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Review

Applications of artificial intelligence in COVID-19 pandemic: A comprehensive review

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ABSTRACT

During the current global public health emergency caused by novel coronavirus disease 19 (COVID-19), researchers and medical experts started working day and night to search for new technologies to mitigate the COVID-19 pandemic. Recent studies have shown that artificial intelligence (AI) has been successfully employed in the health sector for various healthcare procedures. This study comprehensively reviewed the research and development on state-of-the-art applications of artificial intelligence for combating the COVID-19 pandemic. In the process of literature retrieval, the relevant literature from citation databases including ScienceDirect, Google Scholar, and Preprints from arXiv, medRxiv, and bioRxiv was selected. Recent advances in the field of AI-based technologies are critically reviewed and summarized. Various challenges associated with the use of these technologies are highlighted and based on updated studies and critical analysis, research gaps and future recommendations are identified and discussed. The comparison between various machine learning (ML) and deep learning (DL) methods, the dominant AI-based technique, mostly used ML and DL methods for COVID-19 detection, diagnosis, screening, classification, drug repurposing, prediction, and forecasting, and insights about where the current research is heading are highlighted. Recent research and development in the field of artificial intelligence has greatly improved the COVID-19 screening, diagnostics, and prediction and results in better scale-up, timely response, most reliable, and efficient outcomes, and sometimes outperforms humans in certain healthcare tasks. This review article will help researchers, healthcare institutes and organizations, government officials, and policymakers with new insights into how AI can control the COVID-19 pandemic and drive more research and studies for mitigating the COVID-19 outbreak.

1. Introduction

A novel coronavirus disease 19, also referred to as COVID-19, is an infectious disease caused by severe respiratory syndrome coronavirus type 2 (SARS-CoV-2) (Awasthi et al., 2020; de Almeida et al., 2020; Manigandan et al., 2020). The most common symptoms experienced by COVID-19 infected patients are dry cough, loss of smell and taste, fever, fatigue, and respiratory illness such as shortness of breath (Ibrahim, 2020; Jalaber et al., 2020). The cross-sectional view of SARS-CoV-2 shown in Fig. 1, which is comprised of spike protein (S), nucleocapsid protein (N), hemagglutinin-esterase dimer (HE), membrane glycoprotein/ matrix (M), an envelope protein (E), and single-strand RNA, non-segmented, enveloped (Su et al., 2020). The first case of coronavirus infected patient was recorded in December 2019 in Wuhan city, Hubei, China and afterward, the infected cases increased so rapidly throughout the world that the World Health Organization (WHO) has declared it a Public Health Emergency of International Concern (PHEIC) on January 30, 2020 (Deng et al., 2020; Sohrabi et al., 2020).

To control and mitigate the transmission of the novel virus, many countries have announced lockdowns and curfews with immediate effect. Paramedical staff, scientists, and researchers started working day and night to search for new technologies to mitigate the COVID-19 pandemic as a short-term strategy and started research on making a vaccine as an antidote for the virus as a long-term strategy (Li, 2020; Pontone et al., 2020). Currently, two types of standard tests are being

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Nomenclature

AI	Artificial intelligence
ML	Machine learning
DL	Deep learning
SVM	Support vector machine
RF	Random forest
ANFL	Adaptive neuro-fuzzy logic
PCA	Principal component analysis
DBN	Deep belief networks
KNN	k-nearest neighbor's algorithm
ANN	Artificial neural network
RNN	Recurrent neural networks
MLR	Multilinear regression
GBM	Gradient boosting machine
MVNL	Multi variant non-linear
CNN	Convolutional neural network
FL	Fuzzy logic
GPR	Gaussian process regression
SARS-CoV-2	Severe respiratory syndrome coronavirus type 2
IRRCNN	Inception residual recurrent convolutional neural network
DETL	Domain extension transfer learning.
CSEN	Convolution support estimation network
DSCNN	Depth-wise separable convolutional neural network
DFCNN	Dense fully convolutional neural network
FFNN	Feed-forward neural network full image
FBFFNN	Feature-based feed-forward neural network.
FCN	Fully convolution network
GBDT	Gradient boosting decision tree algorithm
RWF	Robust weibull fitting
RS	Reduced space
GPR	Gaussian process regression model
BRNN	Bayesian regression neural network
QRF	Quantile random forest
PDR-NML	Partial derivative regression and nonlinear machine learning
CMC	Composite monte-Carlo
WCRVFL	Wavelet-coupled random vector functional link
CoxPH	Cox proportional hazard
GB	Gradient boosting
SIoT	Social internet of things
ARIMA	Autoregressive integrated moving average
RL	Reinforcement learning
DDPG	Deep deterministic policy gradient
SARSA	State-action-reward-state-action
CSGB	Coxnet stage-wise gradient boosting
CGB	Component wise gradient boosting
FSVM	Fast kernel support vector machine
NLP	Natural language processing
LSTM	Long short-term memory
ISI	Improved susceptible–infected.
SEI	Susceptible-exposed-infected-remove.
SEL	Stacking-ensemble learning
GLEAM	Global epidemic and mobility model
NNAQC	Neural network aided quarantine control
PLSR	Partial least squares regression
EN	Elastic net
BFDA	Bagged flexible discriminant analysis.
ANFIS	Adaptive network-based fuzzy inference system
BFDA	Bagged flexible discriminant analysis.

conducted for the detection of coronavirus disease, the diagnostic tests, and the antibody tests. These techniques are costly, time-consuming, need specific materials and instruments, and are not effective enough to give true positive rates. Therefore, the standard methods are not feasible for the rapid diagnosis and tracking of coronavirus disease (Tahamtan & Ardebili, 2020; Ai et al., 2020; Pham et al., 2020).

Recent studies have shown that artificial intelligence (AI) is a promising technology that can be employed in various sectors such as, in process industries, the agriculture sector, banking, computing, and healthcare (Wirtz et al., 2019; Liu et al., 2020; Abduljabbar et al., 2019). This emerging technology is used in various medical studies and results in better scale-up, timely, most reliable, and efficient outcomes, and sometimes outperforms humans in certain healthcare tasks (Coeckelbergh, 2010; Nadarzynski et al., 2019; Cossy-Gantner et al., 2018). Artificial intelligence is a subfield of computer science that emphasizes the design of intelligent systems that can learn from the data and make decisions and predictions accordingly. Machine learning (ML) and deep learning (DL) are the two main branches of AI out of many. ML is a subset of AI that can automatically learn and improve accordingly from experience without being programmed explicitly. ML-based algorithms depend on the characteristic features. Some of the dominant ML methods include artificial neural networks (ANN), random forest (RF), support vector machine (SVM), and decision tree (DT). While DL is the subset of machine learning that can solve complex schemes through representation learning. Some of the dominant DL methods include; convolutional neural network (CNN), recurrent neural network (RNN),

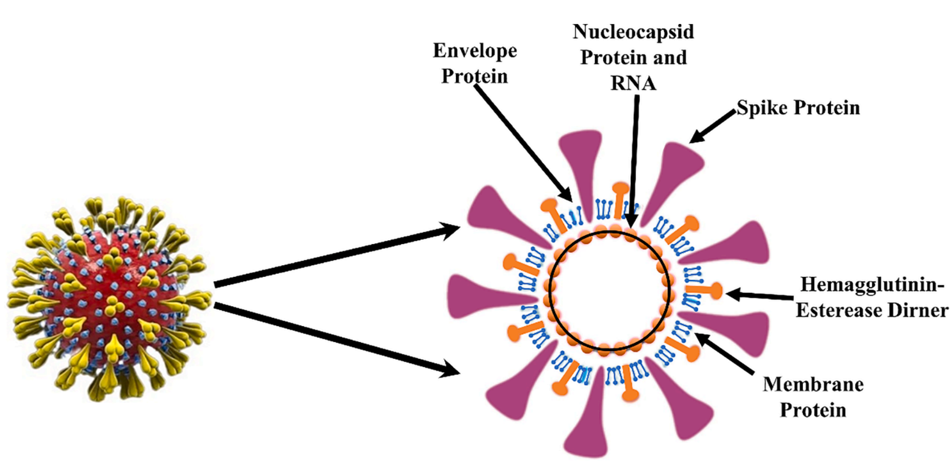

Fig. 1. Cross-sectional View of SARS-CoV-2.

and long short-term memory (LSTM) (Kumar & Thakur, 2012; Fan et al., 2020; Khanum et al., 2015).

Artificial intelligence-based tools, particularly deep learning models, are the promising techniques used to assist radiologists in the early screening of coronavirus. Moreover, it reduces the workload of the radiologists, improves detection more accurately and efficiently, gives a timely response and accurate treatment for the patients of COVID-19 (Albahri et al., 2020; Swapnarekha et al., 2020; Sufian et al., 2020). AI coupled with drug repurposing can detect the drugs that can be used to combat novel diseases like COVID-19. The use of such emerging technologies has the potential to significantly alleviate the main issue associated with drug repurposing, which is the diagnosis and identification of the drug-disease relationship. Various applications of AI to combat the COVID-19 outbreak include virus identification, screening, and diagnostics, drug repurposing or repositioning, prediction and forecasting (Lin et al., 2020; Vaishya et al., 2020; Ahuja et al., 2020; Monshi et al., 2020).

