitivity for parenchymal lung changes and enabling rapid case identification. Given the concerns about radiation exposure, low-dose protocols and judicious use of CT were emphasized to allow safe monitoring of pulmonary changes, particularly in severe cases of the disease. Furthermore, the pandemic accelerated demand for faster and more precise diagnostic tools, stimulating the development of AI technologies to support patient assessment and therapeutic decision making. Appropriately designed AI algorithms have even enabled virtual screening and structural optimization of potential SARS-CoV-2 inhibitors, thereby accelerating early stages of therapeutic discovery [6]. Despite these advances, further research is still needed to validate AI algorithms for predicting severe COVID-19 courses through integrated analysis of CT, chest radiography, and laboratory parameters.

OBJECTIVE

The aim of the review is to provide a comprehensive overview of current evidence on the performance of integrated approaches that combine low-dose computed tomography (LDCT), chest radiography, and laboratory parameters to predict COVID-19 severity. Methodological features and reported diagnostic/prognostic accuracy are synthesized, and how multimodal integration may support clinical decision-making and optimize patient management are discussed.

MATERIALS AND METHOD

PubMed, Scopus and Google Scholar from January 2020 – June 2025 were searched using the key words: 'COVID-19', 'SARS-CoV-2', 'artificial intelligence', 'deep learning', 'chest X-ray', 'computed tomography' and 'prognosis'. Only peer-reviewed articles published in English that applied machine-learning algorithms – particularly deep learning – to computed tomography (CT) or chest radiography (CXR) for diagnosis, severity assessment, or prognosis of COVID-19 were included. Excluded were preprints, case reports, studies using exclusively synthetic data, and articles that did not report sample size or performance metrics. Inclusion and exclusion criteria are summarized in Table 1.

Table 1. Inclusion and exclusion criteria for study selection

Inclusion Criteria	Exclusion Criteria
– Peer-reviewed articles in English. – Original studies applying machine learning or deep learning to the analysis of CXR or CT images for the purposes of diagnosis, prognosis, or severity assessment of COVID-19. – Reported data on the number of patients/images as well as performance metrics (e.g., AUC, sensitivity, specificity).	– Preprints, conference abstracts, and working papers. – Studies involving only synthetic data simulations, or models without real imaging data. – Case reports, letters to the editor, and commentaries.

CXR – chest X-ray; CT – computed tomography; AUC – Area under the curve

STATE OF KNOWLEDGE

Review of diagnostic techniques used during COVID-19. A range of laboratory and imaging methods were used for COVID-19 diagnosis which these differ in availability, turnaround time and accuracy. Current SARS-CoV-2 detection techniques can be grouped into five main diagnostic categories: chest radiography (CXR), computed tomography (often low-dose CT), analysis of cough sounds or respiratory patterns, RT-PCR, and antigen/antibody tests **[7].** The RT-PCR assay detecting viral RNA remains the diagnostic gold standard [8]. These categories are presented in Figure 1.

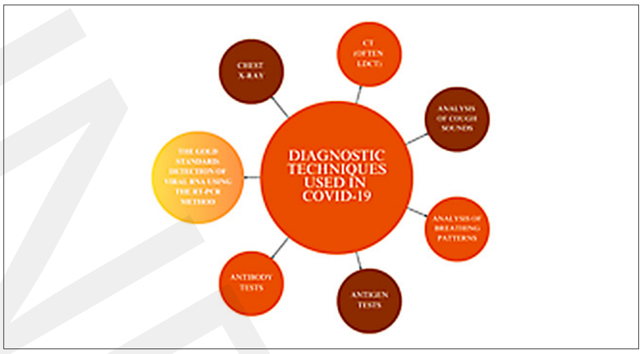

Figure 1. Diagnostic techniques used in COVID-19.
RT-PCR – reverse transcription polymerase chain reaction; LDCT – low-dose computed tomography

Specimens are typically collected from the nasopharynx, although combined oral and oropharyngeal swabs have been proposed as an alternative. Nasopharyngeal samples generally offer higher diagnostic sensitivity, but are less comfortable for patients and require trained personnel; oral and oropharyngeal swabs are technically simpler and less invasive but carry a higher risk of false-negative results. Both sampling approaches are susceptible to errors related to timing and technique [9]. Clinical reports indicate that RT-PCR results commonly reach healthcare facilities no earlier than the day after sampling, whereas CT or CXR interpreted by an AI algorithm can provide results within minutes to hours. This timing difference can meaningfully affect patient triage at admission and, in some instances, may expedite initiation of targeted therapy while awaiting confirmatory RT-PCR results. In one reported example, AI reduced the interval from CT acquisition to interpretation from several days to 1 – 2 hours; the computational step itself averaged approximately 3 minutes. The study also documented improved detection metrics: sensitivity reached 91.6%, specificity – 99.7%, and the proportion of missed lesions fell from 44.8% – 2.6%. These results highlight the potential of AI-augmented CT to deliver rapid, reproducible and precise assessment of pulmonary involvement, thereby supporting clinical decision making and optimization of COVID-19 treatment [10].

