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The COVID-19 epidemic analysis and diagnosis using deep learning: A systematic literature review and future directions

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ABSTRACT

Since December 2019, the COVID-19 outbreak has resulted in countless deaths and has harmed all facets of human existence. COVID-19 has been designated an epidemic by the World Health Organization (WHO), which has placed a tremendous burden on nearly all countries, especially those with weak health systems. However, Deep Learning (DL) has been applied in several applications and many types of detection applications in the medical field, including thyroid diagnosis, lung nodule recognition, fetal localization, and detection of diabetic retinopathy. Furthermore, various clinical imaging sources, like Magnetic Resonance Imaging (MRI), X-ray, and Computed Tomography (CT), make DL a perfect technique to tackle the epidemic of COVID-19. Inspired by this fact, a considerable amount of research has been done. A Systematic Literature Review (SLR) has been used in this study to discover, assess, and integrate findings from relevant studies. DL techniques used in COVID-19 have also been categorized into seven main distinct categories as Long Short Term Memory Networks (LSTM), Self-Organizing Maps (SOMs), Conventional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Recurrent Neural Networks (RNNs), Autoencoders, and hybrid approaches. Then, the state-of-the-art studies connected to DL techniques and applications for health problems with COVID-19 have been highlighted. Moreover, many issues and problems associated with DL implementation for COVID-19 have been addressed, which are anticipated to stimulate more investigations to control the prevalence and disaster control in the future. According to the findings, most papers are assessed using characteristics such as accuracy, delay, robustness, and scalability. Meanwhile, other features are underutilized, such as security and convergence time. Python is also the most commonly used language in papers, accounting for 75% of the time. According to the investigation, 37.83% of applications have identified chest CT/chest X-ray images for patients.

1. Introduction

COVID-19's epidemic and related containment efforts have triggered a global medical catastrophe that has impacted all aspects of life [1,2]. Most of the people affected by this virus were simply cured [3]. However, with the growing increase of time, the WHO has announced COVID-19, an epidemic with an increased risk of harming countless lives in all people, particularly those with weaker healthcare systems. For two simple reasons, the virus is hazardous: firstly, the vaccinations can not be done in a good way, and secondly, it is simply transmitted by indirect or direct contact with an infected individual [4,5]. This spread can be slowed down by diagnosing and isolating early-stage COVID-19 patients, saving multiple lives. The Reverse Transcription Polymerase Chain Reaction (RT-PCR) is one of the most common diagnostic techniques. Besides, RT-PCR examinations are time-consuming and costly; specialized materials, equipment, and tools are often needed. Also, due to constraints on budget and techniques, most countries suffer from a shortage of testing kits [6]. Therefore, the adoption of Deep Learning (DL) technology for effective assessment and diagnosis with X-ray and CT scans was driven by the need for quick detection and surveillance throughout the COVID-19 epidemic, which pushed the implementation of this standard technique [7].

However, during the last few decades, Artificial Intelligence (AI) was already hailed as a promising solution to assisting in disease detection

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and assisting doctors in making accurate diagnoses in a shorter amount of time [8,9]. Machine Learning (ML), one of the commonly used methods in AI, refers to the intelligence shown by computers [10,11]. Deep Learning (DL) is an improved and scalable ML extension to strengthen the structure of learning algorithms and make them easy to use [12]. Being a subset of ML, DL has been used tremendously to build complex models with very large data and a simpler setting [13]. So, the COVID-19 problem could be addressed with DL systems. However, their use in clinical settings has been limited due to their lack of applicability in real-world scenarios [14]. While these DL-based approaches are promising, their predictive success relies extensively on the accessibility of high data volumes [12]. As a consequence, the value of datasets in obtaining results from methods is critical to us. In computer vision research, DL has been widely used in conjunction with Convolutional Neural Networks (CNNs) and is one of the most common methods for disease detection [13]. The main advantage of DL is that it can assist with vast amounts of data during learning [15]. The accuracy can be improved by a large margin as a result [16]. Analyzing and comprehending the predictions of a DL model provides important views into the input data and learned properties, allowing human specialists to comprehend the findings readily [15,16]. Edge devices, on the other hand, including the Internet of Things (IoT), webcams, drones, intelligent medical equipment, robots, and so on, are pretty helpful in any epidemic circumstance [17]. These pieces of equipment help make infrastructures more complex and streamlined, making it easier to deal with outbreaks. Transfer learning (TL) has also been widely utilized to effectively train models with restricted datasets, overcoming both cost and time constraints. It allows models to be trained quickly and accurately by identifying relatively useful spatial features from enormous datasets in many domains at the start of training [18]. So, TL might be a means to combine the necessary computing power and encourage more effective deep learning approaches, which could help address a variety of problems [19].

In all healthcare sectors, the image processing technique has acquired immense attention. Consequently, these methods were also a perfect choice for COVID-19 research. Nevertheless, in the COVID-19 domain, there is no complete and detailed survey of the use of DL techniques. To present a detailed overview of the modern systems provided using these technologies, the study focused on emphasizing the accomplishments, detection, and diagnosis of DL and medical image processing methods to tackle the COVID-19 epidemic, death prediction, estimating health equipment, and so on. The significant contribution of this review is to address the most exciting area of study, given recent reviews on the different DL applications recently created for the identification and cure of COVID-19 disease. A Systematic Literature Review (SLR) is used in this research to discover, interpret, and integrate results from similar studies. We also classify DL methods employed in COVID-19 into seven main distinct categories as Long Short Term Memory Networks (LSTMs), CNNs, Self-Organizing Maps (SOMs), Generative Adversarial Networks (GANs), Recurrent Neural Networks (RNNs), autoencoders, and hybrid approaches. Hybrid approaches combine some methods like Multilayer Perceptrons (MLPs), Radial Basis Function Networks (RBFNs), Restricted Boltzmann Machines (RBMs), and Deep Belief Networks (DBNs). We investigated several properties such as advantages, challenges, dataset, usages, security, and TL for each category and method used DL methods in COVID-19. This article explains the methods and applications of DL methods in COVID-19 and covers a wide range of diseases that can occur at any time and in any place. We have also gone through future work in detail, noting all of the flaws that need to be addressed in the future. In brief, the contributions of the present article are:

- Presenting a broad review of the existing issues related to DL methods in COVID-19;
- Presenting a systematic overview of the existing methods for DL-COVID-19 and other vital actions;
- Presenting an explanation of the important methods in DL combining COVID-19;
- Investigating each approach that referred to DL-COVID-19 with various properties such as benefits, challenges, datasets, applications, security, and TL;
- Outlining the key zones that can improve the mentioned techniques in the future.

This paper's organization is determined by the classifications listed below. The following section covers the fundamental concepts and terminology of DL in COVID-19. The related review articles are examined in Section 3. The study methods and tools for article selection are presented in Section 4. Section 5 explains the categories of the articles that were chosen. Section 6 presents the findings and comparisons. Finally, the open issues and conclusion are presented in the last sections. Besides, Table 1 demonstrates the abbreviation utilized in the article.

2. Basic concepts and corresponding terminologies

This section covers the fundamentals of DL methods, DL applications in COVID-19, and the TL method.

2.1. DL applications in COVID-19 and DL methods in general

AI-based methods are frequently employed to identify, classify, and diagnose medical images. Recent AI innovation has significantly enhanced COVID-19 screening, diagnoses, and prediction, resulting in superior scale-up, timely response, most reliable and efficient outcomes, and occasionally outperforming humans in certain healthcare activities. Out of the various fields of AI, ML and DL are the two most well-known. In the following sections, we will look at how both ML and DL can be used to battle and mitigate the COVID-19 epidemic. DL-based techniques, such as CNN, RNN, and LSTM for COVID-19 detection, diagnosis, and classification, have recently been applied by several researchers to tackle the COVID-19 pandemic. Screening, drug repurposing, prediction, and forecasting are all things that can be done. Furthermore, ML techniques have been routinely employed to discover epidemic trends. Various studies have attempted such strategies to screen, classify, diagnose, repurpose drugs, and anticipate COVID-19 in the context of the COVID-19 pandemic. Concerning the COVID-19 outbreak, several of the most effective ML techniques, including SVM, logistic regression, random forest, and decision tree, are applied [20].

Also, one of the major accomplishments for contemporary AI is DL which is recognized as hierarchical learning [21]. DL approaches are now being successfully extended to various AI-based medical applications, including the study of Magnetic Resonance Imaging (MRI) images for cancer diagnoses. Because of their capacity to learn from context, Neural Networks (NN) and DL have exploded in popularity in modern scientific research. These two approaches have been widely utilized in various applications, including classification and forecast issues, smart homes, image recognition, self-driving vehicles, etc. Due to their ability to adjust to numerous data types in many areas [22]. Various techniques used in DL are represented in Fig. 1. DL mirrors the human brain's filtering of information for correct decision-making [23]. However, DL trains a device to process inputs utilizing various layers, similar to the human brain, to support data prediction and classification. These layers serve as input to the next layer, similar to the layered filters used by NNs in the brain [24]. The feedback loop is continued until the output is the same as before. Weights are assigned to each layer to create the precise output, and they are adjusted throughout training to get the accurate output [25].

There are three types of DL techniques: supervised, semi-supervised, and unsupervised [26]. Each known value serves as an input vector for the supervisory signal, which is the desired value [27]. The method predicts the desired output labels by using existing labels [28]. Classification methods employ supervised learning and can traffic signals,

Table 1
Abbreviation table.

Abbreviation	Definition	Abbreviation	Definition	Abbreviation	Definition
ANN	Artificial Neural Networks	HC	Healthy control	RBMs	Restricted Boltzmann Machines
CAP	Credit Assignment Path	ICU	Intensive Care Unit	RMSE	Root Mean Square Error
CLAHE	Contrast-Limited Adaptive Histogram Equalization	MAPE	Mean Absolute Percentage Error	RNN	Recurrent Neural Network
CNN	Convolutional Neural Network	MCWS	Modified Marker-Controlled Watershed	ROC	Receiver Operating Characteristic
COVID-19	Coronavirus Disease 19	ML	Machine Learning	RTPCR	Reverse Transcription-Polymerase Chain Reaction
DAM	Deep Assessment Methodology	MLP	Multi-Layer Perceptron	PRC	People's Republic of China
DBNs	Deep Belief Networks	MRI	Magnetic Resonance Imaging	SLR	Systematic Literature Review
DL	Deep Learning	NLP	Natural Language Processing	SOMs	Self-Organizing Maps
FDI	Foreign Direct Investment	NN	Neural Network	SNN	Statistical Neural Network
GAN	Generative Adversarial Networks	OSN	Online Social Networks	SPT	Second Pulmonary Tuberculosis
GHS	Global Health Security Index	PHEIC	Public Health Emergency of International Concern	SOFM	Self-Organizing Feature Map
GRNN	Generalized Regression Neural Network	PNN	Probabilistic Neural Network	SVM	Support Vector Machine
GSA	Gravitational Search Algorithm	PPE	Personal Protective Equipment	WHO	World Health Organization
GRUs	Gated Recurrent Units	RBFNs	Radial Basis Function Networks		

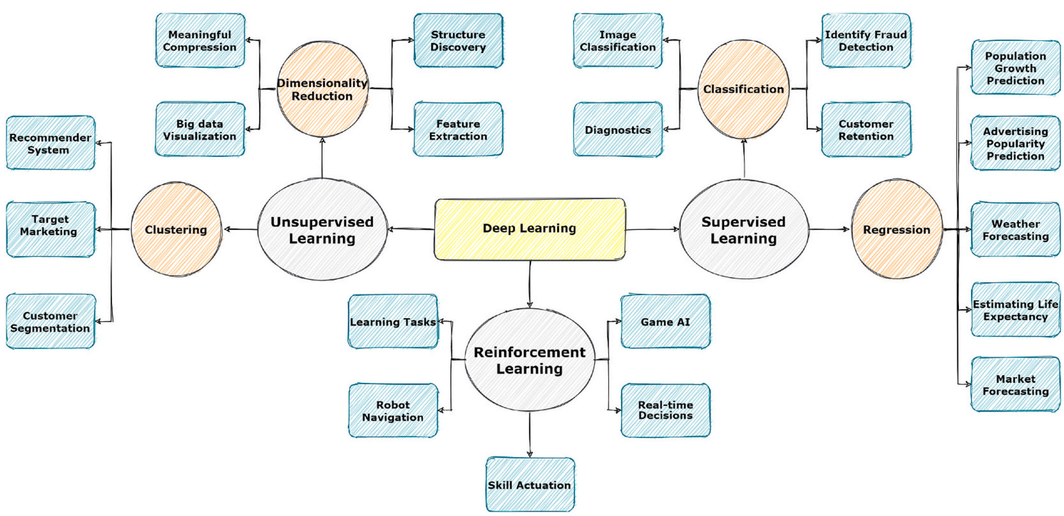

Fig. 1. Different DL approaches and implementations.

detect spam in a file, convert speech to text, recognize faces, and other scenarios [29]. Semi-supervised learning is a procedure that bridges the gap between supervised and unsupervised ML techniques. Semi-supervised learning uses both labeled and unlabeled values as training data. Semi-supervised learning is the middle ground between unsupervised and supervised learning [30]. When combined with a small amount of labeled data, the unlabeled data will significantly increase learning accuracy [11]. Certain theoretical theories arise about DL techniques. The first is that data nearby share the same name. The second possibility is the cluster assumption, which states that all data in a cluster have the same name. The third point is that rather than using the entire input space, the data is restricted to a single dimension [31]. Unsupervised learning determines the interrelationships between the elements and then classifies them. Clustering, anomaly detection, and NN use these techniques. Unsupervised learning is commonly used in security domains to detect anomalies [31]. Most DL techniques utilize Artificial Neural Networks (ANN) for feature processing and extraction. A feedback mechanism is used in the learning process, in which each level changes its input data to produce a summary representation. The term "deep" in the DL technique refers to the number of layers needed to transform the data [32]. Throughout that transformation, a Credit Assignment Path (CAP) was being used. The depth of CAP in a feed-forward NN is determined by multiplying the number of hidden layers by the number of output layers.

The CAP depth cannot be calculated since an RNN's layer may have numerous signals that travel many times [13]. Also, CNN is the most extensively utilized NN technique for image processing. Besides, since the feature extraction approach is automated and conducted throughout the CNN training on pictures, DL is the most precise image processing field [33]. RNN works similarly to CNN, except that RNN is used to compute language. RNN employs feedback loops, in which the output of one layer is fed into the input of the next. Time-series, video, financial data, audio, text, and other datasets can all be used with RNN [34]. Besides, one such groundbreaking model that generates synthetic images is the GAN. It's a powerful way to produce unseen samples without control using a min-max game. GANs combine two NNs to generate new virtual data instances. For image generation, GANs are widely utilized [35]. GANs are based on the generator network and discriminator concepts. The discriminator distinguishes between fake and real data, while the generator network generates fake data [36,37]. GANs are commonly employed by applications to generate images from text. The inception block in Google's inception network is utilized to compute convolutions and pooling operations to process complex tasks efficiently. This process is a higher level of DL used to automate the tasks involved in image processing [38].

The layers of an RNN, commonly referred to as an LSTM network, are built by means of the units of an LSTM. RNNs can recall inputs for a long time, thanks to LSTMs. This process is because of storing the information in memory by LSTMs similar to that of a machine. The LSTM could remove or add information to the cell state controlled by gate structures

[39,40]. Gates are a way of allowing knowledge to pass through with the option of allowing it to pass through. A sigmoid NN layer and a point-wise multiplication operation are used to construct them. In addition to regular units, LSTM networks use special units. A memory cell in an LSTM unit can store data for a long time. When information enters the memory, a series of gates are used to manage it [41].