Our focus is to highlight the applications of AI to combat the COVID-19 pandemic and to discuss the state-of-the-art solutions to tackle COVID-19 with the help of these emerging technologies. Moreover, various challenges associated with AI are highlighted, which inspired us to present a list of recommendations for researchers, academia, governments, and other communities working in a similar area. For this purpose, various citation databases available online were used to retrieve the relevant literature. The citation databases selected in this paper include ScienceDirect, Google Scholar, and preprints from arXiv, medRxiv, and bioRxiv. After screening and filtration, the final literature dataset of relevant articles was obtained and critically reviewed.

The remaining paper is organized as follows. Section 2 presents the applications of AI (ML and DL) to combat COVID-19. In section 3, challenges and limitations faced while using AI are discussed. Finally, the study is concluded in section 4.

2. Applications of AI to Combat Covid-19

Artificial intelligence (AI) based tools are widely used for the identification, classification, and diagnosis of medical images to control the spread of disease (Alsharif et al., 2020; Chen et al., 2020a). Recent research and development in the field of artificial intelligence has greatly improved the COVID-19 screening, diagnostics, and prediction and results in better scale-up, timely response, most reliable, and efficient outcomes, and sometimes outperforms humans in certain healthcare tasks (Sipior, 2020; Beck et al., 2020; Pant et al., 2020). Machine learning (ML) and deep learning (DL) are the two main branches of AI out of many. Applications of both ML and DL in combating and mitigating the COVID-19 pandemic are reviewed in the subsequent sections. Fig. 2 shows the schematic view of applications of machine learning and deep learning in combating COVID-19.

2.1. Applications of Machine Learning in COVID-19 Screening, Diagnostics, Classification, and Prediction

Machine learning is a subset of AI that can automatically learn and improve accordingly from experience without being programmed explicitly. ML-based algorithms primarily depend on characteristic features. A complex and huge amount of data can be developed by using ML-based techniques. These techniques have been widely used for finding the patterns of epidemics and for forecasting purposes. With regards to the COVID-19 pandemic, such techniques have been used by several researchers for screening, classification, diagnosis, drug repurposing, and prediction of COVID-19 (A. Kumar, Gupta, & et al., 2020; Mbunge, 2020; Waleed Salehi et al., 2020). Applications of some of the important ML methods including support vector machine (SVM), logistic regression (LR), random forest (RF), and decision tree (DT) in combating the COVID-19 pandemic are discussed.

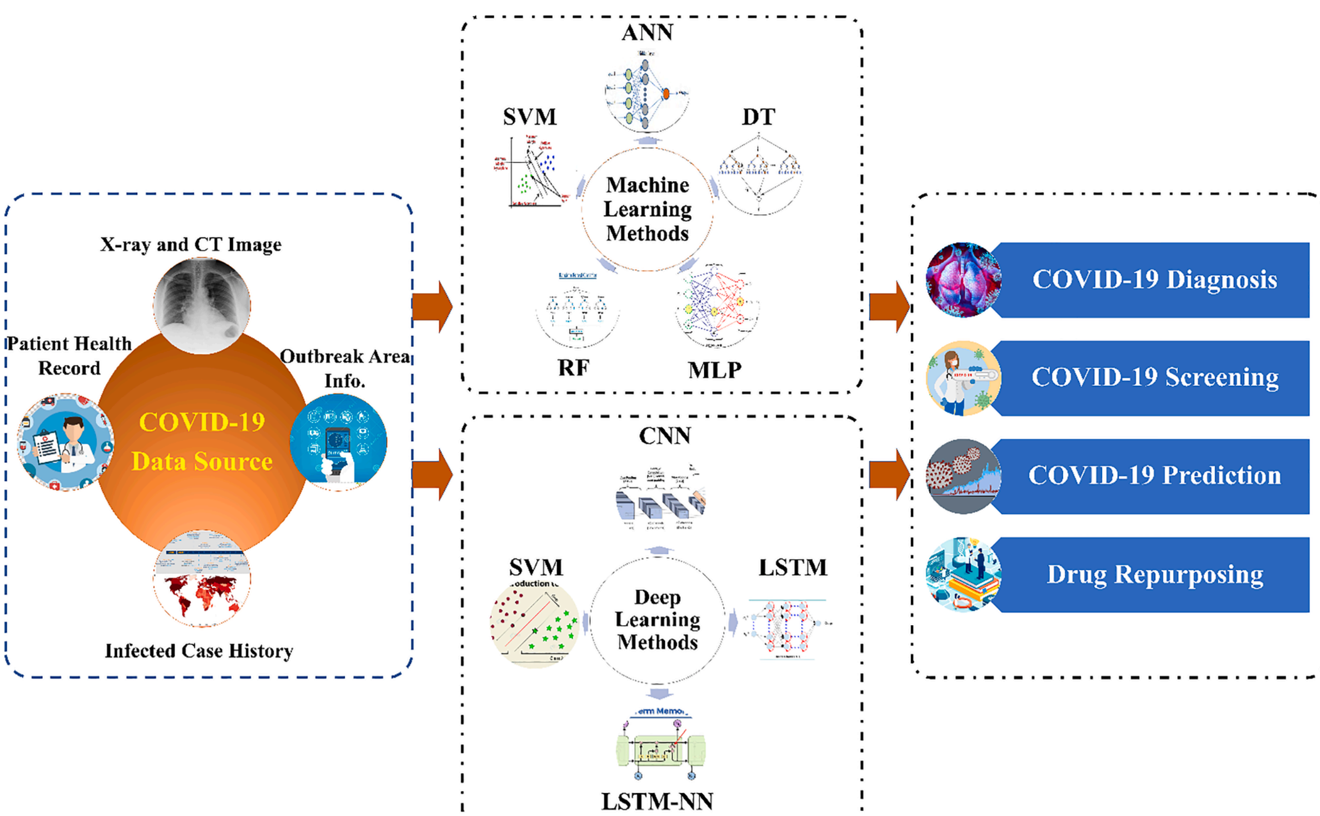

Fig. 2. Schematic view of applications of Artificial Intelligence for fighting COVID-19.

2.1.1. Support Vector Machine (SVM)

Support vector machine (SVM) is a powerful tool used for solving classification and regression problems. It has been in numerous real-world applications, including the health sector, due to its high accuracy and performance. Therefore, recently, SVM has been used for combating the COVID-19 pandemic because of its superior performance (Singh, Poonia, & et al., 2020; Ismael & Şengür, 2021). Various articles published on the detection (Hassanien et al., 2020; Yao et al., 2020; Sethy et al., 2020), classification (Barstugan et al., 2020; Randhawa et al., 2020), and prediction and forecasting (Hazarika & Gupta, 2020; Ribeiro et al., 2020; Pourhomayoun & Shakibi, 2020; Fang et al., 2020; Sun et al., 2020; Ella Hassanien et al., 2020; Batista et al., 2020) have been discussed in this sub-section.

For the early detection and diagnosis of COVID-19 cases, researchers (Hassanien et al., 2020) developed a model based on SVM using X-ray images. The dataset consists of 40 contrast-enhanced lungs X-ray images, among which 15 were normal lungs images while the other 25 were COVID-19 infected chest X-ray images. The suggested model showed high performance (sensitivity = 95.76%, specificity = 99.7%, and accuracy = 97.48%), showing the SVM-based model can be employed efficiently for the identification of novel coronavirus disease. Furthermore, authors (Barstugan et al., 2020) developed an ML-based model for the classification of COVID-19 using computed tomography (CT) images. The sample size comprises 150 CT abdominal images of the 53 infected cases. To enhance the classification performance, various feature extraction methods were applied followed by the classification of extracted features via SVM. During the classification process, 2-, 5-, and 10-fold cross-validations were implemented among which the 10-fold cross-validation achieved relatively high accuracy of (sensitivity = 97.56%, specificity = 99.68%, and accuracy = 98.71%). Finally, the authors suggested that the proposed model should be tested on another COVID-19 CT-images-based dataset.

To predict the symptoms of COVID-19 infected patients, the SVM model has been developed by (Sun et al., 2020) by analyzing more than 200 laboratory and clinical features. Results show the better performance of the suggested model with AUROC equals 0.996 for the training dataset and 0.9757 for the testing dataset. In another study, five ML-based models were developed to predict the diagnosis of COVID-19 in emergency care patients (Ella Hassanien et al., 2020). These models include NN, RF, LR, SVM, and GBT. These models were trained on the dataset collected from 235 adult hospitalized patients from 17th to 30th March 2020. It was concluded by the authors that among five ML-based methods, SVM achieved the best predictive results with an accuracy of 85%. The following Table 1 describes the usage of SVM models in the detection, classification, prediction, and forecasting of the COVID-19 pandemic.

2.1.2. Random Forest (RF)

The random forest algorithm (RF) is a statistical tool and is one of the most promising classifiers used to solve classification and regression problems. Multiple trees are used for the training and prediction of data samples. RF has been widely used in bioinformatics and chemometrics (Pavlov, 2019; Siekmann, 2005). In the context of COVID-19, RF has been extensively used by researchers for mitigating the COVID-19 pandemic. For the rapid and accurate screening of COVID-19, an infectious size aware rapid random forest (iSARF) model was developed by (Shi et al., 2020). In this work, the CT scans of 1658 (COVID-19 positive) and 1027 (CAP) were collected followed by preprocessing of these CT images. The suggested model achieved better results (accuracy = 87.9%, sensitivity = 90.7%, and specificity = 83.3%) in the screening of coronavirus diseases using the 5-fold cross-validation. Furthermore, it was suggested that by including the radionics feature, the proposed model showed more improvements in the results.

