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Artificial Intelligence in the Battle against Coronavirus (COVID-19): A Survey and Future Research Directions

Thanh Thi Nguyen
School of Information Technology, Deakin University, Geelong Waurn Ponds Campus, Victoria, 3216, Australia

E-mail: thanh.nguyen@deakin.edu.au. Tel: +61 3 52278281.

ABSTRACT
Artificial intelligence (AI) has been applied widely in our daily lives in a variety of ways with numerous successful stories. AI has also contributed to dealing with the coronavirus disease (COVID-19) pandemic, which is currently happening around the globe. This paper presents a survey of AI methods being used in various applications in the fight against the deadly COVID-19 outbreak and outlines the crucial roles of AI research in this unprecedented battle. We touch on a number of areas where AI plays as an essential component, from medical image processing, data analytics, text mining and natural language processing, the Internet of Things, to computational biology and medicine. A summary of COVID-19 related data sources that are available for research purposes is also presented. Research directions on exploring the potentials of AI and enhancing its capabilities and power in the battle are thoroughly discussed. It is envisaged that this study will provide AI researchers and the wider community an overview of the current status of AI applications and motivate researchers in harnessing AI potentials in the fight against COVID-19.

KEYWORDS
Artificial intelligence; AI; coronavirus; COVID-19; SARS-CoV-2; pandemic; epidemic; outbreak; survey; review; overview; machine learning; future research directions

INTRODUCTION

The novel coronavirus disease (COVID-19) has created tremendous chaos around the world, affecting people's lives and causing a large number of deaths. Its first cases were detected in Wuhan, China in December 2019 and now it has been spread to almost every country. Governments of many countries have proposed policies to mitigate the impacts of the COVID-19 pandemic. Science and technology have contributed significantly to the implementations of these policies during this unprecedented and chaotic time. For example, robots are used in hospitals to deliver food and medicine to coronavirus patients or drones are used to disinfect streets or public spaces. Many researchers are rushing to produce drugs and medicines to treat infected patients whilst others are attempting to investigate vaccines to prevent the virus. Computer science researchers on the other hand have managed to early detect infectious patients using techniques that can process and understand medical imaging data such as X-ray images and computed tomography (CT) scans. These computational techniques are part of artificial intelligence (AI), which has been applied successfully in various fields. This paper focuses on the roles of AI technologies in the battle against the current COVID-19 pandemic. We provide a comprehensive survey of AI applications that support humans to reduce and suppress the substantial impacts of the outbreak. Recent advances in AI have contributed significantly to improving humans' lives and thus there is a strong belief that proper AI research plans will fully exploit the power of AI in helping humans to defeat this challenging virus battle. We discuss about these possible plans and highlight AI research areas that could bring great benefits and contributions to overcome the battle. In addition, we present a summary of COVID-19 related data sources to facilitate future studies about this deadly disease.

AI AGAINST COVID-19: A SURVEY

We separate surveyed papers into different groups such as deep learning methods for medical image processing, data science methods for pandemic modelling, AI and the Internet of Things (IoT), AI for text mining and natural language processing (NLP), and AI in computational biology and medicine.

Medical Image Processing with Deep Learning

While radiologists and clinical doctors can learn to detect COVID-19 cases based on chest CT examinations, their tasks are manual and time consuming, especially when required to examine a lot of cases. Bai et al. [1] convenes three Chinese and four United States radiologists to differentiate COVID-19 from other viral pneumonia based on chest CT images obtained from a cohort of 424 cases, in which 205 cases are from the United States with non-COVID-19 pneumonia whilst 219 cases are from China positive with COVID-19. Results obtained show that radiologists can achieve high specificity (which refers to the proportion of actual positives that are correctly identified as such) in distinguishing COVID-19 from other causes of viral pneumonia using chest CT imaging data. However, their performance in terms of sensitivity (which refers to the proportion of actual negatives that are correctly identified as such) is just moderate for the same task. AI methods, especially deep learning, have been used to process and analyse medical imaging data to support radiologists and doctors to improve diagnosis performance. Likewise, the current COVID-19 pandemic has witnessed a number of studies focusing on automatic detection of COVID-19 using deep learning systems.

