CASTING OF COVID 19 AND OTHER COMMUNICABLE AILMENTS USING MACHINE LEARNING AND DEEP LEARNING

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Abstract: Background:

In order to combat the impacts of new coronavirus illness, this study presents a thorough evaluation of the use of Artificial Intelligence (AI) in the form of Machine Learning (ML) and Deep Learning (DL) approaches (COVID-19).

Purpose and Approach: The purpose of this project is to conduct a scoping review on AI for COVID-19 according to the principles outlined by the recommended reporting items for systematic reviews and meta-analyses (PRISMA) statement. Relevant papers published between January 1, 2020 and March 27, 2021 were retrieved via a literature search. Full-text reviews were conducted on 440 publications using the keywords AI, COVID-19, ML, predicting, DL, X-ray, and CT to narrow the scope from the original set of 4050 research papers from reputable publishers (CT). In the end, this paper's result synthesis included 52 publications. Predicting the total number of confirmed and fatal cases was the primary focus of this study, during which several ML regression techniques were examined. Second, a thorough study of ML's application to COVID-19 patient classification was conducted. Finally, we examined medical imaging datasets by looking at the total number of pictures, the percentage of positive samples, and the number of classes present. Preprocessing, segmentation, and feature extraction, along with their respective roles in the diagnostic process, were also discussed. As a fourth step, the efficacy of DL approaches on various datasets was assessed by comparing the performance outcomes of various research articles.

Results:

The results demonstrate that DenseNet-201 has the highest accuracy in identifying CT scan pictures, whereas ResNet-18 and DenseNet-169 show great classification accuracy for X-ray images. This shows that ML and DL may help in predicting, screening, and identifying COVID-19 for researchers and medical practitioners.

Conclusion:

Finally, this overview presents future research options for employing AI in controlling COVID-

19, highlighting current problems such as legislation, noisy data, data privacy, and a lack of trustworthy huge datasets.

Keywords: Artificial intelligence, COVID-19, coronavirus, computed tomography, deep learning, machine learning, transfer learning, forecasting, X-ray, ultrasound imaging.

INTRODUCTION

Coronavirus illness, caused by a new coronavirus known as severe acute respiratory syndrome coronavirus 2 (SARs-CoV-2), has been lethal in certain areas of the world since December 2019.

(COVID-19) [1-3]. Although COVID-19 was first identified in Wuhan, China, it has now spread around the globe [4]. More individuals have been harmed by SARs-CoV-2 than by other coronaviruses like severe acute respiratory syndrome coronavirus (SARS-CoV; 774 deaths) and Middle East respiratory syndrome coronavirus (MERS-CoV; 858 deaths) combined [5-7]. COVID-19 is compared to previous pandemics in human history in Table 1. With so many people infected with COVID-19 [8], healthcare systems in many countries are straining to keep up, and the need for intensive care units (ICUs) is rising faster than they can be built.

Table 1. Some pandemics in human history.

Pandemics	Number of Deaths (in Millions)
Russian Flu	1
Spanish Flu	40-50
Asian Flu	1.1
Third Plague	12
Acquired immunodeficiency syndrome (AIDS)	25-35
Swine Flu	0.2
COVID-19 (27 March 2021)	2.78

Predicting the COVID-19 pandemic is crucial because of the virus's high transmission capability and possible damage. In example, accurate illness forecasts allow countries to take the necessary precautions right now. However, there are several obstacles to overcome in the process of illness prediction.

There is a lack of accuracy in the available datasets, period, and strictness of the lockdown, and keeping track of infected people is difficult, there is no definitive treatment option, the odds of death are higher for the elderly or people with other serious diseases, and the incubation period is two weeks. Therefore, it is essential to make reliable predictions about COVID-19.

In recent times, there has been a lot of focus on controlling COVID-19. A significant obstacle is the ever-increasing and ever-changing amount of data associated with COVID-19, which makes it hard to design effective solutions. The use of AI in this context may aid in the control of the COVID-19 pandemic. Artificial intelligence (AI) and its subsets, Machine Learning (ML) and Deep Learning (DL) techniques, may streamline mobilization while conserving medical, logistical, human, and granular temporal resources. It might be mentioned that ML and DL \sare commonly employed in a variety of medical systems for recognizing patterns in data samples. Machine learning and deep learning are able to swiftly learn from fresh data and find patterns in massive datasets. In addition, AI can guarantee accuracy in forecasting the propagation of the virus, categorizing individuals who may be infected, and making a data-driven diagnosis of COVID-19. Big data and AI may be used together to model processes. This is useful for crisis management, treatment planning, and optimizing diagnostic procedures like medical imaging and image processing, all of which are overseen by policymakers. Artificial intelligence (AI)-based automated COVID-19 detection systems may use a remote video diagnostic method in conjunction with robots to make an initial diagnosis. Intelligent robots may aid in medical care without the need for human intervention. In order to stop the spread of disease from patients to radiologists and other medical workers, automated picture categorization is essential. Using AI, we can filter out irrelevant scientific material and spot fraudulent data with greater ease. Monitoring and tracking COVID-19 patients using AI-based systems may aid in preventing the spread of the virus. Differentiating between COVID-19 and non-COPD pneumonia will be a breeze with the enhanced DL models. While AI has great potential, it has not yet been put to good use in the healthcare sector's battle against COVID-19. Experts in AI can bridge the gap between traditional medicine and AI-based therapies. Many studies have employed DL inside AI to create tools to aid in the diagnosis of COVID-19. Images from Computed Tomography (CT) scans and X-rays are also taken into account here. While some help systems use specialized DL networks, others rely on pre-trained transfer learning models. COVID-19 has also been diagnosed, prognosed, predicted, and projected using AI. AI is supported in its efforts to find treatments for COVID-19 by a number of complementary disciplines. These include computer vision, the IoT, smartphone technology, and big data.

Several well-organized reports on the topic of AI for COVID-19 have been published. However, there is a lack of adequate justification in the available literature for the efficacy of the various features of the datasets and the performance of the various DL algorithms. The history of the virus, its transmission dynamics, its pathogenesis, and its clinical features were all examined in one research [9]. Possible strategies for overcoming the condition were discussed in the research, including methods for prevention and therapy [9]. The use of big data and AI in mitigating COVID-19 effects was also explored in another research [10]. Researchers utilized these methods to pinpoint the affected population, monitor the disease's progress, create effective treatments and diagnostic tools, and much more [10]. AI has been used to combat COVID-19, as discussed in a review article [11]. In the context of artificial intelligence, many DL techniques like as Generative Adversarial Networks (GAN), Extreme Learning Machines (ELM), and Long/Short Term Memories (LSTM) were presented [11]. Methods from the machine learning and deep learning communities were used to create the final product [12]. These methods included random forest, Support Vector Machine (SVM), linear and logistic regression, ensemble eXtreme Gradient Boosting (XGBoost), and Convolutional Neural Network (CNN). A literature review on deep learning, deep transfer learning, and edge computing was examined [13]. This literature study looked at the use of DL techniques on multi-modal datasets in the field of radiology. None of the aforementioned researches use ML and DL to track the transmission of COVID-19, identify the virus, and diagnose its presence.

