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A Review of Machine Learning and Deep Learning approaches for COVID-19 Diagnosis

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Abstract

The globe is currently facing a severe coronavirus disease 2019 (COVID-19) threat, with infected cases increasing at an exponential rate. COVID-19 is a disease caused by the SARS-CoV-2 virus, which was first identified by the WHO in March 2020. More than 150 million individuals had been infected as of March 10, 2021, with 3 million deaths. Therefore, Traditional diagnosis approaches have been ineffective due to the exponential growth in the number of infections. As a result, a number of intelligence techniques, including as deep learning (DL) and machine learning (ML), have been developed by researchers to aid the healthcare sector in providing speedy and precise Diagnosis of COVID-19. This article discusses COVID-19 detection utilizing X-ray images scans, as well as data analytics and comprehensive review on of the most recent DL and ML techniques. The study structure of this review paper is based on a recent examination of COVID-19 data to systematize current resources, assist researchers' community and practitioners, and inform on the upcoming progress of ML and DL for COVID-19, as well as stimulate their future work.

Keywords: Deep Learning, Machine Learning, COVID-19, X-ray

1.Introduction

The COVID-19 pandemic is well-defined as a disease or virus stirred up by a new type of coronavirus called the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), which was formally called by 2019-nCoV[1]. It was exposed in Wuhan Hubei City in China. The World Health Organization (WHO) confirmed that the first COVID-19 case was discovered on 31 December 2019. The COVID-19 eruption was announced as a global outbreak on 30 January 2020[2].

The most important symptoms that appear on a person infected with COVID-19 infection are fever, severe cough and hard breathing difficulty. many patients may have muscle pains and extreme tiredness and absence of taste or loss smell , and over 10% have GI-related signs of symptoms, for example diarrhea[3]. As at first thought, one of the expected ways for the infection to spread between individuals is the straight contact. Therefore, Reducing the distance between peoples can decrease the opportunity of being infected. The transmission of infection between people can occur up to 6 feet away. And because of that, the breathing drops created from the infected individuals while talking considered as one of the essential reasons that cause the infection spreading. Additionally, the signs of COVID-19 in some cases are not perceivable[4].

1.1 Diagnoses approaches of Covid-19

Different methods are available for diagnosing COVID-19, for instance chest X-ray (CXR) [5], computed tomography (CT) scan [6], next-generation sequencing [7], nucleic acid-based systems by using polymerase chain reaction (PCR)[8], and paper based detection [9]. These techniques are utilized in checking changes in organs, and patients might have to go through these computerized tests. The most famous of these neurotic tests are CT output and CXR [10-12],In regard to Computed Tomography (CT) and X-ray chest methods used for the diagnosing of COVID-19, many benefits that these technologies have. For example, For example, the CT method, which is characterized by the accuracy and details of the patient's condition, as well as its speed when compared with the rest of the other technologies. On the other hand, the chest X-ray can get the outcomes at a lower cost and low level of radiation. Notwithstanding, these methods have some few disadvantages that might influence their performance and procedure, for instance the CT scans of the brain can be impacted by bone close by, and X-ray technology cannot provide 3D information.

Tragically, a fast and precise methods for COVID-19 detection is yet not available. Generally, Diagnosing of COVID-19 is done by utilizing the medicinal images CT scan and X-ray[13, 14]. An expert examines these photographs and analyzes the material based on his or her diagnostic experience. Doctors can become fatigued as a result of lengthy working hours and make incorrect diagnoses. Many lung disorders are identical to COVID-19, and patients with COVID-19 can have anomalies in their CT or CXR readings. Furthermore, normalcy on a CT scan or CXR does not always imply a negative COVID-19 case. As a result, in the health-care industry, assistance tools are essential to ensure accurate diagnosis. New approaches for detecting COVID-19 based on artificial intelligence (AI) principles, specifically deep learning (DL) and machine learning, have been proposed for faster and more accurate results (ML)[15]. Various scholars have created traditional ML and DL strategies to aid doctors in establishing accurate diagnoses. Such strategies can aid in the classification of chest X-rays or CT scans into two categories: infected and normal. Following various processes, such as reading an X-ray image, prepossessing and extracting unique features from input images, and then inputting features into the ML or DL model for a final prediction choice, a decision is produced. Other uses for such techniques include anticipating an outbreak separation using COVID-19 data and utilizing AI to predict red zones and the number of infected cases.

2. Role of ML and DL for Covid-19

Given the Covid-19 global infection, ML and DL have been utilized to improve the performance of classical COVID-19 diagnosis and prediction techniques. ML methods such as supervised and unsupervised learning have been utilized to detect COVID-19. Numerous DL methods have been employed to detect COVID-19. In addition, Hybrid Techniques are also used to detect and predict COVID-19 by combination of DL and ML approaches. The categorized AI approaches (ML and DL) selected in this survey paper are shown in Figure 1.

