SARS-CoV-2: Has artificial intelligence stood the test of time

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Abstract
Artificial intelligence (AI) has proven time and time again to be a game-changer innovation in every walk of life, including medicine. Introduced by Dr. Gunn in 1976 to accurately diagnose acute abdominal pain and list potential differentials, AI has since come a long way. In particular, AI has been aiding in radiological diagnoses with good sensitivity and specificity by using machine learning algorithms. With the coronavirus disease 2019 pandemic, AI has proven to be more than just a tool to facilitate healthcare workers in decision making and limiting physician-patient contact during the pandemic. It has guided governments and key policymakers in formulating and implementing laws, such as lockdowns and travel restrictions, to curb the spread of this viral disease. This has been made possible by the use of social media to map severe acute respiratory syndrome coronavirus 2 hotspots, laying the basis of the “smart lockdown” strategy that has been adopted globally. However, these benefits might be accompanied with concerns regarding privacy and unconsented surveillance, necessitating authorities to develop sincere and ethical government–public relations.

Keywords: Artificial intelligence; COVID-19; Machine learning

Introduction
In the field of medicine, artificial intelligence (AI) has contributed in terms of disease diagnosis, treatment, and prevention since the middle of the last century. The increased popularity and research of this novel computing medicine merger lead to the development of the first AI-based diagnosis application by Gunn in 1976.[1] This discovery enabled a computer to accurately diagnose acute abdominal pain and list down potential differentials. Since then, the use of algorithm-based computer softwares has gained popularity in healthcare settings. It has enabled physicians and hospitals to store a large number of robust patient records, saving time and improving the quality of patient care. AI has been incorporated in medicine in various ways to process complex information with greater efficacy than human brain.

AI techniques of processing

Artificial neural network (ANN)

ANN is the most popular technique and functions like neurons in the human brain. It is used in the diagnosis of various diseases and aids in data interpretation from sources such as electrocardiograms or electroencephalograms to diagnose myocardial infarction and epilepsy, respectively. Most importantly, it is employed in diagnostic medical imaging whereby it enhances the resolution and quality of image via deep learning. ANN can analyze data from X-rays, magnetic resonance imaging, computed tomography (CT) scans, and retinal images to help formulate diagnosis of any life-threatening visual pathology via computer visioning while saving time and increasing accuracy. In laboratory diagnostics, ANN aids in detecting fluorescent labels and identifying rare cells via ghost cytometry.

Electronic medical records (EMRs)

EMRs help record patients’ medical history, laboratory investigations, and radiological imaging. In addition, they also allow risk prediction for clinically important outcomes, allowing evidence-based interventions to reduce risk of adverse events.

Medical devices and sensors

AI-based wearable devices and sensors can provide accessible medical care at fingertips. An example of this...
would be constant monitoring of heart rate or serum potassium levels by sensors in smartwatches. Data from these sensors are then processed by machine vision and output displayed on smart devices.

**Fuzzy expert systems**

These systems utilize fuzzy logic to process ambiguous data, aiding in diagnoses of various cancers. Furthermore, they can also estimate survival years among patients while processing tumor staging, family history, and radiological and histopathological investigations.

**Robots**

AI-powered robots have found their way in surgery as assistants. In addition, they can be used as care bots to provide companionship to the geriatric population who are restricted to their homes along with assisting them in household work and keeping a track of their medications.

**Evolutionary computation**

Techniques such as “genetic algorithms” allow processing of natural selection, based on survival of the fittest.

Moreover, this system helps in estimating the possible outcomes in critically ill patients, thereby predicting outcomes and prognosis.

**Softbots**

Also known as “psychotherapeutic avatars”, softbots can help manage pain in children suffering from cancer and detect mental health issues among children.

AI algorithms are used in the following aspects of healthcare: (1) Diagnosis—assessing risk of disease onset or early diagnosis of disease via clinical data, EMRs, genetic testing, electrodiagnosis, and medical imaging. (2) Therapeutics—interventions such as AI-based treatment of disease, robots in surgery, and use of pharmacogenomics for delivery of drug therapy. (3) Regulation—monitoring medical care, such as tracking disease process, and handling insurance. (4) Information systems—ensuring population health by creating awareness and mass screening via devices for early detection of disease.