However, the most effective ML and DL algorithms for COVID-19 diagnosis have not been determined. Furthermore, there is a need to analyze the most recent results since new research in ML and DL are being conducted at a rapid rate. Consequently, a work is required that surveys the various COVID-19 datasets and the most recent ML and DL methods that are appropriate for COVID-19 diagnosis.

This study presents an in-depth analysis of the use of ML and DL in the context of the 2019 California Rotavirus Information Dissemination Conference (COVID-19). This article reviews the research done on numerous key questions that need to be answered before AI can be successfully used to COVID-19.

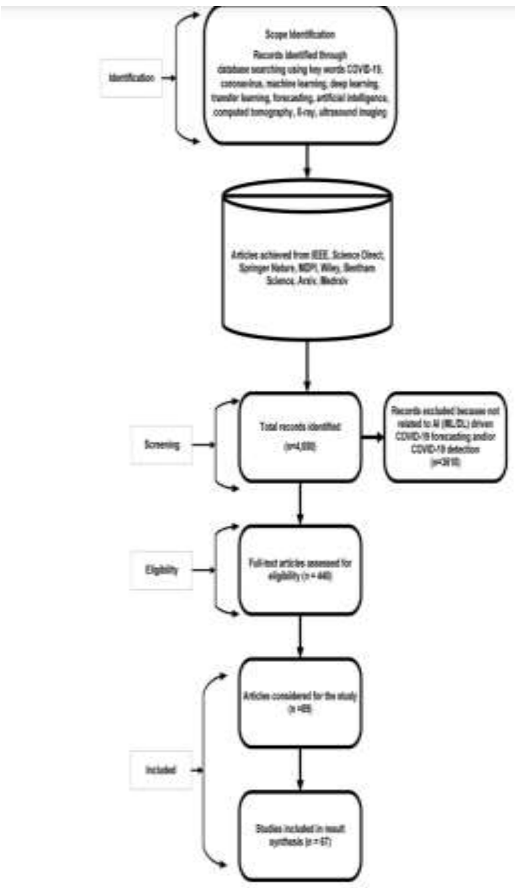

Fig. (1). Systematic review through PRISMA guideline

• Since ML and DL theory and practice are evolving rapidly, it is important to understand where the fields are right now.

It's important to learn about ML's potential for resolving COVID-19 predictions and patient detection.

• It is important to understand DL's potential for making accurate diagnoses and resolving COVID-19-related issues.

There are several forms of learning in the realm of AI. Using supervised learning, we can optimize a loss function by taking into account both predicted labels and ground truth, but this process involves human annotation. For clustering purposes, unsupervised learning is employed to uncover the underlying structure of the data. Predicted labels and ground truth are used in self-supervised learning, which is computationally based rather than annotated by hand. For semi-supervised learning, ground truth includes both annotated and unannotated data. Multitask learning is used to optimize simultaneous loss functions while avoiding conflicting gradients induced by individual losses, while transfer learning is used to train from a previously learned model.

Heuristically labelled data may be used for weakly-supervised learning instead of meticulously annotated data. Multi-modal learning, on the other hand, handles several data kinds all at once, such as visuals, texts, and even electronic health records (e-health data). In the end, reinforcement learning takes action.

so as to increase one's chances of success in a certain circumstance.

Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) criteria were used to conduct the literature review shown in Fig. (1). PRISMA and its expanded form, PRISMA scoping reviews, were used to compile this review's methodology (PRIS MA-ScR). In Fig. (1), we have a graphical representation of the original set of records considered, as well as the records that were subsequently included in the analysis and those that were subsequently removed. All relevant research articles were found via the literature search. From January 1, 2020, to March 26, 2021, a whole calendar year was taken into account. Records written in languages other than English were disregarded in favor of the written word written in the English language. Patient, Intervention, Comparison, and Outcome (PICO) criteria were used to assess the records for inclusion. There was an initial screening for studies that met all four of these criteria. In this context, "patients" refer to those with COVID-19, "intervention" refers to the use of AI in screening or diagnosis, "comparator" refers to "conventional techniques," and "result" refers to a successful automated diagnosis. Two Boolean operators, AND and OR, were used to zero in on the most important terms. COVID-19, coronavirus, artificial intelligence, machine learning, deep learning, forecasting, computed tomography, transfer learning, X-ray, and ultrasound imaging were some of the terms that were looked up. Records for ML regression on COVID-19 spread prediction, ML patient classification, and DL imaging diagnosis were prioritized. Article title, abstract, and keywords were all taken into account throughout the search process. There were three types of papers that were excluded from our analysis: those that focused on fundamental research, epidemiology, and clinical aspects of COVID-19. Following that, content addressing similar ideas was merged or deleted. The next step was information extraction and synthesis, which included the gathering of information such as the study's goals and methodology, the datasets that were made accessible, the types of artificial intelligence used (both ML and DL), and the outcomes of the performance evaluations.

A total of 4,050 AI-related articles from high-quality sources including IEEE, Elsevier (Science Direct), Springer Nature, MDPI, Wiley, Bentham Science, Arxiv, and Medriav were combed through for this COVID-19 study. The Appendix demonstrates the article's search syntax. We manually filtered out 3610 items from the original 4050 materials since they weren't relevant to our study. What this means is that they did not meet the necessary requirements for the implementation of AI on COVID-19. The remaining 440 publications were subjected to a full-text evaluation, from which 89 were ultimately included in the analysis and referenced in the report. Although there were 89 publications initially analysed, only 67 were included in the final analysis because they included performance measurements, COVID-19 datasets, and the performance outcomes of regression or classification algorithms in the context of using ML or DL on COVID-19. That's right; 67 of these studies have mentioned one of the following problems: Diagnostics of COVID-19 in X-ray, CT, and ultrasound images using DL, as well as ML for forecasting and predicting COVID-19 cases, characteristics of various modalities for COVID-19 diagnosis, segmentation techniques for COVID-19 diagnosis, performance metrics utilized in AI on COVID-19.

This literature review provides an overview of the ML regression techniques used to forecast the disease's spread.

classification systems for patients with COVID-19. Additionally, DL techniques that are useful in the diagnosis of COVID-19 are described. The information in this publication should help researchers dig further into the topic.

The remaining sections of this report are structured as follows. The machine learning classifiers for making these distinctions are discussed in Section 2.