A three-dimensional deep learning method, namely COVID-19 detection neural network (COVNet), is introduced in [2] to detect COVID-19 based on volumetric chest CT images. Three kinds of CT images, including COVID-19, community acquired pneumonia (CAP) and other non-pneumonia cases, are mixed to test the robustness of the proposed model, which is illustrated in Fig. 1. These images are collected from 6 hospitals in China and the detection method is evaluated by the area under the receiver operating characteristic curve (AUC). COVNet is a convolutional ResNet-50 model [3] that takes a series of CT slices as inputs and predicts the class labels of the CT images via its outputs. The AUC value obtained is at 0.96, which shows a great ability of the proposed model for detecting COVID-19 cases.

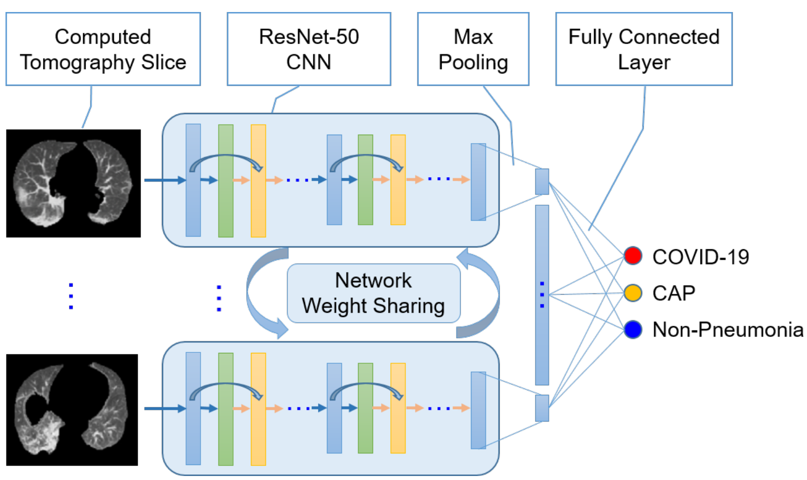

Fig. 1. Illustrative architecture of the COVNet model proposed in [2] for COVID-19 detection using CT images. Max pooling operation is used to combine features extracted by ResNet-50 CNNs whose inputs are CT slices. The combined features are fed into a fully connected layer to compute probabilities for three classes, i.e. non-pneumonia, community acquired pneumonia (CAP) and COVID-19. Predicted class is the one that has highest probability among the three.

Another deep learning method based on the concatenation between the location-attention mechanism and the three-dimensional CNN ResNet-18 network [3] is proposed in [4] to detect coronavirus cases using pulmonary CT images. Distinct manifestations of CT images of COVID-19 found in previous studies [5; 6] and their differences with those of other types of viral pneumonia such as influenza-A are exploited through the proposed deep learning system. A dataset comprising CT images of COVID-19 cases, influenza-A viral pneumonia patients and healthy cases is used to verify the performance of the proposed method. The method's overall accuracy of approximately 86% is obtained on this dataset, which exhibits its ability to help clinical doctors to early screen COVID-19 patients using chest CT images.

In line with the studies described above, we have found a number of papers also applying deep learning for COVID-19 diagnosis using radiology images. They are summarized in Table 1 for comparisons.

Table 1. Summary of deep learning methods for COVID-19 diagnosis using radiology images