A summary of the use of AI in clinical settings is highlighted in Table 1.

**Role of Artificial Intelligence in Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2)**

**Identifying cases**

Due to an increasing number of SARS-CoV-2 patients, early diagnosis is critical for prompt actions on patient management, infection control, and public health control measures. Identifying cases together with rigorous contact tracing, quarantine, and isolation has been recommended to restrain the pandemic. However, this is limited by the labor-intensive testing which has the risk of exposing healthcare professionals. Furthermore, there is a delay in test results, testing techniques are very expensive, and limited kits are available to cater to the growing pandemic. Here, AI-powered radiological diagnostic modalities and screening chat-bots can be employed to solve this issue.

**Radiological imaging**

Several different AI-powered diagnostic radiological modalities are available. While some are limited to SARS-CoV-2, the rest are also capable of diagnosing influenza, viral pneumonia, community-acquired pneumonia, and bacterial pneumonia. These technologies employ readily available X-rays and CT scans for this purpose while ensuring sufficient accuracy [Table 2].

**Diagnostic chatbots**

Multiple countries are using AI-powered chatbots to screen, diagnose, and disseminate safe information among masses. In France, Clevy.io is being used for evaluation of SARS-CoV-2 risk and real-time information sharing by the government and the World Health Organization. Clara, a chatbot powered by Microsoft Azure and Centers for Disease Control and Prevention is available for individuals to help them make informed decisions regarding healthcare services needed, diagnosis, or treatment.

**Assisting in detection and diagnosis**

Different applications and software are also being used to detect and diagnose SARS-CoV-2. Cough for Cure is a tool that provides a score to individuals regarding their likelihood of suffering from SARS-CoV-2, based on the sound of their cough. Another similar tool, Coughvid, also analyses the patient’s cough and helps physicians in a more accurate triage. Researchers have also created a COVID Voice Detector capable of assigning a risk score by comparing voices to those of SARS-CoV-2 patients.

These tools can provide early detection of SARS-CoV-2 and have tremendous applications in global mitigation policies.

**Identifying hotspots**

AI has applications in contact tracing and identification of COVID-19 hotspots. Human mobility tools can be used in the setting of poor network coverage to potentially trace infectious contacts. Similarly, Google location history may also be used to collect human mobility data of confirmed cases from places that they may have visited or stayed at, including restaurants, hotels, airports, train stations, shopping malls, among others. These contact tracing methods have been previously used for disease outbreaks, such as the Ebola outbreak in 2014, tuberculosis, severe acute respiratory syndrome in 2003, and the Middle East respiratory syndrome outbreak in the Middle Eastern Saudi Arabia Peninsula region (2012) and South Korea (2015).
Table 1: Using of artificial intelligence (AI) in medicine.

