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REVIEW

Deep Learning Applications for COVID-19 Analysis: A *State-of-the-Art* Survey

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Abstract: The COVID-19 has resulted in catastrophic situation and the deaths of millions of people all over the world. In this paper, the predictions of epidemiological propagation models, such as SIR and SEIR, are introduced to analyze the earlier COVID-19 propagation. The deep learning methods combined with transfer learning are familiar with classification-detection approaches based on chest X-ray and CT images are presented in detail. Besides, deep learning approaches have also been applied to lung ultrasound (LUS), which has been shown to be more sensitive than chest X-ray and CT images in detecting COVID-19. In the absence of a vaccine, the machine learning-related approaches are applied to analyze vaccine candidates in the realm of biology and medicine. The telehealth system played a major role in combating the pandemic from all aspects and reducing contact with patients during this period. Natural language processing-related methods are utilized to analyze tweets related to the COVID-19 epidemic on social media, and further analyze public sentiment and subject modeling, so as to arrange corresponding measures to appease public sentiment. In particular, this survey is to summarize and analyze the contributions made in various fields during the COVID-19 pandemic by considering both the contribution of deep learning in chest X-ray and CT images, as well as the application of the latest LUS during the COVID-19 pandemic. Telehealth and the importance of public sentiment analysis during a pandemic were also described in detail.

Keywords: COVID-19; epidemiological propagation models; deep learning; transfer learning; classification-detection; lung ultrasound; telehealth system

1 Introduction

A pandemic is an occurrence of a disease or wide-scale outbreak of any infectious disease, which can rapidly increase mortality and morbidity rates across a huge area [1]. The pneumonia is caused by a virus known as “severe acute respiratory syndrome coronavirus 2” (SARS-CoV-2), which is dubbed Coronavirus

Disease 2019 (COVID-19) by the World Health Organization (WHO) [2–6]. The WHO, on March 11, 2020, then proclaimed the COVID-19 outbreak a global pandemic [7]. A virus is a pathogen consisting of genetic material in a protein coating, such as the common flu, colds, Severe Acquired Immunodeficiency Syndrome (AIDS) and Ebola, which are all infectious diseases of varying severity that are usually caused by viruses [8]. Coronaviruses are enveloped, positive single-stranded large RNA viruses that can infect humans and a variety of animals.

The clinical manifestations of patients with COVID-19 infection are extremely complex. Fever, cough, and shortness of breath are the most prevalent symptoms of patients [9,10], and appear as decreased blood oxygen saturation, blood gas deviation etc. Severe patients will suffer from septic shock, pulmonary edema and acute respiratory distress syndrome (ARDS), heart failure, shock, etc., which may lead to the death of the patient [11–14]. Patients infected with COVID-19 can also experience insomnia [15]. Zhang et al. [16] proposed that melatonin could improve sleep quality in patients. Epidemiological studies have shown that elderly patients are more likely to develop serious diseases, while children tend to have milder symptoms [17]. Although COVID-19 mainly affects the lungs, it usually causes multiple organ involvement. COVID et al. [18] proposed the need for an interdisciplinary approach to address the potential acute post-care needs of recovering COVID-19 patients. The medical clinical phenomena play an important role in detection of COVID-19 and monitoring disease progression. However, some diseases don't show any obvious symptoms, and even the proportion of individuals infected by SARS-CoV-2 is still uncertain for the whole period of infection [19], which poses a huge threat to public health. Although reverse transcription polymerase chain reaction (RT-PCR) is considered as the gold standard for detecting SARS-CoV-2 in the analysis of respiratory specimens from patients with suspected COVID-19 [20,21], it usually becomes difficult to effectively screen suspicious cases, even with a high false negative rate [22], due to lack of resources and strict testing environment. Ai et al. [20] used RT-PCR as a reference standard to evaluate the performance of CT in the diagnosis of COVID-19. Compared with RT-PCR, the diagnosis of COVID-19 by chest CT images is more sensitive, more stable and more conducive to epidemic control [20].

COVID-19 spread *via* respiratory and extra-respiratory routes, which may benefit in an explanation of the rapid proliferate of disease [23]. As a result, the use of breathing aid device is very helpful in patients with COVID-19 infection [24]. In addition, in order to limit the number of people infected by means of transmission, simulating the COVID-19 outbreak's transmission process is critical [25]. Mathematical epidemiology is a venerable and well-respected field [26,27]. For numerous years, mathematical modeling has been employed in epidemiological studies [28], the majority of which are based on the Susceptible-Exposed-Infected-Removed (SEIR) and Susceptible-Infected-Recovered (SIR) models [29]. Menon et al. [30] studied the spread of COVID-19 in a broad population using deterministic mathematical models of disease propagation, such as SIR and its variants. To explain the transmission of infection during the incubation phase, Lopez et al. [31] suggested a modified SEIR model. To track and segregate patients, Levesque et al. [32] devised a parsimonious Crump-Mode-Jagers continuous time branching process of propagation. Modeling epidemics by using mathematical models based on SIR models is of benefit to predicting the spread of epidemics and providing epidemiological parameters [29]. In the meanwhile, it can assist the government in developing COVID-19 prevention and control policies. Deep learning is one of the most representation-learning approaches with multiple levels of representation, and it is capable of explaining complicated problems using learning methods from simple depictions [33]. Deep learning methods are capable of representing the ability and characteristics of learning data accurately in a deep manner [34,35], and it is widely utilized in medical systems such as biomedicine [36,37], smart healthcare [38], drug discovery [39], virus severity and infectivity [40], and medical image analysis [41,42].

Deep learning methods are of great significance for the detection of COVID-19 through the chest X-ray or CT images. Apostolopoulos et al. [43] used Convolutional Neural Networks (CNNs) with transfer learning algorithm to present automatic detection methods for chest X-ray images. The appearance of the chest X-ray image is often difficult to explain because of its non-standard and vague terminology, such as airborne disease, pneumonia, infiltration, patchy opacity, and opacity [20,44–46]. The most common CT findings of COVID-19 infection are the typical histologic pneumonia pattern of lung injury, with ground-glass appearance, consolidation, or both predominating in bilateral, peripheral, and basal areas [44,45,47]. Wang et al. [48] used a fully automatic deep learning approach to diagnose COVID-19 from chest CT images. Loey et al. [49] proposed Conditional Generative Adversarial Nets (CGAN) to detect COVID-19 in chest CT scan images. Deep learning-based methods contributed significantly to the discovery of new drugs, in addition to determining whether a patient's chest X-ray and CT images are infected with COVID-19. Patankar et al. [50] used the LSTM deep learning method to calculate medications to explore possible drug candidates for the treatment of COVID-19. Zhang et al. [51] established a deep learning model based on a dense fully convolutional neural network (DFCNN) to implement protein-ligand interaction pairs for further discovery of protease medicines related to COVID-19.

Similarly, in fighting against the epidemic, machine learning (ML) methods can also be viewed as a powerful processing method. Sethy et al. [52] used the Support Vector Machine (SVM) method to analyze the features of coronavirus disease and constructed the classification-detection approach for detection. Ong et al. [53] proposed the newly developed machine learning-based Vaxign-ML reverse vaccinology tools to predict COVID-19 vaccine candidates. In this crisis, some people will experience psychopathology, such as depression and anxiety. Due to the large-scale family quarantine, it has greatly restricted direct psychosocial testing of patients [54]. However, an analysis of public comments on social media platforms can provide insight into how people's mood change during the epidemic. ML has produced promising results in a variety of natural language understanding tasks, including sentiment analysis and text classification. Jelodar et al. [55] presented a systematic framework based on the Natural Language Process (NLP) to extract meaningful comments about COVID-19 on Reddit. Li et al. [56] used NLP and Weibo data to classify the COVID-19-related information. The extraction and classification of social media comments is useful in identifying patient's emotional changes during an epidemic disease, which can encourage the government to make timely effective arrangements.

The rest of this paper is organized as follows: Mathematical modeling-related approaches were used to predict the spread of the COVID-19 pandemic approaches in Section 2; In Section 3, deep learning-related approaches were used to the chest X-ray and CT images and construct the approaches for the diagnosis of COVID-19 infected patients; and deep learning-based method for detecting COVID-19 in LUS was introduced in detail; and the contribution of ML in biology and medicine was introduced to predict vaccine and antibodies; In Section 4, the application of telehealth systems during the pandemic and the application of NLP-related methods to analyze COVID-19 tweets on social media are introduced. The discussion, future research focus and the conclusion are summarized in Sections 5–7, respectively.