Papers	Data	AI Methods	Results
[2]	4,356 chest CT exams from 3,322 patients from 6 medical centers: 1,296 exams for COVID-19, 1,735 for CAP and 1,325 for non-pneumonia	A 3D convolutional ResNet-50 [3], namely COVNet	AUC for detecting COVID-19 is of 0.96
[4]	618 CT samples: 219 from 110 COVID-19 patients, 224 CT samples from 224 patients with influenza-A viral pneumonia, and 175 CT samples from healthy people	Location-attention network and ResNet-18 [3]	Accuracy of 86.7%
[7]	5,941 Posterior-anterior chest radiography images across 4 classes (normal: 1,583, bacterial pneumonia: 2,786, non-COVID-19 viral pneumonia: 1,504, and COVID-19: 68)	Drop-weights based Bayesian CNNs	Accuracy of 89.92%
[8]	1,065 CT images (325 COVID-19 and 740 viral pneumonia)	Modified inception transfer-learning model	Accuracy of 79.3% with specificity of 0.83 and sensitivity of 0.67
[9]	Clinical data and a series of chest CT data collected at different times on 133 patients of which 54 patients progressed to severe/critical periods whilst the rest did not	Multilayer perceptron and LSTM [40]	AUC of 0.954
[10]	970 CT volumes of 496 patients with confirmed COVID-19 and 1,385 negative cases	2D deep CNN	Accuracy of 94.98% and AUC of 97.91%
[11]	CT images of 1,136 training cases (723 positives for COVID-19) from 5 hospitals	A combination of 3D UNet++ [12] and ResNet-50 [3]	Sensitivity of 0.974 and specificity of 0.922
[13]	Chest X-ray images of 50 normal and 50 COVID-19 patients	Pre-trained ResNet-50	Accuracy of 98%
[14]	16,756 chest radiography images across 13,645 patient cases from two open access data repositories	A deep CNN, namely COVID-Net	Accuracy of 92.4%
[15]	CT images obtained from 157 international patients (China and U.S.)	ResNet-50	AUC of 0.996
[16]	1,341 normal, 1,345 viral pneumonia, and 190 COVID-19 chest X-ray images	AlexNet [18], ResNet-18 [3], DenseNet-201 [19], SqueezeNet [20]	Accuracy of 98.3%
[17]	170 X-ray images and 361 CT images of COVID-19 from 5 different sources	A new CNN and pre-trained AlexNet [18] with transfer learning	Accuracy of 98% on X-ray images and 94.1% on CT images

AI-based Data Science Methods for COVID-19 Modelling

A modified stacked autoencoder deep learning model is used in [21] to forecast in real-time the COVID-19 confirmed cases across China. This modified autoencoder network includes four layers, i.e. input, first latent layer, second latent layer and output layer, with the number of nodes correspondingly is 8, 32, 4 and 1. A series of 8 data points (8 days) are used as inputs of the network. The latent variables obtained from the second latent layer of the autoencoder model are processed by the singular value decomposition method before being fed into clustering algorithms in order to group the cases into provinces or cities to investigate the transmission dynamics of the pandemic. The resultant errors of the model are low, which give confidence that it can be applied to forecast accurately the transmission dynamics of the virus as a helpful tool for public health planning and policy-making.

On the other hand, a prototype of an AI-based system, namely α-Satellite, is proposed in [22] to assess the infectious risk of a given geographical area at community levels. The system collects various types of large-scale and real-time data from heterogeneous sources, such as number of cases and deaths, demographic data, traffic density and social media data, e.g., Reddit posts. The social media data available for a given area may be limited so that they are enriched by the conditional generative adversarial nets [23] to learn the public awareness of COVID-19. A heterogeneous graph autoencoder model is then devised to aggregate information from neighbourhood areas of the given area in order to estimate its risk indexes. This risk information enables residents to select appropriate actions to prevent them from the virus infection with minimum disruptions in their daily lives. It is also useful for authorities to implement appropriate mitigation strategies to combat the fast evolving pandemic.

Chang et al. [24] modify a discrete-time and stochastic agent-based model, namely ACEMod (Australian Census-based Epidemic Model), previously used for influenza pandemic simulation [25; 26], for modelling the COVID-19 pandemic across Australia over time. Each agent exemplifies an individual characterized by a number of attributes such as age, occupation, gender, susceptibility and immunity to diseases and contact rates. The ACEMod is calibrated to model specifics of the COVID-19 pandemic based on key disease transmission parameters. Several intervention strategies including social distancing, school closures, travel bans, and case isolation are then evaluated using this tuned model. Results obtained from the experiments show that a combination of several strategies is needed to mitigate and suppress the COVID-19 pandemic. The best approach suggested by the model is to combine international arrival restrictions, case isolation and social distancing in at least 13 weeks with the compliance level of 80% or above.

