



Machine learning applications for COVID-19 outbreak management

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Abstract

Recently, the COVID-19 epidemic has resulted in millions of deaths and has impacted practically every area of human life. Several machine learning (ML) approaches are employed in the medical field in many applications, including detecting and monitoring patients, notably in COVID-19 management. Different medical imaging systems, such as computed tomography (CT) and X-ray, offer ML an excellent platform for combating the pandemic. Because of this need, a significant quantity of study has been carried out; thus, in this work, we employed a systematic literature review (SLR) to cover all aspects of outcomes from related papers. Imaging methods, survival analysis, forecasting, economic and geographical issues, monitoring methods, medication development, and hybrid apps are the seven key uses of applications employed in the COVID-19 pandemic. Conventional neural networks (CNNs), long short-term memory networks (LSTM), recurrent neural networks (RNNs), generative adversarial networks (GANs), autoencoders, random forest, and other ML techniques are frequently used in such scenarios. Next, cutting-edge applications related to ML techniques for pandemic medical issues are discussed. Various problems and challenges linked with ML applications for this pandemic were reviewed. It is expected that additional research will be conducted in the upcoming to limit the spread and catastrophe management. According to the data, most papers are evaluated mainly on characteristics such as flexibility and accuracy, while other factors such as safety are overlooked. Also, Keras was the most often used library in the research studied, accounting for 24.4 percent of the time. Furthermore, medical imaging systems are employed for diagnostic reasons in 20.4 percent of applications.

Keywords Machine learning · Applications, COVID-19 · Medical imaging · Outbreak

1 Introduction

Unfortunately, the COVID-19 outbreak has led to a worldwide healthcare disaster that has affected all elements of society [1–3]. The majority of those who have been affected by COVID-19 have been cured, but a significant

number of people have lost loved ones [4, 5]. COVID-19 and its variations, such as Delta, Omicron, and others, are on the rise, putting hundreds of thousands of people in danger of damage or death, especially those with weakened immune systems [6]. This infection can indeed be reduced by quickly detecting initial COVID-19 victims and effectively monitoring and tracking using information technology [7–9]. One of the used diagnostic procedures is reverse transcription polymerase chain reaction (RT-PCR) [10]. These tests have often been time-consuming, and time is essential in this case [11]. As a result, the requirement for speedy identification during the COVID-19 outbreak spurred the use of deep learning (DL) approaches for successful diagnosis using imaging methods, which accelerated the acceptance of this standard methodology [12, 13].

Artificial intelligence (AI) has lately emerged as a promising tool to allow clinicians to make a precise diagnosis in less time [14]. Machine learning (ML) and DL are

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the two primary subdivisions of AI [15–17]. ML, which refers to the intelligence displayed by systems, is one of the most often employed methodologies in applications during COVID-19 [18]. The second is DL, which is an upgraded ML that strengthens and simplifies the architecture of learning methods [19–21]. In COVID-19, DL is heavily utilized to create complicated applications with massive datasets [22]. In this way, such complicated systems might be used to combat the epidemic [23]. While these ML-based technologies are beneficial in the epidemic, their outcomes are strongly reliant on large datasets; hence, the quantity of datasets used to acquire results from applications is crucial [24]. Convolutional neural network (CNN), which is frequently utilized in cancer diagnosis, is one of the most widely employed DL approaches [25–27]. For researchers in the sector, the accuracy attained from CNN algorithms applications is particularly promising [28–30]. Evaluating and interpreting a DL model's predictions gives vital insights into the input data and learned characteristics, enabling experienced professionals to understand the results easily [19]. Other computing platforms, such as the Internet of drones (IoD), Internet of vehicles (IoV), and Internet of things (IoT), can be extremely useful in outbreak situations [31, 32]. These platforms aid in the creation of more comprehensive and efficient infrastructures, making it simpler to cope with epidemics [33]. Transfer learning (TL) also was frequently used to train models with limited databases while overcoming time and cost restrictions [34, 35]. It enables systems to be trained fast and correctly by finding relatively relevant spatial characteristics from large databases in a variety of sectors at the beginning of the training process [36]. As a result, TL could combine the required computational power and stimulate more effective DL methodologies, which could aid in the solution of several challenges [37, 38]. These technologies and platforms can help improve infrastructures, making it simpler to deal with pandemics [39, 40].

Recently, there has been a lot of interest in combining medical applications with ML/DL methods, such as patient monitoring and medical imaging techniques [41]. In this regard, such hybrid applications are an excellent alternative for all medical areas, such as cancer diagnosis or pandemic management. To the best of our knowledge, there has been no thorough and detailed review of ML application techniques for the present epidemic that incorporates all parts of ML/DL methods and their applications. Our study concentrated on highlighting the advancements of monitoring, tracking, image analysis application, social issues, etc., on fighting the COVID-19 outbreak to draw a detailed outline of the modern applications presented utilizing these ML/DL methods. Our paper's great impact is to examine the most intriguing field of research, considering current studies on the various ML implementations established for

all areas of the outbreak. This study used a systematic literature review (SLR) to discover, interpret, and combine reliable publications. According to the paper, imaging methods, survival analysis, forecasting, economic and geographical difficulties, monitoring methods, drug discovery, and hybrid apps are among the ML/DL methods used in the current pandemic. These applications mostly use ML/DL methods such as CNNs, random forest (RF), generative adversarial networks (GANs), and long short-term memory networks (LSTMs). We looked at practically all of the characteristics for each classification and utilized ML algorithms to do so. The applied SLR includes a variety of problems that may potentially arise in any location, and it discusses the methods and procedures [42]. We will also look at the constraints, challenges, and potential future works in this article; as a result, our contribution in this article will be as follows:

- In COVID-19, a broad assessment of the existing challenges connected to ML approaches is presented;
- Providing a thorough overview of available approaches for ML-COVID-19 and other critical acts;
- Describing the key approaches in ML that combine COVID-19;
- Evaluating each technique that refers to ML-COVID-19 with different attributes including advantages, problems, datasets and dataset size, applications, privacy, and TL;
- Highlighting the important areas where the aforementioned strategies may be improved in the future.

The sections provided below define the arrangement of this work. The section that follows discusses the core principles and jargon of ML in COVID-19. Section 3 looks at the relevant review papers. Section 4 discusses the research tools and methodologies for article selection. Section 5 describes the article classifications that were chosen. The outcomes and analyses are presented in Sect. 6. Ultimately, the open issues and summary are provided in the last parts. In addition, Table 1 shows the abbreviations used in the paper.

2 Fundamental conceptions and terminology

The principles of ML-DL techniques, ML-DL implementations in COVID-19, and the applications are covered in this chapter.

2.1 ML/DL methods in general

To restrict the transmission of illness, AI-based techniques are frequently utilized to recognize, categorize, and analyze

Table 1 Table of abbreviations

Abbreviation	Description	Abbreviation	Description
ASSM	Auxiliary Semantic Supervised Module	IoD	Internet of Drones
AFM	Attention Fusion Module	IoT	Internet of Things
BF	Breathing Frequency	IoV	Internet of Vehicles
BERT	Bidirectional Encoder Representation from Transformer	LR	Logistic Regression
CAD	Computer-Aided Detection	MAPE	Mean Absolute Percentage Error
CNN	Convolutional Neural Network	ML	Machine Learning
COVID-19	Coronavirus Disease 19	MLP	Multi-Layer Perceptron
DT	Decision Tree	MRI	Magnetic Resonance Imaging
DAM	Deep Assessment Methodology	LR	Logistic Regression
DBNs	Deep Belief Networks	NLP	Natural Language Processing
DDCAE	Deep Denoising Convolutional Autoencoder	NN	Neural Network
DL	Deep Learning	RAE	Relative Absolute Error
DT	Decision Tree	RBFNs	Radial Basis Function Networks
DTI	Drug–Target Interactions	RBM	Restricted Boltzmann Machines
EHR	Electronic Health Records	RQs	Research Questions
EID	Emerging Infectious Diseases	RMSE	Root Mean Square Error
ELM	Extreme Learning Machine	RNN	Recurrent Neural Network
ESM	Edge Supervised Module	RT-PCR	Reverse Transcription-Polymerase Chain Reaction
EMA	Ecological Momentary Assessment	RF	Random Forest
FFNN	Feed-Forward Neural Network	SLR	Systematic Literature Review
GAN	Generative Adversarial Networks	Sp ^{O2}	Oxygen Saturation
GPR	Gaussian Process Regression	SOMs	Self-Organizing Maps
GRF	Graphical Random Forest	SNN	Statistical Neural Network
HAR	Human Behavior Recognition	SVM	Support Vector Machine
IoB	Internet of Behaviors	WHO	World Health Organization

medical images [43, 44]. Current AI research and development have dramatically improved pandemic monitoring, diagnosing, and forecasting, resulting in superior scale-up, quick reaction, highly efficient and reliable outputs, and sometimes outperforming humans in specific medical domains [45, 46]. ML and DL are the two most important fields of AI [47]. We will study how DL and ML may be used to fight and mitigate the pandemic [48]. So, ML methods, including such logistic regression (LR), as random forest (RF), decision tree (DT), and support vector machine (SVM), are a subclass of AI that could learn and develop based on experience without being explicitly programmed [49]. ML-based systems rely heavily on distinguishing characteristics. ML-based approaches may be used to create a complicated and massive quantity of data [50]. These approaches are frequently employed for detecting pandemic trends and prediction. Numerous researchers are applied similar approaches in the pandemic for various applications. Many of the most prominent ML approaches are described in the context of combating the epidemic [51].

Also, SVM is a strong technique for dealing with regression and classification issues [52], because of its excellent accuracy and performance have been used in various real-world applications, including the health industry [53]. Furthermore, one of the main strategies is RF, which is a statistical method used to deal with classification and regression challenges [54]. To train and forecast sequence data, several trees are employed. RF was commonly used in chemometrics and bioinformatics. RF has been frequently used in COVID-19 experiments to help minimize the epidemic [55]. Another case is the DT method, which is a mathematical technique used to solve classification and regression issues [56]. Because of its ease of use and robustness, DT is widely employed in a variety of applications, most notably prediction systems [57]. DT has gained popularity in recent years in the medical health and clinical sectors [58]. When the goal variable is categorical, LR is a statistical technique and regression analysis that utilizes a logistic function to describe a binary dependent variable [59]. Lately, LR has been utilized to combat the COVID-19 epidemic [60]. In

addition to RF, SVM, LR, and DT, other ML-based methods such as Gaussian process regression (GPR), multilayer perceptron (MLP), xgboost, and k-means have been employed in COVID-19 applications [61, 62].

Plus, CNN is a DL method for processing data with a grid pattern, such as pictures, that is inspired by the architecture of the animal visual cortex and is designed to learn spatial hierarchies of attributes automatically and adaptively, from low- to high-level patterns [63]. RNN is a cutting-edge method for sequential data that is employed in various applications [64]. It is the first algorithm to recall its input thanks to its internal memory, idealizing ML issues involving sequential data [65]. Besides, GANs are an interesting ML technique [66]. GANs are generative models, which means they produce new data instances that are similar to the training data [67]. GANs, for instance, may generate pictures that resemble photographs of human faces, even though the faces do not belong to any actual person [68]. RNNs, or LSTM networks, may learn order dependency in sequence prediction problems [69]. This is essential in complex problem domains such as machine translation and speech recognition. LSTMs are a challenging subset of DL [70]. The self-organizing map (SOM) technique is an effective tool for visualizing multidimensional data. A low-dimensional display translates complicated, nonlinear statistical correlations among high-dimensional data into simple geometric relationships [71]. The traditional approximation theory is the cornerstone of radial basis function networks (RBFN). It has global approximation capabilities [72]. Because of its simpler structure and speedier training procedure, the RBF network is a preferred alternative to the well-known MLP. Also, MLP is a type of feed-forward Artificial Neural Network (ANN) [73]. Backpropagation is a supervised learning method used by MLP during training. MLP is distinguished from a linear perceptron by its multiple layers and nonlinear activation. Plus, DBN is a method for unsupervised probabilistic DL [74]. The DBN is made up of several layers of stochastic latent variables. Latent variables, often known as feature detectors or hidden units, are binary variables. DBN is a hybrid generative graphical model. A generative stochastic ANN that can learn a probability distribution across its set of inputs is known as a restricted Boltzmann machines (RBM) [75]. DL networks can also employ restricted Boltzmann machines [76]. Nonetheless, for large information analysis, early COVID-19 detection, and reduced human labor, DL approaches are frequently employed in the healthcare sector. In recent scientific studies, ML and neural networks (NN) have risen in popularity. Figure 1 depicts the many applications utilized in ML.

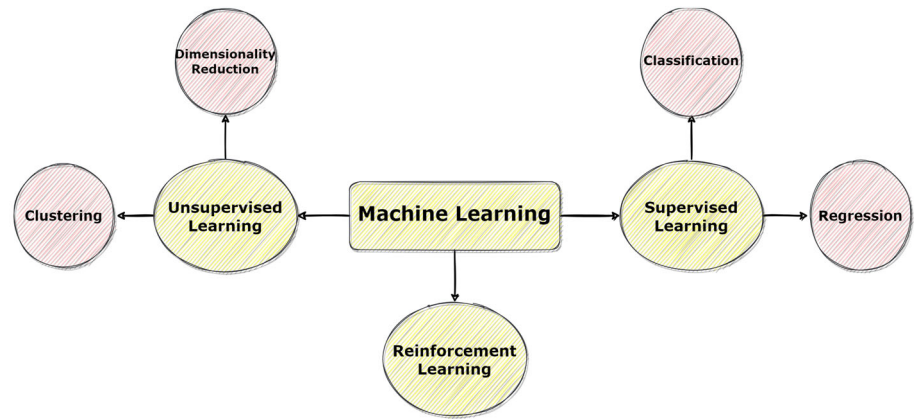
2.2 COVID-19 applications and concepts

With the increasing spread of COVID-19, different ways for identifying COVID-19 infection utilizing medical imaging are gaining popularity. To aid doctors in predicting COVID-19 infection, DL algorithms were utilized to interpret and analyze X-rays and CT scans [77]. In addition, DL methods are widely used to track COVID-19 spread through time and geography. To forecast tachypnea, depth camera video can be utilized instead of medical imaging to examine breathing patterns. Plus, by disease modeling and discovering viable medications in this pandemic, computational biologists are assisting in the fight against COVID-19. It has been used to decipher the protein structure of coronavirus to find medications that may be used to cure it [78]. The disease's dynamic modeling could aid in identifying the critical factors that influence the spread of infection and the impact of intervention in containing the epidemic. In addition, when the RNA genome is introduced into a cell, it works in tandem with the host's protein synthesis to duplicate RNA molecules. This is known as "polymerase," and it is employed as a therapy target. Protein shape is defined by the amino acid sequence that is genetically encoded and influences the protein's function. Template modeling and template-free modeling are two techniques for the prediction job [79]. Template modeling predicts comparable protein structures for template sequences, while template-free modeling suggests unknown related structures. The transmission of knowledge about COVID-19 has indeed been chaotic, leading to the term "infodemic." How could DL be used to combat the infodemic, from causal attribution of 5G networks to fraudulent treatments and reporting of scientific information? Misinformation detection has been formalized as a text classification or semantic similarity issue [80].