2 The Propagation Analysis of COVID-19

In recent years, the analysis method based on mathematical modeling-related approaches has always been favored by researchers and engineers, and has been widely used in various aspects of the application scenes, such as biology [57], epidemiology [58] and medical sciences [59]. This is due to its precise description of the mechanical model. Traditionally, these approaches involved deterministic models based on algebra, vector calculus, regression, differential equations, etc. to solve real world problems [60]. The standard compartmental model such as SIR, can date back to the mathematical tour de force of Kermack et al. [61]. The SIR model is one of the deterministic models employed to simulate the spread of infectious diseases, which comprises three compartments: susceptible (S), infectious (I) and recovered (R) [30]. The two parameters S and R, as the name implies, represent the susceptible part and the infectious part respectively. In particular, R can be viewed from a macroscopic perspective as the composition of all immune individuals, including individuals who have recovered and died. The overall framework of this survey is shown in Fig. 1.

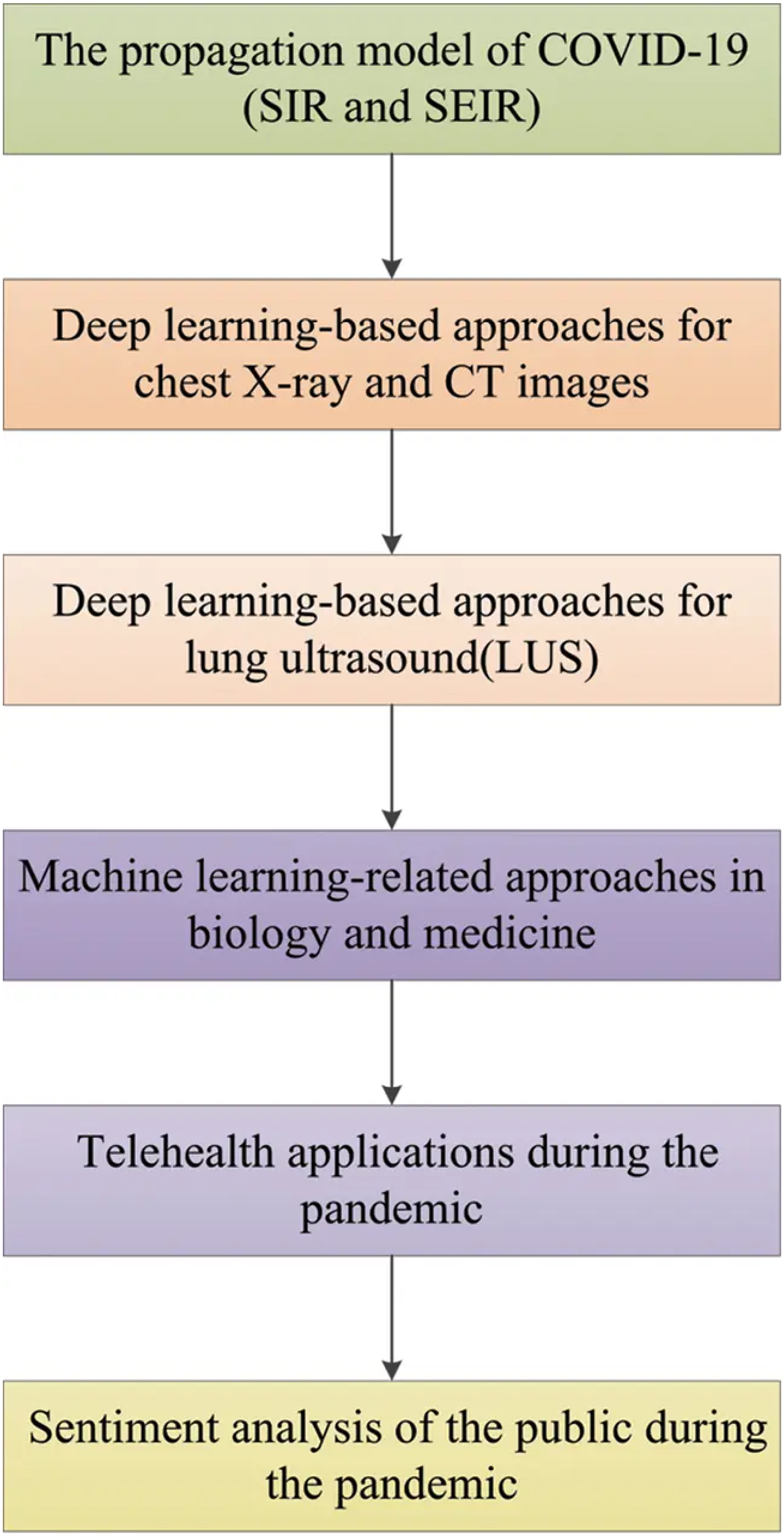
The propagation model of COVID-19 (SIR and SEIR)
Deep learning-based approaches for chest X-ray and CT images
Deep learning-based approaches for lung ultrasound(LUS)
Machine learning-related approaches in biology and medicine
Telehealth applications during the pandemic
Sentiment analysis of the public during the pandemic

Figure 1: The processing diagram of this paper

Menon et al. [30] used the deterministic mathematical model of the SIR and its variants to study the propagation of COVID-19 in the Indian population. Chen et al. [62] proposed a time-dependent SIR model to address undetectable infections in COVID-19, which tracked the transmission and recovery rate. Wang et al. [63] extended the SIR model to incorporate various types of time-varying quarantine protocols, which contribute to timely analysis and evaluation of the timecourse dynamics of a range of infectious disease epidemics. Compared with the traditional static SIR model, the time-based SIR model proposed is more adaptable and robust. Infectious diseases transmission routes are difficult to determine, and the parameters involved are difficult to estimate [64,65]. Many researchers are always trying to assess the relevant parameters of the emerging coronavirus pandemic, in order to improve prediction accuracy. Heritability, severity, sensitivity and specificity etc. parameters have been evaluated by Shearer et al. [66] and Moss et al. [67]. Biswas et al. [68] studied the law of COVID-19 case data using the SIR model on the Euclidean network and reproduced China's data with great accuracy under the premise of known relevant parameters, allowing them to plan appropriate measures in advance to limit the number of infections. To reduce the uncertainty of model prediction as much as possible, Zhong et al. [69] developed a simplified SIR model with only two parameters: the infection rate and the removal rate. In particular, Chikina et al. [70] used a simple SIR-like epidemic model to simulate the effect of age-targeted mitigation strategies for a COVID-19-like epidemic, demonstrating that they can effectively reduce mortality and ICU utilization. Singh et al. [71] used an age-structured SIR model to study the transmission process of COVID-19 among age and inter-age social contacts, emphasizing the role of social distance in moderating virus transmission.

Many infectious diseases are in the incubation period, during which individuals are infected with no spread. Therefore, the 'exposed' individual compartment is added to the SEIR models to migrate the susceptible individuals. Long incubation periods, different age groups, potential immunity deficiency, asymptomatic and symptomatic carriers, and minimum testing are all included in traditional SEIR epidemiology models [72]. The SEIR model has also traditionally been used to explore epidemic spread with various forms of networks of transmission that define the contact topology [73], such as scalefree networks [74–76], small-world networks [77,78], Oregon graph [79,80] and adaptive networks [81]. Zhan et al. [82] published the dynamics of human migration and the process of disease transmission, and used the classic SEIR model to combine inter-city travel data collected by Baidu migration data [83]. The classic SEIR epidemic model has also been used in [72] and incorporated dynamic features to analyze the spread of different age groups in specific dynamic partitions. Prem et al. [84] used an age-structured SEIR model for several physical distancing measures to simulate the ongoing trajectory of an outbreak in Wuhan. To consider the spread of infection during the incubation phase, a modified SEIR model has been proposed in [85]. Aside from the incubation period and the patient's age, temperature and humidity have a potential impact on the spread of infectious diseases. Guo et al. [86] studied the link between temperature and humidity by using the equation derived from the SEIR model to analyze the influence of weather on the transmission rate of COVID-19.

Wearing a mask can reduce the likelihood of viral infection, because COVID-19 is highly contagious through a patient's respiratory tract. Rahman et al. [87] developed systems that automatically detect if pedestrians are wearing masks to limit the growth of COVID-19. Eikenberry et al. [88] developed a compartmental model for assessing the community-wide impact of masks used by the general and asymptomatic public. Self-protection and isolation have effectively controlled the spread of the virus. Peng et al. [89] proposed a generalized SEIR model that improved on the classic SEIR model by accunting for factors such as self-protection mechanism, new isolation status, and preventive measures on the epidemic. The adding of a new quarantined sate is driven by data, which along with the recovery state, constitutes the original R state in the classic SEIR model. The corresponding epidemic model for COVID-19 is shown in Fig. 2.

