Review

Artificial Intelligence in COVID-19 Management: A Systematic Review

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Abstract: With the development of modern technologies in the field of healthcare, the use of Artificial Intelligence (AI) in disease management is increasing. AI methods may assist healthcare providers in the COVID-19 era. The current study aimed to observe the efficacy and importance of AI for managing the COVID-19 pandemic. An organized search was conducted, utilizing PubMed, Web of Science, Scopus, Embase, and Cochrane up to September 2022. Studies were considered qualified for inclusion if they met the inclusion criterion. We conducted review according to the Preferred Reporting Items for Systematic reviews and Meta Analyses (PRISMA) guidelines. There were 52 documents that met the eligibility criteria to be included in the review. The most common item using AI during the COVID-19 era was predictive models to foretell pneumonia and mortality risks in people with COVID-19 based on medical and experimental parameters. COVID-19 mortality was related to being male and elderly based on the Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) logistic regression analysis of demographics, clinical data, and laboratory tests of hospitalized COVID-19 patients. AI can predict, diagnose and model COVID-19 by using techniques such as support vector machines, decision trees, and neural networks. It is suggested that future research should deal with the design and development of AI-based tools for the management of chronic diseases such as COVID-19.

Keywords: COVID-19, SARS-CoV-2, Artificial Intelligence (AI), Deep Learning, Machine Learning, Predicting

Introduction

SARS-CoV-2 the cause of coronavirus disease (COVID-19) primarily emerged in Wuhan, China, in December 2019 and the World Health Organization (WHO) acknowledged a COVID-19 worldwide disease on March 11th, 2020 (WHO, 2020a; Mehraeen *et al*., 2021). The severity of the disease ranges from flu like symptoms including fever, fatigue, cough, headache, diarrhea, myalgia, and sore throat, to atypical pneumonia causing Acute Respiratory Distress Syndrome (ARDS) with dyspnea, loss of consciousness, and chest pain (WHO, 2020b). According to the latest WHO reports, as of August 2nd, 2022, this ongoing catastrophic pandemic has infected 575,887,049 cases and led to 6,398,412 deaths (WHO, 2022). COVID-19's long asymptomatic incubation period, relatively high reproduction numbers, and high mortality rates mostly among vulnerable patients (e.g., >65 years, immunocompromised, morbidities) have put an unprecedented burden on healthcare organizations everywhere. The combat against COVID-19 seemed an arduous task since the beginning due to overwhelmed hospitals, exhausted healthcare providers, medical supplies shortage, and detection tool kits (real time polymerase chain reaction) (Dadras *et al*., 2022). To control the pandemic and halt the rapid spread of the disease, many vaccines were introduced and granted emergent safety approvals by the Food and Drug Administration (FDA) and WHO. As of July 26th, 2022, 12,248,795,623 vaccine doses have been ordered globally. However, despite the efficacy of COVID-19 vaccines, they are not yet a definitive solution because of vaccine inequality, vaccine hesitancy, and new variants of the virus (WHO, 2022; Oliaei *et al*., 2021).

Thus, all these barriers signify the importance of new technologic methods in controlling the pandemic. For this reason, the use of Artificial Intelligence (AI) and Machine Learning (ML) has gained great popularity in different health systems globally over the past two decades. This has occurred due to the easy accessibility of data, the ubiquity of computers, and increasing computational power. Thus, AI and ML-based solutions have the exceptional capability in addressing the aforementioned issues (Shamsabadi *et al*., 2022; Hamet and Tremblay, 2017; Mehraeen *et al*., 2022).

AI and ML can be used in the diagnosis of COVID-19 through image processing and analysis of X-rays, CT scans, and ultrasounds. For instance, these methods can be used to differentiate between COVID-19 and other causes of pneumonia (Ulhaq *et al*., 2020). In addition, AI-based methods are used in COVID-19 control and prevention; deep learning models have been used to recognize mask wearing, infrared thermography techniques were utilized for fever detection (Somboonkaew *et al*., 2017) and mobile based applications were available for self-claimed COVID-19 symptomatic patients (Lahiri *et al*., 2012). Additionally, AI has been used in the clinical management of COVID-19 by selecting the most efficient treatment based on the severity of the disease and the patient's clinical condition (Siam *et al*., 2020). Finally, AI-based technique has also been used in the COVID-19 vaccine and medication development to find the most efficient lead components and chemical substances (Tang *et al*., 2022).

Recently, AI technologies such as ML-based prototypes trained on specific biomolecules have provided low cost and fast implementation approaches for the detection of practical viral treatments. However, there are not many articles on the application of this technology for pandemic management and so we aimed to investigate AI and ML's use, efficacy, and importance amid the COVID-19 pandemic and find the key differences between various ML models.

Materials and Methods

This study is an organized review of current literature pertinent to AI-based detection of COVID-19 disease. We have studied papers available in the English language as of September 2021. With the purpose of reliability and authenticity of the outcomes, this investigation adheres to the Preferred Reporting Items for Systematic reviews and Meta Analyses (PRISMA) checklist (Moher *et al*., 2009).

Data Sources

A search from December 2019 to September 2022 was directed using the following databases: PubMed, Web of Science, Scopus, Embase, and Cochrane. The search strategy employed combining the terms: “COVID-19” OR “SARS-CoV-2" OR "Coronavirus" AND "Artificial Intelligence (AI)” OR “deep learning” OR “machine learning” OR “data mining” OR “artificial neural networks” OR “deep neural networks” OR “convolutional neural networks” AND “detection” OR “diagnosis” OR “prognoses” OR “prognosis” OR “assessment” OR “distinction” OR “recognition”. Searches were limited to documents available in the English language. Titles and abstracts of recovered articles were individually evaluated by five authors to assess their eligibility for review. Any disagreements unable to be solved following discussion were adjudicated amongst the authors. When abstracts did not provide sufficient information to examine study eligibility, the full text was retrieved for evaluation. Subsequently, each study selected in the previous stage was fully evaluated and selected by four reviewers.