AI and the Internet of Things

A framework for COVID-19 detection using data obtained from smartphones' onboard sensors such as cameras, microphones, temperature and inertial sensors is proposed in [27]. Machine learning methods are employed for learning and acquiring knowledge about the disease symptoms based on the collected data. This offers a low-cost and quick approach to coronavirus detection compared to medical Kits or CT scan methods. This is arguably plausible because data obtained from the smartphones' sensors have been utilized effectively in different individual applications and the proposed approach integrates these applications together in a unique framework. For instance, data obtained from the temperature-fingerprint sensor can be used for fever level prediction [28]. Images and videos taken by smartphones' camera or data collected by the onboard inertial sensors can be used for human fatigue detection [29; 30]. Likewise, Story et al. [31] use smartphone's videos for nausea prediction whilst Lawanont et al. [32] use camera images and inertial sensors' measurements for neck posture monitoring and human headache level prediction. Alternatively, audio data obtained from smartphone's microphone are used for cough type detection in [33; 34].

An approach to collecting individuals' basic travel history and their common manifestations using a phone-based online survey is proposed in [35]. These data are valuable for machine learning algorithms to learn and predict the infection risk of each individual, thus help to early identify high-risk cases for quarantine purpose. This contributes to reducing the spread of the virus to the susceptible populations. In another work, Allam and Jones [36] suggest the use of AI and data sharing standardization protocols for better global understanding and management of urban health during the COVID-19 pandemic. For example, added benefits can be obtained if AI is integrated with thermal cameras, which might have been installed in many smart cities, for early detection of the outbreak. AI methods can also demonstrate its great effectiveness in supporting managers to make better decisions for virus containment when loads of urban health data are collected by data sharing across and between smart cities.

AI for Text Mining and NLP

A hybrid AI model for COVID-19 infection rate forecasting is proposed in [37], which combines the epidemic susceptible infected (SI) model, NLP and deep learning tools. The SI model and its extension, i.e. susceptible infected recovered (SIR), are traditional epidemic models for modelling and predicting the development of infectious diseases where S represents the number of susceptible people, I denotes the number of infected people and R specifies the recovered cases. Using differential equations to characterize the relationship between I, S and R, these models have been used to predict successfully SARS and Ebola infected cases, as reported in [38] and [39] respectively. NLP is employed to extract semantic features from related news such as epidemic control measures of governments or residents' prevention awareness. These features are then served as inputs to the long short-term memory (LSTM) deep learning model [40] to revise the infection rate predictions of the SI model (Fig. 2). Epidemic data of Wuhan, Beijing, Shanghai and the whole China are used for experiments, which demonstrate the great accuracy of the proposed hybrid model. It can be applied to predict the COVID-19 transmission law and development trend, and thus useful for establishing prevention and control measures for future pandemics. That study also shows the importance of public awareness of governmental epidemic prevention policies and the role of transparency and openness of epidemic reports and news in containing the development of infectious diseases.

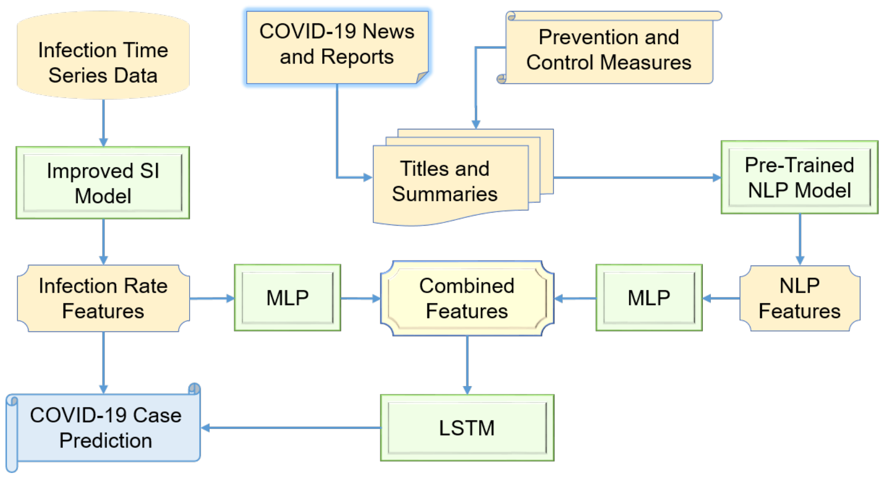

Fig. 2. An AI-based approach to COVID-19 prediction that combines traditional epidemic SI model, NLP and machine learning tools as introduced in [37]. A pre-trained NLP model is used to extract NLP features from text data, i.e. the pandemic news, reports, prevention and control measures. These features are integrated with infection rate features obtained from the SI model via multilayer perceptron (MLP) networks before being fed into LSTM model for COVID-19 case modelling and prediction.