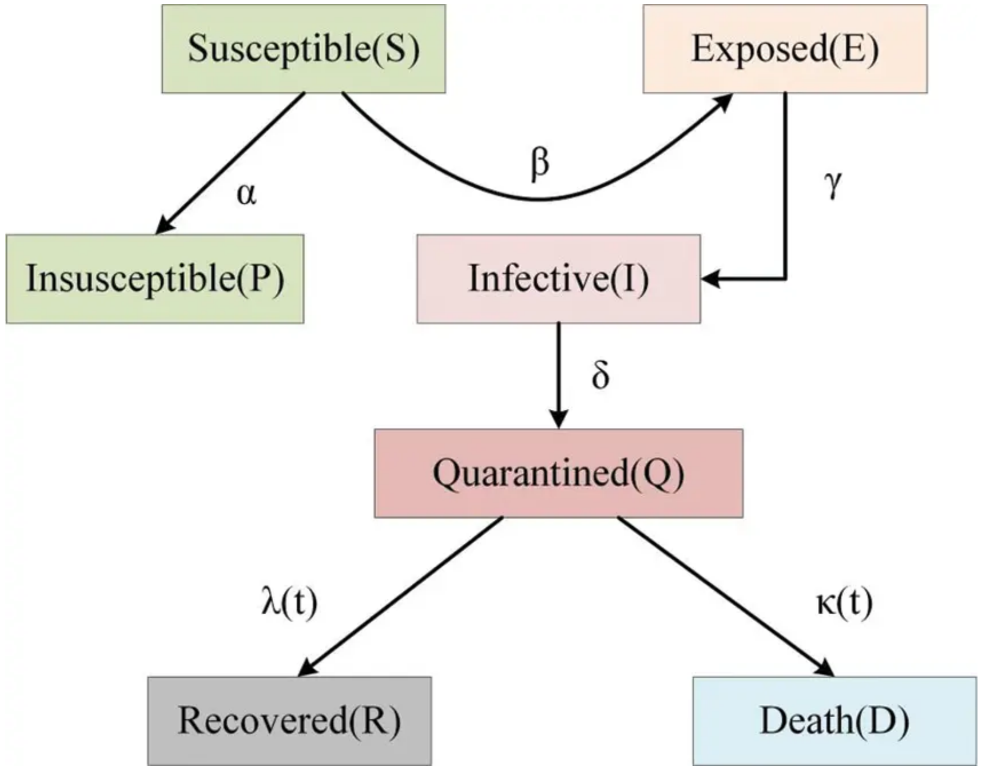

Figure 2: The epidemic model for COVID-19

Many studies have used a hybrid model based on the SEIR model to predict COVID-19 transmission changes more comprehensively and effectively. On the Johns Hopkins COVID-19 dataset, Pandey et al. [90] utilized the SEIR model and the regression model to predict changes in virus's spread, and the findings showed that the regression model prediction had a higher root mean squared log error (RMSLE) that the SEIR model prediction. Considering the long-term impact of measures taken by the government, such as increasing the duration and intensity of isolation, a 4 + 1 penta-group model was established to predict the future trend of disease outbreaks [91]. A mathematical model of bat-host-reservoir-human transmission was proposed by Chen et al. [92] based on the SEIR model to simulate the potential transmission of bat-to-human infections. Others, meanwhile, use purely mathematical approaches to analyze the virus's spread. Chen et al. [93] introduced a novel dynamic system with time-delay, which was applied in the differential equation to analyze the COVID-19 incubation duration. A discrete model has been proposed in [94], to simulate the dynamic process of coronavirus transmission between humans or animals in the same or other regions. The model based on the discrete-time Pontryagin maximum principle was applied to achieve optimal control, and it has been shown to be one of the most cost-effective strategies to control the disease.

Aside from the deterministic methods described above, the infectious disease modeling process can also be stochastic [95], which is useful when no relevant epidemiological parameters are available. Hellewell et al. [96] proposed a stochastic transmission model to assess the impact of contact tracing and isolation on the transmission of COVID-19 cases, which is a branch process model of stochastic modeling. In contrast to [96], Levesque et al. [32] paid more attention to the stochastic formulation of COVID-19 and built a parsimonious Crump–Mode–Jagers continuous time branching process of propagation to provide a basis for making decision for contact tracing and isolation. Furthermore, one of the most important properties of epidemics spread is spatial propagation, which is primarily determined by epidemic mechanism, human mobility and control strategy [97]. An in-depth understanding of the spatio-temporal dynamic characteristics of infectious diseases could be helpful for epidemic prevention and control [98]. Arenas et al. [99] provided a mathematical model based on the Microscopic Markov Chain Approach (MMCA) for the spatio-temporal transmission of epidemics, showing that in the current stage of the epidemics, stricter social distance containment measures are required to avoid the health system collapsing.

SIR and SEIR-based mathematical models are deterministic models that are used to predict the propagation of simulated epidemics. Many studies that predicted the spread of COVID-19 epidemics have been based on SIR and SEIR models, which have been analyzed and modified to take into account things such as the effects of social interventions, age, and social distance. However, there are some limitations to using deterministic models to simulate and predict epidemic diseases. To more properly evaluate COVID-19 propagation, a stochastic model was applied, in which random variables and probability distributions were used to characterize parameter interactions. In addition, model parameters are one of the most significant challenges in predicting the propagation of an epidemic. The more complicated the model structure is, the more parameters need to be determined, which makes it difficult to determine all the parameters in the absence of epidemiological data [69]. However, to some extent, the use of stochastic modeling reduces the uncertainty of parameters. According to the findings of the preceding studies, assessing and forecasting the COVID-19 transmission process is critical for raising public awareness and timely mobilizing resources for effective control and treatment.

3 The Application of Neural Network-Based Detection Methods during the Pandemic of COVID-19

Neural network learning is a process. Some sample patterns are successively input to the network under the incentive of its environment, and the weight matrix of each layer of the network is updated according to a certain learning method. The learning process is completed when the weight of each layer of the network converges to a certain value. The resulting neural network can then be used to classify the real data. Wang et al. [100] proposed a method for classifying heartbeats based on a dual fully connected neural network to determine whether the heart rate is abnormal.

CNNs with strong feature extraction capabilities and the ability to automatically learn features from images in a specific field [101–108], which have been widely used in the field of medical imaging [109]. CNNs strong feature extraction capabilities also come in here. Such as, Qin et al. [110] used a deep twin CNN to detect the misfire of diesel engines under strong environmental noise and different working conditions; In order to better mine meaningful deep information and apply it to the prediction of cutter head torque, Qin et al. [111] also utilized CNN and LSTM to extract the implicit features and sequential features of relevant parameters of shield tunneling machines.

3.1 Deep Learning and Transfer Learning-Based Approaches for the Detection of COVID-19 from Chest X-ray and CT Images

The transfer of learnt knowledge from a pre-trained network that completed one task to a new task is a popular strategy for training CNNs [108]. Transfer learning can be accomplished through the three following aspects [43,112,113]: i) 'shallow tuning', which adjusts only the last classification layer according to a new task without considering the parameters of other layers; ii) 'deep tuning', aiming to retrain all the parameters of the pre-trained network in an end-to-end manner; iii) 'fine-tuning', aiming to gradually train more layers by tuning the learning parameters to improve the performance of the network. In recent years, transfer learning has been often used in the field of medical image classification, such as tumor classification [114], skin lesions [115], cancer classification [116], retinal disease diagnosis [117] and pneumonia detection [118].

To reduce the training network time and computational complexity, the transfer learning algorithm has been used on the pre-trained AlexNet model proposed in [119]. By using the pre-trained AlexNet model to transfer the learning weights, bias and features to the approach of diagnosing COVID-19 from chest X-ray and CT images. To better extract lung features, a two-step transfer learning strategy based on COVID-19Net has been proposed in [48]. It uses the large CT-EGFR dataset for auxiliary training, and the pre-trained COVID-19Net is then applied to the COVID-19 dataset. Narin et al. [120] used five pre-trained transfer CNN models (ResNet50, ResNet101, ResNet152, InceptionV3 and Inception ResNetV2) to automatically classify four aspects of healthy, COVID-19, bacterial and viral pneumonia patients. Kassani et al. [121] used CNNs to extract features from images. Ten CNNs were used to distinguish infection of COVID-19 from non-COVID-19 groups, of which Resnet101 differentiated them with an accuracy of 99.51% [122]. Horry et al. [123] also used a pre-trained deep learning model to detect COVID-19 from chest X-ray images. Islam et al. [124] proposed a method of using VGG19, DenseNet121, InceptionV3, InceptionResNetV2 CNNs for transfer learning and combining with a recurrent neural network(RNN) for chest X-ray image diagnosis of COVID-19.

The transfer learning strategy was adopted to directly transfer the weights trained on other large datasets to the trained CNN model, due to the over-fitting problem caused by the limited number of trained images.