Due to the massive increase in the number of COVID-19 infected patients, the manual severity assessment of COVID-19 becomes difficult and time-consuming. Recently, the ML-based model suggested by (Tang et al., 2020) can be used to automatically identify the more severe and less severe cases of COVID-19 infected patients. The RF model is trained with the CT images of 176 COVID-19 positive patients for the severity assessment. The suggested model presented promising results with 87.5% accuracy using 3-fold cross-validation. According to the authors, various quantitative features were identified with the potential of assessing the severity of COVID-19.

A clinical model for the early prediction of severe cases of COVID-19 using five ML-based models was suggested by (Guan et al., 2020). In this work, the clinical history of 183 (COVID-19 severe) cases was used to

Table 1
Summary of Applications of Support Vector Machine (SVM) in Combating COVID-19.

References	Country	Purpose	Model	Data Type	Sample size	Performance
(Hassanien et al., 2020)	Egypt	Detection	SVM	X-Ray Images	40 contrast-enhanced lungs X-ray 25 infected COVID-19 15 normal images	Sensitivity = 95.76 Specificity = 99.7 Accuracy = 97.48
(Yao et al., 2020)	India	Detection	SVM	Blood and Urine Tests	137 COVID-19 positive	Accuracy = 81.48
(Sethy et al., 2020)	India	Detection	Resnet50 Plus SVM	X-Ray Images	———	ResNet50 plus SVM Accuracy = 95.33 Sensitivity = 95.33
(Barstugan et al., 2020)	Turkey	Classification	SVM	CT Images	150 CT abdominal images, which belong the 53 infected cases	Sensitivity = 97.56 Specificity = 99.68 Accuracy = 98.71
(Randhawa et al., 2020)	Canada	Classification	SVM	Time series	75,752 confirmed cases	Test#6 Classification Accuracy = 100
(Hazarika & Gupta, 2020)	India	Forecasting	SVR	Time series	report on 10th July 2020	based on R^2 Average rank = 4.8
(Ribeiro et al., 2020)	Brazil	Forecasting	SVR	Time series	April 18 or 19 of 2020	RS ODA [MAE = 8.17, sMAPE = 0.97]
(Pourhomayoun & Shakibi, 2020)	USA	Prediction	SVM	Clinical Data	117,000 patients	Accuracy = 90.63
(Fang et al., 2020)	China	Prediction	SVM	Clinical Data	1,040 patients	Accuracy = 76.3 Sensitivity = 0.80 Specificity = 99.5
(Sun et al., 2020)	China	Prediction	SVM	Time series	336 cases	Recall rate, Training = 93.33 Testing = 100
(Ella Hassanien et al., 2020)	Egypt	Prediction	SVM	ID, Age, Sex, City, Province, Country	15 attributes of symptoms	MAE = 0.2155
(Batista et al., 2020)	Brazil	Prediction	SVM	RT-PCR Tests	235 adult patients	Sensitivity = 68 Specificity = 85

develop the model. These five ML-based models (RF, BFDA, LR, EN, and PLSR) were used for the feature selection and prediction of patient outcomes. The performance of the proposed models was measured using the area under the receiver operating characteristic curve (AUROC), which was 0.88 for the external validation and 0.895 for the derivation. The following Table 2 describes the applications of RF in the detection, classification, prediction, and forecasting of the COVID-19 pandemic.

2.1.3. Decision Tree (DT)

The decision tree (DT) algorithm is a mathematical tool used for solving regression and classification problems. Due to its easy usage and robustness, DT has been widely used in several fields (Patel & Rana, 2014; Su & Zhang, 2006). Recently, DT has become well-known in the medical research and health sector. For instance, the model-based decision trees were developed for the severity detection of COVID-19 in children (Yu et al., 2020). The clinical laboratory and epidemiological reports of 105 infected children were obtained from the hospital in China from February 1 to March 3, 2020. Results showed that 105 children, including 41 females and 64 males, were COVID-19 positive. The female infection rate (39.05%) is lower than that of the male (60.95%). The proposed model performed well and achieved an F1 score of 100.

Early detection of COVID-19 suspected cases without using CT scans was suggested by (Feng et al., 2020). The dataset of patients admitted to the hospital (Jan 14 to Feb 26, 2020) was used for training and validating the proposed model. The dataset comprises clinical symptoms, lab reports, and patient history upon admission. Lasso regression was used for feature selection and model development. In this study, four different algorithms were compared, including LR with the LASSO, LR with the ridge regularization, DT, and xgboost algorithm. With an AUC of 0.5 specificities of 100, the model validation cohort performed well.

Comparative study of various ML methods including DT, RF, KNN, SVM, LR, and ANN was used for the prediction of mortality rate in COVID-19 infected patients. The dataset of 117,000 COVID-19 infected cases, including both genders, was used in this study. The model achieved 93% accuracy for the prediction of mortality rate. While individually, DT has achieved an accuracy of 90.63 using 10-fold cross-validation (Pourhomayoun & Shakibi, 2020). Table 3 describes the applications of the DT approach in the detection, prediction, and forecasting of the COVID-19 pandemic.

2.1.4. Logistic Regression (LR)

Logistic regression (LR) is a statistical tool and regression analysis that uses a logistic function to model a binary dependent variable and is used when the target variable is categorical (Field, 2012). More recently, LR has been used in mitigating the COVID-19 pandemic. The diagnosis of COVID-19 was performed using multivariate logistic regression using a dataset of 620 samples from the laboratory. The distribution of samples for the training set was 431 samples and 189 samples for the testing set. The performance of the proposed model was satisfactory with a positive predictive value of 86.35% and 86.62% for the negative predictive value (Meng et al., 2020).

A clinical-based model for the early COVID-19 mortality risk prediction was developed using various machine learning methods. The clinical information of 183 serious COVID-19 cases was collected for developing the model. In this study, five different machine learning

Table 2
Summary of Applications of Random Forest (RF) in Combating COVID-19.

References	Country	Purpose	Model	Data type	Sample size	Performance
(Wu et al., 2020)	China	Identification	RF	Blood test	49 clinical available blood test data	Sensitivity = 95.12 Specificity = 96.97 Accuracy = 95.95
(Sarkar & Chakrabarti, 2020)	India	Identification	RF	Clinical Data	1085 cases of COVID-19	Area under the ROC curve 97
(Cobb & Seale, 2020)	USA	Examining	RFML	Time Series	COVID-19 cases (January 21 to March 31, 2020)	RFML Accuracy = 92.3 MAPE = 92.3
(Shi et al., 2020)	China	Screening	iSARF	CT images	1658 COVID-19 and 1027 CAP cases	Sensitivity = 90.7, Specificity = 83.3, Accuracy = 87.9
(Magar et al., 2020)	Pennsylvania	Antibodies Discovery	RF	Clinical Data	1933 virus-antibody	RF Performance = 89.18
(Tang et al., 2020)	China	Severity Assessment	RF	CT Images	CT images 176 patients (96 male and 80 female) COVID-19	True positive rate = 93.3 True negative rate = 74.5 Accuracy = 87.5
(Chen, Jianguo, & et al., 2020; Chen, Wu, & et al., 2020; Chen, Hu, & et al., 2020)	China	Severity Assessment	RFS	Time Series	106 COVID-19 patients 63 females 43 males	Gender index of 0.022, Hypertension index of 0.035, age index of 0.007 cortisone index of 0.026,
(Batista et al., 2020)	Brazil	Prediction	RF	RT-PCR Tests	235 adult patients 102 received a positive diagnosis of COVID-19	Sensitivity = 75.3 Specificity = 84.6
(Middleton & Rowley, 2014)	China	Prediction	RF	CT Image	52 patients	AUC = 92 Sensitivity = 75 Specificity = 100
(Guan et al., 2020)	China	Prediction	RF	Clinical Data	183 severe COVID-19 patients	AUROC = 92.2
(Pourhomayoun & Shakibi, 2020)	USA	Prediction	RF	Clinical Data	117,000 patients	10-fold cross-validation Accuracy = 91.88
(Qiang et al., 2020)	China	Prediction	RF	Time series	Protein sequences of 2666 coronaviruses	GGAP (g = 3) Accuracy = 98.18 Sensitivity = 99.16 Specificity = 97.26
(Sarkar & Chakrabarti, 2020)	India	Prediction	RF	Clinical data	1085 cases	Area under the ROC curve = 0.97
(da Silva et al., 2020)	Brazil	Forecasting	RF	Time series	April 28th, 2020	TDA [MAE = 6.39, sMAPE = 7.28]
(Ribeiro et al., 2020)	Brazil	Forecasting	RF	Time series	April 18 or 19 of 2020	ODA, TDA, SDA [MAE = 179.5, sMAPE = 20.97]

Table 3
Summary of Applications of Decision Tree (DT) in Combating COVID-19.

References	Country	Purpose	Model	Data Type	Sample size	Performance
(Yu et al., 2020)	China	Detection	DT	Clinical Data	105 infected children	F1 score = 100
(Magar et al., 2020)	Pennsylvania	Discovery of Antibodies	DT	Clinical Data	1933 virus-antibody	Performance = 75.49
(DeCapprio et al., 2020)	USA	Identification	DT	Time series	Training = 1,481,654 Test set = 369,865	ROC AUC = 81.0 Sensitivity at 5%, Alert rate = 32.4
(Feng et al., 2020)	China	Diagnosis	DT	Time series	Feb 10 to Feb 26, 2020	Validation cohort AUC 0.5 Specificity = 100
(Pourhomayoun & Shakibi, 2020)	USA	Prediction	DT	Clinical Data	117,000 patients	10-fold cross validation Accuracy = 90.63
(Yan, Zhang, Xiao, et al., 2020)	China	Prediction	DT	Clinical Data	375 Patients	Accuracy = 91
(Yan, Zhang, Goncalves, et al., 2020)	China	Prediction	DT	Clinical Data	404 patients	Accuracy = 90
(Fong et al., 2020b)	China	Forecasting	DT	Time Series	21 Jan–3 Feb 2020	RMSE 1744.526

methods (LR, RF, PLSR, BFDA, and EN) were used for the feature selection and mortality rate prediction. For the performance evaluation, the area under the receiver operating characteristic curve (AUROC) was implemented. Moreover, 64 serious COVID-19 cases were used for the external validation of the ultimate predictive model. Four features including lymphocyte count, age, C-reactive protein, and d-dimer levels were selected by all models. The proposed model achieved high performance with AUROCs of 0.895 for derivation and 0.881 for the external validation (Guan et al., 2020). Table 4 describes the applications of the LR approach in the detection, prediction, and forecasting of the COVID-19 pandemic.

