Array 17 (2023) 100271

Contents lists available at ScienceDirect

Array

journal homepage: www.sciencedirect.com/journal/array

Combating Covid-19 using machine learning and deep learning: Applications, challenges, and future perspectives

Showmick Guha Paul [a], Arpa Saha [a], Al Amin Biswas [a,*], Md. Sabab Zulfiker [a], Mohammad Shamsul Arefin [a,b], Md. Mahfujur Rahman [a], Ahmed Wasif Reza [c]

[a] Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh
[b] Department of Computer Science and Engineering, Chittagong University of Engineering and Technology, Chittagong, Bangladesh
[c] Department of Computer Science and Engineering, East West University, Dhaka, Bangladesh

ARTICLE INFO

Keywords:
Machine learning
Deep learning
Artificial intelligence
Pandemic
COVID-19

ABSTRACT

COVID-19, a worldwide pandemic that has affected many people and thousands of individuals have died due to COVID-19, during the last two years. Due to the benefits of Artificial Intelligence (AI) in X-ray image interpretation, sound analysis, diagnosis, patient monitoring, and CT image identification, it has been further researched in the area of medical science during the period of COVID-19. This study has assessed the performance and investigated different machine learning (ML), deep learning (DL), and combinations of various ML, DL, and AI approaches that have been employed in recent studies with diverse data formats to combat the problems that have arisen due to the COVID-19 pandemic. Finally, this study shows the comparison among the stand-alone ML and DL-based research works regarding the COVID-19 issues with the combinations of ML, DL, and AI-based research works. After in-depth analysis and comparison, this study responds to the proposed research questions and presents the future research directions in this context. This review work will guide different research groups to develop viable applications based on ML, DL, and AI models, and will also guide healthcare institutes, researchers, and governments by showing them how these techniques can ease the process of tackling the COVID-19.

1. Introduction

COVID-19, a new coronavirus, emerged in December 2019 as a cluster of deadly serious illnesses in Wuhan, China, and rapidly expanded as an outbreak [1]. The illness is driven by the virus SARS-CoV-2, referred to as COVID-19. WHO labeled COVID-19 a worldwide epidemic on March 11th, 2020 [2]. Therefore, as an outcome of this pandemic, more than six million people have died throughout the world [3]. The COVID-19 pandemic spread worldwide, infecting millions of people. Fig. 1 depicts a worldwide heat map of COVID-19 epidemic deaths.

The most typical signs of the COVID-19 infection include terrible cough, failure of flavor and aroma, migraine, exhaustion, and lung ailments such as breathing problems [5,6]. However, medical images such as Chest X-ray (CXR), ultrasonography, computerized tomography (CT), and other imaging techniques have become significant options for diagnosing COVID-19 infection. Because of the extreme contagiousness of this virus, a rapid and precise diagnosis approach is unquestionably essential for combating this pandemic. Many coronavirus diseases like SARS and MERS can persist in a host species without any symptoms. Contagiousness of this virus, a rapid and precise diagnosis approach is unquestionably essential for combating this pandemic. Sometimes these diseases create extremely weak and non-characteristic signs in the infected individuals. Fig. 2 shows the growth pattern of the COVID-19 spread. It can be found that the growth is exponential. Therefore, it may be possible to predict the upcoming COVID-19 wave and be prepared early for it, saving thousands of lives, making prompt detection and treatment of these infections[7].

Since the outbreak of the COVID-19, governments of different countries have implemented strict lockdowns in large cities and urban areas to avoid large gatherings of people and reduce the infection's impact. COVID-19 has various clinical signs in its early stages, including malaise, migraine, headache, difficulty in breathing, muscle pain, dry mouth, backache, vomiting, and stomach cramps [8,9]. The most

* Corresponding author.
E-mail addresses: showmick.cse@gmail.com (S.G. Paul), arpasaha.cse@gmail.com (A. Saha), alaminbiswas.cse@gmail.com (A.A. Biswas), sabab.rumc@gmail.com (Md.S. Zulfiker), sarefin@cuet.ac.bd (M.S. Arefin), mrrajuiit@gmail.com (Md.M. Rahman), wasif@ewubd.edu (A.W. Reza).

https://doi.org/10.1016/j.array.2022.100271
Received 28 October 2022; Received in revised form 5 December 2022; Accepted 7 December 2022
Available online 10 December 2022

prevalent signs for COVID-19 are lack of flavor and aroma [10]. Governments and regulatory organizations throughout the world have implemented a no-compromise lockdown to preserve social isolation and so limit the epidemic as daily notifications of new breakouts have been flooding in at an unprecedented rate. The most impacted nations have closed their borders to transit and travel to stop the spread of COVID-19. In this global health emergency, the health sector is actively searching for new technology and strategies to monitor and manage the spread of the coronavirus epidemic. AI is currently one of the most effective technology since it can monitor the spread of the Coronavirus, assess its danger and severity, and measure its development rate.

AI is a vast field with several sub-fields that may be used to address difficult issues in our daily lives. Learning, planning, representing information, and seeking are some of these sub-areas. The RT-PCR is currently most widely utilized approaches for COVID-19 detection. Using various data types with different AI-based methods, multiple applications have been developed that can now be used as a replacement for traditional RT-PCR tests. Utilizing different AI-based applications, patient management is becoming more effective, as these applications can efficiently predict patients' conditions and needs for hospitalization. The identifying and detecting COVID-19 by AI using CXR can early detect the disease and can be automated as a replacement for RT-PCR. AI has been used in forecasting the upcoming waves of the COVID-19 outbreak. By employing different ML, DL, and AI-based models, sentiment analysis of the public opinions regarding the pandemic has been performed. Also, these models have been used to identify hoax or fake information regarding the COVID-19 pandemic. Which eventually helped to raise public awareness against the pandemic. The ML, DL, and AI-based classification and screening techniques have been used to fine-tune and explore new methods that can more adequately classify and improve the accuracy of detecting the COVID-19 disease. Thus these techniques can be helpful for COVID-19 management. The widespread use of various techniques of AI for different purposes is driving the way to manage and combat of COVID-19 more efficiently.

Therefore, we have taken the initiative to analyze and explore studies that utilized various techniques in the field of AI to combat COVID-19-related challenges. The following are some of the contributions of our review study:

- Various techniques currently utilized in the field of AI have been explored, and the optimal and most utilized techniques with respect to various data types have been filtered.
- This study outlines future research directions and challenges to the researchers who wants to pursue study in the related field.
- The proposed six state-of-the-art questionnaires that tend to uncover issues, future perspectives, and analysis of the current studies to manage COVID-19 have been addressed.

The organization of the remaining sections is as follows: the review methodology used to conduct the study is discussed in section 2. Section 3 of this study presents the analysis and findings. Section 4 of this study presents finding and analysis of the proposed research questions. Section 5 discusses the challenges and the potential scopes for future research to combat COVID-19. Finally, the study is concluded in section 6.

2. Review methodology

As shown by Brereton et al. [11], a review of studies is a technique of discovering, analyzing, and interpreting every accessible material on a particular study topic or topic of attention.

In this study, a comprehensive literature search has been carried out in response to a collection of research queries. Besides, a safe, robust,

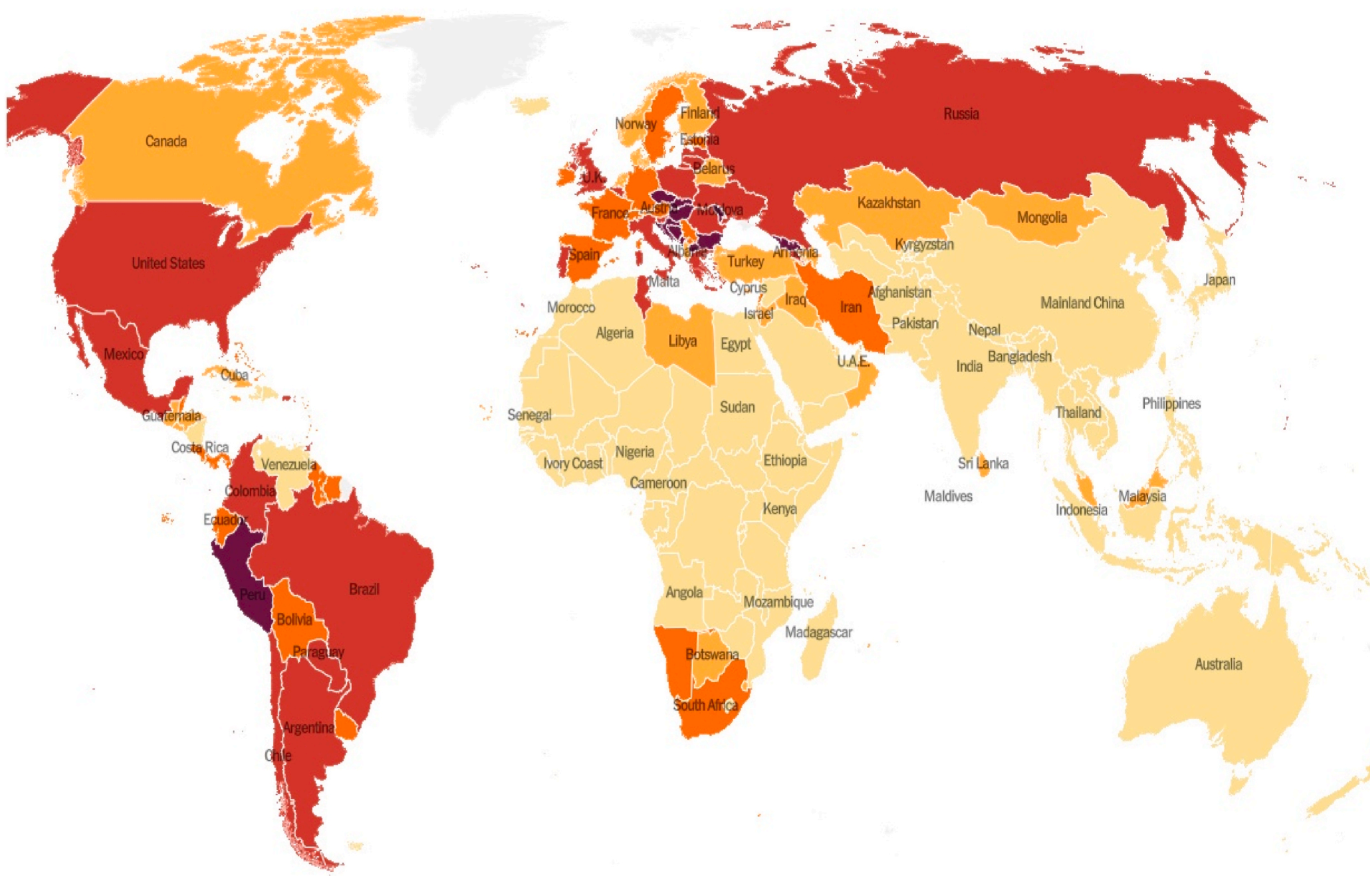

Fig. 1. Global heat map of the COVID-19 outbreak death per capita [4].

and quantifiable procedure has been utilized to provide the answer to those concerns.

2.1. Search strategy

Multiple online academic search engines such as Scopus, Web of Science, ERIC, PubMed, Science Direct, IEEE Xplore, DOAJ, and Google Scholar were utilized to obtain related studies. Table 1 summarizes the keywords that have been applied to extract the relevant works. Relevant studies were mostly chosen by manually using these keywords in various combinations. Some samples of the combinations are (‘COVID-19′ or ’coronavirus’ or ‘CoV2′ and ‘machine learning’), (‘coronavirus’ or ‘CoV2′ or ‘COVID-19′ and ‘deep learning’), (‘COVID-19′ or ’coronavirus’ or ‘CoV2′, ‘machine learning’, and ‘prediction’), etc.

2.2. Inclusion and exclusion criteria

In this study, only the relevant works published in the English language have been considered. The inclusion and exclusion criteria for considering the related works are as followings:

Inclusion criteria:

(a) Papers that propose at least one ML, DL, or combinations of ML/DL/AI models.
(b) Studies that discuss at least one of the COVID-19 issues.
(c) Studies performing experimental works on different datasets related to COVID-19.

Exclusion criteria:

(a) Research works published before 2020.
(b) AI, ML, and DL-based techniques mentioned in research articles which are not associated with the COVID-19 epidemic.
(c) COVID-19 issues mentioned in a research work that does not employ ML, DL, or combinations of ML/DL/AI approaches.
(d) Theoretical research with no practical applicability, survey papers, and review papers.

2.3. Selection of the study

The process of study selection based on the inclusion and exclusion criteria is presented in Fig. 3

In this step, the primary relevant works were selected based on the search strategy discussed earlier. By applying the aforementioned search strategy, 600 studies were identified and selected initially. The duplicate records or studies were then removed in the next phase. After removing the duplicate studies, a total of 512 works remained. 382 studies were excluded during the screening process. Abstract analysis, dataset analysis, and inclusion and exclusion criteria were used to filter the studies. A total of 130 research works became eligible for full-text analysis through the screening process. Later, these 130 research works were reviewed, and 26 of them were eliminated. In the last stage, a total of 104 studies remained to be checked for their methodological qualities. Among those studies, a total of 16 studies were then excluded based on the methodological quality. After completing all these procedures, only 88 studies remained for the systematic review. Among the selected studies, 29 studies are from the Elsevier journals, 16 studies are from the Springer journals, 11 studies are from the MDPI journals, 10 studies are from various journals referred to as "Others Journal", and 6 studies are from the Nature journals. On the other hand, equal numbers of studies have been collected from the Hindawi and the Wiley journals. From each of these two publishers, 3 studies have been considered. The least number of studies have been collected from the IOP science journals. Only 2 studies have been considered from the journals of this publisher. The remaining 8 studies are conference papers.