The aforementioned transfer learning retains the parameters of the pre-trained model, but in order to improve the performance of network, many studies have used a more complex transfer learning strategy, which is applied to the pre-trained model by fine-tuning the parameters. Transfer knowledge *via* fine-tuning mechanism showed outstanding performance in chest X-ray and CT image classification [125–128]. The transfer learning strategy mentioned in [125–128], there have been many studies on the detection and classification of chest X-ray and CT images using transfer learning and deep learning that have been presented recently. Apostolopoulos et al. [43] proposed state-of-the-art CNNs for transfer learning by tuning the parameters, which shared some hyper-parameters and detected COVID-19 automatically. The COVID-19 detection system, proposed by Razzak et al. [129], used seven pre-trained CNNs model and a fine-tune transfer learning method on top of them to diagnose in healthy, bacterial pneumonia, and viral pneumonia scenarios. The overall accuracy of diagnosis was 98.75%. To improve model classification performance and reduce training time, the three-step technique was used to fine-tune the pre-trained model ResNet-50 and screen COVID-19 patients on the COVIDx dataset [130]. A Bayesian Convolutional Neural Network (BCNN) based on Dropweights, which was introduced in [131] based on a pre-trained ResNet50V2 model and fine-tuning the original model, aims to improve the diagnostic performance of human-machine decisions. In addition, Ucar et al. [132] proposed SqueezeNet a pre-trained model for diagnosing COVID-19 from chest X-ray images that is optimized using Bayesian method. Meanwhile, the SqueezeNet model needed to be fine-tuned and the overall classification accuracy of Bayes-SqueezeNet was 98.3%. Brunese et al. [133] fine-tuned VGG16 to perform transfer learning and distinguish between common lung disease and COVID-19 from chest X-ray images, and then highlighted areas of COVID-like symptoms on chest X-ray images. He et al. [134] proposed an efficient sample deep learning method that combines contrastive self-supervised learning and transfer learning to detect chest CT images. Vaid et al. [135] used CNNs for transfer learning to detect chest X-ray images of patients, with a 96.3% accuracy. Wang et al. [136] proposed a model called CCSHNET for detecting COVID-19 in the chest CT images. The model is based on DCFDCA algorithm of the selected two optimal models, for which they developed a SAPNF algorithm is developed to optimally determine the best pre-training model (PTM) and with a hyper-parameter of number of layers to be removed (NLR, Symbolized as L), and then the proposed L2TfL algorithm realized the feature learning process of the two models.

COVID-19 detection accuracy can be significantly improved by preprocessing the dataset. Toaçar et al. [137] proposed preprocessing the data with fuzzy color technology, followed by training the acquired feature sets with a deep learning model and processing them with the Social Mimic Optimization method, rather than using transfer learning directly. Finally, SVM was used to combine and classify the effective features. A generative adverse network (ACGAN) model based on an auxiliary classifier was used to generate the synthesized chest X-ray images, and it was demonstrated that the synthesized images could be used to improve CNN detection performance [138]. Two data enhancement models were proposed by Sedik et al. [139], the first is to enhance the dataset with simple image transformation to achieve the deep learning model's effective learning level, and the second is to enhance the data with a GAN network. COVID-19 was detected using CNNs and convolutional long short-term memory (CONVLSTM) after data enhancement. Using a new technique of multi-path data enhancement, Wang et al. [140] extracted features from a self-created CNNs to learn a single image-level representation, and relation-aware representations were learnt from graph convolutional network (GCN). Then they developed Deep feature fusion (DFF), which fuses individual image-level features and relation-aware features from both GCN and CNN, respectively. In [49], five deep transfer learning models combined with classical data augmentation and Conditional Generative Adversarial Nets (CGAN) were proposed to improve the classification performance of the models, with the ResNet50 model combined with classical data augmentation having a classification accuracy of up to 82.91%. The proposed architecture of the classical data augmentation along with the CGAN and DTL models is shown in Fig. 3.

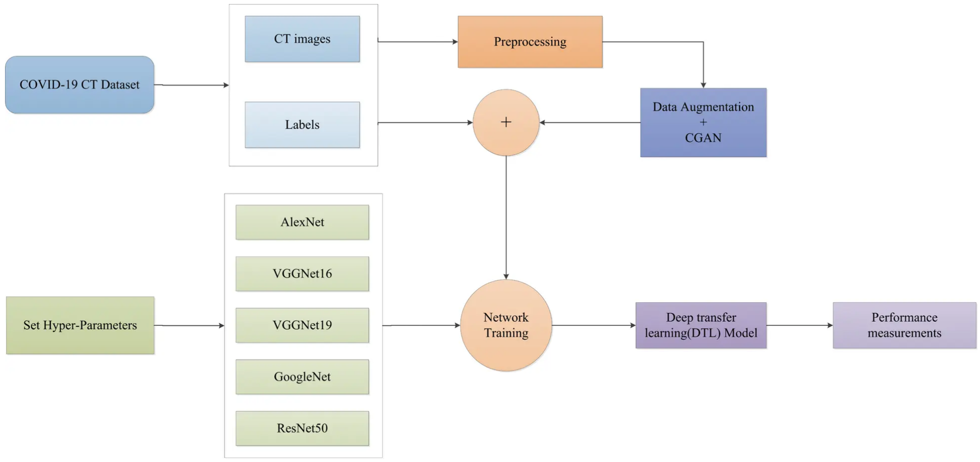

Figure 3: The proposed architecture of the classical data augmentation along with CGAN and DTL models

With an increase in the number of new coronary pneumonia cases worldwide, there are privacy concerns when considering data sharing among hospitals around the world. Ting et al. [141] explored the use of four interrelated digital technologies to enhance COVID-19 response: the Internet of Things, big data analytics, Artificial intelligence (AI), and blockchain. As a result, Kumar et al. [142] proposed using blockchain-based federated learning to train a global deep learning model. Federated learning safeguards the organization's privacy while training the model on a global scale. They also used Capsule Network-based segmentation and classification to identify COVID-19 patients. The comprehensive experiments show improved performance in detecting COVID-19 patients. Deep learning method can not only detect the state of chest X-ray and CT images, but it can also track the disease, facilitate risk assessment, and arrange corresponding measures. Ye et al. [143] proposed an AI-driven system composed of the Attributed Heterogeneous Information Network (AHIN) and using cGAN to enrich it, namely alpha-Satellite, to automatically provide hierarchical community risk assessments related to COVID-19. Chimmula et al. [144] forecasted the COVID-19 transmission in real time in Canada using the Long short-term memory (LSTM) networks. Alazab et al. [145] also used the Prophet Algorithm (PA), the Autoregressive Moving Average (ARIMA) model integration, and the LSTM neural network to predict the number of confirmed COVID-19 deaths and resuscitation over the next seven days.

3.2 The Hybrid Deep Learning Approaches for the Detection of COVID-19 are Based on Chest X-ray and CT Images

Based on detection of chest X-ray images, Hemdan et al. [146] proposed a deep learning framework, COVIDx-Net, with seven different deep networks to automatically diagnose COVID-19. Song et al. [147] created deep learning-based diagnostic CT systems (Deeppneumonia) in three steps: first, extracting key lung features, then designing a DRE-Net neural network to extract K details from chest CT images and make predictions, and finally, diagnosing at the patient level. This system facilitates rapid identification of patients and the results reveal an AUC of 99% and a sensitivity of 93%. To analyze automated detection and patient monitoring based on chest CT images, Gozes et al. [148] proposed a 3D and 2D deep learning models. The 3D deep learning model analyzed the 3D lungs using existing software [149]. The U-net model was used to segment the lung in the 2D deep model, and pre-trained ResNet-50-2D CNNs were used to detect lung abnormalities. A deep learning system was proposed in [150] to screen patients that consists of two classification models. The first is the ResNet-18 model, and the second is to build a position-attention classification model on top of it to increase overall classification accuracy. The deep learning system also includes a 3D deep learning model to segment lungs from chest CT images. Besides, a 3D deep learning framework, COVNet based on RestNet50, was developed in [151] to extract both 2D local and 3D global representative visual features from volumetric chest CT exams for identifying COVID-19.