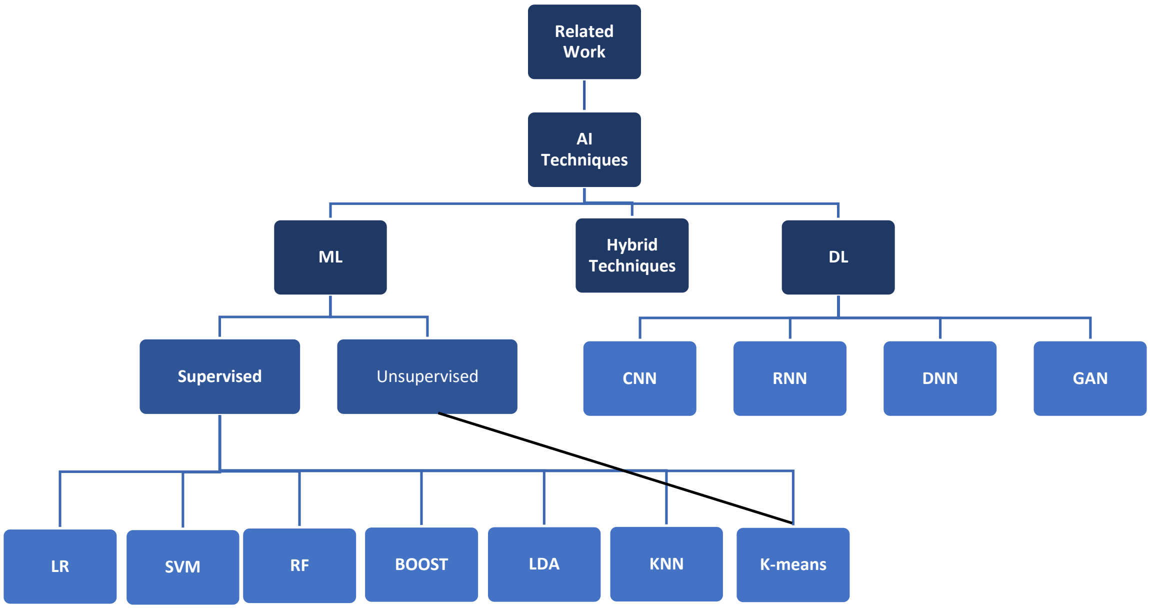

Figure 1: Category of related work

2.1 Machine Learning

Machine learning tells computers what to do and trains them to operate on their own. It is a data analysis process that includes the creation and fitting of models, allowing machines to learn and make a prediction via experience. ML is used to detect COVID-19corona virus by analyzing a set of an X-ray or CT scan input image and extracting distinctive features from it. The predictions of the given images will be presented as a normal or infected case based on these features. generally, the ML algorithms utilized for COVID-19 diagnosis can be divided into two types: supervised learning and unsupervised learning.

COVID-19 has been detected using a variety of regression, classification, and feature extraction approaches[16]. These techniques are used to achieve the following goals (1) determining how the epidemic would end, (2) predicting coronavirus transmission across regions, (3) analyzing the rate of spread and types of cure across different countries, (4) determining the effect of weather on coronavirus, and (5) determining the virus's transmission rate[17].

In 2020, Yadav [17] The unique methodology uses the Support Vector Regression method to identify five different coronavirus tasks in order to diagnose and classify the COVID-19. Finding the spread of COVID-19 across regions, the growth rate of COVID-19 infected patients and their mitigation, how the epidemic will end, analyzing the virus' transmission rate, and the association of COVID-19 with weather conditions are among the tasks. Other regression models (Linear regression, Polynomial regression) are compared with the results, which show promise in terms of accuracy and efficiency.

Fayyoumi [18] In Jordan, he created an online questionnaire for normal and COVID-19 cases. The existence of signs and symptoms in both groups was determined using data from the questionnaire. The researchers produced a COVID-19 dataset comprising diverse patients' indications and symptoms. The researchers then fed this data into a set of machine learning (ML) models (SVM, multi-layer perceptron [MLP]) and statistical techniques (i.e., LR) to predict prospective COVID-19 patients. MLP performed the best in terms of classification accuracy (91.62 %). In terms of precision, SVM gave the greatest results (91.67 %).

Using the k-means technique, **Siddiqui (2020)[19]** studied the relationship between patient temperature and COVID-19 case status (suspicious, confirmed, and deaths). Siddiqui's methodology involved three phases: Database design, clustering, and data collecting. The dataset utilized in the first phase is the WHO's 'coronavirus disease (COVID-2019) situation reports.' The infection rate in different parts of China is included in this dataset. The dataset is described in the second phase, which include seven features for example: region, population [10,000 s], suspected cases, confirmed cases and death. The lowest and greatest temperatures were added to the dataset as new attributes. The explanation for this is that patient temperature is one of the most important elements in determining COVID-19 case status. Clustering methods based on k-means are utilized to detect new patterns in the final phase. The patterns revealed the impact of temperature on each region in the three COVID-19 states: suspected , death and confirmed.

In 2020 Hassanien[20] Using multi-level thresholding and the Support vector machine(SVM), COVID19 was discovered in infected person X-ray pictures. All of the photos are 512*512 pixels in size and in JPEG format. The proposed model's accuracy is approximately 97.48%.

Elaziz (2020) [21] CXR pictures were used to create a visual diagnostic tool that could tell the difference between COVID-19 and normal cases. Traditionally, features were retrieved from CXR pictures using fractional multichannel exponent moments. This is a time-consuming and expensive operation; hence a parallel processing multicore framework was utilized to speed up image and data processing.