The SOM, commonly known as the Kohonen map, is a pattern exploration and visualization model for high-dimensional datasets. Teuvo Kalevi Kohonen was the first to create this pattern in 1982 [42]. SOM is a clustering methodology that provides conventional statistical methods to identify groups in a dataset. There are only two layers in the SOM: the input and the output layers [43]. This NN aims to convert all input data objects with *n* characteristics to the output to connect them. The SOM is focused on unsupervised training with no specific output objective; the goal of the technique is to find a collection of neurons to represent the cluster while adhering to topological constraints [44]. The SOM clustering could spatially group cities, states, and regions based on coronavirus cases with similar activity. As a result, similar techniques to combat the virus's spread in these towns, states, and regions could be beneficial [45].

RBFN is a method of approximating multivariable (also known as multivariate) functions using linear combinations of terms depending on a single univariate equation (the radial basis function). This process is radicalized, allowing it to be used in several dimensions. There are three layers in RBFN: an input layer, a hidden layer, and an output layer. The hidden layer's outputs have Gaussian transfer functions that are inversely proportional to the distance from the neuron's origin. The RBF network has many benefits, including a simple three-layer architecture, good generalization, high input noise tolerance, and online learning capabilities. In addition, RBF networks should react well to patterns that were not used during training from a generalization standpoint [46]. Also, MLPs are often used in supervised learning problems since they train on a collection of input-output pairs and practice to model the association (or dependencies) between those outputs and inputs. The model's parameters, or weights and biases, are adjusted during training to minimize error. The perceptron comprises two connected layers: an input layer and an output layer [46].

Also, a DBN is a kind of DNN that consists of many layers of latent variables ("hidden units") with relationships between them but not between the units within each layer. Images, motion-capture data, and video sequences are recognized, clustered, and produced using DBNs. A continuous DBN is simply a DBN that accepts a continuous range of decimals instead of binary data. Unsupervised networks, such as RBMs, make up DBNs. Every sub-invisible network's layer becomes the visible layer of the next. The secret or invisible layers are conditionally autonomous and are not related to each other [47]. An RBM is also a dimensionality reduction algorithm that may be utilized for classification, collaborative filtering, regression, feature learning, and topic modeling, among other things. The building blocks of DBNs are RBMs, which are shallow two-layer neural nets. The visible, or input layer, is the first layer of the RBM, and the secret layer is the second [48]. So, DL may be used in various fields that require the processing of large amounts of data [49]. However, DL methods are widely used in the healthcare system for extensive data analysis, early disease diagnosis, and reduced manual workload [50].

2.2. Transfer learning method

TL is a strategy that applies previously acquired model information to solve a new task (presumably relevant or unrelated) with minimal retraining or fine-tuning. In comparison to conventional ML approaches, DL needs a large amount of training data. Consequently, the need for a substantial quantity of labeled data is a significant barrier to addressing sensitive domain-specific functions, particularly in the medical field, where creating massive, high-quality annotated medical datasets is difficult and costly. Besides, the standard DL model necessitates many computing resources, including a GPU-enabled server, even though scientists are working hard to improve it. TL significantly decreases the amount of time required to train for a domain-specific task. Many DL models have been proposed in the past, and a few recent ones are listed and discussed in this article. A TL-based DL technique is used to alleviate the dataset. Since the spreading of COVID-19 is so frightening around the earth, monitoring, quarantining, and treating COVID-19 patients is becoming a primary concern in the present situation. However, global standard diagnostic pathogenic laboratory testing takes a long time and costs a lot of money, with many false-negative findings [51]. Also, examinations are rarely performed in community health centers or hospitals due to a lack of funding and space compared to the large number of cases seen at any given time. To deal with such a scenario, researchers in this field are working hard to build some potential TL mechanisms that can help mitigate the problems [52].

3. Relevant reviews

DL is recognized as a brilliant technique for offering innovative ideas in the COVID-19 pandemic. Bhattacharya, Maddikunta [53] described recent attempts about the COVID-19 outbreak for smart and safe cities, inspired by DL applications for medical image processing. COVID-19 disruption was accomplished using DL in several ways, including disease prediction, virus spread monitoring, diagnosis and treatment, vaccine development, and drug testing. Data protection, the variability of outbreak patterns, control and reliability, and the difference between COVID-19 and non-COVID-19 symptoms were among the problems and issues they found in previous studies. Eventually, they addressed a variety of potential directions for DL applications in medical image processing using COVID-19.

Also, as another work, Alsharif, Alsharif [54] indicated the impressive area of study on DL for the COVID-19 treatment plan. Their research illuminated the literature regarding DL technology and the numerous approaches established to prevent COVID-19 disease. They looked at a data-efficient CNN that could detect COVID 19 on CT scans. Their survey identified the areas of research on DL for COVID-19 diagnosis. They classified the papers based on DL and ML approaches and quickly compared ML and DL mechanisms. Their survey did not include a large number of works. Furthermore, it did not compare techniques.

Plus, Alafif, Tehame [55] looked into AI-based ML and DL methods to diagnose and treat COVID-19 diseases. They also summarized AI-based ML and DL approaches and the available datasets, tools, and performance. The paper provided a concise overview of current state-of-the-art methods and implementations for ML and DL investigators and the broader health community and examples of how ML, DL, and data could prevent COVID-19 outbreaks. They classified the ML approaches to diagnosis and treatment, assessed these works, and then proposed future research on these topics. They also investigated the prediction performance of AI-based ML, and DL approaches for diagnosing COVID-19 using chest X-ray and CT images, COVID-19 speech and audio analysis, and COVID-19-based medication development.

In addition, Shorten, Khoshgoftaar [56] investigated how DL dealt with the pandemic and offered suggestions for potential COVID-19 studies. They studied Natural Language Processing (NLP), life sciences, computer vision, and epidemiology DL applications. They explained how the availability of big data affects both of these applications and how learning tasks are built. They assessed the current state of DL and DL's main limitations for COVID-19 applications. Their study focused on how DL might be applied to protein structure prediction, precision diagnostics, and medication repurposing in the life sciences. In epidemiology, DL was also used in spreading forecasting. DL systems to combat COVID-19 were found in abundance in their literature review. They hoped that by conducting this survey, they would be able to speed up the usage of DL in the COVID-19 study.

Finally, Sufian, Ghosh [52] discussed the benefits and drawbacks of deep TL approaches, edge computing, and related problems in combating the COVID-19 epidemic. Also, they introduced a hypothetical combined model, outlining the context and potential implications of working at sensitive sites with real data. Their survey paper also identified several pre-print studies that attempted to mitigate a disease outbreak in progress. The authors' study delved into methodologies that spanned most of the three topics: DL, deep TL, and edge computing. The methods in these three categories were then examined. The number of articles reviewed was limited due to the domain's novelty. One downside of their approach was that the benefits and drawbacks of the studies and aspects such as security and dataset were not taken into account. Table 2 also includes a summary of related works.

4. Methodology of research

This section employs the SLR method to better understand the DL-COVID-19 applications. The SLR is a critical review and investigation of all studies on a given subject. This portion is used to complete a detailed examination of the usage of DL methods in COVID-19. Following that, we look at the study selection methods' validity. The following subsections detail the search process, including research questions and selection criteria.

Table 2
Summary of related works.

Authors	Main work	Advantage	Weakness
Bhattacharya, Maddikunta [53]	Reviewing the papers associated with DL usage for COVID-19 medical image processing.	•Reviewing the challenges of DL-image processing. •Taking into account critical variables.	•The article selection process is not clear. •There was no talk about future projects. •The methods are not compared.
Alsharif, Alsharif [54]	Discussing studies on the various applications of DL in the detection and diagnosis of COVID-19.	•There is a complete introductory guide to the research relating to DL-COVID-19.	•The article selection process is not clear. •There is no comparison between the articles.
Alafif, Tehame [55]	Investigating ML and DL methods for COVID-19 treatment and diagnosis.	•Challenges and potential guidance are discussed.	•The article selection process is not clear.
Shorten, Khoshgoftaar [56]	Covering DL applications in NLP, computer vision, life sciences, and epidemiology.	•Cover a significant portion of the papers •Limitation on the amount of literature provided responsibly.	•The article selection process is not clear. •There is no comparison between the articles. •There has not been any in-depth review of the papers.
Sufian, Ghosh [52]	Examining Covid-19's deep TL methods.	•In the context of COVID-19, brief evaluations and challenges have been given. •A precedent pipeline model of DTL over edge computing has been drawn up for a future scope to mitigate any outbreaks.	•The article selection process is not clear. •There is no comparison between the articles.

4.1. Question formalization

The primary objectives of this study are to classify, distinguish, review, and evaluate all relevant articles found in DL-COVID19 applications. To achieve the goals mentioned earlier, the aspects and features of the methods can be investigated well using an SLR. Another aim of SLR is to comprehend the major issues and problems that this sector faces. The following are a few Research Questions (RQs) that have been defined:

✓ **RQ 1**: What are the applications of DL in COVID-19?
✓ *Section 1 answered this question.*
✓ **RQ 2:** What are DL methods, and what usages do they have?
✓ *Section 2 answered this question.*
✓ **RQ 3**: Is there any research in this area that has been published as a review article? What is the difference between our paper and previous works?
✓ *Section 3 answered this question.*
✓ **RQ 4**: What are the primary potential solutions and open questions in this field?
✓ *Section 5 will present the answers to this topic, while Section 7 will present the open problem.*
✓ **RQ 5**: How can we seek the article and select the DL methods in COVID-19?
This is addressed in Section 4.2.
✓ **RQ 6**: How can the DL mechanisms in COVID-19 be classified in medical healthcare? What are some of their examples?
Section 5 contains the answer to this question.
✓ **RQ 7**: What methods do the researchers use to carry out their investigation?
Sections 5.1 to 5.7 provide answers to this query.

4.2. The process of article selection

The following four phases make up this study's article search and selection process. Fig. 2 depicts this process. The keywords and terms for searching the papers in the first stage are shown in Table 3. The papers in this collection are the outcome of a query of common electronic databases. Scopus, IEEE Explore, Springer Link, Google Scholar, ACM, Elsevier, Emerald Insight, MDPI, Taylor and Francis, Wiley, Peerj, JSTOR, Dblp, DOAJ, and ProQuest are some of the applied electronic databases. In addition, journals, conference papers, books, chapters, notes, technical studies, and special issues are discovered. Stage 1 yielded 830 papers. Fig. 3 depicts the publisher's distribution of papers (see Table 4).

Stage 2 consists of two stages for determining the final number of papers to study. The papers are first considered (stage 2.1) based on the inclusion criteria in Fig. 4. At this time, 252 papers are remaining. The distribution of papers by the publisher is depicted in Fig. 5.

The review articles are omitted in Stage 2.2; out of the remaining 252 articles in the previous stage, 22 (or 8.7%) were review articles. Most research papers are published by Elsevier (42%). Most review papers are published by Springer and Elsevier (4.54%). At this point, there are 230 articles left. The title and abstract of the papers were reviewed in Stage 3. The papers' methodology, assessment, discussion, and conclusion have also been checked to ensure they apply to the research. At this point, 114 papers have been chosen for further consideration. Finally, 37 papers that met the strict standards were chosen to review and examine the remaining articles. Fig. 6 shows the distribution of the chosen articles by their publishers. Elsevier publishes most selected articles (40%, 15 articles). The lowest number is related to PeerJ, Frontiers Media S.A., and Tech Science Press (2.7%, one article). 2021 has the highest number of published articles (62%, 23articles), and 2020 has the lowest number of published articles (37%, 14 articles). Fig. 7 shows the journals that publish the articles. The Applied Soft Computing and IEEE Access publish the most number of articles (8.10%, three articles).

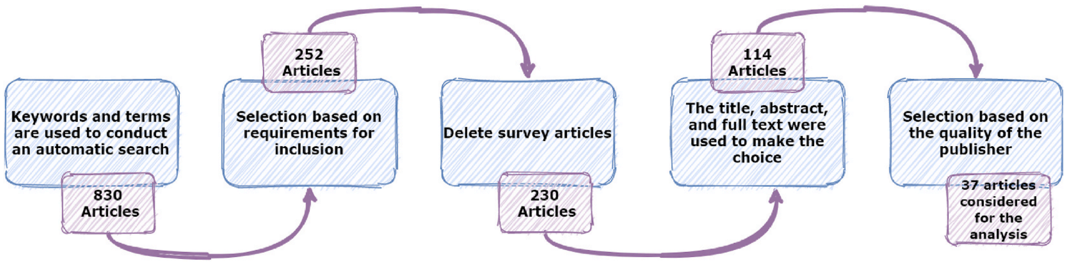

Fig. 2. The phases of the article searching and selection process.

Table 3
Search terms and keywords.

S#	Search Terms and Keywords
S1	"Deep learning" and "Medical issues"
S2	"Machine learning" and "Healthcare"
S3	"Deep learning" and "COVID-19"
S4	"Machine learning" and "COVID-19"
S5	"AI methods covid-19" or "Artificial intelligence COVID-19"
S6	"Deep transfer learning" and "Epidemic diseases"
S7	"Transfer learning" and "COVID-19 disease"

5. COVID-19 detection mechanisms

This section reviews the DL methods for diagnosing and evaluating COVID-19 disease and related conditions. Thirty-seven papers will be discussed in this section, all of which meet our criteria for selection. First, we categorize the approaches into seven main categories: CNNs, LSTMs, RNNs, GANs, SOMs, Autoencoders, and hybrid approaches, combining methods like RBFNs, MLPs, DBNs, and RBMs. Fig. 8 depicts the proposed taxonomy of DL-COVID-19 approaches.

5.1. CNN methods

One of the most important and key methods of DL is the CNN, which has been used in almost all fields of medicine and is one of the most

Table 4
Specifications of the chosen papers (updated on October 30, 2021).