2.1.5. Other Machine Learning methods

Besides SVM, RF, DT, and LR, other ML-based approaches such as multilayer perceptron (MLP), xgboost, k-means, gaussian process regression (GPR), and neural networks have also been used in the screening, detection, prediction, and forecasting of COVID-19. The following Table 5 illustrates the applications of other methods in the detection, classification, prediction, and forecasting of the COVID-19 pandemic.

2.2. Applications of Deep Learning in COVID-19 Screening, Diagnostics, Classification, Drug Repurposing, and Prediction

Deep learning (DL) is the subset of machine learning, that can solve complex schemes through representation learning (Chan et al., 2020; Yan, 2016). Recently, deep learning-based algorithms have been used by various researchers for combating the COVID-19 pandemic, including convolutional neural network (CNN), recurrent neural network (RNN), and long short-term memory (LSTM) for the COVID-19 detection, diagnosis, classification. Screening, drug repurposing, prediction, and forecasting (Bogu & Snyder, 2021; Desai et al., 2020; Ghoshal & Tucker, 2020; He et al., 2020; Hu et al., 2020; Khurana et al., 2021; Mirza Rahim Baig et al., 2019; Pan et al., 2021; Sarv Ahrabi et al., 2021; Sedik et al., 2021; Soni & Roberts, 2020).

2.2.1. Convolutional Neural Network (CNN)

A convolutional neural network (CNN) is a deep learning algorithm

Table 4
Summary of Applications of Logistic Regression (LR) in Combating COVID-19.

References	Country	Purpose	Model	Data Type	Sample size	Performance
(Shi et al., 2020)	China	Screening	LR	CT images	2685 participants 1658 COVID-19	Sensitivity = 89.7 Specificity = 80.5 Accuracy = 86.2
(Magar et al., 2020)	Pennsylvania	Discovery of Antibodies	LR	Clinical Data	1933 virus-antibody	Performance = 81.17
(DeCapprio et al., 2020)	USA	Identification	LR	Time series CV19 index	Training = 1,481,654 Test set = 369,865	ROC AUC = 73.1 Sensitivity at 5%
(Meng et al., 2020)	China	Diagnosis	LR	Time Series	620 samples 431 Training Set 189 Testing Set	AUC = 0.890
(Feng et al., 2020)	China	Diagnosis	LR	Time series	Feb 10 to Feb 26, 2020	Validation cohort AUC = 0.8409 Precision = 40 Recall = 100
(Pourhomayoun & Shakibi, 2020)	USA	Prediction	LR	Clinical Data	117,000 patients	Accuracy = 90.00
(Guan et al., 2020)	China	Prediction	LR	Clinical Data	183 severe COVID-19 Patients	Sensitivity = 83.9 Specificity = 79.4
(Middleton & Rowley, 2014)	China	Prediction	LR	CT Image	52 patients	Sensitivity = 100 Specificity = 89
(Batista et al., 2020)	Brazil	Prediction	LR	RT-PCR Tests	235 adult patients 102 received a positive diagnosis of COVID-19	F1 Score = 75.0 Sensitivity = 78.0 Specificity = 77.4
(Yan, Zhang, Goncalves, et al., 2020)	China	Prediction	LR	CT Images	52 Patients	Sensitivity = 100 Specificity = 89
(Demirci & Adan, 2020)	China	Prediction	LR	Clinical Data	372 non-severe COVID-19 patients	AUC = 0.853 Sensitivity = 77.5 Specificity = 78.4

Table 5
Summary of Applications of other ML methods for Combating COVID-19.

References	Country	Purpose	Model/Architecture	Data type	Sample size	Performance
(Magar et al., 2020)	USA	Screening	XGBoost	Text data	1933 virus-antibody	XGBoost = 90.57
(Mei et al., 2020)	China	Diagnosis	MLP	CT images	905 patients 419 tested positive for SARS-CoV-2	Sensitivity = 84.3 Specificity = 82.8 AUC = 0.92
(Zhang, Liu, & et al., 2020)	China	Diagnosis and Prognosis	U-net, DRUNET, FCN, SegNet, DeepLabv3, GBDT	CT images	617,775 CT images from 4,154 patients	Accuracy = 92.49 Specificity = 91.13
(Al-karawi et al., 2020)	UK	Detection	FFT-Gabor scheme	CT images	Covid-19 275 positive and 195 negatives	Accuracy = 95.37 specificity 94.76
(Carrillo-Larco & Castillo-Cara, 2020)	UK	Classification	k means	Text data	155 countries	$p < 0.001$
(Barstugan et al., 2020)	Turkey	Classification	GLCM, LDP, GLRLM, GLSZM, DWT, SVM	CT images	150 CT images	Accuracy = 99.6% with 10-fold
(Nemati et al., 2020)	USA	Prediction	IPCRidge, CPH, CSGB, CGB, FSVM, FKSVM	Clinical Data	1,182 patients	Stage wise GB Prediction Accuracies 71.47
(Guan et al., 2020)	China	Prediction	LR, PLSR, EN, RF, BFDA	Time series	83 severe COVID-19 patients	Sensitivity = 83.9 Specificity = 79.4
(Ribeiro et al., 2020)	Brazil	Forecasting	ARIMA, SVR, RF, RIDGE, CUBIST	Time series	until April 18 or 19 of 2020	Error One day 0.87–3.51 Three days1.02–5.63 Six days 0.95–6.90
(da Silva et al., 2020)	Brazil	Forecasting	GPR, BRNN, KNN, QRF, SVR	Time-series	April 28th, 2020	NY ODA [RRMSE = 0.92, sMAPE = 0.84]
(Fong et al., 2020a)	China	Forecasting	CMC, GROOMS + CMCM, BFGS + PNN	Time-series	25 Jan 2020 to 25 Feb 2020	BFGS + PNN RMSE = 62077.26 CMC RMSE = 127693.55

primarily designed for image analysis. The main advantage of using CNN over traditional methods is that it requires much lower pre-processing (Indolia et al., 2018; Sony et al., 2021). CNN has several applications in different fields, including medical image analysis (Stephen et al., 2019). Recently, CNN has been widely used for combating the COVID-19 pandemic. For instance, it is used for COVID-19 screening, diagnostics, classification, prediction, and forecasting (Afifi et al., 2021; Cui & Lee, 2020; Huang et al., 2021; Liang et al., 2021; Lorencin et al., 2021; Sheykhivand et al., 2021; Zhang et al., 2021).

a. Detection and diagnosis

The rapid spread of COVID-19 made it very difficult for clinicians and radiologists to precisely detect the virus-infected patients under a huge workload. Artificial intelligence-based tools, particularly deep learning models, are the promising techniques used to assist radiologists in the early detection and diagnosis of coronavirus. Moreover, it reduces the workload of the radiologists, improves detection more accurately and efficiently, gives a timely response and accurate treatment for the patients of COVID-19 (Balamurugan & Duraisamy, 2020; Omoniyi et al., 2021; Siswantining & Parlindungan, 2021). In this regard, the summary of various DL methods used in the detection and diagnosis of COVID-19 is presented in Tables 6 and 7. Since CT images and X-ray images are the most used input variables of the CNN detection and diagnosis models, we have reviewed these separately.

i. CT-Images:

Recently, the rapid increase in the number of publications on detection and diagnosis of COVID-19 with computed tomography (CT) images has been witnessed. The deep CNN-based model for the rapid detection of COVID-19 using CT images has been proposed by (Jin et al., 2019). In this study, a dataset of 10,250 CT scans of COVID-19, community-acquired pneumonia (CAP), influenza, and non-pneumonia was collected. The proposed model achieved high performance (AUC = 97.17% and specificity = 95.76%). In another study by (Razzak et al., 2020), the authors used deep transfer learning and different CNN architectures for the detection of COVID-19 pneumonia using CT images. In this work, nine CNN architectures were used, including AlexNet, ResNet101, SqueezeNet, ResNet18, VGG16, GoogLeNet, MobileNet, ResNet50, and DenseNet. The dataset was divided into an 80% training set and a 20% validation set. Results showed that the model achieved a

Table 6
Summary of Applications of CNN using CT images for Detection and Diagnosis of COVID-19.