Machine-learning (ML) models, and particularly deep-learning (DL) architectures, have shown high performance in identifying COVID-19 from radiological images such as CXR and CT, enabling discrimination from community-acquired pneumonia. Concurrently, abnormalities in haematologic and biochemical parameters have been demonstrated to correlate significantly with disease severity and COVID-19-related mortality. On this basis, algorithms integrating imaging and laboratory data have been developed to predict disease course and optimize therapeutic management [11]. In summary, integrating CT, chest radiography and laboratory parameters achieves a favourable balance between diagnostic accuracy and timeliness, facilitating prompt and accurate identification of patients at elevated risk of intensive care admission or mortality.

Artificial Intelligence in COVID-19 diagnosis – analysis of CT images. AI systems – especially those employing deep-learning (DL) algorithms – show substantial potential to enhance COVID-19 diagnosis from chest computed tomography (CT). In clinical research, AI is used for quantitative CT analysis to improve objectivity, increase measurement reproducibility and minimize human-factor variability [12]. Studies have shown that the use of AI tools enables radiologists to achieve higher diagnostic accuracy (90%), sensitivity (88%) and specificity (91%) when distinguishing COVID-19 from other pneumonias [5].

In one analyzed study, a dataset of 1,065 CT images was assembled, including pathogenetically-confirmed COVID-19 and previously diagnosed typical viral pneumonia. A modified transfer-learning model was developed for classification and evaluated with both internal and external validation. Internal validation yielded an overall accuracy of 89.5%, with sensitivity 0.87 and specificity 0.88; external validation on an independent test set achieved overall accuracy 79.3%, sensitivity 0.67 and specificity 0.83. Notably, among 54 COVID-19 cases in which the first 2 nucleic-acid amplification tests were negative, the algorithm classified 46 as positive, attaining 85.2% accuracy within this subgroup [13].

A meta-analysis further demonstrated the high effectiveness of AI in identifying COVID-19 from CT images versus images of healthy individuals, with pooled sensitivity of 0.90 (95% CI, 0.90–0.91), specificity of 0.90 (95% CI, 0.90–0.91) and an AUC of 0.96 (95% CI, 0.91–0.98). Models reporting particularly strong performance included ResNet-50, ResNet-101, ensemble bagged tree (EBT), Tree-Based Pipeline Optimization Tool (TPOT), Gaussian Naive Bayes (GNB), random forest (RF) and convolutional neural networks (CNNs) [14]. To effectively discriminate SARS-CoV-2 infection from non-COVID conditions, 10 widely used CNN architectures are commonly employed: AlexNet, VGG-16, VGG-19, SqueezeNet, Xception, MobileNet-V2, ResNet-18, GoogleNet, ResNet-50 and ResNet-101 [Fig. 2].

In routine clinical practice based on CT images, all of the aforementioned models demonstrated high diagnostic effectiveness. The ResNet-101 network in particular achieved a very high area under the ROC curve (AUC = 0.994), with sensitivity of 100%, specificity of 99.02% and overall accuracy – 99.51% [15]. The application of machine-learning (ML) algorithms in predictive medicine markedly expands the ability to detect disease early, and to identify patient-level health risks. It also supports clinical decision-making and the planning of preventive measures. Effective implementation of such tools helps maintain patients' physical and cognitive functioning and improves quality of life. From an economic perspective, the benefits of deploying ML tools in health

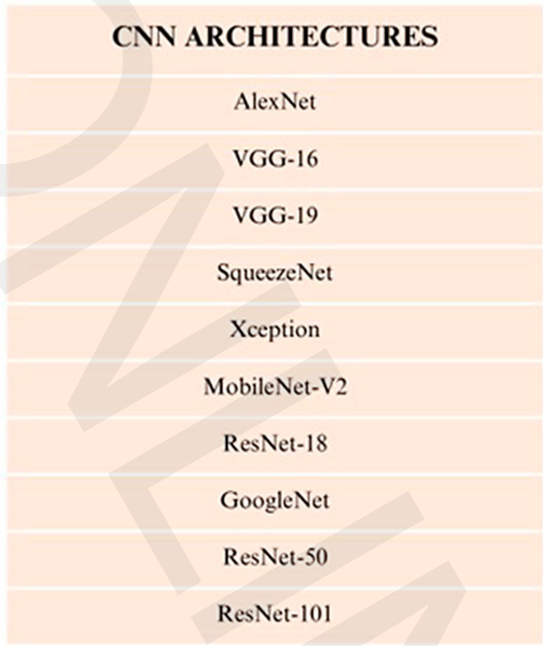

Figure 2. Widely adopted CNN architectures for accurately distinguishing SARS-CoV-2 infections from respiratory diseases unrelated to COVID-19.
CNN – convolutional neural network