Randhawa(2020)[22] established a decision tree ML alignment-free technique for predicting COVID-19 virus gene sequence using intrinsic COVID-19 genomic fingerprints as patterns. Only raw DNA sequence data is processed in the alignment-free approach, which results in quick taxonomic categorization of novel diseases. A huge dataset with over 5000 distinct viral genomic sequences was used to evaluate the suggested methodology. These numbers came from a well-known database called Virus-Host DB. The findings revealed that the proposed method is a viable option for analyzing pathogen genome sequences and providing correct taxonomic classifications for previously unknown sequences in real time.

Pinter (2020)[23] investigated the feasibility of predicting the outbreak of COVID-19 using a hybridization model of network-based fuzzy inference system and multi-layered perceptron-imperialist competitive algorithm based on time series data compiled from Hungary statistical reports of infected cases and death rates. The performance of the proposed prediction model was evaluated using three metrics: mean absolute percentage error, root mean square error (RMSE), and determination coefficient. The proposed prediction model performed well in terms of calculating total mortality and forecasting COVID-19 outbreaks.

Kavadi (2020)[24] developed a new strategy for preventing COVID-19 outbreaks in India. The COVID-19 Indian database was used by the researchers. Nonlinear machine learning (NML) and partial derivative regression are two well-known methods that are combined in the suggested method. PDL was used to normalize the data, and NML was used to forecast the outcome. When compared to prior efforts, the experimental findings showed that this technique is superior in terms of classification accuracy and prediction time.

Cui (2020) [25] present a clustering model (Unsupervised Machine learning) to discover implicit clusters in COVID-19 patients. The research included data from almost 6,000 adult patients who tested positive for SARS-CoV-2 infection at the Mount Sinai Health System in New York, USA. Chronicity and one of the 18 body structures were linked to patient diagnoses, and the optimal cluster count was calculated using the Kmeans algorithm and the elbow technique. They discovered four distinct clusters. COVID-19 scans revealed that all of the patients had respiratory issues. Patients with COVID-19 have the highest rate of comorbidity and chronic illnesses. Although age is a significant determinant, comorbidity and chronicity are significantly linked. Furthermore, when infected, people with a history of immune system abnormalities, metabolic or genitourinary diseases are more susceptible to severe issues or medical conditions in the circulatory system. The finding of these four clusters is a key step toward determining the disease's route and treating patients, as well as increasing disease prevention.

2.2 Deep Learning

CNN, DNN, and RNN are the main DL algorithms applied in diagnosing of COVID-19 which is discussed in Chapter 2. The DL algorithms are frequently used to diagnose and handle COVID-19 disease from various angles. Researchers analyzed and evaluated chest X-ray images using deep learning techniques to detect COVID-19 in recent studies. First, the photos are preprocessed using the CNN technique to extract improved features, which are then supplied as an input into image classification algorithms utilizing deep learning techniques.

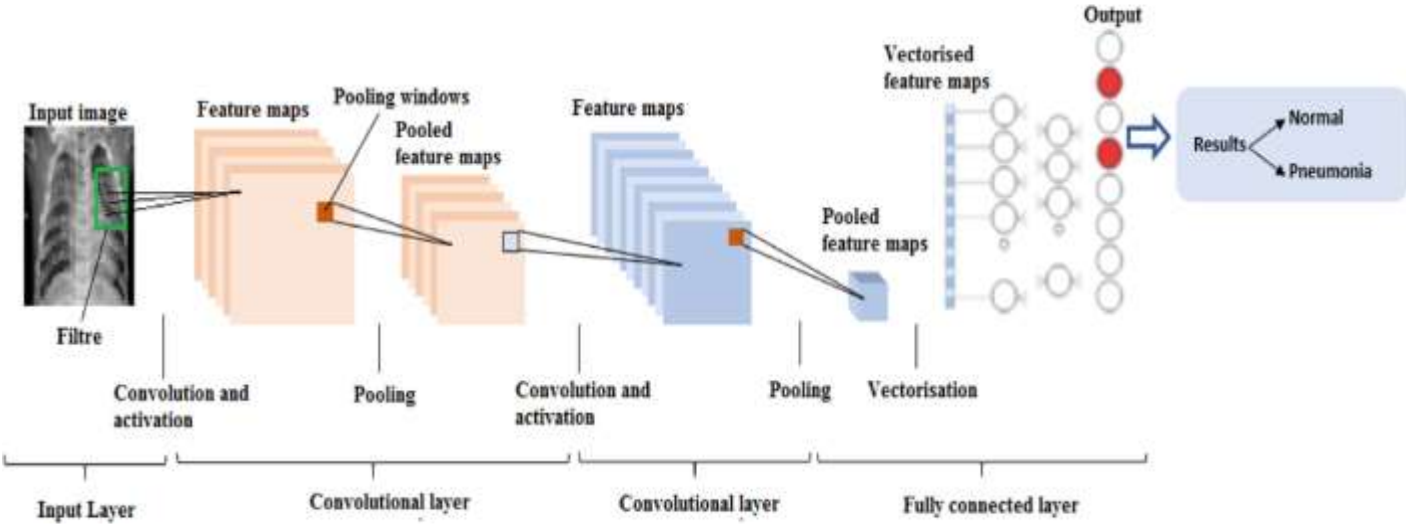

Figure 2: Supervised learning approaches for COVID-19[26]

Ahammed (2020) [27] he proposed a system and applied CNN that achieved high accuracy 94.03% in a deep neural network-based system. The author used normal, pneumonia, and COVID-19 patient chest X-ray pictures to train the algorithm. The work's disadvantage was that it was built on a dataset of just 285 photos, which was insufficient for training a deep learning-based system for COVID-19 prediction.