Patients with COVID-19 and the ML regressors used to forecast future cases, fatalities, etc. In Section 3, we cover the various DL approaches that may be used to identify COVID-19. The steps involved in identifying COVID-19 are detailed in Section 4. In Section 5, we explore a variety of performance indicators. Section 6 details the results of a comparison between several DL algorithms and their performance on COVID-19 diagnoses.

In Section 7, we talk about some of the difficulties that come with AI-based fixes. The report wraps off with some last thoughts and recommendations.

ML's Use in Addressing COVID-19

Here, we'll start by talking about regressors in machine learning that may predict confirmed cases, fatalities, and other outcomes etc., of COVID-19, and then goes on to detail the ML classifiers used to categorize people with COVID-19.

ML Regressors for Predicting the Spread of COVID-19 2.1

In this part, we summarize the studies that have used ML to predict the spread of COVID-19. Works on ML for predicting and forecasting COVID-19 instances are shown in Table 2.

Recently, scientists' curiosity in the coronavirus's likely future trajectory has spiked. Several studies [15-23] have investigated the use of ML methods to various facets of COVID-19. The authors of [15] performed a model-fitting study on the confirmed cases of COVID-19 using three distinct mathematical models. In [10], logistic, Bertalanffy, and Gompertz models were used. Fitting quality was measured by the coefficient of determination (R2) for both previously confirmed instances (C) and newly confirmed cases (N) in the study of [15]. In addition, the aforementioned three models were used to estimate the toll that COVID-19 would take. The quality of the fit of the total number of fatalities was measured using the R2 (DC) metric. Those three models performed better in later phases of the pandemic in terms of their ability to forecast the course of the disease.

The logistic model outperformed the other two in predicting confirmed cases for the Chinese city of Wuhan [15]. The research presented in [17] relied on a dataset housed in the Johns Hopkins University repository. The data set included three tables: one for each confirmed case, one for each death case, and one for each recovered case. Province/state, country/region, latest update, confirmed cases, death cases, and recovered cases were the six variables used to categorize each table. Cases for the following 10 days were predicted using a variety of ML and DL methods in the aforementioned research [17], including Support Vector Regression (SVR), Polynomial Regression (PR), Deep Neural Network (DNN), and Long/Short Term Memory (LSTM). The accuracy of the algorithms in making predictions about the COVID-19 instances was measured using the Root Mean Square Error (RMSE) score.

Table 2. ML for forecasting and prediction COVID-19 cases.

Refs.	Adopted Technique	Prediction Result	Objectives	Dataset
[15]	Logistic model	In Mainland China, R^2(C): 0.9993, R^2(N): 0.9183; In Wuhan, R^2(C): 0.9991, R^2(N): 0.8124.	Prediction of epidemic results of COVID-19.	-
	Gompertz model	In Mainland China, R^2(C): 0.9954, R^2(N): 0.3372; In Wuhan, R^2(C): 0.999, R^2(N): 0.813.		-
	Bertalanffy model	In Mainland China, R^2(C): 0.9993, R^2(N): 0.895; In Wuhan, R^2(C): 0.9999, R^2(N): 0.8085		-
	Logistic model	In Mainland China, R^2(DC): 0.9995; In Wuhan, R^2(DC): 0.9993	Predicting the COVID-19 death toll.	-
	Gompertz model	In Mainland China, R^2(DC): 0.9997; In Wuhan, R^2(DC): 0.9996		-
	Bertalanffy model	In Mainland China, R^2(DC): 0.9991; In Wuhan, R^2(DC): 0.9995		-
[17]	SVR	RMSE for confirmed cases: 27456.47, RMSE for death cases: 1360.47, RMSE for recovered cases: 16762.15	Prediction of future reachability (next 10 days) of the COVID-2019 across the nations.	[16]
[17]	PR	RMSE for confirmed cases: 455.92, RMSE for death cases: 117.94, RMSE for recovered cases: 809.71		[16]
[18]	ARIMA model of order (1,0,3)	Forecast value of COVID-19 incidence at 11 February, 2020: 2070.66, at 12 February, 2020: 2418.47.	Evaluate the incidence of new confirmed cases of COVID-2019 in the next 2 days.	[16]
[19]	ARIMA model of order (0,1,0)	RMSE (Prediction) for USA: 3963.44, RMSE (Prediction) for Italy: 1259.64, RMSE (Prediction) for China: 39.65	-	[16]
[20]	ARIMA model of order (1,1,0) for confirmed and death cases	R^2(Confirmed Case- Italy): 0.761, R^2(Death Case- Italy): 0.927	Forecasting number of daily confirmed cases and deaths.	[21]
	ARIMA model of order (2,1,0) for confirmed cases and (0,1,0) for death cases	R^2(Confirmed Case- Turkey): 0.817, R^2(Death Case- Turkey): 0.714		
	ARIMA model of order (2,1,1) for confirmed cases and (1,1,2) for death cases	R^2(Confirmed Case- Spain): 0.950, R^2(Death Case- Spain): 0.958		
[22]	ARIMA model of order (2,1,2) for Italy, (2,1,0) for China, (1,0,0) for South Korea, (2,3,0) for Iran.	Forecast for 17 days (from 5 March until 21th of March) with 95% confidence interval.	Forecast of confirmed cases of COVID-19 for 17 days.	[16]
[23]	ARIMA(1,2,0) for confirmed cases, and ARIMA(3,2,0) for recovered cases	For confirmed cases, ME=17.84, RMSE=514.74, MAE=324.46, MPE=4.26, MAPE=6.25. For recovered cases, ME=90.80, RMSE=186.85, MAE=132.27, MPE=10.57, MAPE=15.60	-	[28]
[24]	Logistic Model	Error degrees of freedom: 52. Root Mean Squared Error: 1.9e+03. R-Squared: 0.997, Adjusted R-Squared 0.997. F-statistic vs. zero model: 1.61e+04, p-value=4.02e-77	Estimated logistic model parameters for China (data up to 11 Mar 2020).	[29]
[27]	Hybrid Wavelet ARIMA Model	MAE($\times 10^3$): 0.464 (Italy), 0.136 (Spain), 1.341 (USA). RMSE($\times 10^3$): 0.630 (Italy), 0.178 (Spain), 1.974 (USA). R-Squared: 0.9985 (Italy), 0.9996 (Spain), 0.9888 (USA).	Prediction of death cases in the next one-month one-month beyond the data sample end date.	[30]
	ARIMA Model	MAE($\times 10^3$): 1.245 (Italy), 0.693 (Spain), 2.827 (USA). RMSE($\times 10^3$): 1.600 (Italy), 0.884 (Spain), 4.183 (USA). R-Squared: 0.9944 (Italy), 0.9089 (Spain), 0.9806 (USA).		

