Artificial Intelligence in the Fight against COVID-19: A Scoping Review

Alaa Abd-Alrazaq, Mohannad Alajlani, Dari Alhuwail, Jens Schneider, Saif Al-Kuwari, Zubair Shah, Mounir Hamdi, Mowafa Househ

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Abstract

Background: In December 2019, the novel Coronavirus disease (COVID-19) broke out in Wuhan, China leading to major national and international disruptions in healthcare, business, education, transportation, and nearly every aspect of our daily lives. Artificial Intelligence (AI) has been leveraged amid the COVID-19 pandemic, however, little is known about its use for supporting public health efforts.

Objective: The scoping review aimed to explore how AI technology is being used during the COVID-19 pandemic, as reported in the literature. Thus, it is first review that describes and summarizes features of the identified AI techniques and datasets used for their development and validation.

Methods: A scoping review was conducted following the guidelines of PRISMA Extension for Scoping Reviews (PRISMA-ScR). We searched the most commonly used electronic databases (e.g., MEDLINE, EMBASE, PsycInfo) between April 10 and 12, 2020. These terms were selected based on the target intervention (i.e., AI) and the target disease (i.e., COVID-19). Two reviewers independently conducted study selection and data extraction. A narrative approach was used to synthesize the extracted data.

Results: We considered 82 studies out of the 435 retrieved studies. The most common use of AI was diagnosing COVID-19 cases based on various indicators. AI was also employed in drug and vaccine discovery or repurposing, and assessing their safety. Further, the included studies used AI for forecasting the epidemic development of COVID-19 and predicting its potential hosts/reservoirs. Researchers utilized AI for patient outcome-related tasks such as assessing the severity of COVID-19, predicting mortality risk, its associated factors, and length of hospital stay. AI was used for Infodemiology to raise awareness to use water, sanitation, and hygiene. The most prominent AI techniques used were Convolutional Neural Network (CNN) followed by Support Vector Machine (SVM).

Conclusions: The included studies showed that AI has the potential to fight against COVID-19. However, many of the proposed methods are not yet clinically accepted. Thus, the most rewarding research will be on methods promising value beyond COVID-19. More efforts are needed for developing standardized reporting protocols or guidelines for studies on AI.

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Conclusions: The included studies showed that AI has the potential to fight against COVID-19. However, many of the proposed methods are not yet clinically accepted. Thus, the most rewarding research will be on methods promising value beyond COVID-19. More efforts are needed for developing standardized reporting protocols or guidelines for studies on AI.

Keywords: Artificial Intelligence; Machine Learning; Deep learning; Natural language processing; Coronavirus; COVID-19; 2019-nCov; SARS-CoV-2

Introduction

Background

The Coronavirus disease (COVID-19) broke out in Wuhan, Hubei Province, China in December 2019 [1] wreaking havoc across the globe and, as of May 2020, claiming the lives of more than 330,000 [2]. Caused by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), COVID-19 was declared a global pandemic by the World Health Organization (WHO) in March 2020 [3]. Many individuals infected with COVID-19 experienced fever, dry cough, and fatigue; some faced a severe course of the medical condition often requiring intensive care, including mechanical ventilation [4]. The highly contagious COVID-19 and its unprecedented high volume of cases around the globe have caused major national and international disruptions to business, healthcare, education, transportation, and nearly every aspect of our daily lives [5]. Prompt and effective countermeasures are necessary to cap off the effects of this pandemic; comprehensive public health strategies that involve surveillance, diagnostics, clinical treatment, and research are required [6].

Leveraging digital tools and technologies to combat COVID-19 can augment public health strategies [7]. For example, leveraging chatbots to address public inquiries about COVID-19. Additionally, using digital tools, public health professionals can track in real-time the incidence of COVID-19 infections and potentially model their projection. Among such tools is Artificial Intelligence (AI)— a branch of computer science concerned with intelligently analyzing and handling complex information [8,9]—amplifying public health efforts against COVID-19. Despite the enthusiasm for AI applications since the 1950s, only recently have we witnessed interest in AI due to the availability of high-performance computing and vast amounts of data being generated every second [10].

AI enables machines to become intelligent, understand queries, sift through and connect mountains of data points, and draw actionable conclusions [11]. While defining the taxonomy of AI is not trivial, its methods can be categorized based on the objective pursued: learn from knowledge, explore and discover knowledge, extract conclusions, and reason from knowledge [8].

Inspirationally and soon after the COVID-19 pandemic spread across the world, several governments, research institutes, and technology companies have issued calls to action urging researchers to develop AI applications to assist with COVID-19-related research [12]. From a hierarchical perspective, AI can support COVID-19 at different levels: the molecular-level (e.g., drug and vaccine discovery); patient-level (e.g., patient diagnosis); and population-level (e.g., epidemiological surveillance) [13].