prevention may outweigh the costs of treating advanced disease stages. Broad implementation of effective ML-based solutions can therefore contribute not only to better health outcomes, but also to greater financial stability of healthcare systems. Crucially, analysis of the cited cases indicates that the effectiveness of ML implementation depends strongly on the size and quality of available data, their systematic updating, and the representativeness of training sets [16].

In addition, an innovative classifier was developed which – despite omitting the initial lung-segmentation step and using a relatively small open-source dataset – achieved high diagnostic performance, with an AUC of 0.956 on an independent test set. The ML classifier's performance was compared with the assessments of 2 experienced radiologists, revealing only minimal differences in diagnostic accuracy. Notably, unlike radiologists' dichotomous decisions, the ML classifier generated continuous prediction outputs, which enabled selection of thresholds characterized by high sensitivity or high specificity in COVID-19 diagnosis [17].

Identification of anatomical structures in medical images is a key step in radiologic diagnosis. Owing to advances in deep learning and the growing availability of large medical-image datasets, automatic recognition of anatomic structures has become feasible, increasing the precision and efficiency of image analysis [18]. This yields another potential advantage of AI-based diagnostic methods by markedly reducing the time needed to analyze diagnostic findings. The authors emphasize that a key aspect of predicting COVID-19 severity is identifying imaging features that forecast subsequent disease evolution, particularly with respect to temporal changes. A deep-learning model was developed using multi-objective differential evolution (MODE) in combination with a CNN to classify the presence of COVID-19 on chest CT images. The model outperformed other architectures –

such as ANN, ANFIS and conventional CNNs – in terms of accuracy, F-measure, sensitivity, specificity and the kappa coefficient, confirming its real-time usefulness in COVID-19 diagnosis [19].

In another study, deep learning enabled segmentation of COVID-19 infection regions in the lungs on CT, providing the quantitative information needed to monitor disease progression and to analyze treatment-related changes. Preliminary 3-dimensional analyses confirm the effectiveness of CT in assessing COVID-19 severity, with lesions most commonly located in the lower lobes of the lungs [20]. The authors argue that automated CT assessment using AI algorithms can substantially support diagnostic decisions – particularly under conditions of emergency department and intensive care overload – by streamlining triage, resource management and disease monitoring [21].

Artificial Intelligence in COVID-19 diagnosis – analysis of chest X-ray images. Numerous studies have confirmed the high effectiveness of convolutional neural networks (CNNs) in detecting COVID-19 from chest radiographs. An Xception model achieved an accuracy of 97.97% on a dataset comprising 6,432 samples. Other architectures, such as lightweight convolutional neural networks (LWCNN), exceeded 98% accuracy in multi-class analyses across different datasets. These results indicate the strong utility of AI as a clinical decision-support tool for COVID-19 diagnosis in real-world settings [7].

Moreover, it has been emphasized that CNNs can effectively support automated COVID-19 detection and the extraction of salient features from chest X-ray images. VGG-19 and MobileNet-V2 achieved the highest accuracies, with MobileNet-V2 effectively distinguishing COVID-19 from other types of pneumonia. The investigators also highlighted the benefits of transfer learning, reporting 93.48% accuracy for multi-class classification and 98.75% for binary classification using VGG-19 [22].

Similarly, another research group developed a deep transfer-learning approach for automatic identification of COVID-19; the pre-trained ResNet-50 model achieved the highest accuracy among 5 evaluated models, depending on the dataset employed [23]. In a separate study, a ResNet-based architecture (COVIDResNet) reached 96.23% accuracy, underscoring the clinical promise of these methods [24]. The highest percentage accuracies of the models discussed are summarized in Table 2.

