Can AI help in the fight against COVID-19?

Artificial intelligence is being used in several different ways to curb the current pandemic while demonstrating its potential to be even more effective for the next one

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The corolnavirus disease 2019 (COVID-19) pandemic has accelerated efforts to incorporate artificial intelligence (AI) into clinical care at a time when, in many countries, health care systems are facing unprecedented strain on their resources. Before COVID-19, AI was already permeating into health care,[1] and reviews are emerging of how it may assist in efforts to combat the current pandemic.[2–5] We describe several applications of AI relevant to COVID-19, some having had immediate clinical application, others awaiting further refinement and evaluation.

Detecting outbreaks, tracing contacts and shaping public health responses

The AI-automated HealthMap system at Boston Children's Hospital first alerted the world about the novel coronavirus on 30 December 2019, with a Canadian-based AI model, BlueDot, issuing a similar alert a day later. Researchers warned of the top 20 destination cities for passenger arrivals from Wuhan to which the disease could spread.[6] These AI-enabled early warning systems use natural language processing to scan social media, online news articles and government reports for signs of emerging pandemics to help inform governments and agencies such as the World Health Organization. AI-assisted analysis and modelling have also helped reconstruct the progression of an outbreak, elucidate transmission pathways, identify and trace contacts, and determine real or expected impacts of various public health control measures (Box 1).[7–11]

How data are collected, and how these algorithms are deployed, raise difficult issues of consent, privacy, ethics and trade-offs between public and private good. Some countries, like Taiwan, have mandated a top-down approach to data harvesting. Others, including Australia, encourage individuals to voluntarily download apps to input symptoms and COVID-19 status and permit health authorities to access this information in identifying potential contacts. However, the efficacy of app-mediated contact tracing depends on the level of population uptake, its ability to accurately detect infectious contacts, and the extent of adherence to self-isolation by notified contacts.[12] Expert position statements regarding design, scope, security and usage of such apps aim to prevent mission creep towards unauthorised surveillance of society at large.[13]

1 Public health applications

- An AI-mediated analysis of real-time mobile phone data in Wuhan, along with detailed case data including travel history, helped elucidate the role of case importation on transmission in cities across China and showed how the drastic quarantine and lockdown control measures implemented in China substantially mitigated the spread of COVID-19.[7]
- In Taiwan, the government used its rigid household registration system and mobile phone data to build an algorithm that tracked individuals based on their recent travel history.[8] Individuals identified as high risk were quarantined at home and tracked via their mobile phone to ensure compliance during the 14-day incubation period.
- The AI-enabled Australian Census-based Epidemic Model has used data on age, occupation, sex, risk factors and contact rates from COVID-19 cases in predicting the likely impact of various public health control measures.[9] It showed that a combination of international arrival restrictions, case isolation and social distancing for at least 13 weeks, with compliance rates of 80% or above, was the best approach to suppressing the pandemic.
- In the US, streams of both static and dynamic data relating to 3100 counties from various sources (census, socio-economic surveys, housing density, age distribution, population comorbidity burden, and COVID-19 testing and infection rates) are subject to machine learning in generating an interactive pandemic vulnerability index dashboard which is used to identify counties most at risk of major COVID-19 outbreaks and assist government officials, public health professionals and community leaders in implementing protective strategies.[10]
- Machine learning models have assessed the infectious risk of a given geographical area at the community level by analysing large scale, real-time data on numbers of cases and deaths, demographic data, traffic density and social media data (eg, Reddit posts).[11] The models estimate a risk index for that area which individuals and relevant authorities can use to implement appropriate mitigation strategies.

Screening for people who might be infected

Detecting COVID-19 in most health systems currently involves testing symptomatic patients presenting to stand-alone fever clinics, general practices or emergency departments. This takes time, consumes personal protective equipment and testing reagents, and poses transmission risk to staff. Digital symptom checkers soliciting information about symptoms and risk factors may screen out individuals with very low likelihood of COVID-19 who do not require testing. In a pre-clinical study using hypothetical cases, an AI-powered chatbot identified patients with COVID-19 with sensitivity, specificity and overall diagnostic accuracy of 97%, 96% and 96%, respectively.[1] However, a side-by-side test of eight different chat boxes on the same set of symptoms produced conflicting results,[15] suggesting the need to identify all the data elements necessary for highest accuracy.

