Harnessing the Power of Smart and Connected Health to Tackle COVID-19: IoT, AI, Robotics, and Blockchain for a Better World

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***Abstract*—As COVID-19 hounds the world, the common cause of finding a swift solution to manage the pandemic has brought together researchers, institutions, governments, and society at large. The Internet of Things (IoT), Artificial Intelligence (AI) — including Machine Learning (ML) and Big Data analytics — as well as Robotics and Blockchain, are the four decisive areas of technological innovation that have been ingenuity harnessed to fight this pandemic and future ones. While these highly interrelated smart and connected health technologies cannot resolve the pandemic overnight and may not be the only answer to the crisis, they can provide greater insight into the disease and support frontline efforts to prevent and control the pandemic. This paper provides a blend of discussions on the contribution of these digital technologies, propose several complementary and multidisciplinary techniques to combat COVID-19, offer opportunities for more holistic studies, and accelerate knowledge acquisition and scientific discoveries in pandemic research. First, four areas where IoT can contribute are discussed, namely, i) tracking and tracing, ii) Remote Patient Monitoring (RPM) by Wearable IoT (WIoT), iii) Personal Digital Twins (PDT), and iv) real-life use case: ICT/IoT solution in Korea. Second, the role and novel applications of AI are explained, namely: i) diagnosis and prognosis, ii) risk prediction, iii) vaccine and drug development, iv) research dataset, v) early warnings and alerts, vi) social control and fake news detection, and vii) communication and chatbot. Third, the main uses of robotics and drone technology are analyzed, including i) crowd surveillance, ii) public announcements, iii) screening and diagnosis, and iv) essential supply delivery. Finally, we discuss how Distributed Ledger Technologies (DLTs), of which blockchain is a common example, can be combined with other technologies for tackling COVID-19.**

***Index Terms*—Internet of Things (IoT), Artificial Intelligence (AI), Robotics, Big Data, Blockchain, eHealth, Healthcare, COVID-19, Pandemic, Digital Twin, Wearable.**

I. Introduction

The global COVID-19 pandemic, caused by the SARS-CoV-2 virus, has adversely impacted all aspects of daily life and put the functioning of our societies to the test. As virologists work to rapidly develop a vaccine, a multidisciplinary approach has become vitally important for the appropriate tracing, monitoring, and diagnosis of coronavirus patients. The turn of the decade was expected to bring significant medical and scientific advancement due to the development of digital technologies capable of addressing large clinical issues or major diseases. Promising Smart and Connected Health (SCH) technologies, including the Internet of Things (IoT), Artificial Intelligence (AI) as well as robotics and Distributed Ledger Technologies (DLT), is increasingly taking a big leap in almost all healthcare processes [1], [2], [3]. This paradigm shift, characterized by the convergence of these technologies, have generated new opportunities and advantages, such as the availability and accessibility, ability to personalize and tailor content, and cost-effective just-in-time delivery. The rapid growth of Wearable IoT (WIoT), as well as the public embracement of miniature wearable biosensors supports the creation of a highly connected personalized patient-centric health ecosystem. Such a system facilitates the collection, integration, and harmonization of real-time data utilized by deep learning and AI to analyze healthcare trends, project potential risks, forecast possible outcomes, accelerate scientific discoveries, and improve the decision making [4], [5]. These capabilities are amplified by DLTs ability to fix the weaknesses and vulnerabilities of today's client/server cloud IoT models — such as security, privacy, and traceability — by providing a shared, decentralized, and immutable database ledger based on Peer-to-Peer (P2P) networks.

As life transitioned from a nomadic style to living in larger groups or cities, humans have experienced epidemics. The

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gathering of people creates an ideal environment for virus transmission from person to person, producing an epidemic. Greater physical distance between groups is a means of slowing virus spread, because the epidemic only grows if a host travels between groups. As illustrated in Fig. 1, epidemics have generally grown along land, water, or commerce passageways. Many years ago, the speed of travel was much slower and infrequent; therefore, epidemics did not bloom into a pandemic for many years. In today's modern world, there are bigger groups of people in cities and towns that are much larger than in the past, and travel between groups happens much more quickly and often, facilitating the growth of epidemics and pandemics [6].

Over the last 100 years, the world has also seen many epidemics and outbreaks, with influenza viruses such as H1N1, H2N2, and H3N2 as well as coronaviruses being responsible for the majority. In fact, H1N1 has resulted in two pandemics the Spanish Flu of 1918 and the Swine Flu pandemic of 2009. The H2N2 virus resulted in the Asian Flu of 1957 and H3N2 caused the Hong Kong Flu of 1968. Over the last 20 years, multiple coronavirus outbreaks have also occurred, including the 2002 SARS-CoV outbreak and 2012s MERS-Co-V outbreak. These viruses are spherical, positive-sense RNA viruses with diameters ranging from 60 nm to 140 nm [7]. Protruding proteins look like spikes, giving the virus a crown-like appearance when viewed through an electron microscope. The SARS-CoV outbreak started in Chinas Guandong province and spread to impact 37 countries through more than 8000 infections and almost 800 deaths. The initial MERS-CoV case was recognized in Saudi Arabia and led to a large outbreak across the Middle East, resulting in almost 900 deaths. The COVID-19 outbreak began in Wuhan, China in December 2019 and declared a global pandemic by the World Health Organization (WHO) on 11 March 2020. WHO indicates that viral infections, including coronaviruses, will continue to appear, posing serious threats to public health. The outbreaks epicenter was traced back to Wuhan, Chinas outdoor wholesale market where animals such as bats, snakes, and marmots were sold. COVID-19 was distinguished by a long incubation period of up to 14 days and a highly contagious nature. During the incubation period, infected individuals do not necessarily demonstrate symptoms and can unknowingly infect others, resulting in COVID-19s high basic reproduction number [8].

Due to the lack of a solid treatment strategy, social distancing has been advised as the best preventative measure for battling COVID-19. However, social distancing requirements have resulted in lockdowns all over the world and negatively impacted economies around the globe. The shutdown of non-essential services has resulted in the disruption of supply chains and job losses across multiple sectors. The rapid spread of the virus has also resulted in trade restrictions that put international trade in danger of collapse. For example, JP Morgan Chase estimates that the current pandemic will cost the U.S. economy more than 5.5 trillion dollars over the following 18-24 months [8]. In light of the challenges that COVID-19 presents to our societies and healthcare systems and, there is an imperative need for immediate countermeasures. To this end, SCH technologies can be utilized to mitigate the adverse impacts of the pandemic. For instance, a highly vigilant investigation using currently available data in conjunction with expressive predictions may prove very valuable in future policy development and decision making. The massive volume of epidemiological and scientific Big Data is empowering frontline healthcare workers, strategists, scientists, and epidemiologists to make smart decisions during the COVID-19 pandemic. AI may also play a vital role in understanding and suggesting the development of a vaccine for COVID-19. The efficacy and efficiency of clinical trials is another main contribution of Big Data as the world prepares against possible future pandemics. The integration of IoT and AI enables scientists to gather, combine, and fully evaluate global incident data, perform proper screening, analyze, predict and track current patients and likely future patients allowing healthcare systems to handle pandemic impacts better. This paper consolidates several key technological enablers and evaluates a variety of novel SCH solutions to combat COVID-19 and provide opportunities for more holistic research toward solutions to benefit all of humanity.

The rest of this paper is organized as follows. In Section II, we discuss how the healthcare industry could benefit the IoT and what challenges and barriers have to be tackled to grow further. Section III presents the novel use cases of AI. Section IV describes the main techniques and models for the integration of robotics and drone technology into healthcare scenarios. Section V explores the use of DLT and blockchain technologies to help tackle the impact of COVID-19 pandemic. Finally, Section VI concludes the paper.

II. The Role of IoT in Managing COVID-19

A. Contact Tracing

Identifying those who have been exposed or infected by the virus is known as contact tracing. COVID-19s extended incubation period and lack of extensive testing has made it difficult for authorities to accurately quantify the number of infections. The WHO indicates that contact tracing includes three steps:

- Identifying those who have had contact with an infected individual.
- Documenting the details of contacted individuals.
- Testing those individuals as quickly as possible.