Eligibility Criteria

Studies were suitable for inclusion if they met the following measures: (1) Documents published in English; (2) Human studies, original articles, and papers with the experimental data. Studies were excluded if they met the following criteria: (1) Reviews, non-original editorials, and meta analyses; (2) Literature without available full texts, abstract papers, or conference abstracts; (3) Literature with doubts about duplication and/or reliability of results; and (4) Clinical Trials which were in progress without published outcomes and (5) Studies that did not explain the implemented AI-model.

Data Extraction

Four members of our research team individually assessed the full text documents and accompanied data extraction, using a regular template/spreadsheet. Data extracted included first author (reference) ID, type of study, country of study, target population, type of AI program, the purpose of using AI, type of data used, model and type of AI technique used, a sample size of training, classification measures and other information related to the aims of this review. To eliminate possible repetitions and/or crossovers, the selected publications and extracted data were checked by other researchers.

Results

The database search achieved 617 qualified studies and following the screening 52 full text documents met the inclusion standards and included in the final evaluation (Fig. 1).

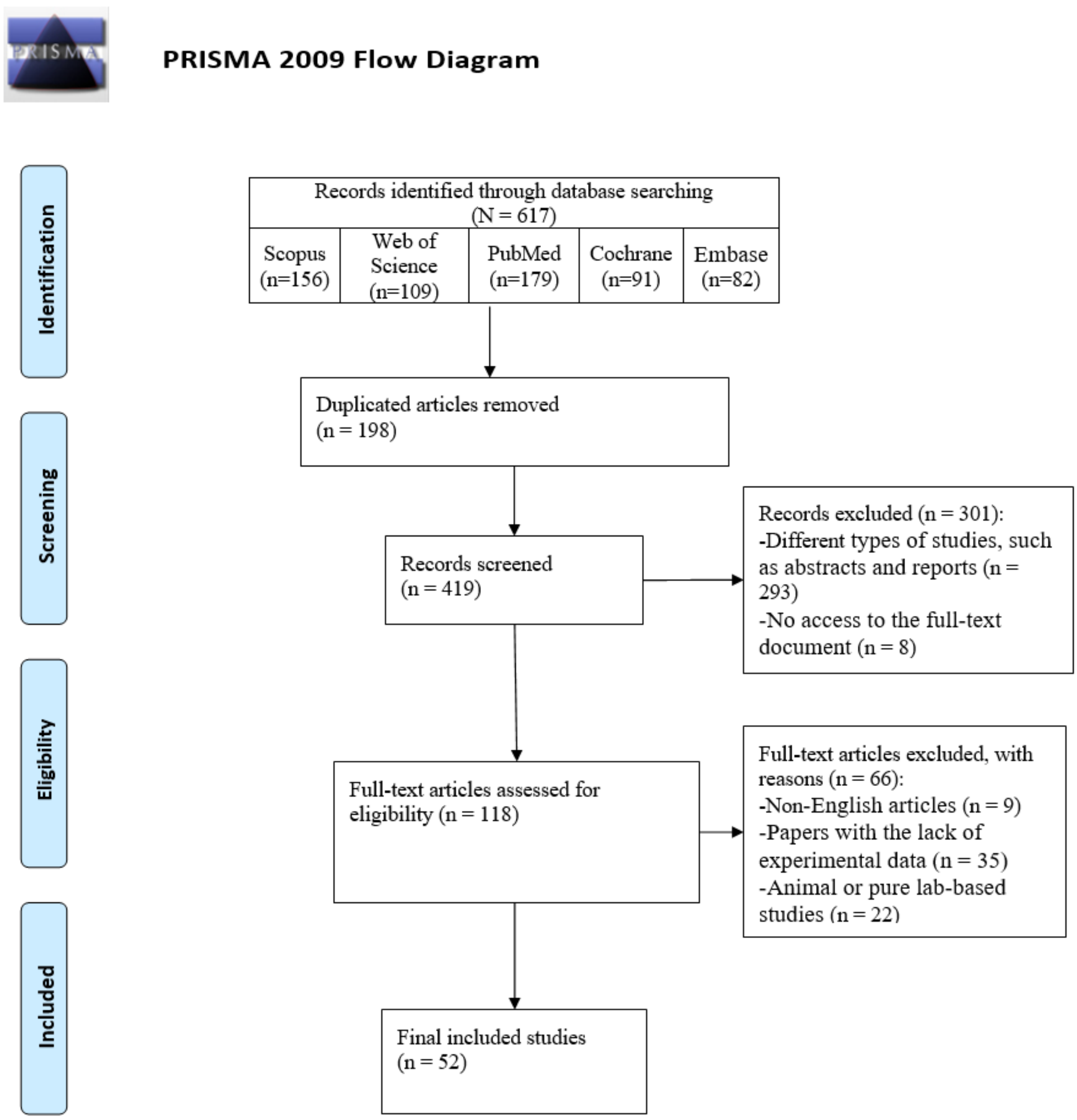

Fig. 1: PRISMA flow diagram of study retrieval process

The included studies were conducted in 10 countries (China = 10, USA = 8, Spain = 5, Italy = 3, Korea = 3, Turkey = 3, Saudi Arabia = 2, Switzerland = 2, Taiwan = 2, India = 2, Brazil = 2 and 1 study from the UK, Australia, Israel, Egypt, Pakistan, Iran, Iraq, Bangladesh, and Mexico. One of the articles was a report on multi-national scientific collaborations (Table 1 shows a summary of the findings).