| Field of medicine | Author          | Year | Usage of AI                                                                                                                                 |
|-------------------|-----------------|------|---------------------------------------------------------------------------------------------------------------------------------------------|
| Oncology          | Sotoudeh et al  | 2019 | Classification of cancer via tumor markers and identifying mutations:                                                                          |
|                   | Arimura et al   | 2018 | Using AI algorithms in predicting the grade of the tumor via imaging had an accuracy of 93%.                                                   |
|                   | Jha et al       | 2016 | Some AI models were used to predict the survival rate in glioma and illustrated an accuracy of 90.66%.                                       |
|                   | Liu et al       | 2018 | Radiomics for precision medicine in radiation therapy:                                                                                      |
|                   | Xu et al        | 2019 | AI-based machine learning algorithms help enhance the role of radiomics in prognosis and treatment.                                          |
| Radiology         | Pesapane et al  | 2018 | Imaging analysis:                                                                                                                              |
|                   | Topol et al     | 2019 | The most common application of AI is in image processing.                                                                                   |
| Cardiology        | Krittanawong et al | 2017 | Cardiac imaging for diagnosis of myocardial infarction, atrial fibrillation, and other cardiovascular diseases:                              |
|                   | Dilsizian et al | 2013 | Use of computer vision for interpretation of echocardiogram via image segmentation.                                                        |
|                   | Johnson et al   | 2018 | Convolutional neural networks (CNN) used to detect hypertrophic cardiomyopathy had an AUC of 0.93. In another study, CNN had an accuracy of 91.7% in echocardiographic interpretation. |
|                   | Diaz et al      | 2020 |                                                                                                                                             |
|                   | Madani et al    | 2018 |                                                                                                                                             |
|                   | Krittanawong et al | 2019 |                                                                                                                                             |
| Neurology         | Lee et al       | 2017 | Intracranial computed tomography (CT) imaging for rapid diagnosis and treatment:                                                            |
|                   | Titano et al    | 2018 | Prompt diagnosis of intracranial hemorrhage was made by machine learning algorithm which analyzed brain CT in less time with an AUC of 0.846. |
|                   | Arbabshirani et al | 2018 |                                                                                                                                             |
| Reproductive      | Topol et al     | 2019 | Evaluation and selection of oocytes for in vitro fertilization (IVF):                                                                            |
|                   | Wang et al      | 2019 | A feed-forward artificial neural network used for the identification of competent or incompetent oocytes had an accuracy of 91.03%.          |
|                   | Lamb et al      | 1993 | Sperm selection and semen analysis:                                                                                                           |
| Ophthalmology     | Wong et al      | 2016 | Since sperm analysis has several parameters and one-third causes of male infertility are idiopathic, diagnosing male infertility can often be challenging. |
|                   | Topol et al     | 2019 | AI algorithms used showed an overall accuracy of 89.92% with a higher accuracy for predicting chromosomal abnormalities (95%).                  |
|                   | Gulshan et al   | 2016 | Selection of embryo for IVF:                                                                                                                  |
| Pediatric diseases | Liang et al     | 2019 | Image segmentation and classification of blastocyst allowed better analysis with an accuracy of 87.8%.                                           |

(continued)
### Table 1

| Field of medicine | Author | Year | Usage of AI |
|-------------------|--------|------|-------------|
| Congenital diseases | Gurovich et al\[^{23}\] | 2018 | Accuracy of the algorithm ranging from 88% to 92%, which was comparable to expert clinicians. |
| Gastroenterology | Topol et al\[^{81}\] | 2019 | AI-based systems showed high accuracy in diagnosing multiple pediatric diseases. These included asthma (AUC 0.92), encephalitis (0.837), gastrointestinal disease (0.86s), pneumonia (0.888), respiratory disease (0.935), and sinusitis (0.932). These values were higher than junior clinicians and approximately equal to or slightly lower than experienced clinicians. |
| Dermatology | Fogel et al\[^{24}\] | 2018 | Facial analysis technologies used by expert clinicians allowed identification of phenotypes of only a few diseases. Using computer version and deep learning algorithms, a facial analysis framework (DeepGestalt) was developed which showed a high accuracy of 91%. This AI algorithm identifies over 215 different genetic diseases and has far superior efficacy than expert clinicians. |
| Dermatology | Esteva et al\[^{25}\] | 2017 | AI used in diagnosis resulted not only in an accuracy of 94% but also provided results in only 35 s. |
| Dermatology | Topol et al\[^{81}\] | 2019 | Finding the presence of sessile or adenomatous polyps <5mm. |
| Mental health | Topol et al\[^{81}\] | 2019 | AI simulated experienced dermatologists with the algorithm reaching an AUC of 0.94 for skin melanoma and 0.96 for carcinoma. |
| Intensive care unit (ICU) settings | Hanson et al\[^{26}\] | 2001 | Improving the efficiency of care in ICU: AI applications, such as bedside devices, waveform analysis, patient records in electronic format, may help improve patient outcomes in ICU because of their high efficacy. |
| Precision medicine | Mesko et al\[^{27}\] | 2017 | Precision medicine is an approach that utilizes AI algorithms to focus on the treatment and prevention of disease on grounds of genetic and environmental factors. |
### Table 2: Use of artificial intelligence in identifying cases.