The state-of-the-art contact tracing solutions can be classified into the following categories:

The spring of 2020 saw the emergence of many smartphone contact tracing application projects, championed in large part by TraceTogether, an app developed by Singapore's government. TraceTogether utilizes Bluetooth to support anonymous, close proximity smartphone-to-smartphone communication. Many of the tracing app projects also center on Bluetooth technology. One of the primary issues in the development of a contact tracing application is the precise perception of distance and discernment using meter-scale. The majority of developers have

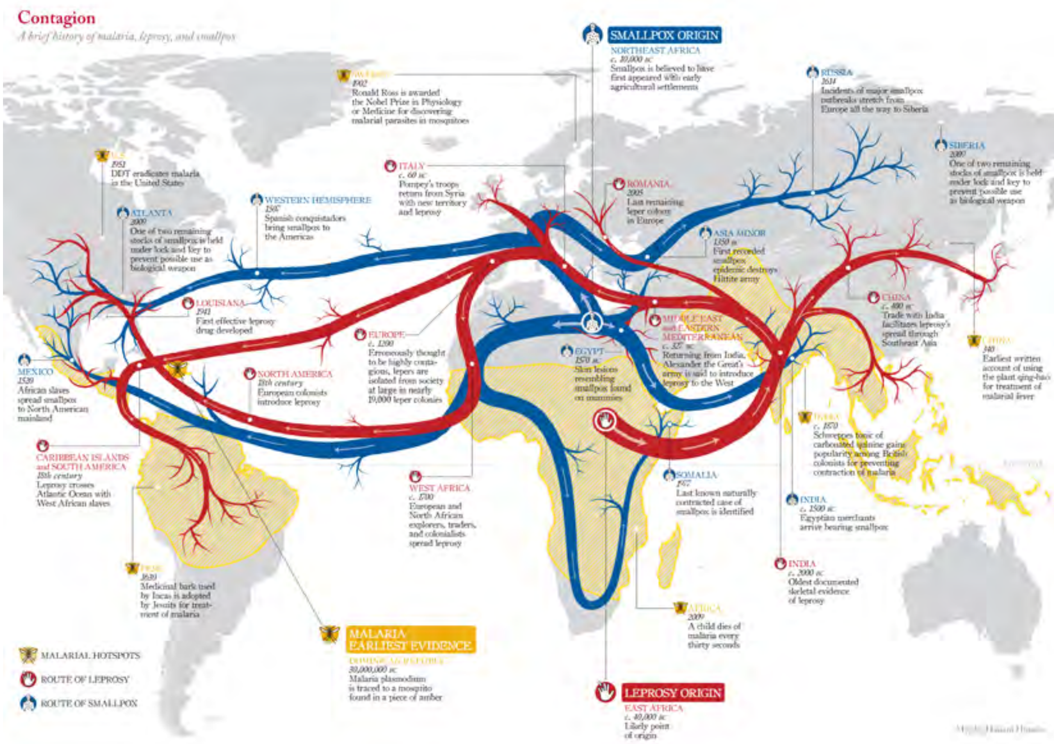


Fig. 1: The origin and spread of smallpox, leprosy and malaria around the globe. Macro-representation. Image credit: Doug Belshaw blog [6].

determined that a 2-meter standard distance for contact tracing apps is ideal.

The implementation of contact tracing applications requires one of the technologies indicated below:

- **Bluetooth**: Applications using Bluetooth measure the distance between two parties by calculating the space between devices with the Received Signal Strength Indicator (RSSI). The apps are capable of storing a device's previous Bluetooth connection history, including data about the amount of time the devices were connected. If an individual is diagnosed with COVID-19, the tracing applications can use Bluetooth connection history to trace all individuals exposed by the infected person.
- **GPS**: Governmental agencies can monitor the location of COVID-19 patients in real-time and view historical GPS data useful in tracing coronavirus exposure.
- **Ultrasonic**: Many argue that Bluetooth is not able to precisely calculate distance. In addition, GPS and Bluetooth are both susceptible to inappropriately logging interaction between parties actually located in separate rooms when signals traverse ceilings or walls. We propose to utilize ultrasonic technology in conjunction with Bluetooth. Because ultrasound measures the time required for sound to travel, it is capable of more precisely measuring device distances. The NOVID application launched in April 2020. An experiment using the publicly accessible features of the application have allowed for systemic testing in a variety of real-world settings. The data suggests that a 9-foot threshold for distance measuring is highly effective. While NOVID was tested in challenging environments, 99.6% of 225 interactions where devices were 12 or more feet apart, were correctly categorized as greater than 9 feet. More than 50% of the 187 interactions where devices were less than 6 feet apart were accurately categorized as less than 9 feet. The experiment indicates that contact tracing applications can substantially benefit from ultrasound.

B. WIoT-based Remote Patient Monitoring (RPM)

During the pandemic outbreaks such as COVID-19, wearable health devices can play a very important role. Due to high increase in patient's daily and lack of appropriate medication, most of the nations has affected seriously by the COVID-19 or Coronavirus. Generally, after exposing to this virus, the human body will show various changes in physiological signs, that can be monitored for treatment purposes. These signs can be in the form of biochemical, electrical and bio-signals, which derived from different body parts [9], [10]. These physiological signs help to easily predict the status of the health in a patient. Consequently, based on these measurements, the appropriate medicine can be administered to monitor the medicinal reactions. These vital bio-signals can be extracted and processed properly by applying wearable sensors and IoT devices. As a result, proper interpretation of the acquired signals and mapping those signals after a drug treatment/reaction is

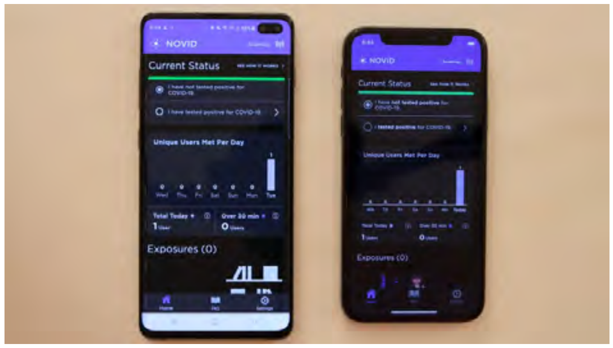


Fig. 2: NOVID application.

crucial [11] and wearable devices may be classified depending on the operation types, environment, and individuals.

Along with the clinical trials, it is recognised as an opportunity to make use of the advanced technology in monitoring patient remotely to aid in early diagnosis of diseases as well as tracking by inspecting systemic infection source. Wearable devices may alarm patients and doctors of a probable COVID-19 condition prior to severe illness. The desire for a non-invasive device to detect and track Coronavirus infections continuously in the home as well as in the hospital encourages significant attraction towards wearable devices. After rapid diagnosis, having the capability to monitor and track vital biological sign can enlighten the doctors to proceed with appropriate action for quick recovery or to reduce the severe deterioration. In wearable technology to monitor cardiac function, Electrocardiogram (ECG) is popularly used [12], [13]. ECG measures the heart's electrical activity [12]. Although ECG sensors are generally mounted as an epidermal patch that attached to the surface of the skin (e.g., Zio Patch) by using a benchtop equipment, the commercialization of predictive algorithm based wrist-worn devices has empowered the heart activity measurement from wearable devices, for example, the Apple Watch 4 and 5 [14]. ECG has the potential to impart meaningful insight toward the onset of COVID-19 as ECG measures the heart function directly. It is already well known that the early indication of COVID-19 infections are high fever (98%), coughing (65%), and breathing difficulties (55%) [15], [16]. There are also cases where symptoms were obtained from mobile applications (e.g. loss of taste and smell) suggesting more analytical advantage. Another indication of COVID-19 contamination and deterioration is the silent hypoxemia [17]. There is evidence implying that COVID-19 is loaded by a greater chance of arrhythmic incidents [18]. Upon analysis on 138 COVID-19 patients by Driggin et al. uncovered that arrhythmias, for example, ventricular tachycardia/fibrillation characterised the prominent impediment (19.6%) after severe respiratory distress syndrome, predominantly to those intensive care unit patients where the prevalence increased to 44.4% [19]. Moving forward future work might involve associating wearable sensors with data analytics which can also enable real-time detection of such arrhythmias in patients infected with COVID-19 in order to improve patient conditions.

Whilst commercially available wearables have the benefit of extensive accessibility, interoperability through commonly existing smartphones, as well as remote data management systems, these devices are largely limited in measurement precision and modalities. These gadgets lack to provide body temperature, pulse oximetry, or measuring high-fidelity respiratory rate. Additionally, popular Oura Ring and FitBit sensors still lacks the FDA approval for remote monitoring. On the other hand, FDA approved devices such as the Apple watch Series 4 can be used for episodic ECG and may provide notification for uneven heart rhythm for people aged over 22, but with such limited specifications, this device is not a substitute for clinical diagnostic systems. These inadequacies may undermine the probable benefit of wearable technologies to monitor, predict, and track Coronavirus patients.