Table 1: Description of the findings reported in the eligible studies

			Target Population						Classification measure		
ID	First Author (reference)	Country	N	Type of disease	Purpose of using AI	Type of data used	Type of technique	Sample size of Training	Prediction accuracy rate	Other	Other findings
1	Abdulkareem *et al.* (2021)	Brazil	600	80 with COVID-19 520 without COVID-19	Diagnosis	laboratory findings	Random Forest (RF)/Naïve Bayes (NB)/ Support Vector Machine (SVM)	480	94.16% RF/92.5% Bernoulli NB/ 95% SVM	-	SVM model had the best diagnosis performance (up to 95%)
2	Aktar *et al.* (2021)	Bangladesh	545	Confirmed positive COVID-19/ 36.3% female/ 47.2% above 65 years/ 48.4% were admitted to the ICU	Modelling	Blood sample results	Decision Tree (DT)/ Random Forest (RF)/ Gradient Boosting Machine (GBM)/ extreme gradient Boosting (XGBoost)/ Support Vector Machines (SVM)/Light Gradient Boosting Machine (LGBM) / k-Nearest Neighbor (KNN)/ Artificial Neural Network (ANN)	436	- 82% DT/ 89% RF/ 89% GBM/ 88% XGB/ 84% SVM/ 88% LGBM/ 84% were KNN/ 83% ANN/		RF and GBM had the highest AUC (89%)
3	Al-Waisy *et al.* (2021)	Iraq	800	400 COVID-19 CXR/ 400 normal CXR	Diagnosis	chest X-ray	DBN and CDBN	600	99.93%	-	--
4	Alsaade *et al.* (2021)	Saudi Arabia	245	140 COVID-19 images/ 95 normal images/ 10 SARS images	Classification	chest X-ray	Support Vector Machine (SVM)/ K-Nearest Neighbor (K-NN)/ deep learning Convolutional Neural Network (CNN)/	196	SVM 88% KNN 80% CNN 97.14%	-	the CNN model showed a great success; it had optimal accuracy, effectiveness and robustness for diagnosing COVID-19
5	Andreu-Perez *et al.* (2021)	Spain and Mexico	8380	2,339 COVID-19 positive/6,041 COVID-19 negative	Diagnosis	Cough sound/ quantitative RT-PCR (qRT-PCR) /Lymphocyte count/	CNN	-	-	-	-
6	Arvind *et al.* (2021)	USA	4087	11.03% of patients were intubated/ COVID-19-positive Patients ≥18 years old were included/ mean age 58.6± 21.90 years old/	Prognostic: (Predicting future intubation in patients diagnosed or suspected with COVID-19)	Demographic, vitals and laboratory data	-	2861	-	-	In patients diagnosed or suspected with with COVID-19, machine learning could be applied to predict future risk of intubation based on clinical features
7	Baktash *et al.* (2021)	UK	405	Adults/ 60% male/ 40% female/ 193 COVID-19 negatives/ 212 COVID-19 positive	Screening: Detection of atypical and asymptomatic presentations of COVID-19	Routine blood tests	Ensemble bagged tree/K-nearest -neighbor/SVM /discriminant analysis classifiers/	405	81.79% EBT/ 78.09% K-Nearest -Neighbour/ 73.97% SVM/ 74.48% discriminant analysis classifiers	-	A machine learning model applying routine laboratory tests can detect atypical and asymptomatic presentations of COVID-19 and could be used for screening
8	Bolourani *et al.* (2021)	USA	11,525	42% female/ Patients aged ≥21 years who had a positive nasopharyngeal PCR test for SARS-CoV-2.	Prognostic: predicting respiratory failure within 48 h of admission	Most invasive mode of oxygen delivery being a nonrebreather mask, ESI value 3, male gender, For the white race, minimum respiratory rate, Black race, ESI value of 2, most invasive mode of oxygen delivery being nasal cannula, ESI value of Hispanic ethnicity	XGBoost/ XGBoost + SMOTEENN/ logistic regression/	-	91.9% XGBoost/ 89.3% XGBoost + SMOTEENN/ 91.5% logistic regression/	-	The XGBoost model had the best accuracy (91.9%). The predictive ability of XGBoost showed that the the model could be used for predicting 48 h respiratory failure in COVID-19 patients
9	Booth *et al.* (2021)	USA	398	43 expired 355 non-expired	Modelling for mortality	-	logistic regression/ Support Vector Machine (SVM)/	318	-	-	Using five Laboratory parameters, resulted in 90% sensitivity and 77% specificity
10	Butt *et al.* (2023)	China	618	219 CT images from 110 patients with COVID-19/ 224 CT images from 224 Influenza-A patients with viral pneumonia/ 175 CT samples from healthy people	Diagnosis	Transverse-section CT images	Convolutional Neural Network (CNN)	528	86.7%	-	The deep learning models used were effective for the of early diagnosis of COVID-19 patients
11	Cabitza *et al.* (2021)	Italy	1624	52% COVID-19 positive/48% COVID-19 negative	Diagnosis	Routine blood tests	Random Forest (RF)/naive Bayes (NB)/logistic regression (LR), /Support Vector Machine (SVM)/ and k-Nearest Neighbors (KNN)/	1299	-	-	-
12	Chen *et al.* (2021)	China	362	Patients with COVID-19	Modelling: Differentiating severe and non-laboratory test	Clinical characteristics,	end-to-end ML analytical framework (Random Forest (RF)	181	Clinical input accuracy :>90% Laboratory	-	Predictive accuracies of >90%, >95% and >99%