A full review of the field of AI is beyond the scope of this work and we would like to refer the reader to some of the excellent surveys [e.g., 14] and lectures [e.g., 15,16]. However, we provide a very compact overview of the AI-based techniques occurring most frequently in included studies in Appendix 1.

Research problem

AI has the ability to analyze big datasets through aggregating and sifting through mountains of healthcare data (including patient data) to generate insights that can enable predictive analysis. The quick ability to obtain these insights helps clinicians as well as the rest of the stakeholders in the healthcare ecosystem to take effective, safe, and timely decisions to better serve patients and public health policy. There has been a steady rise in the number of studies regarding the use of AI techniques to resolve and/or address the COVID-19 pandemic [13]. Much of the AI research effort during the COVI-19 pandemic has been scattered, and a need to explore and summarize how AI technologies are being used to resolve and/or address the many challenges relating to the COVID-19 can help us plan on how to leverage AI technologies in the current or future pandemic. Several reviews have been conducted on AI techniques used to address the COVID-19 pandemic [12,13,17-20]. However, much of the work has been in the form of literature reviews [12,13,17-19] or systematic reviews focusing on one application of AI (i.e. diagnosis and prognosis of COVID-19) [20]. Therefore, it is necessary to conduct a more systematic and comprehensive review that focuses on all applications of AI used amid the COVID-19 pandemic. Accordingly, this review aimed to explore how AI technology is being used during the COVID-19 pandemic, as reported in the literature. The results can be useful for healthcare professionals and policymakers considering leveraging AI to complement public health efforts in response to COVID-19.

Methods

To achieve the objective of this study while ensuring both replicable and transparent methods, we conducted a scoping review following the guidelines of PRISMA Extension for Scoping Reviews (PRISMA-ScR) [21]. Methods used in this review are detailed in the following subsections.

Search Strategy

Search Sources

In this review, we performed search queries between the 10th and 12th of April 2020 on the following online databases: MEDLINE (via Ovid), EMBASE (via Ovid), PsycInfo (via Ovid), IEEE Xplore, ACM Digital library, Arxiv, MedRxiv, BioRxiv, Scopus, and Google Scholar. In the case of Google Scholar, and due to the sheer volume of returned hits, only the first 100 results were considered, as we found that beyond this, results very quickly lose relevance and applicability. In addition to searching bibliographic databases, we screened the reference list of the included studies and relevant reviews to look for other relevant studies that can be added to this review (i.e. backward reference list checking).

Search Terms

The search terms we used to identify relevant studies were specified from the available literature and by referring to subject matter experts. These terms were selected based on the target intervention (e.g., artificial intelligence, machine learning, deep learning) and the target disease (e.g., Coronavirus, COVID-19, 2019-nCOV). Details about the exact search strings used in this study are provided in Appendix 2.

Study Eligibility Criteria

In this review, we focused on any AI-based technology or approach used for any purpose related to the COVID-19 pandemic such as diagnosis, epidemiological predictions, treatment and vaccines discovery, and prediction of patient outcomes. However, we excluded studies providing an overview or proposing a potential AI technique for COVID-19, or studies that were purely discussed from a research perspective.

We consider studies published in English between December 25, 2019 and April 12, 2020 such as peer-reviewed articles, theses, dissertations, conference proceedings and preprints, while excluding other publications such as reviews, conference abstracts, proposals, editorials, and commentaries. We did not enforce any restrictions on the country of publication, study design, comparator, and outcomes.

Study Selection

Two reviewers, namely Alaa Abd-Alrazaq (AA) and Mohannad Alajlani (MA), independently screened the titles and abstracts of the identified studies. They independently read the full-text of studies that passed the ‘title and abstract’ screening. We then investigated any disagreement between AA and AM and resolved them through discussion and consensus. We calculated Cohen’s kappa [22] to measure the reviewer’s agreement and found it to be 0.83 for ‘title and abstract’ screening and 0.94 full-text reading, indicating a very good agreement [23]. Appendix 3 shows a matrix of interrater agreement in each step.

Data Extraction

Appendix 4 shows a purpose-built data extraction form, which was pilot-tested using seven relevant studies to accurately extract data. The two reviewers (AA & MA) independently extracted data related to characteristics of the included studies, AI techniques, and datasets used for the development and validation of AI models. Like the study selection process, any disagreement between the reviewers was resolved through consensus. We calculated Cohen’s kappa [22] and found it to be 0.88, meaning a very good agreement [23].

Data Synthesis

After extracting the data from the identified studies, we used a narrative approach to synthesize it. Specifically, we classify and describe AI techniques used in the included studies in terms of their purposes (e.g., diagnosis and drug/vaccine development), AI area or branch (e.g., traditional machine learning and deep learning), AI models/algorithms (e.g., Decision tree, Random forest, and Naive Bayes), and platform (i.e., computer and mobile). Further, we described the datasets used for development and validation of AI models in terms of sources of data (e.g., public databases and clinical settings), type of data (e.g., radiology images biological data, and laboratory data), size of the dataset, type of validation, and proportion of training, validation, and test datasets. We used Microsoft Excel to manage data synthesis.