| Author(s)       | Modality | Sample size                                                                 | Task                                  | Method                     | Accuracy                              |
|-----------------|----------|------------------------------------------------------------------------------|---------------------------------------|----------------------------|---------------------------------------|
| Wang et al[30]  | CT       | 1065 CT images (325 COVID-19 and 740 viral pneumonia)                        | Diagnose COVID-19                     | Inception transfer-learning    | Accuracy: 79.3%                      |
|                 |          |                                                                              |                                       |                            | Specificity: 83.0%                  |
|                 |          |                                                                              |                                       |                            | Sensitivity: 67.0%                  |
| Chen et al[31]  | CT       | 106 CT images (51 COVID-19 and 55 others)                                    | Diagnose COVID-19 and others          | UNet++                     | Accuracy: 92.5%                      |
|                 |          |                                                                              |                                       |                            | Specificity: 93.6%                  |
|                 |          |                                                                              |                                       |                            | Sensitivity: 100.0%                 |
| Jin et al[32]   | CT       | 1881 CT images (496 COVID-19 and 1385 others)                                | Diagnose COVID-19 and others          | CNN                        | Accuracy: 95.5%                      |
|                 |          |                                                                              |                                       |                            | Specificity: 94.1%                  |
| Xu et al[33]    | CT       | 618 CT images (219 from 110 COVID-19 patients, 224 from 224 influenza-A viral pneumonia patients, and 175 from healthy people) | Diagnose COVID-19 and influenza-A viral pneumonia | 3D deep learning             | Accuracy: 86.7%                      |
| Shi et al[34]   | CT       | 2685 CT images (1658 COVID-19 and 1027 community-acquired pneumonia (CAP))  | Diagnose COVID-19 and CAP             | iSARF                       | Accuracy: 87.9%                      |
| Zheng et al[35] | CT       | 542 CT images (313 COVID-19 and 229 others)                                  | Diagnose COVID-19 and others          | U-Net CNN                  | Specificity: 91.1%                   |
|                 |          |                                                                              |                                       |                            | Sensitivity: 90.7%                  |
| Jin et al[36]   | CT       | 1136 CT images (723 COVID-19 and 413 others)                                 | Diagnose COVID-19 and others          | UNet++ CNN                 | Specificity: 92.2%                   |
|                 |          |                                                                              |                                       |                            | Sensitivity: 97.4%                  |
| Li et al[37]    | CT       | 4356 chest CT exams from 3322 patients                                       | Diagnose COVID-19 and CAP             | COVNet                     | Accuracy: 95.0%                      |
| Song et al[38]  | CT       | 275 CT images (88 COVID-19, 101 bacteria pneumonia, and 86 healthy)          | Diagnose COVID-19, and bacterial pneumonia | ResNet-50                  | Accuracy: 86.0%                      |
| Wang et al[39]  | X-ray    | 16756 CXR images                                                             | Diagnose COVID-19                     | COVID-Net                  | Accuracy: 92.4%                      |
| Narin et al[40] | X-ray    | 100 CXR images (50 COVID-19 and 50 normal)                                   | Diagnose COVID-19                     | ResNet50                   | Accuracy: 98.0%                      |
|                 |          |                                                                              |                                       | InceptionV3                | Accuracy: 97.0%                      |
|                 |          |                                                                              |                                       | ResNetV2                   | Accuracy: 87.0%                      |
| Zhang et al[41] | X-ray    | 1531 CXR images (100 COVID-19 and 1431 other pneumonias)                     | Diagnose COVID-19 and others          | ResNet                     | Accuracy: 95.2%                      |
|                 |          |                                                                              |                                       |                            | Specificity: 70.7%                  |
|                 |          |                                                                              |                                       |                            | Sensitivity: 96%                     |
| Ardakani et al[42] | CT   | 612 CT images (306 COVID-19 and 306 normal)                                 | Diagnose COVID-19                     | CAD                        | Accuracy: 91.94%                     |
|                 |          |                                                                              |                                       |                            | Specificity: 93.54%                 |
|                 |          |                                                                              |                                       |                            | Sensitivity: 90.32%                 |
|                 |          |                                                                              |                                       |                            | AUC: 0.965                          |
| Zhang et al[43] | X-ray    | 5208 CXR images (2060 COVID-19 and 3148 other pneumonias)                    | Diagnose COVID-19 and others          | CV19-Net                   | Sensitivity: 88%                     |
|                 |          |                                                                              |                                       |                            | Specificity: 79%                    |
|                 |          |                                                                              |                                       |                            | AUC: 0.96                           |
| Wehbe et al[44] | X-ray    | 2214 CXR images (1192 COVID-19 and 1022 normal)                              | Diagnose COVID-19                     | DeepCOVID-XR               | Accuracy: 83%                        |
|                 |          |                                                                              |                                       |                            | Sensitivity: 75%                    |
|                 |          |                                                                              |                                       |                            | Specificity: 93%                    |
|                 |          |                                                                              |                                       |                            | AUC: 0.90                           |
| Zhou et al[45]  | CT       | 2814 CT images (793 COVID-19 and 2021 viral pneumonia)                       | Diagnose COVID-19 and viral pneumonia | Trinary scheme             | Accuracy: 91.7%                      |
|                 |          |                                                                              |                                       |                            | Sensitivity: 88.9%                  |
|                 |          |                                                                              |                                       |                            | Specificity: 94.4%                  |
|                 |          |                                                                              |                                       |                            | AUC: 0.95                           |