2.3 Preprocessing and TL

Also, segmentation is a preprocessing method that separates regions of interest from medical images to accelerate image analysis. It is the process of breaking down photographs into meaningful components, which in the case of medical imaging correlate to organs, tissues, and other biological properties. TL is also an improvement that provides for faster development or better performance when modeling the second task. TL is the enhancement of learning in a new assignment by transferring knowledge from a previously learned related activity [81]. In the next part, we go through important related surveys.

Fig. 1 Various methodologies and techniques of ML



3 Relevant surveys

In the COVID-19 pandemic, AI, ML, and DL are acknowledged as great techniques for delivering innovative faces in many fields like drug research, image processing methods, monitoring, and forecasting. Sometimes survey articles span a variety of topics and give a variety of applications. We look at a few survey papers on the COVID-19 topic in this part.

In this regard, Tiwari, Chanak [82] wanted to explore how ML methods and techniques are employed in the COVID-19 investigation. The main aim of their paper was to look at the influence of data kind and nature and data processing challenges for COVID-19. They recognized the value of cognitive technologies such as ML in combating the COVID-19 epidemic. They spoke about how to enhance ML algorithms and several forms of DL for COVID-19 prognosis. They assessed the efficacy and effects of several COVID-19 pandemic tactics. They focused on specific possible challenges in COVID-19 diagnosis to encourage academics to innovate and broaden their expertise and study into other COVID-19-affected businesses.

In the light of the COVID-19 crisis, Abumalloh, Nilashi [83] gave a literature assessment of the currently used medical image processing algorithms. The research was gathered, analyzed, reviewed, and compiled from credible databases. Their research was organized into a conceptual map with three layers: data collection and description, image processing stages, and assessment measures. According to the findings, several approaches were used to categorize the images linked to the detection of COVID-19. The selected methods yielded encouraging results in terms of cost, detection speed, and accuracy.

Liu, Lu [84] described how computational and structural biology, as well as AI technologies, are used. Virtual drug screening and its characteristics using AI approaches were explored in their article. The authors also highlighted the

identification of new medicines, drug repurposing, and the identification of druggable targets. Despite this, challenges with medication design and related areas such as small compounds and neutralizing antibodies are highlighted. Finally, AI and vaccine development techniques were discussed.

Saeed, Shah [85] reviewed the research on invasive/contact and noninvasive/non-contact technologies, consisting of Wi-Fi and software-defined radio for detecting, diagnosing, and monitoring human activities and COVID-19-related symptoms, including irregular breathing. They also focused on cutting-edge ML techniques, including GANs, random forests, MLP, SVM, very randomized trees, k-nearest neighbors, and their importance in smart medical systems. In addition, their research emphasized the limits of noninvasive approaches as well as the future aim of the research.

Subramanian, Elharrouss [90] surveyed the presently offered DL method to detect COVID-19 infection in lung images. Their paper summarized the available methodologies, public datasets, datasets used by each way, and evaluation metrics to aid future researchers. They explored several uses in general, such as detection, individual contact tracking, and early detection and diagnosis of COVID-19. The methods' evaluation metrics are compared and contrasted in detail. The paper's main flaw is the lack of a comparison of dataset sizes.

Also, Naudé [86] conducted an early assessment of AI versus COVID-19. They addressed the primary areas wherein AI may lead the fight against COVID-19. They determined that AI has yet to influence COVID-19. Its application is restricted by a lack of data and an abundance of data. They claimed that overcoming these limits will need a careful balancing between data privacy and public health, as well as thorough human contact. They looked at a few publications on diagnosis, social control, therapies, immunizations, and tracking and prediction. However, there is no comparison between the works.

Vaishya, Javaid [87] conducted a quick review of the literature by using keywords COVID-19 and AI on multiple internet databases. They gathered the most recent material on AI for COVID-19 and studied it to determine its potential applicability for this condition. They identified seven critical AI applications for the COVID-19 pandemic. They explored numerous uses in general, such as medication and vaccine research, case and death projections, individual contact tracking, and early detection and diagnosis of illness. The fundamental flaw of the study is the absence of comparison between the pieces.

Gulati [88] assessed the literature quickly using the keywords COVID-19 and AI from the databases Pubmed, Scopus, and Google Scholar. They gathered the most recent material on AI for COVID-19 and studied it to determine its potential applicability for this condition. They identified seven critical AI applications for the COVID-19 pandemic. They claimed that by collecting and analyzing all past data, this system might detect a cluster of instances and anticipate where this virus would impact in the future.

Nguyen, Nguyen [89] gave an overview of AI technologies being applied in diverse applications in the combat against the COVID-19 epidemic, emphasizing the critical importance of AI technologies in this historic war. They spoke on medical image processing, data analytics, information extraction and natural language processing (NLP), IoT, and computational biology and medicine. A list of COVID-19-related data sources that may be used for the study is also provided. The potential of AI and ways to improve its competence and strength in the fight against pandemics are thoroughly examined. They identify 13 types of issues connected to the COVID-19 pandemic and emphasize viable AI methodologies and tools for dealing with them (Table 2).

4 Research methodology

In the previous section, we evaluated relevant surveys and discussed their features. To further comprehend the DL-COVID-19 implementations, this part uses the SLR approach. The SLR is a comprehensive examination of all research on a certain topic [91]. This section is used to conclude a thorough study of COVID-19's use of ML techniques. The validity of the study selection procedures is next examined. The research procedure is described in-depth in the following subsections, including research questions and eligibility requirements.

4.1 Formalization of questions

The article's main goals are to recognize, differentiate, assess, and analyze all related papers obtained in ML-COVID-19 apps. An SLR could be used to explore the facets of the methodologies to attain the aims specified before [92]. The additional goal of SLR is to understand the fundamental problems and concerns that this industry encounters. A few Research Questions (RQs) which have been established are as follows:

- **RQ 1:** What is the role of ML in the current pandemic?
This question was addressed in Sect. 1.
- **RQ 2:** What are ML approaches, and what are their applications?
This question was answered in Sect. 2.
- **RQ 3:** Is there any study that has been released as a review article in this field? What distinguishes our article from past research?
This question was answered in Sect. 3.
- **RQ 4:** What are the most important possible solutions and unanswered questions in this sector?
The solutions to this issue will be presented in Sect. 5, while the open problem will be presented in Sect. 7.
- **RQ 5:** In the COVID-19 area, how do we find an article and choose ML methods?
Section 4.2 deals with this.
- **RQ 6:** In medical treatment, how can the ML mechanisms in COVID-19 be categorized? What are some instances of their work?
The answer to this question can be found in Sect. 5.
- **RQ 7:** What techniques do the researchers utilize to conduct their studies?

This question is addressed in Sects. 5.1 to 5.7.

4.2 The paper selection procedure

This investigation's article search and selection process is divided into four stages. This procedure is depicted in Fig. 2. Table 3 shows the keywords and phrases used to search the publications in the first step. The articles in this collection result from a search of popular electronic sources. Electronic databases used include Springer, Elsevier, Taylor and Francis, IEEE, Google Scholar, ACM, Emerald, MDPI, Wiley, and Scopus. Books, conference papers, journals, chapters, and special issues are also uncovered. The initial stage produced 890 papers. Fig. 3 displays a radar chart of the distribution of articles by the publisher.

The ultimate number of articles to study is determined in two steps in Phase 2. The publications are initially evaluated (stage 2.1) using the principles shown in Fig. 4. There

Table 2 A list of relevant studies

Authors	Basic goal	Scope	Advantage	Limitation
Tiwari, Chanak [82]	Reviewing ML into COVID-19 diagnosis	ML methods in COVID-19	<ul style="list-style-type: none"> • Limitations are discussed 	<ul style="list-style-type: none"> • There was not a thorough examination of the papers
Abumalloh, Nilashi [83]	Examining medical image processing and COVID-19 through the lens of bibliometric analysis	Image processing methods	<ul style="list-style-type: none"> • The article selection process is clear • The methods of image processing are discussed in detail 	<ul style="list-style-type: none"> • There is no comparison between the articles
Liu, Lu [84]	Reviewing COVID-19 pandemic tactics using computational and structural biology	Structural biology and AI platforms	<ul style="list-style-type: none"> • Challenges and potential drug discovery issues are discussed 	<ul style="list-style-type: none"> • There is no comparison between the papers
Saeed, Shah [85]	Examining COVID-19 patient monitoring with ML and non-contact sensing	COVID-19 patient monitoring	<ul style="list-style-type: none"> • Cover a large majority of the monitoring techniques 	<ul style="list-style-type: none"> • Upcoming work is not mentioned in-depth
Subramanian, Elharrouss [90]	Reviewing COVID-19 lung image processing detection approaches	Lung image processing	<ul style="list-style-type: none"> • Methods for transfer learning and fine-tuning were offered • Providing a comparison study using a variety of assessment measures 	<ul style="list-style-type: none"> • The paper selection method is not transparent • Upcoming work is not mentioned in-depth
Naudé [86]	Giving an early assessment of AI versus COVID-19	AI in general	<ul style="list-style-type: none"> • In COVID-19, several AI applications are presented 	<ul style="list-style-type: none"> • There is a lack of clarity in the article selection process • Upcoming work is not mentioned in-depth
Vaishya, Javaid [87]	Giving a brief overview of AI applications for the COVID-19 epidemic	AI apps in COVID-19	<ul style="list-style-type: none"> • Several significant AI uses in the COVID-19 pandemic are discussed 	<ul style="list-style-type: none"> • There is a lack of clarity in the article selection process • Upcoming work is not mentioned in-depth
Gulati [88]	Examining seven key AI applications for the COVID-19 epidemic	AI apps in COVID-19	<ul style="list-style-type: none"> • Discussing the primary uses of COVID-19 AI applications 	<ul style="list-style-type: none"> • There is a lack of clarity in the article selection process • There was not a thorough examination of the papers
Nguyen, Nguyen [89]	Introducing AI methods in the battle against COVID-19	Considering technologies such as IoT and others, as well as their applications in COVID-19	<ul style="list-style-type: none"> • Several AI algorithms and DL applications are described 	<ul style="list-style-type: none"> • Future works are not discussed • There is a lack of clarity in the article selection process
Ours	Examining ML methods and their applications in the management of the COVID-19 outbreak	All DL techniques and applications utilized in COVID-19 are covered	<ul style="list-style-type: none"> • Future works are discussed • There is clarity in the article selection process • There was a thorough examination of the papers 	<ul style="list-style-type: none"> • Only state-of-the-art works are reviewed

Fig. 2 The stages of the paper discovery and selection procedure

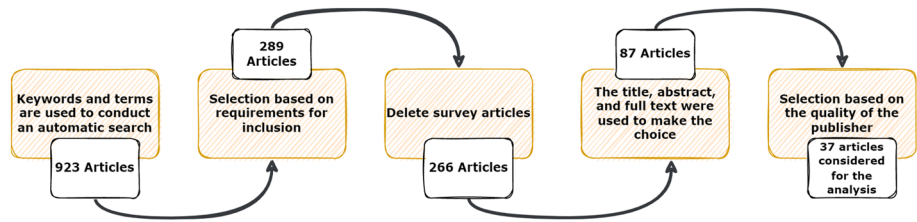


Table 3 Keywords and search phrases

N#	Keywords and Search Terms
1	“Medical issues” and “Deep learning”
2	“Healthcare” and “Machine learning”
3	“COVID-19” and “Deep learning”
4	“COVID-19” and “Machine learning” and
5	“Artificial intelligence COVID-19” or “AI methods covid-19”
6	“Epidemic diseases” and “Deep transfer learning”
7	“COVID-19 disease” and “Transfer learning”

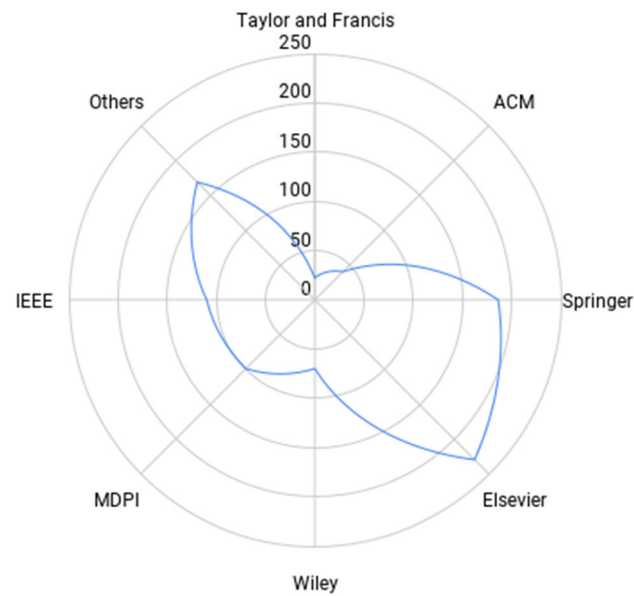


Fig. 3 The first stage is the distribution of the papers by the publisher

are 289 papers left at this moment. The publisher’s distribution of articles is indicated in Fig. 5. Stage 2.2 excludes review papers; of the remaining 289 items in the preceding phase, 23 (or 7.95%) were review articles. Elsevier, with 44% of the sector, publishes most research publications. With a 6 percent share of the sector, Springer publishes the majority of review papers. There are 266 papers left at this time. In Phase 3, the titles and abstracts of the papers were examined. The technique, evaluation, discussion, and results of the publications have all been double-checked to verify that they are relevant to the study. So, 87 articles

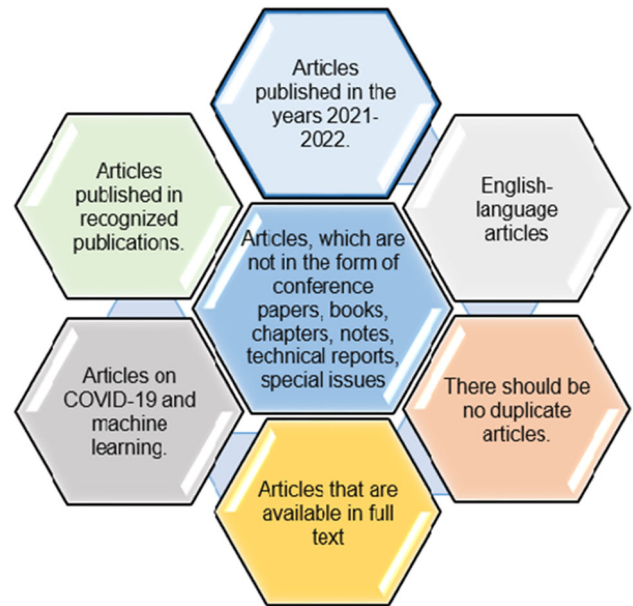


Fig. 4 Factors for consideration in the article screening process

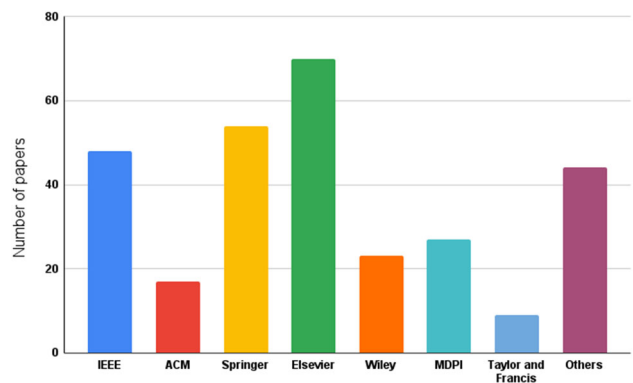


Fig. 5 The articles are published by the publishers in Phase 2.1

have been selected for further review. Eventually, 37 articles were picked to evaluate and study the other publications since they matched the tight criteria. The distribution of the reviewed papers by their publishers is depicted in Fig. 6. Elsevier releases 52 percent of the papers that are selected. The lowest percentage is connected to ACM, accounting for 2.7 percent or one paper. The years 2021 and 2022 have the most published studies, while 2020 will have the fewest. The journals that publish the publications

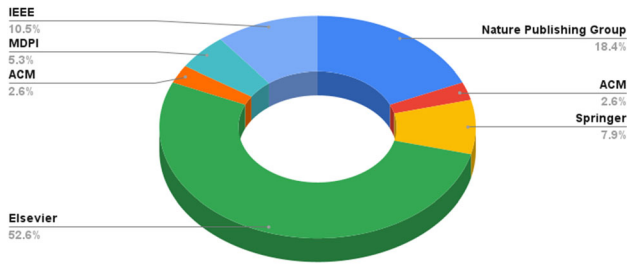


Fig. 6 The arrangement of the selected papers by the publications

are depicted in Fig. 7. With 19 and 14 percent, respectively, the most articles are published in Computers in Biology and Medicine and Scientific Reports (Table 4).