According to [18], the authors used an ARIMA model to predict future COVID-19 case counts. The forecast for the next two days was derived using this model. In [19], a time series model was used to foretell the COVID-19 pandemic. The time span was 60 days, from 22 January 2020 until 21 March 2020. The statistical research in [19] drew attention to the varying epidemiological phases across nations, allowing for more tailored responses to the pandemic. For the time period spanning 2 February 2020 through 27 March 2020, the number of confirmed cases and death cases in Italy, Spain, and Turkey were modeled using the ARIMA model (see [20]). According to [20], the authors predicted a decline in confirmed cases in Spain and Italy in July, and in Turkey in September. Similarly, the ARIMA model was employed in Stata version 12 in the research in [22] to make predictions about the total number of confirmed cases across nations. All information from 22 January 2020 to 1 March 2020 was analyzed. The authors of [22] noted that the number of confirmed cases was fluctuating in Iran and Italy, while remaining rather consistent in China and Thailand. In [23], a simple 'R' model automated forecasting software (AUTOARIMA) was used. In order to estimate how many people would be infected with COVID-19 and how many would recover following a 2-month quarantine, information from Italian patients was gathered. Margin of Error, Root Mean Square Error, Mean Absolute Error, Mean Posterior Estimate, Median Absolute Prediction Error, and Mean Absolute Scaled Error were among the metrics used (MASE). Using the model, we were able to forecast the confirmed instances with a 93.75% success rate and the recovered patients with an 84.4% success rate. The model showed that locking doors and staying inside may significantly cut down on the spread of the infection. Lockdown and isolation, according to the models based on the Italian data set, may reduce confirmed cases by around 35% and increase recovered cases by about 66% [23].

Table 3. Some existing ML methods/classifier with its results.

Ref.	Method	Validation Method	Data Types	Sample Size	No. of Patients	Results
[31]	Classification (Multilayer perceptron)	Holdout	Clinical	5644 samples with 111 attributes. The processed dataset has 1093 records and 61 attributes.	5644	Accuracy: 93.13%, Recall: 93%, Precision: 93%
[32]	Random forest	Cross-validation	Demographics, Clinical	Total 253 samples from 169 patients. Clinical blood test of 49 patients where 24 Covid-19 patients.	253, 169, 49, 24	Accuracy: 95.95%, Specificity: 96.95%
[33]	Support Vector Machine	Holdout	Clinical, Demographics, laboratory features	336 COVID-19 patients where 26 critical cases.	336, 220	Accuracy: 77.5%, AUC: 99%, Specificity: 78.4%
[34]	XGBoost classifier	Cross-validation	Blood samples of 75 features, Clinical	485 samples.	485	Accuracy: 90%

In order to estimate the total number of confirmed cases in China and South Korea [24], the authors used a logistic model. They claim that the worst of the COVID-19 pandemic in China occurred on February 8, 2020, while in South Korea it peaked on March 1, 2020 [24]. According to the research, if a logistic curve shows any kind of systematic departure, it means the illness is spreading uncontrollably. If the epidemic entered a second stage, for instance, the curve would deviate [24]. COVID-19 in India was predicted using ARIMA and Holt's second-order exponential smoothing approach [25]. To do this, we fit the models using data from confirmed cases across 28 Indian states between 30 January 2020 and 21 April 2020. Using these models, we forecasted the number of confirmed and fatal cases over the following 10 days, beginning on April 22, 2020 [25]. Predictions for COVID-19 in Brazil were made using a variety of models [26]. ARIMA, CUBIST, RANDOM FOREST, RIDGE, and SUPPORT VECTOR MULTIPLIER REGRESSION models were used (SVR). CUBIST, RF, RIDGE, and SVR were used as base-learners, while Gaussian processes were used as a meta-learner in stacking-ensemble learning models. In order to do this, we used the confirmed cases across 10 states in Brazil from the commencement of the infection up to April 18, 2020 to fit the models. From April 19, 2020 [26], the models were used to forecast confirmed and fatality cases over the following 1, 3, or 6 days. To evaluate the relative performance of the models, many measures, including the Improvement Percentage index (IP), Mean Absolute Percentage Error (MAE), and Symmetric Mean Absolute Percentage Error (sMAPE), were taken into account. Predictions of COVID-19 cases in Brazil were most accurate using SVR and stacking ensemble approaches [26]. Both a hybrid model and an ARIMA model were used to simulate fatality occurrences in the research presented in [27]. There were 82 days of observations in the dataset evaluated in [27], beginning on 21 January 2020 and ending on 11 April 2020. The United States, Italy, Spain, Great Britain, and France were the five nations considered.

Sixty-six of the 82 days were used as training data, while the other sixteen were used for testing. Mean absolute error (MAE), root-mean-squared-error (RMSE), and R-squared value were used to assess the models' performance.

Subsection 2.2: ML Classifiers for the COVID-19

Patients with COVID-19 may be categorized in a dataset using machine learning (ML) classifiers. The COVID-19 ML classifiers and accompanying research may be shown in Table 3.

A dataset of 5644 individuals with suspected cases of COVID-19 was donated by the Hospital Israelita Albert Einstein in Brazil and was utilized in this study [31] to train a variety of ML classification algorithms. Patients with COVID-19 were effectively diagnosed using Multilayer Perceptron (MLP), XGBoost, and logistic regression, with a 91% accuracy rate [31]. An further research [32] used ML classifiers on 253 samples from China's Lanzhou Pulmonary Hospital and Gansu Provincial Hospital. We gathered a total of 49 characteristics from 169 possible patients to include in our 253 samples [32]. The results showed that 105 of the samples from 27 individuals tested positive for COVID-19.

The remaining samples were analysed for lung cancer, pneumonia, and TB, and were all deemed negative. Using 11 characteristics, the Random Forest Algorithm [[32]] was able to accurately identify COVID-19 patients from the whole sample set. Three hundred and thirty-six patients with COVID-19 were used to test the efficacy of a support vector algorithm for critical case classification[33]. Accuracy of 77.50 percent and an AUC of 99 percent were attained [33] when the holdout approach was employed to divide the samples for training and testing. In a further investigation [34], the XGBoost algorithm was used to analyse 75 characteristics from 485 COVID-19 patient samples. Classifying COVID-19 patients with 90% accuracy was obtained using cross-validation to separate the training and testing samples [34].

Table 4. Distribution of studies for various medical imaging modalities.

Image Types	Reference Studies	No. of Studies
X-ray	[35, 38-53]	17
CT	[36, 37, 54-69]	18
Ultrasound	[70, 71]	2
Multimodalities	[72, 73]	2

Table 5. Summary of features, applications, and limitations of different modalities for COVID-19 diagnosis.