2.4. Extraction of the data

After selecting the studies, data extraction is very much important to analyze and interpret the studies properly. A general structure is required for the extraction of data from studies to obtain meaningful findings. As a response, tables with some preset attributes were developed, and various data from the studies were added to the tables. The first attribute of the tables, “References and Year,” contains the authors’ name and the publication year. The second attribute defines the purposes of the studies. The third and the fourth attributes describe the data types used in the studies and the sample size of the studies, respectively. The fifth attribute specifies the major techniques applied in the studies. Finally, the last attribute mentions the best performing model with its performance.

2.5. Research questions (RQs)

This comprehensive and in-depth review mainly focuses on summing up, evaluating, and synthesizing different research works where several ML, DL, and combinations of ML, DL, and AI-based techniques have been considered. The primary goal of this study is to acquire the answers to the subsequent six research questions and to have a profound as well as a comprehensive understanding of the responses to these questions.

RQ 1. What ML, DL, and combinations of ML, DL, and AI-based mechanisms are widely used in the studies related to COVID-19?

RQ 2. Until now, are there any standard datasets that are publicly available and may be used to analyze different ML, DL, and

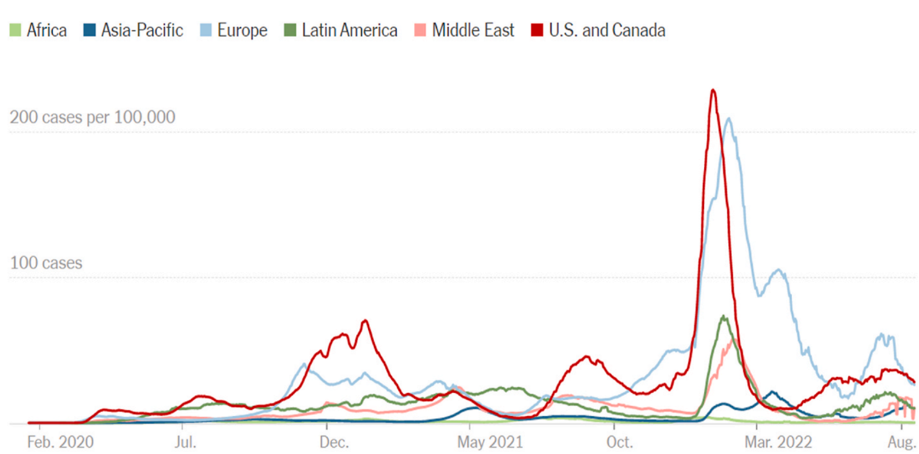

Fig. 2. Growth curve for cases by region with cases per capita [4].

combinations of ML, DL, and AI-based techniques?

RQ 3. Are there any End-to-End Solutions (E2ES) available for COVID-19 diagnosis?

RQ 4. Which countries performed the most research relating COVID-19 by involving ML, DL, and combinations of ML, DL, and AI-based techniques?

RQ 5. What are the most widely utilized criteria for assessing various works already in existence related to COVID-19 using ML, DL, or combinations of ML, DL, and AI-based techniques? Are those criteria enough that have been employed in most of these studies?

RQ 6. What are the biggest challenges for the researchers who are currently planning to do research on COVID-19 using ML, DL, or combinations of ML, DL, and AI-based techniques?

3. Analysis and findings

Multiple studies have analyzed the application of ML, DL, and AI methods in COVID-19-related studies. Dogan et al. [12] have analyzed and reviewed the studies related to the uses of AI and ML mechanisms in the context of various COVID-19-related tasks. In that review study, various studies related to COVID-19 transmission prediction, diagnosis, and detection, and drug/vaccine development have been analyzed, and six predefined questions have been explored. However, the entire context of the COVID-19 pandemic and the application of DL techniques have not been explored in the study.

In another study, Islam et al. [13] reviewed various studies that have employed various AI and ML mechanisms in the process of fighting against the COVID-19 pandemic. Based on the objectives, the studies have been categorized into four groups such as disease detection, epidemic forecasting, sustainable development, and disease diagnosis.

Table 1
Applied keyword

'machine learning' 'artificial intelligence', 'deep learning', 'coronavirus', 'prediction', 'classification', 'detection',
'diagnosis', 'identification', 'pandemic', 'sentiment analysis', 'CoV2', 'covid-19', 'ML',
'combination', 'DL', 'AI'

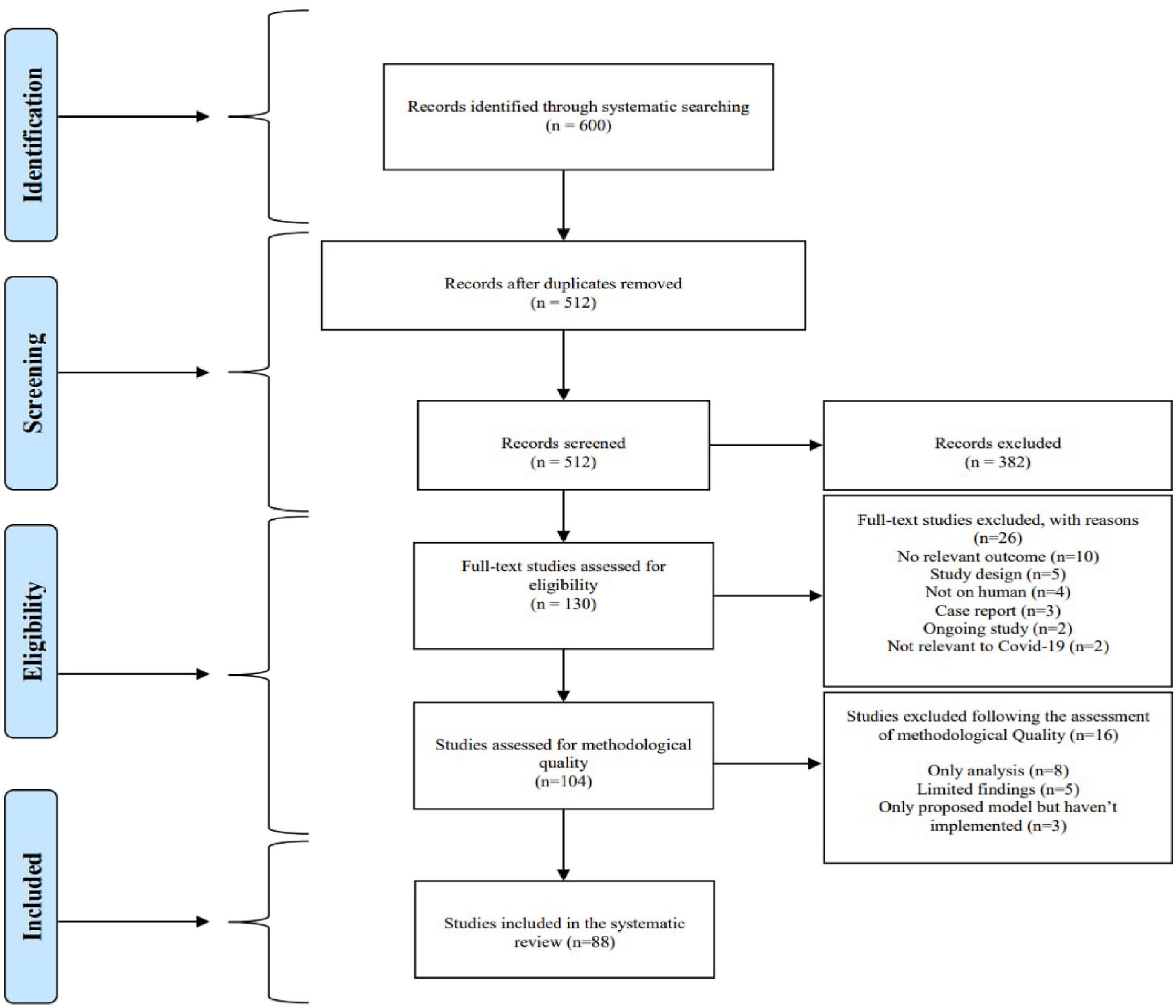

Fig. 3. Prisma flow diagram of the selection process of the study based on inclusion and exclusion criteria.

The application of various models has been reviewed and summarized. Furthermore, six research opportunities have been identified and summarized in the study. However, other objectives (sentiment analysis, vaccine development, etc.) and the application of DL techniques have not been explored.

A comprehensive review of the role of AI, drones, blockchain, and 5G to manage the COVID-19 pandemic has been performed by Chamola et al. [14]. The study explored the use of current technologies to combat the epidemic as well as its effect on the global economy. The role of Unmanned Aerial Vehicles (UAVs), blockchain, AI, and 5G, among others, in mitigating the effects of the COVID-19 outbreak has been explored and discussed in the studies.

Alballa et al. [15] reviewed recent reports on ML algorithms used in relation to the COVID-19 pandemic. In the study, the applications of ML for diagnosis and predicting patient mortality risk and severity were analyzed. The review includes studies published between January 2020 and January 2021. By assessing the studies, a small number of real-time E2E systems and a selection bias due to imbalanced data were identified. Despite analyzing the ML models for diagnosis and prediction, other COVID-19-related objectives such as detection, epidemic forecasting, etc. have not been considered.

Alafif et al. [16] review the studies conducted on the uses of ML and DL towards COVID-19 diagnosis and treatment. The review study provides a summary of the AI-based ML and DL procedures, the available datasets, performance, and currently available tools. By performing a comprehensive analysis of the current ML and DL approaches used to diagnose COVID-19, obstacles to conducting the studies have been highlighted. In addition, the study made some directions for future work. Although the study analyzed the uses of ML and DL approaches only for the diagnosis and treatment of COVID-19, other perspectives on the probable combination of ML, DL, and the COVID-19 pandemic were not covered.

Although various studies have been conducted to review the works related to the use of ML, DL, and AI-based techniques for COVID-19 management. Very few studies have explored the uses of the possible combination of ML, DL, and AI mechanisms. Moreover, this study explored diverse perspectives on the COVID-19 pandemic, utilizing a variety of data types and combinations of data types. In addition, most recent studies conducted on ML, DL, and the combination of ML, DL, and AI-based mechanisms have been included, as well as some earlier relevant studies.

3.1. Distribution and context of the study

Among all the considered works, 92% of studies have been collected from different journals, and 8% of studies have been collected from different conferences. From Fig. 4, it can be found that 96% of studies using ML models have been published in different journals, while the rest 4% of studies have been published in different conferences. The percentages of studies employing DL techniques published in journals and conferences are 80% and 20%, respectively. In terms of applying the combination of ML, DL, and AI-based techniques, 97% of the considered studies are journal papers. The remaining 3% of studies are conference papers.

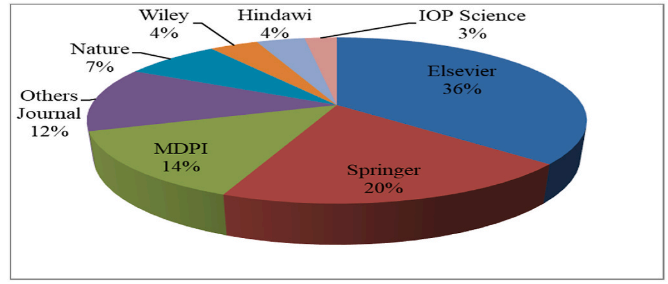

Fig. 5. Percentage of the Journal paper collected from different publishers.

Among the studies collected from the journals, 36% of the studies are from Elsevier, 20% are from Springer, 14% are from MDPI, 7% are from Nature, 4% are from Hindawi, 4% are from Wiley, 3% are from IOP Science, and 12% are from other journals according to Fig. 5.

The yearly distribution of the studies that were chosen for analysis is shown in Fig. 6. In terms of the publication year, a total of 41 studies were published in 2022. On the other hand, 39 studies were included from 2021. Only 8 studies were included from 2020. In 2022, the studies using the combination of ML, DL, and AI-based models have the highest frequency. The majority of the included studies applying ML techniques were published in 2021. Only a limited numbers of studies employing ML and DL techniques were performed in 2020. Furthermore, no studies applying the combination of ML, DL, and AI-based techniques were included from 2020.

Fig. 7 shows the types of data that were used in various studies. The majority of the studies utilized datasets in image formats. Studies employing datasets in image formats used mainly MRI, CT, CXR, ECG, and X-ray images. The studies that used non-image datasets had mainly worked with different clinical, time-series, textual, and audio data. 54%

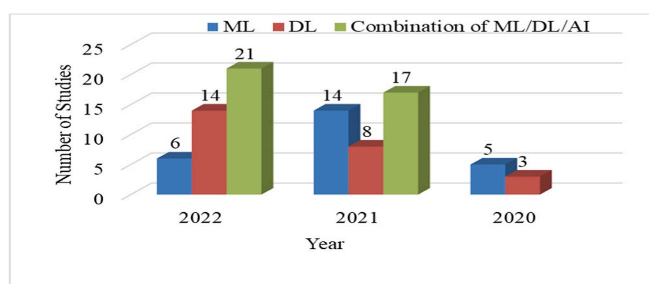

Fig. 6. Year-wise distribution of the final selected studies.

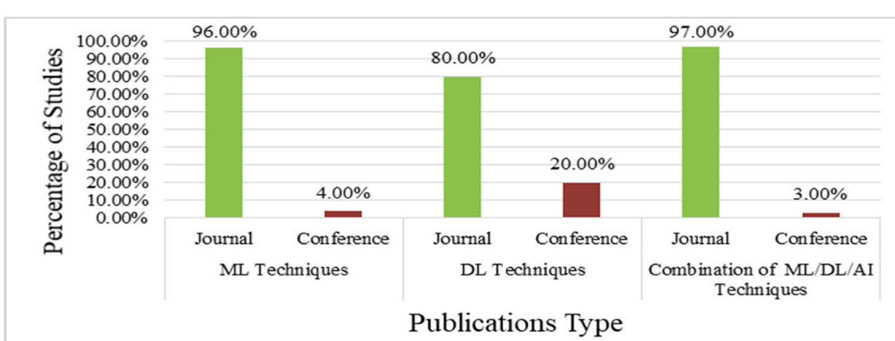

Fig. 4. Percentage of studies from different Journal & Conferences.