4.3 ML and COVID-19 applications

This section discusses the ML approaches for treating the COVID-19 pandemic and similar diseases. This part will discuss 37 papers, all of which fulfill our entry requirements. To begin, we divide the applications into seven broad categories: imaging methods, survival analysis, forecasting, economic and geographical difficulties, monitoring methods, drug discovery, and other apps. Such applications often employ one or more methods such as CNNs, LSTMs, RNNs, GANs, DBNs, SOMs, Autoencoders, MLPs, RBMs, and RBFNs. The suggested classification of ML-COVID-19 management applications is depicted in Fig. 8.

4.4 Imaging methods

AI advancements have resulted in substantial advancements in the production of computer-aided detection (CAD) systems [129]. Since the debut of DL methods, such automated systems, have demonstrated significant decision-making performance in a variety of medical fields,

including radiology. Such technologies can accurately duplicate the human brain in making diagnostic decisions, which could be valuable in real-time screening applications. Furthermore, in the current era of DL-based approaches, CNNs have garnered significant prominence in general and medical image-based applications. In the case of COVID-19 screening, similar networks might be taught to distinguish diseased and normal characteristics in supplied radiographic scans, including CT and X-ray images, in less than a second. In this section, we will go through five different methods.

So, for the identification of COVID-19 from CT scan images, Basu, Sheikh [93] developed an end-to-end architecture comprising deep feature extraction coupled with feature selection. They used three DL-based CNNs to extract features. They employed harmony search, a meta-heuristic optimization technique combined with adaptive-hill climbing, a local search approach for greater performance. The method was tested on the SARS-COV-2 CT scan dataset, including CT scan images. The technique achieved the best accuracy score of 98.87 percent on the specified dataset.

Also, Scarpiniti, Ahrabi [94] suggested a method for detecting COVID-19 from unsupervised CT images. They developed a deep denoising convolutional autoencoder (DDCAE) on various target classes. They then used the histogram of hidden features averaged over all training scans to build a robust statistical representation. The distance between the target histogram and the corresponding histogram analyzed for an unknown test scan is then computed using a successful distribution distance: If the distance is greater than a threshold, the test image is classified as an anomaly, meaning it is affected by the COVID-19; alternatively, it is categorized as the classification model. The suggested concept outperformed cutting-edge techniques in the results obtained tested on an open-source dataset, as it was able to attain the top 100 percent

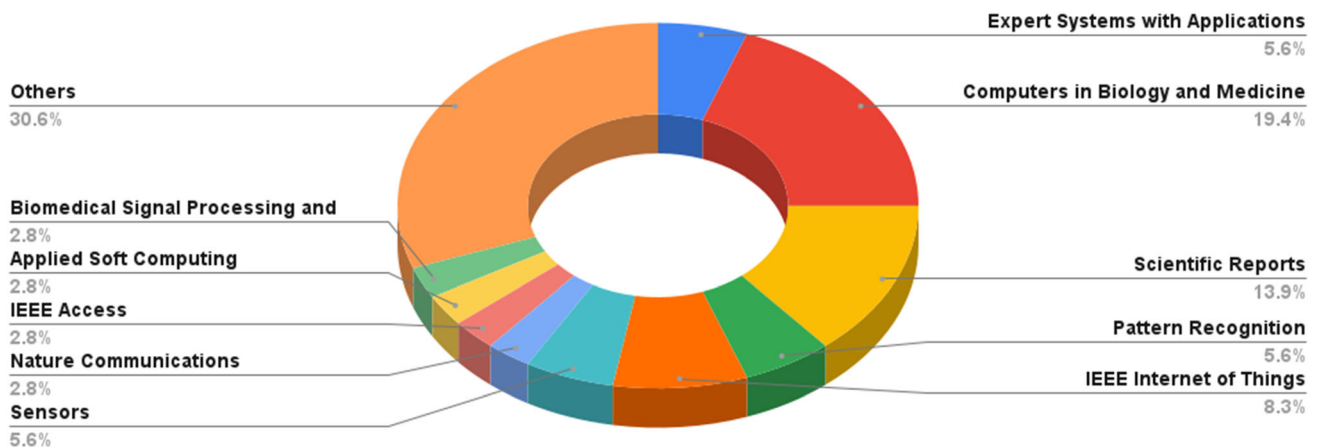


Fig. 7 Journals were used to distribute the selected papers

Table 4 The selected articles' characteristics (updated on February 15, 2022)

Publisher	Writers	Published Year	Citation Based 2022	JCR Based 2021	Scopus Based 2021	Journal Name	H-index Based 2021
Elsevier	Basu, Sheikh [93]	2022	0	Q1	Q1	Expert Systems with Applications	207
Elsevier	Scarpiniti, Ahrabi [94]	2021	0	Q1	Q1	Expert Systems with Applications	207
Elsevier	Hu, Shen [95]	2022	0	Q1	Q1	Pattern Recognition	210
Elsevier	Muhammad, Hoque [96]	2022	0	Q1	Q1	Knowledge-Based Systems	121
Elsevier	Gayathri, Abraham [97]	2022	0	Q1	Q1	Computers in Biology and Medicine	94
IEEE	Zhan, Zheng [98]	2021	8	Q1	Q1	IEEE Internet of Things	97
Springer	Zhan, Zheng [99]	2021	5	Q1	Q1	Neural Computing and Applications	80
Elsevier	Absar, Uddin [100]	2021	–	–	Q1	Infectious Disease Modelling	17
Nature Publishing Group	Chiu, Hwang [101]	2022	0	Q1	Q1	Scientific Reports	213
Nature Publishing Group	Asgharnejhad, Shamsi [102]	2022	6	Q1	Q1	Scientific Reports	213
Elsevier	Dong, Qiao [103]	2021	0	Q1	Q1	Computers in Biology and Medicine	94
MDPI	Jaber, Alameri [104]	2022	0	Q1	Q1	Sensors	172
MDPI	Zhang, Zhu [105]	2021	1	Q1	Q1	Sensors	172
IEEE	Zhang, Liu [106]	2021	11	Q1	Q1	IEEE Internet of Things	97
IEEE	Castiglione, Umer [107]	2021	2	Q1	Q1	IEEE Internet of Things	97
Nature Publishing Group	Schwab, Mehrjou [108]	2021	18	Q1	Q1	Nature Communications	365
Elsevier	Uemura, Näppi [109]	2021	1	Q1	Q1	Medical Image Analysis	135
Springer	Sinha and Rathi [110]	2021	5	Q2	Q2	Applied Intelligence	66
Nature Publishing Group	Näppi, Uemura [111]	2021	3	Q1	Q1	Scientific Reports	213
IEEE	Almars, Almaliki [112]	2022	0	Q1	Q1	IEEE Access	127
Elsevier	Grekousis, Feng [113]	2022	0	Q1	Q1	Health and Place	109
Elsevier	Motuzienė, Bielskus [114]	2020	0	Q1	Q1	Sustainable Cities and Society	61
Elsevier	Li, Zheng [75]	2022	0	–	Q2	Smart Health	9
Elsevier	Zhang, Wei [115]	2022	0	Q1	Q1	Computers in Biology and Medicine	94
Elsevier	Amilpur and Bhukya [116]	2022	0	Q2	Q2	Journal of Molecular Graphics and Modelling	73
Elsevier	Deepthi, Jereesh [117]	2021	0	Q1	Q1	Applied Soft Computing	143
Nature Publishing Group	Yang, Bogdan [118]	2021	43	Q1	Q1	Scientific reports	213

Table 4 (continued)

Publisher	Writers	Published Year	Citation Based 2022	JCR Based 2021	Scopus Based 2021	Journal Name	H-index Based 2021
ACM	Cantini, Marozzo [119]	2021	3	Q1	Q1	ACM Transactions on Knowledge Discovery from Data	59
Elsevier	Pahar, Klopper [120]	2022	5	Q1	Q1	Computers in Biology and Medicine	94
Elsevier	Hayawi, Shahriar [121]	2022	1	Q2	Q2	Public Health	75
Nature Publishing Group	Lee, Kim [122]	2022	0	Q1	Q1	Scientific Reports	213
Nature Publishing Group	Szaszi, Hajdu [123]	2022	0	Q1	Q1	Scientific Reports	213
Elsevier	Hu, Heidari [124]	2021	0	Q1	Q1	Computers in Biology and Medicine	94
Elsevier	Boussen, Cordier [125]	2021	0	Q1	Q1	Computers in Biology and Medicine	94
Elsevier	Attallah [126]	2021	1	Q1	Q1	Computers in Biology and Medicine	94
Elsevier	Jeevan, Zacharias [127]	2022	5	Q1	Q1	Pattern Recognition	210
Elsevier	Soltanian and Borna [128]	2022	0	Q2	Q2	Biomedical Signal Processing and Control	72

of the studied metrics accuracy, precision, recall, F-measure, and AUC with minimum computing complexity.

Besides, Hu, Shen [95] proposed a segmentation approach based on the encoder–decoder design for COVID-19 diseases by augmenting supervised information and merging multi-scale feature maps of distinct levels. To that purpose, a co-supervision approach is presented to direct the network’s learning of edge and semantic properties. An Edge Supervised Module (ESM) is initially intended to emphasize low-level boundary characteristics by inserting edge supervised information into the early phase of down-sampling. Similarly, an Auxiliary Semantic Supervised Module (ASSM) is presented as a way to improve high-level semantic information by incorporating mask supervised data into the latter stage. Furthermore, utilizing an attention mechanism to decrease the semantic gaps between high-level and low-level feature maps, the attention fusion module (AFM) is created to fuse multiple-scale feature maps of various levels. The findings showed that all three of the suggested modules are acceptable.

Also, using reconstruction independent component analysis, Muhammad, Hoque [96] suggested a self-augmentation technique for data augmentation in the feature space rather than the data space. A unified framework including a deep CNN, a feature augmentation technique, and a bidirectional LSTM is suggested. The CNN retrieved

the high-level features at the pooling layer, where the augmentation process selects the most relevant components and creates low-dimensional enhanced features. Lastly, Bi-LSTM is utilized to categorize the processed sequential data. They ran trials on three publicly available datasets to demonstrate that the suggested technique provides state-of-the-art outcomes with 97 percent, 84 percent, and 98 percent accuracy.

Finally, Gayathri, Abraham [81] devised a CAD methodology based on chest X-rays to tackle the pandemic. The model was built using many pre-trained networks and their combinations. The technique detected COVID-19 using features collected from pre-trained networks, a Sparse autoencoder for dimensionality reduction, and a feed-forward neural network (FFNN). Several pre-trained networks were concatenated for feature extraction, which outperformed a single-CNN. The use of sparse autoencoder significantly improved the model’s accuracy. 504 COVID-19 images and 542 non-COVID-19 images were merged from two publicly available chest X-ray imaging datasets to train the model. Using the integration of InceptionResnetV2 and Xception, the technique achieved an accuracy of 0.9578 and an AUC of 0.9821. Experiments showed that using a sparse autoencoder as a dimensionality reduction technique enhances model accuracy.

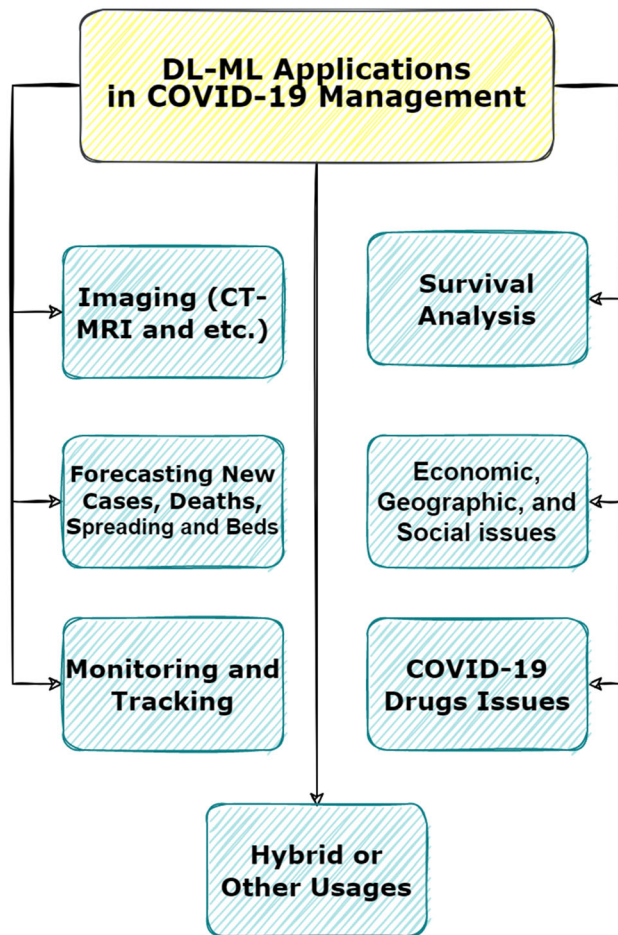


Fig. 8 The suggested ML-COVID-19 classification distinguishes 7 unique apps

Table 5 summarizes the image detection technologies used in COVID-19, as well as their characteristics.

4.5 Forecasting and prediction apps

The ability to predict epidemic consequences as promptly and precisely as possible is crucial for policymaking and implementation. Forecast models face a significant challenge: Not all outbreaks turn into pandemics, making it extremely difficult to anticipate their severity. Meanwhile, analyzing the pros and cons of implementing lockdowns and other mitigating measures about their socioeconomic consequences is difficult and ambiguous. The majority of pandemic modeling approaches use an epidemiological strategy that takes into consideration biology and disease dynamics. This section will take a closer look at five diverse solutions.

So, based on the broad learning system, Zhan, Zheng [98] suggested an ML model for COVID-19 prediction. They used the random forest to screen out the relevant aspects in this case. The bagging approach is then

combined with a comprehensive learning system to create a random-forest-bagging system. A broad learning system technique was used to forecast the COVID-19 pandemic's trajectory. They also compared the forecasting results to those of other approaches. The technique model outperformed other models in terms of root mean square error (RMSE), R2, MAD, and Mean absolute percentage error (MAPE) forecasting. As a result, the model outperformed other standard models in terms of predictive power.