References	Country	Purpose	Model/Architecture	Data Type	Sample size	Performance
(Jin et al., 2019)	China	Diagnosis	CNN	CT Images	10,000 COVID-19 CT scans, influenza-A/B, CAP and non-pneumonia	AUC = 97.17 Sensitivity = 90.19 Specificity = 95.76
(Maghdid et al., 2020)	Iraq	Diagnosing	CNN AlexNet model	CT Images	361 CT images COVID-19	Accuracy = 94.1 Sensitivity = 90 Specificity = 100
(Song et al., 2020)	China	Diagnosis	VGG16 DenseNet ResNet DRE-Net	CT Images	88 COVID-19 101 bacterial pneumonia 86 healthy cases	Recall = 93 Precision = 96 Accuracy = 94 AUC = 99
(Razzak et al., 2020)	Pakistan	Diagnosis	CNN	CT Images	BinaryClass Dataset COVID-2019	Accuracy = 98.75 Specificity = 97.50 Sensitivity = 100
(Qjidaa et al., 2020)	Morocco	Detection	VGG CNN	CT Images	100 images COVID-19 100 images viral pneumonia 100 images of normal cases	Accuracy = 92.5 Sensitivity = 92
(Alom et al., 2020)	USA	Detection	IRRCNN	CT Images	5,216 Total 1341 Normal 3875 Pneumonia	X-ray images Accuracy = 84.67 CT-images Accuracy = 98.78
(Chen, Wu, & et al., 2020)	China	Detection	UNet++	CT Images	106 admitted patients 51 patients COVID-19, 55 control patients of other diseases	Sensitivity = 94.34 Specificity = 99.16 Accuracy = 98.85
(Zheng, Deng, & et al., 2020)	China	Detection	DeCoVNet 2D Unet	CT Images	540 patients	Threshold 0.5 Accuracy = 90.1

Table 7
Summary of Applications of CNN using X-ray images for Detection and Diagnosis of COVID-19.

References	Country	Purpose	Model/Architecture	Data Type	Sample size	Performance
(Shibly et al., 2020)	Bangladesh	Diagnose	CNN	X-Ray Images	Normal 300 non-COVID Pneumonia 950 COVID19 20 Total 1270	Sensitivity = 97.65 Precision = 99.29 Accuracy = 97.36
(Hall et al., 2020)	USA	Diagnosing	CNN	X-Ray Images	135 COVID-19 cases	AUC = 95 Accuracy = 89.2
(Hassantabar et al., 2020)	USA	Detection and Diagnosis	CNN	X-Ray Images	315 images total 271 COVID-19 44 Non COVID-19	Accuracy = 93.2 Sensitivity = 96.1
(Khan et al., 2020)	India	Detection and Diagnosis	CNN CoroNet	X-Ray Images	Normal 310 Pneumonia Bacterial 330 Pneumonia Viral 327 COVID-19 284	Accuracy = 89.6 Precision = 90 Specificity = 96.4
(Ouchicha et al., 2020)	Morocco	Detection	CVDNet	X-Ray Images	219 COVID-19 1341 normal 1345 viral pneumonia	Precision = 96.72 Recall = 96.84 Accuracy = 96.69
(Nour et al., 2020)	Saudi Arabia	Detection	CNN	X-Ray Images	COVID-19 219 Normal 1341 Viral Pneumonia 1345 Total 2905	Accuracy = 97.14 Sensitivity = 94.61 Specificity = 98.29
(Karthik et al., 2020)	India	Detection	CSDB CNN	X-Ray Images	558 COVID-19 Chest X-rays	Precision = 95.93 Accuracy = 93.42 F1 Score = 99.57
(Alqudah et al., 2020)	Jordon	Detection	CNN-Softmax	X-Ray Images	71 chest X-ray images (48 cases for COVID-19 and 23 for Non-COVID-19	Accuracy = 95.2 Sensitivity = 93.3 Specificity = 100
(Ozturk et al., 2020)	Turkey	Detection	DarkCovidNet	X-Ray Images	127 X-ray images 43 Female 82 Male 26 Covid-19 Positive	Sensitivity = 95.13 Specificity = 95.3 Accuracy = 98.08
(Heidari et al., 2020)	USA	Detection	CNN-based CAD scheme	X-Ray Images	757 Cases 37 Covid 460 non Covid 260 normal	Accuracy = 94.5 Sensitivity = 98.4 Specificity = 98.0
(Islam et al., 2020)	Bangladesh	Detection	CNN-LSTM	X-Ray Images	915 overall cases 305 Covid 305 normal 305 pneumonia	Accuracy = 99.4 Sensitivity = 99.3 Specificity = 99.2
(Abbas et al., 2020)	Egypt	Detection	CNN DeTraC	X-Ray Images	norm 80 COVID19 105 SARS 11	Accuracy = 95.12 Sensitivity = 97.91 Specificity = 91.87
(Minaee et al., 2020)	USA	Detection	ResNet18 ResNet50 SqueezeNet DenseNet-121	X-Ray Images	200 COVID-19 images 5,000 non-COVID images	Sensitivity = 98 Specificity = 90
(Haghanifar et al., 2020)	Canada	Detection	CheXNet COVID-CXNet	X-Ray Images	3628 images 3,200 normal CXRs 428 COVID-19 CXRs	Accuracy = 87.21
(Chowdhury et al., 2020)	Bangladesh	Detection	CNN	X-Ray Images	2905 chest X-ray images 219 COVID-19 positive 1341 normal 1345 viral pneumonia chest X-ray images	Accuracy = 96.58 Precision = 96.58 Recall = 96.59
(Apostolopoulos et al., 2020)	Greece	Detection	CNN MobileNet v2	X–Ray Images	3905 X-ray images	Accuracy = 99.18 Sensitivity = 97.36 Specificity = 99.42

high accuracy of 98.75% using 10 k-fold. According to the authors, the proposed model could be successfully used for COVID-19 early screening.

Fast detection of COVID-19 is important to control its spread and take preventive steps. The DL-based model for detecting the COVID-19 using CT scans has been proposed by (Chen, Wu, & et al., 2020). The dataset of 46,096 unspecified scans taken from 106 patients was used to train the model. In this paper, UNet++ architecture is used for image segmentation. Moreover, the model was also compared with the expert radiologist's outcomes. Results showed that the suggested model performed well (sensitivity = 94.34%, specificity = 99.16%, and accuracy = 98.85%) than the expert radiologists in a very short time. The applications of CNN in COVID-19 detection and diagnosis using CT images are depicted in Table 6.

ii. X-ray Images:

Besides CT images, X-ray images have also been used by many researchers in their DL-based models for the diagnosis of COVID-19. For instance, (Shibly et al., 2020) developed a deep learning-based model for the detection of COVID-19 using X-ray images. The VGG-16 (visual geometry group) network-based faster regions with CNN (Faster R–CNN) approach has been used in this study. The dataset comprises 5450 chest X-ray images of 2500 patients. The dataset was distributed into 90% of training and 10% of validation sets. According to the authors, the proposed model achieved high classification performance (accuracy = 97.36%, precision = 99.28%, and sensitivity = 97.65%. Similarly, (Hall et al., 2020) developed a deep CNN model for the detection of COVID-19 using X-ray images of 135 from COVID-19 cases and 320 from viral and bacterial pneumonia cases. Using 10-fold cross-validation, 102 COVID-19 cases and 102 viral and bacterial pneumonia cases were used to tune the Resnet50. Results presented that the suggested model accomplished an accuracy of 89.2%.

For the detection and diagnosis of COVID-9 DL based models have been developed by (Hassantabar et al., 2020). In this article, DNN and CNN have been presented. In addition, for finding the infected tissues in lung images, a CNN architecture is used and achieved good performance (accuracy = 93.2% and sensitivity = 96.1%). According to the authors, their findings could be used for monitoring and controlling cases in of virus-infected regions. The applications of CNN in COVID-19 detection and diagnosis using X-rays are depicted in Table 7.

b. Classification

Besides detection and diagnosis, the classification of COVID-19 using CNN has been reported by many researchers. For instance, a deep learning-based model has been proposed by (Hu et al., 2020) for the classification and detection of COVID-19 using CT images. The dataset used in this study was comprised of 150 3D volumetric CT images of COVID-19, community-acquired pneumonia (CAP), and no-pneumonia (NP) patients, respectively. The proposed model showed good performance (accuracy = 84.9%, specificity = 89.2%, sensitivity = 81.4% and precision = 77.8%). According to the authors, their proposed model could lessen the need for manual CT images and would automatically be used for the classification of COVID-19 pneumonia.

Another novel approach to the classification of COVID-19 has been proposed by (Varela-Santos & Melin, 2021). In this work, a series of experiments have been performed using a deep learning approach for the classification of COVID-19 based on chest X-rays of COVID-19 infected cases and several other related diseases. Initial experimentation includes the use of image texture features, deed forward neural network, and convolutional neural network applied on the database of COVID-19 X-ray images. The dataset includes 338 images, among which 255 were COVID-19 images. In the end, the proposed model was compared with k-nearest neighbors (KNN) and support vector machines (SVM). Among these, the proposed model outperformed the rest of the approaches and achieved good performance (accuracy = 83.02% and AUC = 90.7%) The applications of CNN in the COVID-19 classification are depicted in Table 8.

c. Screening

With the rapid increase in the COVID-19 pandemic, the demand for screening COVID-19 cases has reached its peak. Healthcare providers, clinicians, and doctors are unable to screen such a massive number of cases efficiently. An alternative and automated way of screening mechanism of novel coronavirus disease is needed. The novel deep transfer learning-based model for the screening of COVID-19 has been proposed by (Basu et al., 2020) using X-ray images. In this study, based on deep CNN, a novel domain extension transfer learning (DETL) approach is employed. The dataset comprises 305 COVIID-19 images, normal, 350, pneumonia 322, and other diseases 305 samples. Furthermore, 5-fold cross-validation is employed for the feasibility estimation of using X-ray images of the chest for the diagnosis of COVID-19. The proposed model performed well with an accuracy of 90.13% ± 0.14.