Data from phone hotlines used to pre-screen individuals based on travel history and symptoms,[16] and from sensors (cameras, microphones, temperature and inertial sensors) embedded within smartphones, can all be used to detect COVID-19.[17] Neural networks embedded in cameras can distinguish patterns of tachypnoea caused by COVID-19 from those caused by influenza or the common cold.[18] AI-powered thermal-scanning face cameras, capable of screening up to 200 people per minute, are being used by some Australian private hospitals to remotely detect people with fevers, sweating and discolouration, and prevent them entering public spaces.[19]

Facilitating earlier diagnosis

Diagnosing COVID-19 in sick patients presenting to hospital is currently performed by reverse transcription polymerase chain reaction testing of nasopharyngeal and throat swabs. However, initial tests may only be 70% sensitive and turnaround times can be 24 hours or more.[20] Machine learning (ML) models combined with virus detection systems using CRISPR (clustered regularly interspaced short palindromic repeat; a tool which uses an enzyme to edit genomes by cleaving specific strands of genetic code) can rapidly design severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) assays which have high sensitivity and speed.[21] AI has also been used to design, within a few weeks, point-of-care immunoassays for detecting viral antigens within 20 minutes, and such testing kits are now in use.[22]

For hospitalisations where reverse transcription polymerase chain reaction testing is unavailable, untimely, or yields negative results among patients highly suspected of suffering COVID-19 pneumonitis, deep learning algorithms applied to imaging data captured by chest x-rays or computed tomography (CT) chest scans may help early diagnosis. Studies suggest that such cases show particular image patterns which may, combined with polymerase chain reaction testing, improve sensitivity to more than 90%.[23,24] However, radiological appearances of COVID-19 can overlap with other forms of lung inflammation, imaging can be insensitive or misleading in mild or asymptomatic cases,[25] and CT scanning creates a transmission risk. Hence, the Royal Australian and New Zealand College of Radiology and peer societies overseas do not recommend CT scanning, including AI applications, to screen for COVID-19, or to diagnose it as a first choice test.[26] For patients with lower respiratory tract illness who pose diagnostic uncertainty, deep learning algorithms applied to chest x-rays may be more feasible and impose less risk (Box 2).[27–30] However, current algorithms may perform poorly on the 80% of COVID-19 cases which are mild and under-represented in the data used to train and test these algorithms.[28–30]

2 Diagnostic applications

- A deep learning algorithm trained on 16 756 chest x-rays across 13 645 patients showed a diagnostic accuracy for COVID-19 of 92%.[27] Other algorithms developed using 5941 chest x-rays across four classes (normal, bacterial pneumonia, COVID-19 pneumonia and non-COVID viral pneumonia) have yielded diagnostic accuracy of 90%.[28]
- Using deep learning algorithms trained on computed tomography data, a study of only 312 cases achieved sensitivity, specificity and area under the curve for COVID-19 of 94%, 95% and 0.98, respectively, in an independent validation dataset of 1255 cases.[29] In an accompanying reader study involving five radiologists, only one was slightly more accurate than the algorithm, which was also twice as fast as the radiologists.
- Using data from 4356 chest computed tomography scans of 3322 patients, a deep learning algorithm distinguished between COVID-19 and non-COVID pneumonia in independent test sets with per examination sensitivity, specificity and area under the curve of 90%, 96% and 0.96, and 87%, 92% and 0.95, respectively.[30]

Predicting risk of deterioration and poor outcomes

Predictive models able to identify, on admission, patients likely to deteriorate and require respiratory support can assist triage and resource allocation decisions. While older age, being male, and having certain comorbidities (hypertension, cardiovascular disease, diabetes) portend worse outcomes,[31] these factors do not necessarily predict outcomes at an individual level, especially in younger patients. Some ML algorithms can more accurately estimate risk of death, development of acute respiratory distress syndrome, and duration of hospitalisation (Box 3).[32–36]

Augmenting remote monitoring and virtual care

Patients diagnosed with COVID-19 but not requiring hospitalisation can be monitored remotely at home using wearable devices measuring temperature, blood pressure and arterial oxygen levels, and transmitting these data to central virtual care units,[37] as exist in some Australian hospitals. AI-assisted analysis alerts staff to worsening status with activation of outreach care or patient recall for admission.