Zhan, Zheng [90] devised a pseudocoevolutionary simulated annealing approach to discover these unknown parameters. This model's vast volume of unknown parameters is improved using three co-adapted simulated annealing-based optimization techniques. The findings showed that the strategy is both efficient and robust. The discovered model is then used to anticipate the patterns of the COVID-19 outbreak spreading in these cities. They discovered that the number of illnesses in most Chinese cities peaked between February 29 and March 15, 2020. The total number of sick people in most cities outside Hubei province would be fewer than 100. In contrast, the total number of infected people in most cities in Hubei province (excluding Wuhan) would be less than 3000.

Also, Absar, Uddin [100] developed a model based on the DL method to anticipate the propagation of epidemic trends. The suggested model was developed using the LSTM algorithm and showed strong performance in time series predictions, with good outcomes in the confirmed, recovered, and death cases. According to their model projections, the present COVID-19 epidemic is not likely to stop in the next several months. According to the graphical analysis, it could be concluded that the LSTM model provided a good match for COVID-19 prediction since the actual and prediction curves are extremely near in maximum duration. Furthermore, the estimated RMSE value demonstrates the LSTM model's accuracy in predicting the COVID-19. It is envisaged that the LSTM model would successfully predict infectious illnesses, allowing the relevant government to choose the appropriate preventative measures to avoid additional transmissions in the country.

By utilizing ML technology, Chiu, Hwang [101] attempted to address this topic from the perspective of preventative medicine. They then went on to create the decision tree and DNN prediction models. Their paper looked at the influence of 19 comorbidities and age and gender on the risk of severe illness or fatality in 83,227 hospital admissions with influenza-like illnesses. The findings showed that decision rules built from ML-based prediction models might give useful instructions for healthcare policymakers in developing an effective vaccination plan. In the event that medical centers are overburdened with patients with emerging infectious diseases

Table 5 Techniques, attributes, and characteristics of imaging-COVID-19 applications

Authors	The basic objective	Pros	Limitations in study	Security method?	Simulation environments	Dataset and Size of Dataset	Using TL?	Mechanism	Application?
Basu, Sheikh [93]	Detecting COVID-19 from CT images utilizing an end-to-end architecture	-The accuracy is 98.87%	-High delay	No	Python	SARS-COV-2 CT Scan dataset (Small size)	Yes	CNN	Detection in chest X-ray
Scarpiniti, Ahrabi [94]	Learning features with pre-trained models	-High accuracy, precision, recall, F-measure, and AUC	-Low security -Low robustness	No	Python	COVIDx CT-2 dataset, include 3700 images (Small size)	No	CNN + Autoencoder	Detection in chest CT
Hu, Shen [95]	Offering three modules for deep collaborative supervision and attention fusion based on ResUnet	-High segmentation performance -High generalization ability	-Low scalability	No	Python	COVID-19 segmentation dataset (Small size)	No	Encoder-decoder	Detection in chest CT
Muhammad, Hoque [96]	Presenting a deep feature augmentation system to enhance COVID-19 detection	-The achieved accuracy is 98%	-Lack of volumetric data representation	No	Not mentioned	Cohen JP (Small size)	Yes	CNN + LSTM	Detection in chest x-ray
Gayathri, Abraham [97]	Using DNN to extract features, reduce dimensionality, and classify data	-High accuracy -Low energy consumption	-Low robustness	No	MATLAB	The dataset consists of 783 X-ray images (Small size)	Yes	CNN + Autoencoder	Detection in chest X-ray

(EID), as was the case during the current COVID-19 outbreak, frontline doctors could indeed use the suggested forecasting model to triage patients with minor symptoms without the need for laboratory tests, which may become scarce during an EID disaster. Their research provided an effective method for utilizing the ML method to deal with the issues that arise during an EID pandemic.

Finally, Asgharnezhad, Shamsi [102] explored the ability of deep uncertainty quantification approaches to identify COVID-19. They presented a unique confusion matrix as well as numerous performance criteria for evaluating predictive uncertainty estimations. Their research showed that DL models trained on medical imaging datasets outperformed models taught on some datasets like ImageNet. They also discovered that ensemble approaches capture greater uncertainty associated with predictions, leading to more reliable diagnostic solutions. The suggested uncertainty confusion matrix also showed that uncertainty quantification approaches reach high sensitivity and specificity.

Table 6 covers the forecasting methods and their attributes utilized in COVID-19.

4.6 Monitoring and tracking methods

Medical personnel and high-tech detection equipment were scarce during the peak of the COVID-19 pandemic and in undeveloped regions, resulting in the disease's ongoing spread. So, an auxiliary screening and monitoring approach that is more portable, cost-effective, and automated is required. In this regard, in this part, we look at five different methods.

So, Dong, Qiao [103] proposed to use an ML method and a non-contact monitoring device to assess probable COVID-19 patients automatically. They detected breathing, sleep quality, body movement, heart rate, and a variety of other physiological indications using impulse-radio ultra-wideband radar. They compared 144 radar monitoring data from healthy controls to 140 radar monitoring data from 23 COVID-19 patients at Wuhan Tongji Hospital. The data were then divided into sick and healthy people using the XGBoost and logistic regression (LR) techniques. The XGBoost and LR algorithm outperformed other single ML algorithms in terms of discrimination (precision = 92.5 percent, recall rate = 96.8%, AUC = 98.0 percent). In addition, the SHAP value suggested that the number of apneas during REM sleep, mean heart rate, and other sleep metrics are key classifying factors.

Also, to categorize the COVID-19-patient health status, Jaber, Alameri [104] employed a meta-heuristics optimized CNN technique. To collect patient health data, they employed a three-layer IoT system. Temperature, heart rate, oxygen saturation, and audio signals are among the

physiological variables collected by the wearable sensors. The cough-level infections were calculated using MFCC coefficients applied to the audio data. To identify various health information, additional statistical characteristics are retrieved. The temperature and cough threshold data are then utilized to look into the specific COVID-19 infection characteristics. The fully convolutional layer, subsampling, and activation function are then used to classify normal and pathological health characteristics. The Salp optimization behavior is used to update the neural network parameters during the classification phase. The system provided 98.76 percent accuracy and a low variation rate.

Zhang, Zhu [105] presented a wearable device with inertial and temperature sensors that may be utilized to apply human behavior recognition (HAR) to body surface temperature detection and correction during COVID-19. The sensing device used a microcontroller, a 6-axis sensor, and a temperature sensor to collect data from ten different users in four distinct daily activity situations. After that, signal normalization, data stacking, and resampling are used to preprocess the raw data. Evaluation metrics and method running time were used to compare the performance of some classifiers on the seven-dimensional dataset with temperature sensing signals, and the random forest was found to be the best-performing classifier with 88.78 percent recognition accuracy, which is higher than the case of no temperature data (78 percent).

Zhang, Liu [106] presented an emotion-aware and smart IoT system that includes data sharing, information supervision, patient tracking, data collection and analysis, and healthcare, among other things. In monitoring contexts, intelligent IoT sensors are coupled to capture multimodal data from patients. The most recent data and inputs from official websites and reports are checked for further examination and emotion analysis. According to the biological theory and the abdominal route model, the suggested hierarchal computational cognition simulation model takes the shape of a CNN that models the human brain's layered information processing mechanism. It successfully improved detection and identification accuracy by combining recent scientific achievements in the realm of biological vision. The suggested IoT platform provided remote health monitoring and emotion-aware decision-making, considerably contributing to convenient and continuous emotion-aware healthcare services. In comparison with several popular models, the suggested framework delivers a substantial benefit, according to experimental results on emotion data. The suggested cognition-based dynamic technology is a good technique to accommodate a wide range of devices and the COVID-19 pandemic application.

Finally, Castiglione, Umer [107] demonstrated a method by emphasizing IoT systems that could assist in its control.

Table 6 Techniques, attributes, and characteristics of forecasting-COVID-19 applications

Authors	The basic objective	Pros	Limitations in study	Security method?	Simulation environments	Dataset and Size of Dataset	Using TL?	Mechanism	Application?
Zhan, Zheng [98]	Proposing an ML model for COVID-19 prediction based on a large learning system	-High predictability -High accuracy	-	No	Not mentioned	Dataset from reports made available by national health authorities and the Bureau of statistics (Large dataset)	No	The RF-bagging broad learning system	Prediction
Zhan, Zheng [99]	Proposing a simulated annealing method that is pseudocoevolutionary	-High robustness -High predictability	-Moderate complexity	No	Not mentioned	Real-world records (Large dataset)	No	Simulated annealing	Prediction
Absar, Uddin [100]	Using LSTM to Predict the spread of the epidemic	-High accuracy	-Low flexibility	No	Python-Keras	eHealth division of the government of the Republic of Bangladesh dataset (Small dataset)	No	LSTM	Forecasting pandemic cases
Chiu, Hwang [101]	Determining the axial dependence of the slices using LSTM	-High sensitivity	-Low scalability -A single dataset was used to obtain experimental data	No	Python	NHIRD database (Small dataset)	No	Decision Tree and DNN	Assess the probability of serious disease or death in hospitalized patients
Asghamezhad, Shamsi [102]	Using CXR images to apply three uncertainty quantification approaches	-High sensitivity and specificity	-Low robustness	No	Python	CXR image database (Small dataset)	No	Ensemble Bayesian networks	COVID-19 detection uncertainty predictions

The proposed approach is made up of four parts, all of which are cloud-based: (1) data collection of disease symptoms using IoT-based devices; (2) information gathering of a medical center or quarantine center employing IoT systems; (3) data warehouse analysis utilizing ML models; and (4) treatment by health professionals. They tested five ML models to predict the severity degree of COVID-19 patients based on IoT-based real-time data. RF beat all other models, according to the findings. Management, health experts, and patients will benefit from IoT apps to explore the symptoms of contagious disease and manage the COVID-19 pandemic around the world.

Table 7 summarizes the monitoring and tracking methods and their attributes utilized in COVID-19.

4.7 Survival analysis methods

To compute infection risks, conduct survival analysis, and classify data, ML and AI approach is used. In several fields, including medicine and engineering, survival analysis (time-to-event analysis) is commonly utilized. Survival analysis is a methodology for calculating the amount of time before a specific “event.” Various study obstacles face time-to-event data, including censoring, symptom correlations, high-dimensionality, temporal interdependence, and the difficulty of obtaining adequate event data in a fair amount of time. We will look at four distinct approaches to this topic in this section.

Schwab, Mehrjou [108] demonstrated the COVID-19 early warning system, a risk score method for measuring mortality risk that they created utilizing data from a cohort of 66,430 individuals seen at over 69 medical institutions, totaling over many years of observation time. The technique depends on a time-varying neural Cox model that compensates for risk variables changing over time and any nonlinear interactions between risk factors and COVID-19-related mortality risk. It was developed using de-identified electronic health records (EHRs) from 66,430 COVID-19 patients. The suggested technique is automatically generated from patient EHRs, updated in real-time with no need for manual intervention to reflect the difference in clinical status. It accounts for substantially higher risk variables associated with mortality than existing risk scores. On an external cohort of 5005 patients, the approach predicted mortality with a specificity of 78.8 percent to 69.4 percent at sensitivities more than 95 percent between 1 and 192 h before death.

Also, Uemura, Näppi [109] created a weakly unsupervised conditional GAN method that can be trained to predict time-to-event information for survival analysis straight from a patient’s chest CT images. A fully automated conditional GAN was used to train a complete image-based survival analysis model for producing the time-to-event

distribution from CT images without any explicit segmentation or feature extraction efforts. The model avoided the technical limitations of previous similar image-based COVID-19 predictors. They discovered that method, which is based on CT scans, outperformed conventional laboratory studies and image-based visual and quantitative predictors in predicting disease progression and death in COVID-19 patients. As a result, the method proved to be a viable method for making image-based prognostic predictions. The concordance index (C-index) and relative absolute error (RAE) were utilized as the major assessment of prognostic prediction performance.

In addition, Sinha and Rathi [110] provided an ML-based statistical technique to predict the survival odds of COVID-19 infected patients in South Korea, with an examination of the influence of exploratory parameters such as age range, sex, and temporal evolution. They used ML with hyperparameter tuning and DL models using an autoencoder-based technique to estimate the effect of diverse factors on disease propagation and projected the survival chances of confined patients in isolation to evaluate the coronavirus cases. The model calibrated in their study is based on positive COVID-19 infected patients and offered the analysis over several features that have shown to be significant in analyzing the temporal patterns in the current scenario and the examination of dead cases owing to COVID-19.

Finally, Näppi, Uemura [111] created a U-survival and autonomous image-based survival modeling approach that integrates DL of chest CT images with the well-established survival analysis approach of an elastic-net Cox survival algorithm. In a study of 383 positive cases from two hospitals, U-survival’s prognostic bootstrap prediction performance was higher than that of existing laboratory and image-based reference predictors for COVID-19 progression. The results showed that U-survival might be utilized to generate autonomous and objective prognostic predictions for COVID-19 subjects.

Table 8 describes the survival analysis methods and attributes utilized in COVID-19.

4.8 Economic, geographic, and social issues methods

During the COVID-19 epidemic, spatialization of economic data may be employed and combined with other sources of information to give useful insights. Similar data may be used to infer various changes, including city resident dynamics and geographical and temporal variability [130]. Trying to analyze the relationship between pandemic patterns and socioeconomic, geological, and community welfare could also be used to build a smart pandemic prediction system utilizing DL or ML algorithms, which

Table 7 Techniques, attributes, and characteristics of monitoring and tracking-COVID-19 applications

Authors	The basic objective	Pros	Limitations in study	Security method?	Simulation environments	Dataset and Size of Dataset	Using TL?	Mechanism	Application?
Dong, Qiao [103]	Intending to use the XGBoost and a non-contact monitoring system to assess prospective COVID-19 patients automatically	Precision = 92.5 percent, recall rate = 96.8%, and AUC = 98.0 percent were achieved.-Stable and robust -Low complexity	-High energy consumption	No	Not mentioned	Local dataset (Small dataset)	No	XGBoost + LR algorithm	Non-contact screening system
Jaber, Alameri [104]	Using a CNN model to maximize the illness classification process with the fewest possible deviations	-98.76 percent accuracy -Low variation rate	-Low robustness	No	MATLAB	Open research dataset (Small dataset)	No	CNN	Monitoring COVID-19 patient health
Zhang, Zhu [105]	Proposing body temperature monitoring for COVID-19 prevention regularly based on ML	-High accuracy	-Low flexibility	No	Python	Total of 31,713 entries dataset (Large size dataset)	No	RF	Body temperature monitoring
Zhang, Liu [106]	Offering an emotion-aware system that includes discriminative emotion identification utilizing CNN	-High accuracy -High precision	-Low robustness	No	Python	eNTERFACE' 05 datasets, SEED dataset, and DEAP database (Large dataset)	Yes	CNN	Emotion-aware and monitoring
Castiglione, Umer [107]	Presenting a technique that gathers data from health centers and saves it to a data warehouse for analysis using ML	-0.754 precision -0.794 recall -0.810 recall -F-score of 0.802	-Low security -Low flexibility	No	Python using Scikit-learn	Real-time dataset (Small dataset)	No	Random forest	Monitoring COVID-19

Table 8 Techniques, attributes, and characteristics of survival analysis-COVID-19 applications

Authors	The basic objective	Pros	Limitations in study	Security method?	Simulation environments	Dataset and Size of Dataset	Using TL?	Mechanism;	Application?
Schwab, Mehriou [108]	Utilizing the WOA approach to improve GAN's parameters	-High interpretability;- High scalability;	-High complexity;	No	Python	66,430 COVID-19 patients (Large dataset)	No	Time-varying neural Cox mode	Survival analysis
Uemura, Näppi [109]	Developing a conditional GAN that allows for a direct estimate of the survival time distribution	-High C-index;- High REA	-Low flexibility	No	Not mentioned	Database of 214 COVID-19 patients;(Small size dataset)	No	GAN	Survival analysis
Sinha and Rathi [110]	We present a prediction analysis of quarantined COVID-19 instances using several artificial DL models and hyperparameter optimization	-High accuracy;- High scalability	-High energy consumption	No	Python	The dataset contained 5165 cases that were verified on 1533 quarantined patients. (Medium size dataset)	No	Autoencoder	Survival prediction
Näppi, Uemura [111]	Proposing U-Net for semantic lung segmentation of axial CT images into five unique lung tissue patterns	-High binary classification ability	-Low scalability;- Low robustness	No	PyTorch	Dataset included 383 patients;(Small dataset)	No	U-Net (CNN)	Survival prediction model

dynamically adjusts the prediction parameters in response to changes in epidemic data and economic data over time. In this part, we will look at four various approaches.