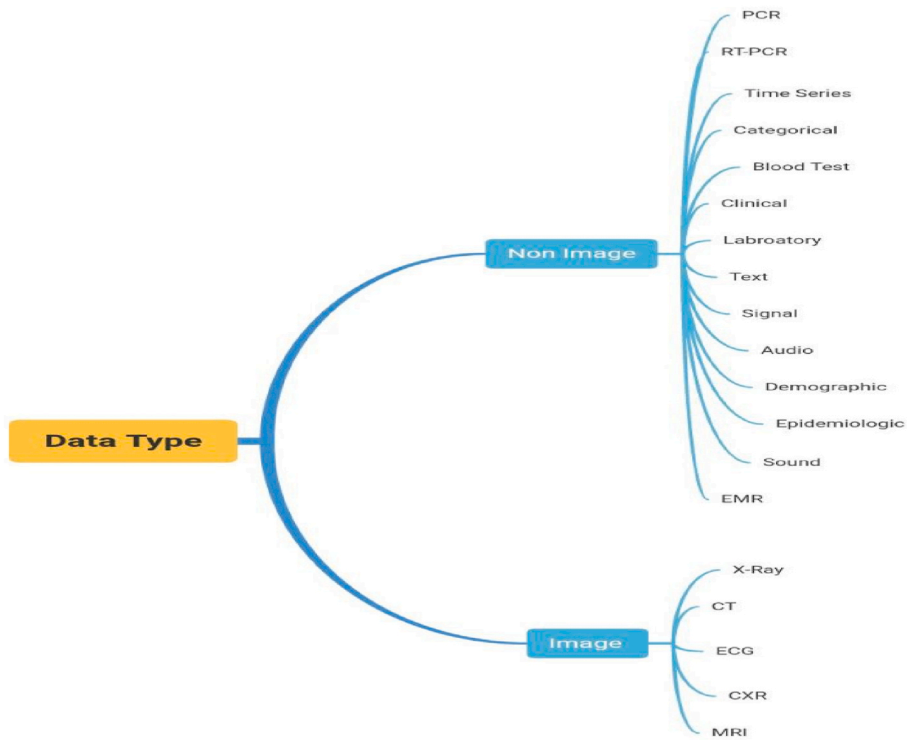

Fig. 7. Different types of data used in various studies.

of the total studies employed datasets of image format, the rest 46% studies used non-image datasets.

Among the image data types, CXR has the most significant percentage, with a percentage of 57%, followed by CT images with a percentage of 28%. X-rays and other images make up the remaining 15% of the data types.

Among the non-image data types, clinical data is the most frequently utilized data format, representing 41% of all the non-image data, followed by laboratory data, which represents 12% of all the non-image data. 11% data of the non-image data are in time series format. On the other hand, 9% data of the non-image data are in text format. Furthermore, the percentages of audio-sound data, blood test data, and RT-PCR data are 8%, 5%, and 3%, respectively. 11% of the non-image data are of other different data formats.

3.2. Applications of machine learning to combat COVID-19

ML is the area of AI that mainly focuses on building systems that are capable of learning without explicit programming to do so. At the beginning of the COVID-19 pandemic, ML algorithms were primarily utilized. Initially, these algorithms were utilized exclusively for geographical and area-wise COVID-19 spread analysis. These algorithms are now being used for various purposes in combating COVID-19. Currently, ML approaches not only can predict COVID-19 by using clinical and laboratory data but also can be used to derive much more complicated aspects of COVID-19. ML approaches show significant performance in the diagnostic process of COVID-19 by utilizing diverse data such as blood images, X-rays, ECG, CT scans, etc. Due to the usage of ML methods for extracting features from images, signals, and audio data, COVID-19's classification is improving day by day. As ML models achieve more desirable outcomes, they are increasingly being combined with other approaches. The use of several ML methods to address different COVID-19-related problems has been reviewed and presented in this section. Table 2 shows the summary of various studies employing ML models to combat COVID-19.

Fig. 8 shows the frequency of different ML models that have been used in the considered studies. The most frequently used ML model is RF in the considered works. The SVM model has achieved the second-highest position, followed by the LR model with the third-highest position. Models like NB, DT, XGB, KNN, and NN have also been used frequently on the other hand.

Fig. 9 shows the percentage of studies by different countries employing ML models to combat COVID-19. The majority of the studies come from the United States. 20% of the studies were conducted in the United States. Each of the countries such as Bangladesh, Iran, and Italy contributed 8% of the studies. However, the remaining 14 countries provided significantly fewer studies using ML models to work on COVID-19-related issues.

From Table 2, it is observed that, various types of data have been used to perform the various studies. According to our in-depth analysis and observations, in the majority of studies for classification purposes, the RF and XGB classification models performed most optimally with the clinical data type. Moreover, regardless of data type or study objective, XGB, RF, and NN models consistently outperform other machine learning algorithms.

3.3. Applications of deep learning to combat COVID-19

DL is a branch of ML that utilizes representation learning to tackle complicated problems. DL-based models, such as CNN, proposed Custom CNN, DCNN, and other methods have lately been used for COVID-19 classification, diagnostics, and detection, by researchers to combat the COVID-19 outbreak. This study has reviewed the application of various DL approaches for combating the COVID-19 epidemic as well as performed comparisons between them. Table 3 shows the summary of the studies employing DL techniques relating to COVID-19 issues.

Fig. 10 represents the applied DL models. Among different DL models, the custom models have the highest frequency of 14, followed by the RESNET50 with the count of 12. Various versions of EFFICIENTNET, which are referred to as EFFICIENTNET(X) algorithms, have achieved the third highest position with a number of 11. Among the next-most used DL models, VGG-16 and VGG-19 have been applied in 10

Table 2
A summary of different machine learning-related studies for COVID-19.

References and Year	Purposes	Data Type	Sample Size	Model	Best Model with Performance
Abdulkareem et al. [17], (2021)	Classification	Laboratory	600	RF, BERNOULLI NB, SVM	SVM(Accuracy 95%)
Callejon-Leblic et al. [18], (2021)	Prediction	RT-PCR	777	LR, RF, SVM	SVM(Mean Sensitivity of 80.74%)
Faisal et al. [19], (2021)	Prediction	Time Series, Categorical	92,400	LR, KNN, RBFK-SVM, PK-SVM, ADB, NB, DT, RF, GB, QDA, ANN	DT(Accuracy 90%)
Cabitza et al. [20],(2020)	Detection	Blood Test, Clinical	3 datasets (1624 patients)	LR, NB, KNN, SVM	CBC dataset(RF Accuracy 93%), COVID-19 dataset (KNN Accuracy 90%), CBC dataset (KNN Accuracy 90%)
Guan et al. [21],(2020)	Prediction	Clinical	1270	LASSO R, XGB	XGB(Sensitivity 85%)
Alves et al. [22],(2021)	Classification	RT-PCR, Laboratory	5644	LR, RF, XGB, SVM, MLP, ENSEMBLE	RF(Accuracy 88%)
Kukar et al. [23],(2021)	Diagnosis	Blood test, Clinical	5333	RF, SVM, NN, XGB	XGB(Sensitivity 81.9%)
Muhammad et al. [24], (2020)	Prediction	Clinical	263,007	DT, LR, NB, SVM, ANN	DT(Accuracy 94.99%)
Zargari Khuzani et al. [25],(2021)	Classification	X-ray	420	PCA, NN	NN(Accuracy 94%)
Statsenko et al. [26], (2021)	Prediction	Clinical	560	GB, ADB, ET,RF, NN,LR	NN(with top value AUC 0.86, With all value AUC 0.90)
Tran et al. [27],(2021)	Detection	Clinical	226	MILO	MILO(Accuracy of 98.3%)
Rezaeijo et al. [28],(2021)	Classification	X-ray	178	ADB, BAG, GNB, DT, GBDT, KNN, RF, L-SVM, LR,RFE,MNB	RFE + KNN(AUC 0.997)
Jimenez-Solem et al. [29], (2021)	Prediction	Clinical	5594	RF	RF(ROC-AUC of ICU admission 0.802, ventilator treatment 0.815,and death 0.902)
Hassan et al. [30],(2021)	Prediction	Time Series	Jan 22- Feb 13	NN, SVM, BN, PR	NN(R-Square score Confirmed Cases 0.989086182, Recoveries Cases 0.989356735, Deaths Cases 0.932880987)
Saadatmand et al. [31], (2022)	Prediction	PCR, Clinical	398	LR, RF, XGB, C 5.0, NN	LR, and NNs achieved the highest Accuracy (86.42%)
Rehman et al. [32],(2021)	Prediction	X-ray, Clinical	646	DT, KNN, NB, ET, RF, SVM	RF(Recall 96.00%)
Guerrero-Romero et al. [33],(2022)	Identification	Clinical, Laboratory	1064	LR	LR(Sensitivity 83%)
Debjit et al. [34],(2022)	Prediction	Clinical, Laboratory	1,023,426	HHOXGB, HHOLGB, HHOCAT, HHORF, HHOSVC	HHOXGB(Accuracy 92.23%)
Almustafa [35],(2021)	Prediction	Laboratory	200,000	NB, SGD, J48, RF, KNN	J48(Accuracy 94.41%)
Erdoğan and Narin [36], (2022)	Classification	Signal	1187 records	ENSEMBLE, BT, SVM-LINEAR, LR, LDA, MKNN	Ensemble-BT(Recall 90.54%)
Sciavicco et al. [37], (2022)	Classification	Audio	9986	TRF, TDT	TRF(Accuracy 99.4%)
Pourhomayoun and Shakibi [38],(2020)	Prediction	Clinical	2,670,000	SVM, NN, RF, DT, LR,KNN	NN(Accuracy 89.98%)
Li et al. [39],(2020)	Diagnosis	Clinical	413	XGB	XGB(Sensitivity 92.5%)
Bayat et al. [40],(2021)	Diagnosis	Clinical, Laboratory	75,991	XGB	XGB(Accuracy 86.4%)
Hussain et al. [41],(2022)	Prediction	Clinical	1085	SVM, DT, RF, LR	RF(Accuracy 99.24%)

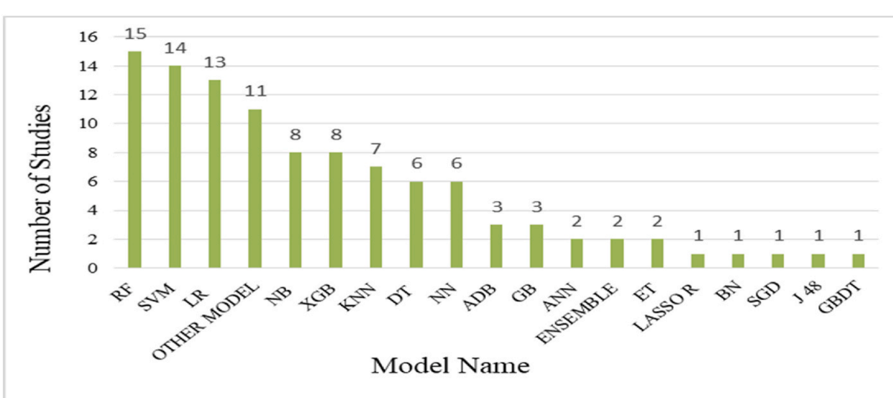

Fig. 8. Applied ML models.

and 9 studies, respectively. Other models that consist of various DL models such as (NASNET, COVIDNet, INCEPTIONREST, LSTM, SQUEEZENET, etc.) have achieved the next position with a frequency of 8, followed by MOBILENET(X) with count of 7. Xception, InceptionV3, and DENSENET(X) have achieved the next position. Each of these models have been used in 5 research works. Besides, various versions of RESNET, referred to as RESNET(X) have been used in studies with a count of 4.

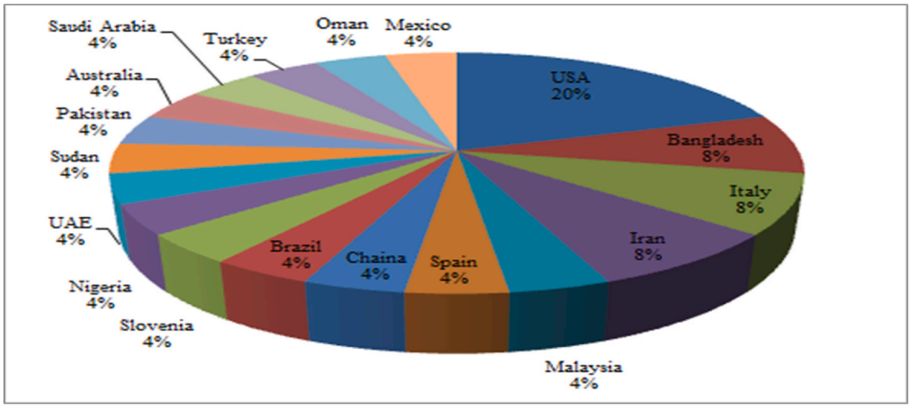

Fig. 9. Country-wise percentage of studies using ML Techniques.

From Table 3, it is observed that despite extensive uses of transfer-learning-based models, in the majority of the studies, custom models have outperformed the transfer-learning-based model. From our analysis and observation, for COVID-19 detection-based works with CXR data type, proposed custom CNN models have outperformed the transfer-learning-based CNN models. However, irrespective of the study's purpose and utilized data type in the uses of transfer-learning-based models, RESNET and DENSENET architecture-based models consisting of various versions have performed best in the majority of the studies. However, regardless of the type of image data used in deep learning-based research work, the usage of custom models may improve performance.

The country-wise percentage of the studies employing DL models is shown in Fig. 11. In terms of using DL models to combat COVID-19, the majority of the research works were performed in India with a percentage of 44%. 8% of the research works were conducted in each of the following countries: Indonesia and Saudi Arabia. On the other hand, countries such as Algeria, Australia, Turkey, Switzerland, and all other countries have ranked in third place in terms of the number of research works employing DL methods.