Developing potential treatments and vaccines

In developing effective treatments for COVID-19, ML-based repurposing frameworks have used algorithms to identify baricitinib (for rheumatoid arthritis),[38] atazanavir (an anti-human immunodeficiency virus drug)[39] and afatinib (for lung cancer)[40] as potential treatments. Deep learning-based algorithms have helped design six new molecules that could halt SARS-CoV-2 replication[41] and identify ten promising agents from among 4895 drugs.[42] Algorithms using

3 Prognostic applications

- In a study of 53 patients from two hospitals in Wenzhou, investigators used clinical and laboratory data to train an algorithm that identified mildly elevated alanine aminotransferase, the presence of myalgias, and elevated haemoglobin, in this order, as being most predictive (70–80% accuracy) of subsequent onset of acute respiratory distress syndrome.[32]
- In a study of 133 patients, multivariate logistic regression identified age > 55 years, hypertension, low serum albumin levels, lymphopenia, elevated high sensitivity C-reactive protein levels and progressive consolidation on chest computed tomography (CT) scans as predictive of acute respiratory distress syndrome.[33] By combining clinical and temporal CT data, deep learning models outperformed the regression model (area under the curve, 0.954 *v* 0.893).
- Regarding mortality risk, machine learning tools applied to 404 patients in Wuhan selected three biomarkers from a pool of 300 features as predicting high risk of mortality with more than 90% accuracy: elevated lactic dehydrogenase levels (measure of cell injury); lymphopenia (measure of cellular immunity); and raised high sensitivity C-reactive protein levels (measure of inflammation).[34] In another study, neural networks trained on 42 clinical and demographic factors demonstrated 94% accuracy in predicting mortality.[35]
- In identifying patients at risk of long term hospitalisation, a machine learning model trained on CT imaging data was able to identify such patients with predictive accuracy of 95%.[36]

natural language processing applied to the PubMed database have identified a poly-ADP-ribose polymerase 1 inhibitor (CVL218) as a potential candidate, currently undergoing clinical testing.[43]

In expediting vaccine development, a deep learning system predicted targetable protein structures of SARS-CoV-2 within weeks compared with the months normally taken using traditional experimental approaches.[44] AI has identified viral protein epitopes most likely to be immunogenic but not cross-reacting with human proteins,[45] while a reverse vaccinology tool integrated with ML has identified genes that code for potential epitopes.[46]

AI-powered knowledge graphs can interrogate thousands of research articles and public documents to link genetic and biological properties of virus-caused diseases with composition and actions of existing drugs. The COVID-19 Open Research Dataset contains over 29 000 articles about SARS-CoV-2 and other coronaviruses,[47] and is linked with several ongoing ML projects that daily attract many questions from research teams worldwide.

Assisting hospital responses

AI mapping tools can track hospital bed capacity, and location, number and utilisation of intensive care unit (ICU) and hospital beds across the United States.[48] Another tool tracks numbers of ventilated patients in that country and uses modelling software to predict breaking points for health care networks,[49] estimating a shortage of 9100 ICU beds and 115 000 non-ICU beds for routine care at the peak of the pandemic. At the frontline, autonomous AI robots can transport drugs around the hospital and disinfect patients and hospital areas by emitting ulraviolet light, reducing interpersonal contact and saving time for medical and ancillary staff.[5]

Cautions and limitations

While AI and ML can support COVID-19 responses across various domains, most applications have not reached operational maturity. The speed of research means that many reports are preprints awaiting peer review, while still attracting media coverage and clinician adoption before proper evaluation. Most ML models have relied on Chinese data, limiting generalisability to other populations. Those trained on limited and unrepresentative data are susceptible to overfitting and can perform poorly on real-world datasets. Many diagnostic and prognostic ML models published to date are poorly reported, lack external validation, and have high risk of bias.[50]

Overcoming these constraints requires scalable approaches to data sharing. An international consortium is assembling electronic health data from over 96 countries for rapid visualisation of regional differences and global commonalities.[51] Such endeavours require balancing data privacy with public health concerns, and collaboration between clinicians, data scientists and policy makers across international borders and between private and public sectors.