Results

Search results

We retrieved 435 studies through searching the identified bibliographic databases (Figure 1). Of those studies, we removed 53 duplicates, then we screened the titles and abstracts of the remaining 382 studies. The screening process led to the exclusion of 234 studies for reasons detailed in Figure 1. After reading the full-texts of the remaining 148 studies, we excluded 73 studies as they did not meet all eligibility criteria. Thus, we included the remaining 75 studies. We identified 7 additional studies by checking reference lists of the included studies and relevant literature reviews. Overall, 82 studies are included in this review.

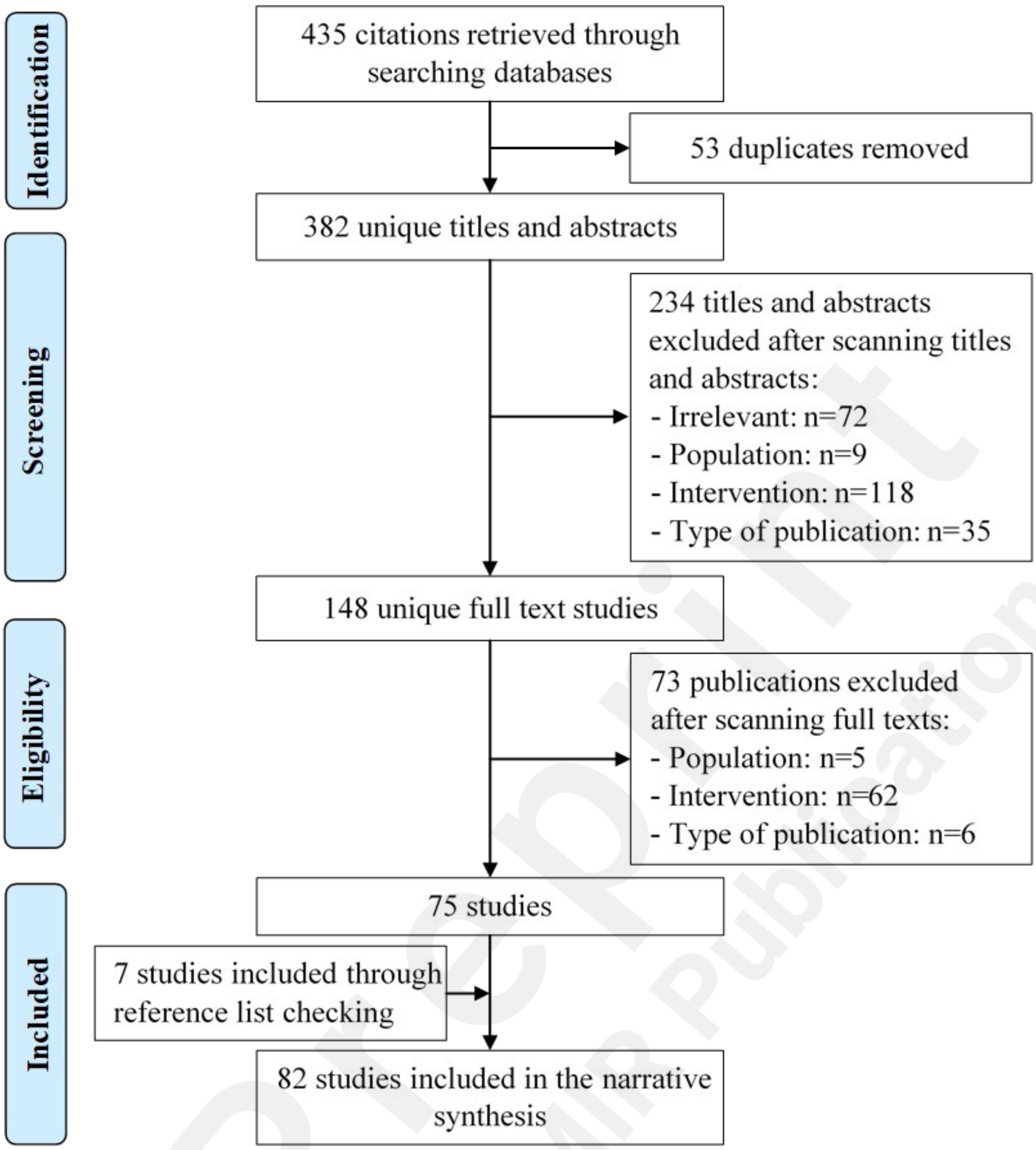

Figure 1: Flow chart of the study selection process

Characteristics of the included studies

Among the included studies, 72 were preprints and 10 were published articles in peer-reviewed journals (Table 1 and Figure 2). About two-thirds (n=53) of the included studies were submitted in March 2020, and the remaining studies were published in February and April 2020. However, no studies were published during the first two months of the COVID-19 outbreak. The included studies were conducted in 19 countries, however, half of the studies (n=41) were published in China. Appendix 5 shows the characteristics of each included study.