In assessing COVID-19 signs and treatment, soft and flexible electronic systems that can be attached comfortably to the skin at positions outside the finger or wrist present crucial benefits. Being a respiratory disease, by measuring numerous respiratory biomarkers, for example, cough intensity/frequency/sound, respiratory effort and rate, taken directly from the thorax, are possibly to provide more vital information. Similarly, it is critically important to make sure to maintain the clinical grade standards for measuring the blood oxygenation through pulse oximetry. In [20], soft sensor is mounted close to the skin near to suprasternal notch, including a precision temperature and high-bandwidth accelerometer sensors mounts, as shown in Fig. 3 [21]. This little position of the body close to the neck offers an exceptional interface for recordings of high-fidelity respiratory activities through cough rate, duration, or frequency as well as respiratory features linked with sneezing and wheezing.

Heart sounds, cardiac amplitude and heart rate are also included in the same data streams. In order to measure skin temperature, the temperature sensor with the thermally insulating is used, which is correlated to core body temperature to make sure ambient conditions does not influence the measurement. Being soft and flexible, these sensors can support the natural movements of the neck. Fig. 3 represents the wearable device as well as few illustrative data gathered from a COVID-19 patient. WIoT technologies for continuous monitoring permit opportunities as well as challenges in data management, in data analytics,

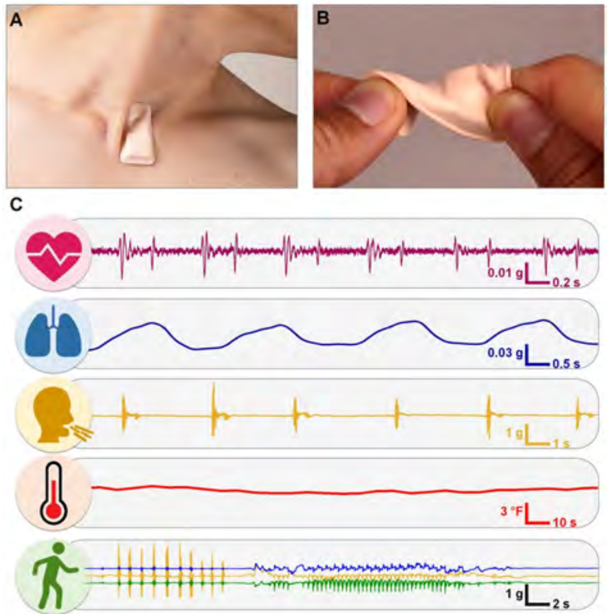


Fig. 3: Soft, wireless, skin-interfaced wearable ECG patch placed on the suprasternal notch. (A) Representation of the ability of the gadget to follow the natural neck movements. (B) Illustration of the mechanical deformation of the device. (C) Recorded data from a COVID-19 patient. Recreated from Ref. [21].

due to the remarkably large amount and broad range of health data produced through each device. As a result, wearable sensor systems must incorporate accessible information backends which securely store, transfer, process and provide required patient data in an amenable way. To add more, the necessity for associating this information to additional distinct sources (e.g. electronic health records) to improve the data content encourages the expansion of strategies for interoperability. With the help of machine learning techniques, by associating this physiological information along with clinical results, the consequence of investigational therapeutics, as well as outcome of molecular assessment will provide a treasured largescale source to identify asymptomatic COVID-19 infections. This will institute digital biomes of anticipated recuperation specific to health status of a patient and offer recommendations for staffs to continue works carefully. The expansion of monitoring continuously from hospital to home represents optimism in overcoming the COVID-19 infections. Wearable technologies with clinical-grade accuracy will illustrate the degree of this benefit through ongoing clinical analyses. An emphasis on information sharing and interoperability empower the growth of predictive algorithms which can be generalized within various populations. Along with worldwide determinations to develop successful drugs and vaccines to treat and counteract COVID-19, compatible skin-integrated devices and sensors, placed at optimal position of the body, resolve the critical and ongoing requirement for continuous, objective, as well as sensitive systems to identify COVID-19 symptoms.

C. *Personal Digital Twins (PDT)*

While we have more fertile ground for epidemics, humanity has also developed tools to battle viruses, such as vaccines. However, it takes significant time to create a vaccine, which is problematic when a virus unexpectedly emerges. This is the case with the coronavirus pandemic of 2020 that likely leapt from bats to humans only months ago. Unfortunately, tools like vaccines can sometimes be in short supply, making it vitally important that potential epidemics be identified as quickly as possible in order to slow the spread. The illustration in Fig. 1 was developed using historical contagion data. However, there needs to be a way to create such a data graphic in real time in order to forecast the development of an epidemic. Modern tools utilize data from a variety of sources and interprets the data using epidemic models that consider how contagions spread and at what speed across different communities and areas.

Social media can be utilized to monitor virus spread and identify habits that increase exposure. The 2020 coronavirus pandemic is being monitored by several organizations, including Northeastern University's Network Science Institute, through social media using big data analytics.While social media can be utilized like a sensor, the level of sensitivity and resolution is not ideal, making space for the role of personal digital twins (See Fig. 4). Personal digital twins represent different personal aspects, such as a person's movement, health status, and interaction with others in geophysical locations. This data can be gathered by a personal digital twin using minimal sensors that are currently available. A person's physical location and movements can be tracked through smartphone data, and health status can be monitored using smartwatch sensors. For example, personal digital twins could be designed to send an alert if gathered data forms a pattern such as increased resting body temperature and rapid breathing, known to be possible indicators of coronavirus infection.

Government healthcare organizations could receive these alerts and analyze linked data, including the prevalence of alerts in a specific location and review the movements of individuals over previous weeks and months to correlate with other emerging alerts. In such a situation, healthcare organizations and governmental agencies may use data analytics and alerts on all personal digital twins in order to gather needed data, increasing awareness of likely epidemics and allowing for better forecasting based on the movement of individuals and groups. This would provide a more accurate and timely picture of the global situation. While these would be positive improvements, it would also raise issues around data privacy and organizational/governmental control as this would push society into unprecedented areas.

While complete epidemic monitoring and control using personal digital twins would still be several years in the future, as it will be explained in Section II-D, the government of South Korea and the Korean Center for Disease Control has already gathered a massive amount of data from smartphone locations using local telecommunications and public security cameras to develop a contagion map using micro-level human interactions. Rapid testing combined with the interaction map enabled the appropriate isolation of specific hosts rather than the large area lockdowns required in China and other countries including Italy, Austria, and Spain.

Outlining the different processes can clarify the differences and similarities between South Koreas model and the use of personal digital twins; however, the goal of containing an epidemic is the same in both scenarios:

- South Koreas Model:
  - **Possible Symptoms Emerge**: An individual with possible symptoms of a coronavirus infection is tested. If positive, the individual is quarantined.
  - **Contact Tracing**: The infected individual's contact with others is traced through technology such as smartphone movements and security camera footage.
  - **Data Analysis**: The individuals contact data is reviewed using data analytics to determine the likelihood of exposure for others. Those contacts are located and tested. If positive, those individuals are quarantined. The sequence repeats to locate any other likely exposures.
- Personal Digital Twin Model:
  - **Prescriptive Analytics**: All personal digital twins are notified by the healthcare organization of a need to send alerts based on specific conditions such as increased resting body temperature, elevated heart rate, rapid breathing at rest, as well as other infection indicators.
  - **Global Analytics** : The healthcare organization obtains the data through personal digital twins and uses global analytics to spot the development of patterns. The organization then tells digital twins that are part of a visible pattern or in a location with a high likelihood of exposure to request that the individual be tested.
  - **Trigger Action**: The coronavirus test results trigger specific action such as quarantine for those infected and provides additional updates to affected digital twins.
  - **Contact Tracing**: The personal digital twins of those who test positive, then report movement and contact history of the infected individual.
  - **Dynamic Updating**: Personal digital twins continue to update the healthcare organization and communicate with the personal digital twins of the people nearby, resulting in warnings of proximity that can help reduce risk.

