The Rise of Machine Intelligence in the COVID-19 Pandemic and Its Impact on Health Policy

INTRODUCTION

The fourth industrial revolution has brought numerous transformations in the world, catalyzed by the advent and rapid adoption of digital tools. One notable disruption that this revolution has brought is the advent of novel computing methodologies and technologies, which are seen to be transforming all spheres of the global economies. These are observed to be the basis for the unquestionable improvements and quality risk assessments that each sector within the global fabric is experiencing. On this note, one sector that has truly been transformed is the medical sphere, which now prides itself of enriched databases following novel application of different technologies such as artificial intelligence (AI), machine learning, natural language processing, big data, and Internet of things (IoT) and others. With the increased data, and the technology, those working in the sector have access to advanced predictive modeling and computing tools that have transformed areas such as personal medicine and epidemiology, medical operations, diagnosis, and drug manufacturing (Allam et al., 2019). In addition, as noted by Watson (2019), the technologies are helping the medical fraternity to draw variable predictions by comparing historical and present medical data. For instance, it is now possible to use such predictions to assess the healthcare labor force and subsequently use the results to initiate recruitment processes in areas that are most deserving in a meritocratic way. Even if AI tools are observed to sometimes extend biases, those are being addressed, a hiring authority can manage to effect the concept of inclusivity and streamline some lingering workforce challenges among other things.

While these computing technologies and tools have already given a glimpse of how they can transform the health sector, it is worth appreciating that most of them are still a "work-in-progress" in the medical field and hence need to continue evolving and streamlined. Therefore, in that regard, it is understandable that some teething problems and challenges are inevitable, but such need to be addressed with time. Additionally, it has been found that some medical professionals and stakeholders in this field are yet to fully embrace the computing tools as part of the advancement in the medical realm; hence, they continue to rely on human-based interpretation, including in life-threatening situations. And, from records, such decisions sometimes tend to be time-consuming and are at times, far from being correct. Therefore, to ensure that such scenarios are minimized, there is a need for frameworks to guide the usage of those technologies so that they can be widely accepted and ultimately lead to saving more lives. In particular, the issues of data collection, storage, management, and sharing require to be urgently addressed, as it is seen as the primary source of the apprehension that some in the health community have against them. On this, for a start, the challenge of standardization of protocols needs to be sorted as this hosts issues such as limiting the scope of data, is associated with incompatibility of devices and networks, and exposes the field to extra costs to name a few.

Addressing such challenges would be key, especially in a period of emergencies like now, when the entire world is hurting from the impacts of COVID-19 pandemic. For instance, despite the challenges raised earlier, some startup companies were able to use the available data from social media, airline ticketing, and medical institutions to identify that the world is experiencing a new virus outbreak days before those in medical fraternity had made similar findings (Gaille, 2019). With these technologies, it also took less time to identify the outbreak, unlike in other previous outbreaks like in the

case of the severe acute respiratory syndrome (SARS) outbreak in 2002 that took relatively 4 months to identify (Qiu et al., 2018). In the case of COVID-19, initially known as 2019-nCoV, it only took 7 days (WHO, 2020b). These breakthroughs in the medical field, therefore, need to be encouraged, and one way of doing this is the streamlining all available obstacles. In support of this, this chapter surveys how AI processes, aided by availability of data managed to allow for early detection of the coronavirus outbreak, and through the findings, showcase that enhanced data sharing protocols hold the key to improved future urban health policies.

THE EARLY DETECTION OF THE CORONAVIRUS

The first official confirmation of novel coronavirus (now known as the COVID-19) was made public by the World Health Organization (WHO) on January 9, 2020, after its officials based in China received reports from the Chinese health official of a new type of infectious virus (WHO, 2020a). But from records, before this actual confirmation, there were reports that some people had started to show signs like those of the virus as early as

December 8, 2019, in Wuhan. Of these, six had presented themselves to the hospital in where they were treated and later discharged. But, the cases of similar symptoms continued, and this raised an alarm among health officials who embarked on a fact-finding mission to establish whether they were dealing with a commonly known virus outbreak or a new type altogether. It was after this that, on December 31, 2019, Chinese officials liaised with the WHO officials to establish that this was truly a new strait of coronavirus. This prompted concerted efforts that lead to the official confirmation of the virus on January 9, 2020, which later became widespread worldwide (Fig. 6.1) and classified as a pandemic.