Table 1: Continue

					-severe COVID-19	results	classification model)		input accuracy :>95% 10 features as input instead of all 52 features:97 are %		
13	Civit-Masot *et al.* (2020)	Spain	396 CXR	COVID-19 + Pneumonia cases	Diagnosis	Lung X-Ray images	Machine learning, convolutional neural network model (VGG16)	105 COVID-19 CXR 105 healthy CXR 106 Pneumonia CXR	The images of patients with COVID-19 are correctly classified at 100%	-	The Areas Under the Curve (AUC) higher than 90%
14	Dantas *et al.* (2021)	Brazil	337 435 People Using the app	COVID-19	Predicting	Combination of symptoms	Logistic Regression (LR) stepwise, Naïve Bayes (NB), Random Forest (RF), Decision Tree uses C5.0 (DT) and eXtreme gradient boosting	57,762 users selected according the model	Final accuracy measured as 73% (Positivity rate increased from 14.9 to 18.1%)	-	--
15	Das *et al.* (2020)	South Korea	3524	COVID-19	To predict mortality among confirmed COVID-19 patients'	Age group, sex, province and exposure	5 techniques were run (logistic regression, support vector machine, K-nearest neighbor, random forest and gradient boosting) logistic regression turned out as the best	3524 to 87.5%	Accuracies ranged from 74.4 -	-	
16	Domínguez-Olmedo *et al.* (2021)	Spain	2547 specific data set and 584 136 lab data	Medical records of COVID-19 hospitalization and emergency admission	Predicting the the severity of infection and mortality	Age + Sex + Lab values 32 in total	Gradient boosting method + shapley Additive explanations (SHAP)	Model was trained using 2547 specific data set And 584136 lab data	0.94	-	-
17	Duran-Lopez *et al.* (2020)	Spain	2589+ 4337 COVID and healthy images	COVID-19	Diagnosis	Chest X-ray images	CNN model	A total of 2589 from 1429 patients 4337 images from 4337	94.43% balanced accuracy	the system achieved of 92.53% sensitivity, 96.33% specificities, 93.76% precision, 93.14% F1-score, 94.43% Balanced Accuracy and an AUC value of 0.988	-
18	Fontanellaz, *et al.* (2021)	Switzerland	7966 Normal cxr + 5451 Pneum-onia + 258 COVID	COVID-19 + Pneumonia	to detect COVID-19 pneumonia on chest radiographs (CXRs)	Chest XRays	learnable strode convolution + inverted bottleneck blocks	7966 normal cases, 5451 with other pneumonia and 258 CXRs COVID-19 pneumonia	Sensitivity 94.3 Specificity 97.2	PPV 94.5	Compare a diagnosis support system to detect COVID-19 on the Chest Radiographs (CXRs) against radiologists of various levels of expertise in chest imaging
19	Gao *et al.* (2020)	China	2160	COVID-19	Mortality risk prediction model for COVID-19 (MRPMC)	34 clinical features, eventually only 14 were in the model	Logistic regression, support vector a machine, gradient boosted decision tree and neural network	2520 consecutive COVID-19 patients with known outcomes	In identifying non-survivors: SFV cohort: 92.4% OV cohort: 95.5% CHWH cohort:87.9%	the Respective AUCs: 0.9621 0.9760 0.9246	Final model used LR, SVM, GBDT, and NN
20	Ghaderzadeh *et al.* (2021)	Iran	10153 scans: 190 Patients and 59 people without respectively - COVID -19	COVID-19	Design a highly efficient Computer -Aided Detection (CAD) system for COVID-19 -	CT Scans	Neural search Architecture Network (NASNet)-based algorithm	10,153 CT scans of 190 patients with and 59 without COVID-19 were used	sensitivity, specificities, an accuracy 0.999, 0.986 and 0.996,		
21	Halasz *et al.* (2021)	Italy	852 patients PCR+	COVID-19	Prediction	Patients' medical history, demographics and clinical data were collected using a electronic health record	Naïve Bayes approach	852 patients diagnosis with COVID-19	Sensitivity of 94% and specificity of 37%	AUC is equal to 0.78 NPV of the Piacenza score was 93% with a PPV of 40%	-
22	Hwang *et al.* (2020)	South Korea	332 patients	COVID-19	Computer Aided Detection (CAD)	CXR	Deep-learning algorithm	Trained with 54221 normal CXR and 35613 abnormal CXR	Using CXR, sensitivity and specificity of 68.8 and 66.7%, respectively CXR with chest CTs, sensitivity 81.5% specificity 72.3%	-	-
23	Hwang *et al.* (2021)	South Korea	172 patients	COVID-19	Computer Aided Detection system (CAD)	CXR	Deep learning -based (CAD)	The CAD was initially trained using 54,221 normal CXRs and 35,613 abnormal CXRs	Sensitivity of 90.3% for patients with symptom duration more than 5 days Sensitivity of 90.6 for patients with consolidation on CT scans	-	-
24	Ikemura *et al.* (2021)	USA	4313	COVID-19	Prediction	Systolic and diastolic blood pressure, age, pulse oximetry	Open-source H_2O.ai autoML package (GBM and	Data from 4313 patients	Best model had AUPRC of 0.790	-	-