In the proposed model by **Abbas 2020 [28]** COVID-19 detection at an early stage can help to prevent the infection from occurring. Abbas demonstrates a strategy for detecting COVID19 from a large dataset of chest X-ray images. On the basis of chest X-ray pictures, the previously implemented CNN architecture Decompose, Transfer, and Compose (DeTraC) was utilized to classify the COVID-19 infected and normally. The proposed model's result analysis showed that the DeTraC mechanism in classification had a high accuracy of 95.12%.

Alqudah 2020[29] present a CNN with the SoftMax classifier, SVM, and random forest were used to classify the photos. CNN is utilized in two scenarios: image classification and graphical feature extraction for a hybrid system. The feature that was extracted was then utilized to train and test parameters. According to the proposed methodology, CNN accuracy is 95.2%, which is better than previous methods.

Minaee 2020[30] proposed a system for the detection of coronavirus (COVID-19) from chest X-ray pictures, a deep learning technique has been implemented. The coronavirus (COVID-19) disease was identified using four pre-trained convolutional models: ResNet18, ResNet50, Squeeze Net, and DenseNet-121. The two datasets, which totaled roughly 5k pictures and were dubbed COVID-Xray-5k, were considered and integrated. The output of the fully pre-trained model is a sensitivity of 97% and a specificity of 90%.

In the model presented by **Tartaglione in 2020 [31]** to categorize the coronavirus (COVID-19) from CXR pictures, researchers used a deep learning technique (ResNet-18, ResNet-50). COVID-19 CXR datasets (CORDA, RSNA, COVID-Chest X-ray, Chest X-ray) were obtained from a Northern Italian emergency hospital. The training with a COVID-Net architecture and COVID-Chest Xray dataset is 85% accurate, while the training with a ResNet-18 architecture and COVID-Chest Xray dataset is 100 % accurate, according to the results of the proposed deep learning methods.

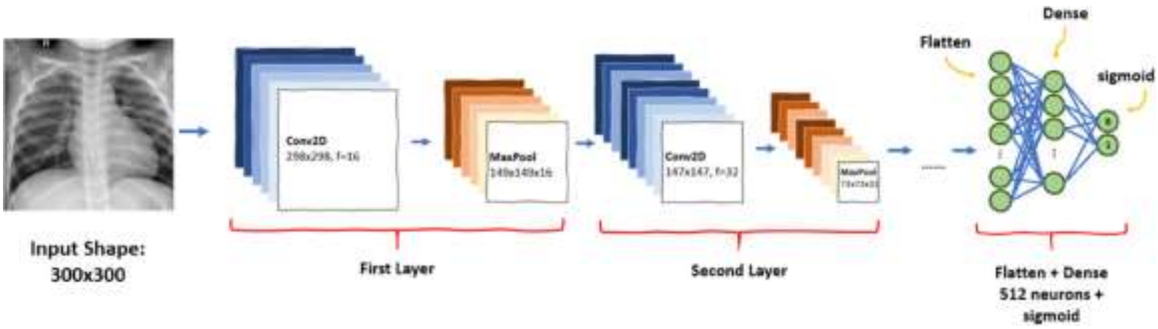

Figure 2 : Deep learning steps for COVID-19[32]

2.2.1 Convolution Neural Network (CNN)

The term 'deep learning,' according to **Albawi (2017) [33]**, refers to multi-layered AI neural networks (ANN). It is now one of the most efficient mechanisms in recent decades, and it is well-known in the literature since it manages a large amount of data. In recent years, the interest in deeper hidden layers in several domains, particularly pattern recognition, has outperformed traditional methods. The most frequent DNNs are CNNs. Convolution is a linear mathematical activity between matrices that goes by that name. Coevolutionary, nonlinear, pooling, and totally linked levels are all present in a CNN. Parameters for convolutional and totally connected layers must be set. A CNN performs exceptionally well in machine learning tasks, especially in applications using picture data, such as the largest image recognition data collection, computer vision, and natural language processing.

With two real-world datasets collected from Australia and Jordan, **Alazab (2020) [34]** proposed an Intelligence technique that used a deep CNN to recognize patients with COVID-19 patients. 1000 X-ray photos of real patients were used to check their method. Their method diagnosed COVID-19 patients with a 95% to 99% accuracy in the lab. With two forecasting techniques : autoregressive integrated moving average model and LSTM, their technology was also used to predict the number of patients with COVID-19 and cured and fatalities cases through the next 7 days. For training and testing, data sets from Australia and Jordan were applied. The accuracy was 94.80% for Australia and 88.43% for Jordan . these results for the number of confirmed COVID-19, recovered, and death cases discovered in these two countries.

Deep CNN can be used to extract picture biomarkers from X-ray images for COVID-19.**Apostolopoulos (2020) [35]** investigated how extracted features are successful in categorizing COVID-19 biomarkers from X-ray images using a CNN dubbed Mobile Net. The results revealed an 87.66% classification accuracy between seven COVID-19 groups, 99.18% accuracy in distinguishing COVID-19 from non-COVID-19, and sensitivity and specificity of 97.36 % and 99.42%, respectively.