Imaging Modalities	Important Features and Applications	Limitations	Refs.
X-ray	Data augmentation is used	Not appropriate for multiclass problems.	[50]
	DL (neural networks) is considered	Only a limited number of X-ray images are taken into consideration.	[43, 45]
	SqueezeNet is used	Not validated for images except for X-ray images.	[35]
	Using data augmentation with auxiliary classifier GAN	1. Small datasets are considered, and image quality is not good.	[48]
CT	DL is considered	The method is not validated on a clinical study.	[60]
	Using a CAD-based scheme	This is only suitable as an adjuvant method for CT scan images.	[59]
	MADE algorithm is used for optimizing the attributes of DBM algorithm	MADE-DBM is validated on chest CT datasets.	[36]
	A residual learning strategy is used to screen CT images	Not appropriate for detecting patients with early COVID-19 infection.	[62]
	Applying Inf-Net to chest CT images.	Accuracy is slightly lower when non-infected regions of the images are taken into consideration. An additional classifier to classify infected and non-infected regions is used to improve the overall accuracy.	[37]
Ultrasound	Using DL for analyzing LUS images.	The dataset has some limitations, for example, not being very large, collected from only a few hospitals in Italy, and the ultrasound was applied to only critically ill patients. There was also poor image quality in some cases.	[70]
Multimodalities	COVID-19 diagnosis using both X-ray and CT images	The combined use of X-ray and CT scan images may not be efficient in real-time practical applications.	[72]
	Combination of ML, DL and data augmentation for COVID-19 detection	Feasible only for limited datasets.	[73]

Third, Differential Diagnosis Techniques for Covivirus Type 19

COVID-19 diagnosis suffers from a lack of available medical imaging. There have not been any conclusive studies on the use of DL techniques on X-ray or CT scan images for COVID-19 diagnosis. The human body is not the only thing that X-rays may pass through. Thus, X-rays may be used to capture pictures of the human body's internal anatomy. Through the use of computers and a special kind of spinning X-ray technology, a CT scan may produce cross-sectional pictures of the body. Compared to an equivalent X-ray picture, CT imaging may provide more details about the item being examined. Sound waves are used to create ultrasound pictures that may be seen as live video. Additionally, some studies use a combination of imaging modalities in order to identify COVID-19 patients. In Table 4, we can see how many studies have been conducted on various methods of COVID-19 detection. It is clear that X-ray and CT imaging research has received the greatest attention, whereas ultrasound and mixed modalities have received very little.

Research works on DL's use with various photos are included in Table 5. Table 5 also includes descriptions of the study's key aspects, its most important applications, and its most significant limitations. Table 5 demonstrates the use of a deep BayesSqueezNet on X-ray images [35]. Memetic Adaptive Differential Evolution (MADE) was developed as an algorithm in a separate research. The parameters of a Deep Boltzmann Machine (DBM) model may be optimized with the use of this MADE method [36]. In [37], a deep network (Inf-Net) was utilized to segment CT images for signs of lung infection.

STAGES OF COVID-19 DIAGNOSTIC PROCESS

The steps involved in making a data-driven diagnosis of COVID-19 are outlined in this section. The five main levels of operation for COVID-19 diagnostics are shown in Fig. (2). First, doctors or the telemedicine system examines the input information to choose the best imaging method to use. Then, diagnostic imaging methods such as X-ray, CT scan, or ultrasound are performed. The data subsequently goes through some kind of processing and optimization based on AI. Afterwards, estimates are made and findings are given. Some more procedures are included in the total diagnosis. Pre-processing, segmentation, feature selection, classification, and detection are the individual phases. In this section, we will examine the research done on the preprocessing and segmentation phases.

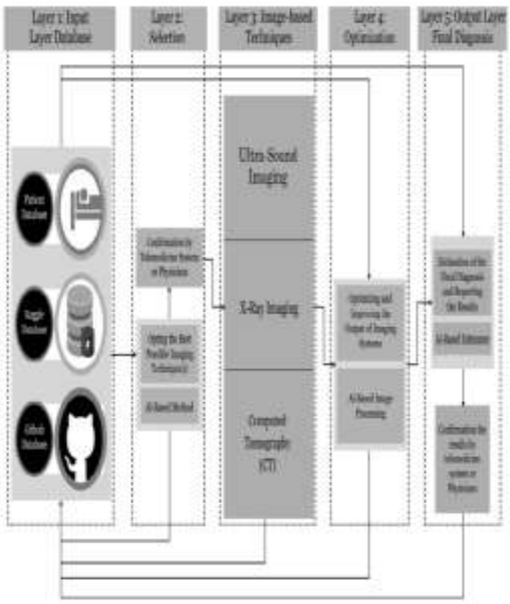

Fig. (2). Framework for COVID-19 diagnosis. (A higher resolution / colour version of this figure is available in the electronic copy of the article).

The preliminary procedures are examined first. In [63], 2D UNet was employed for CT image preprocessing. When dealing with an insufficient number of CT scans, we employed online data augmentation to prevent overfitting.

Random affine transformation and color jittering were two methods used to enhance the data [54]. Composite GAN model CovidGAN [48] also used data augmentation. In such scenario, COVID-19 and baseline CXR classes were synthesized with the help of CovidGAN. Rotational and translational data enhancement techniques are also documented [49]. A research [73] detailed how simple picture processing may be used to improve data. Scaling, rotating across a range of angles, and flipping were among the simple operations used in the quick transformation [73]. In the instance of 618 CT images, ROI was extracted using Visual Basic.NET (VB-net) [74]. Finally, COVID-19 and Influenza A viral pneumonia were separated from healthy individuals using CNN. Images' regions of interest were extracted using a threshold method, and then COVID-19 and viral pneumonia were classified using a modified inception network technique [75]. Using VB-Net, we were able to extract the ROI from pictures to combine with a random forest classifier to distinguish between COVID-19 and regular pneumonia [76].

As a further step, picture segmentation is examined. Several published studies have employed segmentation for COVID-19 diagnosis. It was found that many DCNN-based segmentation techniques [77-82] were effective. Semantic segmentation using a fully convolutional neural network (FCN) was described [77], while other versions of FCN were the topic of other investigations [78–81]. One research project [83] improved upon V-Net and employed 3D U-Net [84] for segmentation. It's worth noting that U-Net was built on top of CNN and tweaked to improve segmentation for COVID-19 diagnosis. Automated detection of COVID-19 pneumonia lesions in imaging has been reported by several researchers [85]. Additionally, U-Net [78] was used in another research [57] to segment lungs from CT images for the purpose of classifying COVID-19 pneumonia and conventional pneumonia. The U-Net technique was used for segmentation in [86] and [87]. UNet++ [88] was also used in another investigation. The aforementioned UNet++ was also put to use in the areas of detection [56] and segmentation [55]. When using V-Net [84] and bottleneck [90] for segmentation, a VB-Net [89] was created. However, noise in the annotations was not taken into account in any of the aforementioned segmentation tests.