So, Almars, Almaliki [112] proposed a hybrid approach to detecting rumors on social media. The method's benefit is that it allowed the main user to capture the relative and essential differences between distinct classes while also explaining the model's judgments. CNN's and Bi-LSTM networks with attention modules are two DNN featured in their technique. The model is trained in this study using a benchmark dataset of 3612 unique tweets crawled from Twitter, including numerous forms of rumors about COVID-19. With 1480 rumors tweets (46.87 percent) and 1677 non-rumors tweets, each data group has a balanced label distribution (53.12 percent). The testing findings showed that the technique outperformed several contemporary models in performance and accuracy by roughly 0.915 percent.

Grekousis, Feng [113] used a nonlinear nonparametric geographical RF model that can account for regional variability as well as nonlinear correlations. They discovered that various variables are connected with the COVID-19 mortality rate across the continental USA by studying how the relevance of risk factors varies regionally. It showed that geographical RF could discover how components' relevance fluctuates regionally due to its capacity to manage spatial heterogeneity. Compared to the local coefficients provided by linear regression models, this is a clearer way to inform decisions. Their results suggested that local and regional authorities, particularly in the West, should promote physical activities during the COVID-19 outbreak, as their absence is the primary cause of high COVID-19 mortality rates. Furthermore, they discovered that in 34.86 percent of US counties, a lack of medical insurance is the most critical issue. Governments could concentrate more on enhancing social security systems and investing more in medical insurance to ensure that individuals access appropriate and inexpensive medical care.

Also, Motuzienė, Bielskus [114] discussed the results of long-term surveillance for two office buildings at different times of the epidemic. They employed extreme learning machine (ELM), a learning method that is tied to ANNs. They wanted to look at real occupancies during the epidemic and how that affected the reliability of occupancy-forecasting models based on the ELM. The real occupancies in the offices are substantially lower than those reported in standards and procedures, and they remain low even when quarantines are lifted. The model's prediction accuracy is poor compared to what was previously specified for the same model under pre-pandemic settings. The notion that the ELM-SA model's prediction reliability declines during pandemic conditions is verified. It is worth noting that predictability is weaker during periods of low

occupancy. Building A had a peak occupancy of 12–20 percent, while Building B had a top occupancy of 2–23 percent for the whole measurement period. Because they are in different businesses, the daily occupancy patterns for each workplace are different. Due to reduced occupancies during pandemic times, the model has poor accuracies $R^2 = 0.27$ – 0.56 .

Finally, Li, Zheng [75] suggested a felt stress prediction method based on micro-ecological momentary assessment (EMA) history data for spotting threats seven days in advance. A regression challenge is the prediction of subjective stress ratings. A single regression model that trains on a collection of features in predictive modeling may contain biases or excessive variability. They used a weighted sum to aggregate the output scores of these three prediction models. They first picked and provided an ideal set of micro-EMA questions to customers each Monday, Wednesday, and Friday to reduce the load. They next retrieved time series features from previous micro-EMA replies and used an Elastic-net regularization approach to eliminate redundant features. Then, selected characteristics are input into an ensemble prediction model to estimate fine-grained felt stress over the next seven days. Experimental findings indicated that their forecasting scheme could improve a mean absolute error of 4.26 (10.65 percent of the scale) for predicting the next Seven days' PSS scores and more than 81 percent accuracy for predicting the next Seven days' stress labels.

Table 9 highlights the economic, geographic, and social strategies employed in COVID-19, as well as their features.

4.9 COVID-19 drugs discovery method

The process of developing new medications is both costly and time-consuming. The overall development cost of a new medicine is often in the millions of dollars, with a typical development duration of 13–15 years. As a result, drug repositioning strategies, particularly COVID-19 drug discovery, have become a popular study area in the field of medication development. In this part, we will look at four various approaches.

For drug–target interaction (DTI) prediction, Zhang, Wei [115] presented a DL model to capture the molecular structural information of drug molecules. The method incorporated a transformer network with multi-layer graph information to capture the properties of a drug's molecular structure. The interactions between atoms of drug compounds may be investigated further. Also, a CNN is used to collect the target sequence's local residue information and efficiently extract the target's feature information. The proposed scheme surpassed earlier models based on the structure of target sequences in testing on the DrugBank dataset. According to the findings, the upgraded

transformer network fuses feature information between layers in the graph CNN and recovers molecular structure interaction data. The suggested model's potential to locate therapeutic medications in drug discovery was proved in a drug repositioning experiment on COVID-19 and Alzheimer's disease.

Also, Amilpur and Bhukya [116] suggested a unique drug discovery strategy based on the LSTM model that generates novel compounds capable of binding to a novel Coronavirus protease. Their research showed that the suggested strategy could produce unique compounds with remarkably similar characteristics to those of taught molecules. They also fine-tuned the algorithm to develop new drug-like compounds with precise target activity. They looked at 3CLPro, the major protease of the COVID-19, as a potential therapeutic target and used docking simulations to assess target structure binding affinities *in silico*. They discovered that 80 percent of the molecules they synthesized have a docking free energy of less than 5.8 kcal/mol. With a docking score of 8.5 kcal/mol, the top-ranked drug candidate has the greatest binding affinity, which is significantly lower than authorized commercial medications like Remdesivir. Because of the low binding energy, the produced compounds might be investigated as possible COVID-19 medication candidates.

Deepthi, Jereesh [117] introduced a DL ensemble model for prioritizing clinically verified antiviral medicines for SARS-CoV-2 effectiveness. The approach uses similarities in medication chemical compounds and viral genomic sequences to build feature vectors. The CNN is used to find the optimum combination of features. The extreme gradient boosting classifier is used to classify the retrieved deep features to predict probable virus–drug relationships. Under fivefold cross-validation, the approach has an AUC of 0.8897, 0.8571 prediction accuracy, and 0.8394 sensitivity. According to the experimental findings and case studies, the proposed DL ensemble system produced competitive outcomes compared to state-of-the-art techniques. The top-scoring medicines are released for additional wet-laboratory testing.

Finally, Yang, Bogdan [118] suggested an *in silico* DL technique for multi-epitope vaccine prediction and design named DeepVacPred. The DeepVacPred computational predicted 26 possible vaccine components from the existing SARS-CoV-2 spike protein sequence using a combination of *in silico* immunoinformatics and DNN techniques. They then employed *in silico* methods to look at the linear B-cell epitopes, cytotoxic T lymphocyte epitopes, and helper T lymphocyte epitopes in the 26 component candidates and pick the best 11 to build a multi-epitope vaccine against the SARS-CoV-2 virus. *In silico* techniques are used to anticipate, refine, and validate the 3D structure of the planned vaccine. Lastly, the codon

Table 9 Techniques, attributes, and characteristics of economic, geographic, and social-COVID-19 apps

Authors	The basic objective	Pros	Limitations in study	Security method?	Simulation environments	Dataset and Size of Dataset	Using TL?	Mechanism	Application?
Almars, Almaliki [112]	Proposing a hybrid DL model for social media rumor detection	-High accuracy -High performance	-High complexity	No	Not mentioned	ArCOV dataset (medium size dataset)	No	CNN + Bi-LSTM	Social media rumor detection
Grekousis, Feng [113]	Using GRF, nonlinear connections between the COVID-19 mortality rate were computed	-High scalability -Low complexity	-Low robustness -High energy consumption	No	Not mentioned	Dataset of 3021 data countries (large dataset)	No	GRF	Ranking the significance of demographic, socioeconomic, and underlying health variables
Motuzienė, Bielskus [114]	Using the ELM to analyze real occupancies during different epidemic durations	-High flexibility -High reliability	-Low scalability	No	MATLAB	Real-time dataset	No	ELM	Analyze the occupancy of office buildings during COVID-19
Li, Zheng [75]	Establishing a micro-EMA-based prediction system comprised of optimum micro-EMA selection	-Moderate accuracy -High flexibility -High MAE	-Scalability is not considered	No	Not mentioned	2862 samples (Small dataset)	No	Ensemble prediction model	COVID-19 social isolation impacts

sequence was adjusted and inserted into a plasmid to assure cloning and expression efficiency. Finally, the approach vaccine discovery framework speeds up the vaccine development process generates a 694aa multi-epitope vaccine with 16 B-cell epitopes, 82 CTL epitopes, and 89 HTL epitopes that are promising in fighting SARS-CoV-2 viral infection and may be tested in clinical trials.

Table 10 covers the drug discovery methodologies and attributes employed in COVID-19.

4.10 Hybrid or others apps

Hybrid apps are one of the advanced applications used in COVID-19 realms. Such apps combine two or more solutions for tackling problems in diverse contexts. In this regard, we mentioned which approaches were used to build the reviewed applications in these assessments. It is a widely utilized application in a wide range of sectors relevant to this pandemic. In this part, we will look at 10 various ways.

Cantini, Marozzo [119] introduced a model hashtag recommendation system that used Sentence-to-hashtag embedding translation to suggest a collection of appropriate hashtags to a particular post. The method used two separate latent spaces to incorporate a post's content as well as the hashtags it includes. The translation from the semantic aspects of the text to the latent representation of its hashtags is then learned via a mapping procedure based on an MLP. They tested different strategies for semantic expansion and analyzed the effectiveness of two language representation models for sentence embedding, finding that the combination of Bidirectional Encoder Representation from Transformer (BERT) and a global expansion strategy produces the best recommendation results. On the COVID-19 pandemic, the method was tested. With an average F-score of 0.82 and a recommendation hit rate of 0.92, the findings confirmed the method's efficacy in predicting one or more right hashtags. The technique outperformed previous works by improving F-score by up to 15% in the hashtag suggestion job and 9% in the topic discovery task.

Also, Pahar, Klopper [120] conducted studies on the usefulness of TL and bottleneck feature extraction in identifying COVID-19 from cough, breath, and speech voice recordings. They pre-trained three DNNs, including a CNN, an LSTM, and a Resnet50, using datasets that contained sneeze, speech, cough, and other sounds but did not contain COVID-19 labels. In the process of TL, these pre-trained models are either fine-tuned utilizing smaller datasets of coughing with COVID-19 labels or employed as bottleneck feature extractors. The findings showed that a Resnet50 classifier trained using this TL approach performed optimally or near-optimally across all datasets, with areas under the receiver operating characteristic (ROC) of 0.98, 0.94, and 0.92 for all three sound classes:

Table 10 Techniques, attributes, and characteristics of drug discovery-COVID-19 apps

Authors	The basic objective	Pros	Limitations in study	Security method?	Simulation environments	Dataset and Size of Dataset	Using TL?	Mechanism	Application?
Zhang, Wei [115]	Using fused graph information and CNN, propose a transformer network for predicting DTIs	-High scalability -High generalization ability	-High delay	No	Python	DrugBank dataset (Large dataset)	No	CNN	Drug discovery
Amilpur and Bhukya [116]	Proposing a generative LSTM model that learned the molecular language and produced unique compounds	High predictability -Low delay	-Poor flexibility	No	Keras with Tensorflow	ChEMBL and MOSES (Large dataset)	Yes	LSTM	Drug discovery
Deepthi, Jereesh [117]	Using a CNN model to rank clinically approved antiviral medicines according to their effectiveness against SARS-CoV-2	-The approach has an AUC of 0.8897, prediction accuracy of 0.8571, and a sensitivity of 0.8394 -High accuracy	-Low security -High delay	No	DLEVDA with the python	The dataset contains 455 human drug-virus associations between 219 drugs and 34 viruses	No	CNN + XGBoost	COVID-19 drug repurposing
Yang, Bogdan [118]	Providing an in silico DL technique for multi-epitope vaccine prediction and design	-High accuracy	-Low robustness	No	GalaxyRefine	The dataset included 5000 latest known B-cell and 2000 T-cell (Medium size dataset)	No	CNN	Vaccine discovery

coughs, breaths, and speech, respectively. Coughs have the highest COVID-19 signature, which is followed by breath and speech. The findings demonstrated that using larger datasets without COVID-19 labels and implementing TL and extracting bottleneck features improve and reduce the standard deviation of the classifier AUCs, evaluated over the outer folds during nested cross-validation, indicating better broad generalization. They discovered that TL and bottleneck feature extraction could enhance COVID-19 cough, breath, and speech audio categorization, resulting in more consistent and accurate COVID-19 identification.

Also, Hayawi, Shahriar [121] presented a powerful ML-based system for detecting COVID-19 vaccination misinformation. They gathered and interpreted COVID-19 vaccination tweets and trained ML methods to detect vaccine misinformation. Medical specialists labeled over 15,000 tweets were labeled as disinformation or generic vaccination messages using reputable sources. Preprocessing the text of tweets is an important stage in the strategy for effective model training. External links, punctuation, and content in brackets were first deleted. All text was also changed to lower case. Stop words are commonly used terms like 'the,' 'and,' 'in,' and 'for.' Eliminating these low-information terms that give minimal contextual information could help minimize training difficulty. XGBoost, LSTM, and the BERT transformer model were the classification models investigated. The results indicated that BERT provided the best classification performance, with a 0.98 F1-score on the test set. Precision and recall were 0.97 and 0.98, respectively.

Besides, Lee, Kim [122] presented a DL approach to accelerate COVID-19 RT-PCR diagnosis. They created a DL model using the LSTM approach using a dataset of 5810 RT-PCR test cycles' fluorescence values. They employed the LSTM approach, which is commonly used with current RNNs for time series data to overcome the vanishing gradient problem. The RT-PCR findings, such as positive or negative, were employed as the output variable to train the models. From the trained model with the fluorescence value of the first RT-PCR cycle through the model trained with the fluorescence value of all 40 RT-PCR cycles, a total of 40 models were produced and verified. Among the DL designs created, the 21st model had an AUROC, sensitivity, and specificity of 84.55 percent, 93.33 percent, and 75.72 percent, respectively. The diagnostic efficiency of the 24th model was 91.27 percent AUROC, 90.00 percent sensitivity, and 92.54 percent specificity, respectively.