Table 1: Characteristics of the included studies

Characteristics	**Number of studies**			
Paper status	Preprint: 72	Published: 10		
Submission month	February: 13	March: 53	April: 16	
Country of publication	China: 41 Canada: 4	US: 9 UK: 3	India:6 Bangladesh: 2	Turkey: 5 Austria: 1

	Egypt: 1	Greece: 1	Hong Kong: 1	Hungary: 1
	Japan: 1	Korea: 1	Netherlands: 1	Pakistan: 1
	Qatar: 1	Sudan: 1	Switzerland: 1	

Figure 2: Publications by month and country. Whereas China dominates publications in February and March, April seems to suggest a more balanced research landscape.

AI-based techniques used for COVID-19

Purposes or Uses of AI against COVID-19

As shown in Table 2, AI techniques are used for five purposes amid the pandemic. In 31 studies [24-54], AI is used for diagnosing COVID-19 cases or identifying suspected COVID-19 cases based on various indicators, which are Computed Tomography (CT) images [24-38], X-ray images [39-50], laboratory tests [52,51], genome sequences [53], and respiratory patterns [54].

In 20 studies [55-74], AI is also harnessed for treatment and vaccines for COVID-19. Specifically, nine studies use AI for discovering drugs suitable for combating COVID-19 [55-63], and two studies utilize AI for repurposing commercially available drugs that could be used for treating COVID-19 [64,65]. One study employs AI to predict the safety of using Traditional Chinese Medicine for COVID-19 [66]. In four studies [67-70], AI is used for discovering COVID-19 vaccines. Another four studies utilize AI for predicting the protein structure of SARS-COV-2, thereby aiding researchers and pharmaceutical companies to discover drugs for COVID-19 [71-74].

Seventeen studies use AI for epidemiological modelling tasks [75-91]. In particular, 14 of these studies employ AI for forecasting the epidemic development (e.g., numbers of confirmed, recovered, death, suspected, asymptomatic and critical cases, lengths, ending time) [75-79,81,80,82-88], and 3 studies [89-91], utilize AI for predicting the potential hosts/reservoirs of SARS-COV-2.

In 14 studies [33,92-104], AI is used for patient outcome-related tasks. In particular, 6 studies use AI for segmentation and quantification of infected regions in the lungs due to COVID-19, thereby

assessing the severity of the disease [92-97]. AI is also used in 4 studies for identifying cases at high risk of progression to severe COVID-19 [33,98-100]. Furthermore, AI is also used for predicting mortality risk [101,102], its associated factors [103], and length of hospital stay in patients with COVID-19 [104].
AI has also been used for Infodemiology [105]. Specifically, AI is used for raising awareness to use water, sanitation, and hygiene through combining authentic sources of information with daily news [105]. Appendix 5 presents the purposes or uses of AI techniques in each included study.

Table 2: Purposes and uses of AI against COVID-19

Purposes/uses	**Number of studies**		
Diagnosis	CT images:15 Genome sequence:1	X-ray images:12 Respiratory patterns:1	Laboratory tests:2
Treatment & Vaccines	Drug discovery:9 Drug repurposing:2	Vaccine discovery:4 Treatment safety:1	Protein structure:4
Epidemiology	Epidemic development:14	Potential reservoirs:3	
Patient outcome	Severity:6 Risk factors:1	Progression to sever:4 Hospital stay:1	Mortality risk:2
Infodemiology	Raising awareness:1		

Features of AI-based techniques used for COVID-19

In 29 studies [24,31,47,51,52,58,63,68,70,74,79,83-86,88,90,91,95-105], AI techniques used against COVID-19 are based on traditional machine learning models and algorithms (Table 3). The most commonly used machine learning models and algorithms are Support Vector Machines (SVM) [24,31,47,58,68,70,79,91,98,101], Random Forests (RF) [31,58,68,74,90,96,101,103,104], Decision Trees (DT) [52,58,68,74,79,97,99,101,102], and Logistic Regression (LoR) [31,51,52,58,68,99-101,104].
In 60 studies, AI techniques utilized against COVID-19 are based on deep learning models and algorithms [25-50,53-57,59-67,69,71-73,75-82,87,89,92-95,98,101]. The most commonly used learning models and algorithms in the included studies are Convolutional Neural Networks (CNN) [25-50,53,62,64,72,73,82,89,92-95] and Recurrent Neural Networks (RNN) [54,55,57,59,71,73,77,98].
In two studies [64,105], AI techniques used against COVID-19 are based on models related to natural language processing (NLP) such as Continuous Bag of Words (CBOW) model, Skip-gram models, and Porter Stemming. While AI techniques were implemented in mobile phones in one study [105], computers were the platform for AI techniques in the remaining studies. Appendix 5 shows features of AI-based techniques used in each included study.