Table 1: Continue

						level, blood urea nitrogen level, lactate dehydrogenase level, D-dimer level, troponin level, respiratory rate and Charlson comorbidity score	XGBoost models)				
25	Irmak (2020)	Turkey	4575	COVID-19	Classifying	X-ray image	Convolutional Neural Network (CNN)	1828 images for training for task 1/2745 for task 2	98.92% average accuracy on COVID vs normal 98.27% on COVID vs normal vs pneumonia	-	Of 4575 total CXRs: 1524 COVID 1524 normal 1527 pneumonia
26	Karthikeyan *et al*. (2021)	China	2729 1766 datapo-ints after process	COVID-19	Prediction	Neutrophils, lymphocytes, Lactate Dehydrogenase (LDH), High-sensitivity C-Reactive Protein (hs-CRP) and age	XGBoost feature importance and neural network classification	1418 dataset for training and 348 datasets for testing	Accuracy of 90% as early as 16 days before the outcome	-	-
27	Khan (2021)	Saudi Arabia	340 CXRs 170 healthy and 170 COVID -19	COVID-19	Detection	CXR	SVM-based classier (showed better result than CNN)	68 training CXR	Accuracy up to 94.12%	-	272 testing CXR
28	Langer *et al*. (2020)	Italy	199	Patients with influenza-like symptoms	Diagnosis	Clinical data and CXR images	Neural network	100	91.4%	-	--
29	Lim *et al*. (2021)	China	2924	COVID-19 patients	Prediction	Clinical data	Logistic regression Simplified logistic regression gradient boosting decision tree	2339	GBDT: 88.9% Logistic regression: 86.8% Simplified LR:88.7%	-	Mortality occurred in 0 mild cases,4.86% in moderate cases, 20.8% in severe cases and 62.2% in critically severe cases 8.8% of patients died during hospitalization
30	Lin *et al*. (2021)	Taiwan	467	Hospitalized COVID-19 patients	Prediction	Demographics, clinical data, Laboratory tests	Artificial neural network convolutional neural network random forest random tree logistics	361	ANN: 97% CNN: 92%	-	There is a correlation between COVID-19 mortality and being male and elderly
31	Marcos *et al*. (2021)	Spain	1270	Hospitalized COVID-19 patients'	Prediction	Demographics, comorbidities, clinical data, chronic treatment	Logistic regression random forest XGboost ventilation. Patients	918	-	-	36.3% of patients died, or required mechanical with older age (average of 79.2) cardiovascular, central nervous system kidney diseases and cancer had more severe prognosis
32	Pan *et al*. (2020)	China	123	ICU patients with COVID-19	Prediction	Baseline information, Clinical diagnosis, vital signs, laboratory tests, treatments	Logistic regression Gradient Boosting Decision Tree (GBDT) XGBoost CatBoost AdaBoost	98	XGBoost & CatBoost: 84% Logistic regression & AdaBoost & GBDT:76%	-	52.8% of patients survived, and 47.2% died during the hospitalization The best prediction performance was observed with XGBoost
33	Parchure *et al*. (2022)	USA	567	Hospitalized COVID-19 patients'	Prediction	Demographics, Vital signs, laboratory test results, ECG results	Random forest	396	65.5%	-	The mortality rate was 17% and overall median time to death was 6.5 days (range of 1.3-23.0)
34	Quiroz *et al*. (2021)	Australia	346	Patients with COVID-19 Diagnosed through RT-PCR test	Modelling: severity assessment & prioritize treatment	Clinical data, symptoms, comorbidities, laboratory tests, CT scan	Logistic regression Gradient boosted trees NNs	230	-	-	Differences between patients with severe COVID-19 and those with mild COVID-19 is related to comorbidities such as cardiovascular diseases (P = 0.002), hypertension (P = 002), diabetes (P = 0.01) and cancer (P = 0.01) and among all signs and symptoms, increased respiratory rate (P = 0.002) and dyspnea (p<0.001) were more common among patients with severe COVID-19
35	Roimi *et al*. (2021)	Israel	2675	Hospitalized COVID-19 patients	Prediction	Demographics, Patient history, clinical data	Cox regression	-	-	-	-
36	Sankaranarayanan *et al*. (2021)	US	11807	Patients with positive PCR test	Prediction	Clinical data and laboratory tests	Neural network random forest XGBoost CatBoost	80%	78% in prospective 89% in cross -validation	-	-
37	Zhang *et al*. (2020)	Egypt	Develo-ping a offline analysis model	COVID-19 Coronavirus	Predicting	Prediction on twitter streaming data	AI and machine learning	1000-3000	84.71% And 81.7% And 83.3%	-	SVM and logistic regression
38	Yuan *et al*. (2021)	USA	6.12 million reports	Infectious disease	Modelling: Reporting Odds Ratio (ROR), data mining the algorithm	US food and drug antiviral agents such as antibiotics such as the azithromycin	Reporting Odds Ratio (ROR), a data mining algorithm	6.12 million reports from 2015-2020	Not used this features	-	-The current pharmacotherapies for COVID-19 are associated with increased the risks of

Table 1: Continue

											cardiac adverse events
39	Yu *et al*. (2021)	Taiwan	Work on AI Systems	COVID-19	Modelling: Neural network/ multilayer perceptron/ MLP neural Network	Data repository and clinical databases	Deep learning techniques LSTM algorithm	6,368,591 Records from 171 country	-	LSTM demonstrated better forecast accuracy with fewer errors than the other models	-
40	Xu *et al*. (2020)	China	224	COVID-19	Real-time Reverse Transcription-Polymerase Chain Reaction (RT-PCR) deep learning	Hospital Data collection CT samples	Region Proposal Network (RPN) Deep learning model for classification	224 patient and 618 CT samples	Average F1-score and the overall accuracy rate the two models' was 0.750/ 0.764 and 78.5, 79.4%	Recall, precision, F1-score and accuracy rate COVID-19 0.867 0.813 0.839	-
41	Xiao *et al*. (2020)	China	408	COVID-19	Deep learning based-model using multiple instances learning and residual convolutional neural network	Clinical databases	Neural network deep learning models	408 confirmed COVID-19 patients set,	Accuracy 97.4	In the training 0.987 (95% confidence interval [CI]: 0.968 -1.00) and an accuracy of 97.4%	In the test set training set, whereas it had an AUC of 0.892 (0.828-0.955) and an accuracy of 81.9%
42	Wang *et al*. (2020)	China	5732	COVID-19 and other Pneumonia groups	Diagnostic and prognostic	Tomography images from seven cities	Pretrain the deep learning system,	5372 images from patients	Sensitivity: 78.93% Specificity: 89.93%	-	-
43	Ünlü and Namlı (2020)	Turkey	28, 2020	COVID-19	Prediction	Medical record	Support Vector Machines (SVM), Long Short Term Memory (LSTM) forecasting models regression models	110130 confirmed cases	-	-	-
44	Turkoglu (2021)	Turkey	746 images	COVID-19	Detection of novel coronavirus disease	CT scan images	Deep neural network Convolutional Neural Network (CNN)	746 CT-scan images	Accuracy 98.36	-	Sensitivity 98.28 Precision 98.22 Specificity 98.44
45	Yang *et al*. (2021)	China	543 samples	COVID-19	Prediction	Association rules mining and Supervised Techniques Data from virtual education systems'	Multilayer Perceptron (MLP)	543 samples as student's information	93.7% for achieving maximum precision 96.8% to select relevant features for predicting satisfactory status	-	Accuracy of 98.3%
46	Stachel *et al*. (2021)	USA	3395 Health Record	COVID-19	Prediction	Clinical databases	Logistic Regression (LR), Decision Tree (DT), Gradient Boosting decision trees (GB), support vector machine (SVM) and Neural Network (NN)	laboratory, vital and demographic information	Accuracy 0.83	-	-
47	Singh *et al*. (2022)	India	4356 CT Scans of the chest from 3322 patients	COVID-19	Prediction	PCR laboratory CT Scan	Deep learning, Internet of Things (IoT), Image processing web of things comprising Naive Bayes (NB), Random Forest (RF) and Support Vector Machine (SVM)	Two datasets, 4356 CT-scans the chest from 3322 patients + 1136 positive PCR cases	Sensitivity, specificity and Dice-coefficient, of system achieves 84.5, 93.9, and 65.0%, respectively	-	WoT based deep learning framework has appeared as one of the most effective approaches for predicting COVID-19 infections
48	Siddiqui *et al*. (2021)	Pakistan	527 images	COVID-19	Prediction	Computer Tomography (CT) scan images chest X-ray	Intelligent decision support system with deep learning Convolutional neural network (CNN) Internet of medical things (IoMT)	527 images of the dataset training phase 70% (370) images was used and 30% (157) validation was used	Accuracy for training and is around 98.11%	Sensitivity specificity for training are 98.03 and 98.20% respectively	Accuracy 95.54% with a sensitivity of 94.38% and specificity of 97.06 % on the X-ray and of CT scan datasets
49	Shah *et al*. (2022)	India	28,637 from different countries	COVID-19	Prediction	Data from open the data set those countries reported curve artificial	Susceptible Infected Recovered (SIR) model deep learning 28,637 from recurrent neural the network is used in deep learning is a Long Short Term Memory (LSTM)	Actual count patient was given as different countries	99.82% accuracy reported	The highest accurate in date was the general trend of by 99.99% but only to a region of Delhi and heir accuracy t in other regions have gone down below 98.8%	Data analysis-based the prediction model helped in analyzing the simulation curve and predict valuable information for India
50	Schöning *et al*. (2021)	Switzerland		459	COVID-19	Modelling and laboratory values hospital group EHR	Medical history models statistical and ML models decision tree induction regression trees Support Vector Machines (SVM)	Machine learning and 158 requiring hospitalization	419 out patients 0.96 (SVM) accuracy	0.85 accuracy	ML models based on commonly available laboratory values can help predict the likelihood of a severe clinical course early on during COVID-19 disease
51	Liang *et al*. (2022)	China	4804	COVID-19	Deep learning	CT scan images	Deep learning	4804 Patients with more than 3 consecutive CT	0.98	-	--
52	Ohno *et al*. (2022)	Japan	32	COVID-19	Prediction	Chest CT	Machine Learning (ML)-based algorithm	32 COVID-19 patients underwent initial chest CT	87.5%	-	ML-based CT texture analysis is equally or more useful for predicting time until CT for favipiravir treatment on COVID-19 patients than CT disease severity score