Furthermore, **Civit-Masot (2020) [36]** used the VGG16 structure to develop a DL model for detecting COVID-19 in X-ray lung images. The findings shows a high sensitivity at about 100% and a high specificity.

Brunese (2020)[37] demonstrated a deep learning strategy for detecting COVID-19 from X-rays. There were three steps to the strategy. Initially, CXR was used to look for signs of pneumonia. Secondly, COVID-19 was distinguished from pneumonia. Eventually, COVID-19's places in the X-ray was discovered. The observed results were promising, with a detection time of about 2.5 seconds and an average accuracy of 97%.

Islam (2020) created an automated disease detection system. The approach aided clinicians in detecting COVID 19 and provided accurate and timely results that demonstrated a reduction in mortality risk. This article aims to offer a deep learning technique based on LSTM and CNN models for diagnosing COVID-19 based on CXR pictures. Deep functions were extracted using CNN, and generated elements were identified using LSTM. A total of 4575 X-ray images, including 1525 COVID-19 images, were installed in the machine. The testing revealed that the proposed approach had a precision of 99.4 %, a specificity of 98%, a sensitivity of 99.2%, a precision of 99.3%, and an F1 score of 98.9%.[38]

Panwar (2020) used CT scans and X-rays to detect COVID-19 in the lungs. The authors presented a DL nCOVnet neural network system for evaluating patient X-rays as an alternative quick testing method for COVID-19 detection. After using multiple layers of CNN and unbiased sets of data, the suggested model attained a true positive rate of 97%.[39]

Al-Waisy (2021)[40] introduced a parallel architecture (COVID-DeepNet) that combined a deep belief network with a convolutional deep belief network that was trained from scratch with a large-scale dataset. With a detection measures of 1. accuracy rate of 99.93 %, 2. sensitivity of 99.90 %, specificity of 100%, precision of 100%, F1-score of 99.93%, MSE of 0.021%, as well as RMSE of 0.016 %, the system accurately detected patients with COVID-19.

In terms of validation accuracy, **Monshi (2021)** suggested a CovidXrayNet system based on EfficientNet-B0 to improve data augmentation and CNN hyperparameters for detecting COVID-19 from CXRs. For only 30 epochs of training, CovidXrayNet achieves 95.82 % of accuracy on the COVIDx dataset. This improvement also improves the accuracy of common CNN architectures like the Visual Geometry Group network (VGG-19) and the Residual Neural Network (ResNet-50) by 11.93% and 4.97%, respectively.

2.2.2 Deep neural network (DNN)

Since 2006 DL techniques have been presented as a fast learning algorithm for deep beliefs. Because of their intrinsic capacity to overcome traditional neural networks' drawbacks. In addition, DL techniques were found to be suitable for comprehensive computer vision application testing, pattern recognition, speech recognition, reading, and natural language recommendation systems. **Liu 2017[41]**, discussed some DL architectures and feasible configurations (2017). Auto encoders, neural networks, Boltzmann machines, and deep belief networks were the four DL architectures described. The selection of possible DNN models for solving issues in various circumstances, such as speech processing, pattern identification, and computer vision, was explained in detail.

Checking contamination using RT-PCR kits takes 6–9 hours, according to **Das (2020)[42].** Because of its reduced sensitivity, RT-PCR produces a high number of false results. COVID-19's marker and diagnosis focus on X-ray and computed tomography (CT) radiography to address this conundrum. Deep machine learning is used to construct an automatic recognition technique. To improve the algorithm's operation, CXR are directly analyzed utilizing DL approaches. The approaches use large datasets to train network weights and small datasets to maximize weight with pretrained networks.

Wang, Zheng, and colleagues (2020) studied 5372 patients with CT pictures from seven cities or provinces retrospectively. The DL technique was first pre-trained on CT images of 4106 patients. The scans were helpful in determining the characteristics of the lungs. 1266 patients (924 with COVID-19; 471 had follow-up of more than 5 days) and 342 with pneumonia from six municipalities or provinces were enlisted according on the duration of qualified and externally validated success of the DL framework. In the four prior validation sets, the DL technique was effective in distinguishing COVID-19 from other pneumonia (AUC 0.87 and 0.88) and viral pneumonia (AUC 0.86) cases. The patients were stratified using the DL approach, and there was a significant difference in the amount of time they spent in the hospital. Without human interaction, the DL gadget automatically positioned itself in the centers of the questionable spots, demonstrating features that are similar to radiological findings. DL provides a simple method for quick COVID-19 screening and identifies potential high-risk individuals, allowing care services to be maximized and serious symptoms to be avoided.

2.2.3 Recurrent neural network (RNN)

Newly infected and recovered COVID-19 cases must be predicted in order to plan resource distribution and update curfew rules in order to slow disease progression. Within 17 days, **Zeroual (2020)[43]** compared five DL techniques to forecast the number of new COVID-19 cases and recovered COVID-19 cases. LSTM, simple RNN, gated recurrent units, Variational AutoEncoder (VAE), and bidirectional LSTM (BiL-STM) algorithms were all compared. The study used data from Spain, Italy, China, France, Australia, and the United States. In terms of Loss, MAE, RMSE, MAPE, EV, and RMSLE, the results revealed that VAE outperformed the other algorithms.