Table 3: Features of AI-based techniques used for COVID-19

Features	**Number of studies**				
AI branches[1]	Deep learning:60	Machine learning:29		Natural language processing:3	
AI models/ algorithms[2]	CNN:37	SVM:10	RF:9	DT:9	LoR:9
	RNN:8	ANN:6	TL:4	AE:4	DNN:3
	KNN:3	LASSO:3	PNN:3	MLP:2	ADQN:2
	AB:1	ARIMA:1	BA:1	BERT:1	CBOW:1
	EM:1	GA:1	GAN:1	GLM:1	HAM:1
	LDA:1	LiR:1	LM:1	MDM:1	NB:1
	PS:1	RL:1	SM:1	TSF:1	USEL:1

	VAR:1
Platforms	Computer:81 Mobile:1
Abbreviations	**AB**: AdaBoost; **ADQN**: Advance Deep Q-learning network; **AE**: Auto-encoders; **ANN**: Artificial Neural Network (unspecified); **ARIMA**: Auto-Regressive Integrated Moving Average Model; **BA**: Bayesian analysis; **BERT**: Bidirectional Encoder Representations from Transformers; **CBOW**: Continuous Bag of Words; **CNN**: Convolutional neural network; **DNN**: Deep neural network; **DT**: Decision tree; **EM**: Eureqa Modelling; **GA**: Genetic algorithm; **GAN**: Generative adversarial network; **GLM**: Generalized Logistic growth Model; **HAM**: Holistic Agent-based Model; **KNN**: K-Nearest Neighbors; **LASSO**: Least Absolute Shrinkage and Selection Operator; **LDA**: Linear Discriminant Analysis; **LiR**: Linear Regression; **LM**: Language model; **LoR**: Logistic Regression; **MDM**: Multi-task deep model; **MLP**: Multilayer perceptron; **NB**: Naive Bayes; **PNN**: Polynomial Neural Network; **PS**: Porter Stemming; **RF**: Random Forest; **RL**: Reinforcement learning; **RNN**: Recurrent Neural Network; **SM**: Skip-gram model; **SVM**: Support Vector Machine; **TL**: Transfer learning; **TSF**: Time Series Forecasting; **USEL**: Universal-sentence-encoder-large; **VAR**: Vector Auto Average.

[1] Numbers do not add up as AI techniques in some studies were based on more than one AI branches.

[2] Numbers do not add up as several studies used more than AI model/algorithms

Features of datasets used for development and validation of AI models

As shown in Table 4, public resources (e.g., NCBI, GitHub, Kaggle) are the most commonly used data source for development and validation of AI models [24,27,29,36,39-50,53,55-65,67-75,77,80-85,87-89,91-93,103,105]. Other data sources used by the included studies are as follows: clinical settings (e.g. databases in hospitals and medical centres) [25-35,37,38,51,52,63,94-98,100,102,104], government sources (e.g., Chinese Center for Disease Control and Prevention) [53,76,78,79,84,86,90,99,101], literature (e.g., previous studies and books) [36,40,42,61,66,101], news websites [101,105], participants recruited by the study [54].

Types of data collected from these data sources are as follows: radiology images (e.g., CT and X-ray) [24-50,54,92-96,98,104], biological data (e.g., protein and genome sequences) [53,55-65,67-74,89-91], epidemiological data (e.g., number of infected and recovered cases) [75-85,87,88,97,102], clinical data (e.g., signs, symptoms, physician notes, and patients' history) [25,51,52,66,97-103], laboratory data (blood/PCR test results) [25,51,52,86,97,98,100,102], demographic data (e.g., age, gender, ethnicity) [52,99-102], guidelines [105], and news articles [105].

Dataset size is reported by 50 studies, ranging from 31 to 3,000,000. The dataset size is less than 1,000 samples in half of these studies [24,27,32,34,36,37,39,41,44,45,47,51-53,69,86,92,94-98,100,102-104] and only eight studies reported a size of 10,000 samples or more [25,26,54,59,61,87,99,101].

Validation of models is reported in 53 studies. Three types of validation are used in the included studies: train-test split [25,29,30,34-39,41,43,44,47-50,59,75,87,88,93,94,99,100,103], K-fold cross-validation [24,31,40,42,45,46,52,53,58,66,68,90-92,96,98,101,104], and external validation [26,27,29,32,33,38,51,54,82,95,102].