3.4. Application of combination of ML/DL/AI to combat COVID-19

The combinations of ML, DL, and AI-based techniques are crucial in better understanding and dealing with the COVID-19 situation. The combinations of these methods are rapidly being used since these approaches can open up new avenues for various forms of diagnosis, sentiment analysis, public surveillance, and illness prevention. Several COVID-19 diagnostic approaches based on images aided by DL and AI-based techniques have been developed, and their association with RT-PCR has been evaluated. Image and non-image types of data are integrated by the combination of ML, DL, and AI-based methods to investigate several new alternatives to combat COVID-19.

The study demonstrates the combination of ML, DL, and AI methodologies and applications for combating COVID-19. Table 4 shows the summary of the combination of ML, DL, and AI-based techniques to combat COVID-19.

Fig. 12 shows that among the ML techniques, SVM has been the most frequently used model in the studies that utilized the combination of ML, DL, and AI-based and it has been used in twenty-three studies. Other ML models like ARIMA, LRG, GB, Total Boost, etc., models have been used in 15 studies. Among the other ML models, RF, DT, KNN, LR, NB, and XGB models have been used in 13, 12, 10, 9, 8 and 7 studies, respectively. The ADB model has been used less frequently among the ML techniques.

Various AI techniques have been used most frequently in the studies. In Fig. 12, for AI technique, we have counted only the numbers of different AI technique instead of showing the number of studies that have employed these techniques. Different DL models such as ATTENTION RESNET-50, DBN, IPCNN, DECNN, DEEPLABV3, SGAN, etc., models have appeared in 19 different studies in total. CNN has been used in 14 studies. Various versions of RESNET, referred to as RESNET (X) has been used in 12 studies. Furthermore, LSTM is the next most frequently used model, followed by various versions of DENSENET and INCEPTION, which have been referred to as DENSENET(X) and INCEPTION(X).

From Fig. 12, it is observed that there is a trend to use custom models among the studies, which outperformed other DL models in terms of usage in different studies. However, various transfer learning DL models have been used frequently.

From Table 4, it is observed that there are diverse patterns or combinations of mechanisms that have been used to perform the studies. In studies using ML in combination with other techniques, the SVM (ML model) has been utilized and tends to perform better compared to other ML models. Therefore, to construct mechanisms combining the ML model with other techniques, researchers might consider using the SVM model. Furthermore, to perform the study on the amalgam of the various data types, it is important to combine techniques from various domains and examine the performance.

Fig. 13 Depicts the country-wise percentages of the studies employing the combination of ML, DL, and AI models. In India, 18% of the studies were conducted. Saudi Arabia carried out 13% of the studies. China, Bangladesh, and Turkey each conducted 11% of the studies. 8% of the studies conducted in the United States, whereas 5% were performed in Iran. The remaining 3% of the studies were conducted in other regions of the world.

3.5. Evaluation procedure for different study

Evaluation is studying a system, an initiative to determine how effectively a system fulfills its objectives. Evaluations assist in determining what works effectively and where improvements can be made in a program.

According to Fig. 14, accuracy is the most used evaluation metric, followed by sensitivity/recall and AUC. Other metrics have been employed in a limited number of studies. Accuracy has been applied most frequently in the combination of ML, DL, and AI-based studies, while in ML and DL studies, accuracy metrics have been used equally. The sensitivity/recall metric has been mostly used in the studies employing the combination of ML, DL, and AI-based techniques followed by DL and ML-models-based studies. AUC metric has been used in all these three types of studies.

Specificity and R-Square have been only used in ML models-based and combinations of ML, DL, and AI models-based studies. ML-based studies haven't used the Dice scores. F1 score, precision, MAPE, and RMSE have been only employed in the combination of ML, DL, and AI models-based studies.

Table 3
A summary of different deep learning-related studies for COVID-19.

References and Year	Purposes	Data Type	Sample Size	Model	Best Model with Performance
Ferroukhi [42], (2022)	Diagnosis	CT	4708	VGG16, RESNET 50, MOBILENET, GOOGLENET, XCEPTION, DENSENET121	RESNET 50(Accuracy 90%)
Sitaula and Hossain [43], (2020)	Classification	CXR	Three datasets of(1125, 1638, 2138 image per dataset)	VGG16, VGG19, PROPOSED(ATTENTION-BASED VGG-16)	ATTENTION-BASED VGG-16(Accuracy (79.58%, 85.43%, 87.49%))
Gour and Jain [44], (2021)	Classification	CXR	Three datasets includes (3040,627,2905) CXR	VGG19, RESNET-152, XCEPTION, DENSENET-169, MOBILENET, NASNET LARGE, INCEPTION-V3, EFFICIENTNET, PROPOSED(UA-CONVNET)	UA-ConvNet(Sensitivity multiclass = 98.02%, binary = 99.16%)
Khan et al. [45], (2022)	Diagnosis	Clinical, Demographic, CXR	270	DEEP CNN, FFNN, EFFICIENTNETB7, FUSION MODEL	Fusion model (Recall 98.6%)
Irmak [46],(2022)	Classification	ECG Trace	1937	CNN, RESNET-101, VGG-19, DENSENET, RESNET-50, VGG-16, INCEPTIONV3	CNN-proposed model(Accuracy of 98.57%, 93.20%, 96.74%)
Shiri et al. [47], (2021)	Detection	CT	2558	COLI-NET	COLI-Net(mean Dice coefficients 0.98 and 0.91 l for lung and lesions segmentation)
Malik et al. [48], (2021)	Classification	CT	660	RESNET-50, BDCNET, VGG-16, INCEPTION V3,VGG-19,	BDCNet(Recall of 98.31%)
Kumar et al. [49], (2021)	Detection	CXR	13,975	VGG-16, VGG-19, RESNET18, ALEXNET, RESNET-50, SARS-NET	SARS-Net(Sensitivity 92.90%)
Mousavi et al. [50],(2022)	Detection	CXR	12,931	CNN, SARS-NET PROPOSED(CNN-LSTM), XCEPTION, RESNET50, INCEPTION, VGG 19	CNN-LSTM(Accuracy 90% all scenarios)
Kavya et al. [51], (2022)	Detection	CXR	15,153	VGG16, RESNET50	ResNet50(Accuracy 91.39%)
Sundaram et al. [52],(2021)	Classification	CXR	4050	RSQZ-SEGNET	RSqz-SegNet(Accuracy 99.69% binary 99.48% three class)
Luz et al. [53], (2021)	Detection	CXR	13,800	EFFICIENTNET B0-X, EFFICIENTNET B1-X , EFFICIENTNET B2-X, EFFICIENTNET B3-X , EFFICIENTNET B4-X, EFFICIENTNET B5-X , MOBILENET, MOBILE NET V2, RESNET50, VGG-16, VGG-19	Approach Flat EfficientNet B3-X(Sensitivity of 96.8%)
Djuniadi et al. [54],(2022)	Detection	Images	4095	MOBILENET V2	MobileNet V2(Accuracy 99%)
Chaudhary et al. [55],(2020)	Detection	CXR	14,000	EFFICIENTNET-B1, VGG-19, RESNET-50, COVIDNET	EFFICIENTNet-B1(Accuracy 95%)
Kogilavani et al. [56],(2022)	Detection	CT	3873	VGG16, DESENET121, MOBILENET , NASNET, XCEPTION, EFFICIENTNET	VGG16(Accuracy 97.68%)
Muralidharan et al. [57], (2022)	Detection	CXR	D1 contains 1225 images, D2 contains 9000 images.	MULTISCALE DCNN	Multiscale DCNN(dataset A(multiclass and binary accuracy of 96% and100%), dataset B(multiclass and binary accuracy of 97.17% and 96.06%))
Haghanifar et al. [58],(2022)	Detection	CXR	9600	CHEXNET, COVID-CXNET.	COVID-CXNet(Accuracy 87.88%)
Nassif et al. [59], (2022)	Detection	CXR, Audio	1159 sound samples, 13,808 CXR Image	LSTM, VGG16, VGG19, DENSNET201, RESNET50, INCEPTIONV3, INCEPTIONRESNETV2, XCEPTION	LSTM (Accuracy of 98%), VGG16 (Accuracy 89.64%), InceptionResNetV2 (Accuracy 82.22%)
Nayak et al. [60], (2020)	Detection	CXR	406	ALEXNET, VGG16, GOOGLENET, MOBILE NET-V2, SQUEEZENET, RESNET-34, RESNET-50, INCEPTION-V3	ResNet-34(Accuracy 98.33%).
Verma et al. [61], (2022)	Detection	CT	63,849	RESNET50 V2, EFFICIENTNET B0	EfficientNet B0(Sensitivity 99.69%)
Sim et al. [62], (2022)	Detection	CXR	5717	DENSENET121	DenseNet121(Sensitivity 95%)
Srivastava and Ruchilekha [63],(2022)	Detection	CXR, CT	4271	DEEPCOVX, DEEPCOVCT	DeepCovX(Sensitivity 100%), DeepCovCT (Sensitivity 97.06%)
Muljo [64],(2022)	Detection	CXR	133,280	DENSENET121	DenseNet121(AUC average of 0.82, best AUC 0.99)
Panwar et al. [65], (2021)	Classification	CXR	4563	CNN, ALEXNET	CNN(Accuracy 98%)
Nasser et al. [66], (2021)	Detection	CXR	6000	RESNET50	ResNet50(Sensitivity 97.3%)

From Fig. 14 it is obvious that all three approaches use accuracy as the primary evaluation metric. Despite sensitivity/Recall being the second most utilized metric, ML and DL-based studies have used this metric less frequently compared to accuracy. As misclassification of the COVID-19 disease can threaten the patient and their family's lives in addition to complicating COVID-19's spread control. Therefore, it is necessary to emphasize the sensitivity/recall metric more for evaluating the model's performance.

4. Finding and analysis of proposed research questions

In this section, the predefined research questions have been discussed. For each of the research questions, we have discussed the significance of the question as well as the findings based on the question that has been explored via the analysis of the studies. In addition, we have provided directions and some precautions for the researchers who aspire to conduct COVID-19 pandemic-related studies.

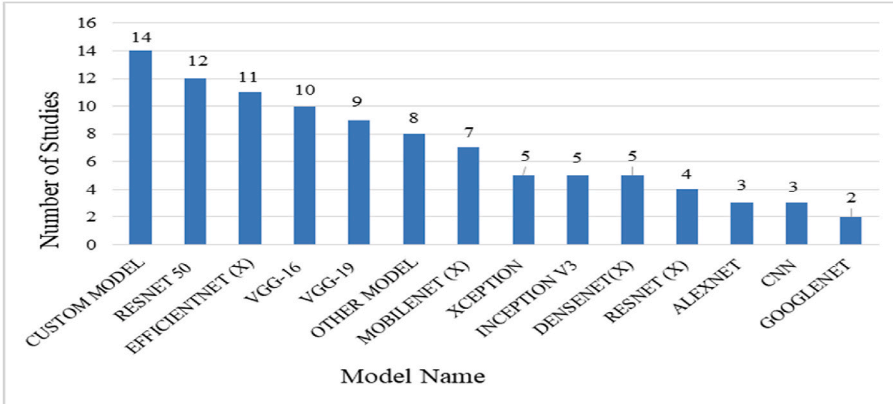

Fig. 10. Applied DL models.

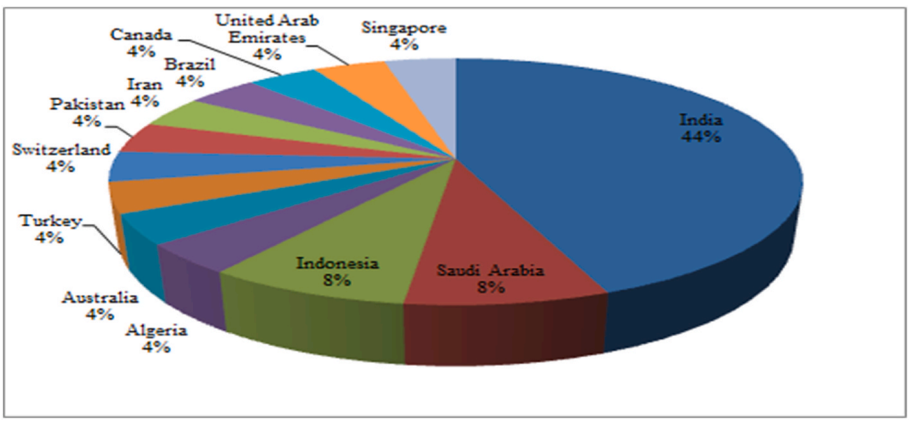

Fig. 11. Country-wise percentage of studies using DL models.

RQ 1: In the domain of AI, there are different types of algorithms, each with its own set of advantages and disadvantages. Many factors influence the model's performance in a positive or negative manner, resulting in less optimum performance and complicating the task of finding ways to combat COVID-19. As a result, it is necessary to identify widely used specific ML, DL, and AI mechanisms so that model selection for a certain purpose becomes simple and effective.

Various models have been applied in the application of the ML model in COVID-19-related tasks. The majority of the studies employed multiple ML models and compared the results. Therefore, the finding of some top-utilized models can be very beneficial. RF, SVM, LR, NB, XGB, and KNN are some of the most frequently used models. In addition to the use of specific ML models, various diversified but not widely used models have also been applied.

Analyzing the studies, it can be observed that XGB has performed as the best model among utilized ML mechanisms, followed by RF and NN. Therefore, while using the ML model for prediction, classification, detection, and diagnosis, XGB, RF, and NN models can be considered, which may aid in achieving the best possible result.

Many studies have developed custom models and compared them to other existing mechanisms in the use of DL relevant to the COVID-19 study. In the use of specific DL models, RESTNET50, EFFICIENTNET, VGG-16, VGG-19, and MOBIELNET have been the most widely applied models. Analyzing the studies, it can be shown that custom models performed the best among the used DL mechanisms, followed by ResNet-(X) referring to various versions of ResNet particularly ResNet-50.