Szaszi, Hajdu [123] researched the relationship between demographic characteristics and one specific behavior, the avoidance of social gatherings. They did it in a broad sample of 41 nations, making the findings more

generalizable and applicable across cultures. They employed an ML approach that allowed them to discover the primary effects of demographic parameters and subtle patterns and examine country heterogeneity. Random forests are widely employed in ML for regression and classification issues because they are resilient to data nonlinearity, do not require data to be standardized, and prevent overfitting without considerable parameter adjustment. They also talked about how these findings may be applied to better public health strategies. They developed and ran random forest models for each nation based on the criteria outlined above. Even during the early stages of the pandemic, the models accurately predicted attendance of social events based on demographic characteristics, although there was significant cross-country variation ranging from 0.52 to 0.84.

Plus, Hu, Heidari [124] suggested a technique for detecting COVID-19 severity using blood gas analysis parameters and an extreme learning machine designed by Harris Hawks. Their approach, which involved fusion with the KELM classifier, extracts important characteristics from a blood sample collection. The suggested technique is fused with numerous classifiers to test its effectiveness, and it is proved that the method provided good results employing many of these classifiers. It is possible to obtain an accuracy of about 100 percent. The approach is then proven to work best on blood samples when fused with the KELM classifier. Following the selection of the best classifier, the approach is compared against others. It was discovered that the approach attained nearly 100% specificity, accuracy, sensitivity, and MCC. The approach consumes significantly less time than other feature selection methods.

Boussen, Cordier [125] developed a system that combines the breathing frequency (BF) and oxygen saturation (SpO₂) data to evaluate COVID-19 patients' severity and dynamic intubation demands as well as estimate their duration of stay. Even during initial and subsequent outbreaks of the pandemic in France, they monitored the BF and SpO₂ signals for confirmed COVID-19 patients were admitted to the ICU of a teaching hospital. For clustering, an unsupervised ML approach (the Gaussian mixture model) was employed to the patients' data. The algorithm's robustness was validated by comparing its output to actual intubation rates. They used the system to forecast intubation rates every hour, allowing them to do a severity assessment. For intubation identification, the approach exhibited an accuracy rate of 87.8 percent (AUC = 0.94, True Positive Rate 86.5 percent, True Negative Rate 90.9 percent). At 48 h before intubation, the S24 score of intubated patients was considerably greater than that of non-intubated patients. The MS24 score distinguished three severity levels associated with an increased probability of

intubation: green (3.4 percent), orange (37 percent), and red (37 percent). (77 percent). An MS24 score of 40 or above was significantly predictive of an ICU stay of more than 5 days, with an 81.0 percent accuracy rate (AUC = 0.87).

Attallah [126] studied the possibilities of diagnosing COVID-19 utilizing ECG data. It suggested ECG-BiCoNet, a pipeline based on the integration of DL approaches for the automated diagnosis of COVID-19 using ECG trace image data. Binary and multi-class classifications are available in the pipeline. The binary-class distinguishes between COVID-19 and normal individuals, whereas the multi-class distinguishes between normal, COVID-19, and additional cardiac abnormalities. From five CNNs, ECG-BiCoNet extracted two levels of in-depth features: pooling and fully connected layers. It then used the discrete wavelet transform to lower the dimension of the pooling features before merging them with fully linked features. After that, it investigated how combining these factors affects diagnostic accuracy. It was then investigated if feature selection might lower the number of features while improving classification performance. Eventually, it developed multiple classifier systems to investigate the prospect of improving accuracy even more. The findings showed that integrating features enhanced accuracy.

Also, Jeevan, Zacharias [127] devised and carried out a series of experiments comparing the masked face recognition accomplishments of CNN architectures currently available, as well as investigating possible changes in loss functions, architectures, and training techniques that could enable current techniques to fully extract and leverage the limited facial information available in a masked face. They compared the performance of existing CNN-based face recognition systems to databases solely constituted of masked faces, as opposed to previous standard assessments in which masked or occluded faces are uncommon. In comparison with traditional facial recognition, the study found that network depth had a greater influence on performance. According to their findings, the addition of masked faces to the training set resulted in significant performance increases. The study also found that certain parameter choices that are good for regular face recognition are not always good for masked face recognition. They developed new value recommendations for various parameters and settings based on empirical investigation.

Finally, Soltanian and Borna [128] looked at a simple DL model that could identify COVID-19 and Non-COVID cough information. The approach not only delivers state-of-the-art performance on the well-known and publicly available Virufy dataset, but it also proves to be a promising candidate for deployment in low-power devices ideal for hand-held apps. Their method is a quadratic extension of the ordinary convolutional layer, which, when

combined with the idea of kernel separation, resulted in an efficient and accurate layer that is particularly appealing in computationally constrained environments where resource constraints prevent the use of complex, highly deep networks. The suggested technique might be promising for implementation in handheld devices like mobile phones to distinguish cough noises and provide early Covid-19 alerts because of its high recall, accuracy, F-score, and relatively low order of computational complexity.

Table 11 summarizes the attributes of the hybrid applications utilized in COVID-19.

5 Results and comparisons

The integration of ML approaches in general, and DL in particular, with medicine and biology, is a hopeful move forward in technical improvement and disease treatment, resulting in less strain on medical staff during pandemics. Our survey reveals 37 unique applications that reflect this pattern, which is highly useful one by one during the COVID-19 epidemic, and the majority of them can aid in numerous sectors. It is hard to formulate understanding in various apps, including drug discovery, vaccine discovery, CT or Chest x-ray imaging, monitoring, tracking, and forecasting. Nonetheless, we believe that limiting datasets to input tasks to learning variations offers a consistent foundation for too many breakthroughs in ML to propagate across systems. We urge readers to investigate these significant aspects, which have recently piqued the interest of numerous academics from other professions. We noticed in our study that a large percentage of COVID-19-ML applications focus on novel combinations of learning tasks or the creation of new databases. Furthermore, ML has grown in use and acceptability for medical data processing, and it has produced extremely impressive results with CT imaging. So, there are several disadvantages to achieving a comparable degree of performance in CAD with big datasets. Plus, one of the most limiting constraints leading to the use of GAN techniques to produce fake generated datasets is the unavailability of big datasets and databases of high-quality images for training. The bulk of ML methods was trained on 2D images, which had varying quality and a lot of noise. CT and chest X-rays are generally 3D and so provide a new dimension, highlighting the importance of preprocessing approaches in this region. Because the efficacy of any ML method is highly dependent on the amount of the dataset. The absence of standard datasets, particularly in imaging datasets, is one of the most critical issues in ML and COVID-19 systems. As data expands, so does the need for bigger databases to guarantee that ML generates accurate results, especially in terms of classification accuracy. The easiest method to handle this

problem is to employ TL, which allows for effective preprocessing while avoiding acquisition issues.

5.1 Comparison metrics

Performance metrics are mathematical functions that provide constructive feedback and evaluate an ML/DL model's quality. Matthews correlation coefficient (MCC), recall, accuracy, precision, Confusion Matrix, and F1 Score are some of the metrics used to assess the ML-COVID-19's performance. As a result, one of the most significant measures is accuracy, which is defined as the proportion of accurately identified observed to expected observations. The ratio of true negatives to true positives is derived when all the values in a confusion matrix are combined. The total number of photographs is given by t , and the number of images successfully categorized is denoted by n in this equation [131].

$$A = \frac{n}{t} * 100 \quad (1)$$

Precision indicated by P is a metric used to determine our confidence level in predictions. The proportion of true positive predicted observations compared to all positively predicted observations. Also, S_{TP} represents the sum of all true positives, while A_{FP} represents all false positives [132].

$$P = \frac{S_{TP}}{S_{TP} + A_{FP}} * 100 \quad (2)$$

Recall which indicated by Re_{Call} is a measurement that tells us how many actual positive observations we can accurately predict. Also, A_{FN} denotes all false negatives in Eq. (3).

$$Re_{Call} = \frac{S_{TP}}{S_{TP} + A_{FN}} * 100 \quad (3)$$

Also, the F1 Score is an overall performance metric made up of precision and recall. The Harmonic mean of precision and recall represents it [133].

$$F1_{score} = \frac{2 * Re_{Call} * P}{Re_{Call} + P} * 100 \quad (4)$$

Plus, the confusion matrix is a measuring performance matrix that compares actual and predicted observations using true negatives, true positives, false negative, and false positives labels. The total correct predictions are the sum of true positives and true negatives, whereas the total incorrect predictions are the sum of false positives and false negatives [50].

$$\begin{vmatrix} S_{TP} & A_{FP} \\ A_{FN} & TN \end{vmatrix} \quad (5)$$

Table 11 Techniques, attributes, and characteristics of hybrid apps-COVID-19 applications

Authors	The basic objective	Pros	Limitations in study	Security method?	Simulation environments	Dataset and Size of Dataset	Using TL?	Mechanism	Application?
Cantini, Marozzo [119]	Proposing a model for suggesting a meaningful collection of COVID-19 hashtags for a given post	-High F1-score -High scalability	-Low robustness	No	Python	Online social networks (Large dataset)	No	MLP	COVID-19 discovery from hashtags and sentences from online social networks
Pahar, Klopfer [120]	Demonstrating that TL may be utilized to increase the performance and robustness of DNN classifiers for COVID-19 identification	-Cough with an AUC of 0.982, followed by breath with an AUC of 0.942, and speech with an AUC of 0.923 -Strong robustness	-Low scalability	No	Python	Coswara and ComParE dataset (Small dataset)	Yes	CNN + LSTM + Resnet50	Cough, breath, and speech detection
Hayawi, Shahrar [121]	Offering an ML-based COVID-19 vaccine misinformation detection framework	-High accuracy -High scalability	-High delay	No	NLTK library in Python	dataset from Twitter (Large size)	No	XGBoost, LSTM, and BERT transformer model	Detection of COVID-19 vaccination disinformation
Lee, Kim [122]	Using the LSTM approach to shorten the time required for RT-PCR in COVID-19 detection	-Moderate accuracy -High predictability -Low delay	-High delay -Low security	No	Python	The dataset from 5810 patients (medium size)	No	LSTM	Reduce the time required for RT-PCR in COVID-19
Szaszi, Hajdu [123]	Proposing an ML investigation of the association between demographics and social gathering attendance in 41 nations during the epidemic	-High predictability -Low delay	-Poor robustness	No	Not mentioned	The information was acquired from 112,136 people who participated in the survey from 175 countries	No	Random forests	An examination of the association between demography and social gathering participation
Hu, Heidari [124]	Using a strategy in conjunction with the KELM classifier to achieve the best results on blood samples	-Low delay -High accuracy	-High complexity	No	Python	UCI dataset (small)	No	Extreme learning machine	COVID-19 diagnostic assistance in blood specimens
Boussen, Cordier [125]	Recognizing intubation patterns with a Gaussian mixture model-clustering technique	-High clustering ability -High robustness	-Low scalability	No	Python	Local dataset	No	Gaussian mixture model	COVID-19 patient triage

Table 11 (continued)

Authors	The basic objective	Pros	Limitations in study	Security method?	Simulation environments	Dataset and Size of Dataset	Using TL?	Mechanism	Application?
Attallah [126]	Investigating the feasibility of using ECG trace pictures for COVID-19 diagnosis using CNN and TL	-High accuracy	-Low scalability -High energy consumption	No	Python	A total of 1937 ECG images from various classifications (Small size)	Yes	CNN	Analyzing ECG data to diagnose COVID-19
Jeevan, Zacharias [127]	Using the CNN model to provide masked face recognition	-Moderate accuracy -Low convergence time	-Low security	No	TensorFlow	CASIA-WebFace dataset (Medium size)	Yes	CNN	Masks on face recognition
Soltanian and Borna [128]	Providing a simple CNN for differentiating between COVID and Non-COVID	-High accuracy -Low complexity -High precision	-Low robustness -Low flexibility	No	Python sklearn library	Verify dataset (Small)	No	CNN	Recognition of COVID-19 based on cough sounds

Plus, true positives are predictions for a class that are both positive and correct. Also, true negatives are incorrect predictions but are negative to a class. False positives (Type 1 Error) are both positive and incorrect predictions for a class. False negatives (Type 2 Error) are negative predictions to a class but are wrong. Also, the MCC is a single value performance indicator that encapsulates the whole confusion matrix. It gives a more informative and true result than accuracy and F1 score in assessing classification issues. Only if the prediction findings are beneficial in all four confusion matrix areas generates a high score [131].

$$MCC = \frac{TN * S_{TP} - A_{FN} * A_{FP}}{\sqrt{(TN + A_{FP})(S_{TP} + A_{FN})(A_{FN} + TN)(S_{TP} + A_{FP})}} \tag{6}$$

5.2 DL and ML methods

Many ML and DL approaches have recently been used to create a viable solution against COVID-19; however, not all of them are mentioned in this paper. One of the most widely used methods is CNN, which is employed in almost every field of medicine and biology which is one of the most interesting techniques for experts. So, CNN is one of the main DL methods. The CNN is most commonly used for feature extraction and classification for identifying CT images in the case of COVID-19 and related backgrounds, as described in previous sections. The autoencoder approach is already a crucial topic for researchers in the COVID-19 realms, and it is one of the most important techniques, especially in predicting applications, and survival assessments. Another option is the RNN technique, which has long been a prominent method in medicine and is the most extensively used methodology for prediction and forecasting, as stated in Sect. 2. As indicated in the second part, the LSTM was applied in several fields of COVID-19, and the method is most typically used for forecasting. In the absence of large image datasets, GAN approaches were employed to build fake datasets, according to the report. We also observed that the SOM technique was utilized to examine the geographical and temporal distribution, which is highly beneficial in many industries. CNN is advantageous to image classification algorithms since it allows them to learn abstract characteristics and work with fewer parameters. The most prevalent issues include explosive gradients, class imbalance, and overfitting when utilizing CNN to train the system. Plus, as demonstrated in Sect. 5, LSTMs offer professionals a broad range of variables requiring no precise changes. The difficulty of updating each weight using LSTMs is lowered to O(1), comparable to Back Propagation over time, which

is one of the mechanism's advantages. Nevertheless, there are several drawbacks to LSTMs, such as the fact that they need more storage to learn and take much longer to train, that dropout is significantly more complicated to accomplish in LSTMs. The RNN technique, which is more appropriate for high accuracy applications with analytical capabilities than the CNN, is one of the most commonly utilized methods in research. As various studies have shown, this strategy improves the accuracy of a system. Exploding issues and gradient vanishing, trouble training an RNN, and incapacity to evaluate very lengthy sequences when using Relu are drawbacks of this method that occurred in numerous of the investigated applications.