Training set proportion of the total dataset is reported in 49 studies. The proportion of the training set ranges from less than or equal to 25% in three studies [25,27,28], >25%-50% in two studies [26,95], >50%-75% in 16 studies [32,33,35,36,38,39,47,51,59,75,87,88,100,96,102,103], and more than 75% in 28 studies [24,29-31,34,37,40-46,48,50,52-54,58,66,90-92,94,98,99,101,104]. The mean of the proportions of the training set in the 49 studies is 72.7%.

Validation set proportion of the total dataset is reported in 11 studies; it ranges from less than or equal to 25% in eight studies [26,28,35,36,38,47,48,53] and >25%-50% in three studies [25,100,102]. The mean of the proportions of the validation set in the eleven studies is 18.7%.

Test set proportion of the total dataset is reported in 49 studies, ranging from less than or equal to 25% in 35 studies [24,29-31,34,36,37,40-48,50,52-54,58,59,66,75,87,90-92,94,98-102,104], >25%-

50% in ten studies [26,32,33,35,38,39,51,88,96,103], >50%-75% in three studies [25,28,95], and more than 75% in one study [27]. The mean of the proportions of the test set in the 49 studies is 22.9%. Appendix 6 presents features of datasets used for development and validation of AI models in each included study.

Table 4: Features of datasets used for development and validation of AI models

Features	**Number of studies**			
Data sources[1]	Public databases:52 Literature: 6	Clinical settings:24 News websites:2	Government sources:9 Participants:1	
Data types[2]	Radiology image:35 Clinical data:11 Guidelines: 1	Biological data:23 Laboratory data: 8 News articles:1	Epidemiological data:15 Demographic data:5	
Dataset size[3]	<1000:26	1000-9999:16	≥10000:8	
Type of validation[4,5]	Train-test split:25	K-fold cross-validation:18	External validation:11	
Proportion of training set[6]	≤25%:3	>25%-50%:2	>50%-75%:16	>75%:28
Proportion of validation set[7]	≤25%:8	>25%-50%:3	>50%-75%:0	>75%:0
Proportion of test set[8]	≤25%:35	>25%-50%:10	>50%-75%:3	>75%:1

[1] Numbers do not add up as several studies collected their data from more than data source.
[2] Numbers do not add up as several studies collected more than one type of data.
[3] Dataset size was reported in 50 studies
[4] Type of validation was reported in 53
[5] Numbers do not add up as one study used two different types of validation
[6] Proportion of the training set was reported in 49 studies
[7] Proportion of the validation set was reported in 11 studies
[8] Proportion of the training set was reported in 49 studies

Discussion

Principal Results

In this study, we conducted a scoping review of the use of AI against COVID-19. We found a lack of publications in December 2019 and January 2020. This is not surprising, given that (a) SARS-CoV2 was only identified on January 7th [106], (b) insufficient data was not available to back scientific publications, in particular internationally, and, (c) the contagiousness and aggressiveness of the virus were underestimated (first lockdown in China January 23rd [106]). Half of the studies in this report were published in China. Since SARS-CoV2 originated in China and affected it the most during the first 3 months of the pandemic, it had the most data related to COVID-19. Considering lengthy publication processes and the vast number of COVID-19 related manuscript submissions, it is also not surprising that most of the included studies are preprints.

In the included studies, AI is used for five purposes: diagnosis, treatment and vaccine discovery, epidemiological modelling, patient outcome-related tasks, and infodemiology. None of the included studies uses AI for other purposes such as contact tracing of the individuals, providing training to students and healthcare professionals, or robotics to deal with suspected and quarantined cases.

Most of the AI techniques used in the included studies are based on deep learning approaches such as CNN and RNN. All but one study use desktop machines, workstations and clusters as opposed to mobile platforms. This can be explained by the computational demand in training AIs. While all major mobile phone manufacturers equip their flagship models with AI co-processors, these co-processors accelerate inference, a computationally much lighter task. Also, *federated* learning [107] (a machine learning privacy-preserving technique usually used in mobile phones) is still in its infancy and raises issues such as data sovereignty, scalability, and performance.

Data sources used in the included studies usually come from the public domain (e.g., NCBI, GitHub, Kaggle) and proprietary databases (less common). Radiology images are the most commonly used type of data, followed by biological data. The number of samples is still comparably small (less than 1,000 in half of the studies). The diversity and size of data indicate a lack of publicly available data despite COVID-19 cases having surpassed 5 million as of the time of writing. We, therefore, second Wynants et al. call "for immediate sharing of the individual participant data from COVID-19 studies worldwide" [20].

Practical and Research Implications

While this work explores the use of AI against COVID-19, some applications could prove useful far beyond this pandemic. For instance, Kiwibot designs autonomous medical delivery robots to minimize interpersonal contact [108]. Whiteboard Coordinator developed a high precision thermal screening device eliminating individual measurements, leading to higher throughput and larger social distances [109]. While mobile phones are not yet the AI-platform of choice, the first apps to track interpersonal contact using mobile phones have been published to prioritize COVID-19 testing [110]. Finally, whereas a Real-Time RT-PCR test takes around 25 minutes and requires stocks of chemical reagents, AI can inspect chest CTs to provide preliminary diagnoses in seconds. We believe that increasing social distance and providing fully autonomous checkups will be the most valuable use of AI beyond the current pandemic.