Publisher	Author	Year	Citation	JCR	Scopus	Journal Name	H-index
Elsevier	**Kedia and Katarya** [57]	**2021**	**5**	**Q1**	**Q1**	**Applied Soft Computing**	**143**
Elsevier	**Wang, Nayak** [58]	**2021**	**52**	**Q1**	**Q1**	**Information system**	**1o7**
Elsevier	**Ismael and Şengür** [59]	**2021**	**109**	**Q1**	**Q1**	**Expert Systems with Applications**	**207**
Elsevier	**Abdel-Basset, Chang** [60]	**2021**	**36**	**Q1**	**Q1**	**Knowledge-Based Systems**	**121**
Elsevier	**Ezzat, Hassanien** [61]	**2020**	**28**	**Q1**	**Q1**	**Applied Soft Computing**	**143**
Elsevier	**Demir** [62]	**2021**	**15**	**Q1**	**Q1**	**Applied Soft Computing**	**143**
Springer	**Koç and Türkoğlu** [63]	**2021**	**2**	**Q3**	**Q2**	**Signal, Image and Video Processing**	**42**
Elsevier	**Gautam** [64]	**2021**	**15**	**Q1**	**Q1**	**ISA transactions**	**79**
IEEE	**Mohammed, Wang** [65]	**2020**	**20**	**Q1**	**Q1**	**IEEE Access**	**127**
IEEE	**Karaçuha, Önal** [66]	**2020**	**6**	**Q1**	**Q1**	**IEEE Access**	**127**
Springer	**Alakus and Turkoglu** [67]	**2021**	**3**	**Q3**	**Q3**	**Interdisciplinary sciences, computational life sciences**	**19**
Elsevier	**ArunKumar, Kalaga** [68]	**2021**	**13**	**Q1**	**Q1**	**Chaos, Solitons and Fractals**	**139**
IOP Publishing Ltd.	**Kumari and Sood** [69]	**2021**	**0**	**-**	**-**	**Materials Science and Engineering**	**44**
Springer	**Li, Jia** [70]	**2021**	**6**	**-**	**Q3**	**Journal of Healthcare Informatics Research volume**	**6**
Elsevier	**Shastri, Singh** [71]	**2020**	**62**	**Q1**	**Q1**	**Chaos, Solitons and Fractals**	**139**
Springer	**Goel, Murugan** [72]	**2021**	**7**	**Q1**	**Q1**	**Cognitive Computation**	**52**
Springer	**Rasheed, Hameed** [73]	**2021**	**24**	**Q3**	**Q3**	**Interdisciplinary sciences, computational life sciences**	**19**
PeerJ	**Elzeki, Shams** [74]	**2021**	**6**	**Q3**	**Q1**	**PeerJ Computer Science**	**24**
Springer	**Singh, Pandey** [75]	**2021**	**13**	**Q1**	**Q1**	**Neural Computing and Applications**	**80**
Elsevier	**Melin, Monica** [44]	**2020**	**60**	**Q1**	**Q1**	**Chaos, Solitons and Fractals**	**139**
MDPI	**Galvan, Effting** [45]	**2021**	**3**	**Q2**	**Q3**	**Medicina**	**36**
MDPI	**Simsek and Kantarci** [76]	**2020**	**22**	**-**	**Q2**	**Journal of Environmental Research and Public**	**113**
ICIC Express Letters Office	**Triayudi** [77]	**2021**	**0**	**-**	**Q3**	**ICIC Express Letters**	**20**
IEEE	**Chen, Zhang** [78]	**2020**	**4**	**Q1**	**Q1**	**IEEE Transactions on Medical Imaging**	**224**
Springer	**Li, Fu** [79]	**2020**	**7**	**Q1**	**Q2**	**Applied Intelligence**	**66**
Springer	**Atlam, Torkey** [80]	**2021**	**3**	**Q3**	**Q2**	**Pattern Analysis and Applications**	**55**
Elsevier	**Wen, Wang** [81]	**2021**	**6**	**Q1**	**Q1**	**Journal of Biomedical Informatics**	**103**
Elsevier	**Abdel-Basset, Chang** [60]	**2021**	**36**	**Q1**	**Q1**	**Knowledge-Based Systems**	**121**
MDPI	**Pereira, Guerin** [82]	**2020**	**32**	**-**	**Q2**	**International Journal of Environmental Research and Public Health**	**113**
–	**Chaves-Maza and Martel** [83]	**2020**	**5**	**Q1**	**Q1**	**Entrepreneurship and Sustainability Issues**	**25**
Elsevier	**Leichtweis, de Faria Silva** [84]	**2021**	**5**	**-**	**Q1**	**One Health**	**22**
Tech Science Press	**Al-Waisy, Mohammed** [85]	**2021**	**21**	**Q2**	**Q1**	**Computers, Materials and Continua**	**40**
IEEE	**Rosa, De Silva** [86]	**2020**	**9**	**Q1**	**Q1**	**IEEE Access**	**127**
Springer	**Hooshmand, Ghobadi** [87]	**2020**	**13**	**Q2**	**Q2**	**Molecular Diversity**	**57**
–	**Ibrahim, Kamaruddin** [46]	**2020**	**5**	**Q4**	**Q4**	**International Journal of Advanced Trends in Computer Science and Engineering**	**18**
Elsevier	**Shoaib, Raja** [88]	**2021**	**19**	**Q1**	**Q1**	**Computer Methods and Programs in Biomedicine**	**102**
Frontiers Media S.A.	**Dhamodharavadhani, Rathipriya** [89]	**2020**	**31**	**-**	**Q2**	**Frontiers in Public Health**	**41**

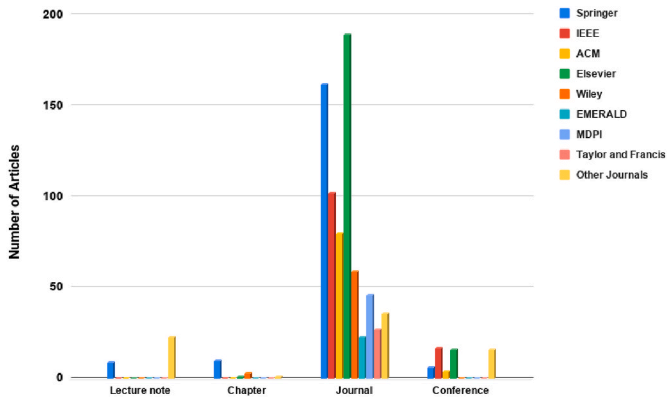

Fig. 3. Stage 1 is the publisher's distribution of the papers.

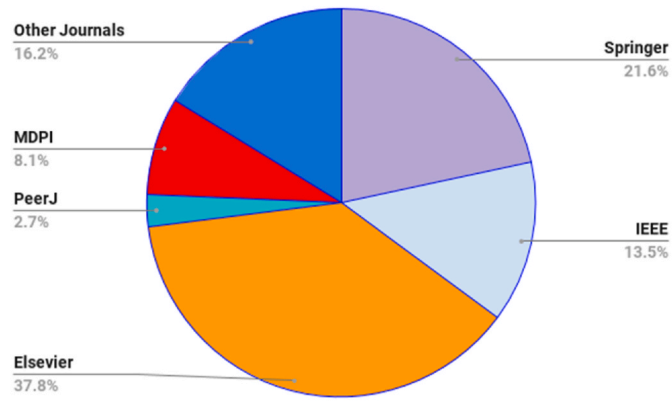

Fig. 6. The publishers' distribution of the selected articles.

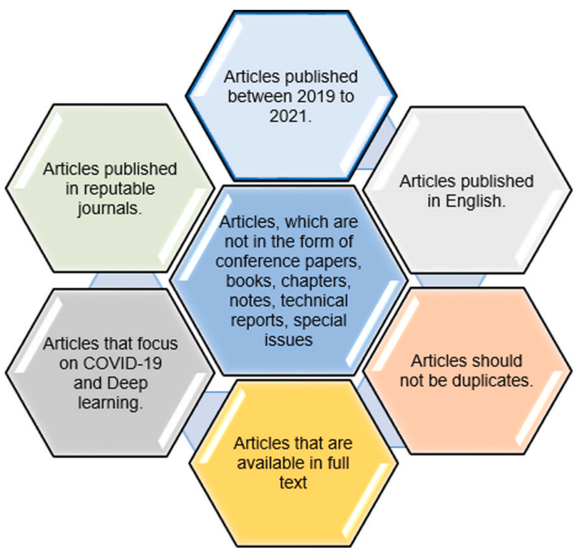

Fig. 4. Criteria for inclusion in the paper selection process.

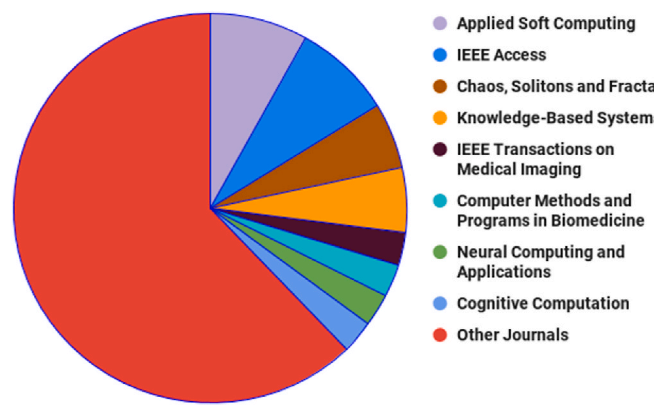

Fig. 7. Distribution of the selected articles based on journals.

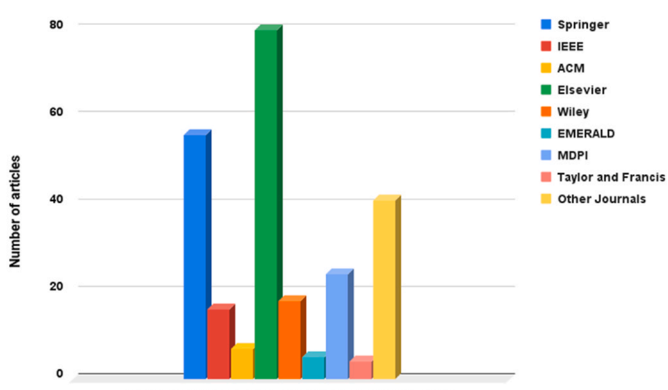

Fig. 5. In Stage 2.1, the papers are distributed by the publishers.

appealing methods for researchers. The method is most commonly used for detecting CT scans and MRI images, and related backgrounds, as discussed in the second section. We will go through five methods in this section. So, Kedia and Katarya [57] employed deep CNNs to create an automated model for forecasting COVID-19. Their research attempted to build a supervised DL ensemble model to categorize Chest X-ray images into normal, non-COVID, and COVID infected persons. Also, they conducted binary classification of COVID-19 vs. non-COVID-19 chest X-ray images. Multiple open-source online sources were used to assemble the dataset. These resources were free to use for academic purposes. These freely available datasets enabled us to train complex DNN and deliver highly satisfying results.

Also, Wang, Nayak [58] suggested a model nominated CCSHNet to detect COVID-19 in CCTs. CCSHNet. It is an abbreviation for the four categories examined in their research: COVID-19, Healthy Control (HC), and Community-Acquired Pneumonia (CAP), Second Pulmonary Tuberculosis (SPT). Their study is based on the proposed deep CCT fusion discriminant correlation analysis algorithm. They created a pre-trained network selection algorithm for fusion to optimally evaluate the best pre-trained models and the number of layers to be removed. The proposed TL algorithm was used to complete the feature learning procedures for models. Generally speaking, their findings showed that the CCSHNet can produce the best results and can help radiologists diagnose COVID-19 more accurately and quickly using CCTs. According to the findings, their method can help with decision-making by using CCTs to diagnose lung diseases. Furthermore, their algorithm can be re-deployed to a new hospital's server with minimal costs using cloud-computing methods.

Besides, to separate COVID-19 and normal chest X-ray images, Ismael and Şengür [59] provided a DL method that included deep feature extraction, fine-tuning of a pre-trained CNN, and end-to-end training of an established CNN model. Deep CNN models that had been pre-trained were used to extract deep features. The Support Vector Machines (SVM) classifier was also used to classify the deep features, with various kernel functions such as Linear, Quadratic, Cubic, and Gaussian. The fine-tuning technique used the aforementioned pre-trained deep CNN models. The study's success was measured using classification accuracy, and the outcome revealed a high level of accuracy.

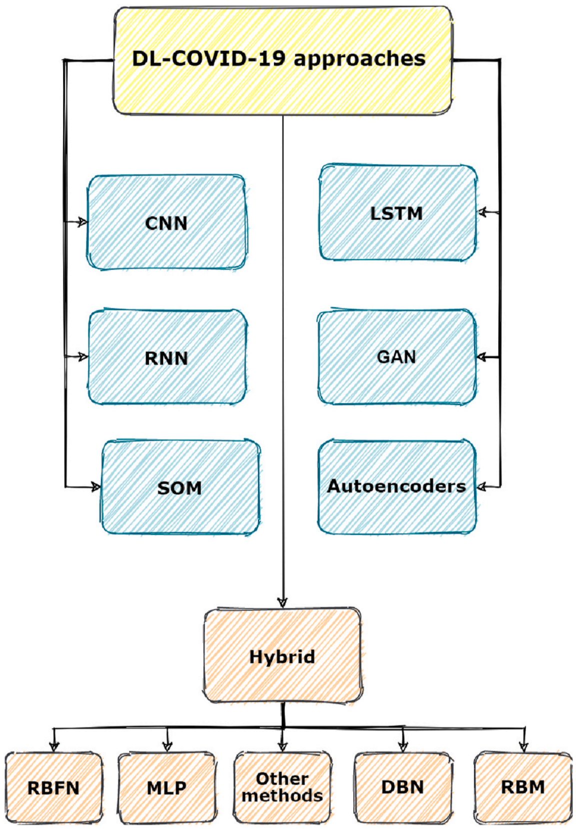

Fig. 8. The proposed DL-COVID-19 taxonomy, which separated seven distinct methods.

Abdel-Basset, Chang [60] suggested a new dual-path architecture-based semi-supervised few-shot segmentation model for COVID-19 segmentation from axial CT scans. The encoder architecture was built on a pre-trained ResNet34 architecture to make the learning process easier. They suggested that recombination and recalibration be combined with transferring learned information from the support set to question slice segmentation. The model improved generalization efficiency by adding unlabeled CT slices and marking one during training in a semi-supervised strategy. They also presented detailed architectural selection studies involving RRblocks, skip links, and proposed building blocks. After all, given the limited monitoring, the suggested FSS-2019-nCov's segmentation output was unable to obtain very precise segmentation, which can be addressed using a generative learning schema.

Finally, Gravitational Search Algorithm (GSA)-DenseNet121-COVID-19 was proposed by Ezzat, Hassanien [61] to diagnose COVID-19 cases using chest X-ray images. The data preparation, the hyperparameters selection, the learning, and the output assessment are the four main stages of their system GSA-DenseNet121-COVID-19. The binary COVID-19 dataset was treated from the imbalance in the first level, and then it was divided into three sets: preparation, validation, and test. Following the first stage's use of various data augmentation techniques to increase the number of samples in the training collection, they were used in the second stage for the validation set. GSA is then employed in the second stage to enhance hyperparameters in the DenseNet121 CNN architecture. DenseNet121 was fully trained in the third stage using the hyperparameters' values identified in the previous stage, allowing this architecture to make a diagnosis of 98.38% of the test set in the fourth stage. The findings demonstrated that the method was effective in detecting COVID-19. Table 5 discusses the CNN methods used in COVID-19 and their properties as well.

5.2. LSTM methods

The LSTM method, which has been used in many fields of medicine and is one of the most appealing methods for researchers, is one of DL's most common and primary methods. As described in the second section, the method is most widely used for forecasting. In this part, we look at five different approaches. So, Demir [62] developed a new approach for detecting COVID-19 with high precision from CT images. For the COVID-19, Pneumonia, and normal classification tasks, the recommended model, based on a deep LSTM model, achieved a success rate. It was also discovered that feeding the deep LSTM model with Modified Marker-Controlled Watershed (MCWS) images rather than raw images improved classification efficiency. The best result was obtained as 100% in all parameters concerning the accuracy, sensitivity, precision, and F-score with an 80% −20% training testing rate. As the COVID-19 cases are accelerating, AI-based applications with high success rates would greatly assist experts in the decision-making process during this period. Because this approach prevents an increase in the number of instances, an expert can detect more COVID-19 cases in a single day.

Also, Koç and Türkoğlu [63] suggested a DL methodology focused on a deep LSTM network for predicting medical device demand and the number of cases in the COVID-19 outbreak. A normalization layer, a multilayer LSTM network, a dropout layer, a completely connected layer, and a regression layer are all used throughout the scheme. The model developed with their system is used to forecast the number of intensive care beds, respiratory equipment, and cases required in the coming days. A dataset containing 77 days of COVID-19 data was used to assess the system's validity: 68 days for training and nine days for testing. The findings revealed that the model for estimating the number of intensive care beds and respiratory equipment has a high level of accuracy.

Besides, Gautam [64] developed a method that employs TL and uses it in an LSTM network to learn patterns in new cases and deaths due to COVID-19. Single-step and multistep predictions were tested from the prepared models in Brazil, France, India, Germany, and Nepal. These predictions have shown that the suggested models can accurately predict outcomes for a variety of intervention types, strategies, and healthcare systems. The findings showed that the proposed models accurately predicted new cases and deaths. From mature datasets, such as previously infected nations, complex trends of steep rises, spikes, and flattening effects can be learned. This method is more useful for countries that are still in the early stages of virus transmission, as it allows them to forecast based on the models of other countries. Governments and policymakers will benefit greatly from such predictions.