In order to improve model's generalization capabilities, Amyar et al. [152] proposed a multi-task deep learning model to complete image reconstruction, classification and segmentation to screen for COVID-19 pneumonia. To solve image reconstruction and segmentation, the U-Net architecture was used as encoder and decoder, and CNNs was used to classify images. Hasan et al. [153] provided a method for differentiating between COVID-19 coronavirus, pneumonia, and healthy lungs that combined extracted features from deep networks with Q-deformed entropy handcrafted features. In this study, nine-layer CNNs and the Q-deformed entropy algorithm were used to extract features, which were then given to an LSTM neural network classifier to be classified. Islam et al. [154] proposed a deep learning technology integrating CNN and LSTM to achieve 99.4% accuracy in the automatic diagnosis of COVID-19 from chest X-ray images. Bandyopadhyay et al. [155] adopted LSTM and Gated Recurrent Unit (GRU) models to predict the positive, negative, death, and release of COVID-19 cases, and their predictions matched the clinicians'. The disease may be efficiently predicted and accurately recognized by using deep learning method, allowing appropriate actions to be implemented to effectively prevent the virus's spread. To detect cases from chest X-ray images, Wang et al. [156] designed a COVID-Net framework. The COVID-Net utilized a lightweight residual projection-extension (PEPX) design pattern to enhance presentation capabilities while reducing computational complexity. Muhammad et al. [157] employed epidemiological data of COVID-19 patients in South Korea and a data mining algorithm to predict the recovery of COVID-19 patients. The results demonstrate that the decision tree's data mining algorithm has the highest overall accuracy rate in the prediction outcomes, at 99.85%. Saha et al. [158] proposed an automatic detection scheme named EMCNET, which extracted deep features from the chest X-ray images of infected patients using CNN. Four ML methods, namely random forest, support vector machine, decision tree and Adaboost, were used to integrate a binary classifier to detect COVID-19 quickly. Parts of the aforementioned results are tabulated in Tabs. 1–3.

Table 1: Summary of deep learning based COVID-19 diagnosis on X-ray or CT images

References	Data source	Data type	Class	Method	Accuracy (%)
Apostolopoulos et al. [43]	COVID-19 X-ray [159], Kaggle dataset [160], Kermany et al. [161]	X-ray	3 (COVID-19, pneumonia, normal)	VGGNet19; MobileNetv2; Inception; Xception; Inception-ResNet V2	96.78
Narin et al. [120]	COVID-19 X-ray [159], Kaggle chest X-ray [162]	X-ray	2 (COVID-19, normal)	ResNet50; ResNet101; ResNet152; InceptionV3; Inception-ResNetV2	98
Kassani et al. [121]	COVID-19 X-ray [156], Kaggle chest X-ray [162], CT images [163]	X-ray, CT	2 (COVID-19, healthy)	MobileNet; DenseNet; Xception; ResNet; InceptionV3; XceptionRes-NetV2; VGGNet; NASNet	99
Loey et al. [49]	COVID-19 X-ray [159], Kermany et al. [161], dataset [164]	X-ray	2 (COVID-19, nonCOVID-19)	GAN; AlexNet; VGGNet16; VGGNet19; GoogleNet; ResNet50	82.91

Table 2: Summary of deep learning based COVID-19 diagnosis on X-ray or CT images

References	Data source	Data type	Class	Method	Accuracy (%)
Razzak et al. [129]	GitHub Kaggle chest X-ray [162]	X-ray CT	2 (COVID-19, healthy, COVID-19, bacterial pneumonia, COVID-19, viral pneumonia) 3 (healthy, COVID-19, pneumonia-bacterial) 4 (Healthy, COVID-19, pneumonia-bacterial, pneumonia-viral.)	AlexNet; SqueezeNet; GoogLeNet; MobileNet; various ResNet; DenseNet	98.75
Farooq et al. [130]	COVIDx dataset [159]	X-ray	4 (COVID-19, normal, bacterial, viral)	COVID-ResNet	96.23
Ucar et al. [132]	COVID-19 X-ray image database [159], COVIDx dataset [159], Kaggle chest X-ray [165]	X-ray	3 (COVID-19, normal, pneumonia)	Bayes-SqueezeNet	98.3
Hemdan et al. [146]	COVID-19 X-ray image database [159]	X-ray	2 (COVID-19, normal)	VGGNet19; DenseNet201; ResNetV2; InceptionV3; InceptionResNetV2; Xception; MobileNetV2	90
Song et al. [147]	CT images from the Renmin Hospital of Wuhan University and the Third Affiliated Hospital	CT	2 (COVID-19, bacteria pneumonia)	VGG16; DenseNet; ResNet; DRE-Net	86

Table 3: Summary of deep learning based COVID-19 diagnosis on X-ray or CT images

References	Data source	Data type	Class	Method	Accuracy (%)
Xu et al. [150]	Zhejiang University, Hospital of Wenzhou, Hospital of Wenling	CT	3 (COVID-19, Influenza-A-viral-pneumonia, irrelevant-to-infection)	ResNet18	86.7
Li et al. [151]	Multiple hospitals Environment	CT	3 (COVID-19, CAP, non-pneumonia)	ResNet50	–
Amyar et al. [151]	COVID-CT [166], COVID-19 CT segmentation dataset [167], a hospital named Henri Becquerel Center	CT	2 (COVID-19, non-COVID-19)	Encoder-Decoder with multi-layer perceptron	86
Hasan et al. [153]	COVID-19 [168], SPIE-AAPM-NCI Lung nodule Classification Challenge dataset [169]	CT	3 (COVID-19, pneumonia, healthy)	QDE-DF	99.68
Wang et al. [156]	COVID-19 X-ray image database [159], RSNA Pneumonia detection challenge dataset [170]	X-ray	3 (Normal, Non-COVID-19, COVID-19)	VGG19; ResNet-50; COVID-Net	92.4

3.3 Deep Learning Approaches for the Detection of COVID-19 Based on LUS

The mixing of air and water in the chest cavity causes the signs of LUS [171]. LUS has become a helpful diagnostic and testing tool in recent years. LUS is frequently used to diagnose lung parenchymal and pleural diseases, as well as in intensive care units [172,173]. LUS offers the advantages of being simple to use, repeatable, radiation-free, and inexpensive [174]. During the current pandemic, LUS has got a lot of attention and has been pushed as a potentially useful tool for real-time detection of COVID-19 [175–177]. LUS, on the other hand, has certain limits. Ultrasonography can not detect lesions in the deep lung, because the inflated lung hinders its conduction. In a nutshell, the anomaly must extend to the pleura's surface in order to be visible on ultrasound; Otherwise, it needs to be examined by CT [178]. LUS can reduce patient exposure to ionizing radiation and the incidence of cross-contamination by minimizing the need to move the patient, whereas CT requires moving the patient and controlling the long-term risks associated with ionizing radiation [179]. LUS, in particular, is safer for examining pregnant women [180,181].

During the pandemic, Soldati et al. [182] stated that the current clinical evidence strongly suggests that the LUS has the potential to be a diagnostic tool. Soldati et al. [183] also proposed a standardized method for optimizing the LUS examination of COVID-19 patients by using two pocket devices for LUS examination to reduce exposure to medical staff. In developing countries, LUS is an effective tool for diagnosing pneumonia. LUS imaging has emerged as a safe bedside imaging alternative that avoids exposing patients to radiation and minimizes the risk of infection [184]. Bedside LUS has shown better sensitivity than chest X-ray images in the diagnosis of pneumonia in Nepal [185]. Unlike most previous studies that focused on chest X-ray and CT image scanning, Roy et al. [186] studied the use of deep learning approach in the analysis of LUS images. They proposed a deep network called Regularised Spatial Transformer Networks (Reg-STN), which can predict the disease severity score associated with the input frame while also locating pathological artifacts in a weakly supervised manner. To classify COVID-19 from LUS images, Muhammad et al. [187] proposed a light CNN model. Carrer et al. [188] proposed an automatic and unsupervised method for detecting and locating the pleural line in LUS data, as well as using SVM to classify the patients. Controlling the COVID-19 pandemic necessitates the use of a quick and safe diagnostic tool. In comparison to chest X-rays and CT images, LUS has numerous practical advantages [189]. Born et al. [190] developed a frame-based CNN that correctly classifies COVID-19 from LUS datasets. Awasthi et al. [191] established Mini-COVIDNet, a light weight deep neural network, based on COVID-19 detection using LUS video. Dastider et al. [192] proposed an integrated autoencoder-based hybrid CNN-LSTM model that detects COVID-19 severity scores from LUS images very well.

LUS, as previously stated, is effective in detecting COVID-19 pneumonia. In relevant studies in China [178] and Italy [183], the physical basis and LUS pattern of COVID-19 patients were provided, indicating that LUS can be a useful tool for the diagnosis and monitoring of COVID-19 pneumonia. However, no data on the use of LUS in children with COVID-19 pneumonia are currently available. Although COVID-19 infection in children is rarely as severe as in adults, it has been showed in several studies to impact children of all ages, from newborns to adolescents [193–196]. The observation that LUS can detect COVID-19 pneumonia in children is of clinical significance because LUS has been shown to be accurate in diagnosing pediatric pneumonia of any origin [197–201]. Musolino et al. [202] described LUS features of 10 consecutively admitted children with COVID-19 in two tertiary-level pediatric hospitals in Rome, it is mainly manifested as vertical artifacts (70%), pleural irregularities (60%), areas of white lung (10%) and subpleural consolidations (10%). This study is crucial since children with COVID-19 have fewer data on LUS. LUS will be an effective method for detecting children with COVID-19 if physicians have LUS experience recording children with COVID-19.