Table 2. Accuracy of CNN in detecting COVID-19 from chest X-ray images

Model	Accuracy (%)
Xception	97.97
LWCNN	>98
VGG19	98.75 (2-class)
MobileNet v2	97.40 (2-class)
ResNet50	99.70
COVIDResNet	96.23

CNN – Convolutional neural networks; LWCNN – lightweight convolutional neural network

Furthermore, the COVID-Net model is characterized by a high positive predictive value (PPV) for identifying SARS-CoV-2 infection, reaching 98.9%, which indicates a very low rate of false-positive results. This performance surpasses classical solutions based on the VGG-19 (PPV = 90.5%) and ResNet-50 (PPV = 91.3%) architectures. An innovative deep-neural-network design developed with a human-in-the-loop strategy enabled effective tailoring of the model to the specifics of detecting COVID-19 from chest X-ray (CXR) images. This approach increases the diagnostic precision of clinical decision-support systems in the pandemic context [25].

In one study, a deep-learning model based on the SqueezeNet architecture with Bayesian optimization was developed to classify COVID-19 cases from CXR images. Using off-line data augmentation together with the Bayes-SqueezeNet design yielded an efficient diagnostic model that outperformed the reference COVID-Net model. The system achieved 98.3% classification accuracy when distinguishing normal, pneumonia and COVID-19 classes, and 100% accuracy for unambiguous identification of COVID-19 among the remaining classes. In the context of the global health crisis caused by the COVID-19 pandemic, this model shows considerable potential as a component of tools for monitoring and early infection detection. Its relative implementation simplicity makes it an attractive candidate for clinical and system-level deployment. Taken together, these factors suggest that deploying deep-learning solutions can complement traditional laboratory methods and improve diagnostic-system efficiency under pandemic conditions [26].

Recent directions in research. In a study aimed at detecting SARS-CoV-2 infection from radiological images (CXR and CT), a deep-learning architecture named DarkCovidNet was employed. The model was trained on a dataset totaling 1,125 images: 125 confirmed COVID-19 cases, 500 non-COVID-19 pneumonia cases, and 500 images of healthy lungs. High classification performance was achieved – 98.08% accuracy for the binary task (COVID-19 vs no COVID-19) and 87.02% for the 3-class task (COVID-19, pneumonia, healthy). These results outperformed classification performance reported in other comparable studies in the literature [27].

In another prospective study including 300 patients, an AI-derived affected lung area index reached an AUC of 0.857 (95% CI, 0.809–0.905), whereas the semi-quantitative Brixia score achieved an AUC of 0.863 (95% CI, 0.818–0.908); the difference was minimal [28]. The authors noted that AI can support diagnosis in resource-constrained settings, but emphasized the need for larger prospective studies.

Recent research has also highlighted that algorithms may learn so-called demographic shortcuts (e.g., predicting disease based on race or gender). An analysis of 6 global CXR datasets showed that fairness corrections applied within the training set may not be optimal on novel test sets; models with less encoded demographic information may better preserve fairness across populations [29]. In another study using MIMIC-CXR data, over-sampling and synthetic augmentation were evaluated as fairness-improvement strategies; they reduced disparities between demographic groups by 74.7% and 10.6%, respectively, without a meaningful loss of AUC [30].

The most recent meta-analyses indicate that neural networks achieve the highest AUCs for predicting COVID-19 severity (AUC ≈ 0.893, sensitivity ≈ 0.75, specificity ≈ 0.91), yet 88% of the analyzed studies exhibited a high risk of bias [31]. This underscores the need for external validation and sustained attention to data quality. Table 3 summarizes the key

Table 3. Comparative analysis of dataset properties, architectures, and model performance

Author	Data (No. of cases)	Architecture	Key Results	Citation
Wang et al., 2021	259 patients (1065 images)	Modified Inception V3	Internal AUC: 0,93; External AUC: 0,81	[13]
Gielczyk et al., 2022	6432 CXR (COVID-19, pneumonia, healthy)	Xception / ResNeXt / InceptionV3	Xception: Accuracy 97,97%	[32]
Rahman et al., 2023	930 patients (396 'low risk', 534 'high risk')	BIOCXRNET (CXR + 25 biomarkers)	F1 = 0,89	[34]
Verma et al., 2024	2470 CXR (470 COVID)	UNet + VGG16 + SVM	Accuracy 98%	[33]
Dipaola et al., 2023	1296 patients	Multimodal ANN (text + tabular data)	AUC = 0,87; F1 = 0,62 (30-day mortality prediction)	[35]

AUC – area under the curve; F1 – F1-score; CXR – chest X-ray; ANN – artificial neural networks

characteristics of the datasets, the model architectures, and the reported performance metrics across the analyzed studies.

In one of the analyzed studies, the authors employed the BIOCXRNET model, which integrates features from chest radiographs (CXR) with 25 biochemical and clinical parameters obtained from 930 patients. Using FPN-based segmentation with DenseNet121 and CheXNet for classification, the model achieved an F1 score of 0.89 and improved accuracy by 6 percentage points relative to unimodal models [34]. Another group developed a neural network that fused textual data (clinical interviews, radiology reports) with tabular laboratory results in 1,296 patients. The network achieved an AUC of 0.87 and an F1 score of 0.62 for predicting 30-day mortality, outperforming models based solely on tabular data [35].