Plus, Mohammed, Wang [65] provided a weakly supervised DL-based method for COVID-19 detection. For extracting spatial, axial, and temporal features from the CT volume, their system uses a mixture of lung segmentation masks, attention-aware mechanisms, and LSTM. To solve the shortage and disparity of binary class data delivery, first resampling with data augmentation techniques is used. Stochastic and tone-mapping-based image enhancement systems were assessed as a pre-processing stage for performance improvement. According to the findings, the best output comes from combining all attention modules with the segmentation mask. Their approach worked flawlessly on all evaluation criteria and experimental cases when it came to volume level prediction. However, different experimental cases showed different results when it came to slicing level prediction. In general, incorporating slice focus helps radiologists to concentrate only on the most critical areas of the CT volume. Therefore, from a clinical standpoint, the structure could make it easier for radiologists to diagnose COVID-19.

Finally, under the present pandemic conditions, Karaçuha, Önal [66] provided practical guidance about better forecasting case numbers to better manage health services for patients. Starting with the first verified incident, they utilized their previously disclosed Deep Assessment Methodology (DAM), which is based on Fractional Calculus, to model the COVID-19 data. The DAM's performance was then evaluated by

Table 5
The methods, properties, and features of CNN-COVID-19 mechanisms.

Authors	Main idea	Advantages	Research challenges	Security mechanism?	Dataset	Using TL?	Method	Usage?
Kedia and Katarya [57]	Using deep CNN model "CoVNet-19" is being used to find COVID-19 patients.	-The combined classification accuracy of Pneumonia and Normal is 98.28%, with average precision and recall of 98.33 for both.	-The high complexity of network	No	There are 6214 chest X-rays in five separate datasets.	Yes	CNN	Detection in chest X-ray
Wang, Nayak [58]	Learning features with pre-trained models.	-Quicker diagnoses time -High accuracy	-It cannot handle heterogeneous data, such as CCT and CXR mixed data, patient history, and other information. -This study's dataset is both size and category restricted.	No	284 COVID-19, 281 pneumonia, 293 secondary pulmonary tuberculosis, and 306 normal images were included in the dataset.	Yes	CNN	Detection in chest CT
Ismael and Şengür [59]	Detecting COVID-19 using three deep CNN based on chest X-ray images.	-High accuracy -Low response time	-Data is not enough for to TL method	No	COVID-19 images (180) and normal chest X-ray images (200).	Yes	CNN	Detection in chest X-ray
Abdel-Basset, Chang [60]	Proposing a semi-supervised few-shot segmentation model.	-The FSS-2019-nCov's generalization efficiency improves as a result of the semi-supervised learning	-Lack of volumetric data representation -Owing to a lack of supervision, it was impossible to achieve a very accurate segmentation.	No	The Italian Society of Medical and Interventional Radiology dataset.	No	CNN	Detection in chest CT
Ezzat, Hassanien [61]	Using a pre-trained CNN that combined with an optimization algorithm.	-High accuracy -Low delay	-High complexity -High energy usage	No	The University of Montreal has made the COVID-19 Chest X-ray dataset available.	Yes	CNN + GSA	Detection in chest X-ray

making a one-step prediction using the DAM and LSTM. The study's third section focused on the short-term pandemic forecast. The Time-Dependent SIR and Gaussian models were based on the derivative of the number of reported cases received from DAM being used to forecast the next 30 days. The goal of the Gaussian modeling was to forecast the pandemic's future by analyzing regular shifts in pandemic data and predicting the peak number of cases. The finding suggested that, except in Turkey, the current number of confirmed pandemic cases was primarily determined by the last 14 days, corresponding to COVID-19's incubation duration. In contrast to the United States and Germany, Italy, France, and the United Kingdom have a shorter average incubation duration.

Table 6 discusses the LSTM methods used in COVID-19 and their properties.

5.3. RNN methods

The RNN method, which has been a very appealing method in the healthcare and medicine realms, is one of the most interesting methods for researchers. As stated in the second section, it is the most commonly used method for prediction and forecasting. We look at five different approaches in this section. So, Alakus and Turkoglu [67] suggested a protein-mapping approach for predicting the interactions of COVID-19 non-structural proteins. The interactions were discovered using a bidirectional RNN model. Protein sequences were mapped using the suggested AVL model and three separate mapping approaches in the first part of the analysis, which used proteins from the NCBI dataset. The mapped protein sequences were then normalized and classified using the Deep BiRNN model that had been established. Good interaction accuracy was obtained with the proposed procedure, with an average of 85.33% accuracy.

Also, ArunKumar, Kalaga [68] proposed DL-RNN models for predicting combined reported cases, recovered cases, and fatalities across countries. The Gated Recurrent Units (GRUs), LSTM cells, and the RNN were formed to forecast COVID-19's future trends. They utilized data from John Hopkins University's COVID-19 database, which is open to the public. They highlighted the importance of various factors such as population density, preventive measures, healthcare facilities, age, and so on, all of which play a role in the COVID-19 pandemic's rapid spread. As a result, their predicted outcomes are extremely useful in helping countries plan for the pandemic better.

Kumari and Sood [69] used COVID-19 time-series datasets and developed a DL model for case prediction. They used two DL-based NNs, RNN and LSTMs, to develop the model. In the first case, they used RNNs to create a prediction model, and then they used LSTMs to create the second model. The Python language was used to create and run these networks, and the results were assessed using 6 metrics. A simple RNN-based prediction model was applied to these datasets, resulting in unpredictably unstable outcomes. In addition, different results were obtained each time NN was run, resulting in vanishing gradient point error. The second prediction model was then built using an LSTM neural network. Out of these two NNs, the model based on LSTMs generated promising results, with an accuracy of 98%. They provided these models using NNs to help predict future patterns, deaths, and recovered cases, as the number of cases is rising at an alarming pace.

Li, Jia [70] suggested ALeRT-COVID, a TL solution that uses attention-based RNN architecture to forecast disease patterns in various countries. Each target country received a source model trained on the pre-defined source countries. The attention function was used to learn the diverse contributions of the reported cases in the past days to the future pattern. The lockdown measure was applied to their model as an indicator. The findings demonstrated that the TL strategy is beneficial, especially for developing countries. ALeRT-COVID displayed an important improvement in prediction output after incorporating the lockdown predictor and the attention mechanism. They expected reported cases in one week when extending and easing lockdown separately. Several

Table 6
The methods, properties, and features of LSTM-COVID-19 mechanisms.

Authors	Main idea	Advantages	Research challenges	Security mechanism?	Dataset	Using TL?	Method	Usage?
Demir [62]	Incorporating the Sobel gradient and MCWS operations into raw images to improve the model's pre-processing efficiency.	-The best performance was obtained as 100% in all parameters involving accuracy, sensitivity, precision, and F-score with an 80% −20% training–testing average.	-The dataset is insufficiently large. -All scenarios not considered	No	The dataset contained 1061 CT images gathered from various open public data sources.	No	Deep LSTM	Detection in chest X-ray
Koç and Türkoğlu [63]	Proposing a normalization layer and a multilayer LSTM network	-MAPE values of (2.89%, 3.29%, 4.80%) and R2 values of (99.90%, 99.85%, 99.72%) were obtained from forecasting the number of intensive care beds, respiratory equipment, and cases, respectively.	-All scenarios not considered -High complexity of network -High delay	No	COVID-19 data was verified in Turkey between March 27, 2020, and June 11, 2020.	No	LSTM	Medical equipment forecasting
Gautam [64]	Using TL for the LSTM network to learn new cases and new deaths trends.	-From mature datasets, such as data from previously infected nations, complex trends of steep rises, spikes, and flattening effects of new cases and deaths can be learned.	Due to all of the variations across nations, developing a generalized forecasting model that encompasses a larger area is difficult.	No	The European center for disease prevention and control provides a daily dataset.	Yes	LSTM	Forecasting new COVID-19 cases and deaths
Mohammed, Wang [65]	Using LSTM, determining the slices' axial dependency.	According to experimental results collected from publicly available datasets, the precision is 81.9%, and the F1 score is 81.4%.	-The dataset excludes common and other viral Pneumonia, which is crucial for detecting COVID-19. -High complexity of network	No	A total of 302 CT volumes were used, with 3520 positive and 19,353 negative case slices.	No	LSTM	Detection in chest CT
Karaçuha, Önal [66]	Using the DAM and Long-Short Term Memory	-High accuracy -Low response time -Low energy consumption	-Randomness, noise, and error changes are not taken into account -Low robustness	No	From their previous approach, DAM is used to model the dataset.	No	LSTM	Anticipate the pandemic's short-term (30-day) future

countries also need lockdown steps, according to their findings. Their findings can aid various countries in making better decisions about lockdown steps.

Finally, Shastri, Singh [71] utilized DL models to illustrate COVID-19 prediction for India and the United States. COVID-19 has been investigated, and death cases from both countries have been taken into account. The limitations of Covid-19 data make predicting time series data difficult. The RNN is extended as an LSTM cell to model the forecasts, with variants containing Stacked LSTM, Bi-directional LSTM, and Convolutional LSTM. The best model is selected based on prediction error rates, which are determined utilizing Mean Absolute Percentage Error (MAPE). The convolutional LSTM model outperforms the other two models for all four datasets, with error rates ranging from 2.0 to 3.3%. In their experimental comparative analysis, the Stacked LSTM model performed the worst. According to their predictions, both countries' reported and death cases will increase over the next month. Statistical data and methods are used to explain the validity of this analysis. The reliability rate of their best-proposed model, which produces art results, is satisfactory when using real-time COVID-19 data.

Table 7 discusses the RNN methods used in COVID-19 and their properties.

5.4. GAN method

As discussed in the second section, the GAN method is the most widely used to classify and detect images. It has recently become a popular method to use in the healthcare and medicine fields, and it is one of the most appealing methods for researchers. In this part, we investigate four different approaches in this field. Goel, Murugan [72] suggested using CT images to monitor COVID-19 using automated identification software tools. Since fewer datasets are accessible, making training DL networks hard, their method uses a GAN to produce more CT images. The Whale Optimization Algorithm (WOA) is utilized to optimize the hyperparameters of GAN's generator. The proposed system is evaluated and validated utilizing the SARS-CoV-2 CT-Scan dataset, including COVID-19 and non-COVID-19 images. The generative model's efficiency metrics, the specificity of 97.78%, the sensitivity of 99.78%, the accuracy of 99.22%, the F1-score of 98.79%, and the positive predictive value of 97.82%, and negative predictive value of 99.77%, show that it outperforms other methods. Thus, their model would aid in the automated screening of COVID-19 patients, reducing the burden on healthcare systems.

Also, with the support of X-ray images, Rasheed, Hameed [73] examined the application of ML methods for identifying COVID-19-infected patients. Their approach is particularly useful for rapidly identifying patients to deliver appropriate medical treatment as soon as possible. Furthermore, it offers a low-cost option for developing countries where testing kits are unavailable or costly to perform standard testing on a large scale. A data augmentation method based on GAN has been used to improve the classification accuracy of classifiers by reducing the chance of overfitting. When a deviation of 0.99 was used, the procedure obtained a maximum accuracy of 100%. Furthermore, the use of PCA resulted in a significant reduction in training time while maintaining 100% accuracy on testing data.

In addition, Elzeki, Shams [74] proposed the Chest X-Ray COVID Network (CXRVN) as an architecture for classifying the input X-Ray COVID-19 images. Their approach used a GAN network to complement a small number of unbalanced datasets from various sources and manage them efficiently and reliably. The design can manage each convolutional layer's extracted feature, and the results showed that the proposed framework is more stable and has more advantageous to other benchmark approaches. The first experiment used a balanced dataset of images for two classes, standard and COVID-19, with a testing accuracy of 92.85%, while the second experiment used an imbalanced dataset of 455

Table 7
The methods, properties, and features of RNN-COVID-19 mechanisms.

Authors	Main idea	Advantages	Research challenges	Security mechanism?	Dataset	Using TL?	Method	Usage
Alakus and Turkoglu [67]	Normalizing and classifying the mapped protein sequences using the DeepBiRNN model.	−97.76% accuracy, 97.60% precision, 98.33% recall, 79.42% f1-score, and an overall AUC of 89%. -Stable and robust	-There has been no comparison with the modern approaches.	No	NCBI dataset	No	RNN + AVL tree	Protein interactions in COVID-19 disease prediction
ArunKumar, Kalaga [68]	Using RNN and GRUs, predict future patterns in cumulative reported cases, cumulative recovered cases, and cumulative fatalities in the top 10 countries.	-High accuracy -Great analysis of results.	-High energy consumption -High delay	No	Datasets from John Hopkin's university are publicly accessible	No	RNN + GRU	Forecasting cumulative reported cases, cumulative recovered cases, and cumulative fatalities by region
Kumari and Sood [69]	Using RNN to construct a prediction model.	-A 98% overall accuracy -Low system complexity	-There has been no comparison with the modern approaches.	No	Kaggle dataset	No	Simple RNN	Forecasting future, fatalities, and recovered cases patterns
Li, Jia [70]	Using attention-based RNN architecture to predict the epidemic trends for different countries.	-High accuracy -Useful tool for predicting the need for a county-wide lockdown. -High scalability -Large dataset used.	-High delay -The number of cases recovered, deaths, and available healthcare services are not taken into account.	No	The dataset includes daily, the lockdown history, and populations from 83	Yes	Attention-based RNN	Forecast epidemic patterns in various countries
Shastri, Singh [71]	Using RNN-based LSTM variants, propose a technique for forecasting Covid-19 cases for one month ahead.	-High accuracy -High predictability	-High complexity -High delay -High energy consumption	No	Dataset from the India and USA Department of Health.	No	RNN	Covid-19 forecasting for India and USA

images for two classes with a testing accuracy of 96.70%. They utilized 603 images for three class labels in the third experiment: COVID-19, standard, and Pneumonia, and the accuracy in the testing process was 91.70%. They studied the image data augmentation using GANs to demonstrate the capacity of the proposed CXRVN architecture on a large scale, which resulted in a major enhancement of the architecture.

Finally, Singh, Pandey [75] suggested a DL-based approach that uses chest X-rays to assist COVID-19 patient triaging. They tested several GAN architectures and their ability to produce practical synthetic COVID-19 chest X-rays to deal with small numbers of training samples. To identify chest X-rays into three groups, the system utilizes image segmentation, image enhancement, and a modified stacked ensemble model with four CNN base-learners and Naive Bayes as a meta-learner to categorize them into COVID-19, Pneumonia, and regular. The framework's successful pruning strategy improves model performance, generalizability, and reduced model complexity. They used Grad-CAM visualization to integrate explainability into their paper to create confidence in the medical AI system. The approach outperforms current approaches on standard datasets, achieving 98.67% precision, 0.98 Kappa, and F-1 scores of 100, 98, and 98 for COVID-19, natural, and pneumonia classes.

Table 8 discusses the GAN methods used in COVID-19 and their properties.

5.5. SOM methods

As mentioned in the second section, the SOM method is the most widely used for analyzing geographic and temporal distribution. It has become a very appealing method in the COVID-19 domains, and it is one of the most appealing methods for researchers. In this part, we study four different approaches. So, Melin, Monica [44] provided a study on the spatial evolution of the COVID-19 disease outbreak worldwide employing a specific form of unsupervised NN. They classified the related countries based on their coronavirus cases using the clustering capabilities of SOMs, allowing them to recognize which countries are acting similarly and therefore benefit from using various methods in coping with the virus's spread. The study relied on publicly accessible databases of COVID-19 cases worldwide. There have been some significant observations that could aid in determining the best methods for coping with this virus. Furthermore, their method was evaluated concerning the spatial distribution of cases around Mexico and its relationship to Diabetes and Hypertension cases. Most previous papers dealing with Coronavirus data have focused on the problem's temporal aspect, which is significant, but their method is primarily concerned with numeric information forecasting.