Clinical survival analysis can be used to predict the likelihood of a specific clinical outcome. Using clinical variables available at admission, **Liang (2020)[44]** used a DL-based survival model to predict the risk level of COVID-19 patients developing to severe disease. The suggested model was tested using data from three different cohorts in China: Guangdong, Hubei, and Wuhan. An online calculating platform https://aihealthcare.tencent.com/COVID19-Triage en.html utilizes the built model to determine patient prioritizing at admission. Patients who were at high risk of acquiring a serious illness were able to get the help they needed as quickly as feasible.

Arora (2020)[45] used DL models to predict COVID-19 positive patients in India. The RNN used LSTM versions in their method. The following LSTM variations were used in this study: In predicting positive COVID-19 cases, deep LSTM, convolutional LSTM, and bi-directional LSTM models were used. In terms of prediction errors, the bi-directional LSTM produced the best results, while the convolutional LSTM produced the lowest results. The bi-directional LSTM produced astounding results in terms of daily and weekly predictions, with 3% or less for short-term prediction.

2.2.4 Generative adversarial networks (GAN)

The authors introduced deep transfer learning and GAN for COVID-19 case recognition using CXR pictures in **Loey, Smarandache [46]**. A dataset containing 307 photos was used to test this technique. Pneumonia virus, COVID-19, bacterial pneumonia, and normal were the four classifications used. Alexnet, Googlenet, and Restnet18 were employed as deep transfer models. For the detection of COVID-19 instances, three experimental scenarios were presented. The first scenario had four picture classes, whereas the second only had three. The third example includes two types of photos. COVID-19 photos were included in each experimental scenario's dataset. In the first experimental case, the Google net as a deep transfer model achieved the best accuracy results. The COVID-19 photos were included in each experimental scenario's dataset. In the first experimental case, the Googlenet as a deep transfer model achieved the best accuracy results. In the second experimental case, Alexnet as a deep transfer model had the best accuracy, whereas Googlenet had the best accuracy in the third experimental scenario.

To diagnose patients with COVID-19, **Jamshidi (2020)[47]** used deep learning techniques such as GANs, intensive learning machines, and LSTM. They presented an applied bioinformatics technique that would integrate several knowledge components from a variety of structured and unstructured data sources into doctor and scientist-friendly interfaces. The enhanced speed of COVID-19 evaluation and care is a fundamental benefit of these AI systems.

2.3 Hybrid Techniques for ML and DL

Rajaraman, Siegelman, and colleagues[48] proposed an iteratively trimmed DL model (2020). The researchers used X-ray images of COVID-19- pulmonary symptoms. In this methodology, the unique feature representations of COVID-19 were learned using a customized CNN and a trained model using ImageNet. Patients were then classified as COVID-19-viral abnormalities, normal, or bacterial pneumonia cases using the newly acquired knowledge. The suggested model performs well in experiments, with an accuracy of 99.01 % and an AUC 0.9972.

Rajaraman and Antani (2020)[49] used weakly labeled data to enhance the amount of data used for training to detect COVID-19. COVID-19 shares many similarities with pulmonary viral infections, which is why it was chosen. The training data was expanded to include the X-ray pathogens for bacterial or viral pneumonia that were only weakly labeled. The chosen photos were utilized to train a CNN algorithm and compare the results to those of a non-augmented data trained model. For the evaluation, six datasets were employed. On training, the weakly labelled data augmentation outperformed the baseline non augmentation in classifying COVID-19 symptoms as viral pneumonia in one experiment.

Likewise, in **Zhu (2020)[50]**, the authors used a deep-learning CNN to identify the degree of lung sickness in COVID-19 patients. Their method was evaluated using a real-world dataset of 131 CXRs collected from 84 COVID-19 patients in US health facilities. The data was split into two halves. About 80% of the data was used for training, with the remaining 20% being used for testing. The proposed approach is evaluated using correlation analysis and mean square error analysis. The authors stated that their approach should be tested with a larger dataset because the results were satisfactory in a small sample. Furthermore, the scientists stated that their method might be used to determine the severity of lung disorders in COVID-19 patients, as well as examine sickness progression and therapy response.

To detect, locate, and quantify COVID-19 pneumonia, **Zhang (2020)[51]** used DL-based software. A 3D CNN was integrated with V-Net bottleneck structures in the suggested AI algorithm. 2460 photographs from Huoshenshan Hospital in Wuhan, China, were used to evaluate their method. Their approach produced great results in the lab, making it more suitable for disease assessment and therapy planning.

2.3 Comparative Analysis

A detailed summary of certain researches on X-ray images, CT scans, and other techniques of diagnosing COVID-19, which were performed in multiple worldwide locations utilizing different AI approaches, together with comparisons, is described in the next section. As shown in Table 1-1, Table 1–2. The comparisons are made depending on the type of applications, AI methodologies, locations/time, input information and research results.