3.4 Machine Learning-Related Approaches for the Analysis of Biology and Medicine

Deep learning methods have begun to replace traditional methods to develop drugs that effectively combat this epidemic, because traditional methods take a long time for developing a drug. Zhang et al. [203] established a 3D-like protease protein model using homology modeling and detected potential drugs for the 2019-nCoV protease. In order to swiftly and accurately reverse search for the drug targets, a Dense Fully Convolutional Neural Network (DFCNN) deep learning model has been built to accurately sort/identify protein-ligand interaction pairings.

Based on immune profiling data, ML approaches have also been successfully used to predict antigen-specific immunological signatures in vaccines [204,205]. In order to pick the most promising vaccine candidates, Le et al. [206] compiled and shared information on the status of COVID-19 vaccine development activities around the world. Ong et al. [53] applied the Vaxign and the newly developed machine learning-based Vaxign-ML reverse vaccinology tools to predict COVID-19 vaccine candidates. In addition, finding peptides or antibody sequences that can suppress the SARS-CoV-2 virus's epitope is critical for efficiently inhibiting the virus's propagation [207]. Magar et al. [207] used a variety of ML approaches, including XGBoost, Random Forest, Multilayer perceptron, SVM and Logistic Regression, to predict the possible inhibitory synthetic antibodies for SARS-CoV-2. ML methods can also be used to complete case diagnosis tasks and prevent the spread of disease. Sethy et al. [52] map the image features collected from CNNs to a higher-dimensional space and implement coronavirus disease classification-detection. COVID-19 infection can be detected using the Routine Blood Exams with ML method, in addition to chest X-rays and CT images. Brinati et al. [208] developed two ML classification models to distinguish between positive and negative SARS-CoV-2 patients, as well as an interpretable Decision Tree model for clinicians interpreting blood tests (even off-line) for COVID-19 suspect cases. Machine learning-related methods for detecting COVID-19 were proposed in [209] based on the clinical text data. Textual clinical reports are divided into four categories using ML methods: COVID, SARS, ARDS, and both (COVID, ARDS). The test accuracy of logistic regression and multinomial *Näive* Bayes was 96.2%, outperforming other ML approaches. For the purpose of control and treatment of COVID-19 from the root cause, it is necessary to explain the origin of the virus and the viral genomic sequence as soon as possible. Randhawa et al. [210] identified an intrinsic COVID-19 virus genomic signature and related methods together with a machine learning-based alignment-free approach for classification of whole virus genomes.

4 The Telehealth and Sentiment Analysis-Based Analysis Framework of COVID-19 during the Pandemic

4.1 The Telehealth Analysis of COVID-19 during the Pandemic

The implementation of public health measures has a potential effect. In the absence of vaccines, it aims to reduce virus spread by reducing population exposure. For example, Wearable technology can provide real-time remote monitoring to reduce contact between doctors and patients [211]. Multiple interventions stratified together can effectively reduce population exposure and thus viral infections [212]. The concept of telehealth has always existed [213,214]. During the COVID-19 pandemic, scalable telehealth systems were widely used, which were critical to improving the quality of the medical system, ensuring the safety of patients and doctors, and lowering the infection rate [215]. Telemedicine can also support triage and classification of susceptible people before they are referred to the hospital [216].

Smith et al. [217] introduced key requirements for using telehealth, such as flexible funding arrangements, health worker training and accreditation. However, remote systems are still subject to licensing, integration and reimbursement issues in the majority of countries [218]. Wosik et al. [219] describe the role of telehealth in transforming healthcare delivery during the COVID-19 pandemic in the United States (US). Iran offers diagnostic expertise for COVID-19 *via* teleradiology services delivered *via* social media platforms [220]. Long-term social isolation may limit physical activity and affect mental health in COVID-19 patients with other conditions, such as cardiovascular diseases, so the use of telehealth health care intervention systems can reduce the morbidity and mortality of acute diseases caused by COVID-19

[221]. Vandekerckhove et al. [222] believe that video counselling in cardiology for further telehealth is essential for a flexible healthcare system for emergency needs outside of the COVID-19 pandemic. Moreover, children and adolescents are using telehealth [223]. Bokolo et al. [224] looked at how telemedicine and virtual software helped patients following the pandemic, as well as the social, organizational, and technical factors that influence patient and physician acceptance of telemedicine and virtual platforms. The social, organizational, and technical aspects of telemedicine and virtual platforms are illustrated in Fig. 4.

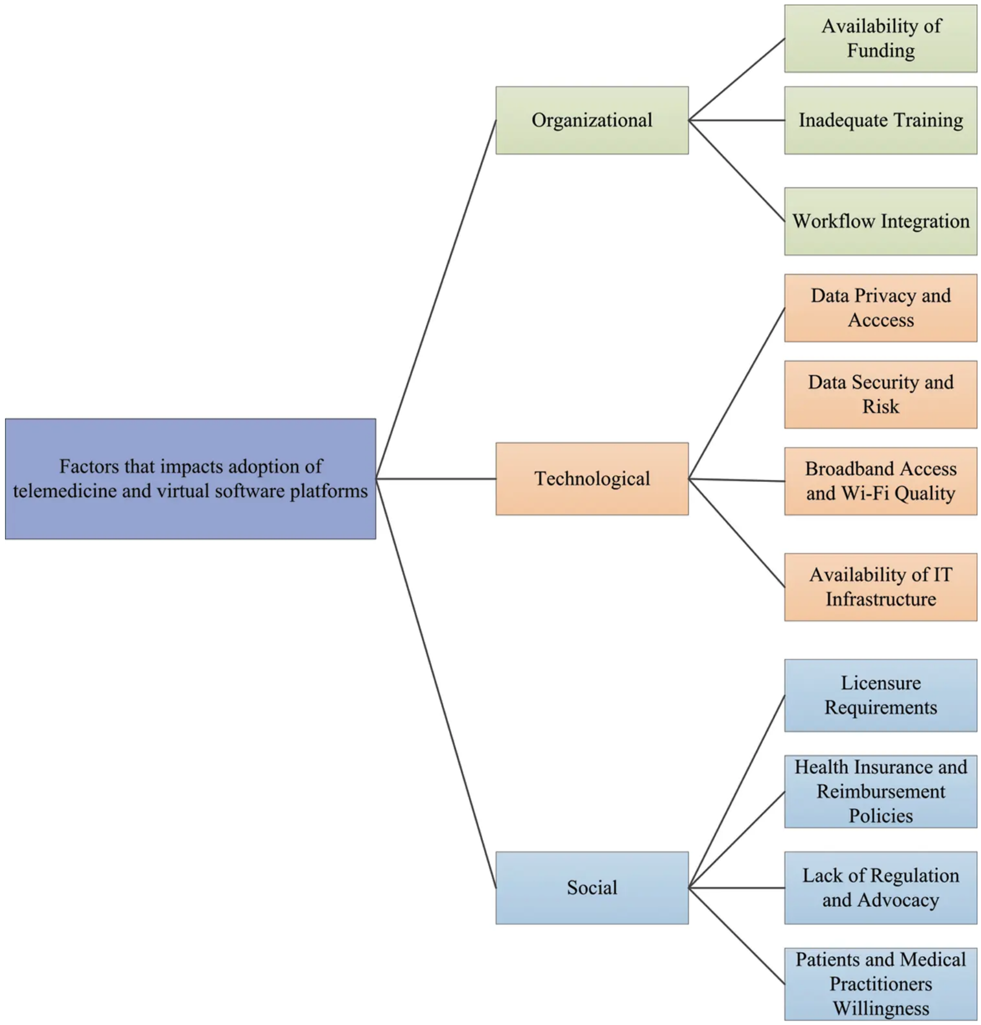

Figure 4: The social, organizational, and technical aspects of telemedicine and virtual platforms

Aslani et al. [225] briefly outlined the needs addressed by telemedicine, as shown in Fig. 5. It is also recommended that all countries respond to COVID-19 using telemedicine capabilities in accordance with their own national measures. Besides, during the COVID-19 pandemic, Jnr et al. [226] introduced practical guide to the use of telemedicine and virtual care. This study fully demonstrates the potential of virtual care solutions.