The result of this study showed that forecasting or prediction was the main reason for applying AI in COVID-19 management; online AI for forecasting outpatients' COVID-19 disease severity (Schöning *et al*., 2021; Domínguez-Olmedo *et al*., 2021; Xiao *et al*., 2020; Yu *et al*., 2021), differentiating severe and non-severe COVID-19 (Chen *et al*., 2021), predicting outpatients' respiratory failure (Bolourani *et al*., 2021) and risk of intubation (Arvind *et al*., 2021).

Most of the included studies (n = 24) stated "prediction" as the purpose of using AI for managing COVID-19. Other AI objectives, in order of frequency, were: "diagnosis", "detection", "modeling", "deep learning" and "classifying" (Fig. 2).

Various predictive models to predict mortality (Das *et al*., 2020; Ünlü and Namlı, 2020; Booth *et al*., 2021; Gao *et al*., 2020; Karthikeyan *et al*., 2021; Marcos *et al*., 2021; Pan *et al*., 2020; Stachel *et al*., 2021) based on clinical and laboratory parameters of confirmed COVID-19 patients were the most used technologies of AI in COVID-19 pandemic management. Other studies predicted a 30-day mortality risk in patients with COVID-19 pneumonia (Halasz *et al*., 2021) and patients' chances of surviving a SARS-CoV-2 infection (Ikemura *et al*., 2021). For instance, there was a correlation between COVID-19 mortality and being male and elderly in the Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) logistic regression analysis of demographics, clinical data, and laboratory tests of hospitalized COVID-19 patients (Lin *et al*., 2021).

Building a predictive model as a screening tool to identify people and areas with a higher risk of SARS-CoV-2 infection to be prioritized for testing (Booth *et al*., 2021; Dantas *et al*., 2021; Singh *et al*., 2022), early detection of COVID-19 (Siddiqui *et al*., 2021) and prediction system for discharged patients based on Computer Tomography (CT) scan images, (Shah *et al*., 2022) was reported by several studies.

In a related article, this vital finding mentioned that data mining could be used as a model to predict the side effects of COVID-19 (Yang *et al*., 2021). Another study reported the Odds Ratio (OR) and a data mining algorithm to investigate the risks of cardiac adverse events associated with the possible pharmacotherapies for COVID-19 outpatients (Yuan *et al*., 2021). Deep Neural Network and Convolutional Neural Network (CNN) models were used to detect coronavirus disease from CT Scan images (Turkoglu, 2021). We also identified that the presence of several techniques was used (logistic regression, Support Vector Machine (SVM), K-nearest neighbor, random forest, and gradient boosting) to diagnose and predict mortality among confirmed COVID-19 patients (Schöning *et al*., 2021; Das *et al*., 2020; Ünlü and Namlı, 2020; Singh *et al*., 2022; Abdulkareem *et al*., 2021; Zhang *et al*., 2020).

A review of the articles showed that predicting systems had good efficiency and the accuracy ranged from 73 (Dantas *et al*., 2021) to 99.8% (Al-Waisy *et al*., 2021) (mostly above 90%) (Chen *et al*., 2021; Duran-Lopez *et al*., 2020; Ghaderzadeh *et al*., 2021; Irmak, 2020). Therefore, they could be applied in clinical settings for diagnosing COVID-19 infection and treatment follow-up.