Author/Ref.	Dataset					Technique	Accu.
	COVID-19	Pneumonia	Normal	Total	Type		
Ahammed[27]	285	1345	1341	2971	CXR	CNN	94.03%
Loey [52]	69	158	79	306	CXR	AlexNet+ Googlenet+Restnet18	100%
Khan.[53]	195	-	862	1057	CXR	VGG16+VGG19	99.3%
Azemin [54]	154	-	5828	5982	CXR	ResNet-101 CNN	71.9%
Chowdhury [55]	219	1345	1341		CXR	Parallel-dilated CNN	96.58%
El-Rashidy[56]	250	-	500	750	CXR	CNN/ConvNet	97.95%
Abbas[28]	105	11	80	196	CXR	CNN/DeTraC	93.1%
Khan[57]	284	-	310	594	CXR	CNN/CoroNET(Xception)	99%
Minaee [30]	184	-	5000	50,184	CXR	ResNet 18 ,50+ SqueezeNet +DenseNet-121	98%
Ozturk [32]	125	-	500	625	CXR	CNN (DarkNet)	98.08%
Panwar[39]	142	-	142	284	CXR	CNN(nCOVnet)	88.1%
Sekeroglu[58]	225	4292	1583	6100	CXR	CNN	98.50%
Alqudah [29]	48	-	23	71	CXR	CNN	95.2%
Wang[59]	140	9576	8851	18,567	CXR	ResNet-101 + ResNet-152	96.1%
Khair Ahammed	219	1345	1341	2905	CXR	CNN	94.03%
Duran-Lopezet[60]	2589	-	4337	6926	CXR	CNN	94.43%
Benbrahim[61]	160	-	160	320	CXR	Transfer learning with CNN (Inceptionv3 and ResNet50)	99.01%

Table 1: A comparison of the most available Techniques in the detection of COVID-19

2.4 Evaluation Metrics

The effectiveness of DL and ML approaches for detecting COVID-19 is often assessed using a variety of measures. Classification accuracy is the most widely used metric. Other measures are used and extensively detailed with mathematical formulation in this section. The evaluation measures used to evaluate the results of the DL and ML algorithms for COVID-19 classification are listed in table 2.

Metrics	Formula	References
Accuracy	Acc = $\frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} * 100$	[48, 49, 62-66]
Precision	Pre = $\frac{No.of\ true\ positive\ prediction}{\sum True = TP+FP}$	[18, 48, 49, 63, 66]
Sensitivity (Recall)	Sen= $\frac{No.of\ true\ positive\ prediction}{\sum Number\ of\ all\ positive\ assessment = TP+FN}$	[35, 48, 49, 63, 64, 66, 67]
F1-score	Fs = $\frac{2\ X\ precision\ X\ recall}{precision+recall}$	[34, 48, 49, 63, 66]
Specificity	$Spe = \frac{No.of\ true\ negative\ prediction}{Total\ no.of\ negative\ prediction} = TN + FP$	[35, 48, 63, 64, 66, 67]
Mean absolute error	MAE= $\frac{1}{N}\sum_{t=1}^{N}\lvert e_t \rvert$	[16, 43, 50, 68]
Mean absolute percentage error	MAPE = $\frac{1}{N}\sum \left\lvert\frac{A_t - F_t}{A_t}\right\rvert$	[23, 43, 45]
Root mean square error	RMSE = $\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{d_i - f_i}{\sigma_i}\right)^2}$	[23, 34, 43]
Logarithmic loss	LogLoss =$-\frac{1}{N}\sum_{i=0}^{N}[y_i\ .\log_e(\hat{y}_i) + (1 - y_i)\ .\ \log_e(1-\hat{y}_i)]$	[65]
Area under curve	AUC=$\int_a^b f(x)dx$	[48, 49, 62, 67-70]
Explained variance	EV = $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - \bar{X})^2}$	[43]
Average time for COVID-19 detection	M = $\frac{1}{N} * \sum_{j=1}^{N} t$	[37]
Receiver operating characteristic	ROC = $\int_a^b f(x)dx$	[48, 62, 71-73]
Matthews correlation coefficient	MCC = $\sqrt{\frac{X^2}{N}}$	[49, 74]
G_Mean	GM= $\sqrt{Sen\ X\ Spe}$	[18]

Table 2: Evaluation metrics

Figure 3 depicts the evaluation metrics used to evaluate COVID-19 diagnosis models. Most researchers utilize accuracy as their primary evaluation criterion, followed by sensitivity. The classifiers used to evaluate the ML and DL algorithms for COVID-19 are shown in Figure 11. The SVM classifier is the most commonly employed technique in the COVID-19 area, as seen in Figure 11. According to the percentages of research papers that use these classifiers, Boost, K-means, and logistic regression are ranked second.

