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Original Contribution

Exploring Machine Learning in Healthcare and its Impact on the SARS-CoV-2 Outbreak

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Machine learning can be defined as a comprehensive range of tools utilized for recognizing patterns in data. Owing to its reliance on artificial intelligence in lieu of age-old, traditional methods, machine learning has established itself as an exceedingly quicker way of discerning patterns and trends from bulk data. The advanced system can even update itself on the availability of new data. This paper intends to elucidate different techniques involved in machine learning that have facilitated the prediction, detection and restriction of infectious diseases in the past few decades. Moreover, in light of the unprecedented COVID-19 pandemic, such tools and techniques have been utilized extensively by smart cities to curb the proliferation of the SARS-CoV-2 virus. However, the strengths and weaknesses of this approach remain abstruse and therefore, this review also aims to evaluate the role of machine learning in the recent coronavirus outbreak.

INTRODUCTION

Rapid technological progression in the past few decades has led to the establishment of a global information and communications technology (ICT) foundation that has evolved our lives for the better. For instance, throughout the course of the SARS-CoV-2 pandemic, also known as COVID-19, ICT development has vastly assisted in the maintenance of social distancing while enabling professional businesses to flourish via secure online networks.

Along with immense developments in the ICT sector that have transformed the way we work, live and play, the past decade has also witnessed an exponential incline in the population of planet Earth that has worryingly catalyzed the emergence of novel pathogens from foreign hosts instead of humans. While diseases such as tuberculosis have been present throughout human history, it is only in the last decade that we have seen a rise in novel viruses that can spread across international borders and cause catastrophic global crises, much like the SARS-CoV-2 [1]. This is where the breakthrough of advanced techniques revolving around machine learning come in to aid healthcare professionals to combat such biological threats to humankind.

Machine learning is a broad term that includes a host of tools and techniques to discern patterns in data [2]. Traditional methods of pattern identification provide a rather precarious outlook and approach towards disease management as we use our presumptions to determine which components of data such as age, sex and pre-existing health issues influence patient mortality and morbidity. This can be avoided through machine learning, as we only have to provide the data to a machine that identifies the patterns for us.

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We can later use these patterns to devise a suitable model to predict the outcome for patients.

The following review outlines a comprehensive but brief study of these tools and their usage in healthcare, ranging from prediction to management of COVID-19. It has also been mentioned how these tools have been used in the past, in the case of outbreaks of viruses including SARS-CoV-1 and MERS-CoV and how that information influenced the management of COVID-19 in smart cities. The content has been sub-headed as techniques for outbreak surveillance, epidemic prediction, vaccine development, detection and tracking, prognosis prediction of affected patients, and drug repurposing. Lessons learned from the COVID-19 pandemic are also discussed.

OUTBREAK SURVEILLANCE

Biosurveillance can be defined as the timely detection and prevention of an infectious disease outbreak in a particular community [3]. Tools accelerating biosurveillance include analytics, machine learning, and natural language processing (NLP) [4]. One such tool is offered by BAIOTEQ, a Canadian company that provides an AI platform for infectious disease surveillance, diagnostic imaging and infection prevention management. It is of extreme significance to keep track of localized disease outbreaks using social media, news reports and other reliable online data to prevent the disease taking form of a pandemic [5]. Early detection of COVID-19 in Wuhan, China by the end of December 2019 was possible through machine learning, used by BlueDot [6, 7]. Certain other effective methods of early detection of a pandemic used in the past include extensive big data analysis of medical records and satellite imaging for clues such as cars crowding around hospitals [8, 9]. For instance, the most recent Zika virus outbreak was detected using GoogleTrends and dynamic forecasting models [10].

Additionally, in order to understand the thought-process and emotions of a population towards a pandemic, sentiment analysis can be used to process the natural language in social media [11]. Unofficial sentiment analysis has also been presented as an efficient way of timely detection of diseases spreading in a population [12]. This method can be used in understanding the reactions of a community towards the outbreak and therefore, it can be used to gauge how effective the efforts of the government towards public education are [13–15]. For that reason, sentimental biosurveillance can become a considerably valuable tool towards timely detection of a disease, allowing local and global healthcare systems to prepare for prevention and management of the disease outbreak before it is classified as a pandemic.