In the application of the combination of ML, DL, and AI techniques related to the COVID-19 study, many studies applied the combination of diverse mechanisms and analyzed the performance, limitations, and potentiality of those mechanisms. Among the mechanisms, various AI techniques, SVM (ML model), custom models, diverse but not widely used DL models, CNN (DL model), and RF (ML model) are some of the widely applied mechanisms in the studies. Analyzing the studies and the best model, it can be found that the majority of the studies employed Al methods with ML or DL models and emphasize increasing the performance.

By analyzing the studies, we have observed that there is a significant association between model's performance and the pattern of data used in the studies. This is discovered by analyzing and observing the results of studies with a similar type of data that applied a variety of techniques. As a result, it is essential for the researcher to choose standard dataset and select the suitable model according to the data type. To perform a study with the usage of ML models in COVID-19-related work, the researcher might consider XGB, RF, and NN models since they have outperformed other models and are widely used too. For performing a DL-based study, researchers should concentrate on constructing custom CNN models since they outperform transfer-learning-based DL algorithms most of the time. However, in the uses of the combination of ML, DL, and AI-based techniques, various studies have been used a diverse amalgam of techniques. Therefore, while conducting a study based on a combination of several techniques, it is essential to select and analyze possible combinations of techniques by reviewing previously conducted related work.

RQ 2: A dataset is one of the main defining parts of any study. Therefore, the dataset used in the studies needs to be trustworthy and standard. As the COVID-19 virus can mutate quickly, collecting virus-specific data is very challenging. To stop the spread and identify any mutated COVID-19, data should be collected in a short span of time. For

Table 4
A summary of different combination of ML/DL/AI related studies for COVID-19.

References and Year	Purposes	Data Type	Sample Size	Model	Best Model with Performance
Tariq et al. [67], (2021)	Prediction	EMR, Clinical	3194	FM, LR, LASSO R, XGB, RF, CNN	FM(F1-score 84%)
Wang et al. [68], (2021)	Classification	CT	1418	V-NET, 3D U-NET++, DPN-92, RESNET-50, RESNET, FCN–8S, U-NET, INCEPTION NET-WORKS, ATTENTION RESNET-50	ResNet-50 with 3D U-Net++ (Sensitivity 97.4%)
Chung et al. [69], (2021)	Prediction	Clinical	5601	ADB, RF, XGB, DNN	DNN(Sensitivity 90.2%)
Afshar et al. [70], (2022)	Diagnosis	CT, Clinical	160	MLP, DNN	Two-stage time-distributed capsule network(Sensitivity of 94.3%)
Sheela and Arun [71], (2022)	Identification	MRI	200	HYBRID PSO-SVM, SVM, PSO, DBN, SAE	Hybrid PSO-SVM (Sensitivity 95.6%)
Babaei Rikan [72], (2021)	Diagnosis	Laboratory, Blood Tests	D1 279,D2 1624, D3 600	SVM, NB, ET, RF,LR, KNN, DT, XGB, DNN, CNN, LSTM, RNN	DNN(D1 (accuracy 92.11%), D2 (Accuracy 93.16%), D3 (Accuracy 93.16%)
Yildirim et al. [73], (2022)	Classification	CXR	15,470	ALEXNET, RESNET50, GOOGLENET, DENSENET201, DARKNET53, MOBILENETV2, EFCIENTNETB0, INCEPTIONV3, NCA, DT, DA, NB, SVM, KNN, SE	Darknet53 + NCA + SVM(Accuracy 99.05 and 97.1%)
De Falco et al. [74], (2021)	Classification	CXR	13,808	BN, NB, RBF, SVM, AB, OR, DEREX	RBF(Average Accuracy 79.60%), DEREx(Best Accuracy 80.67%)
Lella and Pja [75], (2021)	Diagnosis	Sound,Clinical	18,000	DAE, GFCC, IMFCC,DCNN, VGG NET, SVM	DCNN(Accuracy 95.45%)
Hipolito Canario et al. [76],(2022)	Identification	CXR	722	M-QXR	M-qXR(Identify pulmonary opacities Sensitivity 94%), detecting pulmonary opacities Sensitivity 94%), Identify pulmonary consolidation Sensitivity 91%), PPV 89.7%, and NPV 80.4%
Kini et al. [77], (2022)	Screening	CT	12,146	JLM, AGGDF, WSDL, DECNN, DLCRD, PARL, GCNN, GOOGLENET, IPCNN, RESNET152V2, DENSENET201, IRNV2, ENSEMBLE DL (PROPOSED)	Proposed(Recall 98.58%)
Messaoud et al. [78],(2022)	Detection	Clinical, X-ray, CT	270 patient,2251 and 746 image	LR, KNN, SVM, VGG19	VGG19(Accuracy 90%)
Liang et al. [79], (2022)	Diagnosis	CT	1,552,988	RESNET-18, RESNEXT50, GRU, DCNN, SVM, LK, PK, RBF KERNEL, DEEPLABV3, DENSENET121, GPR, FL FRAMEWORK	Boosting (AUC 0.98), DL + FL(Dice's coefficient of 0.77)
Tan et al. [80], (2022)	Classification	CXR, CT	Covid-19 1394, Pneumonia 11,712, Negative 20,431	COVID-NET, MULTI-MODAL	Multi-modal(AUC 0.93)
Chen et al. [81], (2022)	Diagnosis	Sounds	1486	KNN, CNN, MFCCS	CNN(Accuracy 97%)
Alkhaldi et al. [82], (2022)	Sentiment Analysis	Text	2750	TF-IDF, CRNN, RNN, RF, XGB, SVM, ET, DT, SFO, SFODLD-SAC	SFODLD-SAC(Accuracy 99.65%)
Mahbub et al. [83], (2022)	Screening	CXR	C1: COVID-191,200, C2: Pneumonia 3,875, C3:Tuberculoss 3,500, C4: Healthy 6182	RESNET50, RESNET152V2, PROPOSED DNN (COVTBPNNET), INCEPTIONNETV3, MOBILENETV2	CovTbPnNet Accuracy (healthy CXR Screening(99.87% on COVID-19, 99.55% on Pneumonia versus, for TB versus 99.76%), non–healthy CXR Screening(98.89% on COVID-19 versus Pneumonia, 98.99% on COVID-19 versus TB, and Pneumonia versus TB 100%))
Koç and Türkoğlu [84],(2021)	Forecasting	Time Series	77-day	DEEP LSTM NETWORK, ADAM, LSTM, ARIMA, SVM, DT, LR	The Deep LSTM network(beds, respiratory equipment, and cases number yielded MAPE values of (2.89%, 3.29%, and 4.80%) and R Squared values (99.90%, 99.85%, and 99.72%), respectively)
Elharrouss et al. [85],(2021)	Segmentation	CT	100	U-NET,ATTENTION-UNET, GATED-UNET, DENSE-UNET, U-NET++, SEMI–INF–NET, MULTI-CLASS U-NET, DEEPLABV3+, FC8S, PROPOSED METHOD (MULTI-TASK DL METHOD)	Proposed Method (78.6% Dice Score, 71.1% Sensitivity, 99.3% Specificity, 85.6% Precision, 0.062 Mean Average Error metric)
Loey et al. [86], (2022)	Detection	CXR	10,848	PROPOSED MODEL (BAYESIAN-BASED OPTIMIZED DEEP LEARNING MODEL)	Proposed Model(Accuracy 96%)
Shastri et al. [87], (2021)	Forecasting	Time Series	421-days	LSTM, BI-LSTM, CONVLSTM, COBID-NET ENSEMBLE	CoBiD-Net ensemble model(Accuracy 98.10–99.13%)
Zhang et al. [88], (2022)	Classification	Time Series, Text	11,303,850	FINE-TUNING BERT, LRG, TF-IDF, KNN, SVM, DPCNN, EXPERT SYSTEM	Fine-tuning BERT(Recall 99%)
Tavakolian et al. [89],(2022)	Screening	Clinical	5,435,996	LR, RF, XGB, SGAN	SGAN (Accuracy 99.2%, 99.6% for COVID-19 and H1N1)
Choudrie et al. [90], (2021)	Classification	Text	143	SVM, DT, RF, SGD, LSTM, CNN	DT (Accuracy 86.7%, Sensitivity 88.89%)
	Diagnosis		4600		

(*continued on next page*)

Table 4 (*continued*)

References and Year	Purposes	Data Type	Sample Size	Model	Best Model with Performance
Saha et al. [91], (2021)		CXR		EMCNET, CNN, RF, SVM, DT, ADB, ENSEMBLING	EMCNet(Accuracy 98.91%, Precision 100%)
Zulfiker et al. [92], (2022)	Sentiment Analysis	Text	1075	LSTM, 1D-CNN, BI-LSTM, TCN, DT, GB, SVM, LDA	Bi-LSTM with word2vec embedding (Sensitivity 88.52%)
Shiri et al. [93], (2021)	Classification	CT	14,339	CNN, LR, LASSO, LDA, RF, ADB, NB, MLP, ANOVA, KW, RFE, RELIEF	ANOVA feature selector, and RF classifier(Sensitivity 81%)
Aslan et al. [94], (2022)	Classification	CXR	2905	ALEXNET, INCEPTIONV3, RESNET18, SVM, RESNET50, ANN, DT, NB, DENSENET201, INCEPTIONRESNETV2, MOBILENETV2, GOOGLENET, KNN	DenseNet201 and SVM(Sensitivity 96.42%)
Goel et al. [95], (2021)	CXR	2700	2700	DT, KNN, SVM, NB, RF, CNN, SE,RESNET50, INCEPTIONV3,EDLN, PROPOSED(MULTI-COVID-NET)	Multi-COVID-Net(Sensitivity 99.63%)
Kanwal et al. [96], (2021)	Detection	CXR	18,394	DNN, CNN, 2DCNN, BI-LSTM, SVM LINEAR, SVM RBF, SVM POLYNOMIAL, LR, COVID-OPT-AINET	COVID-opt-aiNet(Accuracy of SVM 98%–99%, Accuracy of CNN 70.85%–71% ,Accuracy of DNN 96%–97%)
Bhattacharyya et al. [97],(2021)	Detection	CXR	247	C-GAN, VGG-19, SCNN, DENSENET-169, VGG-16, DENSENET-201, SOFTMAX, SVM, RF, XGB, SIFT, BRISK	VGG-19 with BRISK(Accuracy 96.6%)
Davazdahemami et al. [98],(2022)	Prediction	Clinical, Time Series	27,215	RF, GA, DNN, SHAP	GA with DNN(AUC 0.883)
Karim et al. [99], (2022)	Detection	CXR	27,605	CNN, NB, SVM, SOFTMAX, KNN, DT	NB + Ant Lion Optimization + CNN (98.31% Accuracy, 100% Precision)
Khan et al. [100], (2021)	Prediction	Epidemiological	2,676,311	DT, LR, RF, XGB, KNN, DNN	DNN(Sensitivity 97%)
Dhruv et al. [101], (2022)	Diagnosis	CT	17,104	INRFNET AND INNET, DENSENET-121, RESIDUAL ATTENTION, ENSEMBLE WITH FC, ENSEMBLE WITH FC + SVM	InRFNet Sensitivity(94.48%)
Janbi and Elnazer [102], (2021)	Diagnosis	CXR	6308	SVM-LINEAR, SVM-POLYNOMIAL, SVM-RBF, VGG-16, INCEPTIONV3, XCEPTION, RESNET50, CCGAN,	RESNET50(Recall 99.49%)
Islam and Nahiduzzaman [103], (2022)	Detection	X-ray	2482	GNB, SVM, DT, LR, RF, CNN, ENSEMBLE	Ensemble(Recall 99.73%)
Alabrah et al. [104], (2022)	Sentiment Analysis	Text	464 records	LSTM, SVM, FINE-KNN, ENSEMBLE, BOOST, TOTAL BOOST	Fine-KNN and Ensemble boost (Accuracy 94.01%)

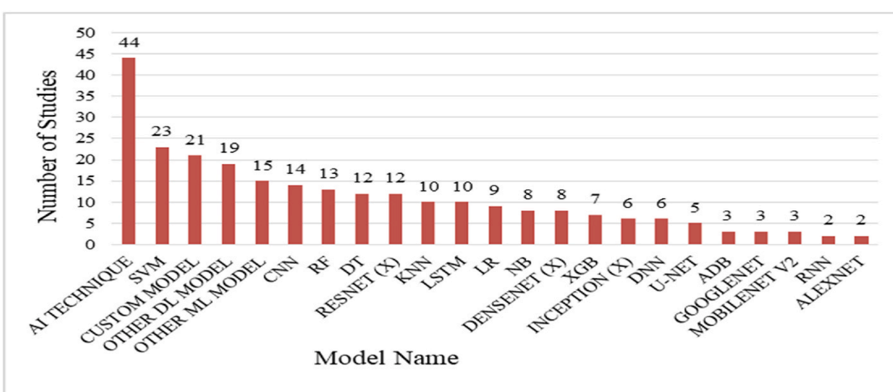

Fig. 12. Applied combination of ML/DL/AI models.

this reason, sometimes there could be some lagging in the data collection procedure, which can create imbalanced and nonstandard data. Therefore, creating a standard dataset is important. Comparing the study results with the standard dataset is also important.

As COVID-19 is a global pandemic, many governments and NGOs have released open-access COVID-19 datasets, which mostly involve vaccination-related and spread-related datasets. But to identify the COVID-19 virus in the human body, an image type dataset is needed. Due to various constraints, there is a shortage of publicly available image datasets at the beginning of the period. Now there are some individual studies that have given open access to their dataset. But most of the individual datasets have some limitations, such as being imbalanced, lacking representative data samples, biased, and so on. Due to the data sample size quantity, some balanced datasets can't be categorized as standard datasets. Therefore, there is still storage of the global standard dataset, which can be used to reevaluate studies applying model performance. Furthermore, there is a lack of standard datasets related to sound and audio types of data for the COVID-19 disease. Also, there are very limited open-access sound-related standard datasets.

As there are shortages and limitations of data regarding COVID-19, the researchers have to check the quality and limitations of the dataset before conducting the research work. In addition, the collection procedure for research datasets should be standard, and the privacy of volunteers should be protected.