In another study, a shallow CNN-based model has been proposed by (Mukherjee et al., 2020) for COVID-19 pandemic screening using X-ray images of the chest. Fewer parameters are used for developing shallow CNN-tailored architecture compared to other DL-based approaches (This finding was validated by using 130 positive COVID-19 X-ray images). After successful implementation of the model, it was concluded by the authors that the proposed models achieved good performance (accuracy = 96.92%, specificity = 100%, and sensitivity = 94.2%). The applications of CNN in COVID-19 screening are depicted in Table 9.

d. Prediction and Severity Assessment:

Besides the COVID-19 detection, diagnosis, screening, and classification, CNN has been widely used by many researchers for the prediction and severity assessment of the COVID-19 pandemic. For instance, (Cohen et al., 2020) proposed a deep learning-based model for the prediction of COVID-19 using x-ray images. In this work, a DenseNet model is trained on the 94-poster anterior chest x-ray images. The best correlation coefficient is achieved by the single "lung opacity" output was 0.80. In another work by (Kumar, Arora, & et al., 2020), the deep learning-based model is developed for the prediction of the COVID-19 pandemic using x-ray images. A deep feature learning model is used for feature extraction. The extracted features are used to train the ML-based classification models including random forest (RF) and xgboost. SMOTE was used for balancing data. The proposed predictive xgboost classifier achieved good performance (accuracy = 97.7% and specificity = 98.8%). According to the authors, their proposed model will help better and early management of the epidemic. The applications of CNN in COVID-19 prediction and severity assessment are depicted in Table 10.

2.2.2. Long-short Term Model (LSTM)

Long short-term memory (LSTM) networks are a type of recurrent neural network (RNN) with the capability of learning order dependence in sequence prediction problems. LSTM can store knowledge of previous states and can be used in memory-based problems. LSTM has been widely used for the time series sequential data prediction (DiPietro & Hager, 2019; Navares & Aznarte, 2020; Verma & Kumar, 2019). Recently, many researchers have used LSTM based models for COVID-19 detection, diagnosis, classification, prediction, and forecasting. A deep CNN-LSTM coupled approach has been proposed by (Islam et al., 2020) for COVID-19 detection using X-ray images. First, CNN is trained for the extraction of deep features and based on these extracted features, the LSTM model is trained for the detection of COVID-19. The dataset comprises 4575 X-ray images, among which 1525 images were from COVID-19 cases. The proposed model achieved high performance (accuracy = 99.4%, specificity = 99.2%, and sensitivity = 99.3%). According to the authors, their proposed model can help clinicians and doctors with rapid and automatic detection of COVID-19 using X-ray Images.

Many studies reported the applications of LSTM in the time series prediction and forecasting of the COVID-19 pandemic. Three different deep learning-based models have been proposed by (Shahid et al., 2020) for the prediction of COVID-19. In this article, support vector regression (SVR), autoregressive integrated moving average (ARIMA), long short-term memory (LSTM), and bidirectional long, short term memory (Bi-LSTM) were developed for the time series forecasting of confirmed infected cases, number of deaths and recoveries in different countries. The proposed models showed good performance with Bi-LSTM with the highest performance and lowest MAE (0.0070) and RMSE (0.0077) values followed by LSTM > GRU > SVR and ARIMA for the death cases. For the recovered cases, the best results of the correlation coefficient achieved were 0.9997. According to the authors, the Bi-LSTM outperformed the other models, showing its robustness and high prediction accuracy. Due to this, Bi-LSTM can successfully be used for the early prediction of a pandemic. That would help policymakers and government officials to take preventive steps. The applications of LSTM for COVID-19 detection, diagnosis, classification, prediction, and forecasting are depicted in Table 11.

2.2.3. Other Deep Learning methods

Besides CNN and LSTM, the applications of various deep learning (DL) methods for COVID-19 drug repurposing are discussed in this section.

a. Deep learning for drug repurposing

The COVID-19 pandemic is spreading very quickly, and to date, no vaccine has been developed since drug discovery is a complicated, prolonged, high-risk, and expensive process. Scientists and researchers are working day and night to formulate a drug for curing the novel disease (Mohanty et al., 2020a). Meanwhile, a quick and instant cure

Table 8
Summary of Applications of CNN using for Classification of COVID-19.

References	Country	Purpose	Model/Architecture	Data Type	Sample size	Performance
(Hu et al., 2020)	China	Classification	CNN	CT Images	450 patient scans 150 3D volumetric chest CT exams of COVID-19, CAP and NP patients	Accuracy = 84.9 Precison = 77.8 Sensitivity = 81.4 Specificity = 89.2
(Varela-Santos & Melin, 2021)	Mexico	Classification	CNN	X-Ray images	338 images 255 COVID-19 images	AUC = 90.7 Accuracy = 83.02
(Ozkaya et al., 2020)	Turkey	Classification	VGG-16 GoogleNet ResNet-50	CT Images	150 CT images	Accuracy = 98.27 Sensitivity = 98.93 Specificity = 97.60 Precision = 97.63
(Singh, Kumar, & et al., 2020)	India	Classification	CNN ANFIS MODE-based CNN	CT Images	———	Accuracy = 1.9789% Sensitivity = 1.8262% Specificity = 1.6827%
(Amyar et al., 2020)	France	Classification	U-NET CNNs	CT Image	1044 patients 449 patients COVID-19 100 normal ones 98 lung cancer 397 different pathology	Accuracy = 86 Sensitivity = 94 Specificity = 79

Table 9
Summary of Applications of CNN for Screening of COVID-19.

References	Country	Purpose	Model/Architecture	Data Type	Sample size	Performance
(Basu et al., 2020)	India	Screening	AlexNet VGGNet ResNet DETL	X-Ray Images	normal 350 Pneumonia 322 other disease 300 Covid-19 305	Accuracy = 90.13
(Mukherjee et al., 2020)	India	Screening	MobileNet VGG16 Shallow CNN (proposed)	X-Ray Images	130 COVID-19 positive 51 non-COVID-19	Accuracy = 96.92 Sensitivity = 94.2 Specificity = 100
(Hou et al., 2020)	USA	Screening	CNN ResNet ResNet23-based ResNet-18	CT Images	618 transverse-section CT samples	Accuracy = 86.7 Sensitivity = 98.2 Specificity = 92.2
(Zhang, Saravanan, & et al., 2020)	China	Screening	DFCNN	CT Images	18 patients 2019-nCoV	DFCNN Score ≥ 0.999
(Wang, Zha, & et al., 2020)	China	Screening	CNN M-Inception	CT Images	44 cases SARS-COV-2 55 cases typical viral pneumonia CT images (99 patients)	Accuracy = 82.9 Specificity = 84 Sensitivity = 81

Table 10
Summary of Applications of CNN for prediction and Severity Assessment of COVID-19.

References	Country	Purpose	Model/Architecture	Data Type	Sample size	Performance
(Cohen et al., 2020)	Canada	Prediction	DenseNet model	X-Ray Images	94 images COVID-19 positive	Opacity Score R2 = 0.58 ± 0.09 MAE = 0.78 ± 0.05 MSE = 0.86 ± 0.11
(Kumar et al., 2020)	India	Prediction	ResNet152 SMOTE algorithm	X-Ray Images	5840 images, 5216 images for training 624 testing	XGBoost Accuracy = 97.7 Sensitivity = 97.7 Specificity = 98.8
(Takahashi et al., 2020)	China	Forecasting	CNN RNN LSTM GRU MLP			MAE = 8.5% GRU = 2599.1 LSTM = 2992.976 MLP = 5710.293 CNN = 102.943
(Obeid et al., 2020)	USA	Assessment	CNN	Telehealth	6813 Total 498 tested positive 6315 tested negative	Precision = 75.4 Recall = 45.3 F1 Score = 56.6
(Zhu et al., 2020)	USA	Severity	CNN VGG16	Chest Radiographs	31 portable CXR 84 COVID-19 patients	MAE = 8.5% R2 = 0.90

Table 11
Summary of Applications of LSTM for Diagnosis, Classification, and Prediction of COVID-19.

References	Country	Purpose	Model/ Architecture	Data Type	Sample size	Performance
(Islam et al., 2020)	Bangladesh	Detection	CNN-LSTM	X-Ray Images	915 overall cases 305 Covid 305 normal 305 pneumonia	Accuracy = 99.2 Sensitivity = 99.3 Specificity = 99.2
(Alazab et al., 2020)	Jordon	Detection	LSTM	Chest X-Ray Images	1000 X-ray images of real patients	R2 = 0.98 Accuracy = 92.76 RMSE = 0.207
(Shahid et al., 2020)	Pakistan	Prediction	Bi-LSTM	Time Series	deaths and recovered cases of 158 samples	Deaths MAE values = 0.0070 RMSE values = 0.007
(Yang, Zeng, & et al., 2020)	China	Prediction	LSTM	Time Series	No. of cumulative infection from Jan 16, 2020, to Jan 25,2020 (3845)	Epidemic Size = 95,811
(Pal et al., 2020)	Norway	Prediction	LSTM-FCNS	Time Series	starts from 22 to 01-2020 to 10–03-2020	RMSE COVID-19 = 3293.3 Recovered = 747.2 Death = 211.0
(Zheng, Du, & et al., 2020)	China	Prediction	ISI + NLP + LSTM	Time Series	data before February 12, 2020 13 436 confirmed cases on February 12, 2020	MAPE = 0.05% MAE = 0.17
(Yang, Yu, & et al., 2020)	China	Prediction	LSTM	Time Series	test set data starts from February 17th to March 8th	MAPE = 8.15%
(Wang, Zheng, & et al., 2020)	China	Prediction	LSTM	Time Series	January 22– July 7 2020	DI does not exceed 0.03
(Chimmula & Zhang, 2020)	Canada	Forecasting	LSTM	Time Series	confirmed cases until March 31, 2020	Long-Term RMSE = 45.70 Accuracy = 92.67
(Huang & Kuo, 2019)	China	Forecasting	LSTM	Time Series	January 23, 2020, to March 2, 2020	Low to High RMSE (2994.851, 3331.925) MAE (2992.976, 3324.591)

option for the coronavirus disease will be therapeutic medicine that is clinically approved and can be used for resolving the current pandemic situation. With the rise of AI in the healthcare sector, the technique of dug repurposing enabled by AI has become increasingly important in the current situation of the COVID-19 pandemic (Ke et al., 2020). Drug repurposing or drug repositioning is a term that refers to the utilization of existing clinically approved drugs for the treatment of novel and challenging diseases, like COVID-19 (Mohanty et al., 2020b). For instance, Toremifene, a medicine used for the treatment of breast cancer. It is a first-generation non-steroidal drug approved in 1997 for the treatment of breast cancer in women. It was identified by the network medicine analysis that Toremifene can significantly be used for treating COVID-19 disease (Zhou et al., 2020).