In another work, Lopez et al. [41] recommend the use of network analysis techniques as well as NLP and text mining to analyse a multilanguage Twitter dataset to understand changing policies and common responses to the COVID-19 outbreak across time and countries. Since the beginning of the pandemic, governments of many countries have tried to implement policies to mitigate the spread of the virus. Responses of people about the pandemic and the governmental policies may be collected from social media platforms such as Twitter. Much of information and misinformation is posted through these platforms. When stricter policies are applied such as social distancing and country lockdowns, people's lives are changed considerably and part of that can be captured via people's reflections on social media platforms as well. Analysis results of these data can be helpful for governmental decision makers to mitigate the impacts of the current pandemic and prepare better policies for possible future pandemics.

Likewise, three machine learning methods including support vector machine, naive Bayes and random forest are used in [42] to classify 3,000 COVID-19 related posts collected from Sina Weibo, which is the Chinese equivalent of Twitter, into seven types of situational information. Identifying situational information is important for authorities because it helps them to predict its propagation scale, sense the mood of the public and understand the situation during the crisis. This contributes to creating proper response strategies throughout the COVID-19 pandemic.

AI in Computational Biology and Medicine

Being able to predict structures of a protein will help understand its functions. Google DeepMind is using the latest version of their protein structure prediction system, namely AlphaFold [43], to predict structures of several proteins associated with COVID-19 based on their corresponding amino acid sequences. They have released the predicted structures in [44], but these structures still need to be experimentally verified. Nevertheless, it is expected that these predictions will help understand how the coronavirus functions and potentially lead to future development of therapeutics against COVID-19.

An AI-based generative chemistry approach to design novel molecules that can inhibit COVID-19 is proposed in [45]. Several generative machine learning models, e.g. generative autoencoders, generative adversarial networks, genetic algorithms and language models, are used to exploit molecular representations to generate structures, which are then optimized using reinforcement learning methods. This is an ongoing work as the authors are synthesising and testing the obtained molecules. However, it is a promising approach because these AI methods can exploit the large drug-like chemical space and automatically extract useful information from high-dimensional data. It is thus able to construct molecules without manually designing features and learning the relationships between molecular structures and their pharmacological properties. The proposed approach is cost-effective and time-efficient and has a great potential to generate novel drug compounds in the fight against COVID-19.

On the other hand, Randhawa et al. [46] aim to predict the taxonomy of COVID-19 using a machine learning-based alignment-free method [47] based on genomic signatures and a decision tree approach. The alignment-free method is a computationally inexpensive approach that can give rapid taxonomic classification of novel pathogens by processing only raw DNA sequence data. By analysing over 5000 unique viral sequences, the authors are able to confirm the taxonomy of COVID-19 as belonging to the subgenus *Sarbecovirus* of the genus *Betacoronavirus*, as previously found in [48]. The proposed method also provides quantitative evidence that supports a hypothesis about a bat origin for COVID-19 as indicated in [48; 49]. Recently, Nguyen et al. [50] propose the use of AI-based clustering methods and more than 300 genome sequences to search for the origin of the COVID-19 virus. Numerous clustering experiments are performed on datasets that combine sequences of the COVID-19 virus and those of reference viruses of various types. Results obtained show that COVID-19 virus genomes consistently form a cluster with those of bat and pangolin coronaviruses. That provides quantitative evidences to support the hypotheses that bats and pangolins may have served as the hosts for the COVID-19 virus. Their findings also suggest that bats are the more probable origin of the virus than pangolins. AI methods thus have demonstrated their capabilities and power for mining big biological datasets in an efficient and intelligent manner, which contribute effectively to the progress of finding vaccines or medicines for COVID-19.