In view of this historical perceptive, it is true that there was a time lag between when the first symptoms were reported and when the confirmation was done (WHO, 2020b); thus, since it is now clearly known how the virus is transmitted (from person-to-person), there must have been a sizable number of people contracted the virus. This prompted Chinese health officials to place the entire region of Wuhan city under a total lockdown as from January 23, 2020, to prevent further spread (Li et al., 2020). But, unfortunately, noting that this is a busy city, people from other regions, and countries, as was

FIG. 6.1 Representation of the COVID-19 global spread.

later established by BlueDot, who may have contracted the virus had already traveled back to their countries, and this opened the door for further spread across regions and finally into the breadth and length of the world.

In respect to the actual origin of the virus, for now, only theories have been advanced. But, reports to date (Retamal, 2020) support that the first victims of this virus contracted it from the Huanan Seafood Wholesale Market in Wuhan city. And as noted earlier, being a new virus, the tests were initially being conducted only in China, specifically in Wuhan, with the health officials suspecting it to be SARS virus, but this was ruled out on January 5, 2020. This raised alarms, and when it was officially identified and provisionally named "2019-nCoV" on January 7, 2020, and the data subsequently shared to public, an Australian Virus Identification Laboratory based at the Peter Doherty Institute for Infection and Immunity immediately embarked on its research and by January 25, 2020, it was able to clone the virus (Nature, 2020). But this is not the only institution that took the virus outbreak seriously. According to Niiler (2020), BlueDot, whose profile is shared in the following, was able to employ the services of AI-driven algorithms, to analyze data gathered from sources such as new reports, air ticketing, and animal disease outbreaks to predict that the world is facing a new type of virus outbreak. Besides the prediction of the new virus outbreak, this startup and another called Metabiota (both profiles shared in the following) were able to predict (independently) correctly some of the areas that would experience the virus spread next. Among regions and countries predicted by each of these startups that turned to be true include Japan, Taiwan, South Korea, Singapore, Thailand, and Hong Kong (Heilweil, 2020). Such predictions came days earlier before any of the said country reported their first case.

The information from these different quarters became instrumental in combating the virus. It was through the spread prediction mapped by BlueDot and Metabiota that the rest of the world and concerned institutions and agencies came to learn that the world is confronting a highly infectious virus that was spreading at alarming rates. On the same, after successfully cloning the virus, the Virus Identification Laboratory shared the data in an open database where authorized researchers and labs can access and conduct further research on cures and vaccines (Nature, 2020). All these efforts prove that with technologies, it is now possible to confront pandemics of global magnitude. But such drive needs to be backed by concerted efforts aimed at eliminating data sharing obstacles associated with different advanced computing technologies and tools.

A BRIED SURVEY ON INFECTIOUS DISEASE OUTBREAK IN A 20-YEAR PERIOD

The current case of COVID-19 is not the most devastating nor the only virus that the world has had to struggle with. Indeed, looking at the historical fact, there have had some more contagious, devastating, and widespread pandemics experienced before. In the early 14th century, it is documented that a deadly plague dubbed the *Black Death (*Bubonic plague) struck the world and killed approximately 50 million people in a span of 5 years (Duncan and Scott, 2005). Fast forward, in 1918, another deadly pandemic was the *Spanish flu* (H1N1 influenza virus) struck. This is a type of influenza that is believed to have originated in Étaples, France, and it went on to infect over 500 million people, killing around 50 million of these globally (Martini et al., 2019). Between 1957 and 1958, another type of influenza (A subtype H2N2) also known as *Asian flu* broke in China, and by the time it was contained, it had claimed the lives of 1.1 million people. Ten years later (1968), the world suffered another outbreak; this time influenza A (H3N2) first reported in Hong Kong, killing over 1 million people. Later on, in 2009, the swine flu (H1N1 influenza virus) killed 12,469 people in the United States alone (CDC, 2019). Before this, in 2002, there was an outbreak of SARS in China that killed 774 people (Song et al., 2019). There was also Ebola (Zaire Ebola Virus) that was first reported in Democratic Republic of Congo that claimed approximately 11,315 people, followed by the Zika Virus in 2015 that infected approximately 500,000 people, killing 18 people. In 2020, the world is now confronting the coronavirus, which has spread to over 200 countries, and the end to it is not predictable at the time of writing of this chapter.

In all the examples cited earlier, the common denominator is that the success of containing any of these viruses depends on detection and identification. That said, it is worth noting that these pandemics were caused by different types of viruses. These include the influenza virus, Henipavirus (Nipah virus), Filoviruses like those responsible for Ebola, and Flavivirus that is responsible for Zika (Aris-Brosou et al., 2017; Madhav et al., 2018) to name a few. This process usually equates to extensive laboratory testing, as illustrated in Fig. 6.2.