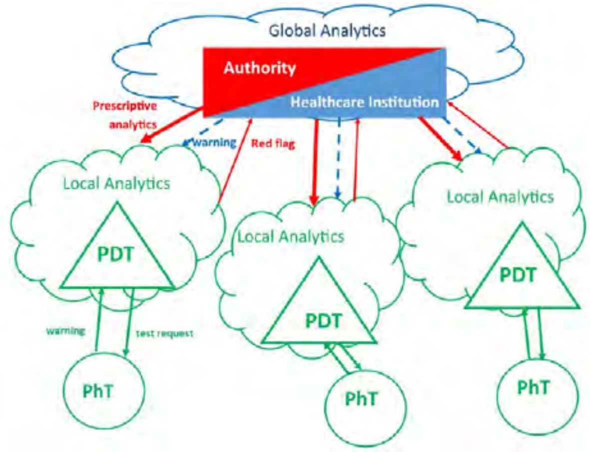


Fig. 4: Schematic representation for using Personal Digital Twins, PDT, in epidemic control. The Healthcare institution set the parameters that PDT shall monitor, also based on global data analytics. The Authority enforces the behavioural framework, proposed by the Healthcare Institution (e.g. when Rt is greater than 1.5 in a given area people have to stay home) if it is between 1.1 and 1.5 people must not share cars, if the physical twin is Covid positive the Physical Twin has to stay home). This framework becomes the reference for the PDT that will ensure awareness to its Physical Twin and will signal the Authority a deviation from the framework if this takes place. In this way privacy is protected, it is only when a behaviour is inconsistent with the framework that Authority is notified. A person notifies the Healthcare institution of a positive test result, not the Authority, thus preserving privacy. However, a behaviour that is not in line with the Authority enforced framework will generate a report.

The advantages of the PDT approach are:

- **Self-Generation of Alerts**: The auto-generation of alerts allows people to be more aware of a possible critical.
- **Widespread Analytics**: Vast community or country-wide analytics helps anticipate significant spread.
- **Clearer Focus**: A clearer focus leads to fewer widespread

restrictions where the risk is lower and more robust restrictions in high risk areas.

- **Lower Cost**: More focused restrictions reduces economic impact.
- **Greater Adaptability**: This approach is more dynamic and allows groups or individuals to react to specific situations.
- **Better Personal Awareness**: Personal digital twins enable greater personal awareness and prompts behavior appropriate to the situation.
- **Quicker Feedback** : Personal digital twins allow for real-time or near real-time feedback regarding actions taken using the data gathered and shared.
- **Reduced Effort**: Personal digital twins are more effortless and offer a lower-cost means of monitoring people.
- **Service Development**: Personal digital twins facilitate the development of services aimed at infected individuals by creating virtual groups or communities.
- **Better Resource Use** : Personal digital twins enable the efficient use of resources in light of the availability or resources and competing needs.
- **Faster Triage**: Individuals can gain access to needed support services more appropriately through cyberspace.

In the world of healthcare, actions taken are shaped by multiple factors including social concerns, cost, ethics, resource availability. Even now, newspapers are exploring the importance of protecting privacy when it comes to monitoring people to identify infection. Nations that did not previously favor lockdowns and businesses are now adjusting guidelines and policies. The West took a macro-level approach, and South Korea took a micro-level approach. To date, it appears that South Koreas model did a better job of reducing virus spread and protecting business operations. The trade-off between the two models is between civil rights and privacy. Every society operates on a system of trade-offs among community and personal rights and societal versus personal advantages. The larger issue on which there is no global agreement is where personal rights end and societal rights begin.

Technology can be beneficial in identifying the line between personal privacy and the needs of society by protecting privacy as much as possible while still meeting societal safety needs. Personal digital twins can serve to separate social and private spheres by protecting the privacy of personal data and sending metadata to the social sphere. This generates a buffer zone that can be defined by a regulator. Personal digital twins may be capable of developing a privacy shield able to transmit only information required to meet community needs. As we will discuss in Section V, Blockchain technology may also be helpful in monitoring data flow and safeguarding privacy globally.

D. Real-Life Use Case: Korean Solution

In Korea, a large-scale epidemic occurred mainly at the Shincheonji Church in Daegu, followed by sporadic community infections, such as a group infection at a call centre in Seoul. At one time, the number of confirmed cases per day recorded single digit, but the group infection in a night club for young people was at risk of developing a large-scale secondary infection. However, it was possible to induce a rapid diagnosis of the confirmed person through a thorough epidemiological investigation based on the identification of the movement line of the confirmed person thanks to IoT technologies. Furthermore, by inducing the voluntary diagnosis and isolation of the citizens through the disclosure of the movement line, the large-scale secondary infection was successfully prevented. In this section, we describe how the Korean government uses information and communication technologies (ICT) to detect and prevent the spread of COVID-19.

1) IoT systems for COVID-19 in South Korea: At the time of writing this article, various applications and services are available in South Korea to provide useful information to citizens as follows:

- **Pandemic tracking app**: There exist about ten webpages and 50 mobile apps that disclose the path of confirmed patients. Such apps provide various functions such as linkage display between confirmed patients and providing traffic line information using reactive maps. However, there is a limit to the information displayed because only the traffic line information disclosed by the quarantine authorities and local governments is used.
- **Self-Quarantine safety protection app**: The self-quarantine safety protection app developed by the Ministry of Public Administration and Security is an app that needs to be voluntarily installed on smartphones owned by self-quarantine people. The main function is to automatically notify the officials in charge when symptoms develop during quarantine and to notify when leaving the quarantine area.
- **Mask inventory checking app**: A government organization developed a platform that provides real-time sales quantities of available masks that can be purchased at pharmacies, post offices, and marts.
- **QR code-based entry log app**: A government organization in Korea introduced Quick Response (QR) code-based electronic access lists for facilities at risk of group infection in cooperation with social media companies. Such applications try to solve problems for false statements of confirmed persons and concerns about leakage of personal information in handwritten lists.
- **Epidemic Investigation Support System (EISS)**: Government agencies and research centres have developed an IoT-based epidemiological investigation support system. For the epidemiological investigation of infectious diseases, the system systematically acquires the access information to the base station of telco companies and card usage information for the confirmed person authorized by the domestic infectious disease prevention law. It quickly uses collected information to analyze the travel route of the confirmed person. This system is being used by the epidemiological investigators of local governments for rapid epidemiological investigations on COVID-19.

Table I shows the comparison of various available COVID-19 solutions in Korea.

2) Enhanced smart city platform for COVID-19: As EISS provides the most useful information collected from various sectors, we describe the EISS system in details [22]. Upon the outbreak of COVID-19, a responsible government organization conducted an epidemiological investigation by collecting information on the movement lines of confirmed patients and payment details by credit card based on the epidemic law which as legislated at 2015 for the Middle East Respiratory Syndrome Coronavirus (MERS-CoV). However, as all data was collected and handled through e-mail, the analysis for the movement line data takes much time and requires a lot of human resources. Therefore, there was a strong need for the development of ICT-based system that enables rapid epidemiological investigations through the systematization of requests for information provision and provision of traffic data analysis functions.

The EISS system was developed to further collect and analyze information related to COVID-19 by expanding the IoT-based smart city platform called CityHub that was previously developed as a national R&D project. According to the infectious disease prevention method, data related to confirmed patients are collected in real time from mobile carriers and credit card companies, purified and analyzed, and used for epidemiological investigations.

Fig. 5 shows the additional functions and procedures of the EISS system. The EISS system provides three functions: (1) data collection of confirmed patients, (2) purification of movement data, and (3) analysis based on the movement of confirmed patients. A security function to prevent leakage of personal information that may occur during this process has also been added to the EISS system.

- **Data collection of confirmed patients**: Data collection of confirmed patients: In order to collect the data of a confirmed case, the epidemiological investigator registers the confirmed case in the system. The EISS system receives data related to the confirmed case through an interface connected to the National Police Agency system, the credit card network system, and the telecommunication system. EISS analyses the data and converts it into a standard-based data format referring to oneM2M global IoT standards [23]. The converted data to CityHub can be accessed through a context-aware application programming interface (API), i.e., NGSI-LD API, that can process semantic data developed by ETSI [24].
- **Data refining of confirmed cases**: The location data collected from the telecommunication company is the location information of a base station to which the confirmed person is connected. Therefore, there is a difference between the actual location data of the confirmed person. In order to correct this deviation, EISS infers the moving path of the confirmed patient by applying machine learning technology through various interpolation, clustering and classification algorithms based on the location information and access time of the base stations to which the confirmed terminal is connected.
- **Analysis of confirmed patient movement**: As shown in Fig. 6, EISS provides a map-based location service that supports epidemic investigators to analyze the movement of the confirmed person. EISS also supports a function that analyses infection hot spots to derive and display the contact area between infected people. EISS visualizes the connection network between infected people based on the results of epidemiological investigations.
- **Security concerns**: EISS provides two-factor authentication using One-Time Password (OTP) via a Virtual Private Network (VPN) connection and password-based web login to allow access only to authorized users. In the case of user accounts and access rights, indiscriminate use of the system is prevented by creating an account only through official letters issued by an authorized government agency.