Conclusion

It is still too early to know the extent to which AI will have an impact on the COVID-19 outbreak. Although its role may be limited during the present pandemic, it may certainly help with the next one.

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References are available online.

1 Scott IA, Cook D, Coiera E, Richards B. Machine learning in clinical practice: prospects and pitfalls. *Med J Aust* 2019; 211(5): 203–205. https://www.mja.com.au/journal/2019/211/5/machine-learning-clinical-practice-prospects-and-pitfalls.

2 Nguyen TT. Artificial intelligence in the battle against coronavirus (COVID-19): a survey and future research directions [preprint]. *arXiv* 2020; https://doi.org/10.13140/rg.2.2.36491.23846.

3 Bullock J, Pham KH, Luengo-OROZ M, et al. Mapping the landscape of artificial intelligence applications against COVID-19 [preprint]. *arXiv* 2020; arXiv:2003.11336.

4 Pham Q, Nguyen DC, Huynh-The T, et al. Artificial intelligence (AI) and big data for coronavirus (COVID-19) pandemic: a survey on the state-of-the-arts [preprint]. *Preprints* 2020;. https://doi.org/10.20944/preprints202004.0383.v1.

5 Alwashmi MF. The use of digital health in the detection and management of COVID-19. *Int J Environ Res Public Health* 2020; 17: 2906–2922.

6 Bogoch I, Watts A, Thomas-Bachli A, et al. Pneumonia of unknown aetiology in Wuhan, China: potential for international spread via commercial air travel. *J Travel Med* 2020; 27: taaa008.

7 Kraemer MUG, Yang C-H, Gutierrez B, et al. The effect of human mobility and control measures on the COVID-19 epidemic in China. *Science* 2020; 368: 493–497.

8 Wang CJ, Ng CY, Brook RH. Response to COVID-19 in Taiwan. Big data analytics, new technology, and proactive testing. *JAMA* 2020; 323: 1341–1342.

9 Chang SL, Harding N, Zachreson C, et al. Modelling transmission and control of the COVID-19 pandemic in Australia [preprint]. *arXiv* 2020; arXiv:2003.10218.

10 Marvel SW, House JS, Wheeler M, et al. The COVID-19 Pandemic Vulnerability Index (PVI) Dashboard: monitoring county-level vulnerability using visualization, statistical modeling, and machine learning [preprint] *medRxiv* 2020; https://doi.org/10.1101/2020.08.10.20169649.

11 Ye Y, Hou S, Fan Y, et al. α-Satellite: An AI-driven system and benchmark datasets for hierarchical community-level risk assessment to help combat COVID-19 [preprint]. *arXiv* 2020; arXiv:2003.12232.

12 Ferretti L, Wymant C, Kendall M, et al. Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. *Science* 2020; 368: eabb6936.

13 Australian Digital Health Academy, Australian Healthcare and Hospitals Association. Principles for the COVID-19 contact tracing app. https://digitalhealth.org.au/wp-content/uploads/2020/04/COVID-19-App_AIDH_V3.pdf (viewed Sept 2020).

14 Martin A, Nateqi J, Gruarin S, et al. An artificial intelligence-based first-line defence against COVID-19: digitally screening citizens for risks via a chatbot [preprint]. *bioRxiv* 2020; https://doi.org/10.1101/2020.03.25.008805.

15 Ross C. I asked eight chatbots whether I had Covid-19. The answers ranged from 'low' risk to 'start home isolation'. *STAT* 2020; 23 Mar. https://www.statnews.com/2020/03/23/coronavirus-i-asked-eight-chatbots-whether-i-had-covid-19/ (viewed Sept 2020).