Galvan, Effting [45] developed SOM-type unsupervised NNs, which were used to determine the spatial and temporal distribution of COVID-19 in Brazil, based on the number of cases and deaths. The SOM does not determine the steps to help curb the virus's spread, but the datasets reflect the consequences of the country's measures. This method demonstrated that the disease's spread in Brazil does not follow a predictable pattern, varying by area, state, and city. According to the findings, cities and states in the country's northern part were the hardest hit by the disease, with the largest volume and deaths per 100,000 people. According to their coronavirus events, the SOM clustering could spatially group cities, states, and regions with similar activity. As a result, similar strategies to combat virus spread in these towns, states, and regions may benefit.

Also, Simsek and Kantarci [76] suggested an AI-driven mobilization strategy for mobile evaluation agents of epidemics. Their paper developed a scheme for mobilizing assessment centers in an epidemic or pandemic to monitor, model, and the project confirmed cases to assist decision-makers at various levels of government in developing proactive management and logistics strategies for the public. To do so, a

Table 8
The methods, properties, and features of GAN-COVID-19 mechanisms.

Authors	Main idea	Advantages	Research challenges	Security mechanism?	Dataset	Using TL?	Method	Usage?
Goel, Murugan [72]	Using the WOA approach to optimize GAN's hyperparameters.	-Specificity 97.78%, sensitivity 99.78%, F1-score 98.79%, accuracy 99.22%, positive predictive value 97.82%, and negative predictive value 99.77%.	-Vanishing gradients mode collapse instability.	No	There are 2482 COVID-19 CT scan images in the dataset, with 1252 COVID-19 and 1230 non-COVID-19 images.	No	GAN + The Whale optimization algorithm	Detection in chest CT
Rasheed, Hameed [73]	Using GAN to increase the number of training samples and reduce the issue of overfitting.	-Positive cases recognition accuracy ranges from 95.2 to 97.6% without PCA and 97.6–100% with PCA.	-High complexity -High energy consumption	No	GAN was used to generate 500 X-ray images from an online dataset.	No	GAN + logistic regression	Detection in chest X-ray
Elzeki, Shams [74]	Proposing a lightweight architecture based on a single completely connected layer representing the critical features	The accuracy was 96.7% for two classes, and for three classes, it was 93.07%, with the model's overall accuracy being 94.5%.	-Different modified cases of the COVID-19 X-Ray image must be studied.	No	COVID-19 X-Ray datasets from three separate sources.	No	GNN	Detection in chest X-ray
Singh, Pandey [75]	Proposing a GAN-based approach to assist in the quicker triage of COVID-19 patients, thus reducing the risk of human error.	–98.67% accuracy, 0.98 Kappa score, and F-1 scores of 100, 98, and 98, respectively. -Low energy consumption	-The size of the training data set must be increased. -High delay	No	The open-source NIH chest X-ray dataset used in the RSNA pneumonia detection challenge on Kaggle was used.	No	GAN	Detection in chest X-ray

Self-Organizing Feature Map (SOFM) is trained using data from past mobile crowdsensing campaigns to predict individual mobility trends in many districts within a region to maximize the evaluated population with the fewest agents in the shortest time. According to a real street map on a mobile crowdsensing, the method reduces the unassessed population size when evaluation agents are randomly dispersed across the whole city on the 15th day after the initial verified case in the city.

Finally, Triayudi [77] presented the SOM to visualize the connection between socioeconomic factors and the coronavirus outbreak. They divided Indonesia's 34 provinces into five clusters using the SOM algorithm and the requisite distribution of eight social and economic variables. The distribution of cases is then compared to the clusters calculated by SOM. The findings showed a connection between socioeconomic factors and COVID-19 transmission. To obtain more information, data must be gathered from various sources, including the task force for the acceleration of COVID-19 handling, which will retrieve outbreak case data, and the central statistics agency, which will retrieve economic data for all Indonesian provinces. Hidden information can be found from a vast volume of data using the SOM algorithm, offering intuitive visualization. In addition, they can have a simpler web layout, good automatic learning capacity, and calculate quickly due to this.

Table 9 discusses the SOM methods used in COVID-19 and their properties.

5.6. Autoencoders method

The autoencoder approach has been a highly important way for researchers to employ in the COVID-19 areas, and it is one of the most fundamental methods. It is the most commonly used method for identifying COVID-19 using CT scans and survival analysis to assist hospitals. In this part, we study four different approaches. Chen, Zhang [71] suggested a hash addressing memory autoencoder with the multi-scale attention block, particularly for COVID-19 detection. The anomaly produces a high reconstruction error when their encoder and decoder network reconstructs the input, while regular samples produce a lower error. Multi-scale attention block combines pixel patch and channel attention layer, which can be easily plugged into any network for sampling, downsampling, and upsampling, to address today's challenges of limited stationary convolution operators. Since the memory has only been trained to record prototypical normal cases, it can recreate normal samples while amplifying the anomaly reconstruction error. However, soft-addressing via cosine similarity for quick retrieval is presented. Their framework outperforms other benchmarks, while their model is a more general paradigm extended to various situations.

Also, to detect COVID-19 cases from chest CT images, Li, Fu [79] suggested a fast and accurate stacked autoencoder detection model. Their model is also completely automated, with an end-to-end layout that eliminates the necessity for function extraction by hand. The model can detect COVID-19 cases rapidly and efficiently in the current extreme epidemic. Front-line practitioners may use the stacked autoencoder detector model to help them diagnose suspicious cases. Furthermore, the auxiliary diagnostic developed model using artificial intelligence, including the DL, is critical for preventing and controlling infectious diseases in countries and regions where medical supplies and equipment are scarce. Moreover, as more COVID-19 chest CT scan image datasets become available, the detection accuracy of DL models like the stacked autoencoder detector will improve significantly. It will be critical in preventing and controlling the COVID-19 outbreak and breaking the transmission chain.

Atlam, Torkey [80] provided two systems, Cox_COVID-19 and Deep_Cox_COVID-19, focused on Cox regression to investigate COVID-19 survival and help hospitals forecast the most significant symptoms affecting survival chances. Deep_Cox_COVID-19 is a mixture of autoencoder DNN and Cox regression to improve prediction accuracy. Cox_COVID-19 is based on Cox regression. The findings demonstrated that reconstructing features with an autoencoder before using the Cox

Table 9
The methods, properties, and features of SOM-COVID-19 mechanisms.

Authors	Main idea	Advantages	Research challenges	Security mechanism?	Dataset	Using TL?	Method	Usage?
Melin, Monica [44]	Utilizing an unsupervised SOM based on clustering can spatially group countries together.	-High scalability -High accuracy	-It is not considered to integrate both the spatial and temporal dimensions of the COVID-19 spread problem. - Low robustness -Low dependability	No	The Humanitarian Data Exchange was used to collect the dataset.	No	SOM	Analyze the global coronavirus pandemic's spatial evolution
Galvan, Effting [45]	Using SOM's spatial clustering capability to spatially group related towns, states, and regions based on COVID-19 cases.	-Able to spatially group cities, states, and regions based on the prevalence of coronavirus -Low complexity	-Comorbidities, the number of hospital beds available, trained staff, the human development index, and the environment are not considered.	No	The Brazilian Ministry of Health dataset on May 31, 2020.	No	SOM	To determine COVID-19's geographic and temporal distribution in Brazil
Simsek and Kantarci [76]	Proposing a mobile epidemic assessment agent mobilization approach based on AI.	-The results show that a 5 km coverage restriction achieves 99.783% coverage -High robustness	-Dataset is not mentioned. -Low dependability -High energy consumption	No	Not mentioned	No	SOM	To monitor, model and forecast reported cases
Triayudi [77]	Using SOM, visualize the relationship between socioeconomic factors and outbreaks.	-Low response time -Low energy consumption -High accuracy	-It is necessary to conduct additional tests to expand the data coverage -High complexity	No	The Indonesian central statistics agency provided the data.	No	SOM	Depicts the connection between socioeconomic factors and the outbreak of the COVID-19

regression algorithm improves the performance by increasing concordance, accuracy, and precision. Age, muscle pain, pneumonia, and throat pain are the most significant factors influencing mortality. The Cox_COVID-19 and Deep_Cox_COVID-19 prediction systems can predict the likelihood of survival and identify significant symptoms that distinguish extreme cases from death cases. In addition, Deep_Cox_Covid-19 outperforms Cox_Covid-19 in terms of precision. Both systems may provide doctors with precise details about disease diagnosis and treatment options, potentially lowering mortality.

Finally, using a DL-based method, Wen, Wang [81] investigated conducting sentinel syndromic surveillance for COVID-19 and other influenza-like illnesses using data from 2019 to 2020 in the sense of a COVID-19 syndromic surveillance mission. Their approach focuses on aberration detection using autoencoders that use symptom prevalence distributions to differentiate outbreaks of two ongoing diseases with identical symptoms, even though they co-occur. The first shows that this method can be used to identify influenza outbreaks with well-defined temporal boundaries. They also show how the autoencoder can be configured to ignore well-known and well-managed influenza-like illnesses like the common cold and influenza. Ultimately, they showed how the implementation of such a system might have provided early warning of an epidemic of a unique influenza-like sickness that did not fit the symptom profile of influenza and other recognized influenza-like illnesses.

Table 10 discusses the autoencoder methods used in COVID-19 and their properties.

Table 10
The methods, properties, and features of autoencoders -COVID-19 mechanisms.

Authors	Main idea	Advantages	Research challenges	Security mechanism?	Dataset	Using TL?	Method	Usage?
Chen, Zhang [78]	Introducing the autoencoder's hash addressing memory module.	-High robustness -Low delay -High accuracy	-Need to test on more difficult datasets -High complexity	No	COVID-19 CT images, X-Ray Images, and reference image database	**No**	Autoencoder	Detect the anomaly, especially in the case of COVID-19 detection
Li, Fu [79]	Using autoencoders to extract deeper information from CT images.	-Low response time -High accuracy	-The data set is not very big. -Low robustness	No	COVID-CT dataset includes 275 positive images and 195 negative images.	No	Autoencoder	Detection in chest CT
Atlam, Torkey [80]	Presenting a Cox regression-based autoencoder technique.	-High accuracy -High scalability	-High delay -High energy consumption	No	There are 1085 patients in this dataset.	No	Autoencode + Cox regression	COVID-19 survival analysis
Wen, Wang [81]	Using an autoencoder-based anomaly detection technique for COVID-19 surveillance.	-High robustness -High accuracy	-Data is not available because the results of the symptom extraction procedure are considered confidential health information -Low scalability	No	The dataset was compiled from clinical documentation created between January 1st, 2011, and May 1st, 2020.	No	Autoencoder	COVID-19 syndromic surveillance

5.7. Hybrid method

One of the sophisticated mechanisms employed in COVID-19 domains is hybrid techniques. These approaches are made up of two or more approaches for dealing with difficulties. In these evaluations, we specified the reviewed mechanisms that were built using which methodologies. It is a commonly used approach in a variety of fields related to this epidemic. In this section, we study ten different approaches. Abdel-Basset, Chang [60] suggested a new dual-path architecture-based semi-supervised few-shot segmentation model for COVID-19 segmentation from axial CT scans. The encoder architecture was built on a pre-trained ResNet34 architecture to make the learning process easier. They suggested that recombination and recalibration be combined with transferring learned information from the support set to question slice segmentation. The model improved generalization efficiency by adding unlabeled CT slices and marking one during training in a semi-supervised strategy. On publicly available COVID-19 CT scans, they studied the proposed FSS-2019-nCov and a range of baselines. They also presented detailed architectural selection studies involving RRblocks, Skip links, and proposed building blocks. After all, given the limited monitoring, the suggested FSS-2019-nCov's segmentation output could not obtain very precise segmentation, which can be addressed using a generative learning schema. A lack of volumetric data representation was also a constraint, which could be overcome by extending their model to 3D CT volumes of COVID-19.

Also, Pereira, Guerin [82] used a network model called LSTM for Data Training-SAE (LSTM-SAE). To designate eligible nations for training ANN models, they clustered the world's areas where the epidemic is at an advanced level. The various clusters are utilized to choose the relevant nations for model training. They are based on manually designed traits representing a country's reaction to the pandemic's early growth. Modified autoencoder models trained on these clusters and learning to forecast possible data for Brazilian states are the final models retained. Important data about the disease, including such peaks and the number of confirmed cases, are estimated using these forecasts. Eventually, curve fitting is used to determine whether the distribution matches the MAE outcomes better and refine estimates of the pandemic's peaks. Depending on the nations, the predicted end of the pandemics (97% of cases concluding) ranges from June to August 2020.

Chaves-Maza and Martel [83] examined entrepreneurship policy in 20 countries following the COVID-19's emergence to contextualize it. They used AI to look at variables that have a huge effect on the survival rate of entrepreneurs. Their paper sought to determine whether it is necessary to help entrepreneurs by predicting the likelihood of a business project's success depending on the other variables that influence the entrepreneur and their community. By integrating SOM and MLP, a technique based on AI could be created. SOM and MLP are two different types of artificial networks used. The application of NNs to a data set of 2221 entrepreneurs from Andalusia (Spain) and 769 variables collected during the recovery after the financial crisis from 2008 to 2012 revealed that the estimation of entrepreneurial survival and business performance is reasonable in more than 98% of those studied.

Besides, Leichtweis, de Faria Silva [84] studied the formation of a connection between SARS-basic CoV-2's reproduction number (R0) and various climate variables, as well as the Global Health Security Index (GHS). From December 31, 2019, to April 13, 2020, they gathered information from reported cases of COVID-19 and their respective GHS notes and climate data for 52 countries. Utilizing the GAN, the influence of temperature, sun radiation index, relative humidity, and GHS score on COVID-19 spread rate was studied. The Kohonen SOM technique was used to group countries that were close to each other to examine the role of each variable in the disease's spread. The temperature variable had a linear relationship (p 0.001) with the R0, with a 36.2% explained difference, while the relative humidity variable did not. The solar radiation response curve revealed a major nonlinear relationship (p 0.001) with a 32.3% explained variance. The GHS index variable had the most significant explanatory response in the control of COVID-19, with an explained variance of 38.4%; further, the countries with the highest GHS index scores were less affected by climate variables, with a substantial nonlinear relationship (p 0.001).

Al-Waisy, Mohammed [85] developed the COVID-DeepNet system, a hybrid multimodal DL system for identifying the virus in CX-R images to assist expert radiologists in rapid and accurate image interpretation. The Contrast-Limited Adaptive Histogram Equalization (CLAHE) and Butterworth bandpass filters improved contrast and removed noise in CX-R images. These two separate DL methods focused on including a DBN and a convolutional DBN were then studied. The parallel architecture was suggested because it gives radiologists a high level of trust in identifying safe and COVID-19-infected individuals. In a large-scale dataset, the system has a detection accuracy rate of 99.93%, sensitivity of 99.90%, specificity of 100%, precision of 100%, F1-score of 99.93%, MSE of 0.021%, and (Root Mean Square Error) RMSE of 0.016%. Thus, this method demonstrates reliability and precision. It can be used in a real clinical setting for early COVID-19 virus diagnosis and treatment follow-up in less than 3 s per picture.