3) Effectiveness of EISS and lessons learned: Simplify the collection process. The process of requesting and collecting data for confirmed cases, which was done through the official letters or e-mails, has been simplified to be possible with just a few clicks in EISS. This improvement reduces unnecessary waiting time so that the processing time was shortened from 2-3 days to within 10 minutes.

Data standardization. Existing movement data and card payment details from individual companies are not standardized. Different data formats and storing mechanisms were used for each provider and person in charge. This was one of the factors that hindered the rapid analysis of COVID-19 data. EISS purified these data and saved them in a standardized manner in the system according to the international IoT standard, i.e., oneM2M, thereby reducing the time related to data processing. As a result, by enabling automatic analysis of movement routes and infection hot spots, the epidemiological investigation time could be drastically reduced from 24 hours to 10 minutes.

The necessity of IoT-based common smart city platform. CityHub provides a standardized framework for smart city services based on the convergence of various data, easy connection of new data sources and services, and standardized APIs. A horizontal IoT service platform that can be used in common with various applications plays a crucial role in quickly and easily accepting various services in the city. EISS was able to quickly respond to COVID-19 by developing and linking the necessary service functions for epidemiological investigation as a separate module by utilizing the standardized interface of CityHub. As such, the use of a common IoT service layer platform in a city using global standards can support various smart city services and connect data. Such systems can be a solution that can quickly respond to various urban problems that may arise in the future.

III. The Role of AI in Managing COVID-19

During this global public health crisis, the healthcare industry is seeking technology capable of monitoring and controlling the spread of COVID-19. AI is capable of tracing the virus, identifying at-risk individuals, and controlling infection rates

TABLE I: Comparison of ICT services and applications for COVID-19.

Service/App	Service Target	Data Type	Supporting Functions	Limitations
Pandemic tracking app	Personal	Public data	Linkage display between confirmed patents	Limited route information
Self-quarantine safety protection app	Government	GPS	Mask inventory	Voluntary app installation
Mask inventory checking app	Personal	Government data	Mask inventory	No available information for confirmed persons
QR code-based entry log app	Government	QR code	Access lists for high risk places	Only available information for the visited persons
EISS	Government	Location data Credit card usage	Rapid investigation results on the travel route of confirmed persons	Only government people can use the information

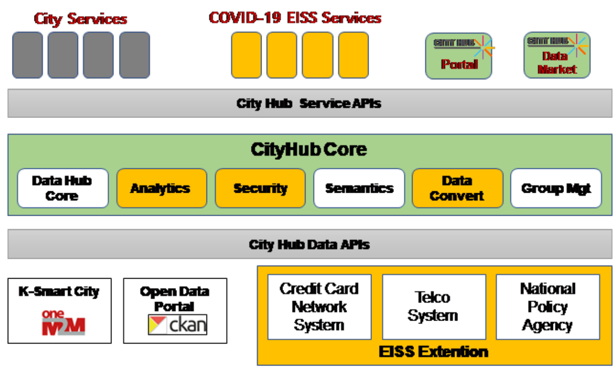


Fig. 5: Smart CityHub architecture with EISS extension.

(a) (b) (c)

Fig. 6: Analysis of movement routes of confirmed cases to response epidemiological investigation. (a) Route analysis; (b) Infection host spots; (c) Visualization of connection network.

in real-time. AI is also able to predict the risk of mortality by analyzing patients previous medical data. Artificial Intelligence can provide further help through population screening and notification and may also enhance the treatment and outcomes of COVID-19 patients as an evidence-based healthcare tool.

A. The COVID-19 Open Research Dataset

Scientific literature is an important source of technical information about COVID-19. The majority of findings about COVID-19 progression, diagnostics, treatment, and vaccines, as well as the social impacts of disease, are eventually disseminated to the scientific audience, as well as to health officials, through published research papers and preprints. The rate and speed of publication around COVID-19 has been unprecedented, and several hundred new papers or preprints have been released every day since March 2020 and continue to be released. AI-powered text mining systems, and systems that leverage natural language processing (NLP) techniques to provide search, discovery, and summarization over the literature are desperately needed. Several corpora of structured, machine-readable scientific literature have emerged to assist in development of these systems. These include the COVID-19 Open Research Dataset (CORD-19)[1] [25], LitCovid[2] [26], and other organization-specific databases such as the World Health Organization's (WHO) COVID-19 database.[3]

CORD-19 was the earliest corpus released for this purpose, and has been used in the majority of COVID-19-related automated text mining systems. The CORD-19 corpus is released by the Allen Institute for AI in conjunction with seven

[1] https://www.semanticscholar.org/cord19/download
[2] https://www.ncbi.nlm.nih.gov/research/coronavirus/
[3] https://www.who.int/emergencies/diseases/novel-coronavirus-2019/global-research-on-novel-coronavirus-2019-ncov

other institutions. CORD-19 is a fairly comprehensive dataset of coronavirus and COVID-19 papers, incorporating papers and preprints from PubMed Central, PubMed, the WHO's COVID-19 database, bioRxiv, medRxiv, and arXiv. Metadata is collected from these sources, harmonized and deduplicated, and the full text of open access publications is extracted and represented in the S2ORC JSON format [27] to support downstream text mining applications. Detailed descriptions of the data processing pipeline and design motivations of CORD-19 can be found in [25].

CORD-19 has been incorporated into dozens of COVID-19 search and discovery systems; a survey of these text mining resources and applications is provided in [28]. Of these resources, some integrate the literature data of CORD-19 with other documents (patents, clinical trial documentation) as well as biomedical and clinical knowledgebases (e.g. CovidGraph[4]). Other systems focus on tasks such as: (a) Search, e.g. Neural Covidex [29], (b) Question-answering, e.g. COVIDASK [30], (c) Summarization, e.g. CAiRE-COVID [31], (d) Scientific claim verification, e.g. SciFact [32], (e) Assistive literature review, e.g. ASReview [33], and more. The CORD-19 corpus has also been leveraged as the foundation of several community shared tasks: the Kaggle CORD-19 Challenge,[5] TREC-COVID ad-hoc retrieval challenge[6] [34], [35] at TREC 2020, and the Epidemic Question-Answering challenge[7] at TAC 2020, which aim to evaluate and compare the performance of various text mining and NLP systems.

Challenges such as the availability of open access full text (over 60% of COVID-19 papers from 2020 do not have an associated license allowing redistribution), and difficulties in PDF parsing and metadata harmonization impede our ability to expand and improve the quality of CORD-19. We believe these challenges are surmountable, and we continue to work with publishers and the community to improve the dataset. Based on preliminary responses, the CORD-19 corpus offers a strong example of how text mining and NLP can be used to help address and respond to major scientific challenges like COVID-19.

B. Multi-Modal Diagnosis of COVID-19

With the global spread of COVID-19 pandemic, early diagnosis of the disease and identifying the risk of infection in potential patients who may not be showing visible critical symptoms, can assist the medical staff when allocating limited resources. In this section, we propose solutions using machine learning methods that can help doctors to improve the diagnosis and further prognosis of patients using the knowledge extracted from the available data of all patients. For this purpose, a dataset comprising more than 2000 samples from individual triaged patients has been constructed. Data collection is carried out during triage and follow-ups by medical experts, at Sina

[4]https://covidgraph.org/
[5]https://www.kaggle.com/allen-institute-for-ai/CORD-19-research-challenge
[6]https://ir.nist.gov/covidSubmit/
[7]https://bionlp.nlm.nih.gov/epic_qa/

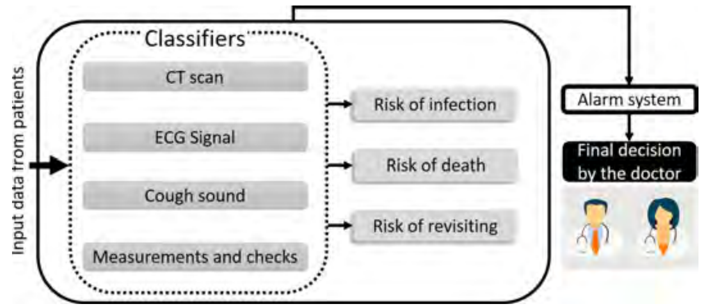


Fig. 7: An overview of the main components of the proposed framework.