Regarding their detection, it is dependent on the type of technology use; hence, from the emergence of the digital revolution, things are seen to be changing in respect to amount of time taken for detection. However, here too, other factors such as the availability of data, quality of the same, and sharing methods are critical. For instance, despite having some levels of modern technology, it took approximately 4 months to identify the SARS

FIG. 6.2 Laboratory testing at the Centers for Disease Control and Prevention (CDC).

virus. Such delays, however, are credited to the action or inaction of the Chinese health officials to withhold information concerning the virus outbreak. In cases where there were concerted efforts between different players, like in the case of 2014 Ebola outbreak in West Africa, it is reported that the virus was identified in a record time, and this prevented its spread beyond the three countries (Liberia, Sierra Leone, and Guinea) that it was first reported (Wojda et al., 2015). In the current case of COVID-19, as noted earlier, it only took only 7 days to detect and identify the virus and to also predict how it would spread from the original epicenter (Wuhan). This was possible due to availability of technologies such as AI (Bini, 2018), machine learning, and natural language processing; the aforementioned startups were able to use to gather and analyze the data. In particular, the advancement in AI-based infectious disease-surveillance algorithms is understood to reduce the amount taken to detect a virus outbreak. It is evident that since the emergence of the AI-based surveillance, there is a notable level of improvement and efficiency. This is particularly important noting that technological advancements in other sectors such as transport have made movement of people relatively cheaper, quicker, and comfortable; thus, importation of virus and diseases from regions of high concentration to those with little or no virus or disease has become relatively high. This is the reality with the COVID-19, which was first imported from China and then later from some European countries such as Italy to the rest of the world.

In this regard, it is true that there are ongoing works and discussion aimed at revising existing policies to ensure the loopholes that have existed, thus allowing that spread of diseases and other outbreaks to nonendemic regions have been sealed. But, with the current happening, it is true that much effort is still needed. The amount of emerging computing literature on infectious diseases demonstrates that substantial research, supported by development of AI-based algorithms, has been increasing exponentially supporting an incline in use of AI technologies involved in diseases and virus surveillance.

The increased use of AI-based tools to monitor and survey outbreaks in different regions, through a forward step toward early prevention, needs to be complimented by the availability of substantial data. Therefore, as has been stamped in this chapter, it is paramount to have a framework that clearly outlines how specific data need to be shared with the public. In particular, this would help to overcome challenges of insufficient data that are instigated by the act of withholding information by some entities or countries surfing on private interest. On this, a positive step toward its actualization was

made in 2016 by the WHO after the Zika virus outbreak where through unfettered sharing of data, different agencies and stakeholders were able to utilize advanced technologies to prevent the spread of the virus. And, as noted earlier, such efforts were fruitful in that, unlike other previous virus outbreaks, this had the least number of casualties (18). Henceforth, the use of technologies is seen to be gaining traction with use of analytical tools such as AI algorithms becoming popular as it allows for data scouring from diverse targets (Lau et al., 2019) and it is also compatible with other technologies such as machine learning and natural language processing. Such technologies, as noted earlier, are what allowed BlueDot and Metabiota to obtain the correct predictions they made about the outbreak and spread of COVID-19 to different regions. The use of these modern tools is also hailed for they have the potential to lead to quick diagnosis, help in development of vaccines and cures of outbreaks, and also would prompt development of raft of preventive strategies in areas that would be predicted to be of high risk of experience an outbreak (Martins, 2019). This is what the two aforementioned companies, whose description is given in the next section, achieved in the current case of COVID-19.

THE TWO COMPANIES THAT PROVIDED EARLY DETECTION OF COVID-19

This section highlights some briefs on how BlueDot and Metabiota were able to utilize modern computing technologies to accurately, and in record time predict coronavirus outbreak, and the target countries that were at risk of experiencing the outbreak.

BlueDot

BlueDot is a web-based startup that was pioneered in 2003 by Dr. Kamran Khan after the SARS outbreak. Initially, it was known by the trade name of Bio-Diaspora, but in 2014, it seeded round with a Sri Lankan private venture (Horizons Ventures) prompting its renaming to BlueDot. The startup came into limelight in 2009 when the H1N1 influenza pandemic broke, where it was able to correctly predict that global pathway of the virus by relying on worldwide air travel data. It cemented its authority in the use of modern computing technologies in 2014, where it developed risk assessment models that allowed it to predict the spread of Ebola virus outbreak that struck three West Africa countries (Allen, 2016). In the current predicament of COVID-19 pandemic, BlueDot was among the first to predict (9 days before official announcement) that the world was experiencing a new outbreak and also correctly identified countries that were at high risk of being next target of the outbreak (Bowles, 2020).