Furthermore, Rosa, De Silva [86] suggested an event prediction method focused on changes in user activity in an Online Social Networks (OSN) at the early stages of an event. Since this method can identify any subject's case, it can be used for various functions. The suggested event detection framework is made up of five key modules: (1) user position estimation, (2) message extraction from an OSN, (3) subject recognition employing NLP and DBN, (4) user behavior shift analyzer in the OSN, and (5) effective and useful evaluation for emotion identification using a tree-CNN. Early incident identification is critical for the community and officials in public health to take corrective measures. As a result, they use the COVID-19 as a case study in their research. In the performance evaluation, the event detection system had a precision greater than 0.90, while other equivalent approaches had less than 0.74. Furthermore, their system was capable of detecting an incident almost three days before the other approaches. Moreover, the system's data allows users to comprehend the most important aspects of a case, including keywords and emotional messages.

Hooshmand, Ghobadi [87] presented the Multimodal Restricted Boltzmann Machine Method (MMRBM), which can solve drug repurposing by connecting information from multiple modalities. Their method combined two types of data: chemical structures of small molecules and differentially expressed genes, as well as small molecule perturbations, using MM-RBM. Two different RBMs were used to determine each datum's features and specific probability distributions. Furthermore, RBM was used to incorporate the identified features, identifying the combined data's probability distribution. The findings confirmed the significance of the clusters discovered by their model. These clusters were used to find drugs that were strikingly similar to the proposed COVID-19 treatments. Furthermore, the chemical structures of certain small molecules and the effect of dysregulated genes led us to believe that these molecules could be used to treat COVID-19. The findings also suggested that the approach could be useful in identifying highly effective COVID-19 treatments with few side effects.

Also, to investigate the contributing factors for COVID-19 spread and death, Ibrahim, Kamaruddin [46] developed a performance assessment of MLP and RBF networks. While RBF and MLP networks are commonly used in the same applications, their internal calculation structures differ. A COMPARISON WAS MADE using COVID-19 cases from 41 Asian countries in April 2020. Cases, deaths, high temperature, low temperature, population, percentage of cases overpopulation, percentage of death overpopulation, average temperature, and total cases are nine contributing factors that acted as covariates in the network. The experimental sets revealed that the two neural structures could detect spread and death factors. However, the RBF network outperformed the MLP by a tiny difference.

Shoaib, Raja [88] suggested a nonlinear autoregressive with radial base function-based hybrid NN to model the SITR model's collection of differential equations. To model the COVID-19 abrupt distribution, an error term dependent on stochastic variation is used. This deep-learning-based computational methodology has outperformed the competition in terms of precision and convergence. The findings of this study will be useful in predicting COVID-19 progression in different parts. In addition, the impact of many main parameters on the spread of the pandemic is preferably modeled, which can aid in preparation, tracking, and avoiding COVID-19 pandemic spreading.

Finally, Dhamodharavadhani, Rathipriya [89] examined appropriate Statistical Neural Network (SNN) models and hybrid versions for COVID-19 mortality prediction in India and estimated possible COVID-19 death cases. The COVID-19 mortality rate prediction model was developed using SNN models including RBFNN, Probabilistic Neural Network (PNN), and Generalized Regression Neural Network (GRNN). They used two datasets, D1 and D2, for this reason. RMSE and "R," a correlation value between real and expected values, are used to assess the efficiency of these models. The designed models were created by integrating SNN models and the non-linear autoregressive neural network to increase prediction accuracy. This process is done to predict the SNN models' potential error, which is then added to the expected value of these models to get a stronger MRP value. For D2 and D1, the analysis indicates that the PNN and RBFNN-based MRP models significantly improved than the other models.

Table 11 discusses the hybrid methods used in COVID-19 and their properties.

6. Results and comparisons

The combination of DL with medicine is a promising step forward in technological advancement. This study identifies several innovative applications that demonstrate this pattern. Developing knowledge in applications as diverse as image classification, information retrieval, and protein structure prediction is challenging. Nevertheless, we agree that reducing data to input tensors and tasks to learning variants provides a standard basis for many advances in DL to spread through frameworks. One of the objectives of this research was to encourage respondents to consider how their data is entered into DNN and develop a learning task. Images and other data types are entered as pixel grids, while categorical variables are stored in dense representation tables. We have concentrated mainly on the categories listed previously in terms of learning. We also invite readers to look into these topics. In our literature analysis, we discovered that the majority of COVID-19-DL research focuses on unique combinations of learning tasks or the development of new datasets and annotation protocols. However, DL has gained tremendous popularity and acceptance, and it has shown some excellent outcomes with simple 2D images. Still, there are some drawbacks in reaching a similar level of performance in medical image processing. In this regard, research is still ongoing, and some of the lessons learned are described below: The lack of large datasets of high-quality images for training is one of the most limiting factors. In this scenario, data synthesizing may be a viable option for integrating data from various sources. The majority of today's DL models have been trained on 2D images. CT and MRI scans, on the other hand, are normally 3D and thus add a new dimension. One of the most serious problems in medical image processing is the lack of standardization of image data collection. It is vital to remember that as the variety of data grows, the need for larger datasets to ensure that the DL produces reliable results is increased. The application of TL, which makes pre-processing effective and avoids acquisition problems, is the best way to resolve this problem.

In addition, data samples for the medical image processing section are taken from two standard imaging techniques: CT and X-ray. We discovered 14 systems for identifying COVID-19 among the medical image processing systems, with seven systems relying on X-ray data and the other seven systems using CT samples. The bulk of the systems employed many data sources, while a minority used only one. The data sources are the benchmark dataset or real-time data from the healthcare environment. Some systems employed an extensive collection of images, whereas the COVID-19 instances have a modest number of samples. Throughout the examination, both binary and multi-class options are evaluated. A few of the methods employed cross-validation methods for data partitioning, while others used the hold-out approach. The pre-trained model, as well as the bespoke DL architecture, are both taken into account. For diagnosis, almost all of the systems employed CNN or variations of CNN. Specific assessment measures such as accuracy, specificity, sensitivity, F1-score, AUC, precision, and others are used throughout the analysis. Sections 5.1 and 5.7 describe the CT scan-based COVID-19 diagnosis using a pre-trained model and a modified DL approach. The findings showed that majority of the created methods utilized benchmark data. The datasets that are used in the reviewed systems numerous times are entirely different. The studied systems employed a maximum of 25,230 images for the experiment cases and a minimum of 120 images for the experiment cases, respectively. When it came to the variety of classifications, most established systems employed binary classifications like COVID-19 and non-COVID-19, while others used several categories, including COVID-19, secondary TB, pneumonia, and normal. The 10-fold was studied in some situations, while others constructed systems and employed random partitioning, and the bulk of them looked into the data splitting hold-out approach. Only one created system achieved 100% sensitivity in terms of performance. The majority of the frameworks with more than 85% metrics obtained superior accuracy, specificity, sensitivity, precision, F1-score, and AUC among the examined systems. Using the pre-trained model and customized network, the greatest accuracy of 99.93% was achieved. Using a pre-trained model with deep DL and hybrid DL architecture, several techniques represent the medical image-based diagnosis of COVID-19. According to our findings, almost all of the created systems employed a separate dataset of COVID-19 X-ray or CT chest images with varying input sizes or different quality. Several of the solutions employed the data normalization method to make images from multiple sources of the same size and quality. For the experiment, all of the proposed methods used benchmark data; no system used real-time data.

Furthermore, because they employed various datasets for the experiment, most of the produced systems did not indicate the computing time; however, a few of the systems did compute the computing time. Even though the examined systems performed better in X-ray situations for both pre-trained and hybrid networks, the produced systems have not been tested with the intended users in real time. Several of the systems under evaluation outperformed the custom network when compared to the pre-trained model. Because different data sizes were used in almost every experiment, the performance of the produced systems varies depending on the dataset and cannot be compared. When comparing imaging modalities, X-ray-based systems outperformed CT-based systems. On the other hand, most X-ray-based frameworks used benchmark data, whereas CT-based systems used real-time hospital data. The techniques proposed utilizing CT samples might theoretically be used for real-time testing, while X-ray-based schemes would require real-time testing with target persons before being used. The datasets used in the studies vary in various characteristics, including the number of individuals, image size, samples and classes, and accessibility status (public or private). In addition, the majority of the datasets did not explicitly identify the participants, the image size for all datasets varies widely, and none of the datasets are publicly available. Finally, because the information is updated daily as the number of COVID-19 patients grows, pinpointing the particular details of the utilized datasets is impossible.

The feature extraction element of DL models is also utilized to implement traditional ML techniques. This method looks to be more effective. In most cases, the SVM algorithm is employed. Also, the majority of research does not employ any form of cross-validation. We believe that this reduces the results' dependability. Because it is unclear how the test data are differentiated, it is possible to generate a high-

Table 11
The methods, properties, and features of hybrid -COVID-19 mechanisms.

Authors	Main idea	Advantages	Research challenges	Security mechanism?	Dataset	Using TL?	Method	Usage?
Abdel-Basset, Chang [60]	Proposing a semi-supervised few-shot segmentation model.	-The FSS-2019-nCov's generalization efficiency improves as a result of semi-supervised learning.	-Lack of volumetric data representation -Owing to a lack of supervision, it was impossible to achieve a very accurate segmentation.	No	The Italian Society of medical and interventional radiology made two annotated CT datasets available for model evaluation.	No	CNN	Detection in chest CT
Pereira, Guerin [82]	Predicting the COVID-19 pandemic dynamics using a data-driven approach.	-Moderate accuracy -High robustness	-High energy consumption -High delay -High complexity	No	JHU dataset	No	LSTM-SAE + Autoencoder	Estimating statistics, such as peaks and the number of reported cases
Chaves-Maza and Martel [83]	Using SOM + MLP to investigate factors that significantly impact the survival rate	-High prediction ability -High scalability	-Dataset is insufficient -High complexity -High energy consumption	No	The dataset included 2221 Spanish entrepreneurs and 769 variables collected between 2008 and 2012 during the financial crisis.	No	SOM + MLP	Examining the key factors that have an impact on the survival rate of entrepreneurs during the COVID-19
Leichtweis, de Faria Silva [84]	Exploring the impact of many factors on the spread rate of COVID-19 using the GAN model.	-Showing that the development of COVID-19 has a negative association with local temperature, according to the findings.	-High complexity -Low security	Yes	The dataset was collected from reported cases of COVID-19 and their respective GHS notes and climate data for 52 countries.	No	SOM + GAM	To investigate how temperature, relative humidity, solar radiation index, affect COVID-19 spread rate
Al-Waisy, Mohammed [85]	Providing a hybrid multi-model DL System for COVID-19 detection.	-Accuracy rate of 99.93% sensitivity of 99.90% specificity of 100 the precision of 100% F1-score of 99.93% MSE of 0.021%	-A broad and difficult dataset containing numerous COVID-19 cases is not taken into account.	No	Cohen's GitHub Repository + Radiopaedia dataset, Italian society of medical and interventional radiology.	No	DBNs + Convolutional DBN	Detection in chest X-ray
Rosa, De Silva [86]	Using the DBN for subject recognition and tree–CNN–based affective analysis for emotion identification.	-Accuracy higher than 0:90 -Can detect an event almost three days before other approaches.	-High complexity -High delay	No	A total of 18,597,314 messages were extracted from online social networks to create the dataset.	No	DBN+ Tree CNN	In the case of COVID-19, event detection
Hooshmand, Ghobadi [87]	Finding drugs on COVID-19 using a multimodal RBM technique	-High clustering ability -Low energy consumption	-Clinical trials, such as in vitro or in vivo experiments, must be conducted.	No	Harmonizome and LINCS dataset	No	mm-RBM	Finding similar drugs to treat COVID-19
Ibrahim, Kamaruddin [46]	Considering 9 different factors for performance evolution of MLP and RBF methods.	-High accuracy -Low complexity	-All possible scenarios aren't taken into account.	No	In April 2020, a dataset of COVID-19 cases was collected in 41 Asian countries.	No	MLP + RBF	Look into the spread of COVID-19 and the factors that contribute to death
Shoaib, Raja [88]	Using a hybrid model based on nonlinear autoregressive with radial base function.	-High accuracy -Low convergence time -High stability	The data set is sparse and inadequate.	No	The use of a network obtained the data set.	No	Nonlinear autoregressive + RBF	COVID-19 progression forecasting for various countries
Dhamodharavadhani, Rathipriya [89]	Proposing SNN models and their hybrid versions with the NAR-NN for COVID-19 mortality prediction.	-Appropriate accuracy	-High complexity -High delay -High energy consumption	No	From January 20, 2020, to May 30, 2020, the dataset includes India's confirmed cases and death cases.	No	PNN + RBFNN + GRNN	Estimate the number of COVID-19 death cases in India in the future

performance test dataset. This grossly exaggerates the outcomes. It should be highlighted that research should employ a cross-validation procedure in which the entire data set is evaluated. Although numerous research uses DL-based methodologies, it is extremely difficult to create sufficiently transparent, robust, and dependable models. Furthermore, as COVID-19 detection becomes a prominent study topic for multidisciplinary research, many heterogeneous data, including findings and analysis, is becoming more readily available. These data are often gathered from various sources, including clinical, behavioral, physiological, and pharmacology information. This data must be evaluated to extract knowledge to make it worthwhile. This is one of the most challenging problems that data mining and ML approaches might address. In life science, various answers to the difficulty mentioned above are offered in ML and data mining techniques for data analysis. Additionally, whereas the policymakers and citizens try to accept the constraints of lockdown and social distancing, ML can establish more intelligent robots and autonomous machines to assist health workers and reduce their workload by disinfecting, working in hospitals, distributing food, and assisting patients. Consumers have little faith in self-driving vehicles and would prefer to be serviced by a person, even if there is a chance of virus transmission, which is a concern with this technique. Doctors must also provide a considerable amount of medical data when entrusting chatbots with patient diagnoses. Furthermore, language differences across countries make an already challenging process even more demanding. On the other hand, when it comes to speech analysis, there are still a lot of obstacles to overcome. For example, until recently, annotated data from patients' voices have not been publicly available for COVID-19 detection and diagnostic studies. These data are generally collected in unrestricted settings, such as using cellphones or other speech recorders in the wild. Noise and reverberation are common in these locations, resulting in poor data quality and hindering COVID-19 diagnosis and detection. One of the most significant future tasks will be to minimize the false-negative rate and the false-positive rate to the maximum extent possible to distinguish viral from bacterial pneumonia reliably.

However, the cooperation of ML with biology and healthcare is an exciting step forward in technological advancement. This survey identifies several ground-breaking applications that demonstrate this trend. We motivate DL researchers to investigate broad applications and to take part in exercises recognizing changes in various domains, including COVID-19 or pandemic response. Developing expertise in applications ranging from image classification, information retrieval, and protein structure prediction is challenging. However, one of the survey's objectives was to encourage respondents to consider how their data is fed into DNNs and build a learning task. Learning algorithms like multi-task training and reinforcement learning have only been mentioned briefly. We also motivate readers to look into these topics. In our analysis of relevant literature, we discovered that most DL-based COVID-19 research focuses on combinations of learning tasks or the development of new datasets and annotation protocols. Key technologies in NLP are very compelling, considering the prevailing trend in DL research. The evolution of NLP, powered by DL, is underway. This study identifies several downstream applications that have benefited from the success of these models. We can expect significant advancements in information retrieval, question answering, summarization, and text classification shortly. TL models pre-trained on ImageNet be successful in some papers. Investigators in ML need search engines to send queries like "What is the benefit of ImageNet TL for Medical Image Analysis?" We should also mention that the ease of use is probably one of the reasons for its popularity. Models with ImageNet trained weights can be easily interfaced using DL frameworks like TensorFlow, Keras, and PyTorch. There is no requirement for the investigators to do any ImageNet training beforehand.