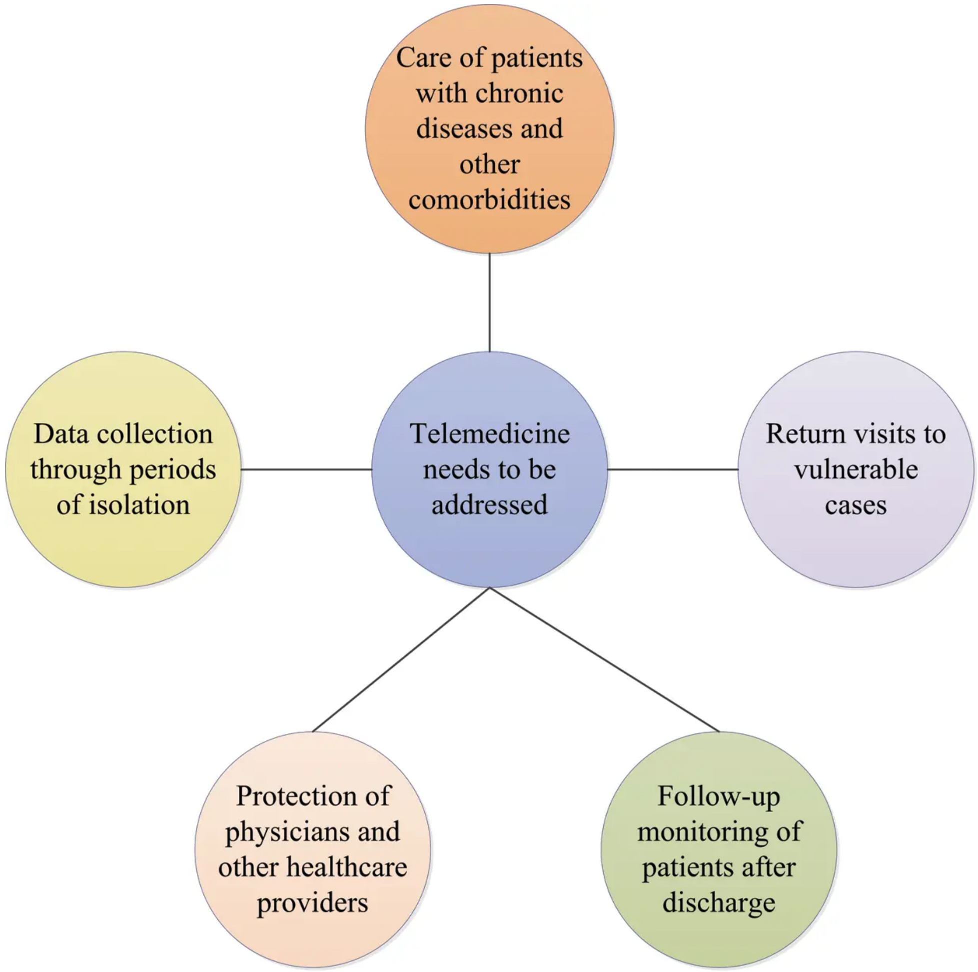

Figure 5: The processing strategy of the telemedicine

4.2 The Sentiment Analysis of the Public during the COVID-19 Pandemic

As we all know, in today's world, it is common for people to use social media to learn about current events and share their thoughts. During the COVID-19 pandemic, social media played a huge role in keeping people connected and informed. Reports on the epidemic may be viewed online, and people can express their emotions through various social platforms. Hence, analyzing public sentiment has become extremely critical in preventing a series of psychological problems, such as depression.

To better understand the information crisis of COVID-19, it is indispensable to assess public sentiment. Samuel et al. [227] identified public sentiment related to the pandemic using coronavirus-specific tweets, and R statistical software, and its sentiment analysis software package, revealing the growth process of COVID-19 fear and negative sentiment in the US. When short tweets are classified using the *Näive* Bayesian method, the accuracy rate can reach 91%. Based on RNN, Nemes et al. [228] created an emotion prediction model. They utilized the model to analyze tweets on Twitter, search for words associations, and categorize various types of text into clearer categories of emotional intensity, such as weak positive/negative and strong positive/negative.

As the epidemic worsens, India has adopted blockade measures to prevent the increase in cases. After the lockdown, Indians' comments on Twitter were studied by Barkur et al. [229]. The full analysis process was carried out using the R software, and a word cloud describing the sentiment of the tweet was generated. According to the study's findings, the vast majority of Indians are quite in favor of the blockade measures. To assess the sentiment on Twitter in India during the peak of COVID-19 new cases in 2020, Chandra et al. [230] also proposed a deep learning-based LSTM RNN model and a multi-label sentiment classification framework using global vector (Glove) embedding. The results show that the majority of people are pleased with how the authorities handled the epidemic, while a small number are dissatisfied. Chintarapudi et al. [231] used the Bidirectional Encoder Representations from Transformers (BERT) model to analyze tweets from the Indian public during the COVID-19 lockdown and achieved an accuracy rate of 89%. Wang et al.

[232] also used the fine-tuned BERT classification model to classify postings linked to the new crown on Chinese social media Weibo, including positive, neutral, and negative, and used the term frequency-inverse document frequency (TF-IDF) topic model to summarize the topics of the posts. This research also uncovered crucial depression-related motifs. Moreover, Fig. 6 depicts the workflow of the sentiment analysis model.

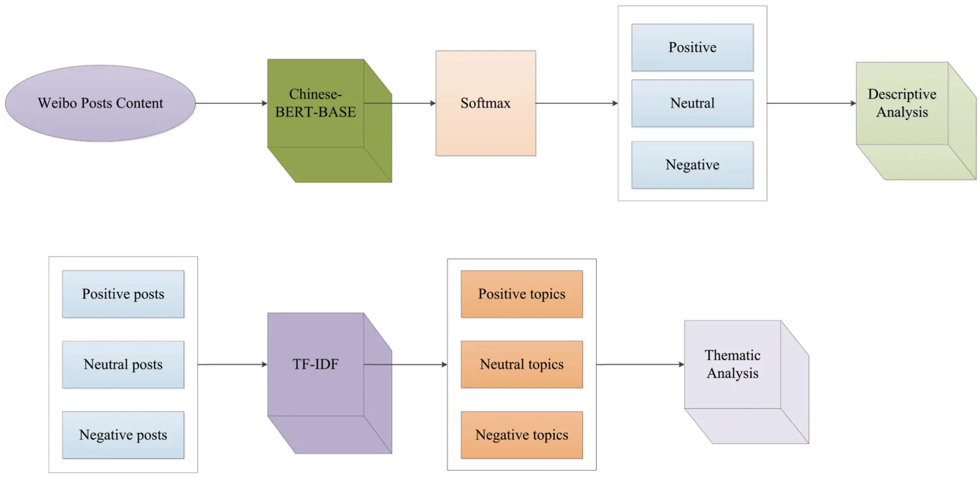

Figure 6: The workflow of the sentiment analysis model

Tclustvid, an intelligent cluster-based classification and topic extraction model, was proposed to categorize COVID-19-related tweets into positive, neutral, and negative emotions, as well as identify the most common topics [233]. The widely unsupervised Latent Dirichlet Allocation (LDA) [234] ML methods have been applied by Xue et al. [235], to analyze tweets concerning epidemics on Twitter. The subjects of 1,597,934 tweets made by 1,299,084 users from 18,413 news media articles and social media were modeled using LDA by de Melo et al. [236]. This research contributes to a deeper understanding of the COVID-19 pandemic's observations and gives a more meaningful emotional timeline. Furthermore, to see if Twitter and traditional news media cover similar COVID-19 categories and topic kinds, the popular cosine similarity was employed as a measure of topic similarity and defined by Eq. (1),

[Math Processing Error] (1)

where t_a and t_b are essential the vectors used to describe the topics a and b, respectively, and the value of the corresponding similarity range from 0 to 1. The NLP approach can automatically extract COVID-19-related discussions from social media. A systematic framework based on NLP has been presented in [55], which is able to extract meaningful topics about COVID-19 from Reddit. This research has certain significance for the government to promulgate measures related. Lopez et al. [31], like [55], recommend using network analysis techniques, NLP and text mining to analyze a multilanguage Twitter dataset to understand changing policies and common responses to the COVID-19 outbreak across time and countries. Li et al. [56] classified COVID-19-related information into seven types of situational information using NLP and Weibo data. Data classification using SVM, *Näive* Bayes and random forest classifiers is quite useful in assisting the public in effectively and quickly understanding the novel disease.