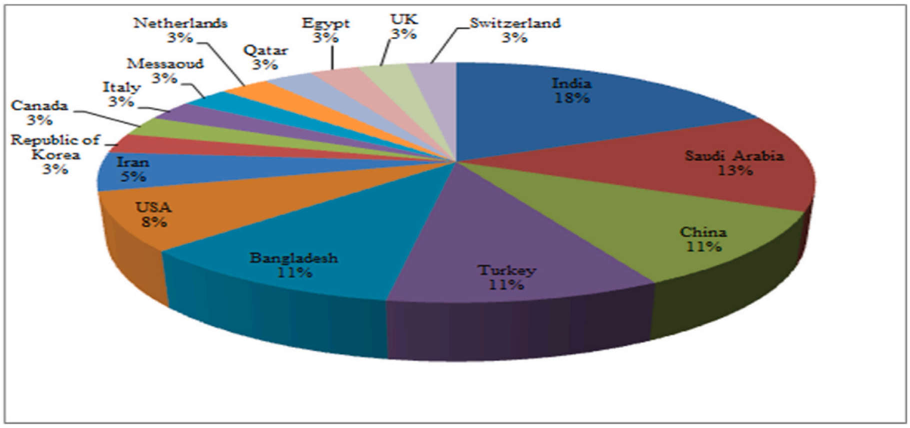

Fig. 13. Country-wise percentage of studies using combination of ML/DL/AI models.

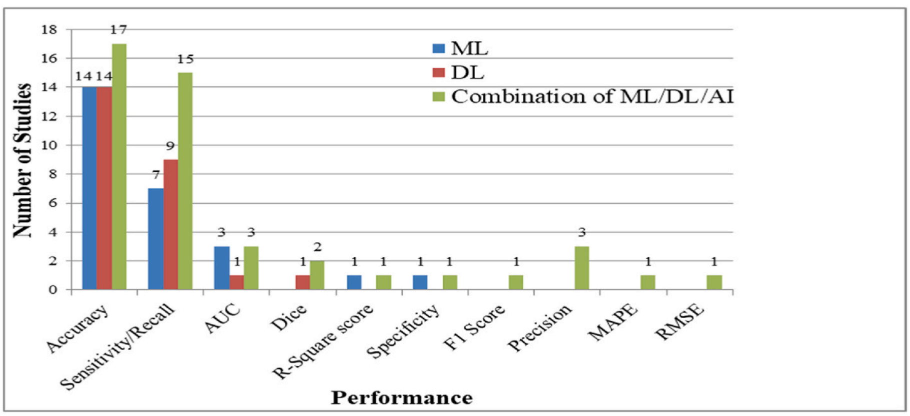

Fig. 14. Performance evaluation metrics used in various studies.

RQ 3: RT-PCR is the traditional method used to detect COVID-19 disease in the human body. Patients must physically visit a hospital to give samples for testing the suspected COVID-19 present in their bodies while using the traditional testing method. However, between the waves of the COVID-19 pandemic, visiting the hospital is a risky step. Because visiting the hospital in the middle of the COVID-19 wave can affect healthy people, who can further act as hosts and further spread the disease. Therefore, it is important to find some End-to-End solution based on AI, which can remotely and effectively diagnose COVID-19 in a suspected person.

But most of the studies have not emphasized building an End to End solution for diagnosis. Despite that, many studies have been conducted in order to develop an application for an End-to-End diagnosis solution [61,81]. Most studies consider image data types such as X-ray, CT, MRI, etc. to build COVID-19 diagnosis E2ES. As a result, using those applications, the patient's standard form of X-ray, CT, and MRI data sample is needed, which must be primarily obtained from the clinic or hospital. Therefore, the E2ES hardly solves the problem of remote E2ES systems. Some studies have considered using sound and audio data to build E2ES for the COVID-19 diagnosis system, which can diagnose COVID-19 remotely. However, low sound-quality recording devices and environmental noise can downgrade the quality of captured audio and sound data, which may affect the performance of the application. Furthermore, these studies and applications have some certain circumscribed. Therefore, there is still a lack of standard and reliable E2ES for the diagnosis of COVID-19.

As there is a lack of E2E systems regarding various COVID-19-related work. The researchers should more focus on the issue and develop more E2E systems. Furthermore, the researcher should concentrate on removing the issues that users encounter when using the E2E system and improve quality (noise reduction, low-quality images handling). The system should be available and compatible with the maximum possible number of devices and platforms. In addition, researchers must promote campaign of the E2E system so that the wider populace can utilize the resource.

RQ 4: As COVID-19 spread as a global pandemic, the virus's devastation was felt throughout the country and regions. Therefore, the majority of the country's governmental and non-governmental organizations and NGOs have taken COVID-19-fighting measures, such as allocating funds, encouraging researchers, providing data, applauding researchers, and so on. These steps and opportunities have aided in the local and global combat of the COVID-19 pandemic by encouraging researchers to work on the issue of the COVID-19 pandemic. As a result, determining which country contributes the most to combating COVID-19 by conducting more research is a useful step toward appreciating their contribution. Furthermore, identifying countries with less significant contributions to research work is important so that those countries can be encouraged and financially aided so that as human civilizations, we can advance equally. Identifying the countries contributing to the COVID-19 pandemic, on the other hand, is a broad perfective work that requires dedicated research work, which may include research type, the technology used, and the discovery of performed studies.

Analyzing the studies considered in this research work reveals that India has conducted the most studies using ML, DL, and combinations of ML, DL, and AI-based techniques, followed by Saudi Arabia and the USA. Other developed countries as well as developing countries have contributed less in conducting research work regarding combating the COVID-19 pandemic.

RQ 5: For combating the COVID-19 pandemic, many studies have been conducted for various purposes and using various mechanisms. Various domains of AI have been used with diverse modifications and combinations. Furthermore, various types of data and a mixture of data types have been used to perform studies. Therefore, there is a need to evaluate the studies with a standard form of evaluationmetrics. Additionally, there is a need to identify the criteria that have been used in those studies to evaluate the trustworthiness of the studies. Most of the studies have used some of the evaluation metrics such as accuracy, sensitivity/recall, precision, F1 score, AUC-ROC curve, etc. From analyzing the studies' utilized metrics, the accuracy metric has been used in most of the studies, followed by sensitivity and recall. Other evaluation metrics have been used less frequently in the related studies. However, the researchers should focus on the True Positive Rate instead of accuracy.

As COVID-19 is a pandemic and can transmit from person to person very rapidly, the top priority is to stop the spread. Therefore, it is crucial not to misidentify an infected person rather than misidentify a healthy person. Therefore, the researchers should prioritize the True Positive Rate or recall value rather than accuracy, as recall value focuses on capturing all true positives, even if it increases false positive rate.

RQ 6: Due to the COVID-19 pandemic, there have been instanced number of research works conducted to manage and to combat the pandemic by the use of ML, DL, and combinations of ML, DL, and AI-based techniques. Those research works have been analyzed and identified various factors and purposes associated with COVID-19 using ML, DL, and combinations of ML, DL, and AI-based techniques. However, from those studies, some common challenges and limitations can be outlined. Identifying those challenges can be beneficial for the researchers who are planning to do research by applying the ML, DL, and AI methods as they can study those challenges to overcome in their study or can make their study particularly based on finding the solution to those challenges.

Selection of an effective model from the variety of models available from various domains of ML, DL, and AI is a challenging and time-consuming task. Some traditional ML, DL, and AI methods have already been extensively researched. However, there is still scope for improvements, but it will be challenging. Additionally, finding an effective combination of ML, DL, and AI is a challenging task that requires a significant amount of time and expertise. The scarcity of standards and enough sample data is one of the fundamental challenges when it comes to working with COVID-19. These are the two most fundamental challenges for researchers who intend to conduct research using ML, DL, or combinations of ML, DL, and AI-based techniques.

5. Challenges and future research opportunities

Many ML, DL, and other AI approaches depend on massive training data, such as clinical data, medical images, and other types of medical data. Large-scale training data is scarce and unavailable. It should be noted that determining the best models for COVID-19 diagnosis is challenging because of the scarcity of data. Further research is required to solve this issue. Moreover, a benchmark dataset is required for diagnosing COVID-19.

Since the COVID-19 virus's arrival, various variants have appeared due to mutations. Gathering data for different variants in a short period is complex, and there is always a shortage of COVID-19-related updated datasets. A combined and effective data gathering strategy is required to address this issue. Furthermore, a change in the variant might alter the performance of a model, which has been trained by a different variant previously. Hence, more research works are needed to investigate the performance of the previous studies on the new variants of COVID-19.

COVID-19 samples have a low count of CT, MRI, and X-ray images compared to pneumonia infection and healthy human case samples. Data argumentation tries to generate new image sample from the existing samples by flipping, rotating, zooming, adding random noise in the existing images. Further studies are needed to measure the performance of this strategy and its limitations.

Using imbalanced datasets is an obvious shortcoming of recent studies. Data balancing is required for handling imbalanced datasets. The performances of the different models before and after balancing the datasets need to be compared.

Similarly, there are many potential combinations of various sorts of data type, namely demographics, MRI, X-ray and CT images, sound/audio data, and clinical, laboratory, and blood test data. However, combining multiple types of datasets (organized and unstructured) for various purposes of COVID-19 is needed for additional investigation.

Furthermore, some factors in COVID-19 research impede AI-based ML and DL applications. Some of these factors are as follows.

- Slow Legislation process
- Security equipment and resource
- Lack of large-scale data.
- Vast rumors and noisy data.
- The researchers have limited expertise at the intersection of computer science and medical science.
- Data security and privacy issues in collecting data.

For tackling COVID-19, one of the necessary steps is to coordinate the participation of specialists who belong to other sectors and to include data from several studies. Most researchers' backgrounds are in computer science. However, a strong specialty in bioinformatics and various other relevant domains is needed for applying ML and DL to include additional knowledge of medical science in the COVID-19-related studies.

In the middle of a pandemic wave, using the traditional diagnosis method to identify COVID-19 is a dangerous process. Because visiting a hospital for a COVID-19 test can spread the virus to others who haven't already been exposed to the virus. Therefore, a remote COVID-19 End-to End diagnosis solution must be established in order to resolve the problem. In the future, it will be necessary to examine the problem by overcoming constraints and developing reliable and accurate End-to-End diagnosis solutions.

Remote video diagnostics and consultations are available nowadays in different clinics and hospitals. In the future, by combining AI and NLP-based technologies, remote video diagnostic programs can be developed to replace the COVID-19 patients' primary visits to the hospital.

In ML, DL, and AI-based systems, various simulations may be utilized to examine how different social approaches affect the spread of disease. Furthermore, this technique may be applied to verify the trustworthiness and explore scientific methods for the control and prevention of disease among citizens.

AI-powered ML, DL, and other systems can create social networks and knowledge graphs to keep an eye on and follow the traits of individuals living next to COVID-19-affected patients, precisely anticipating and monitoring the disease's spread.

Intelligent robots can be utilized in initiatives such as, product distribution programs and medical treatment where human resources can be replaced. Taking those initiatives may halt the propagation of the COVID-19 epidemic.

6. Conclusion

This study focuses on ML, DL, and combinations of ML, DL, and AI-based studies that may help fighting the COVID-19 pandemic. The primary objective of this study is to outline prior research works and how these works have been used to fight COVID-19. For that purpose, multiple academic search engines have been searched by using various keywords to find relevant studies. Those studies are filtered by using the defined criteria. Based on the abstract analysis, dataset analysis, inclusion and exclusion criteria, and methodological quality, a final selection of 88 studies has been made. Among these studies, 25 studies employed ML techniques, 25 studies employed DL techniques, and the rest 38 studies utilized the combination of ML, DL, and AI-based methods. This study has analyzed the prior research works by summarizing the applied methods in those works, comparing the performance of different models used and identifying the purpose of those works.

92% of these studies are from different journals, and the rest 8% of these studies are conference papers. Most of the studies analyzed in this work are from 2022. USA conducted the maximum number of research works employing ML methods. On the other hand, the maximum number of works utilizing DL methods and the combination of ML, DL, and AI-based methods have been performed in India. RF model has been used most frequently in studies employing ML models, whereas different custom models have the highest frequency in DL-based studies. A variety of AI-based techniques have the highest frequency in the studies utilizing the combination of ML, Dl, and AI-based methods. In the evaluation process, most studies have emphasized accuracy to evaluate the performance of the proposed models.

The significant information discovered, investigated, and reported in this study are contemporary and up-to-date regarding COVID-19. For the appropriate content, we utilized precise keywords. These search terms yielded valuable results to achieve the aim of this study, though there is a chance we may have missed significant resources that are not shown by these terms. Some data might have been missed during the extraction of data from the selected studies.

Various ML, DL, and combinations of ML, DL, and AI-based methods have emerged in recent years. In future, more combinations of different methods and complicated approaches can be analyzed for fighting against COVID-19. Future research works can consider combining a variety of data formats to precisely identify COVID-19.

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.

Data availability

No data was used for the research described in the article.