5.3 Image processing methods and datasets

Furthermore, the databases for the medical imaging part are derived from two common imaging techniques: X-ray and CT. We detected several studied COVID-19 detection methods among medical imaging systems that use X-ray data and others that use CT samples. Many systems employed various sources, but only a small proportion of works used a single database to assess their work. The datasets used in studies had unique characteristics and attributes that distinguished them from other sources. Some research, for example, used smaller CT datasets with between 100 and 2000 images, which was a very unreliable dataset. Some research employed medium-sized datasets with between 2000 and 5000 photographs, while others used large datasets with over 5000 images. Large datasets provide reliable outcomes. During the evaluation, binary-class, four-class, and multi-class options are evaluated, with classifications such as healthy, pneumonia, TB, and COVID-19. TL or preprocessing approaches were utilized in almost all of the imaging methods, and both the pre-trained model and the bespoke DL architecture were considered. So many of the methods used CNN or versions of CNN in conjunction with other works for medical imaging diagnosis. Throughout the study, particular assessment measures, as specified in Sect. 6.1, are applied, and practically all of the works emphasize the accuracy metric. The datasets utilized in various imaging systems that have been examined are completely different. For example, one of the analyzed systems used a maximum of 11,413 CT images for the trials, and another used a maximum of 783 images for the investigation scenarios, resulting in totally distinct results in terms of accuracy and generalization ability. According to certain reports, one built system attained 100 percent precision in terms of performance. In datasets of small size, among the studied systems, the majority of the systems with more than 91 percent metrics achieved greater accuracy. The highest accuracy of 98.87 percent was attained using the TL model. Analysis indicated that

virtually all of the developed approaches used a distinct database of COVID-19 images with various input dimensions or resolution and that such approaches used the data normalization methods to produce images of the same size and quality from disparate sources. Like we showed in Sect. 5, CNN could evaluate vast volumes of data, and it is now frequently utilized in medical imaging. The primary benefit of CNN over many other approaches is that it detects important qualities without requiring human interaction and is computationally more efficient, as it employs parameter sharing and sophisticated convolution and pooling techniques. As we saw in GANs implementations, its primary job is to learn from a set of training data and generate new material with much the same qualities as the training data. It is indeed useful in a variety of domains, including creating data augmentation datasets in COVID-19 databases. The basic shortcoming of GAN is that it is unable to predict the accuracy of the assessed model.

5.4 Different issues in COVID-19 area

Feature extraction plays an important part in COVID-19 apps; these aspects of the ML system were used to apply traditional ML techniques, and it appears to be more effective in all COVID-19 apps. The SVM and RF approaches were used in the majority of circumstances. Furthermore, our envisaged methods do not use any type of cross-validation, which is exceptional and affects the dependability of the results. It can construct a high-performance test dataset since it is unclear how the test datasets are distinguished. This drastically exaggerates the results; hence, studies should use a cross-validation technique that evaluates the full dataset. Many research employs ML-based approaches, yet it is exceedingly challenging to construct reasonably specific, resilient, and trustworthy models. Likewise, since COVID-19 applications seem to be a popular area of research for diverse studies ranging from medical to engineering, a wealth of heterogeneous data, including results, comparisons, conclusions, and assessment, becomes more and more readily accessible. This sort of information is frequently acquired from a diversity of ways. This information should always be assessed to obtain information, which is one of the most difficult challenges that big data and ML applications may handle. There are several solutions to the aforementioned problem in big data and ML algorithms for data analysis or pattern recognition. However, while politicians and citizens struggle to absorb the restrictions of shutdown and social isolation, ML can develop more intelligent monitoring and tracking systems to follow patients or design such devices to aid physicians and patients. Further, changes in language and vocalization between nations make an already difficult procedure harder more difficult in

many applications, such as recognizing COVID-19 patients from their coughs. In this regard, whenever it relates to voice recognition or speech analysis, there are still many challenges that must be addressed. For instance, there was no publicly released labeled data from patients' voices for COVID-19 diagnostic investigations until recently, but now there is a public dataset in such areas. Because noises and reverberation are widespread in all of these areas, these datasets are acquired in unconstrained circumstances, such as using smartphones and online social networks, resulting in poor data quality and complicating illness diagnostics.

5.5 ML with COVID-19 systems in broad view

As we have shown in previous sections, ML-based techniques, especially DL models, are performed considering for assisting experts or doctors in pandemic early detection. Furthermore, it minimizes medical staff burden, enhances detection accuracy and efficiency, and provides fast reaction and appropriate therapy for COVID-19 patients while properly monitoring them. Although ML-based investigations are not widely employed, they might be highly useful in providing quick replies and useful information to medical professionals and policymakers. Nonetheless, due to a lack of large datasets and low data quality, there are still several hurdles to overcome while developing DL-based models. In this context, research groups are working around the clock to collect and extract more useful data from the databases that are now accessible. Furthermore, it was discovered that the majority of the DL models lacked cross-validation approaches that can be used to confirm that findings are generalizable to additional databases. According to this research, the results of investigations based on traditional ML-based models such as SVM, MLP, and RF revealed low performance when used alone. Mixed ML systems that used optimization approaches like particle swarm optimization [134] and evolutionary algorithms, on the other hand, fared well. Compared to typical ML-based models, all of these models and applications performed quite well. It is worth mentioning that certain COVID-19 patients could become viral transmitters while being asymptomatic. Even if PCR verifies the infection, COVID-19 patients with pneumonia signs could exhibit a pattern on CT scans or chest X-ray images which is only minimally typical for clinicians. It is indeed tough to spot those who are currently infected with COVID-19 yet are asymptomatic. The COVID-19 transmission rate is determined by the capacity to detect infected individuals with low false-negative rates consistently. Furthermore, by preventing unnecessary hospital quarantine, effective false-positive monitoring will relieve the burden on the healthcare system. Pneumonia or tuberculosis symptoms can be visualized using medical imaging. Image processing

technologies are intriguing in the disciplines of biomedicine and cancer diagnosis, especially lung cancer detection. It is well known that ML-based medical image diagnosis seems to have had a huge success. In detecting a range of illnesses, methods like CNN, federated learning, and RNN are beneficial. Even though some individuals were exposed to SARS-Cov-2, their chest CT pictures are normal. So, CT scans of the chest have a low negative predictive value and do not completely rule out the disease. A single ML diagnosis' specificity has also been challenged. ML-based systems for COVID-19 identification are predicted to combine chest imaging with clinical symptoms, contact records, and laboratory testing to meet healthcare demands.

5.6 Analysis of results

As we saw in Sect. 5, there were thirty-seven papers investigated, and we divided them into seven categories based on how they used ML-COVID-19 apps in the research, such as imaging methods, survival analysis, forecasting, economic and geographical challenges, monitoring methods, drug discovery, and hybrid apps. One of the drawbacks in these applications was a lack of comparative study between them and earlier apps, especially in the monitoring and drug research categories, which is acceptable given the pandemic's freshness. Because of their freshness, existing applications' weaknesses were difficult to extract. Another source of contention was the pseudocode and computational complexity of the suggested technique, which were not explicitly described. One of the key expectations of the suggested applications is a detailed description of the techniques used, which, however, virtually none of the methodologies, pseudocode utilized to provide. This section includes a detailed data analysis based on the outcomes of the techniques presented in several areas, such as databases, database size, applications, criteria employed, security, TL, and simulation environment. During our investigation, we discovered that Python is the most common tool for modeling and simulation, which is a highly tempting component for experts to employ in upcoming projects because it has a broad range of libraries that can be used in practically any area. Keras is the most popular library, as seen in Fig. 9, with a usage rate of 24.4%. Tensorflow takes the second position in simulation environments with 15.6 percent of the use. Pytorch and MATLAB are in the third position, with 13.3 percent of studies. Scikit-learn has 8.9%, Caffe has 6.7, and other tools handle the remainder. There are many simulation environments and settings that are used in these domains, such as Python, MATLAB, and so on. Additionally, Google Colab has somewhat countered the sophisticated equipment needed to undertake ML structures with GPUs. Joining such contexts in actual medical research labs

continues to be a big procedure. Figure 10 shows the status of the countries under research, with extensive studies continuing to focus on imaging methods, survival analysis, forecasting, economic and geographical difficulties, monitoring methods, drug discovery, and hybrid apps in China with ten papers, the USA with eight papers, India with six, Iran with five, and Canada with five. The greatest study has been done on these five countries.

In the context of COVID-19, Fig. 11 displays the many ML applications. We looked at COVID-19's ML applications in this epidemic in-depth and realized that 6 papers utilized imaging apps to identify patients' from images, with many of the benefits of these apps including attempting to help radiologists diagnose the disease with the minimum detecting errors and high accuracy. Patient monitoring is at second position with five articles. Such applications can assist medical personnel in lowering stress and providing better care to patients. Forecasting and survival analyses tied for third place with four studies; such applications may estimate future COVID-19 needs in terms of mortality forecasting or predicting the number of hospital beds necessary. Furthermore, the study of COVID-19's economic impact during a pandemic has received inadequate emphasis.

Because of the difficulty of implementing ML methods to deal with epidemics due to their complexity and a lack of sufficient datasets, TL approaches may be useful in this situation. An ML model, like TL, may be trained using huge databases, and learned features might then be applied. Only 8 out of 37 studies examined attempted to employ TL for diverse purposes in which TL conducts task adaptation necessary for investigating, diagnosing, and managing. When it comes to novel information technologies like cloud computing, edge computing, fog computing, IoT, IoD, or IoV platforms, the authors could use them to make medical data processing easier. If ML collaborates and

forms a model with these novel technologies, many of the applications listed in Sect. 5 could be made easier. One of the most significant aspects of patient privacy is the protection of the records since patient data are kept secret for legal and ethical reasons. As a consequence, while designing a privacy system for medical challenges, maximum attention needs to be given to protect data through the use of safety systems like blockchain. During our review of the articles, we discovered that none of them used privacy methods to keep safe patient data. Table 12 and Fig. 12 demonstrate that the lowest parameter examined in the articles is security with zero papers. The accuracy was the most targeted in studies, with 44.6 percent, whereas the flexibility came in second with 12.5 percent. Robustness is ranked fourth with 10.7 percent, and scalability is third with 8.9 percent. Moreover, the problem with studies is that a large number of articles focus on only one or two objective parameters and ignore the rest almost entirely. Fig. 13 depicts the environments utilized in the publications.

During data analysis, we discovered that the IoT and cloud environment are the most commonly used in articles for processing and surveillance reasons, contributing to 25% of all articles. Additionally, hybrid systems used in conjunction with merging two or more different settings are ranked second in the papers with 21.9 percent. Further, edge computing is the third most regularly utilized option in these publications, accounting for 9.4 percent of all utilization. Furthermore, fog computing is placed fourth with a share of 6 percent. In recent years, we have seen wearable devices known as the Internet of behaviors (IoB) that incorporate IoT systems and are expected to influence wellness greatly. Pattern recognition is considered to be a beneficial means of obtaining valuable data when IoB/IoT is combined with big data. Information produced by IoB devices may directly impact human behavior, which may

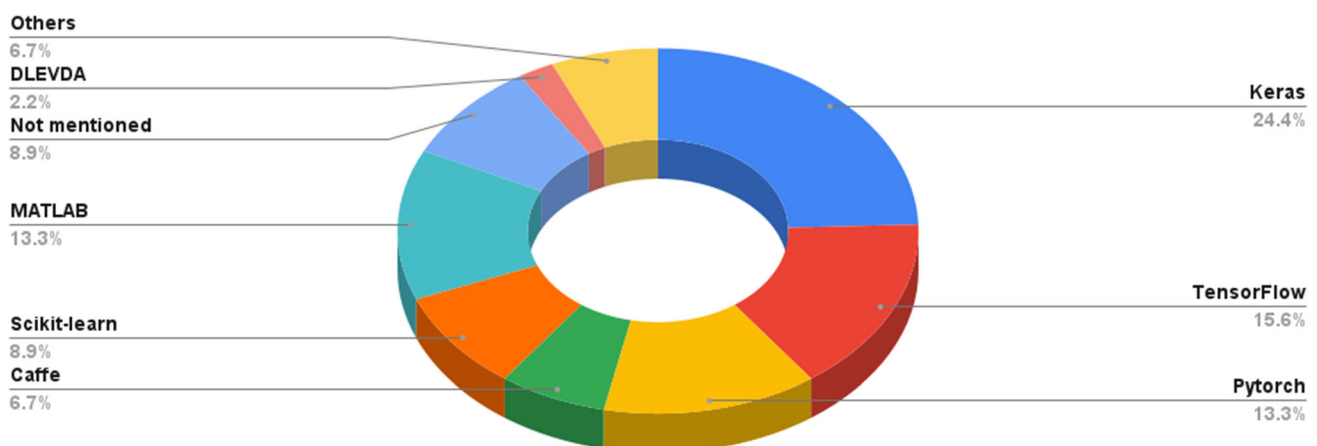


Fig. 9 In DL-COVID-19 applications, the spread of simulation environments

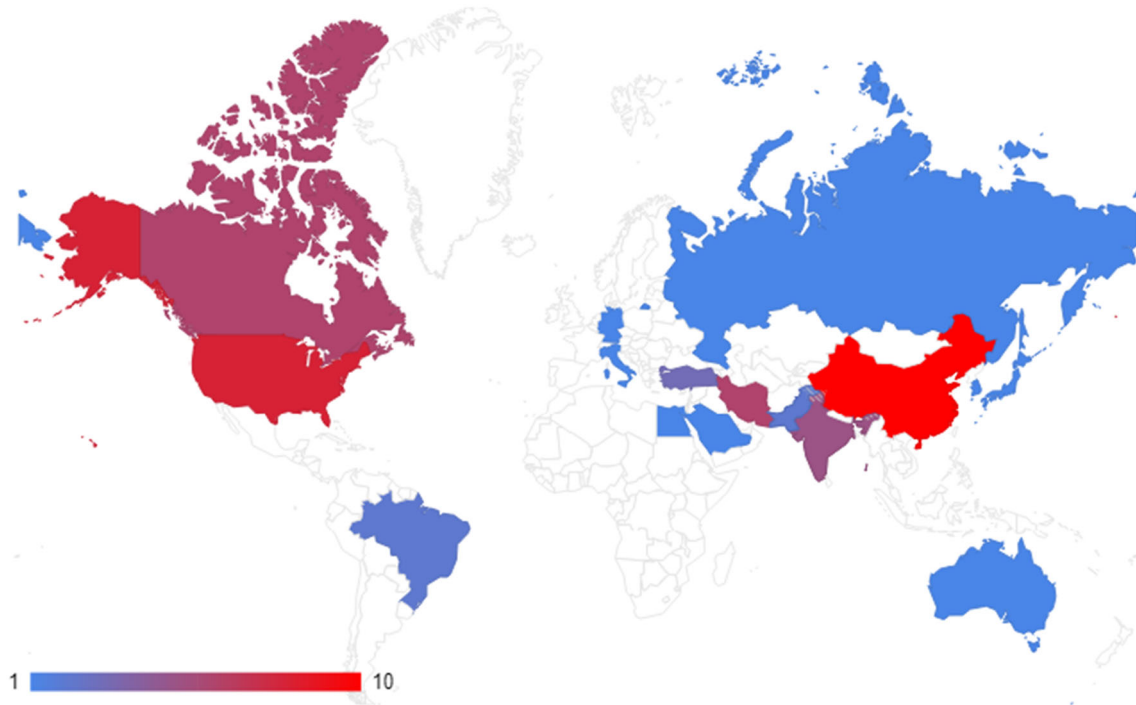
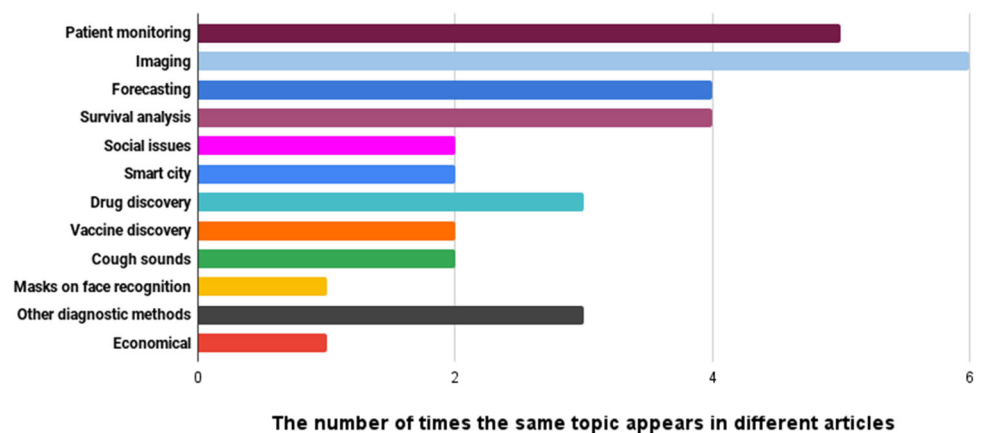


Fig. 10 The map illustrates the distribution of nations when it comes to reviewed articles

Fig. 11 An in-depth look at COVID-19-ML applications



be studied using data to make better recommendations. Large volumes of data collected from smartwatches, smartphones, and other sources could be forwarded to integrated assessment, stored on computing systems for learning, and attempting to find statistical properties.