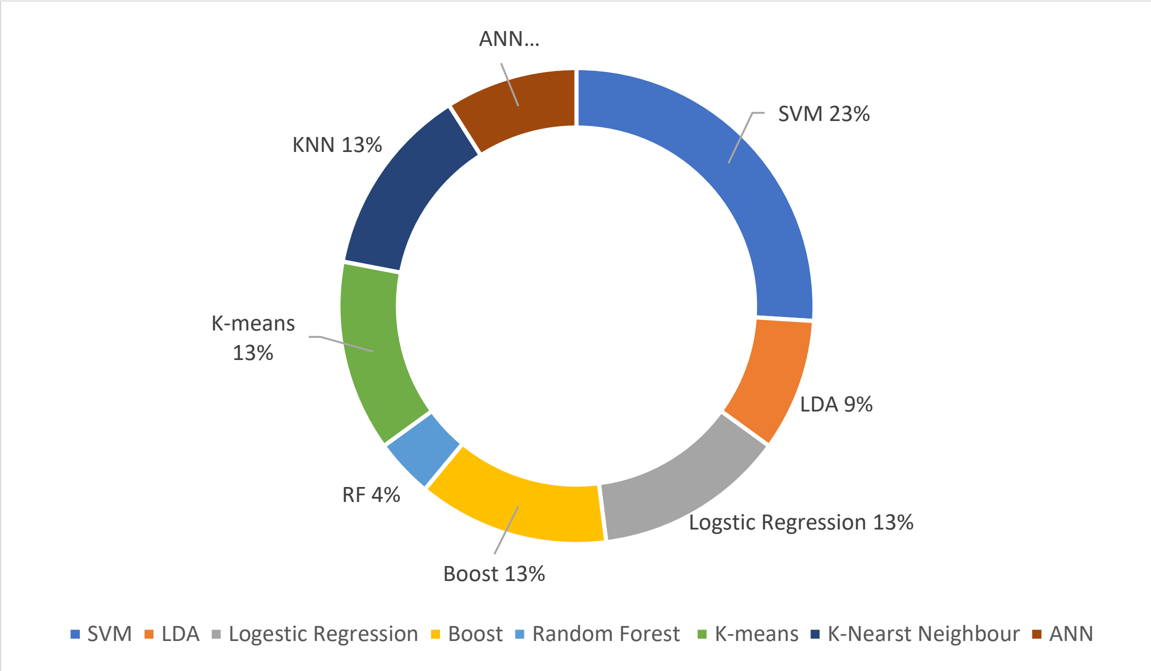

Figure 3: The percentage of ML Techniques utilized for COVID-19 Detection

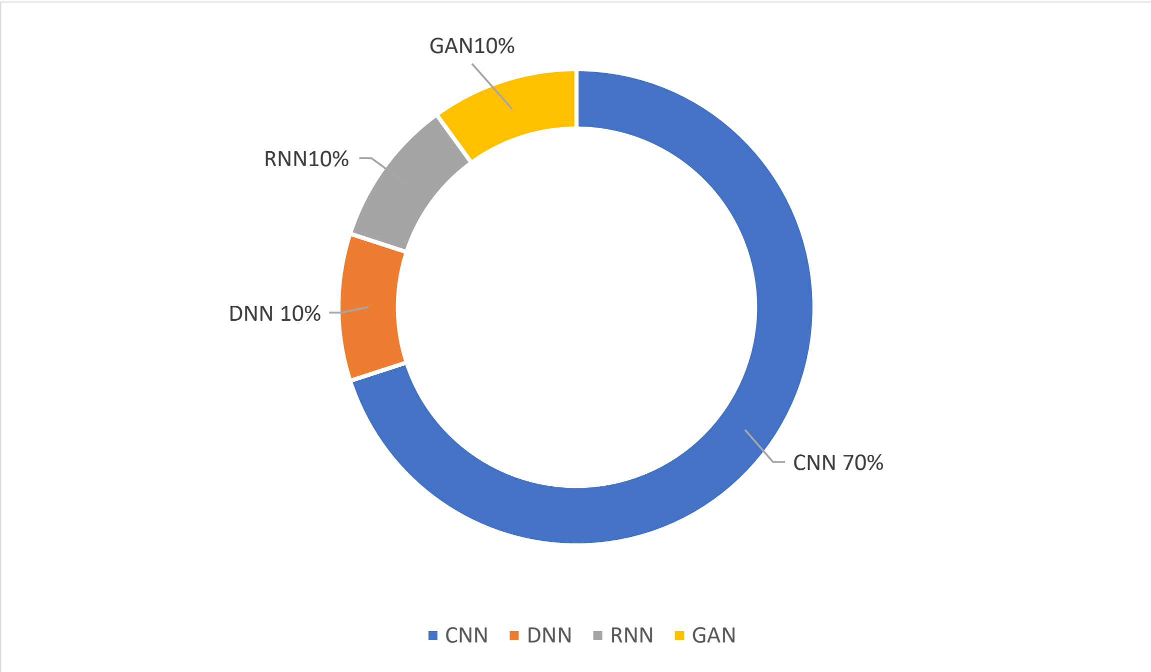

Figure 4: The percentage of DL Techniques utilized for COVID-19 Detection

2.5 Conclusion

This study provides a clear and comprehensive review of the machine learning and deep learning utilized to detect and recognize the COVID-19 epidemic. The major goal of this paper is to outline prior research and how it has been applied to COVID-19. The reviewed works came from a variety of public and well-known academic resources, including IEEE, Springer, Elsevier, MDPI, MedRxiv, and others.

In overall, the COVID-19 summary research are reviewed and discussed using three methodologies: machine learning, deep learning, and hybrid approaches. Machine learning research is divided into two categories: supervised learning and unsupervised learning. Similarly to a deep learning studies are classified as CNN, DNN, RNN and GAN. All of the aforementioned studies were used to diagnose COVID-19 by the analysis of X-ray and CT scan pictures. In addition, only a few research used either machine learning or deep learning to predict the COVID-19 epidemic in the countries. as a summary , For COVID-19 diagnosis and infection prediction, machine learning algorithms like SVM, LDA, KNN, ANN, Boost, RF, K-means, and LR are used, and deep learning algorithms like CNN, DNN, RNN, and GANs are utilized.

The evaluation metrics used to identify COVID-19-based machine learning and deep learning algorithms are listed and summarized in table . In past investigations, the most commonly utilized metrics were accuracy, sensitivity, specificity. This is consistent with prior research that used deep learning and machine learning methodologies to predict outcomes.

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