In the past, fundamental AI research was focused mainly on faster (or, even feasible) training. We believe that, in the future, this must be complemented with public education. AI mistrust, because of our still lacking understanding of how AI works at the deepest level, further raises ethical questions that need to be answered before AI will be uniformly accepted. We also found that AI features and results are reported in a very inconsistent manner, potentially fueling AI mistrust and making a direct comparison between studies difficult. We found that only 64% of the studies included in this review disclose training-testing split, 61% mention the data size, a mere 35% report validation after training, while more than 7% do not even specify the type of AI used. It is therefore important that we as a community develop a standardized reporting protocol to (1) slow down the barrage of poorly conducted COVID-19 studies that threaten to overwhelm serious scientists (1,916 related papers were retrieved before April 5th in [20]), (2) strengthen properly conducted studies and (3) improve reproducibility.

We found that, explicably, the landscape of studies is still dominated by Chinese institutions, which bears the potential for cultural, technological, and geospatial biases. However, we see a recent move towards a more balanced landscape (see also Figure 2). Although we identified more than 100 models developed in the included studies, we did not assess their quality as it is out of the scope of this review. Therefore, further reviews are needed to assess the quality of AI models used in the fight of COVID-19.

Given the current "infodemic" [13] we find it surprising that NLP is not used more often. We see AI-based analysis of effective advertisement of non-pharmaceutical interventions (NPIs) as one research opportunity to answer questions like what manner of speech results in maximum public acceptance?

Strengths and Limitations

Strengths

Given that this review includes all AI techniques used for the COVID-19 pandemic regardless of their characteristics, study design, study setting, and country of publication, it may be considered the most comprehensive review in this research area. This helps readers to speculate how AI is being leveraged amid the COVID-19 pandemic. In comparison with similar reviews [12,13,17-20], our review is the only one that describes and summarizes features of the identified AI techniques and datasets used for their development and validation. Furthermore, unlike previous reviews [12,13,17-19], this review follows the full scientific rigor of PRISMA-ScR [21].

In contrast to other reviews, we searched the most commonly used databases in health and information technology fields to identify as many relevant studies as possible. Thus, the number of studies included in this review is much higher than in other reviews [12,13,17-20]. Additionally, we strove to retrieve gray literature and minimized the risk of publication bias by searching Google Scholar and conducting backward reference list checking. Furthermore, we minimized selection bias by having two independent reviewers conducting study selection and data extraction with a very high agreement in both processes.

Limitations

Given that our review excludes proposals of AI techniques, it is likely that we miss other applications of AI for COVID-19. The review, therefore, might not identify all potential uses of AI for the current pandemic. Owing to practical constraints, the search was restricted to English studies. Therefore, we probably missed several studies written in other languages, especially Chinese. The search query did not include terms related to specific types of models or algorithms such as CNN, RNN, and SVM. Thus, it is likely that we missed some studies that used such terms in their title and abstract instead of the terms that we used (i.e., AI, machine learning, and deep learning). The findings of this review are mostly based on preprints, which are more likely to have inaccurate or missing information. Therefore, the accuracy of the information in the included studies may affect the accuracy of our findings.

Conclusions

In this study, we provide a scoping review of 82 studies on AI against COVID-19. Given that many of the proposed methods are not yet clinically accepted, we remark that the most rewarding research will be on methods promising value beyond COVID-19. We believe that mobile phones offer unexploited potential, but more research in the direction of energy-efficient and federated learning is needed. We also believe that the use of NLP to assess effective communication of non-pharmaceutical interventions is a largely unexplored research direction, especially since data driving this research is available in the public domain, unlike much of the data produced by clinical studies. For AI to gain broad acceptance, standardized reporting protocols, to be followed by studies on AI, are needed. Likewise, more research on AI ethics and explainable AI is needed, paired with public education initiatives.

Conflicts of Interest

None declared.