EPIDEMIC PREDICTION

Historically, a significant number of disease outbreaks have been successfully predicted through statistical, mathematical and dynamic predictive models [16–21]. The current predictive models based on big data are much more effective than age-old, traditional models of epidemic detection, as the current models use adaptive machine learning- they can reboot themselves based on newer discoveries regarding the disease and provide flexibility in terms of prevention. They can also estimate interventions such as social distancing and their impact and success rates [22]. The most ubiquitous predictive model that is currently being used to detect and mitigate the risks posed by COVID-19 is the Susceptible-Exposed-Infectious- Recovered (SEIR) modeling method [23, 24].

Furthermore, these methods can determine various factors regarding the pandemic, such as under-reporting of cases, efficiency of interventions and the accuracy of testing methods [25, 26]. For instance, a modeling algorithm tried to simulate the setting in which Ebola could cause an outbreak in the Chinese society and the productiveness of the four levels of governmental interventions was estimated in such conditions [27]. Such predictive models have also been created to comprehend and predict the spread of Zika virus in the American continents and were known to have around 85% accuracy in quantitative evaluations [28]. Upon comparing various machine learning algorithms, it was found that backward propagation neural network (BPNN) showed the highest predictive accuracy in modelling Zika virus propagation [29]. In addition, a COVID-19 prediction model was presented by scientists at the Johns Hopkins University based on a former general model for metapopulation epidemic [30]. Pitting this theoretical model with real-life data showed gaps in the understanding of the virus's mechanisms and what the model lacks [31, 32].

It is to be remembered, however, that a predictive model is based on the data it is fed. Thus, it becomes even more important to share data across populations during a global pandemic. This was an important lesson learnt from the 2013-2016 Ebola virus epidemic, where the predictive models were lacking in adequate data [33]. The World Health Organization (WHO) has come to a consensus on sharing every new information that comes forward on the COVID-19 spread to encourage intercommunity learning and analytics in this regard.

VACCINE DEVELOPMENT

Antigenic regions with a high number of antigenic hotspots in the membrane protein of Severe Acute Respiratory Syndrome Coronavirus (SARS-CoV) were predicted previously using Artificial Neural Networks (ANN) [34, 35]. This data is of utmost importance to vaccine development. Machine learning can quickly scan the entire viral proteome to allow for faster and cheaper vaccine development. Six potential vaccine target proteins were spotted in the SARS-CoV-2 proteome using machine learning and reverse vaccinology [36].

Previously, machine learning had been used to predict influenza virus outbreak so that seasonal influenza vaccines for the coming year could be curated. Successful prediction of the spread of small subtrees of hemagglutinins (HA) part of the viral antigenic set in the future was achievable from training H3N2 and testing on H1N1, using reconstructed timed phylogenetic tree [37]. Hosts of novel viruses which were only recently discovered can also be predicted using machine learning based on examination of nucleoprotein gene sequences and spike gene sequences, and can be an extra tool for tracing back the origins of the virus, especially when a bulky data set prevents cross comparison [38].

DETECTION AND TRACKING

In order to control and manage a pandemic such as the one caused by SARS-CoV-2, proper identification, quarantining and social distancing between communities is crucial and non-negotiable. Online or mobile phone-based surveys can aid in early detection of cases, particularly in quarantined zones [39, 40]. Such web-based surveys have been useful in handling influenza spread in Italy [41].

Moreover, artificial intelligence tools can be used to collect analyze bulk data, predict trends, divide patients on the basis of risk, and present solutions to the populations as opposed to individuals. Individual phenotypes can be produced via digital phenotyping using both active data (e.g. surveys) and passive data (e.g. texts, voices, screen time, etc.) [42, 43]. This method can be used to acquire multiple data points and allow separation of individuals on the basis of their risk. A recently launched app by the government of India called "AarogyaSetu" follows its users' exposure to individuals who might be infected by COVID-19, using the Bluetooth function to scan the neighboring area for other smartphone users. The app can track down every individual who uses the app that a potentially infected person came across in the last 30 days [44].