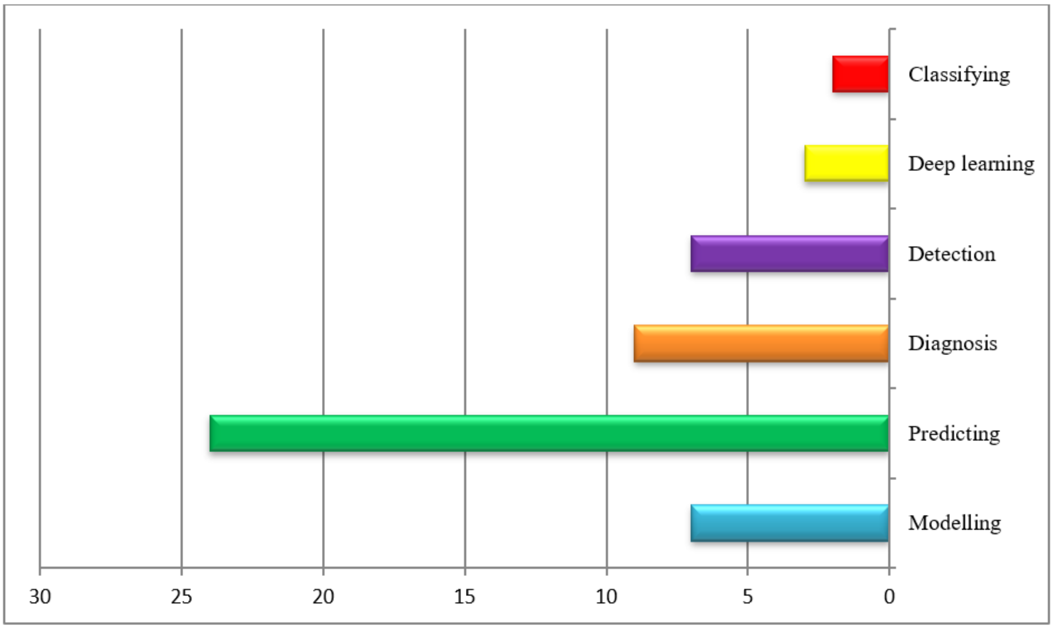

Fig. 2: The frequency of AI using purpose for the management of COVID-19

Discussion

The main objective of this study was to consider AI and ML's use, efficacy, and importance amid the COVID-19 pandemic and find the main variances among various ML models. Our results demonstrated that AI methods such as data mining, machine learning, deep learning, logistic regression, support vector machine, neural networks, K-nearest neighbor, random forest, and gradient boosting could help manage COVID-19. A similar article (Ohno *et al*., 2022) reported that ML-based CT texture analysis is equally or more useful for predicting the time until CT for favipiravir treatment on COVID-19 patients than CT disease severity score (Ohno *et al*., 2022). Also, Liang *et al*. (2022) in a related article concluded that a new AI system based on deep learning and federated learning has high reliability in diagnosing COVID-19 based on CT, with or without clinical data (Liang *et al*., 2022). Finally, existing literature on the use of AI during the COVID-19 epidemic determines the benefits of AI use in the pandemic such as early diagnosis, predictions, and even though modeling of treatments.

Discussing the type of program and the purpose of each study simultaneously provides a helpful understanding of the setting of each study. Many studies shared the same frameworks, like using AI to diagnose COVID-19 patients, but they applied different methods such as deep learning, data mining, machine learning, logistic regression, and support vector machines on targeted populations. But simply said, the diagnosis and prognosis of COVID-19 were the global aims of these studies. Interestingly, 11 studies used models to predict the prognosis of COVID-19 patients. This was the most abundant framework, followed by models diagnosing COVID-19, which was the setting of 9 studies. Mix methods of AI were also used in the management of COVID-19, such as using a model to develop an app to diagnose or assess the prognosis of patients. The outstanding results of each framework are discussed in detail below.

By using laboratory markers or chest radiograph imaging, researchers provided their models with data necessary for diagnosing COVID-19 regardless of patients' history, manifestations, and physical exam results. Applying routine laboratory test results as data, (Baktash *et al*., 2021) established a ML model to detect asymptomatic individuals infected with COVID-19. The accuracy of their model covered a range of 74.48% up to 81.79% depending on the technique and algorithm (Baktash *et al*., 2021). By comparation of people's signs and the results of traditional COVID tests Machine learning algorithms and models can predict COVID-19 infection. Populations, where access to testing is limited, can be examined by these diagnostic methods. During the COVID-19 pandemic mobile health apps that monitor patients, by gathering signs such as persistent coughing, fever, fatigue, and anosmia in daily reports on their health status, can predict COVID-19 infection. Development of a mobile application for self-management and self-monitoring among patients with COVID-19 allows data gathered to be used to forecast severe COVID-19 patients by ML models (Mohammad *et al*., 2021). ML algorithms allow identifying of COVID-19 patients. This method of AI is a tendency towards the application of innovative statistical approaches to defining results as a function of inputs. For example, (Cabitza *et al*., 2021) established compound ML models using data retrieved from 21 to 34 blood test results of 1624 patients reaching precisions of 75-78% to differentiate those infected with COVID-19 from those who were not (Cabitza *et al*., 2021).

Image processing and modeling for prediction were the two common methods of AI for the management of the pandemic. Clinical image processing is the basis of many diagnostic models, such as chest X-rays and chest CT scans that play a major role in diagnosing respiratory infections, especially COVID-19. AI image processing and interpretation algorithms can detect/recognize, assess, and classify COVID-19 by segmenting, detecting, and quantifying the images' suspicious regions. Segmentation, localization, pattern classification, and extraction of Regions of Interest (RoIs) of chest X-rays or CT images play a particular role in Image classification (Kaheel *et al*., 2021). Outstanding results from different countries show that using image processing to analyze lung X-ray images, COVID-19 cases could be identified among pneumonia and healthy controls (Irmak, 2020; Alsaade *et al*., 2021; Civit-Masot *et al*., 2020; Fontanellaz *et al*., 2021; SeyedAlinaghi *et al*., 2022). Yang *et al*. (2021) designed a framework to find out the best architecture, pre-processing and training parameters by pre-trained Convolutional Neural Network (CNN) models and using deep learning techniques for the COVID-19 CT-scan classification tasks. The accuracy score was above 96% in the diagnosis of COVID-19 using CT-scan images that confirm the results (Yang *et al*., 2021).