Also, Fig. 14 depicts the popularity of ML/DL techniques in the region under consideration. According to the findings, CNN is by far the most widely employed approach in papers, contributing to 31.9 percent of all publications used in practically all applications. RF and LSTM are ranked in the second position at 10.6 percent. Furthermore, autoencoders are rated third with 8.5 percent.

Likewise, with a 2.1 percent use frequency, SOM and DBN are the least used approaches in these articles.

The outcomes of this research indicate that the efficiency of the tactics differs substantially. Because of the evaluation limitations, the investigation has various restrictions that were emphasized in the study. This study is important for scholars and practitioners who aim to pursue ML-COVID-19 applications. The study unearthed a plethora of information on ML’s potential and existing achievements in the pandemic’s battle, and we hope that this paper will aid investigators in developing more improved methodologies.

Table 12 in the studies used parameters

Type	Authors	Latency	Accuracy	Convergence time	Complexity	Safety and privacy	Consumption of Energy	Scalability	Robustness	Flexibility
Imaging	Basu, Sheikh [93]	•	✓	•	•	•	•	•	•	✓
	Scarpiniti, Ahrabi [94]	•	✓	•	•	•	•	•	•	•
	Hu, Shen [95]	•	✓	•	✓	•	•	•	•	•
	Muhammad, Hoque [96]	•	✓	•	•	•	•	•	•	✓
	Gayathri, Abraham [97]	•	✓	•	•	•	✓	•	•	•
Forecasting	Zhan, Zheng [98]	•	✓	•	•	•	•	•	•	•
	Zhan, Zheng [99]	•	✓	•	•	•	•	•	✓	✓
	Absar, Uddin [100]	•	✓	•	•	•	•	•	•	✓
	Chiu, Hwang [101]	•	✓	•	✓	•	•	•	•	•
	Asgharnezhad, Shamsi [102]	•	✓	•	•	•	•	•	•	•
Monitoring	Dong, Qiao [103]	•	✓	•	•	•	•	•	✓	•
	Jaber, Alameri [104]	•	✓	•	•	•	✓	•	•	•
	Zhang, Zhu [105]	•	✓	•	•	•	•	•	•	•
	Zhang, Liu [106]	•	✓	•	•	•	•	•	✓	•
	Castiglione, Umer [107]	•	✓	•	•	•	•	•	•	•
Survival Analysis	Schwab, Mehrjou [108]	•	•	•	•	•	•	✓	•	•
	Uemura, Näppi [109]	•	•	•	•	•	•	•	•	•
	Sinha and Rathi [110]	•	✓	•	•	•	•	✓	•	•
	Näppi, Uemura [111]	•	✓	✓	•	•	•	•	•	•
Economic, etc	Almars, Almaliki [112]	•	✓	•	•	•	•	•	•	•
	Grekousis, Feng [113]	•	•	✓	•	•	✓	•	•	•
	Motuzienė, Bielskus [114]	•	•	•	•	•	•	•	•	✓
	Li, Zheng [75]	✓	✓	•	•	•	•	•	•	•
Drugs Issues	Zhang, Wei [115]	•	•	•	•	•	•	✓	•	•
	Amilpur and Bhukya [116]	✓	•	•	•	•	•	•	•	•
	Deepthi, Jereesh [117]	•	✓	•	•	•	•	•	•	•
	Yang, Bogdan [118]	•	✓	•	•	•	•	•	•	•
Hybri	Cantini, Marozzo [119]	•	✓	•	•	•	•	•	•	✓
	Pahar, Klopper [120]	•	✓	•	•	•	•	•	✓	•
	Hayawi, Shahriar [121]	•	✓	•	•	•	•	✓	•	•
	Lee, Kim [122]	✓	✓	•	•	•	•	•	•	•
	Szaszi, Hajdu [123]	✓	•	✓	•	•	•	✓	•	•
	Boussen, Cordier [125]	•	✓	•	•	•	•	•	✓	✓
	Attallah [126]	✓	✓	•	•	•	•	•	•	•
	Jeevan, Zacharias [127]	•	✓	✓	•	•	•	•	•	•
Soltanian and Borna [128]	•	✓	•	•	•	•	•	✓	•	

6 Open issues

ML and its applications have immense promise for combating and diagnosing the COVID-19 outbreak and monitoring, tracking, and regulating its spread. Along with the various benefits and potential outcomes, there have been several issues and limitations regarding the deployment of ML that should be investigated and addressed. Additionally, a constructive perspective has previously been offered depending on such hurdles and limits.

6.1 Standard data

There are several obstacles in this sector, and one of the most significant is the lack of standard datasets, particularly in imaging datasets and tracking databases. The use of these prediction technologies necessitates a large quantity of data. Furthermore, only the adoption of standard data could assure that both systems are reliable and effective in combating pandemics. Various applications of ML are proposed in the literature examined in Sect. 5, but they

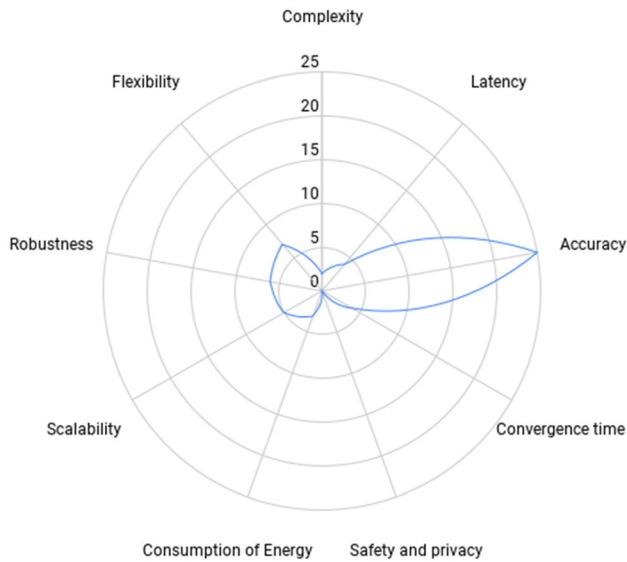


Fig. 12 Targeted parameters are depicted on a radar chart

have not been evaluated using similar datasets. Because diverse samples are used, it is impossible to determine which model is superior for detecting COVID-19. Furthermore, given the lack of publicly available standard datasets, the majority of data sources were created by scholars and researchers by combining data from multiple sources and systems. A joint effort between many well-known institutions or the generation of new real-world datasets from the revised COVID-19 data might address this problem. Imaging datasets, personal information, and GPS data are all examples of data sources.

6.2 Security and safety

The key issues that must be handled are personal security and privacy. A large quantity of data is required to train the systems to implement ML for COVID-19 applications. These data comprise X-ray or CT scans images, travel history, and regular activities in the setting of the COVID-19 pandemic. This information can then be used to train

algorithms that can assist in viral predictions, diagnosis,

Fig. 13 The number of settings is employed in the publications that have been reviewed

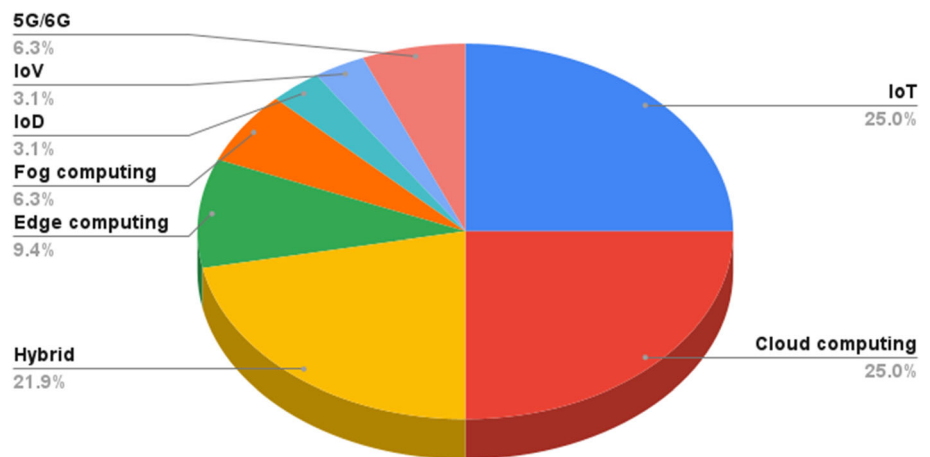
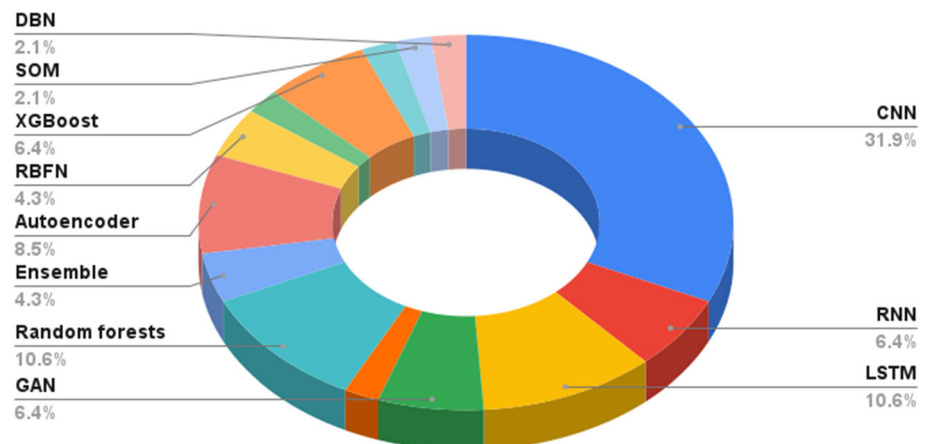


Fig. 14 Use of ML methods in studies



management, and vaccine development. Nevertheless, no one wants to share their data with others until it is formally declared or requested due to privacy and security concerns.

6.3 Cross-validation

Furthermore, given the lack of publicly available standard datasets, the majority of data sources were created by scholars and researchers by combining data from multiple sources and systems. A joint effort between many well-known institutions or the generation of new real-world datasets from the revised COVID-19 data might address this problem. Imaging datasets, personal information, and GPS data are all examples of data sources.

6.4 Utilization of sophisticated methods

The most commonly utilized data sources in this research were medical imaging systems. Yet, several additional sophisticated ways of treating COVID-19 are rarely publicized, including MRI and ultrasound scans. Such sophisticated techniques are tried-and-true techniques that outperform X-ray and CT scans pictures. As a result, these techniques must be addressed in COVID-19 predictive modeling, which is mostly dependent on the quality and consistency of the database used to train the models.

6.5 Differences in the pattern of pandemic data

The information accessible from open sources from throughout the world exhibits a complicated structure with fluctuation. So, the validity and dependability of the COVID-19 outbreak forecasting methods confront several difficulties and obstacles. Furthermore, various hospitals and laboratories have varying sample collecting, testing protocols, and findings generating requirements. As a result of this fluctuation in the dataset, the predictability of the predicting system based on an unreliable dataset is called into doubt. Also, applying some new learnings ways based on semi-supervised [135] or small sample learning [136] can boost the speed of the algorithm.

6.6 Similarities in symptoms

The similarity in their symptoms makes distinguishing COVID-19 infection from other related viral diseases challenging. So, identifying acceptable ML-based models to screen, identify, diagnose, and categorize COVID-19 contaminated patients with the best possible results is a difficult challenge that must be tackled. Though numerous research publications on the use of ML in combating the COVID-19 outbreak have indeed been released, there is still a gap in the investigation, and various research issues

may be generated from this research that needs to be solved. Furthermore, medical images frequently confront limited collections and costly labeling costs. Several investigators have offered numerous strategies, but there are still unanswered questions.

6.7 Miscellaneous

Additional advancements in the application of ML in the fight against the COVID-19 outbreak can indeed be developed and handled by examining the research gaps and possibilities discussed in this research: To enable better COVID-19 detection and treatment, ML methods must be improved to increase the accuracy and reliability of data analytics. Combining ML with other new approaches may provide efficient and productive COVID-19 alternatives. For example, Oracle cloud computing data processing capabilities are used to produce a vaccine to combat the COVID-19 outbreak. The majority of ML-based systems do not include cross-validation techniques, which must be used to confirm that the results are generalizable to additional databases. Ultrasound scans and MRI are sophisticated procedures that have been demonstrated to be more effective than CT scans and X-ray images. As a result, these techniques should be addressed in COVID-19 predictive modeling, which is mostly dependent on the level and standardized dataset used to train the models.

7 Conclusion and limitation

This work offered a systematic evaluation of ML-COVID-19 management applications before discussing this paper's goal. We examined the merits and drawbacks of certain systematic and examined studies regarding COVID-19-related ML. Imaging methods, survival analysis, forecasting, economic and geographical issues, monitoring methods, drug development, and hybrid apps were examined as well as the merits and downsides of each of the applications and their approaches. According to an evaluation of publications based on qualitative characteristics, most publications are rated based on flexibility, reaction time, accuracy, energy consumption, scalability, precision, and other qualitative features. In the meantime, some characteristics, including complexity and security, go unused. The reviewed applications are evaluated and implemented using a variety of tools or libraries, with Python contributing for 74% of the effort. The survey found that 20.4 percent of applications categorize imaging techniques. Monitoring earns 16% of the total. In addition, 14 percent of support goes to prediction and forecasting apps. In the fight against the COVID-19 epidemic, we hope that our research will serve as a useful reference for future research

on ML and medical applications. Utilizing ML to manage pandemics takes a huge amount of effort, coordination, and collaboration between industry and academia in terms of prospective discoveries. Furthermore, ML has been recognized as a wonderful tool for developing intelligent ways to combat the epidemic. So, ML is used to degrade pandemics in a variety of methods, including patient monitoring, imaging methods, diagnosis and therapy, drug discovery, and tracking viral propagation. Authors anticipate that perhaps the study findings could aid in advancing ML applications in practical situations.

We ran across a few challenges while working on the research, one of which was the lack of availability of non-English publications. Another drawback of our research is that some of the studies we looked at had large gaps in their explanations of their utilized datasets. Another issue we encountered was that papers frequently did not compare to other works on a variety of specialized subjects, such as tracking or monitoring. An additional issue discovered was a lack of availability to the dozens of papers produced by certain publishers.

Declarations

Conflict of interest There is no conflict of interest.

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