This type of digital phenotyping can even work on entry level smartphones, thus becoming effective for developing and under-developed countries where smartphone availability is not high and can aid in stratifying the population [45].

Furthermore, Taiwan being so geographically and economically close to China, should have had statically higher mortality rates due to COVID-19. However, they were able to prevent this using machine learning to predict the number of infected patients, which were far lower than what was initially predicted. They moved early and effectively, identifying the threat on its onset, deploying their national health insurance database and customs and immigration database to generate big data for analytics. The big data analysis, especially that of travel history helped separate their population based on the risk level using machine learning. High risk patients were quarantined in their homes and their movements were monitored through mobile phones to ensure proper isolation. Proper machine learning usage and handling ensured that the case numbers for COVID-19 in Taiwan were far lower than what was initially expected [46].

Additionally, deep learning algorithms have been used to recognize patterns of infectious disease connections in imaging studies such as CT and MRI. With CT scanning showing high connections to PCR-positive COVID patients, such algorithms have been highly useful in their ability to detect findings consistent with COVID-19 in CT images of patients [47–49].

PROGNOSIS PREDICTION

Prognosis in MERS Co-V patients has been previously assigned using machine learning [50]. The major elements towards patient recovery were predicted to be the patient's age, severity of disease upon reporting to the healthcare facility, if the patient was a healthcare professional, and any other health complications that the patient may have. These discoveries were found to be similar to the trends found in the case of COVID-19 [51, 52].

A mobile application called Ebola CARE (Computational Assignment of Risk Estimates) was developed using the data visualization tool, Mirador, to predict a patient's results after being infected with Ebola [53, 54]. The tool pointed out twenty four clinical and laboratory factors that could possibly affect a patient's prognosis. There is a need for alteration of these algorithms to assist physicians in their decision making process while managing COVID-19. Recovery prediction tools help determine resource allocation, triage, treatment determination, as well as how prepared the healthcare system is.

DRUG REPURPOSING

Machine learning tools help to understand large gene expression data to present new uses for currently available drugs. Having said that, they also help immensely in drug development, drug testing, and drug repurposing. Deep generation models, also called AI imagination, can create new therapeutic agents with possible desired activity [55]. Such tools help in time management and cost effectiveness of drug development, develop new therapeutic agents, as well as prediction of possible off-label uses for some therapeutic agents [56]. Bayesian Machine Learning tools have been used to develop drugs against Ebola in laboratory settings and the results translated well to patients as well [57].

LESSONS FROM COVID-19

Owing to widespread globalization and technological advancements, every city in this world is extensively interconnected. The first major mismanagement issue regarding COVID-19 is how highly this fact was underestimated. Wuhan being the epicenter, was considered to be the most problematic area. Governments of various nations organized means to evacuate their own citizens stuck in Wuhan- this led to the spread of the novel coronavirus not only in China, but in almost all countries and continents across the world. COVID-19 was declared to be a pandemic by the World Health Organization (WHO) on 11 March 2020 [58]. Throughout the following months, the number of confirmed cases of the virus, as well as the number of confirmed deaths increased exponentially. The gravity of the situation was finally recognized and governments tried to take control by implementing several measures to curb further growth of the pandemic. Many private and non-governmental bodies took up managing social distancing to prevent close interactions that could cause further transmission. In case of sudden shocks to the population such as flooding or a disease outbreak, the reaction can be comprised under different phases: pre disaster, during the disaster, and post disaster. During the pandemic, however, the population showed mostly irrational panic responses, both financially and psychologically, such as bulk buying non-perishables like food, sanitizers, facemasks, and toilet paper [59].