CT: Computed tomography; COVID-19: Coronavirus disease 2019; CNN: Convolutional neural networks; CXR: Chest X-ray; AUC: Area under the curve.

The structured or unstructured data collected from AI-based human mobility sources can be processed using big data analytical tools to find hotspots of SARS-CoV-2 cases and implement control measures. A comprehensive summary of the use of AI in identifying hotspots during the recent SARS-CoV-2 outbreak have been shown in Table 3. Identifying hotspots of disease incidence allows public health organizations to focus on preventative, isolation and curative measures towards these specific locations, thus allowing governments to enforce smart lockdowns and open up communities in a controlled manner, minimizing the socioeconomic impact of a complete...
| Authors                  | Year  | Location                        | Area captured and Population | Effectiveness                                                                                                                                                                                                 |
|-------------------------|-------|---------------------------------|------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Petropoulos et al       | 2020  | China and Austria               | Not mentioned                | The geographical spread of the virus and individual’s health are being monitored by AI-powered smartphone applications. Individuals can be notified of potential infection hotspots in real time. AI is not yet playing a significant role in the fight against COVID-19. |
| Dasgupta et al           | 2020  | India                           | Not mentioned                | Prediction through social networking data proves to be effective. Tweets with hashtags of “COVID” and “coronavirus” were used to determine hotspots in different Indian states and territories. The results were compatible with the report published by the Indian government. |
|                         |       | United States of America,       |                              | Similarly, Twitter was used with the same hashtags as above to compare the total number of tweets of each country to the total number of confirmed COVID-19 cases (till April 15, 2020). The results showed a correlation (correlation coefficient of 0.995) between the two variables. |
|                         |       | United Kingdom,                 |                              | Canadian health monitoring company BlueDot was able to send out a warning to its clients about the COVID-19 outbreak in China and the rest of the world as early as December 31, 2019, in contrast to WHO, which notified the public nine days later. They were also able to predict the most suspected cities and countries that COVID-19 would infect using global air ticket data. The first places affected by COVID-19 were among the top 11 listed countries by BlueDot. |
|                         |       | New Zealand                     |                              | Results of this cohort study showed that the spatiotemporal spread of reported COVID-19 cases could be predicted at a global level by analyzing openly available geolocated Twitter social media data. |
| Kreuzhuber et al         | 2020  | (Article in Europe),            | Global                       | Developed by Boston Children’s Hospital and Harvard Medical School, COVID-19 Near You is a real-time health reporting website in which users can report their symptoms. It shows patterns and hotspots by locations. Undetermined effectiveness. |
|                         |       | Assessing global impact         |                              | Combines features such as providing a geomap of countries across America using information from the US CDC, John Hopkins University, and other public sources; shows a real-time Twitter feed of COVID-19 news as well as data about hospitals and other useful information to local users. |
| Bisanzio et al           | 2020  | Global                          | Global                       |                                                                                                                                                                                                                |
| COVID Near You           | 2020  | US, Canada, Mexico              | All three countries.          |                                                                                                                                                                                                                |
|                         |       | Total No. reported on website:  |                              |                                                                                                                                                                                                                |
|                         |       | 1,484,109 (US)                  |                              |                                                                                                                                                                                                                |
|                         |       | 595,911 (Canada)                |                              |                                                                                                                                                                                                                |
|                         |       | 6640 (Mexico)                   |                              |                                                                                                                                                                                                                |
| Lee et al                | 2020  | US                              | Not mentioned                |                                                                                                                                                                                                                |
|                         |       | Assumption: area of US          |                              |                                                                                                                                                                                                                |
| Jana et al               | 2020  | US and Italy                    | Not mentioned                |                                                                                                                                                                                                                |
|                         |       | Assumption: area of both countries |                             |                                                                                                                                                                                                                |