AI vs. radiologists – image interpretation time comparison. Studies indicate that the average interpretation time for radiologists was 6.5 minutes, whereas analysis by the AI system took only 2.73 seconds. These findings indicate a substantial potential for AI solutions to increase radiologists' efficiency and streamline diagnostic workflows. Notably, only in the cohort comprising cases with pneumonia or no pneumonia did the AI system perform slightly worse than human readers. In differentiating community-acquired pneumonia from COVID-19, 37.5% of cases (3/8) that were misclassified by the AI system were also misinterpreted by radiologists. This underscores the high complexity and diagnostic difficulty of these imaging cases, regardless of the analysis method used [36].

Limitations of the study. Despite encouraging results, several important limitations should be noted. CT images often originate from different scanners and acquisition protocols, which can lead to variability in image quality, contrast and noise. Differences in exposure, spatial resolution, reconstruction algorithms and device calibration introduce input heterogeneity and may affect AI performance. Standardization of acquisition protocols and development of harmonized repositories are necessary to ensure adequate prediction quality. In addition, variability in biochemical parameters may stem from the timing of sample collection, the dynamic nature of inflammatory responses and inter-laboratory analytical methods. Implementing uniform laboratory procedures and standardized sampling time frames can improve the reliability of input data.

Another limitation is the heterogeneity of AI models themselves – their architectures, depth, training procedures, validation strategies and data-augmentation techniques differ, which limits comparability and the ability to draw definitive conclusions. A key challenge is the limited availability of large, balanced datasets. For example, the COVIDX-Net model was developed using only 50 chest radiographs, raising concerns about reliability [37]. Others attempted to improve classification on imbalanced datasets by proposing DeTraC, which achieved 93.1% accuracy; however, its effectiveness requires further validation [38]. To increase data availability, some groups used generative adversarial networks (GANs). A PGGAN-based approach reportedly improved classification accuracy to 99.2% by generating realistic radiographs [39]. Another team emphasized that CovidGAN is not an alternative to laboratory testing, but may contribute to more efficient and reliable radiology decision-support systems [40]. Establishing unified guidelines for the design and evaluation of AI models could improve reproducibility and clinical utility. Further studies should focus on algorithm optimization and their integration with healthcare information systems to enable broader application of AI in COVID-19 diagnostics.

Moreover, most models were trained on data from a single region or individual hospitals, limiting generalizability. Recent meta-analyses indicate that 88% of studies exhibit a high risk of bias [31]. Additionally, studies show that algorithms can learn 'demographic shortcuts', leading to disparate performance across ethnic groups; fairness corrections may help in training data but not necessarily in external tests [30]. Accordingly, reporting fairness metrics (e.g., differences in FPR/FNR across groups) and employing methods that increase data diversity are recommended.

Finally, despite the continued status of RT-PCR as the standard diagnostic method for detecting SARS-CoV-2, its use involves notable limitations, including the absence of a fully standardized diagnostic protocol, strong dependence of test performance on disease phase, potential sampling errors, and relatively long turnaround times [41, 42].

CONCLUSIONS

This review synthesizes evidence on multimodal artificial intelligence (AI) that integrates chest computed tomography, chest radiography and laboratory/clinical data to augment imaging-based diagnosis, triage and prognostication in COVID-19. Across study designs, these tools consistently deliver rapid, objective and reproducible quantification; reduce reader-to-reader variability; and can shorten time-to-result – capabilities that are particularly valuable during surges and in settings with limited specialist availability. When embedded in acute-care workflows, multimodal AI can inform ICU resource planning, help prioritize patients at risk of deterioration, and support timely therapeutic decisions.

Translating these advances into routine practice requires standardized image acquisition and reporting, robust data quality pipelines, rigorous multi-centre external validation, and seamless integration with clinical information systems. Equally important are model calibration and monitoring, safeguards for fairness across demographic subgroups, and transparent methods that support clinician understanding. AI systems should support, not replace, clinical judgment; patient-level decisions must remain contextual and physician-led.

Future research should prioritize prospective, impact-oriented studies; openly described benchmarks and reporting standards; richer multimodal fusion (imaging, laboratory data and clinical text); reproducible workflows; and continuous auditing of performance, bias and explainability in real-world use. Addressing these priorities will improve the reliability and accessibility of care while strengthening system resilience beyond the current disease context.

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