Dataset	#Features	Deceased patients	Recovering patients
D_{F_1}	81	15	1985
D_{F_2}	81	4	196
D_H	1186	104	507

TABLE II: Dataset specifications.

hospital in Tehran. Additionally, there is a subsequent validation step to minimize entry-level error in the collected data.

By means of feature selection methods, the large initial feature set has been reduced to simplify the process for both patients and the medical staff. Machine learning techniques have been employed to create prediction models for specifying the risk of Corona disease in patients. This system is currently deployed at Sina Hospital for diagnosis and clinical condition monitoring of COVID-19 patients. One key strength of this work, is the close continuous collaboration with the medical team at Sina hospital and regular information updates about the patients. This helps to create more robust models that are less prone to bias and over-fitting. The proposed framework, adopted methods and highlighted preliminary results are briefly presented in the following.

1) System Overview: Our proposed system is composed of four classifiers that are fused for achieving more robustness as seen in Figure 7. The four data modalities used in our system are i) the information gathered during triage and the following tests, ii) cough sound recordings, iii) CT scans, and iv) ECG signals. In this section, we focus on estimating the of risk of infection among the risks shown in Fig. 7, since this is the most vital information requested by the doctors. This risk measure, can be used as a tool for the doctors to consult with in the diagnosis stage, and also for activating an alarm system in case the clinical conditions of a hospitalized patient dramatically changes.

2) Data Collection: As the first step, we have gathered information of more than 2000 patients in three categories of the first follow-up (F1), hospitalized (H), and the second follow-up (F2). All of the data is entered and verified by the medical staff and is later checked again using our scripts for data cleaning. The data collection procedure is briefly explained in the following. After visiting the hospital, a patient will go through triage. They are either discharged in which case a follow-up happens between 1-4 weeks with information

Method	#Features	Accuracy	M-I F1 Score	Sensitivity	Precision	Specificity
MLP (Relu)	16	81.99	62.43	56.22	70.19	91.31
SVM (Linear)	15	79.81	65.03	70.76	60.41	83.21
Decision Tree using Entropy	9	74.75	59.1	68.65	52.72	77.22
Random Forest using Entropy	11	75.21	59.52	68.50	52.71	77.68
Logistic Regression	15	78.97	64.47	71.84	58.60	81.63
SVM (Polynomial)	14	77.05	62.29	71.22	55.43	79.2
			M-II			
SVM (Linear)	30	72.34	79.14	80.29	78.24	57.12
Decision Tree using Entropy	6	67.59	74.53	72.32	76.93	58.54
Logistic Regression	28	72.01	77.88	75.32	80.84	65.71
MLP (Relu)	10	72.17	80.32	86.53	74.95	44.69
Adaboost	7	71.36	77.36	74.56	80.38	65.21
Bagging KNN	23	73.32	80.46	83.77	77.45	53.25

TABLE III: Performance of the different trained models for COVID-19 diagnosis and the clinical condition classification problems.

contributing to (D_{F1}) dataset. In case of hospitalization, more information is added to the patients' records resulting in a more complete entry in the (D_H) dataset. Unfortunately, some patients will pass away but hopefully, most would return home and will be contacted in 1-4 weeks for another follow-up leading to (D_{F2}) dataset. The selected features comprise the clinical information collected upon arrival, CT scan image information, laboratory test results of patients admitted to the ICU as well as additional information of patients in that unit, and patient medications and corresponding reactions. Table II contains the specification of these datasets.

3) Feature Selection: Due to the different conditions of the patients and the corresponding treatments and medications, not all data fields are present in the collected samples and we have many missing values for some of the patients. Therefore, we have selected the features that are more frequently available while considering the inherent importance of some less frequent features. We can choose a threshold that will ensure that the top k% of the features are preserved by considering the histogram of their weighted frequency. Thus, a feature selection step in performed prior to training our models based on i) a cut-off threshold on a weighted histogram of features, and ii) the expertise of the doctors. We have further refined the features by means of Chi-squared method, eventually, narrowing down the features to 17 for D_{f_1}, and 18 for D_H.

Heart diseases	High blood pressure	Diabetes
Gender	Age	Smoking
COPD	Asthma	Rheumatological
Malignancy	Body temperature	SPO_2
Vaccination background	BMI	Opium

TABLE IV: Features selected for Logistic Regression model.

4) Trained Models: We have trained two sets of models for the diagnosis of COVID-19 (M-I), and clinical condition classification of virus-infected patients (M-II). M-I is trained based on D_{F_1} and D_H, with two class labels of low and high risk. Patients who have died of Coronavirus, been hospitalized, have suspected CT scans (diagnosed by a radiologist based on: bronchopneumonia, ground glass opacity, and patchy airspace) or have been revisiting the hospital for COVID-19 related symptoms are identified as high risk (695 cases), and all else are considered low risk (1916 cases).

Although having a richer dataset and a higher-dimensional feature space leads to more accurate representation and possibly better predictions, providing the required information for constructing these samples can be very costly in terms of time and the limited available resources. Additionally, training such complex models relies on having many more samples compared to simpler models and is more prone to over-fitting. Therefore, as the first step for COVID-19 diagnosis, our objective is to construct models that take as input the data obtained from the measurements and initial checks by the medical staff and the recorded cough sounds, since these data modalities can be provided fast and comparably more conveniently, leading to a faster diagnosis, and a larger and more diverse dataset.

For clinical condition classification (M-II), we have used the hospitalized dataset (D_H), with two class labels of mild to moderate, and severe/critical conditions based on the doctors request. Patient's showing mild to moderate symptoms are in the first class (210 cases) and patients showing more severe symptoms such as respiratory failures, low oxygen levels in their blood ($SPO_2 < 93$), etc, are in the second class (401 cases). These labeling conditions are defined by our medical collaborators.

5) Model Performance: A series of classification methods have been used for finding the model with the best performance. Table III lists a number of these methods along with their complexity and their performance for both models. All models have been validated using 3-fold cross validation. As the doctors have a preference for firstly, better sensitivity, and secondly, better specificity (stated in our discussions with the medical team), we have chosen the Logistic Regression model as our classifier for M-I. The selected features used by this model can be found in Table IV. For clinical condition classification $M-II$, the best sensitivity performance is obtained using an Multi-Layer Perceptron (MLP) model with two layers, and the best specificity belongs to the Logistic Regression model.

$M' - I$	Accuracy	F1 Score	Precision	Sensitivity
Healthy	0.91	0.90	0.93	0.88
Affected		0.92	0.89	0.94

$M' - II$	Accuracy	F1 Score	Precision	Sensitivity
COVID-19 infected	0.80	0.68	0.66	0.70
Other		0.86	0.87	0.85

TABLE V: Performance of the two trained models using patients' cough sounds.

6) Cough Sound Analysis for COVID-19 Diagnosis: One respiratory symptom in many COVID-19 patients is dry coughs and having a model that can predict the risk of infection based on the cough sound can be very useful as a preliminary tool for both triaged patients and people who have just started showing symptoms and have not yet visited a doctor. In order to create models for predicting the infection risk, we have constructed a dataset composed of cough sound recordings gathered by a nurse using a mobile device, at a $0.3\ m$ to $0.4\ m$ distance from a patient, recording three incidents per patient.

Such samples collected from diagnosed and hospitalized patients are very limited and costly, since finding nurses that would agree to this risky step of getting close to infected patients is very difficult. Moreover, the ward environment is very noisy and uncontrolled in terms of presence of different sounds. Nonetheless, 133 samples comprising 65 healthy, 39 COVID-19 infected cases and 29 cases with other respiratory diseases have been collected. The first 25 coefficients of Mel-Frequency Cepstral Coefficients (MFCCs) [36] of the cough signal are selected as the features for an SVM model with RBF kernel, validated using 10-fold cross validation as our classifier. We have trained two models each with two class labels, i) ($M' - I$) with healthy and affected patients that may have any respiratory disease, and ii) ($M' - II$) with two classes of COVID-19 infected and other patients. Table V shows the performance of both models. Results show that the performance of $M' - I$ is better than $M' - II$ and it is easier to differentiate healthy cases from infected cases, and correctly classifying COVID-19 infected cases is considerably more difficult.