Nomenclature

SVM	Support Vector Machine
BERNOULLI INB	Bernoulli Naive Bayes
RF	Random Forest
LR	Logistic Regression
KNN	K-Nearest Neighbor
DT	Decision Tree
RBFK-SVM	Radial Basis Function SVM
RNN	Recurrent Neural Network
ANN	Artificial Neural Network
ADB	Adaboost
NB	Naive Bayes
GB	Gradient Boosting
QDA	Qualitative Data Analysis
RFE	Recursive Feature Elimination
LASSO R	Lasso Regression
XGB	Xgboost
MLP	Multilayer Perceptron
NCA	Necessary Condition Analysis
DEREx	Differential-Evolution-based Rule Extractor
DAE	De-noising Auto Encoder
LASSO	Least Absolute Shrinkage and Selection Operator
ConvLSTM	Convolutional Long Short Term Memory
IMFCC	Improved Multi-frequency Cepstral Coefficients
CRNN	Cascaded Recurrent Neural Network
LDA	Latent Dirichlet Allocation Model
LDA	Linear Discriminant Analysis
GFCC	Gamma-tone Frequency Cepstral Coefficients
KW	Kruskal-Wallis
EDLN	Ensemble Deep Learning Network
DBN	Deep Belief Network
BN	Bayesian Network
SAE	Stacked Auto-Encoder
DCNN	Deep Cnn
PK	Polynomial Kernel
FM	Fusion Model
SWEM	Semantic Word Embedding Models
LGBM	LightGBM
LK	Linear Kernel
ARIMA	Autoregressive Integrated Moving Average
RBF	Radial Basis Function
OR	One Rule
RBF	KERNEL Radial Basis Function (Gaussian) Kernel
PCA	Principal Component Analysis
GPR	Gaussian Process Regression
FR-CNN	Faster RCNN
CAPS Net	Capsule Neural Network
DTL	Duplication Transfer Loss
ET	ExtraTrees
GRAD-CAM	Gradient Weighted Class Activation Mapping
MFCCs	Mel Frequency Cepstral Coefficients
SGAN	Semi-Supervised Gan
BD-LSTM	Bi-directional LSTM
SHAP	Shapley Additive exPlanations
NN	Neural Network
SGD	Stochastic Gradient Descent
LSTM	Long Short-Term Memory
CNN	Convolutional Neural Network
MNB	Multinomial Naive Bayes
MLIO	Machine Intelligence Learning Optimizer
GBDT	Gradient Boosted Decision Trees
LDA	Latent Dirichlet Allocation
TCN	Temporal Convolutional Network
L-SVM	Lagrangian Support Vector Machines
LRG	Linear Regression
GBM	Gradient Boosting Machine
PR	Polynomial Regression
ET	Extremely Randomized Trees
HHOSVC	HHO-Based Support Vector Classifier
HHOLGB	HHO-Based Light Gradient Boosting
BSOA	Bayesian Search Derived Optimal Architecture
HHORF	HHO-Based Random Forest
GNB	Gaussian Naive Bayes
BT	Bagged Trees
HHOXGB	HHO-Based EXtreme Gradient Boosting
MKNN	Medium Knn
ANOVA	Analysis of Variance
DTL	Deep Transfer Learning
HHOCAT	HHO-Based Categorical Boosting
GA	Genetic Algorithm
TDT	Temporal Decision Trees
TRF	Temporal Random Forests
FFNN	Feed-Forward Networks
DNN	Deep Neural Network
PSO	Particle Swarm Optimization
JLM	Joint Learning Model
WSDL	Weakly Supervised Deep Learning Model
IPCNN	Iteratively Pruned Ensemble Convolutional Neural Network
DECNN	Dense CNN Models
ED-LSTM	Encoder-decoder LSTM

PARL Prior-attention Residual Learning
AGGDF Adaptive Feature Selection Guided Deep Forest
GCNN Genetic CNN
GRU Gated Recurrent Unit
TF-IDF Term Frequency–Inverse Document Frequency
SCNN Self-Customized Simple CNN
SIFT Scale-Invariant Feature Transform
BRISK Binary Robust Invariant Scalable Key-Points
CCGA Continuous Conditional Generative Adversarial Network
DLCRD Deep Learning-based Chest Radiograph Diagnosis
ADAM Adaptive Moment Estimation
PK-SVM Polynomial Kernel Support Vector Machines
BAG Bagging
MERS Middle East Respiratory Syndrome
AI Artificial Intelligence
CXR Chest X-ray
MRI Magnetic Resonance Imaging
SARS Severe Acute Respiratory Syndrome
CT Computerized Tomography
RT-PCR Reverse Transcription-Polymerase Chain Reaction
ECG Electrocardiogram
ML Machine Learning
SARS-CoV-2 Severe Acute Respiratory Syndrome Coronavirus 2
DL Deep Learning
WHO The World Health Organization
NLP Natural Language Processing
MAPE Mean Absolute Percentage Error
DOAJ Directory of Open Access Journals
RMSE Root Mean Square Error

References

[1] Wu Y-C, et al. The outbreak of COVID-19: an overview. J Chin Med Assoc Mar. 2020;83(3):217–20. https://doi.org/10.1097/JCMA.0000000000000270.

[2] WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020. Available: https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19—11-march-2020 [Accessed 26 June 2022].

[3] Worldometer: COVID-19 Coronavirus Pandemic. Available: https://www.worldometers.info/coronavirus/ [Accessed 26 June 2022].

[4] Coronavirus World Map: Tracking the Global Outbreak. Available:https://www.nytimes.com/interactive/2021/world/covid-cases.html [Accessed 26 June 2022].

[5] Jalaber C, et al. Chest CT in COVID-19 pneumonia: a review of current knowledge. Diagnostic and Interventional Imaging 2020;101(7–8):431–7. https://doi.org/10.1016/j.diii.2020.06.001.

[6] Ibrahim NK. Epidemiologic surveillance for controlling Covid-19 pandemic: types, challenges and implications. Journal of Infection and Public Health 2020; 13(11):1630–1638, Nov. https://doi.org/10.1016/j.jiph.2020.07.019.

[7] Oran DP, Topol EJ. Prevalence of asymptomatic SARS-CoV-2 infection: a narrative review. Ann Intern Med 2020;173(5):362–7. https://doi.org/10.7326/M20-3012.

[8] Wu Z, McGoogan JM. Characteristics of and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in China: summary of a report of 72 314 cases from the Chinese center for disease control and prevention. JAMA 2020;323(13). https://doi.org/10.1001/jama.2020.2648.

[9] Pang KW, et al. Frequency and clinical utility of olfactory dysfunction in COVID-19: a systematic review and meta-analysis. Curr Allergy Asthma Rep 2020;20 (12):76. https://doi.org/10.1007/s11882-020-00972-y.

[10] Rocke J, et al. Is loss of sense of smell a diagnostic marker in COVID-19: a systematic review and meta-analysis. Clin Otolaryngol Nov. 2020;45(6):914–22. https://doi.org/10.1111/coa.13620.

[11] Brereton P, et al. Lessons from applying the systematic literature review process within the software engineering domain. J Syst Software 2007;80(4):571–83. https://doi.org/10.1016/j.jss.2006.07.009.

[12] Dogan O, Tiwari S, Jabbar MA, Guggari S. A systematic review on AI/ML approaches against COVID-19 outbreak. Complex Intell. Syst. 2021;7(5): 2655–78. https://doi.org/10.1007/s40747-021-00424-8.

[13] Islam MN, Inan TT, Rafi S, Akter SS, Sarker IH, Islam AKMN. A systematic review on the use of AI and ML for fighting the COVID-19 pandemic. IEEE Trans. Artif. Intell. Dec. 2020;1(3):258–70. https://doi.org/10.1109/TAI.2021.3062771.

[14] Chamola V, Hassija V, Gupta V, Guizani M. A comprehensive review of the COVID-19 pandemic and the role of IoT, drones, AI, blockchain, and 5G in managing its impact. IEEE Access 2020;8:90225–65. https://doi.org/10.1109/ACCESS.2020.2992341.

[15] Alballa N, Al-Turaiki I. Machine learning approaches in COVID-19 diagnosis, mortality, and severity risk prediction: a review. Inform Med Unlocked 2021;24: 100564. https://doi.org/10.1016/j.imu.2021.100564.

[16] Alafif T, Tehame AM, Bajaba S, Barnawi A, Zia S. Machine and deep learning towards COVID-19 diagnosis and treatment: survey, challenges, and future directions. IJERPH 2021;18(3). https://doi.org/10.3390/ijerph18031117.

[17] Abdulkareem KH, et al. Realizing an effective COVID-19 diagnosis system based on machine learning and IoT in smart hospital environment. IEEE Internet Things J 2021;8(21):15919–28. https://doi.org/10.1109/JIOT.2021.3050775.

[18] Callejon-Leblic MA, et al. Loss of smell and taste can accurately predict COVID-19 infection: a machine-learning approach. JCM Feb. 2021;10(4):570. https://doi.org/10.3390/jcm10040570.

[19] Faisal F, et al. Covid-19 and its impact on school closures: a predictive analysis using machine learning algorithms. In: 2021 international conference on science & contemporary technologies (ICSCT), dhaka, Bangladesh; Aug. 2021. p. 1–6. https://doi.org/10.1109/ICSCT53883.2021.9642617.

[20] Cabitza F, et al. Development, evaluation, and validation of machine learning models for COVID-19 detection based on routine blood tests. Clin Chem Lab Med Feb. 2021;59(2):421–31. https://doi.org/10.1515/cclm-2020-1294.

[21] Guan X, et al. Clinical and inflammatory features based machine learning model for fatal risk prediction of hospitalized COVID-19 patients: results from a retrospective cohort study. Ann Med Jan. 2021;53(1):257–66. https://doi.org/10.1080/07853890.2020.1868564.

[22] Alves MA, et al. Explaining machine learning based diagnosis of COVID-19 from routine blood tests with decision trees and criteria graphs. Comput Biol Med May 2021;132:104335. https://doi.org/10.1016/j.compbiomed.2021.104335.

[23] Kukar M, et al. COVID-19 diagnosis by routine blood tests using machine learning. Sci Rep 2021;11(1):10738. https://doi.org/10.1038/s41598-021-90265-9.

[24] Muhammad LJ, et al. Supervised machine learning models for prediction of COVID-19 infection using epidemiology dataset. SN COMPUT. SCI. 2021;2(1):11. https://doi.org/10.1007/s42979-020-00394-7.

[25] Zargari Khuzani A, et al. COVID-Classifier: an automated machine learning model to assist in the diagnosis of COVID-19 infection in chest X-ray images. Sci Rep 2021;11(1):9887. https://doi.org/10.1038/s41598-021-88807-2.

[26] Statsenko Y, et al. Prediction of COVID-19 severity using laboratory findings on admission: informative values, thresholds, ML model performance. BMJ Open 2021;11(2):e044500. https://doi.org/10.1136/bmjopen-2020-044500.

[27] Tran NK, et al. Novel application of automated machine learning with MALDI-TOF-MS for rapid high-throughput screening of COVID-19: a proof of concept. Sci Rep 2021, Dec;11(1):8219. https://doi.org/10.1038/s41598-021-87463-w.

[28] Rezaeijo SM, et al. Screening of COVID-19 based on the extracted radiomics features from chest CT images. XST Mar. 2021;29(2):229–43. https://doi.org/10.3233/XST-200831.

[29] Jimenez-Solem E, et al. Developing and validating COVID-19 adverse outcome risk prediction models from a bi-national European cohort of 5594 patients. Sci Rep 2021;11(1):3246. https://doi.org/10.1038/s41598-021-81844-x.

[30] Faculty of Engineering, University Mashreq, North Khartoum, Sudan A H M Hassan, et al. Visualization & prediction of COVID-19 future outbreak by using machine learning. IJITCS Jun. 2021;13(3):16–32. https://doi.org/10.5815/ijitcs.2021.03.02.

[31] Saadatmand S, et al. Predicting the necessity of oxygen therapy in the early stage of COVID-19 using machine learning. Med Biol Eng Comput 2022;60(4):957–68. https://doi.org/10.1007/s11517-022-02519-x.

[32] Rehman MU, et al. Future forecasting of COVID-19: a supervised learning approach. Sensors 2021;21(10):3322. https://doi.org/10.3390/s21103322.

[33] Guerrero-Romero F, et al. Magnesium-to-Calcium ratio and mortality from COVID-19. Nutrients 2022;14(9). https://doi.org/10.3390/nu14091686.

[34] Debjit K, et al. An improved machine-learning approach for COVID-19 prediction using harris hawks optimization and feature analysis using SHAP. Diagnostics 2022;12(5):1023. https://doi.org/10.3390/diagnostics12051023.

[35] Almustafa KM. Covid19-Mexican-Patients' dataset (Covid19MPD) classification and prediction using feature importance. Concurrency and Computation 2022;34 (4). https://doi.org/10.1002/cpe.6675.

[36] Erdoğan YE, Narin A. Comparison of classification algorithms for COVID19 detection using cough acoustic signals. 2022. https://doi.org/10.48550/ARXIV.2201.04872.

[37] Sciavicco G, et al. The voice of COVID19: breath and cough recording classification with temporal decision trees and random Forests. SSRN Journal 2022. https://doi.org/10.2139/ssrn.4102488.

[38] Pourhomayoun M, Shakibi M. Predicting mortality risk in patients with COVID-19 using machine learning to help medical decision-making. Smart Health 2021;20: 100178. https://doi.org/10.1016/j.smhl.2020.100178.

[39] Li WT, et al. Using machine learning of clinical data to diagnose COVID-19: a systematic review and meta-analysis. BMC Med Inf Decis Making 2020;20(1):247. https://doi.org/10.1186/s12911-020-01266-z.

[40] Bayat V, et al. A severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) prediction model from standard laboratory tests. Clin Infect Dis 2021;73(9): e2901–7. https://doi.org/10.1093/cid/ciaa1175.

[41] Hussain SA, et al. Prediction and evaluation of healthy and unhealthy status of COVID-19 patients using wearable device prototype data. MethodsX 2022;9: 101618. https://doi.org/10.1016/j.mex.2022.101618.

[42] Ferroukhi M. Automatic diagnosis of COVID-19 using deep learning. In: 2022 7th international conference on image and signal processing and their applications (ISPA), mostaganem, Algeria; May 2022. p. 1–6. https://doi.org/10.1109/ISPA54004.2022.9786357.

[43] Sitaula C, Hossain MB. Attention-based VGG-16 model for COVID-19 chest X-ray image classification. Appl Intell May 2021;51(5):2850–63. https://doi.org/10.1007/s10489-020-02055-x.

[44] Gour M, Jain S. Uncertainty-aware convolutional neural network for COVID-19 X-ray images classification. Comput Biol Med 2022;140:105047. https://doi.org/10.1016/j.compbiomed.2021.105047.