You may find a summary of the various segmentation techniques utilized in the diagnosis of COVID-19 in Table 6. Based on Table 6, it seems that traditional U-Net [54, 57, 69, 86, 87, 91], UNet++ [55, 56], and VB-Net [89] are the most widely-used segmentation techniques in the literature. Compared to computed tomography (CT) pictures, X-rays are both cheaper and more accessible. The difficulty of X-ray image segmentation is higher than that of CT images. As a result of the projection of the ribs onto soft tissue in 2D X-ray imaging, image contrast is lost. Therefore, in the context of COVID-19 diagnosis, no technique exists for segmenting X-ray pictures. COVID-19 detection may be similar to pneumonia detection using Attenuation-U-Net, as shown in a previous work [94].

Table 6. Summary of segmentation methods for COVID-19 diagnosis.

Modality	Target ROI	Method	Remarks	Refs.
CT	Lung	U-Net	The method is weekly supervised with pseudo labels	[54]
	Lesion	UNet++	-	[55]
	Lesion and Lung	UNet++	Joint classification and segmentation	[56]
	Lesion	U-Net	-	[57]
	Lesion and Lung lobes	U-Net	-	[69]
	Lesion and Lung	U-Net	-	[86]
	Lung, Lesion and Lung lobes	U-Net	-	[87]
	Lung, Lesion, Lung lobes and Lung segments	VB-Net	Human-in-the-loop	[89]
	Lesion and lung	Commercial Software U-Net	Combination of 3D and 2D methods	[91]
	Lesion, Lung Bronchus and Trachea	Commercial Software	-	[92]
	Lesion	Threshold-based region growing	-	[93]

Table 7. Performance metrics used in each selected primary study.

Performance Matrix	Refs.	Number of Studies
Accuracy	[35, 36, 38, 41, 43-55, 59-60, 62-65, 67, 68, 70, 72, 99, 100]	30
Recall	[35-38, 41, 45-53, 55, 57-60, 62, 64, 65, 67, 68, 70, 72, 73, 99, 100]	31
Specificity	[35, 37, 38, 43-46, 48-53, 55, 57, 59, 62, 64, 67, 68, 73, 99, 100]	23
Precision	[35, 36, 38, 41, 44-51, 54, 55, 59-60, 62-65, 68, 70, 72, 73, 99]	26
Negative predictive value (NPV)	[54, 55, 59, 63, 68, 73]	6
F-measure	[35, 36, 38, 41, 45-51, 58, 60, 62, 65, 67, 68, 70, 72, 73, 99]	23
AUC	[36, 44, 47, 50, 51, 57-60, 62-65, 67, 100]	15
Matthews correlation coefficient (MCC)	[35, 47, 58, 73]	4
Mean absolute error (MAE)	[57]	1

INDICATORS OF PERFORMANCE

COVID-19 was categorized and diagnosed using a variety of different measures. The research on COVID-10 diagnosis use a variety of performance indicators, some of which are included in Table 7. Here are only a few examples: [95-98] accuracy, recall, precision, specificity, negative value predictor, F-measure, etc. Below, you'll find an expression of each of them. Classifying normal cases as normal and abnormal ones as abnormal with a high degree of accuracy. The recall or sensitivity of a test measures how many COVID-19-positive patients out of a certain number of suspects were really diagnosed as having the virus. Precision in ruling out abnormal situations is measured by a concept called "specificity." The percentage of correctly identified positive instances relative to the total number of expected positive cases is known as the precision or positive predictive value. How well negative samples are classified is measured by the negative predictive value. Fmeasure balances accuracy and memory perfectly. The area under the curve (AUC) is a metric used to evaluate the efficacy of positive/negative case categorization. The MAE is the standard deviation of the absolute differences between the predicted and observed values.

Sixth, a comparative study of DL for COVID-19

In this piece, we examine the studies that have investigated using DL to identify COVID-19. X-ray and CT scan pictures are evaluated for this purpose.

Several studies [38-42, 54-59, 101] examined the effectiveness of DL methods in identifying COVID-19 cases. The various DL approaches for detecting COVID-19 in X-ray pictures are listed in Table 8. Both the Kaggle Chest X-ray dataset [102] and the dataset [103] were utilized in the work cited in [38]. Fifty individuals with abnormal X-rays and fifty healthy controls were used in the tests. According to the research [38], the highest results in terms of classification accuracy were obtained using the residual neural network 50 (ResNet50) technique, whereas InceptionV3 and Inception-ResNetV2 obtained values of 97% and 87%, respectively. Using X-ray scans from patients suspected of having COVID-19, Wang et al. [39] trained a model using a deep convolutional neural network and found it to be 83.50% accurate. There were a combined 5941 chest X-ray pictures from 45 COVID-19 patients, 660 individuals with viral pneumonia, 931 people with bacterial pneumonia, and 1203 healthy persons in the two internet datasets [104] utilized. Using a ResNet-based model, Zhang et al. [42] analyzed X-ray images. There were two goals in using the ResNet model [42]. The primary objective was to sort potential patients into healthy (disease-free) and unhealthy (illness-indicative) categories. The second goal was to identify unusual patterns in the classification of possible patients. Sensitivity was found to be 96%, specificity to be 70.7%, and area under the curve (AUC) to be 95.2% for data sets consisting of 70 patients and 1008 normal (non-patient) individuals, respectively [42]. Based on what has been said above, it is clear that ResNet18 achieves the maximum accuracy of 100%, followed by DenseNet-169 at 99.70%.

Table 8. DL for diagnosis of COVID-19 for X-ray images.

Refs.	Dataset	Methods	Accuracy	Recall
[38]	[105, 106]	ResNet 50	98%	96%
		Inception V3	97%	94%
		Inception ResNetV2	87%	84%
[39]	[105, 107, 108]	COVID-Net network architecture	92.4%	87.1%
[40]	[103]	Bayesian ResNet50V2	92.9%	-
[41]	[103, 105]	AlexNet for 4 classes	66.67%	66.67%
		AlexNet for 3 classes	85.19%	85.19%
		AlexNet for 2 classes	100%	85.19%
		GoogleNet for 4 classes	80.56%	80.56%
		GoogleNet for 3 classes	81.48%	81.48%
		GoogleNet for 2 classes	100%	100%
		ResNet18 for 4 classes	69.46%	69.46%
		ResNet18 for 3 classes	81.48%	81.48%
		ResNet18 for 2 classes	100%	100%
[42]	Collected from 6 institutions	Deep anomaly detection model	-	96%
[43]	[103, 109]	DarkCovidNet (multi-class classification task)	87.02%	85.35%
		DarkCovidNet (binary classification task)	98.08%	95.13%
[44]	[110], Custom	CovXNet (COVID-19/ Normal)	97.4%	97.8%
		Residual Network (COVID-19/ Normal)	92.1%	93.4%
		CovXNet (COVID-19/ Bacterial Pneumonia)	94.7%	94.4%
[45]	[105, 106]	ConvNet	89.6%	-
[99]	[105, 111]	MobileNetV2	96.54%	97.87%
		SqueezeNet	97.81%	100%
		SqueezeNet & MobileNetV2	99.27%	100%
[35]	[103, 110]	Bayes-SqueezeNet	98.3%	-
[48]	[105, 107, 112]	Actual data (CNN-AD)	85%	65%
		Actual data & Synthetic augmentation (CNN-SA)	95%	90%
[49]	[102, 105, 108, 113-115]	DenseNet201	99.70%	99.70%

The use of DL techniques on CT scans for COVID-19 diagnosis is shown in Table 9. Work in [55] used a UNet++-based segmentation model on chest CT scan images from a dataset including 51 patients and 55 healthy persons.