COVID-19: Coronavirus disease 2019; WHO: World Health Organization; CDC: Center for Disease Control.
nationwide lockdown. Although it seems to prove useful in a crisis like this, a major limitation to this is a breach of privacy and potential long term misuse of data.

Many organizations, universities, and governments around the globe have worked together to develop combined geographical information systems, AI, and big data-enabled analytics dashboards to track and map the dynamics of the SARS-CoV-2 pandemic.

John Brownstein, chief innovation officer at Harvard Medical School, is working with a team that is using artificial intelligence and machine learning, to analyze big data consisting of social media posts, news reports, and information supplied by doctors and official health public channels about the manifestations of the virus outside of China.

Using an ensemble of convolutional long short-term memory based spatiotemporal epidemic spread model on data obtained from USA and Italy revealed high prediction accuracy with high resolution. Studies predicting the incidence rate of SARS-CoV-2 using artificial neural network modeling showed that the Getis-Ord Gi* could identify the location of hotspots of disease incidence rates with a significant P value of <0.05. The employed model indicated a reasonable but not a large consistency with ground-truth on holdout samples.

In Naudé’s early rapid review of AI against SARS-CoV-2, he concludes that AI has not yet been wholly impactful against SARS-CoV-2 and argues it is unlikely to be of much use in the present pandemic due to its current limitations. Models of dynamic neural networks used to track spatiotemporal epidemiology of previous pandemics such as the 2015 Zika virus need to be retrained using data collected from the SARS-CoV-2 pandemic. Unfortunately, there is a lack historical and unbiased data available for the AI model to be trained with. This is further accentuated by the problem with using big data such as social media to track SARS-CoV-2 activity.

Hua and Shaw state that SARS-CoV-2 is an infodemic as much as it is a pandemic. The sudden rise of social media posts and Google searches of nonspecific symptoms due to widespread panic leads to “noise” on social media. This noise requires filtration to discern meaningful trends.

Aiding government decision making

AI has numerous applications in informing governmental policies and decision making during the SARS-CoV-2 pandemic. Many countries have successfully mitigated their local outbreaks by employing sophisticated AI-based tools for imposing implementation of travel restrictions policies, ensuring the use of personal protective measures, quarantine enforcement, and deployment of resources.

Travel restrictions

Travel restrictions are an integral component of community mitigation measures. Early and effective implementation of these restrictions can slow down the progression of the disease spread. This puts less strain on the already limited medical resources and allows medical staff to provide adequate care to infected individuals. However, non-compliance with these restrictions poses a risk of potential exacerbation of viral spread, which needs to be addressed.