During the COVID-19 pandemic, Hung et al. [237] used NLP to determine whether tweets on Twitter were positive, neutral, or negative. Topic modeling using LDA and identifying five general themes. Overall, positive tweets outnumbered negative tweets, according to the study. Sanders et al. [238] built a new pipeline that used state-of-the-art NLP technology to analyze sentiment on topics related to mask wearing on Twitter. The analysis pipeline to extract, label, summarize, and present the themes, topics and sentiment present in tweet *corpus*. Retrieval and Sampling, Embedding and Sentiment Scoring, Clustering and Subclustering, Cluster and Subcluster Labeling, and Cluster and Subcluster Summarization are the primary sections of the analysis pipeline. Cluster and Subcluster Labeling is the fourth step, in which each word is scored based on its contribution to the Kullback-Leibler divergence, defined by Eq. (2), as it is relates to the word distribution of the cluster and the word distribution of the entire *corpus* sample,

[Math Processing Error] (2)

where W_s and W_c are the word probability distributions for thecorpus sample and sub-sample (cluster), respectively.

Moreover, public sentiment will be influenced by the COVID-19 vaccine's research and development. To foster public faith in the vaccination, it is vital to analyze public sentiment about the vaccine. From March 1 to November 22, 2020, Hussain et al. [239] extracted social media posts on the COVID-19 vaccine from Facebook and Twitter in the United Kingdom (UK) and the US. And they created a hierarchical hybrid ensemble AI model for sentiment analysis, which consists mostly of the Valence Aware Dictionary for Sentiment Reasoning (VADER), TextBlob and BERT based on deep learning. The study's findings show that the public's sentiment towards vaccines in the UK and the US on the two platforms is mostly positive and similar. This is in relation to the country's recent announcements about vaccine development, testing, and supply, which have allayed public fears and concerns. Different from the method used by Hussain et al. [239], Ritonga et al. [240] employed the *Näive* Bayes algorithm to analyze the Indonesian public's remarks on the COVID-19 vaccination in January 2021 in order to better understand people's perspectives on the vaccine. According to the findings, up to 56% of the public had an unfavorable attitude toward vaccines during this time period.

5 Discussion

COVID-19 has wreaked havoc on public health and safety, which have become a global concern [241,242]. Epidemiological propagation models, deep learning and the application of ML methods will aid people understand the transmission process of epidemics and increase our understanding of disease detection so that timely preventive measures may be adopted. Most studies of the COVID-19 propagation process mathematical modeling use the classic SIR and SEIR deterministic models, which take into account the effects of age, temperature, humidity, mitigation measures and other parameters on the epidemic's transmission. The more complex the structure of the model, the more epidemic parameters are required. The determination of too many unknown parameters will result in a high level of uncertainty in the model's forecast. To forecast the impact of COVID-19 transmission, a few studies have used stochastic modeling. The goal is to lessen the level of uncertainty caused by parameters. However, thorough stochastic modeling has not yet been solved, and further studies on the application of stochastic modeling methods in epidemiology is required in the future. In particular, insufficient information is always caused by the distribution of different datasets. This is usually because different regions in a dataset may contain irrelevant information as a result of improper data processing and incorrect prediction accuracy of epidemic speed. Furthermore, even with limited samples, the majority of research results indicate that the performance of the residual network is the best among the pre-trained networks. In other fields, for example, Jin et al. [243] used attention residuals network to improve the accuracy of diagnosing actual bearing compound faults. The challenge of detecting COVID-19 can also be exacerbated by the imbalance of the sample in the dataset, which always leads to biases during the deep learning training phase, especially the issues caused by the lack of confidence intervals [33]. In order to address the aforementioned problem, freezing technology was introduced, which resulted in higher performance in the case of fewer COVID-19 data [244,245]. In the setting of modest amounts of data, this evidence shows that ensemble learning [246,247] and multi-tasking learning 152 [248] are more suitable for diagnosing COVID-19. Meanwhile, data preprocessing technology, such as image rotation and clipping, as well as data sample expansion using GAN network, can effectively improve the training test's accuracy.

During the COVID-19 pandemic, deep learning was used not only for COVID-19 detection on chest X-ray and CT images, but also in the field of LUS. LUS was more sensitive to identifying COVID-19 than chest X-ray and CT images. Current clinical studies implies that LUS has potential accuracy in diagnosing a pandemic. Deep learning and ML approaches have played an extraordinary role in biology and medicine in combating the COVID-19 pandemic, and are now being used to test potential drugs that can successfully target COVID-19. In the biology and medicine fields, ML methods have also been applied, such as using random forest and SVM to analyze and predict the possible inhibitory synthetic antibodies of SARS-CoV-2. Meanwhile, to timely understand the public mood, some studies use NLP-related method to analyze the tweets about COVID-19 on social media, so as to arrange corresponding measures in time to calm the public mood and prevent causing serious public psychological problems.

In this paper, the method proposed has not been applied in real life, because the data results in real data are more easily affected by noise and human factors. As a result, practical considerations should be factored into future design methods. Biology, medicine, AI and other fields have all made great contributions to the global spread of COVID-19. Despite the fact that a vaccine has been developed and is now available for free nationwide vaccination, there are still many problems to be solved in the future, such as risk assessment of human infection and complete resolution of viral infection. The most essential aspect of this paper is full explanation of the epidemiological transmission model and the application of deep learning and transfer learning methods in COVID-19. Because most research on chest X-ray and CT images is based on CNNs, we can pay more attention to its studies in other directions. The study of LUS is less than that of chest X-ray and CT images, and the limitations of LUS can also become a research direction. Finally, the majority of the research is theoretical, and the detection network can be deployed to mobile terminals.

6 Future Research Focuses

The survey is primarily used to introduce the usage of deep learning and transfer learning detection of COVID-19 in chest X-ray and CT images, as well as deep learning in the detection of viruses in LUS. To effectively combat COVID-19, machine learning-based approaches are used to predict and screen vaccine candidates that can resist the virus, and the importance of the telehealth system throughout the epidemic period, as well as the analysis of public comments on social platforms using NLP and other methods to better understand the public mood and make appropriate arrangements. This paper attempts to provide a comprehensive survey and provides systematic literature reference for subsequent research based on the summary and analysis of the studies during the COVID-19 pandemic period. Some future directions and the facing challenges are shown in Tab. 4.

Table 4: Some future directions and the the facing challenges

Theme	The future direction	The challenge
Propagation analysis	The factors of the spread of infectious diseases should be taken into consideration	The parameters are difficult to determine precisely
Deep learning	1) Network structure optimization 2) 2D/3D images of chest were segmented by X-ray and CT	Adjustment of parameters Accurate standard classification of medical images is difficult
LUS	Make LUS available in any situation	The inflated lung hinders the conduction of ultrasonography
Telehealth	Make telehealth available in any situation	The problem caused by power outage

7 Conclusions

The rapid spread of COVID-19 has triggered a great crisis to the world. This is an ongoing epidemic that has had a profound impact on all areas of the world, especially public health. Epidemiological propagation models, deep learning, and ML methods have all proven to be powerful tools in the fight against the epidemic. In this survey, we mainly make the following contributions: Firstly, we introduce in detail the prediction of COVID-19 transmission by epidemiological propagation models, including deterministic models (such as SIR and SEIR models) and stochastic models. Mathematical modeling of infectious diseases can effectively predict the intensity, incubation period and duration of infection, as well as the impact of mitigation measures on the spread of COVID-19, allowing appropriate measures to be effectively arranged to control the spread of the virus and reduce the number of infected people to a certain extent, relieving the country's pressure. Secondly, this paper introduces the application of the combination of deep learning and transfer learning in the classification detection based on chest X-ray and CT images, so as to improve COVID-19 patients' screening and provide an accurate solution for controlling the epidemic's spread. Thirdly, unlike most studies in the literature that use chest X-ray and CT images to detetct COVID-19, LUS has a stronger sensitivity in detecting COVID-19. LUS has been demonstrated to have a higher accuracy rate in clinical medicine, and it does not expose patients to radiation when used at the bedside. Fourthly, ML methods have also made great contributions to biology and medicine, including the prediction of potential vaccines and antibodies, etc., aims to prevent the public from becoming infected with diseases from the root. Fifth, in the absence of a vaccine at the time, telehealth systems were used during the pandemic. The adoption of telehealth systems has greatly reduced the rate of contact between health care workers and patients, thereby reducing virus's spread. Sixth, to interpret the influence of COVID-19 from various aspects, an NLP-related method is introduced to analyze tweets relevant to the COVID-19 epidemic on social media, so that public health departments can timely understand the public mood and prevent serious psychosocial problems from causing human panic. This survey, in particular, tries to provide a detailed description of the research on the diagnostic classification of chest X-ray and CT images during the pandemic period, with a focus on systematically introducing the application of deep learning-based and transfer learning-based methods, as well as highlighting innovations and classification accuracy. More specifically, this survey also presents the employ of LUS in COVID-19, which has been proven to be a safer and more sensitive method. In our future work, the better accurate epidemic spread models that can be applied to accurately simulate the transmission of infectious diseases, and even the clinical diagnosis advice from radiologists in the medical assistance system will be considered.

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