In order to practice thorough social distancing, organizations, businesses, schools and universities adopted online modes of communication and information exchange. Teaching modes have been changed to online learning in most universities across the world and in-person classes have been cancelled effectively [60]. Additionally, robot nurses were introduced in hospitals in Italy to care for patients infected with the virus [61] and some medical consultations were held via online conversations. Social gatherings were prohibited beyond 50 people in an area, with at least 1.5m distance between each person or 4m2 per person. Stricter policies were adopted like shutting down non-essential services, religious gatherings. Most services were changed to online or drive-ins. Even though the policies being placed were quite severe, the pandemic situation demanded it enough to overrule the freedom of movement and social and political activities within the population. ICT infrastructure, a core element to smart cities, was an enabler to the actions taken by key actors. The daily lives and economic conditions of the populations were greatly disrupted. However, without proper ICT infrastructure in place, the damages could have been far worse.

In business [62], in-person and face-to-face communications play a major role, particularly in intra-governmental decision-making process [63]. Ceasing in-person contact resulted in major losses in productivity and efficiency. However, ICT eventually assisted in creating a proper online environment for learning, meetings, shopping, entertainment and food delivery. Online activity, despite being relatively small, is an important part of smart cities. It was easier for smart cities with ICT infrastructure to switch from in-person to online essential activities. This pandemic has aided in quite a paid development in online modes across various fields. In-person methods are expected to naturally come in place once the pandemic is over, but the adoption of some online modes is foreseeable. Using online modes results in an overall connection cities, countries and continents. But the same hyper-connectedness has been a bane to the spread of COVID-19. ICT tools help maintain this connectedness across regions virtually.

As an illustration, ICT technology was used effectively by South Korea through surveillance tools such as CCTVs, smartphone location data, tracking of banking cards. While many countries let matters take their own course, South Korea implemented some very promising policies [64]. These surveillance tools worked to alert citizens to the location of confirmed cases to identify possible contact with patients [64]. The approach undertaken by South Korea was often said to be the best means of slowing down the outbreak without declaring complete lock-down of all facilities. The only weakness to this approach was the exposure of private information of the patients, which was utilized by the government and healthcare system to alert citizens of the precise location of confirmed cases via geographic information system (GIS)-based apps [64]. They received or accessed updated data more easily than ever before. Citizens were not socially isolated due to alternative ways of communication, work, study, and entertainment. This was a great example of how smart cities with proper technological advancements are better able to handle external shocks such as a pandemic. Although ICT technology might not be completely used in ordinary mundane life, it can easily recover and develop available functions using the infrastructure.

CONCLUSION

This paper emphasizes that ICT has become an integral sector within city planning where smart cities must be equipped with relevant technologies and tools to handle emergency epidemic situations through machine learning. Data analytics are adding valuable information and for that reason, cities are assuming data handling as one of their fundamental roles. With rapidly developing technologies like machine learning, cities can most definitely ensure maximization of benefits for all by promoting and strengthening technological and social innovation. Moreover, machine learning provides a wide range of paraphernalia that are flexible enough to allow their release in any stage of the pandemic. In contrast to the labor-intensive and time-consuming approach of traditional, mathematical and statistical models, machine learning can analyze extensive amounts of data that is being generated during the study of a disease while rapidly identifying patterns and suggesting ways to combat them in a much quicker timeframe. It is flexible, adaptable, can be recalibrated based on new findings and data and does not deal with human prejudice and error. All these make machine learning an exceptional tool in managing infectious diseases. For instance, BAIOTEQ's AI platform for infection control can help smart cities in protecting populations by providing machine learning tools to manage outbreaks and reduce risks. However, these advantages also come with the expectation and demand for greater quality control in storage, collection and processing of information. Standardized data structures across the planet allow for the system to access and learn data from all over the globe and this is highly useful in management of an unprecedented pandemic such as COVID-19. It is also essential to be mindful of the fact that new data especially that related to a new pandemic tends to contain a lot more 'noise' and therefore, the AI algorithm should not be fed with unnecessary and immature data.

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