Some countries are using AI-powered identity recognition systems and geolocation services to improve public compliance. For example, a program named “Oyoon” is employed by the United Arab Emirates (UAE) Police to limit the movement of Dubai residents. The program integrates facial, voice, and license plate recognition, feeds this information through a database, and analyzes it to determine whether a traveling resident has a valid travel permit or not.

AI-based behavioral analytics can also predict the time and location of potential events of non-compliance by accounting for the dynamics of human behavior, culture, and individual perceptions. This can inform the deployment of enforcement units by governments in advance. Furthermore, AI can also model mobility with SARS-CoV-2 transmission dynamics, allowing policymakers to predict the speed of transmission with different levels of travel restrictions.

Personal protective measures

The utilization of personal protective equipment is being enforced with the help of AI-driven tools by several governments. China has combined infrared cameras with facial recognition systems to recognize citizens not wearing masks or individuals with high body temperatures. AI-powered robots are also being used in China, capable of scanning temperatures of multiple individuals simultaneously within a certain radius. These robots alert relevant authorities when individuals with fever or without masks are detected—reducing the potential risk of exposing authorities to SARS-CoV-2 while conducting temperature measurements.

Similar AI-based technology has also been employed in taxis in UAE. This technology uses computer vision and machine learning algorithms to scan human faces, verify if masks are worn properly, and calculate the distance between passengers and drivers.

Quarantine enforcement

The World Health Organization recommends quarantine of all diagnosed with SARS-CoV-2, and their contacts for 14 days to prevent further transmission. However, authorities are forced to allow self-quarantine at homes or hotels because of limited quarantine facilities in many countries. In these circumstances, ensuring that patients are complying with their quarantine restrictions is imperative, and AI has played a vital role in enforcing this.

Bahrain, Kuwait, and Qatar have developed AI-powered applications that use computing and geolocation services to track diagnosed and suspected cases. Bahrain’s application, BeAware, also allows residents to track
proximity to individuals with SARS-CoV-2. South Korea is using algorithms that use geolocation data, surveillance-camera footage, and credit card records to trace patients. In China, a red, yellow, and green color coding is assigned to residents indicating contagion risk via a smartphone program. Moreover, Austria, Poland, China, South Korea, and Singapore are also using location-based contact tracing systems to identify possible infection routes and break the transmission lines.

Resource deployment
With increasing cases, healthcare facilities can face a scarcity of resources, that is, testing kits, hospital beds, ICU beds, ventilators, and healthcare professionals. COVID-19 has different patterns of disease progression and outcomes, ranging from asymptomatic patients to those with multiorgan failures. Considering this heterogeneity and limited resources, it is important to deploy systems capable of providing early warnings for disease progression and informing which patients will benefit from what resources and when.

AI-based systems can be employed to streamline healthcare operations and optimize scarce resources. They can be used to anticipate expected patient numbers, provide risk and symptom assessment, and cross-reference them with the availability of required medical staff, materials, and equipment. This can allow for evidence-based decision making, allowing limited resources to be allocated as effectively as possible.

Aiding physicians
Healthcare professionals have a very high workload due to a massive increase in SARS-CoV-2 patients. They are also at a higher risk of infection due to their proximity to the patients. With an already shortage of healthcare workers, protecting them and alleviating their workload should be a priority in the fight against SARS-CoV-2. Here, AI can be employed for digital healthcare delivery, limiting patient contact, disinfecting hospital premises, screening healthcare professionals, and relieving their workload. A comprehensive summary is elicited in Table 4.