Same as diagnosis, by predicting the diagnosis of COVID-19 patients, we require clinical data, upon which physicians provide the patient with less or more intensive care. Due to the characteristics of SARS-CoV-2 infection, to predict the outcome, we could focus on respiratory signs and symptoms. Bolouran *et al*., designed a model which was able to predict the 48 h respiratory failure of COVID-19 patients, using 10 parameters including oxygen delivery mode, ESI value, gender, and race (Bolourani *et al*., 2021). Another diagnostic model designed in Italy predicted 30-day mortality based on clinical data as well as medical history and demographics. This model showed high sensitivity (94%) but had low specificity (37%) (Halasz *et al*., 2021). Vital signs have also been involved in this process which includes: Systolic blood pressure, respiratory rate, and pulse oximetry level, as well as other laboratory test results. The result is a prognostic model that predicts patients' survival chances. In this method, by comparing the vital signs of a sick person with the vital signs of a healthy person, taking into account age and gender, the survival chances of COVID-19 patients are predicted (Ikemura *et al*., 2021). Ivano Lodato *et al*. (2022) developed a ML model to predict both the mortality and severity associated with COVID-19 based on data gathered from medical records and test results collected during their hospitalization. Decision tree, random forest, gradient, and RUS Boosting models of ML were used to test the accuracy of these models. Their results showed that random forest and gradient boosting classifiers were highly accurate in predicting patients' mortality (average accuracy ∼of 99%) (Lodato *et al*., 2022). COVID-19 computer model using the biochemical markers, inflammatory biomarkers and a Complete Blood Count (CBC) was another method mentioned in most of the studies included in this review. This model helps the physicians form an idea about the patient's overall status (Domínguez-Olmedo *et al*., 2021; Karthikeyan *et al*., 2021; Aktar *et al*., 2021).

Biochemical markers, such as Arterial Blood Gases (ABG), including pH, HCO_3, O_2, and CO_2, are useful indicators of hemoglobin saturation status and are of great importance in COVID-19. Using these values in combination with inflammatory markers and CBC results along with some demographics, (Arvind *et al*., 2021) developed a model skilled at predicting the COVID-19 patients' necessity for intubation (Arvind *et al*., 2021). The unquestionable role of inflammatory biomarkers, during the course of COVID-19 made them one of the data targets for AI models and systems in COVID-19. Mimicking the follow-up protocols, some studies used inflammatory biomarkers as predictors of patients' outcomes. Levels of Lactate Dehydrogenase (LDH) and high-sensitivity C-Reactive Protein (hs-CRP) as useful indicators of a patient's inflammatory status helped with developing a model that predicted COVID-19 mortality with 90% accuracy 16 days before the outcome (Karthikeyan *et al*., 2021). Other laboratory values have also been integrated into AI models and systems. Some examples of these other laboratory markers include levels of D-dimer, troponin (Ikemura *et al*., 2021), and interleukin 6 (Chen *et al*., 2021).

Plain chest X-rays and chest CT scans are well-known diagnostic tools for COVID-19 and many other respiratory conditions and infections. Apart from COVID-19, interdisciplinary researchers have aimed to develop systems with the ability to interpret medical imaging modalities. Identifying chest radiographs or CT-scans that belong to known COVID-19 cases, while healthy and non-COVID-19 pneumonia cases were used as controls, describes the majority of study frameworks in this field (Ghaderzadeh *et al*., 2021; Irmak, 2020; Hwang *et al*., 2020; Khan, 2021; Xu *et al*., 2020; Sheikhbahaei *et al*., 2022; Behnoush *et al*., 2022). Age, demographics, chronic medical condition (Arvind *et al*., 2021), vital signs, exposures, and even gender were extracted from medical records and used to make the artificial models more realistic. In addition, novel approaches to diagnosis gathered attention among scientists. For instance, the system designed by Andreu-Perez *et al*. (2021) uses cough sounds in combination with quantitative RT-PCR and lymphocyte count to diagnose individuals infected with COVID-19 (Andreu-Perez *et al*., 2021).

One of the limitations of the current research was the breadth of methods and sub-branches of AI used in clinical care, so researchers had to study all the included articles in more detail and extract data in order to complete the table of results. Also, as interdisciplinary works, the included studies in this review were designed and conducted by researchers from different branches of science, mainly medicine, and computer sciences. Therefore, the interpretation of their results would have best been done through an interdisciplinary exchange of views. However, due to the specific aim of this review, it proceeded mostly from a medical point of view.

Conclusion

Managing difficult conditions in human life requires advanced technologies. COVID-19 is one of the important challenges in the health field that has involved the whole world. Information and communication technology tools such as AI can help manage this pandemic. In this research, the applications of artificial intelligence for managing COVID-19 were investigated and it was stated that AI can predict, diagnose and model COVID-19 by using techniques such as support vector machine, decision tree, and neural network. It is suggested that future research should deal with the design and development of AI-based tools for the management of chronic diseases such as COVID-19.

Declarations

Availability of Data and Material

The authors stated that all information provided in this article could be shared.

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Author's Contributions

Samaneh Mohammadi: The conception and designed of the study.

SeyedAhmad SeyedAlinaghi, Esmaeil Mehraeen and Daniel Hackett: Final approval of the version to be submitted.

Mohammad Heydari, Parsa Mohammadi, Ghazal Arjmand, Yasna Soleimani, Ayein Azarnoush, Hengameh Mojdeganlou, Mohsen Dashti, Hadiseh Azadi Cheshmekabodi, Sanaz Varshochi, Mohammad Mehrtak and Ahmadreza Shamsabadi: Drafted the article.

Zahra Pashaei, Pegah Mirzapour and Amirali Karimi: Acquisition of data.

Amir Masoud Afsahi and Peyman Mirghaderi: Analysis and interpretation of data.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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