C. Image-based Diagnosis of COVID-19

AI has the potential to drastically improve the medical diagnosis process based on imaging. COVID-19 has spread quickly due to transmission between individuals. Confirmation of SARS via lab testing is performed with RT-PCR, but this test may require up to 48 hours for completion. A chest CT can be an important element in diagnosing and evaluating patients suspected of having SARS. Chest CT results may be normal for some newly infected patients. Therefore, a chest CT alone has limited predictive value when it comes to infection. This highlights the need for including clinical information during diagnosis. AI algorithms may contribute to the diagnostic process by combining chest CT results with symptomology, lab testing, and history of exposure.

We propose a dataset composed of 4173 CT-scans of 210 different patients which are divided into: 80 patients infected by SARS-CoV-2; 80 patients with other pulmonary diseases as non-COVID pneumonia, DPOC, and lung cancer; and 50 patients with healthy lung conditions [37]. Data was collected from March 15 to June 1 2020 in the Public Hospital of the Government Employees of Sao Paulo, and the Metropolitan Hospital of Lapa, Sao Paulo – Brazil. Table VI details the patient's used in this study.

The inclusion criteria for this study are listed as follows:

- Patients with a positive new coronavirus nucleic acid antibody and confirmed by the CDC;
- Patients who underwent thin-section CT;
- Age$>=18$;
- Presence of lung infection in CT images.

Fig. (8) illustrates the data distribution for the patients infected by SARS-CoV-2 and considered in this study.

The median duration from the onset of the illness to CT scan was 5 days, ranging from 1 to 14 days. The CT protocol was as follows: 120 kV; automatic tube current (180 mA-400 mA); iterative reconstruction; 64 mm detector; rotation time, 0.35 sec; slice thickness, 5 mm; collimation, 0.625 mm; pitch, 1.5; matrix, 512×512; and breath hold at full inspiration. The reconstruction kernel used is set as "lung smooth with a thickness of 1 mm and an interval of 0.8 mm". During reading, the lung window (with window width 1200 HU and window level-600 HU) was used. Fig. 10 illustrates some examples of CT scans found in the dataset.

We relied on xDNN classification approach [38] to the proposed SARS-CoV-2 CT scan data set to detect those patients suffering from COVID-19. We divided the dataset into 80% for training purposes and 20% for validation purposes, but we have to stress that xDNN does not require full re-training if new data is presented- it keeps all prototypes identified so far and may add new if the data pattern requires that [39].

Using the xDNN method we generated (extracted from the data) linguistic *IF...THEN* rules which involve actual CT scans of all classes (COVID-19, other pulmonary diseases and healthy) as illustrated in Fig. 10. Such transparent rules can be used by specialists to support a clear early diagnostics for COVID-19 infection or other diseases. Rapid detection with high sensitivity of viral infection may allow better control of the viral spread. Early diagnosis of COVID-19 is crucial for the disease treatment and control.

D. Forecasting Spread of COVID-19

Anticipating and monitoring disease spread is vital. Generally, there are three methods for identifying the rise and decline of illnesses such as the flu.

- **Nowcast**: An estimate of the number of current infections; Labs collect historical and current data from the CDC and other organizations as well as data about illness-related Google searches, medical website traffic, and Twitter activity. Such data streams are analyzed using machine learning algorithms to make predictions.

Condition	Num. Patients	Num. CT-Scans	Average Num. CT-Scans per patient
Healthy	50	758	15
COVID-19	80	2168	27
Other pulmonary diseases	80	1247	16
TOTAL	210	4173	20

TABLE VI: This table demonstrates the number of patients considered to compose the dataset. In this case, we considered data of 80 patients infected by SARS-CoV-2, out of which 41 were male and 39 were female. We also considered data of 80 patients presenting other pulmonary diseases as lung cancer, DPOC, etc. The dataset is also composed of CT scans that do not present any pulmonary disease, These data refers to data of 50 patients.

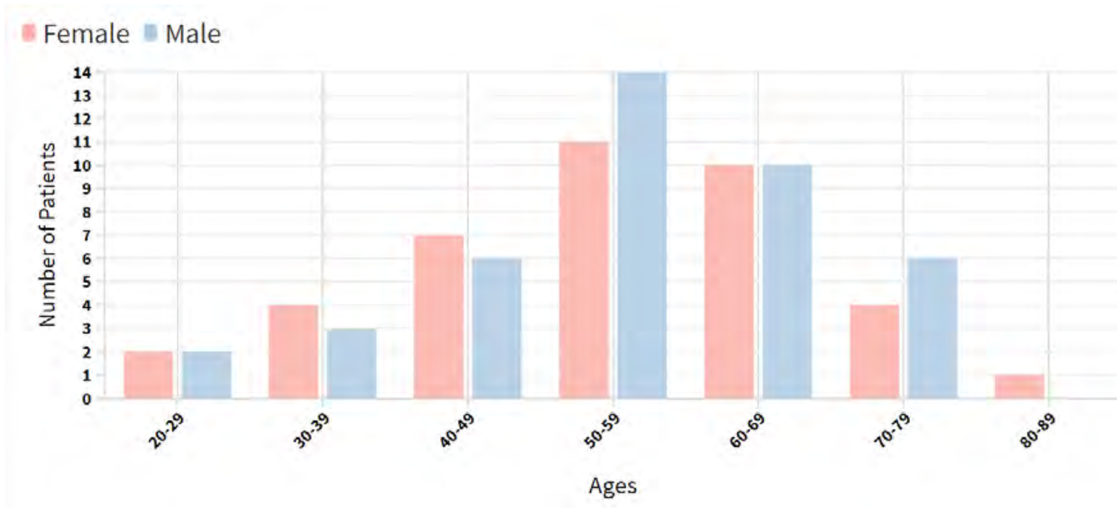


Fig. 8: The study considered data for 80 different patients (41 male and 39 female patients). The data revealed that the major of the patients are with 50-59 years-old.

- **Machine Learning Forecasting**: Predicts up to 4 weeks in advance and anticipates milestones such as the maximum number of cases and when an outbreak will peak; This information enables healthcare providers and the CDC to anticipate and prepare for capacity needs. Machine Learning forecasting considers both the nowcast and previous CDC data. With 20 years of U.S. flu season data available, the algorithm has plenty of information.
- **Crowd Sourced Opinion Forecasting**: This forecasting method utilizes volunteers. Each week both experts and amateurs log in to a system illustrating the trajectory of the current and past flu seasons. These groups of volunteers then forecast the current curve by projecting the number of cases over time. While individuals may not accurately predict the trajectory, in groups they are as accurate as Machine Learning Forecasting.

The nowcast and machine learning forecast use many of the same data sources, but utilize different prediction models. Algorithms must learn new correlations between the ground truth and data signals. This is because of increased panic around COVID-19, which results in different online activity patterns as people search for coronavirus information. Because people who are not ill will still search for the information, it can be difficult to know who is experiencing symptoms. In the event of a pandemic, there is also little historical data available, which can impact forecasting. While the flu occurs cyclically, pandemics are rarer and less predictable. The H1N1 pandemic of 2009 was characteristically different from the COVID-19 pandemic. In contrast to COVID-19, H1N1 impacted younger people as opposed to older individuals. In addition, back in 2009, tracking systems were not completely developed. Teams are relying on historical data from the current pandemic due to a lack of data from prior pandemics. Researchers are including data from countries who experienced earlier cases and will continue to update Machine Learning models as data is provided. At the end of each week, the CDC reports on the updated U.S. case trajectory and revises prior numbers. This allows labs to update models and eliminate the gaps in rolling statistics and original predictions.

E. Risk Prediction

AI may be applied to predicting COVID-19 risks. In general, risk prediction is categorized into three areas:

- Risk of Infection.
- Risk of Severe Symptom Development.
- Risk of Specific Treatment Use for an Infected Individual.