Lesions associated with COVID-19 were segmented using this approach, setting the stage for a definitive patient or non-patient classification. There was a 95.2 percent success rate, a 100 percent sensitivity rate, and a 93.6 percent specificity rate for the model. A second dataset consisting of 16 individuals with viral pneumonia and 11 healthy controls was correctly classified by this algorithm [55]. The CT scan images of 1136 patients, 723 of whom had COVID-19, were fed into a hybrid UNet++ and ResNet50 classification model [56]. CT scan images from 4356 patients (1296 with COVID-19, 1735 with community-acquired pneumonia, and 1325 without pneumonia) were analyzed using a ResNet50 classification model [57].

ResNet50 was used to categorize 2D slices with common weights in this research [57]. The model was able to obtain 90% sensitivity, 96% specificity, and 96% AUC.

Table 9. DL for diagnosis of COVID-19 for CT images.

Refs.	Dataset	Methods	Accuracy	Recall
[54]	Custom	2D UNet and DeCoVNet	90.8%	90.7%
[55]	Dataset from Renmin Hospital of Wuhan University	UNet++	95.2%	100%
[56]	-	UNet and CNN	-	97.4%
[57]	[116]	ResNet 50	-	90%
[58]	[91]	ResNet 50	86%	-
[59]	CovNet[117, 118]	AlexNet	Training: 82.60% Validation: 78.92%	Training: 93.38%, Validation: 89.21%
		ResNet 50	Training: 98.28% Validation: 94.12%	Training: 96.56% Validation: 90.28%
[60]	[119, 120]	VGG16	99.20%	99.30%
		VGG19	98.85%	99.50%
		Xception	99.60%	99.80%
		ResNet 50	99.20%	99.60%
		ResNet 50V2	99.35%	99.30%
		DenseNet121	99.45%	99.60%
		Inception V3	99.60%	99.60%
		Inception ResNet V2	99.65%	99.70%
		DenseNet 169	99.80%	99.80%
[72]	[102, 105, 106]	VGG16	91%	94%
		VGG19	90%	94%
		Xception	96%	98%
		ResNet 50	98%	96%
		ResNet 50V2	96%	96%
		DenseNet121	99%	98%
		Inception V3	89%	99%
		Inception ResNet V2	94%	96%
[64]	Custom	weakly supervised deep learning	96.2%	94.5%
[65]	From hospitals in Shandong Province	ADSD-MIL	94.3±0.7%	90.5±0.5%
[36]	Custom	MADE-DBM (For multilevel classification)	96.19%	96.23%

The dataset included 88 individuals with COVID-19, 101 people with bacterial pneumonia, and 86 healthy persons; this data was used to train a deep learning (DL) model called DeepPneumonia [58].

Slices of full lungs were created from CT scan images in this work [58], and these slices were utilized as input for the DeepPneumonia algorithm. When separating patients with COVID-19 from those without, the model obtained an accuracy of 86%, while when separating COVID-19 patients from healthy individuals, it reached an accuracy of 94%. It was found that DenseNet169 had a recall and accuracy of 99.80 and 99.80, respectively [60]. Multiple properties were extracted from X-ray pictures using a model called CovXNET [44]. For this purpose, CovXNET was applied to two datasets, where it demonstrated superior performance than competing models. There were a total of 5856 X-ray pictures in a dataset obtained from the Guangzhou Medical Center in China, with 1583 representing healthy individuals with no signs of infection, 1493 representing conventional pneumonia, and 2780 representing bacterial pneumonia [110].

The second group of X-ray pictures was gathered from patients at Sylhet Medical College in Bangladesh. The MobileNetV2 model [99] was implemented in mobile devices. Those with COVID-19 were classified with 100% accuracy, while patients with pneumonia were classified with 99.27% accuracy [99]. The authors created their own dataset and used transfer learning, picture augmentation, and CNN on it [49]. For example, there were 423 COVID-19 patients, 1845 patients with viral pneumonia, and 1579 healthy controls in the dataset. When utilized to distinguish between normal, viral pneumonia, and COVID-19 cases, the accuracy values were 99.7% and 97.9%, respectively [49].

The above discussion reveals that DenseNet169 achieved an accuracy of 99.80%, with Inception ResNet v2 coming in as a close second at 99.65%. Table 10 provides a summary of the top results from Tables 6, 7, 8, and 9. Table 10 details the segmentation techniques and performance measures used in these researches, in addition to the top models for X-ray and CT imaging. Table 10 shows that when employing GAN segmentation to classify X-ray images, the research [41] gets the highest values of 100% for accuracy, precision, recall, and F1 score. However, utilizing BConvLSTM, U-Net, and GAN segmentations to classify CT images into binary classes, the research in [60] obtains the highest accuracy, precision, recall, and F1 score values of 99.80%.

Accuracy scores of several DL classifiers on X-ray and CT scan pictures are shown in Fig. 3. The greatest accuracy value for X-ray pictures is shown to be 100%, while the best accuracy value for CT scans is shown to be 99.80%.

OBSTACLES FACED BY INTELLIGENCE ASSISTANT SOLUTIONS

The difficulties of utilizing ML and DL for COVID-19 prediction, detection, and management are highlighted here.

Multiple measures were made by many nations during the COVID-19 pandemic to combat the spread of the virus.

Table 10. Overall summary of the DL in COVID-19 diagnosis.