COVID-19 DATA SOURCES

This section summarises available data sources relevant to COVID-19, ranging from numerical data of infectious cases, radiology images, Twitter, text, natural languages to biological data (Table 2). These data are helpful for research purposes to exploit the potentials and power of AI technologies in the difficult battle against the deadly coronavirus disease.

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

The coronavirus disease has terrifically affected lives of people around the globe. Many people have lost their loved ones with the number of deaths worldwide currently goes beyond 47,000 and keeps increasing. While AI technologies have penetrated into our daily lives with many successes, they have also contributed to helping humans in the extremely tough fight against COVID-19. This paper has presented a survey of AI applications so far in the literature relevant to the COVID-19 crisis's responses and control strategies. These applications range from medical diagnosis based on chest radiology images, virus transmission modelling and forecasting based on number of cases time series and IoT data, text mining and NLP to capture the public awareness of virus prevention measures, to biological data analysis

Table 2. Available data sources about COVID-19 number of cases, radiology images [51], text and Twitter data, and biological sequences

Sources	Data Type	Links
Johns Hopkins University [52]	Web-based mapping global cases	https://systems.jhu.edu/research/public-health/ncov/
C. R. Wells's GitHub [53]	Daily incidence data and airport connectivity from China	https://github.com/WellsRC/Coronavirus-2019
Conference of State Bank Supervisors	U.S. county-level map of coronavirus cases (updated hourly)	https://www.csbs.org/information-covid-19-coronavirus
DataHub	Time series data on cases	https://datahub.io/core/covid-19
China CDC (CCDC)	Daily number of cases in China	http://weekly.chinacdc.cn/news/TrackingtheEpidemic.htm
U.S. CDC	Cases in U.S.	https://www.cdc.gov/coronavirus/2019-ncov/index.html https://www.coronavirus.gov/
U.S. National Institutes of Health	Cases in U.S.	https://www.nih.gov/health-information/coronavirus
Italy Ministry of Health	Cases in Italy	http://www.salute.gov.it/nuovocoronavirus
Kaggle	Cases in South Korea	https://www.kaggle.com/kimjihoo/coronavirusdataset
W. Zeng's website	Global cases and country cases	http://open-source-covid-19.weileizeng.com/
J. P. Cohen's GitHub [54]	Chest X-ray and CT images	https://github.com/ieee8023/covid-chestxray-dataset
European Society of Radiology	Chest X-ray and CT images	https://www.eurorad.org/advanced-search?search=COVID
Italian Society of Medical Radiology (SIRM)	Chest X-ray and CT images	https://www.sirm.org/category/senza-categoria/covid-19/
British Society of Thoracic Imaging (BSTI)	Chest X-ray and CT images	https://bit.ly/BSTICovid19_Teaching_Library
Kaggle	Chest X-ray and CT images	https://www.kaggle.com/bachrr/covid-chest-xray
UCSD-AI4H [55]	CT images	https://github.com/UCSD-AI4H/COVID-CT
MedSeg (medseg.ai)	CT images	http://medicalsegmentation.com/covid19/
Point-of-Care Ultrasound (POCUS) [56]	Lung ultrasound images and videos	https://github.com/jannisborn/covid19_pocus_ultrasound/tree/master/data
COVID-19 Radiography Database [16]	Chest X-ray images	https://www.kaggle.com/tawsifurrahman/covid19-radiography-database
A. G. Chung's GitHub - Actualmed Initiative	Chest X-ray images	https://github.com/agchung/Actualmed-COVID-chestxray-dataset/tree/master/images
A. G. Chung's GitHub - Figure 1 Initiative	Chest X-ray images	https://github.com/agchung/Figure1-COVID-chestxray-dataset/tree/master/images
Georgia State University's Panacea Lab [57]	Twitter chatter dataset in many languages	http://www.panacealab.org/covid19/
COVID-19 Open Research Dataset (CORD-19) [58]	45,000 scholarly articles about COVID-19 and the coronavirus family	https://pages.semanticscholar.org/coronavirus-research https://www.kaggle.com/allen-institute-for-ai/CORD-19-research-challenge
World Health Organization	Latest scientific findings and knowledge on COVID-19	https://www.who.int/emergencies/diseases/novel-coronavirus-2019/global-research-on-novel-coronavirus-2019-ncov
NCBI GenBank	SARS-CoV-2 sequences	https://www.ncbi.nlm.nih.gov/genbank/sars-cov-2-seqs/
The GISAID Initiative	SARS-CoV-2 sequences	https://www.gisaid.org/
China National GeneBank	COVID-19 sequence database	https://db.cngb.org/datamart/disease/DATAdis19/
EMBL-EBI	Sequences, gene and protein expression, protein structures	https://www.covid19dataportal.org/