Digital healthcare delivery
With the introduction of travel restrictions and social distancing measures to mitigate viral spread, telehealth modalities have shown the potential to deliver care to patients with mild diseases. AI can take this one step further—allowing automating of basic processes such as taking patient history, or powering remote consultations

| Location | Category | Applications |
|----------|----------|--------------|
| United Kingdom | Doctorlink App | Symptoms assessment platform; video consultations (SARS-CoV-2 and other diseases). |
| United States of America | WhatsApp chatbot | SARS-CoV-2 information service. |
| China | UV-light-zapping germicidal robots | Early detection of SARS-CoV-2 in healthcare professionals by tracking their heart rates, temperatures, movements, and sleep patterns. |
| Italy | CT scan interpreter | Interpreting CT scan images to identify SARS-CoV-2 when radiologists are unavailable. |
| Denmark | UVD Robots | Allowing visual and acoustic patient-doctor communication; measuring blood pressure and oxygen saturation; disinfecting the premises. |
| Belgium | Robots | UV light disinfection. |
| India | Robots | Speaking 53 languages for communication; scanning QR codes; measuring temperature; determining if face masks are being worn properly. |
| Tunisia | Robots | Delivering medicine and food; UV light disinfection; registering patients; conducting preliminary screening; directing patients to relevant departments. |
| Rwanda | Robots | Measuring heart rate, temperature, and oxygen saturation; allowing virtual communication. |
| Multinational | Suki, Kara Voice Assistant Programs | Updating medical records automatically (for SARS-CoV-2 and other consultations). |

CT: Computed tomography; QR: Quick response; SARS-CoV-2: Severe acute respiratory syndrome coronavirus 2; UV: Ultraviolet.
and triage such as symptom assessment platforms.[70] These technologies allow efficient delivery of care to the population during these restrictions while putting less strain on healthcare professionals and facilities.

Screening healthcare professionals

Healthcare professionals are at a higher risk of SARS-CoV-2 infection due to their proximity to patients. Hence, it is important to periodically screen them to catch any early symptoms. For this purpose, researchers in the US are testing AI-powered programs that employ common wearables, that is, rings, to monitor vital signs including heart rate, temperature, sleep cycle changes, etc.[71] This information is fed into an algorithm capable of giving hospitals early warning about professionals who need to be isolated and provided medical treatment.

Utilizing robots in healthcare settings

AI-powered robots have been employed in healthcare settings in many countries, including Belgium, China, Denmark, India, Italy, Rwanda, Tunisia, and the United States. They can deliver food and medications, monitor crucial patient parameters, disinfect healthcare premises, and complete other routine tasks. These programs can also allow virtual communication between patients and health professionals, permitting remote diagnoses.[66] This limits patient contact and helps to alleviate the workload on healthcare professionals. Since personal protective equipment (PPE) is not required by robots, they also help to reduce the strain on the limited PPE resources.

Other AI-powered tools

Several AI-powered voice assistant programs have been developed, allowing healthcare professionals to record, autocomplete clinical notes, and update medical records in realtime. This saves crucial time and reduces the workload of healthcare professionals.

Prospect of AI in SARS-CoV-2

As discussed, SARS-CoV-2 was a medical nightmare, with the healthcare systems stretched thin and tested to their limits. The resources were limited, and the unforeseen burden on the hospitals was evident, not just in the low-income countries, but also in the developed world. However, what perhaps made up for the scarce manpower was the use of AI. The virtual chatbots with pre-fed answering algorithms were available round the clock to help the masses; the virus tracking, and local spread helped in implementing “smart lockdowns” to minimize the impact on economy and business. Moving forward, the AI can be effectively used in tracking vaccination status, availability, and compliance. This will help ensure an equitable distribution of vaccine, both, nationally and globally.

Conclusion

AI has found its way into the healthcare system and is occupying various niches, making it more efficient and reliable than humans themselves. It has facilitated in identifying key diagnoses and in predicting patient outcomes, aiding physicians in non-biased decision making. In times of SARS-CoV-2, AI has stood the test of time in terms of preventing the spread of the virus, by identifying cases and hotspots, and thereby guiding key government officials in formulating communal policies such as travel restrictions and resource allocation. This review will serve as a gateway to future implementation of AI in the field of medicine, particularly in monitoring various diseases and exploring their potential to spread. The key to integration of AI in medicine would be a global availability, even to the low- and middle-income countries where the disease burden of communicable diseases remains high.

Conflicts of interest

None.

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