Refs.	Images of Used Dataset	Imaging Modalities	Segmentation	Adapted Model	Precision	Recall	F1 Score	Accuracy
[41]	COVID-19: 69, Normal: 79, Bacterial Pneumonia: 79, Viral Pneumonia: 79	X-ray	GAN	ResNet 18	100	100	100	100%
[60]	COVID-19: 1252, Healthy: 1668	CT	BConvLSTM U-Net and GAN	DenseNet 169	99.80	99.80	99.80	99.80%
[49]	COVID-19: 423, Normal: 1579, Viral Pneumonia: 1485	X-ray	-	DenseNet 201	99.70	99.70	99.70	99.70%
[60]	COVID-19: 1252, Healthy (Normal): 1668	CT	BConvLSTM U-Net and GAN	Inception ResNet V2	99.60	99.70	99.65	99.65%
[60]	COVID-19: 1252, Healthy (Normal): 1668	CT	BConvLSTM U-Net and GAN	Inception V3	99.60	99.60	99.60	99.60%
[60]	COVID-19: 1252, Healthy (Normal): 1668	CT	BConvLSTM U-Net and GAN	Xception	99.40	99.80	99.60	99.60%
[39]	COVID-19: 295, Normal: 65, Pneumonia: 98	X-ray	Fuzzy Color and Stacking	SqueezeNet & MobileNetV2	98.69	98.33	98.58	98.27%

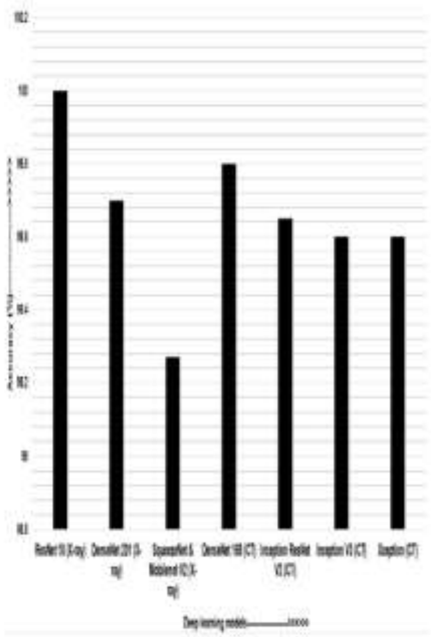

Fig. (3). Bar diagram of the accuracy values of different classifiers for X-ray and CT images. (A higher resolution / colour version of this figure is available in the electronic copy of the article).

Some of these included isolating themselves from friends and family. Developing legislation was crucial in giving residents, business owners, medical professionals, scientists, and others with instructions to stop the spread of the virus. While ML and DL techniques show promise in COVID-19 management, the strategies' efficacy is data-dependent. Disease prediction is complicated by the fact that some datasets have missing or incorrect labels. Hand-labeling X-ray or CT scans is not only inefficient but also expensive. As a result, techniques like self-supervised DL and transfer learning might be helpful. Most DL approaches based on AI need substantial amounts of high-quality data, especially for model training.

Training data sample analysis is a resource-intensive process that demands fast computers.

It is also important to have medical professionals label data samples. However, substantial, credible, and well-balanced datasets on COVID-19 are hard to come by despite the need for them. Relevant information may be buried behind mountains of data, making extraction difficult at times. It is extremely challenging to locate confirmed patient treatment outcomes. To remove the many forms of noise and distortion seen in real-world medical photographs, many distinct denoising techniques must be used. The performance of AI algorithms is hampered by the inclusion of this false information. In addition, there is not a standard dataset against which methods may be compared. Artificial intelligence should be utilized properly to distinguish between reality and fiction. This is especially helpful in the context of COVID-19, where numerous reports, audio files, video files, social media statuses, blogs, and other forms of media provide erroneous or unsubstantiated information. Integrating an ML or DL-based COVID-19 diagnostic system with an X-ray or CT scan system is necessary for clinical use, since this will guarantee that high-quality pictures are generated with little exposure to radiation and improve the entire system's efficacy. Combining the knowledge of professionals in virology and computer science is essential for making AI successful in the battle against COVID-19. Creating a reliable collaboration platform for specialists from many fields remains difficult. Data protection is another area of difficulty, since it necessitates safeguarding fundamental human rights and personal privacy.

In this research, we take a look at the most recent work using AI-based algorithms to make predictions about the spread, classification, and diagnosis of COVID-19. As a result of the ever-evolving nature of the literature, this review's conclusions are inherently tentative. The clinical and epidemiologic details of COVID-19 are beyond the scope of this review. In addition, the treatment and development of a vaccine for COVID-19 are outside the scope of this study and will be the subject of future research.

CONCLUSION

In this study, we take a look back at how ML and DL techniques have been used to combat the spread of COVID-19. The PRISMA guidelines are used to conduct the systematic review. Based on the findings of the review, it can be concluded that the number of verified cases may be accurately predicted using ARIMA models of varying orders, PR models, RIDGE models, SVR models, logistic models, and the hybrid wavelet ARIMA model. Methods like multilayer perceptron, support vector machines, random forests, XGBoost, etc. are also helpful in distinguishing COVID-19 sufferers from healthy individuals. It has been shown that random forest may get an accuracy of 95.95% in classification in one specific scenario. There are several steps involved in DL-based COVID-19 diagnosis, including as image preprocessing, segmentation, feature extraction, and classification. This literature review demonstrates the efficacy of DL techniques such CNN, ResNet, COVIDNet, VGG-16, VGG-19, and hybrid neural networks in the diagnosis of COVID-19 in X-ray and CT scan pictures. When applied to a short dataset of 148 samples and when binary classification is done to distinguish COVID-19 patients and normal persons in X-ray pictures, ResNet 18, GoogleNet, and AlexNet algorithms show 100% accuracy. DenseNet 201, however, achieves a maximum accuracy of 99.70% when classifying normal, COVID-19, and viral pneumonia cases from a dataset of 3,487 samples. DenseNet 169, when tested on a dataset of 2,900 CT images, has a binary classification accuracy of 99.80%. UNet++ applied to 58,924 ultrasound pictures, on the other hand, yields an accuracy of 97%.

However, many obstacles must be solved in the future before the advantages of AI can be used in practice. There are several obstacles, but some of the most significant ones are rules and laws, a dearth of trustworthy huge datasets, inaccurate or noisy data, a lack of overlap between AI and medicine, and concerns about data privacy. Also, massive, high-quality medical databases will be essential in the not-too-distant future. Also, COVID-19 patients at various phases should be included in the datasets, since it will be necessary to include borderline individuals in order to assess the performance of a classifier. Multiple imaging modalities, such as ultrasound, X-ray, CT scan, and Magnetic Resonance Imaging (MRI), should be used for every patient suspected of having COVID-19 to increase diagnostic accuracy. Because a system that incorporates many imaging modalities may better exploit the strengths of each individual modality.

It may be helpful to employ unsupervised learning techniques on the COVID-19 medical picture dataset since there are many images without proper labeling. Finally, it is anticipated that the COVID-19 pandemic will be effectively managed with the arrival of innovative ML and DL algorithms.

The search criteria used in this review are outlined in the appendix. For the time period of 1 January 2020 through 27 March 2021, 4050 scholarly articles were chosen from Google Scholar using the following search terms: (("COVID-19") OR ("coronavirus"))AND (("machine learning") OR ("deep learning") OR ("transfer learning")OR("forecasting"))AND("artificial intelligence") AND(("computed tomography") OR ("X-ray") OR ("ultrasound imaging")).

APPROVAL TO PUBLISH

This does not apply.

The PRISMA criteria for REPORTING STANDARDS were followed.

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