The answer to the success of this startup in making correct predictions lies on their reliance on modern, advanced, computing technologies and availability of data from different spheres. In respect to technologies, the company is observed to heavily rely on AI-based tools, machine learning technology, and natural language processing technologies. Using different models and algorithms, the company managed to scour valuable data from different sources such as diverse, global news outlets, global airline ticketing data (Heaven, 2020), population density data, global infectious disease alert, climate report, and Insect Vectors and Animal Diseases Reservoirs. In its website (2020b), it is clearly noted that it relies on over 10,000 official and media sources drawn from over 60 languages each day. It also queries reputable databases such as World Factbook and national statistics reports from different regions. With the available technologies, the company is able to employ filters on information from the different sources to narrow the results to the issue at hand (BlueDot, 2020a). On the same, the technologies also allow the use of modern clustering tools that allow it to quickly, and in real time, identify areas or regions with the potential to become hot spots, cold spots, and/or spatial outliers. It also relies on the power of machine learning to train its system using the assorted dataset, and in turn, the systems are able to generate real-time and regular alerts on issues of interest to the company's clients. It is through this that it was able to flag out coronavirus as an outbreak that had potential to spread to other regions quickly.

Metabiota

The history of Metabiota takes us back to 2009 when it was initiated. During those early days, its main engagements were in research focusing on how human and animal health were linked, especially in the African context. In 2014, when the Ebola virus broke in West Africa, the company was already active, and through its work attracted the attention of the US government, which at the time was actively involved in combating this outbreak (Rossi, 2019). Having experience on the African context, Metabiota was requested to assist, and it did a remarkable job, but after the Ebola situation was contained, the US government withdrew the funding to the company. The reduction of the funds took a toll on the company, hence prompting a paradigm shift, which entailed the company expanding its operation scope to enable it to serve more clients. In this regard, its target market was insurance companies, who would benefit from information concerning disease outbreaks. Henceforth, the company embarked on enriching its disease database, which today is among the most comprehensive ones (Rossi, 2019). To achieve this,

the company embarked on investing and utilizing advanced computation and predictive technologies, and such included AI, machine learning, big data, and natural language processing (NLP) algorithms. Through this, the San Francisco—based company serves a wide range of clients including government agencies, insurance companies, contractors, diverse non—profit-making organizations, NGOs, and others that, in one way or the other, depends on information of infectious diseases outbreaks to enhance their decision-making.

With these technologies, it has become among the leading startups in rendering predictions about infectious diseases outbreaks, spread, interventions, and event severity (Heaven, 2020). It uses NLP algorithms to scour data from diverse sources (both official and unofficial sources). From its website (Metaboita, 2020), it sources range from biological, political, socioeconomic, environmental, and social media among others. The data gathered from these are analyzed and categorized using reputable analytical and visualization technologies into clusters such as frequencies, severity, and time (duration of outbreaks), and these are shared with its clients depending on information being sought. In the recent case of COVID-19, Metaboita was in the forefront to analyze the outbreak, and during the analysis of the data, some even sourced from social media, the company was able to predict which neighboring countries were at high risk of being the next target of the virus spread, more so because the panic in Wuhan had stated to trigger some fear, forcing people to flee. By relying on AI, machine learning, and NLP, the company analyzed human predictive behaviors and scare levels, thus managing to correctly make the predictions a week earlier before any of the said countries (Japan, Thailand, Hong Kong, and others) had reported any case of the virus (Tong, 2020).

THE INCREASING ROLE OF BIOINFORMATICS

When it comes to pandemics, one sure way of protecting the masses and averting related negative impacts on the social fabric, the economy and human lives to name a few are providing early detection. Today where there are enough digital tools and technologies with capacity to allow for real-time data collection, fast and comprehensive computation, and prediction, early detection ought to be emphasized. But even with these technologies, any lapses, especially in data sharing, are bound to delay the detection and identification of the outbreak and that can prove to be fatal. For instance, in 2002, when SARS (SARS-CoV) broke in Guangdong local market in China, health officials and Chinese authorities

withheld information on the outbreak, and this prompted the identification of the virus to drag for around 4 months. While the fatalities from this virus outbreak were only 774 reported across 17 countries where the virus had spread, such could have been avoided. By the time the virus was contained, it had already spread to 29 countries. In a totally different case, as reported earlier, due to collaborative measures taken in 2016 when Ebola virus broke in West Africa, the virus was identified in a reasonable time, and this prevented further spread of the virus beyond Liberia, Guinea, and Sierra Leone. Though this virus is very infectious and tends to have high casualties, it leads to the unfortunate death of 11,310 people. If the outbreak here was to take the same route that SARS, it could have been disastrous and would have spread to numerous countries.