As we saw in Section 5.1, CNN is a DNN-based learning architecture that can analyze large amounts of data, such as X-ray images, and it is currently widely used in medical imaging analysis. Because it does not require any human feature extraction or particular segmentation, the CNN is commonly employed compared to other ML approaches. The fundamental advantage of CNN over its methods is that it discovers essential traits without the need for human intervention. In addition, CNN is computationally efficient. It performs parameter sharing and uses special convolution and pooling algorithms. Image classification algorithms benefit from CNN since they can learn abstract features and work with fewer parameters. Overfitting, explosive gradients, and class imbalance are the most common problems encountered while using CNN to train the model. Also, LSTMs provide us with a wide range of parameters, such as learning rates and input and output biases, as shown in Section 5.2. As a result, no precise modifications are required. With LSTMs, the complexity of updating each weight is reduced to O(1), similar to Back Propagation Through Time, which is an advantage of this method. However, some disadvantages of LSTMs are identified, including the fact that they take longer to train, require more memory to train, dropout is much more difficult to implement in LSTMs, and finally, LSTMs are sensitive to different random weight initializations. Plus, the RNN strategy, as described in Section 5.3, is better suitable for a high-accuracy system with analytical skills than the CNN method. RNN-based functions improve a system's precision. Gradient vanishing and exploding difficulties, difficulty in training an RNN, and inability to analyze very long sequences when employing Relu as an activation function are all downsides of this approach. However, the basic purpose of GANs, as stated in Section 5.4, is to learn from a collection of training data and produce new data with the same properties as the training data. On the other hand, the fundamental disadvantage of this strategy is that we can not forecast the correctness of the evaluated model's density and declare that this image is dense enough to proceed with. Also, the main advantage of using a SOM is that the data is easy to read and understand. Because of the reduced dimensionality and clustering, the data can be easily compared. Furthermore, as we saw in section 5.5, the main disadvantage of a SOM is that it requires essential and sufficient data to create meaningful clusters. The weight vectors must be based on data that allows inputs to be categorized and identified accurately. When it comes to using autoencoders, they provide an advantage by decreasing the dimensionality of the data being used and the learning time for situations. Another advantage of backpropagation coding is its compactness and speed. Autoencoders are useful for extracting features. In terms of picture reconstruction, autoencoders are not as effective as GANs. Autoencoders struggle to keep up with the increasing complexity of the images, and the visuals get hazy. Finally, as detailed in Section 5.7, hybrid approaches are an advanced strategy used in COVID-19 domains. These methods are more difficult to utilize since they combine two or more methods for solving problems. On the other hand, these techniques are well suited to complicated environments in which we must deal with real-world scenarios.

However, we investigate seven categories and 37 papers in the previous section about using DL techniques in the research, treatment, diagnosis, and other applications of COVID-19 disease. The biggest flaw in these methods was the lack of comparison between the proposed and previous methods, which is understandable given the epidemic's novelty. As a result, the flaws in existing methods are difficult to extract. Another point of debate has been the proposed methods' algorithm, which was not primarily stated; the very least expected from the proposed methods is a thorough explanation of the methods and algorithms employed, which sadly, almost none of the methods, algorithms used, or pseudo-code. Therefore, we include a thorough overview of the methods discussed in various fields, such as the simulation environment, applications, parameters targeted by the papers, protection mechanisms, TL methods, etc. Python is the most popular programming language for this type of job in the case of a simulation, theoretical, or implementation setting about the proposed methods, which is a very appealing part for researchers to use in future work and has a wide range of applications. As seen in Fig. 9, TensorFlow is the most common method, with 43.2% use. MATLAB is one of the most common environments, accounting for

18.9%. With 10.8% of use, Scikit-learn is in third place. Keras has 8.1%, PyTorch has 8.1%, and Caffe has 5.4%, with the rest of the work being done with other packages. Although settings such as Amazon and Google Colab have mostly overcome the powerful hardware required to execute DL architectures with GPUs, enrolling these environments in real medical laboratories remains a complicated process. Also, Fig. 10 depicts a geographical map of the countries under investigation, with further research focusing on forecasting, mortality, disease propagation patterns, and other applications in the United States (9 papers), China (9 papers), India (8 papers), Turkey (7 papers), and Iran (7 papers). The number of studies on these five countries is the largest.

Also, another study of the DL-applications COVID-19's in this epidemic discovered that 14 papers (37.83%) used apps to classify patients' chest CT/chest X-ray images. Some of the advantages of this method include helping radiologists diagnose the disease with the lowest error detection coefficient, distinguishing between different forms of pneumonia and COVID-19, and quickly diagnosing patients with high accuracy. With nine articles (24.32%), the second-place predicts new COVID-19 cases and deaths. Predicting the future needs to deal with COVID-19, predicting the required hospital beds, indicating the number of medical ventilators needed, or anything else required in the hospital is the third most exciting topic with four papers (11%), this is one of the most critical applications of DLs in this field. In addition, the research into effective drugs and drug combinations to combat COVID-19 has gotten the least attention. However, Fig. 11 depicts the various applications of DL in the context of COVID-19. Section 2 discussed TL in general. This section explains how TL could aid in the mitigation of COVID-19-like pandemics. As previously stated, developing with enough datasets of COVID-19 or any other running pandemic in a short period is challenging. As a result, utilizing the benefits of DL to deal with epidemics is a bit difficult. TL might be helpful in this situation. A DL model could be trained using a large-scale benchmark dataset, just like TL, and learned features can be used for the COVID-19. Only six papers in our review attempt to use this TL in the domain COVID-19 for various uses. TL performs task adaptation critical for examining, trying to diagnose, and mitigating COVID-19 outbreaks. The numerous studies are small, and most of the existing COVID-19 research and experiments were used for chest image analysis. Wearing Personal Protective Equipment (PPE) Monitoring, Patient Care, Intensive Care Unit (ICU) Monitoring, Monitoring Systematic Social Distancing, Automatic fever detection, Hygienic Practice Monitoring, rumor detection, economic and social impact, etc., could help mitigate this pandemic. So many of these jobs could be made easier if AI collaborates and forms a model with IoT or edge computing. TL might be able to help with some issues. However, a better system can be delivered when the most appropriate algorithm is applied to edge computing.

The most important aspect is security, as the patient's information is kept strictly confidential on ethical and legal grounds. As a result, when developing security structures for medical domains, the highest priority must be given to data security. One of the most surprising findings of this study was that none of the mechanisms investigated are considered security mechanisms for ensuring patient security in COVID-19 and the confidentiality of patient test results and physician prescriptions. It is the most significant disadvantage of reviewed methods. One of the most important areas for future research could be ensuring the confidentiality and security of users' information and processed data. The minimum parameter considered in the articles, as shown in Table 12, is related to security and scalability. Since COVID-19 disease is one of the most dangerous diseases humans have ever faced, it is hoped that researchers will conduct more studies to deal with the disease and its consequences and complications, taking into account all of the disease's dangerous aspects. As previously stated, security and scalability are also the lowest parameters considered in the publications, as seen in Table 12 and Fig. 12. With 48.8%, the accuracy parameter receives the most attention in studies, while the delay/response parameter comes in second with 20.8%. With 7%, energy consumption is ranked fourth, and robustness is ranked third with 9.3%. Furthermore, the issue with articles is that the vast majority of them just have one target criteria and nearly wholly neglect the others.

In addition, our data indicated that the hybrid environment (IoT-edge-fog) is the most widely utilized in papers for computing utilization, accounting for 37.8% of all papers, and is used in practically every category. Furthermore, cloud computing platforms utilized simply without integration with other settings are in the second position in the papers with 24.3%. Furthermore, with an 18.9% usage rate, IoT is the third most commonly used setting in these papers. In addition, Fig. 13 shows how frequently environments are employed in COVID-19 detection applications. Wearable gadgets that combine IoT technology are predicted to significantly impact healthcare and lifestyles. When paired with big data analytics, IoT is expected to be a valuable tool in transferring traditional methodology to more advanced technology. Data generated by these devices may be analyzed using big data techniques to make better decisions. As a result, the large volume of data generated by wearable devices opens the door to future AI applications such as DL Intelligent IoT (IIoT) systems are produced by combining AI with edge platforms, enhancing existing IoT applications. As a result, future contact tracing solutions might incorporate IIoT-enabled wearable devices such as watches and phone apps and additional capabilities such as complicated data processing and intelligent data presentation. The Python programming language and deck. gl techniques might be used in the system for complex data processing and smart data visualization, respectively. COVID-19 analysis is expected to benefit from IIoT by anticipating approaching disease-related occurrences. As a result, large amounts of data gathered from smartphone applications and wearable technology can be delivered to integrated data analysis and visualization systems, which will be kept on a cloud server for training and finding data patterns, respectively, to forecast COVID-19 clustering. Epidemiologists might have access to this data through secure online interfaces. The IIoT structure may be decentralized to meet security and safety issues, with user privacy strategies employed at the protocol level in wireless systems.

Furthermore, our analyses revealed that CNN is the most commonly utilized method in papers, accounting for 18.2% of all articles and that it is used in practically medical image processing. Furthermore, with a use rate of 2.6%, RBM is the least utilized approach in these papers. With 13.6%, SOM and LSTM are tied for second place. In addition, RNN and autoencoders are ranked third. The frequency of DL approaches in the COVID-19 domain is seen in Fig. 14.

The research's main contributions are establishing DL methods and techniques for illness prediction, measurement and data kinds, DL method in drug development, existing treatments and vaccinations, and current models and datasets for the COVID-19 pandemic. The most commonly utilized DL algorithms against COVID-19 are CNN methods.

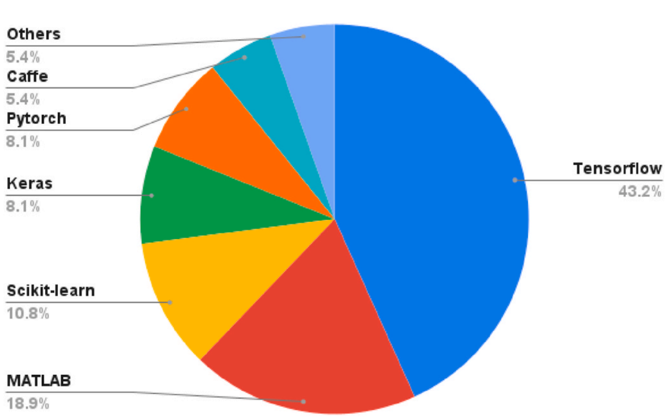

Fig. 9. The distribution of the use of different simulation environments in DL-COVID-19.

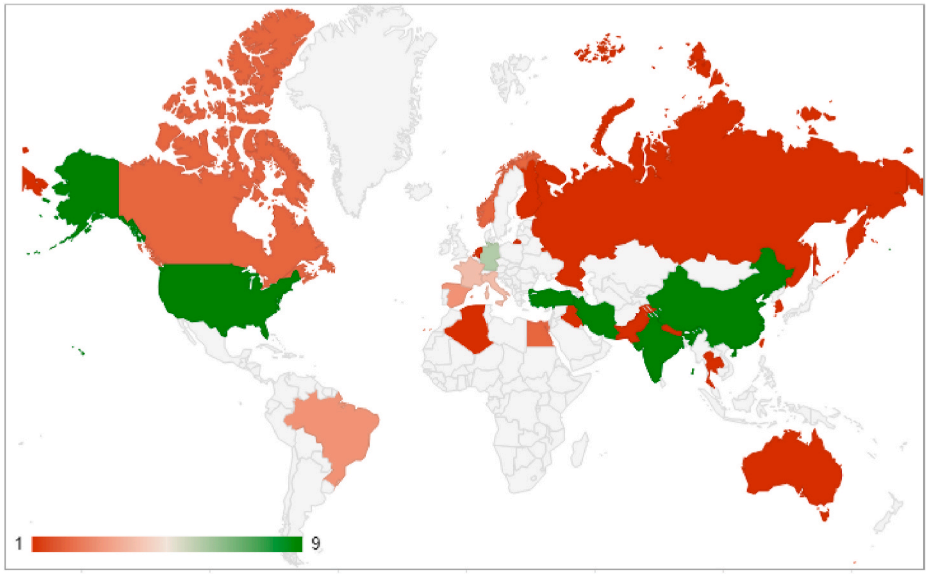

Fig. 10. The geo-chart about the studied countries by the investigated papers.

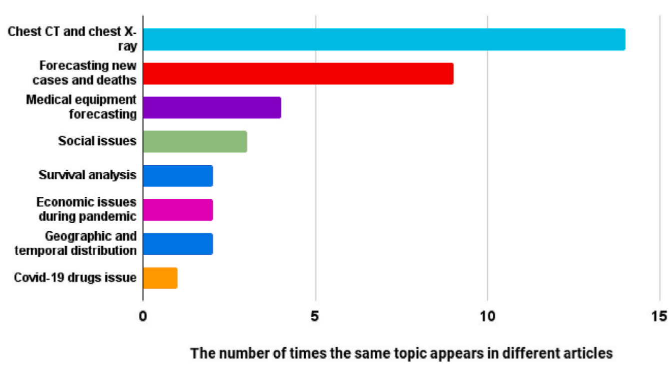

Fig. 11. In the context of COVID-19, DL application usages.

These methods were used to attain a variety of objectives. The most common DL goals are prediction, diagnosis, and classification. ResNet is utilized for classification and diagnosis, whereas regression is used for prediction research in specific cases. The results of this study show that the strategies' effectiveness varies greatly. The research contains certain constraints that were highlighted in the study because of the evaluation boundaries. This research is significant for new practitioners and academics who want to build a COVID-19 DL/ML model or medication. Instead of designing from scratch, they may utilize existing models and medications, saving future research and investigations time. Furthermore, this study serves as a foundation for various areas, including illness detection and diagnosis, medication and vaccine development, and DL/ML models and approaches. The research has uncovered a wealth of information on DL's prospective and current contributions to the pandemic's fight. Several studies used CNN models, as evidenced by the literature study. The key reason might be because they are effective in medical images for spatial coherence or local pixel correlations. The CNN approach was commonly used for classification or diagnosis. Nevertheless, before using CNN for COVID-19 investigations, writers should be aware of the mentioned shortcomings.

7. Open issues

This section covers a wide range of important issues and challenges that will require future research. AI-based ML and DL researchers have a background in computer science. Still, To include other medical information into the COVID19 war's utilization of ML and DL, a significant specialty in medical imaging, bioinformatics, virology, and other relevant disciplines. To cope with COVID-19, specialists from many disciplines must collaborate, and results from different research must be included. Also, it can be difficult to work with ambiguous and incorrect information in text descriptions. Large amounts of data from various sources can be incorrect. Furthermore, excessive data makes it impossible to extract valuable pieces of information. Attempting to deal with unbalanced datasets because of insufficient medical imaging and a long training period knowledge from COVID-19 and unable to explain the findings. By creating social networks and knowledge graphs, an AI-based ML and DL system can monitor and track the features of people living near COVID-19 patients, accurately predicting and monitoring the disease's potential spread. Furthermore, AI-based ML and DL systems can identify potential drugs and vaccines and mimic drug-protein and vaccine-receptor interactions, predicting future drug and vaccine reactions in people with various COVID-19 patients. In the context of biological research, AI-based ML and DL systems can be used to accurately analyze biomedical knowledge, such as significant protein structures, genetic sequences, and viral trajectories, to identify protein composition and viral factors. Here are some ideas for future research studies.