for drug discovery. Although various studies have been published, we observe that there are still relatively limited applications and contributions of AI in this battle. This is partly due to the limited availability of data about COVID-19 whilst AI methods normally require large amounts of data for computational models to learn and acquire knowledge. However, we expect that the number of AI studies related to COVID-19 will increase significantly in the months to come when more COVID-19 data such as medical images and biological sequences are available. Current available datasets as summarized in Table 2 are stored in various formats and standards that would hinder the development of COVID-19 related AI research. A future work on creating, hosting and benchmarking COVID-19 related datasets is essential because it will help to accelerate discoveries useful for tackling the disease. Repositories for this goal should be created following standardized protocols and allow researchers and scientists across the world to contribute to and utilize them freely for research purposes.

Among the published works, the use of AI deep learning techniques for COVID-19 diagnosis based on radiology imaging data appears to be dominant. As summarized in Table 1, numerous studies have used various deep learning methods, applying on different datasets and utilizing a number of evaluation criteria. This creates an immediate concern about the difficulties when utilizing these approaches to the real-world clinical practice. Accordingly, there is a demand for a future work on developing a benchmark framework to evaluate and compare the existing methods. This framework should facilitate the same computing hardware infrastructure, (universal) datasets covering same patient cohorts, same data pre-processing procedures and evaluation criteria across AI methods being evaluated.

Furthermore, as Li et al. [2] pointed out, although their model obtained great accuracy in distinguishing COVID-19 with other types of viral pneumonia using radiology images, it still lacks of transparency and interpretability. For example, they do not know which imaging features have unique effects on the output computation. The benefit that black box deep learning methods can provide to clinical doctors is therefore questionable. A future study on explainable AI to explain the deep learning models' performance as well as features of images that contribute to the distinction between COVID-19 and other types of pneumonia is essential. This would help radiologists and doctors to gain insights about the virus and examine future coronavirus CT and X-ray images more effectively.

Compared to the 1918 Spanish flu pandemic [59], we are now fortunately living in the age of exponential technology. AI has been applied successfully in almost every corner of humans' lives. When everybody, every company, organization and government must try their best in the battle against the deadly coronavirus pandemic, the power of AI should be fully explored and employed to support humans to encounter this battle. AI can be utilized for the preparedness and response activities against the unprecedented national and global crisis. For example, AI can be used to create more effective robots and autonomous machines for disinfection, working in hospitals, delivering food and medicine or looking after patients. AI and NLP technologies can be employed to develop chatbot systems that are able to remotely communicate and provide consultations to people and patients about the coronavirus. AI can be used to eradicate fake news on social media platforms to ensure clear, responsible and reliable information about the pandemic such as scientific evidences relevant to the virus, governmental social distancing policies or other pandemic prevention and control measures.

In the field of computational biology and medicine, AI has been used to partially understand COVID-19 or discover novel drug compounds against the virus [44; 45]. These are just initial results and thus there is a great demand for AI research in this field, for example to investigate genetics and chemistry of the virus and suggest ways to quickly produce vaccines and treatment drugs. With a strong computational power that is able to deal with large amounts of data, AI can help scientists to gain knowledge about the coronavirus quickly. For example, by exploring and analyzing protein structures of virus, medical researchers would be able to find components necessary for a vaccine or drug more effectively. This process would be very time consuming and expensive with conventional methods [60]. Recent astonishing success of AI deep learning in identifying powerful new kinds of antibiotic from a pool of more than 100 million molecules as published in [61] gives a strong hope to this line of research in the battle against COVID-9.

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