AI coupled with drug repurposing can detect the drugs that can be used to combat novel diseases like COVID-19. The application of such emerging technologies has the potential to significantly alleviate the main issue associated with drug repurposing, which is the diagnosis and identification of the drug-disease relationship. Motivated by this, it was found by the researchers that the COVID-19 and the 2003 SARS virus have similarities between them. Based on the data available on SARS, AI-based models can be developed for the prediction of drug structures that can significantly treat COVID-19 disease (Mak & Pichika, 2019).

Besides, confirmed, and affirmative repurposed drugs, there are some requirements for the recognition of more repurposed drugs. Such procedures can be supported by AI and ML. With the help of these emerging technologies, the drugs possessing the adequacy against coronavirus disease can be recognized rapidly and hence overcome the challenges and barriers associated with new drug discovery such as laboratory testing, and approval of a final drug. The information from various healthcare organizations becomes accessible on one open platform (Riva et al., 2020; Shende et al., 2020; Wang & Guan, 2020). Fig. 4 represents the AI-based strategy to be adopted for drug repurposing. The input to the AI-empowered model for drug repurposing is a repurposed or repositioned drug database, and an open chemical or open drug database followed by the various algorithms to be applied to this input, and finally, the desired drug could be obtained.

3. Discussions

In this study, first, we have presented the applications of ML and DL in the COVID-19 screening, diagnostics, tracking, classification, drug

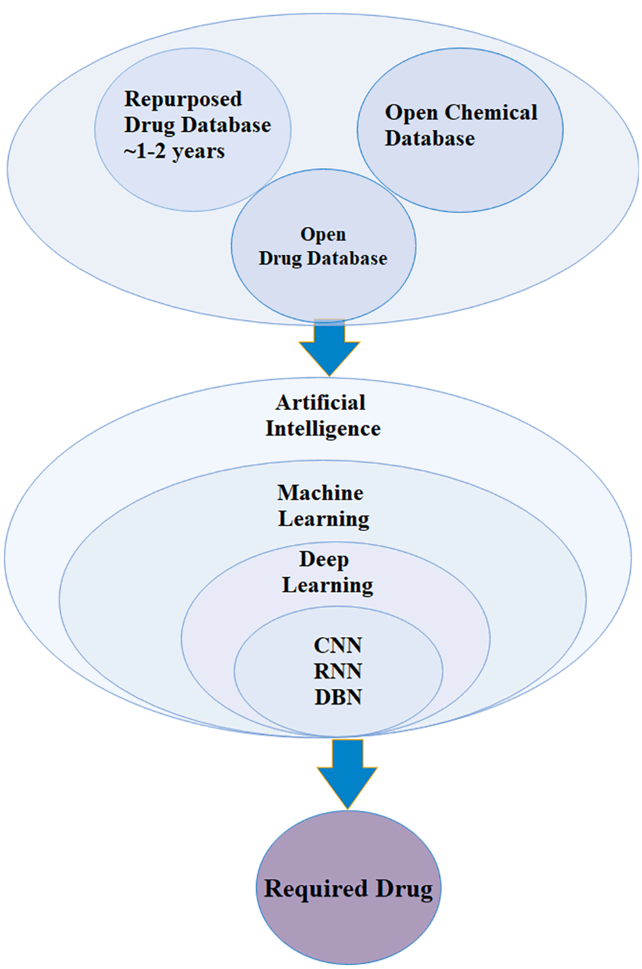

Fig. 4. Artificial intelligence (AI) empowered drug repurposing (Pham et al., 2020).

repurposing, prediction, and forecasting. The applications of ML methods reviewed in this study include support vector machine (SVM), logistic regression (LR), random forest (RF), and decision tree (DT), multilayer perceptron (MLP), xgboost, k-means, gaussian process regression (GPR), and neural networks. While the applications of DL methods include convolutional neural networks (CNN) and long short-term memory (LSTM). All the general and technical data including author name, country, model used, sample size, data type, and performance of the applied model, associated with the implementation of AI for combating COVID-19 have been summarized and presented in Tables 1–11.

The datasets used to train and validate the ML and DL models comprise medical images (CT scans and X-ray Images), time series, and clinical data. Among these, medical images were widely used as an input parameter to the ML and DL models. If the outbreak progresses, medical imaging will become increasingly important, particularly where access to RT-PCR tests is scarce or unavailable due to lack of resources. Furthermore, imaging meets more formal procedures and is less reliant on the expertise of the operator. The appearance of COVID-19 in medical images and scans has been linked to the seriousness of the disorder, allowing for the monitoring of its progression. The RT-PCR results, on the other hand, do not reveal the magnitude or stage of the disorder. Medical images (CT scans and X-ray images) play an important role in the treatment and control of COVID-19 and have also been recognized as the most sensitive imaging modality for detecting abnormalities due to their high sensitivity and easy accessibility.

Artificial intelligence-based tools, particularly deep learning models, are the promising techniques used to assist radiologists in the early screening of coronavirus. Moreover, it reduces the workload of the radiologists, improves detection more accurately and efficiently, gives a timely response and accurate treatment for the patients of COVID-19. Though the AI-based studies are not used on a large scale and are not clinically approved, they are very helpful and give fast responses, save time, and provide meaningful information to healthcare staff and government officials. However, many challenges and limitations are faced while building AI-based models due to the lack of massive data and the poor quality of data available. In this regard, research communities are working day and night to gather and extract more meaningful information from the available datasets. Moreover, it was observed that most of the AI models were lacking the implementation of cross-validation techniques, which should be employed to ensure the generalization of results for other unseen datasets.

We observed that the studies based on the conventional ML-based models (SVM, DT, RF, and MLP, etc.) showed poor performance while implemented standalone. However, hybrid ML models coupled with optimization techniques such as genetic algorithms or particle swarm optimization performed well. Recently, deep learning-based algorithms have been used by various researchers for combating the COVID-19 pandemic, including convolutional neural network (CNN), recurrent neural network (RNN), and long short-term memory (LSTM) for the COVID-19 detection, diagnosis, classification. Screening, drug repurposing, prediction, and forecasting. All these models performed well with exceptional accuracy compared to traditional ML-based models.

It is worth noting that even though certain COVID-19 patients are asymptomatic, they can become virus transmitters. Coronavirus victims with pneumonia symptoms can have a pattern on chest X-ray images or CT scans that is only mildly characteristic for doctors, even though the infection may be confirmed by a PCR. People that are currently afflicted with COVID-19 but are asymptomatic are difficult to identify. The ability to reliably identify contaminated patients with low false-negative rates determines the COVID-19 transmission rate. Meanwhile, efficient false-positive monitoring will reduce the pressure on the healthcare system by avoiding unwanted hospital quarantine.

Biomedical imaging (X-rays images and CT scans) allows for the visualization of pneumonia symptoms. In the fields of biomedicine and cancer detection, image processing approaches are appealing. It is common knowledge that AI-based biomedical picture diagnosis has had a lot of success. Methods such as machine learning and deep learning are useful in the identification of a variety of diseases. And if some patients have already been contaminated with SARS-Cov-2, their chest CT images are fine. As a result, chest CT images have a small negative predictive potential and do not fully rule out infection. The specificity of a single AI diagnosis is also being questioned. As a result, AI-based models are expected to integrate chest imaging with clinical signs, contact history, and laboratory testing in the detection of COVID-19 to satisfy healthcare needs.

The bibliometric analysis of the literature is shown in Fig. 5, which includes the percentage of articles published on AI applications for the COVID-19 pandemic, the type of data used for training the ML and DL based models including CT scans, X-ray images, Clinical data (Blood tests, PCR tests), and Time-series, and the percentage of articles on ML and DL for combating the COVID-19 pandemic. The share of articles published on ML and DL for combating the COVID-19 pandemic is shown in Fig. 5 (A). The statistics show that DL accounts for 53%, followed by the share of ML, which is 47%. The state-of-the-art DL-based models are a proven technology and can significantly be used for the COVID-19 pandemic. The individual shares of each ML and DL methods are shown in Fig. 5 (B) The individual distribution ML methods are as follows, RF 22%, SVM 17%, LR 16%, DT%, other ML methods 34% while that of DL methods is as follows, CNN 72% and LSTM 28%. The type of data used for training the ML and DL-based models includes CT scans, X-ray images, clinical data (blood tests, PCR tests), and time-series as shown in Fig. 5 (C). From the literature survey, it is summarized that the dataset X-ray images account for 42% of the overall datasets used, followed by CT scans that account for 30 %. Moreover, time series which combine X-ray images and CT scans, and clinical data account for 19%, 5%, and 4% respectively. Fig. 5 (D) shows that preprints such as medRxiv, bioRxiv, and arXiv accounted for 47% of the total, followed by Elsevier, whose number of published articles on the current topic accounted for 35%. The percentage of articles published in IEEE, Springer, and others were 8%, 4%, and 6% respectively.