16 Rao ASS, Vazquez JA. Identification of COVID-19 can be quicker through artificial intelligence framework using a mobile phone-based survey in the populations when cities/towns are under quarantine. *Infect Control Hosp Epidemiol* 2020; 41: 826-830.

17 Maghdid H, Ghafoor K, Sadiq A, et al. A novel AI-enabled framework to diagnose coronavirus COVID-19 using smartphone embedded sensors: design study [preprint]. *ArXiv* 2020;. https://doi.org/arXiv:2003.07434.

18 Wang Y, Hu M, Li Q, et al. Abnormal respiratory patterns classifier may contribute to large-scale screening of people infected with COVID-19 in an accurate and unobtrusive manner [preprint]. *arXiv* 2020; arXiv2002.05534.

19 Allam Z, Jones DS. On the coronavirus (COVID-19) outbreak and the smart city network: universal data sharing standards coupled with artificial intelligence (AI) to benefit urban health monitoring and management. *Healthcare (Basel)* 2020; 8: 46.

20 Wang W, Xu Y, Gao R, et al. Detection of SARS-CoV-2 in different types of clinical specimens. *JAMA* 2020; 323: 1843–1844.

21 Metsky HC, Freije CA, Kosoko-Thoroddsen T-SF, et al. CRISPR-based COVID-19 surveillance using a genomically comprehensive machine learning approach [preprint]. *bioRxiv* 2020; https://doi.org/10.1101/2020.02.26.967026.

22 Sheridan C. Fast, portable tests come online to curb coronavirus pandemic. *Nat Biotechnol* 2020; 38: 515–518.

23 Ai T, Yang Z, Hou H, et al. Correlation of chest CT and RT-PCR testing in coronavirus disease 2019 (COVID-19) in China: a report of 1014 cases. *Radiology* 2020; 296: E32–E40.

24 Xie X, Zhong Z, Zhao W, et al. Chest CT for typical 2019-nCoV pneumonia: relationship to negative RT-PCR testing. *Radiology* 2020; 296: E41–E45.

25 Inui S, Fujikawa A, Jitsu M, et al. Chest CT findings in cases from the cruise ship "Diamond Princess" with coronavirus disease 2019 (COVID-19). *Radiol Cardiothor Imag* 2020; 2: e200110.

26 Royal Australian and New Zealand College of Radiologists. Position statement: Artificial intelligence and COVID-19. Sydney: RANZCR, 2020. https://www.ranzcr.com/whats-on/news-media/389-artificial-intelligence-and-covid-19 (viewed Sept 2020).

27 Ghoshal B, Tucker A. Estimating uncertainty and interpretability in deep learning for coronavirus (COVID-19) detection [preprint]. *arXiv* 2020; arXiv:2003.10769.

28 Wang L, Wong A. COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest radiography images [preprint]. *arXiv* 2020; arXiv:2003.09871.

29 Jin C, Chen W, Cao Y, et al. Development and evaluation of an AI system for COVID-19 diagnosis [preprint]. *medRxiv* 2020; https://doi.org/10.1101/2020.03.20.20039834.

30 Li L, Qin L, Xu Z, et al. Artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT. *Radiology* 2020; 296: E65–E72.

31 Guan W, Ni Z, Hu Y, et al. Clinical characteristics of coronavirus disease 2019 in China. *N Engl J Med* 2020; 382: 1708–1720.

32 Jiang X, Coffee M, Bari A, et al. Towards an artificial intelligence framework for data-driven prediction of coronavirus clinical severity. *Computers Materials Continua* 2020; 63: 537–551.

33 Bai X, Fang C, Zhou Y, et al. Predicting COVID-19 malignant progression with AI techniques [preprint]. *medRxiv* 2020; https://doi.org/10.1101/2020.03.20.20037325.

34 Yan L, Zhang H-T, Goncalves J, et al. A machine learning-based model for survival prediction in patients with severe COVID-19 infection [preprint]. *medRxiv* 2020; https://doi.org/10.1101/2020.02.27.20028027.