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Abbreviations

AA: Alaa Abd-alrazaq
CBOW: Continuous Bag of Words
CNN: Convolutional neural network
COVID-19: Corona Virus 2019
CT: Computed Tomography

DT: Decision tree
LoR: Logistic Regression
NCBI: National Center for Biotechnology Information
RF: Random Forest
RNN: Recurrent Neural Network
SARS-CoV-2: Severe Acute Respiratory Syndrome Coronavirus 2
SVM: Support Vector Machine
WHO: World Health Organization

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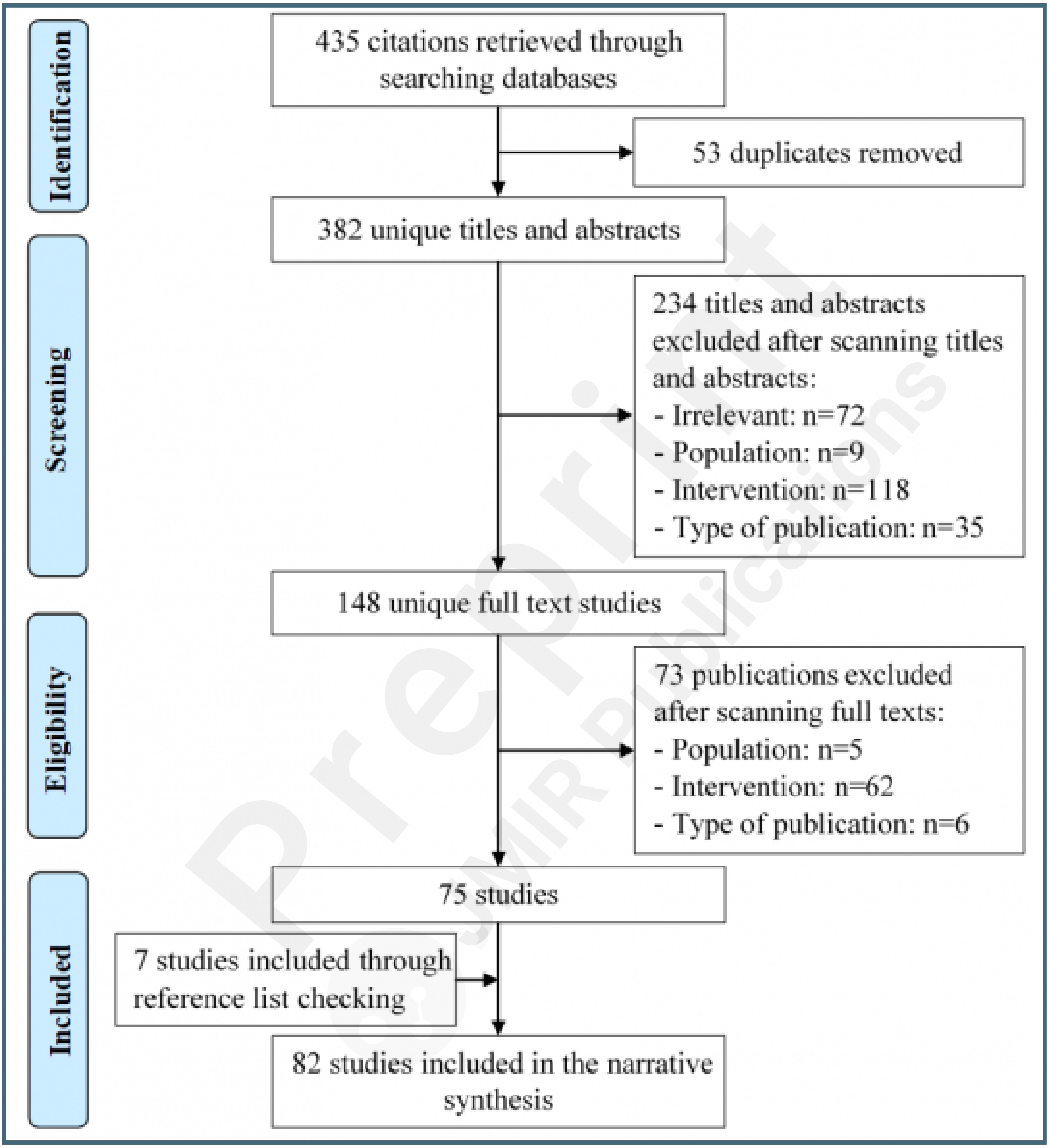
Supplementary Files

Untitled.
URL: https://asset.jmir.pub/assets/6b24e1e946509a3a0eaa1eabeb0f6841.docx

Figures

Flow chart of the study selection process.



Publications by months and country.

Multimedia Appendixes

Search strategy.
URL: https://asset.jmir.pub/assets/cf298a3d5c52c9ce50489ebdbb845a02.docx

Interrater agreement matrices for study selection steps.
URL: https://asset.jmir.pub/assets/ed5b3d9560c58ae7130aa31a8b541a0b.docx

Characteristics of the included studies and features of AI techniques used for COVID-19.
URL: https://asset.jmir.pub/assets/266896d00c96865f08b04d89e175c002.docx

Features of datasets used for development and validation of AI models.
URL: https://asset.jmir.pub/assets/4055b81f7b402fb70d34c679eb795eb7.docx

Data extraction form.
URL: https://asset.jmir.pub/assets/59e6d77e7f5debabf6eaaf07283a21b3.docx

Overview of AI-based techniques.
URL: https://asset.jmir.pub/assets/72fefd493491542306549dc0804d4032.docx