4. Challenges and Perspectives

Artificial intelligence (AI) has great potential and can significantly be used for combating and mitigating the spread of the COVID-19 pandemic. Besides many advantages and positive outcomes, there are several challenges and limitations associated with the implementation of AI which need to be evaluated and addressed. Moreover, a useful outlook has been provided based on these challenges and limitations.

4.1. Unavailability of Standard Data

One of the main challenges associated with the use of AI is the lack of standard datasets. The implementation of these predictive tools requires a massive amount of data. Moreover, only the use of standard data can ensure both platforms a trustful and significant solution to combat COVID-19. In the literature reviewed above, various models of AI are presented but they were not tested using similar datasets. Due to the use of different samples, one cannot decide which model is best for the detection of coronavirus disease. Moreover, due to the lack of standard datasets, most of the datasets were generated by authors and researchers themselves by gathering data from various literature and platforms such as WHO. Such an issue can be addressed by the collaborative work of various well-known organizations like WHO or by generating more real-world datasets from the updated COVID-19 data. Similarly, a variety of

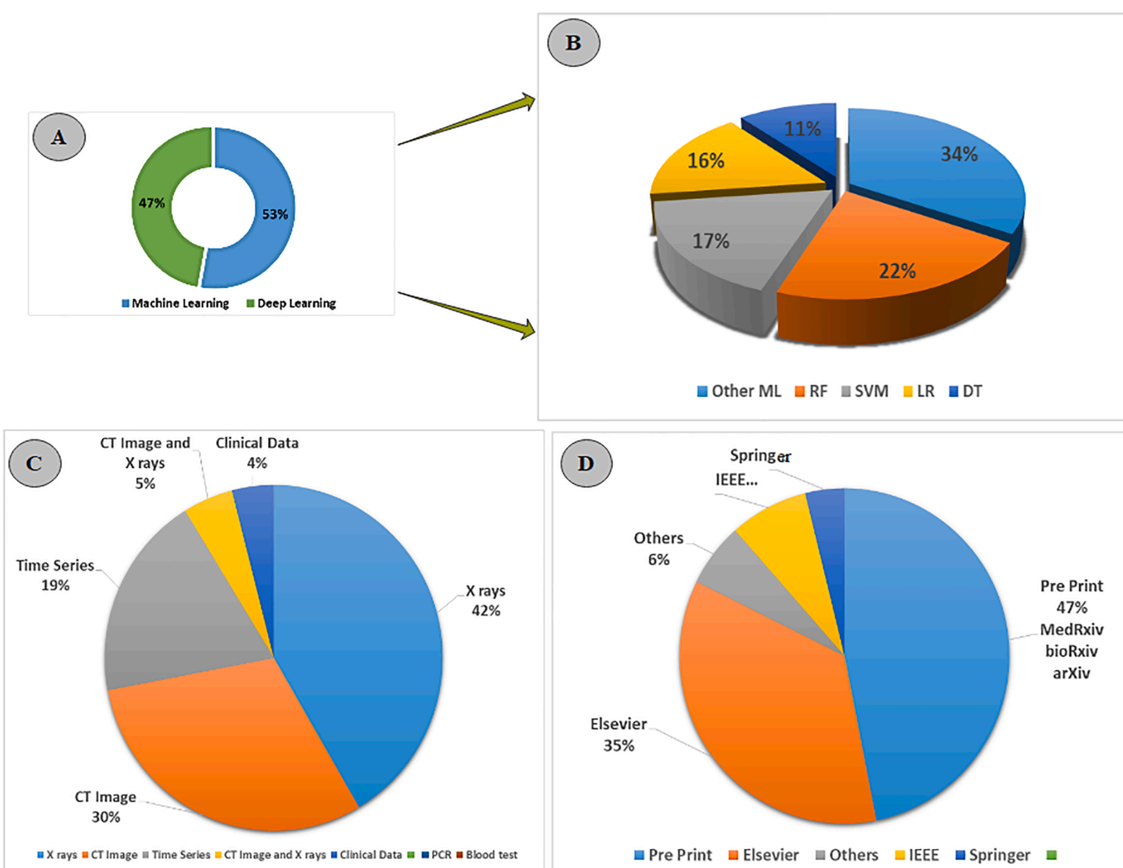

Fig. 5. Bibliometric Analysis of the Literature. (A) shows the percentage of articles on ML and DL. (B) shows the individual percentages of various ML methods. (C) shows the distribution of various datasets used in AI based models. (D) shows the percentage of articles published by various publishers.

data can be provided by such sources, including CT scans, chest X-rays, personal information, and GPS data.

4.2. Cross-validation

There is always a possibility of gray areas and uncertainties in the research field based on historical data learning on rapidly produced data which ultimately leads towards the associated hidden risk. Most of the articles lack the cross-validation of their trained models, which leads to biases that could influence the decisions made by the government's officials and healthcare organizations. Reproducing the proposed frameworks and models for finding uncertainties in the research can only ensure the validity of the data.

4.3. Privacy and Security

Personal privacy and security are the major challenges that need to be addressed. For the implementation of AI for combating COVID-19, a huge amount of data is needed to train the models. In the context of the COVID-19 pandemic, this data includes X-ray images, CT scans, travel history, patient history, GPS location, and routine activities. Such data is then used to train the models that can help in virus prediction, detection, policymaking, and vaccine production. However, if not officially announced or requested, no one wants to share their data with others due to privacy and security concerns.

4.4. Usage of advanced approaches

In this review, the most used data sources were CT scans and X-ray images. However, there are some other advanced approaches such as ultrasound scans and magnetic resonance imaging (MRI) which are barely discussed in combating COVID-19. These advanced approaches are proven technologies and have shown better performance than CT scans and X-ray images. Therefore, these approaches need to be considered in predictive modeling for COVID-19 which primarily depends upon the quality and standard dataset for training the models.

4.5. Variations in pandemic data pattern

The data available on open sources from across the globe has a complex pattern with variability in the data. Therefore, the credibility and reliability of the predictive models for the COVID-19 pandemic face lots of complexities and challenges. Moreover, different hospitals and laboratories have different criteria for sample collection, testing procedures, and results generation. Due to which variability in the dataset may occur, which ultimately questions the reliability of the predictive model based on an uncertain dataset.

4.6 Symptom's similarities

The differentiation of COVID-19 infection and other related viral infections is difficult due to similarities in their symptoms. Therefore, the recognition of an appropriate ML or DL-based model to screen, detect, diagnose, and classify the COVID-19 infected cases with optimum outcomes is a challenging task that needs to be addressed.

Although many research articles have been published on the application of AI in fighting the COVID-19 pandemic, there is still a gap in the study and several research questions can be derived from this study that needs to be addressed. Moreover, medical images often face limited collections and the high cost of labeling. Some researchers have proposed various techniques but there remain unexplained gaps.

Further advances in the application of AI in combating the COVID-19 pandemic can be planned and solved through the following research gaps and prospects that are identified from the present study:

To enhance the accuracy and reliability of the data analytics, the algorithms of AI must be optimized to ensure the better diagnosis and treatment of COVID-19.

The incorporation of AI with other emerging techniques can offer effective and efficient solutions for combating COVID-19. For instance, data analysis tools from Oracle cloud computing are coupled to develop a vaccine for fighting the COVID-19 pandemic.

Most of the ML-based models lack the implementation of cross-validation techniques, which should be employed to ensure the generalization of results for other unseen datasets.

The advanced approaches such as ultrasound scans and magnetic resonance imaging (MRI) are proven technologies and have shown better performance than CT scans and X-ray images. Therefore, these approaches need to be considered in predictive modeling for COVID-19 which primarily depends upon the quality and standard dataset for training the models.

5. Conclusions

Artificial intelligence (AI) is a promising technology that is widely used in various sectors, including the healthcare sector. In this study, a comprehensive review of state-of-the-art AI applications to combat the COVID-19 pandemic is highlighted. The application of AI includes screening and diagnostics, drug repurposing, and prediction and forecasting. It was discovered that the convolutional neural network (CNN) and its modified models were mostly used for COVID-19 pandemic prediction, whereas in the case of machine learning (ML), the support vector machine (SVM), k-means, linear regression (LR), and random forest (RF) were mostly used for COVID-19 pandemic combat. This paper also highlighted and addressed the challenges associated with the use of AI for the COVID-19 pandemic. Furthermore, in this study, the deep learning methods were the most popular and account for 53% of the total literature, showing its potential, robustness, and advancement among other methods. Most of the models, however, have not been deployed sufficiently to demonstrate their real-world functionality, but they are nevertheless capable of combating the pandemic. This paper will help researchers, healthcare institutes and organizations, government officials, and policymakers with new insights into how AI can control the COVID-19 pandemic and drive further research and studies into mitigating the COVID-19 outbreak.

Declaration of Competing Interest

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.

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