In the present case of coronavirus (C0VID-19) pandemic that originated in Wuhan city, China, the response was totally different from the 2002 SARS incident. This time round, the Chinese authorities were quicker and forthright in their reporting, and also in sharing subsequent information and data. Nevertheless, some quarters continue to accuse the Chinese authorities for the global spread of the virus. But while mistrust exists, the steps taken by Chinese authorities have been lauded. Additionally, as noted earlier, when the WHO officials were notified of this outbreak, they were also quick to identify the virus and to take decisive measures in ensuring that the spread was contained. It only took 7 days for the identification, but as noted earlier, it had taken approximately 23 days (from December 8, 2019—31 December 2019) to detect that the world was confronting a new type of coronavirus.

The breakthrough in the early detection being witnessed in these recent years can be credited to several factors. First, the reasons learnt from previous occurrences may have prompted some changes on how governments and stakeholders perceive the issue of pandemic outbreak. Secondly, and more importantly, the emergence and subsequent acceptability of a wide range of computational technologies has made it possible for faster data collection, data sharing, and advanced computation and analysis. The availability of data from different sources, including smart devices and health-wearable devices, social media, and existing health database, has also been handy and influential in determining the detection period and tracking of outbreaks. For this reason, Gaille (2019) notes that besides technologies, availability of data in large quantities is now seen as the world's new "gold rush" of this century. The availability of these not only influences health outcomes but is also seen to determine geopolitical standing, with those in position to collect, store, and control most of the data

seen to be positioned as a global power house and, hence, the push and pull on the 5G Internet between power economies (Allam, 2019a; Allam and Dhunny, 2019; Allam and Jones, 2019; Allam and Newman, 2018; Kharpal, 2018). In addition, even in lower levels of governance, the control of data is seen to be raising heat with large ICT corporations competing to control the market share such that they can have exclusive control of data, thus increasing their profit standing (Allam and Jones, 2020). But, beyond selfish interests, it is possible for corporations and governments and organisations with capacity to manage large quantities of data to work together for the sake of the economic landscape, the welfare of the social fabric, and the improvement in the health sector (Allam, 2019b; Allam, 2020c; Allam, 2020d). Such calls are valid in a time like now when the entire global economy, the health sector, and societies are in limbo due to the impacts of COVID-19.

To achieve such noble goals, however, as noted in the previous sections, there are several things that need to be addressed to streamline the data usage landscape. Among these include addressing some notable challenges with computing technologies used in analyzing big data. First, there needs to be a framework that guides how data have for long been highly guarded, collected, shared, and accessed in such a way that it does deem to be compromising the security and privacy of individuals. By doing this, it would be possible to increase personal data even further as the ethical and moral issues associated with data sharing would be lifted (Allam, 2020a; Allam, 2020b). In particular, this would be important when it comes to accessing and using data comprising personal genome, personal demographic information, and other personal identifying details (Vayena and Blasimme, 2018). In cases where such must be accessed, the use of strategies like k-anonymity (i.e ensuring that datasets have no combination of user identifying attribute) (Sweeney, 2002) to anonymise data, or the use of technologies such as blockchain or quantum cryptography must be made to ensure total anonymization of data. The framework should also address issues to do with standardization of protocols and networks, which have for long been seen to reduce communication of systems, especially in urban areas. On this, as shared by Allam and Jones (2020), standardization would then support seamless flow at an urban, regional, and international scale.

Besides streamlining on the use of technologies, and data-related issues, as has comprehensively been shared earlier, the war against COVID-19, as has been done already in different countries, needs to be supported by strengthening instituted quarantines, self-isolation, and lockdowns. These actions are in their part enough in enriching health databases, as it is from these that data on people contracting, recovering, and succumbing from the virus are being collected, in addition to those already sourced in medical facilities.

CONCLUSION

This work has candidly explored the role of various technologies, especially AI, machine learning, and NLP and big data in early detection of COVID-19, especially by exploring how such were instrumental in assisting Blue-Dot and Metabiota companies make their groundbreaking predictions for rendering early detection of the coronavirus. The exploration has demonstrated that the future of the health sector, among others, is promising, if such predictive achievements are to continue. To make this even better, it is the position in this paper that data sharing practices need to be encouraged by adopting best practices such as standardization of protocols, enhancing anonymization, and employing modern technologies such as blockchain and quantum cryptography, which have proven to be novel in such fields. There is also needed to emphasize cooperation between different agencies, institutions, and corporations to ensure that corporate monetary interest on data does not overshadow work aimed toward improving global health, economic equity, and social welfare.

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