35 Pourhomayoun M, Shakibi M. Predicting mortality risk in patients with COVID-19 using artificial intelligence to help medical decision-making [preprint]. *medRxiv* 2020; https://doi.org/10.1101/2020.03.30.20047308.

36 Qi X, Jiang Z, Yu Q, et al. Machine learning-based CT radiomics model for predicting hospital stay in patients with pneumonia associated with SARS-CoV-2 infection: a multicenter study [preprint]. *medRxiv* 2020; https://doi.org/10.1101/2020.02.29.20029603.

37 Watson AR, Wah R, Thamman R. The value of remote monitoring for the COVID-19 pandemic. *Telemed J E Health* 2020; 26: 1110–1112.

38 Richardson P, Griffin I, Tucker C, et al. Baricitinib as potential treatment for 2019-nCoV acute respiratory disease. *Lancet* 2020; 395: e30–e31.

39 Beck BR, Shin B, Choi Y, et al. Predicting commercially available antiviral drugs that may act on the novel coronavirus (2019-nCoV), Wuhan, China through a drug-target interaction deep learning model [preprint]. *bioRxiv* 2020; https://doi.org/10.1101/2020.01.31.929547.

40 Avchaciov K, Burmistrova O, Fedichev PO. AI for the repurposing of approved or investigational drugs against COVID-19 [preprint]. *ResearchGate* 2020;. https://doi.org/10.13140/RG.2.2.20588.10886.

41 Zhavoronkov A, Aladinskiy V, Zhebrak A, et al. Potential COVID-2019 3C-like protease inhibitors designed using generative deep learning approaches. https://2019ncov.s3.ap-east-1.amazonaws.com/Insilico-Medicine-Generative-Sprint-2019-nCoV-Project.pdf (viewed Sept 2020).

42 Hu F, Jiang J, Yin P. Prediction of potential commercially inhibitors against SARS-CoV-2 by multi-task deep model [preprint]. *arXiv* 2020; arXiv:2003.00728, 2020a.

43 Ge Y, Tian T, Huang S, et al. A data-driven drug repositioning framework discovered a potential therapeutic agent targeting COVID-19 [preprint]. *bioRxiv* 2020; https://doi.org/10.1101/2020.03.11.986836.

44 Senior AW, Evans R, Jumper J, et al. Improved protein structure prediction using potentials from deep learning. *Nature* 2020; 577: 706–710.

45 Malone B, Simovski B, Moliné C, et al. Artificial intelligence predicts the immunogenic landscape of SARS-CoV-2: toward universal blueprints for vaccine designs [preprint]. *bioRxiv* 2020; https://doi.org/10.1101/2020.04.21.052084.

46 Ong E, Wong MU, Huffman A, He Y. COVID-19 coronavirus vaccine design using reverse vaccinology and machine learning [preprint]. *bioRxiv* 2020; https://doi.org/10.1101/2020.03.20.000141.

47 CORD-19: COVID-19 Open Research Dataset. https://www.semanticscholar.org/cord19 (viewed Sept 2020).

48 Definitive Healthcare: US Hospital Beds Dashboard. https://www.arcgis.com/apps/opsdashboard/index.html#/8c4dcccd9e3845eb89f6401f919007f2 (viewed Sept 2020).

49 Qventus. Predicting the Effects of the COVID Pandemic On US Health System Capacity. 13 Mar 2020. https://qventus.com/blog/predicting-the-effects-of-the-covid-pandemic-on-us-health-system-capacity/ (viewed Sept 2020).

50 Wynants L, Van Calster B, Bonten MMJ, et al. Prediction models for diagnosis and prognosis of COVID-19 infection: systematic review and critical appraisal. *BMJ* 2020; 369: m1328.

51 Brat GA, Weber GM, Gehlenborg N, et al. International electronic health record-derived COVID-19 clinical course profile: the 4CE Consortium [preprint]. *medRxiv* 2020; https://doi.org/10.1101/2020.04.13.20059691. ■