- **TL method**

Future COVID-19 research will connect hierarchical image datasets with other clinical data to perform multi-omics modeling for better disease prediction. TL is a potential research path that could detect anomalies in smaller datasets and produce impressive results since the accessible datasets are rare, inadequate for yielding robust predictions. The significance of early disease detection in COVID-19 diagnosis cannot be overstated. TL helps accomplish the same goal, and it is a great pairing for COVID-19 detection, where time-to-delivery and training data availability is important. This method uses pre-trained models from academia, research institutes, or open source communities to perform ML tasks, saving time and money. It uses various algorithms' designed features to pass the learned parameters or information. When more data are useable, DL produces good results, but TL can achieve the same results with a smaller labeled dataset. Intelligent robots are also expected to use public sanitation, product delivery, and patient treatment that do not require human resources. It will slow or stop the spread of the COVID-19 virus.

Table 12
Considered parameters in the examined papers..

Type	Authors	Delay/Quicker response time	Accuracy	Convergence time	Complexity	Security	Energy consumption	Scalability	Robustness
CNN	Kedia and Katarya [57]	•	✓	•	•	•	•	•	•
	Wang, Nayak [58]	✓	✓	•	•	•	•	•	•
	Ismael and Şengür [59]	✓	✓	•	•	•	•	•	•
	Abdel-Basset, Chang [60]	✓	•	•	•	•	•	•	•
	Ezzat, Hassanien [61]	✓	✓	•	•	•	•	•	•
LSTM	Demir [62]	•	✓	•	•	•	•	•	•
	Koç and Türkoğlu [63]	•	✓	•	•	•	•	•	•
	Gautam [64]	•	✓	✓	•	•	•	•	•
	Mohammed, Wang [65]	•	✓	•	•	•	•	•	•
	Karaçuha, Önal [66]	✓	✓	•	•	•	✓	•	•
RNN	Alakus and Turkoglu [67]	•	✓	•	•	•	•	•	✓
	ArunKumar, Kalaga [68]	•	✓	•	•	•	•	•	•
	Kumari and Sood [69]	•	✓	•	✓	•	•	•	•
	Li, Jia [70]	✓	•	•	•	•	•	✓	✓
	Shastri, Singh [71]	•	✓	•	•	•	•	•	•
GAN	Goel, Murugan [72]	•	✓	•	•		•	•	•
	Rasheed, Hameed [73]	•	✓	•	•	•	•	•	•
	Elzeki, Shams [74]	•	✓	•	•	•	✓	•	✓
	Singh, Pandey [75]	•	✓	•	•	•	•	•	•
SOM	Melin, Monica [44]	•	✓	•	•	•	•	•	•
	Galvan, Effting [45]	•	✓	•	✓	•	•	•	•
	Simsek and Kantarci [76]	•	✓	•	•	•	•	•	✓
	Triayudi [77]	✓	✓	•	•	•	✓	•	•
Autoencoders	Chen, Zhang [78]	✓	•	•	•	•	•	•	•
	Li, Fu [79]	✓	•	•	•	•	•	•	•
	Atlam, Torkey [80]	•	•	•	•	•	•	•	•
	Wen, Wang [81]	•	•	•	•	•	•	•	•
Hybrid	Abdel-Basset, Chang [60]	•	•	•	•	•	•	•	•
	Pereira, Guerin [82]	•	•	•	•	•	•	•	•
	Chaves-Maza and Martel [83]	•	•	•	•	•	•	•	•
	Leichtweis, de Faria Silva [84]	•	•	•	•	✓	•	•	•
	Al-Waisy, Mohammed [85]	•	•	✓	•	•	•	•	•
	Rosa, De Silva [86]	•	•	•	•	•	•	•	•
	Hooshmand, Ghobadi [87]	•	•	•	•	•	•	•	•
	Ibrahim, Kamaruddin [46]	•	•	•	•	•	•	•	•
	Shoaib, Raja [88]	•	•	•	•	•	•	•	•
	Dhamodharavadhani, Rathipriya [89]	•	•	•	•	•	•	•	•

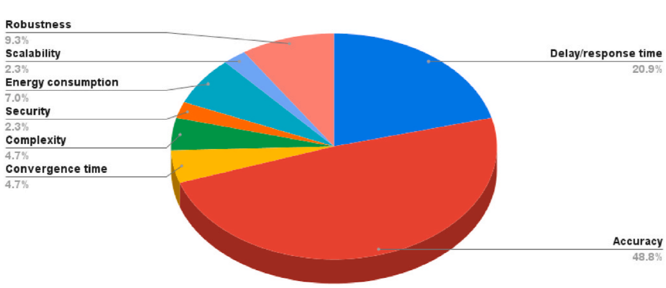

Fig. 12. Evaluated parameters in the articles.

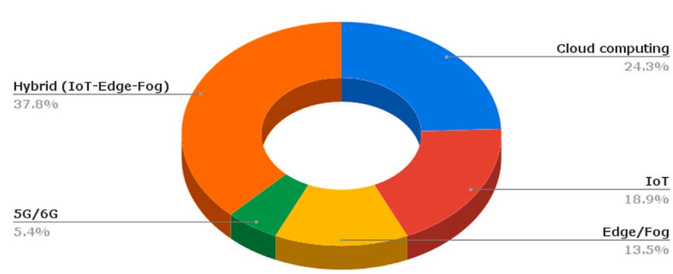

Fig. 13. The frequency of environments is used in COVID-19 detection applications.

- **Dataset**

Data are the lifeblood of today's computing. Data are the most valuable asset in the medical field or the retail market. The majority of recent AI techniques are data-driven. The dataset is almost entirely dependent on DL-based algorithms. As a result, data is one of the motivating factors in dealing with a disease outbreak. Seasonal behavior, chest X-rays, pathological images, geographical region-based

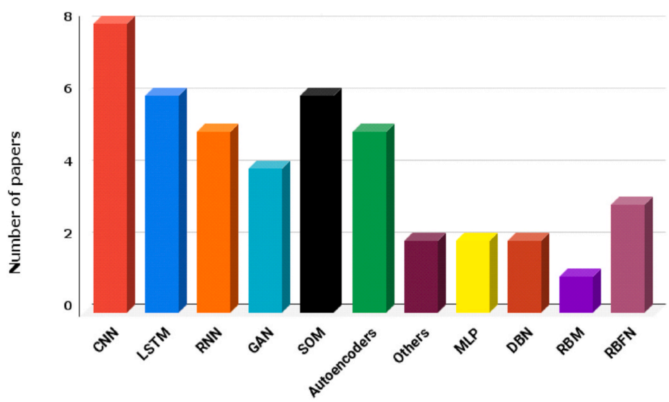

Fig. 14. Utilization of DL approaches and their frequency in selected articles.

spreading patterns, CT images, regional mortality rates, economic impact, and so on could be included in the dataset for a pandemic like COVID-19. As previously stated, data is the driving force behind knowledge creation, but it is not readily available. Gathering data and organizing it in a useful format, especially in COVID-19 or a sudden pandemic, is not expected to be an easy task. Since many sectors are very active in the COVID-19 pandemic, many data sources are rapidly oriented to the pandemic. The main challenges are insufficient datasets, particularly machine-readable datasets, in every affected sector. As a result of these challenges for data-driven AL algorithms or models, there are few studies on real-world data and analysis. As previously stated, this novel coronavirus behaves differently in different geographic regions, environments, and so on. As a result, data from one region may not improve knowledge in other areas. One of the most important issues is data privacy and security. The accessibility of datasets, specially labeled ones, is an obvious challenge in this COVID-19 pandemic, and thus TL has enormous ability to facilitate the objective of COVID-19 diagnosis. Besides, when the pre-trained information was fed into the CNN architecture, the COVID-19 detection results were more accurate. As a result, establishing a centralized data repository for patient data is critical for developing predictive, diagnostic, and therapeutic approaches to tackle potential COVID-19 crises and related pandemics in innovative, safe cities. There are numerous DL implementations implemented on different datasets using a variety of assessment standards where radiology imaging datasets were already prevalent, as reflected and checked in the current studies. However, using these implementations in real-world cases is a key problem, necessitating the immediate development of benchmarking tools for assessing and comparing existing methodologies. These systems can make it possible to use computational equipment infrastructures that consider identical clinical notes, data pre-processing processes, and assessment requirements for different AI methods, ensuring data transparency and interpretability.

- **Scarcity of large-scale training data**

Numerous AI-based DL techniques rely on large-scale training data, such as diagnostic imaging and various environmental information. However, because of the rapid growth of COVID-19, there are insufficient datasets for AI. In practice, interpreting training samples takes time and can require the assistance of qualified medical personnel. Also, different types of simulations may use AI-based ML and DL systems to analyze the effect of various social control modes on disease transmission. They can then evaluate scientific and reliable disease control and prevention approaches in the general public.

- **Regulation**

The people of today's world are far luckier than those who lived through the 1918 Spanish flu pandemic since we have access to far more sophisticated technology. Since AI has permeated all facets of life, it should be used and extensively investigated to tackle the pandemic. Throughout that situation, AI can be combined with NLP technologies to create chatbots that can interact with patients remotely and provide appointments. Apart from the above advantages, AI will play a significant role in preventing the dissemination of fake news on social media sites. AI will filter out knowledge about government policies, pandemic prevention procedures, and the science behind virus dissemination and containment, ensuring that only authentic information reaches the general public, reducing the risk of needless panic. The invention of a novel COVID-19 vaccine is the only ray of hope at this point in the never-ending war with the virus. In this regard, AI has enormous potential for studying the virus's genetic and protein structure to speed up the drug development process. Utilizing conventional approaches, this procedure is time-consuming and costly. Still, using AI and DL approaches, it will quickly be feasible to determine the most suitable antibiotic from a comprehensive data set of hundreds of millions of molecules. This is undoubtedly the most exciting and important ongoing research direction for combating the COVID-19 pandemic. As the disease outbreak spreads and the number of infected and deceased cases rises, various measures, such as lockdown and social distancing, have been considered to contain the outbreak. Authorities play a critical role in defining laws and policies that promote the interests of residents, business owners, medical centers, scientists, technology giants, researchers, and large corporations in the event of a pandemic.

- **Online rumors and Noisy data**

The difficulties arise from relying on portable online social media; vast amounts of audio information and misleading claims regarding COVID-19 have been published in various online outlets without any substantial changes. Even so, AI-based ML and DL algorithms tend to be slow when judging and filtering audio and error data. Furthermore, when noisy data is used, the findings of AI-based ML and DL algorithms become skewed. This problem reduces intelligence techniques' use, functionality, and efficiency, especially in pandemic predictions and spread analysis. It is also necessary to clarify the efficiency of DL models or the graphical aspects that contribute to distinctions between COVID-19 and other kinds of pneumonia. It will help radiologists, and other healthcare professionals better understand the virus and analyze potential Coronavirus X-ray and CT images. AI-based ML and DL systems can be utilized to reduce false news regarding the COVID-19 epidemic by providing reliable, factual, and scientific information.

- **Edge computing and IoT**

In pandemic-like situations, sophisticated equipment based on edge or IoT devices, such as intelligent medical equipment, webcams, drones, wearable sensors, and so on, can be very useful. Edge computing moves computation to devices that are close to the edge. It reduces latency, as well as security and privacy concerns. As a result, this computing paradigm will be extremely useful in the event of a pandemic. Researchers worldwide are working hard to combine this with other AI techniques to combat the current COVID-19 pandemic. Only a few studies have looked into using edge computing to develop a COVID-19 mitigation system that is both efficient and effective. Because edge computing operates on-site, there are numerous advantages to using an edge device in conjunction with the Internet of Things. However, as previously stated, IoT or edge node computing resources are limited. As a result, taking advantage of modern AI algorithms like DL is still difficult. Researchers from all over the world are working hard to come up with a variety of solutions to these problems. Many critical COVID-19-related tasks could be aided by edge computing, such as remote sensing patient monitoring, hygienic practice monitoring, and systematic social distancing monitoring. The use of offloading technology to transfer data from COVID-19 applications to the edge, a process that data on edge platforms, and return results to the device itself, which reduces energy consumption and response time, is one of the most appealing and exciting aspects of using edge or fog computing. This technology, when combined with blockchain, can provide additional security.

- **Miscellaneous**

More robust details about the performance of the various suggested mapping methods can be obtained by employing more DL techniques or conducting protein prediction in different areas. As a result, the proposed method's working area can be expanded and used effectively in the following areas: determining drug-target interactions, drug development investigations, protein family identification and classification, phylogenetic analysis studies, drug therapy, determining viral–host protein interactions, and predicting cancer–protein interactions. To boost the efficiency of the approaches in identifying COVID-19, the number of samples used to train it may be increased in future research. Furthermore, the number of diseases that cause pneumonia could increase, and the methods can be used to differentiate them from COVID-19.

- **COVID-19 software packages**

As discussed in Section 5, AI in general and DL systems in particular are the remedies for the epidemic. However, their use in clinical settings has been limited due to their lack of applicability in real-world scenarios. However, only a few studies published software tools for clinical use for this purpose. COVID-19 apps or software packages might include mobile-software applications for cough pattern identification, CT image diagnosis, patient health analysis, or digital contact tracing. Digital contact tracing is the process of identifying people who may have come into touch with an infected person. Infectious disease control relies heavily on contact tracing, but as the number of cases grows, time restrictions make it more difficult to prevent transmission successfully. DL contact tracing may be more successful than traditional contact tracking approaches, mainly if extensively used. Privacy issues have been raised in this case, particularly with systems that track the geographical position of app users. In addition, few articles published their application for CT image detection. Several apps have attempted to detect COVID-19 patients based on their cough patterns. All of these initiatives are worthwhile, but they could be expanded.

8. Conclusion and limitation

A systematic review of the DL-COVID-19 mechanisms was presented in this paper. We first discussed the benefits and drawbacks of some systematic and reviewed articles about COVID-19-related DL mechanisms before explaining the purpose of this paper. The benefits and drawbacks of each of the mechanisms were discussed based on seven main categories. The DL-COVID-19 tools and platforms were also evaluated. According to a review of articles based on qualitative characteristics, most articles are evaluated based on accuracy, delay, robustness, and scalability. Meanwhile, some features, such as security and convergence time, are underutilized. Various programming languages are used to evaluate and implement the proposed mechanisms, with Python accounting for 75% of the time. According to the study, 37.83% of apps classify patients' chest CT/chest X-ray images. The prediction of new COVID-19 cases and deaths receives 24.32%. In addition, predicting the number of needed hospital beds, medical ventilators, or anything else in the hospital receives 11%. We also expect our study to serve as a valuable guide for future research on DL and medical applications in the struggle against the COVID-19 outbreak. We have outlined ongoing attempts about the outbreak for smart, safer cities, inspired by many applications of DL for medical image processing. Regarding the potential findings, using DL to process COVID-19 medical images involves significant time and effort and close collaboration between government, industry, and academia. However, DL has been hailed as a brilliant methodology for providing intelligent solutions to fight against this pandemic. COVID-19 disruption has been accomplished using DL in several ways, including disease prediction, drug testing, diagnosis and treatment, vaccine development, and virus spread monitoring. We hope that the findings of this research will be helpful in the development of DL mechanisms in real-world settings.

We have encountered several limitations, including the inaccessibility of non-English articles, which has prevented us from benefiting from many research initiatives. Another limitation of our work is that several of the papers we reviewed have significant shortcomings in clear descriptions of the algorithms used. Because this topic is completely new and there is no maturity in papers and methods, limitations such as not comparing the suggested approach to other existing methods made the effectiveness of the approaches not properly assessable. Also, papers that did not directly address COVID-19 were eliminated from the review. Other articles that were identical to COVID-19 were also deleted from our review process. Another problem we encountered was the lack of accessibility to the various articles published by particular publications.

Data availability

All data are presented in this research.

Declaration of competing interest

The authors have declared no conflict of interest.

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