[45] Khan IU, et al. Using a deep learning model to explore the impact of clinical data on COVID-19 diagnosis using chest X-ray. Sensors Jan. 2022;22(2):669. https://doi.org/10.3390/s22020669.

[46] Irmak E. COVID-19 disease diagnosis from paper-based ECG trace image data using a novel convolutional neural network model. Phys Eng Sci Med Mar. 2022;45(1):167–79. https://doi.org/10.1007/s13246-022-01102-w.

[47] Shiri I, et al. COLI-Net : deep learning-assisted fully automated COVID -19 lung and infection pneumonia lesion detection and segmentation from chest computed tomography images. Int J Imag Syst Technol Jan. 2022;32(1):12–25. https://doi.org/10.1002/ima.22672.

[48] Malik H, et al. BDCNet: multi-classification convolutional neural network model for classification of COVID-19, pneumonia, and lung cancer from chest radiographs. Multimed Syst Jun. 2022;28(3):815–29. https://doi.org/10.1007/s00530-021-00878-3.

[49] A. Kumar at al. "SARS-Net. COVID-19 detection from chest x-rays by combining graph convolutional network and convolutional neural network. Pattern Recogn 2022;122:108255. https://doi.org/10.1016/j.patcog.2021.108255.

[50] Mousavi Z, et al. COVID-19 detection using chest X-ray images based on a developed deep neural network. SLAS Technology Feb. 2022;27(1):63–75. https://doi.org/10.1016/j.slast.2021.10.011.

[51] Sri Kavya N, et al. Detecting Covid19 and pneumonia from chest X-ray images using deep convolutional neural networks. Mater Today Proc 2022;64:737–43. https://doi.org/10.1016/j.matpr.2022.05.199.

[52] Sundaram SG, et al. Deep transfer learning based unified framework for COVID19 classification and infection detection from chest X-ray images. Arabian J Sci Eng 2022;47(2):1675–1692, Feb. https://doi.org/10.1007/s13369-021-05958-0.

[53] Luz E, et al. Towards an effective and efficient deep learning model for COVID-19 patterns detection in X-ray images. Res. Biomed. Eng. Mar. 2022;38(1):149–62. https://doi.org/10.1007/s42600-021-00151-6.

[54] Djuniadi, et al. Face mask detection services of Covid19 monitoring system to maintain a safe environment using deep learning method. IOP Conf Ser Earth Environ Sci 2022;969(1). https://doi.org/10.1088/1755-1315/969/1/012016. 012016.

[55] Chaudhary Y, et al. Efficient-CovidNet: deep learning based COVID-19 detection from chest X-ray images. In: 2020 IEEE international conference on E-health networking, application & services (HEALTHCOM). Shenzhen, China: Mar.; 2021. p. 1–6. https://doi.org/10.1109/HEALTHCOM49281.2021.9398980.

[56] Kogilavani SV, et al. COVID-19 detection based on lung ct scan using deep learning techniques. Comput Math Methods Med 2022:1–13. https://doi.org/10.1155/2022/7672196.

[57] Muralidharan N, et al. Detection of COVID19 from X-ray images using multiscale deep convolutional neural network. Appl Soft Comput 2022;119:108610. https://doi.org/10.1016/j.asoc.2022.108610.

[58] Haghanifar A, et al. COVID-CXNet: detecting COVID-19 in frontal chest X-ray images using deep learning. Multimed Tools Appl; 2022. https://doi.org/10.1007/s11042-022-12156-z.

[59] Nassif AB, et al. COVID-19 detection systems using deep-learning algorithms based on speech and image data. Mathematics 2022;10(4):564. https://doi.org/10.3390/math10040564.

[60] Nayak SR, et al. Application of deep learning techniques for detection of COVID-19 cases using chest X-ray images: a comprehensive study. Biomed Signal Process Control 2021;64:102365. https://doi.org/10.1016/j.bspc.2020.102365.

[61] Verma A, et al. Detecting COVID-19 from chest computed tomography scans using AI-driven android application. Comput Biol Med 2022;143:105298. https://doi.org/10.1016/j.compbiomed.2022.105298.

[62] Sim JZT, et al. Diagnostic performance of a deep learning model deployed at a national COVID-19 screening facility for detection of pneumonia on frontal chest radiographs. Healthcare Jan. 2022;10(1):175. https://doi.org/10.3390/healthcare10010175.

[63] Srivastava V, Ruchilekha. Diagnosing covid-19 using AI based medical image analysis. In: 5th joint international conference on data science & management of data (9th ACM IKDD CODS and 27th COMAD); Jan. 2022. p. 204–12. https://doi.org/10.1145/3493700.3493730. Bangalore India.

[64] Improving lung disease detection by joint learning with COVID-19 radiography database. Commun. Math. Biol. Neurosci. 2022. https://doi.org/10.28919/cmbn/6838.

[65] Panwar A, et al. COVID 19, pneumonia and other disease classification using chest X-ray images. In: 2021 2nd international conference for emerging technology (INCET); May 2021. p. 1–4. https://doi.org/10.1109/INCET51464.2021.9456192. Belagavi, India.

[66] Nasser N, et al. A deep learning-based system for detecting COVID-19 patients. In: ICC 2021 - IEEE international conference on communications. Montreal, QC: Canada; Jun. 2021. p. 1–6. https://doi.org/10.1109/ICC42927.2021.9500460.

[67] Taeiq A, et al. Patient-specific COVID-19 resource utilization prediction using fusion AI model. npj Digit. Med. 2021;4(1):94. https://doi.org/10.1038/s41746-021-00461-0.

[68] Wang B, et al. AI-assisted CT imaging analysis for COVID-19 screening: building and deploying a medical AI system. Appl Soft Comput 2021;98:106897. https://doi.org/10.1016/j.asoc.2020.106897.

[69] Chung H, et al. Prediction and feature importance analysis for severity of COVID-19 in South Korea using artificial intelligence: model development and validation. J Med Internet Res 2021;23(4):e27060. https://doi.org/10.2196/27060.

[70] Afshar P, et al. Human-level COVID-19 diagnosis from low-dose CT scans using a two-stage time-distributed capsule network. Sci Rep 2022;12(1):4827. https://doi.org/10.1038/s41598-022-08796-8.

[71] Sheela MS, Arun CA. Hybrid PSO–SVM algorithm for Covid-19 screening and quantification. Int. j. inf. tecnol. 2022;14(4):2049–56. https://doi.org/10.1007/s41870-021-00856-y.

[72] Babaei Rikan S, et al. COVID-19 diagnosis from routine blood tests using artificial intelligence techniques. Biomed Signal Process Control 2022;72:103263. https://doi.org/10.1016/j.bspc.2021.103263.

[73] Yildirim M, et al. COVID-19 detection on chest X-ray images with the proposed model using artificial intelligence and classifiers. New Generat Comput May 2022. https://doi.org/10.1007/s00354-022-00172-4.

[74] De Falco I, et al. Classification of Covid-19 chest X-ray images by means of an interpretable evolutionary rule-based approach. Neural Comput & Applic; 2022. https://doi.org/10.1007/s00521-021-06806-w.

[75] Lella KK, Pja A. Automatic diagnosis of COVID-19 disease using deep convolutional neural network with multi-feature channel from respiratory sound data: cough, voice, and breath. Alex Eng J 2022;61(2):1319–34. https://doi.org/10.1016/j.aej.2021.06.024.

[76] Canario DAH, et al. Using artificial intelligence to risk stratify COVID-19 patients based on chest X-ray findings. Intelligence-Based Medicine 2022;6:100049. https://doi.org/10.1016/j.ibmed.2022.100049.

[77] Kini AS, et al. Ensemble deep learning and internet of things-based automated COVID-19 diagnosis framework. Contrast Media & Molecular Imaging; 2022. p. 1–10. https://doi.org/10.1155/2022/7377502.

[78] Messaoud S, et al. Virtual healthcare center for COVID-19 patient detection based on artificial intelligence approaches. Can J Infect Dis Med Microbiol 2022:1–15. https://doi.org/10.1155/2022/6786203. Jan. 2022.

[79] Liang H, et al. Artificial intelligence for stepwise diagnosis and monitoring of COVID-19. Eur Radiol 2022;32(4):2235–2245, Apr. https://doi.org/10.1007/s00330-021-08334-6.

[80] Tan T, et al. Multi-modal trained artificial intelligence solution to triage chest X-ray for COVID-19 using pristine ground-truth, versus radiologists. Neurocomputing May 2022;485:36–46. https://doi.org/10.1016/j.neucom.2022.02.040.

[81] Chen Z, et al. Diagnosis of COVID-19 via acoustic analysis and artificial intelligence by monitoring breath sounds on smartphones. J Biomed Inf 2022;130:104078. https://doi.org/10.1016/j.jbi.2022.104078.

[82] Alkhaldi NA, et al. Leveraging tweets for artificial intelligence driven sentiment analysis on the COVID-19 pandemic. Healthcare 2022;10(5):910. https://doi.org/10.3390/healthcare10050910.

[83] Mahbub Md K, et al. Deep features to detect pulmonary abnormalities in chest X-rays due to infectious diseaseX: covid-19, pneumonia, and tuberculosis, vol. 592. Information Sciences; May 2022. p. 389–401. https://doi.org/10.1016/j.ins.2022.01.062.

[84] Koç E, Türkoğlu M. Forecasting of medical equipment demand and outbreak spreading based on deep long short-term memory network: the COVID-19 pandemic in Turkey. SIViP 2022;16(3):613–21. https://doi.org/10.1007/s11760-020-01847-5.

[85] Elharrouss O, et al. An encoder–decoder-based method for segmentation of COVID-19 lung infection in CT images. SN COMPUT. SCI. 2022;3(1):13. https://doi.org/10.1007/s42979-021-00874-4.

[86] Loey M, et al. Bayesian-based optimized deep learning model to detect COVID-19 patients using chest X-ray image data. Comput Biol Med 2022;142:105213. https://doi.org/10.1016/j.compbiomed.2022.105213.

[87] Shastri S, et al. CoBiD-net: a tailored deep learning ensemble model for time series forecasting of covid-19. Spat. Inf. Res. Feb. 2022;30(1):9–22. https://doi.org/10.1007/s41324-021-00408-3.

[88] Zhang Y, et al. An intelligent early warning system of analyzing Twitter data using machine learning on COVID-19 surveillance in the US. Expert Syst Appl 2022;198:116882. https://doi.org/10.1016/j.eswa.2022.116882.

[89] Tavakolian A, et al. Fast COVID-19 versus H1N1 screening using optimized parallel inception. Expert Syst Appl 2022;204:117551. https://doi.org/10.1016/j.eswa.2022.117551.

[90] Choudrie J, et al. Machine learning techniques and older adults processing of online information and misinformation: a covid 19 study. Comput Hum Behav 2021;119:106716. https://doi.org/10.1016/j.chb.2021.106716.

[91] Saha P, et al. EMCNet: automated COVID-19 diagnosis from X-ray images using convolutional neural network and ensemble of machine learning classifiers. Inform Med Unlocked 2021;22:100505. https://doi.org/10.1016/j.imu.2020.100505.

[92] Zulfiker Md S, et al. Analyzing the public sentiment on COVID-19 vaccination in social media: Bangladesh context. Array 2022;15:100204. https://doi.org/10.1016/j.array.2022.100204.

[93] Shiri I, et al. COVID-19 prognostic modeling using CT radiomic features and machine learning algorithms: analysis of a multi-institutional dataset of 14,339 patients. Comput Biol Med 2022;145:105467. https://doi.org/10.1016/j.compbiomed.2022.105467.

[94] Aslan MF, et al. COVID-19 diagnosis using state-of-the-art CNN architecture features and Bayesian Optimization. Comput Biol Med 2022;142:105244. https://doi.org/10.1016/j.compbiomed.2022.105244.

[95] Goel T, et al. Multi-COVID-Net: multi-objective optimized network for COVID-19 diagnosis from chest X-ray images. Appl Soft Comput 2022;115:108250. https://doi.org/10.1016/j.asoc.2021.108250.

[96] Kanwal S, et al. COVID-opt-aiNet : a clinical decision support system for COVID -19 detection. Int J Imag Syst Technol Mar. 2022;32(2):444–61. https://doi.org/10.1002/ima.22695.

[97] Bhattacharyya A, et al. A deep learning based approach for automatic detection of COVID-19 cases using chest X-ray images. Biomed Signal Process Control 2022; 71:103182. https://doi.org/10.1016/j.bspc.2021.103182.

[98] Davazdahemami B, et al. An explanatory machine learning framework for studying pandemics: the case of COVID-19 emergency department readmissions," Decision Support Systems. 2022. p. 113730. https://doi.org/10.1016/j.dss.2022.113730.

[99] Karim AM, et al. New optimized deep learning application for COVID-19 detection in chest X-ray images. Symmetry May 2022;14(5):1003. https://doi.org/10.3390/sym14051003.

[100] Khan IU, et al. Computational intelligence-based model for mortality rate prediction in COVID-19 patients. IJERPH 2021, Jun;18(12):6429. https://doi.org/10.3390/ijerph18126429.

[101] Dhruv M, et al. InRFNet: involution receptive field network for COVID-19 diagnosis. J Phys: Conf. Ser. 2022;2161(1). https://doi.org/10.1088/1742-6596/2161/1/012064. 012064.

[102] Janbi J, Elnazer S. Comparing ML and DL approaches to diagnosis COVID-19 from CCGAN augmented CTX dataset. In: 2021 national computing colleges conference (NCCC). Taif, Saudi Arabia; 2021. p. 1–6. https://doi.org/10.1109/NCCC49330.2021.9428800.

[103] Islam Md R, Nahiduzzaman Md. Complex features extraction with deep learning model for the detection of COVID19 from CT scan images using ensemble based machine learning approach. Expert Syst Appl 2022;195:116554. https://doi.org/10.1016/j.eswa.2022.116554.

[104] Alabrah A, et al. Gulf countries' citizens' acceptance of COVID-19 vaccines—a machine learning approach. Mathematics Jan. 2022;10(3):467. https://doi.org/10.3390/math10030467.