During the flood of COVID cases and the lockdown phase, the intensive care in Italy has been pushed to the limit, reaching a peak at the end of March of about 4000 of hospitalized patients in Intensive Care Units (ICUs). Italian doctors were forced to choose their ICU patients who have the best chance for

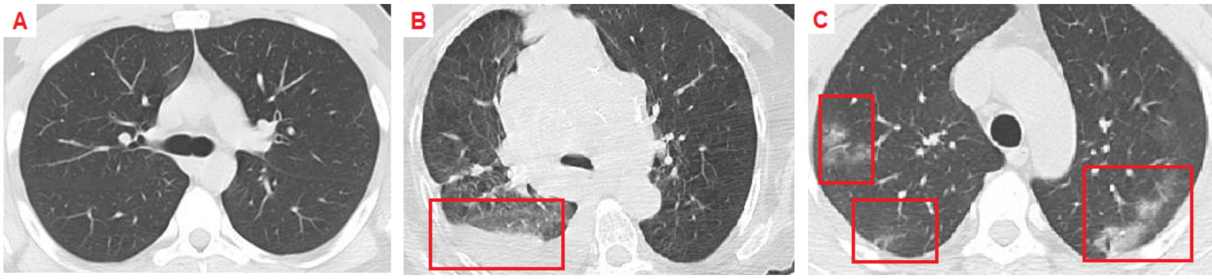


Fig. 9: **A)** A 27-year-old male patient presenting fever and headache for 2 days. CT scan do not show the presence of any pulmonary disease. The RT-PCR test revealed negative for SARS-CoV-2 infection. **B)** A 63-year-old woman patient presenting shortness of breath and cough for 4 days. CT scan shows the presence of subpulmonic pleural effusion. The RT-PCR test revealed negative for SARS-CoV-2. **C)** A 31-year-old woman presenting fever, dry cough, shortness of breath for 4 days. CT scan revealed multifocal bilateral consolidation with ground-glass opacities with typical distribution. The RT-PCR tested positve for SARS-CoV-2.

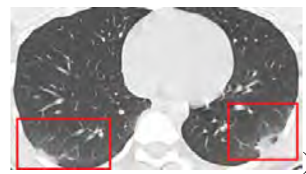
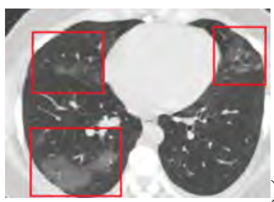
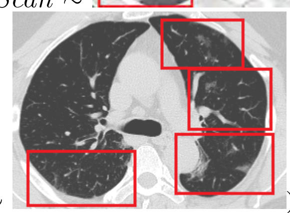
R: IF ($CT\ Scan \sim$ ) OR ($CT\ Scan \sim$ ) OR ($CT\ Scan \sim$ ) OR ... OR ($CT\ Scan \sim$ ) THEN 'Infection by SARS-CoV-2'

Fig. 10: Final rule given by xDNN classifier for the COVID-19 identification. Differently from typical deep neural networks, xDNN provides highly interpretable rules which can be visualised and used by human experts for the early evaluation of patients suspected of COVID-19 infection.

survival. In particular, the last data of the 8th April confirmed the reaching of the peak and the stabilization of the trend in Italy. The Civil Protection bulletin reported that 3693 people are admitted to the ICU, 99 less than the day before. 28485 people were hospitalized with symptoms, 233 less than the day before. The contagion was reducing: the incidence of positive was 7.4%. On April 8th 542 people died (there were 604 victims the day before), reaching a total of 17669 deaths in Italy. This worldwide emergency has highlighted the need to define a predictive care model that can provide an accurate estimation of resources and preventive medicine. At the moment, the conditions that predispose people to develop complications are largely unknown and the ability to understand them by using patient records is hampered by numerous challenges. These obstacles include a difficulty in finding structured clinical data, a non-uniform data sampling leading to several missing values, and a lack of annotation with respect to a target variable that may represent the patient's own risk level. Under these conditions, understanding and predicting the risk of a particular patient to develop complications associated with COVID-19 is a very important and topical challenge. Thereby, we proposed to design and develop Machine Learning (ML) algorithms for early-stage prediction of complications and risk stratification of COVID-19 patients in ICUs using heterogeneous longitudinal Electronic Health Record (EHR) data. In particular, the study has been performed as part of the Collaborative international ICU registry for critically ill COVID-19 patients - RISC-19-ICU . The aim of the registry is to collect real-time data of COVID patients admitted to non-ICU or ICU wards. The registry was launched on the 13th of March and it includes already 97 ICU centers from 16 countries collecting data. The registry includes more than 1000 patients and more than 400 fields (e.g. laboratory analysis, ICU analysis). The idea behind our project is to better prevent and treat the complications that appear in the patient affected by COVID-19 by developing a clinical decision support system (CDSS) that allows computing:

- Risk profiles of individual patients from which a different intensity of care can be deduced, with consequent modification of the control time according to the needs; this approach would produce a shortening of the waiting time

and an increase in the appropriateness of care.
- Prediction of risk of short-term complications which will activate personalized prevention systems directly addressed to the patient: from targeted recalls to targeted motivational and training activities.

The EHR data as well as the ICU data poses different challenges within the machine learning community. These challenges should be taken into account for the prediction of complications associated with COVID-19. The ML model should be able to achieve higher predictive performance but at the same time ensuring high interpretability (i.e. localize the most discriminative features). The model should deal with high dimensional data, representing also irrelevant and redundant features and the naturalistic unbalanced setting of this task (e.g. huger sample size of the control class with respect to the pathological class). At the same time, the temporal evolution of the features should be encapsulated. However, the employed EHR/ICU data reflects the clinical use-case scenario, where not all laboratory exams are prescribed uniformly over time. This problem leads to a highly sparse dataset where each patient can have missing features and/or sparse annotations of diagnosis over time. Our recent work in this field aimed at overcoming these challenges by proposing ML methodologies for providing the prediction of type 2 diabetes (T2D) [40] and the early temporal prediction of T2D risk conditions [41] using EHR data collected by General Practitioners. The ML algorithm represents the core of the CDSS (see Fig. 11).

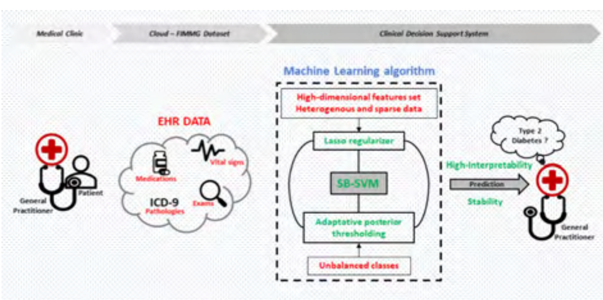


Fig. 11: The General Practitioner stores the EHR data in the FIMMG dataset . The features were used for training the sparse balanced Support Vector Machine (SB-SVM) model and providing a T2D prediction. The SB-SVM is formulated with sparse regularizer and adaptive posterior thresholding.

The Sequential Organ Failure Assessment score (SOFA score), is used to track a person's status during the stay in ICU to determine the extent of a person's organ function or rate of failure. The SOFA score can be measured daily on all patients admitted to the ICU in order to determine the level of acuity and mortality risk. The accurate prediction of SOFA may be relevant to the clinical scenario in order to provide risk profiles of individual patients from which a different intensity of care can be deduced, with consequent modification of the control time according to the needs.We aim to predict the SOFA worsening or SOFA improvement at day 5 of ICU by solving a classification task. We are currently adopting a no-temporal approach based on the eXtreme Gradient Boosting (XGboost) algorithm. The predictors consist of patient characteristics during hospitalization time and at ICU admission. The model should be able to generalize across subjects. Thus, we performed a leave-one-subject-out cross-validation procedure.

The algorithm was tested on a subset of 100 patients of the RISC-19 ICU registry. Fig. 12 shows the predictive performance and the feature importance of the XGboost algorithm. The model achieved an accuracy, macro-precision, macro-recall and macro-f1 of 0.69, 0.70, 0.69 and 0.68 respectively.

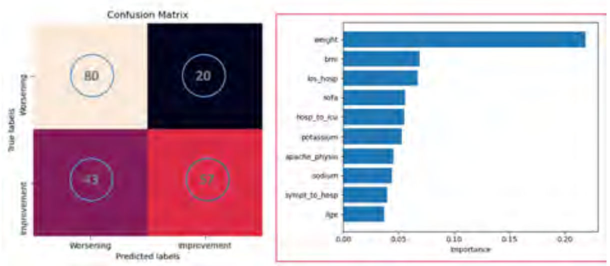


Fig. 12: Predictive performance (confusion matrix, left side) and feature importance (right side) of the XGboost algorithm tested on a subset of 100 patients of the RISC-19 ICU registry.

The proposed framework (see Fig. 13) aims to provide a coordinated, evidence-based, fair and global public-health response. For this reason, the effectiveness and robustness of our framework are not limited in the accuracy of the ML algorithm, but it depends on the ICU data-sharing, multi-disciplinary collaborations, interpretability, reproducibility and transparency of the extracted results. The continuous expansion of the RISC-19 ICU registry with the collaboration of new ICU centers leads to the creation of a standardized benchmark to support worldwide researchers in the fight against COVID-19. Thus, our framework can be encapsulated in a Smart Healthcare Internet of Things (IoT) solutions which may improve the medical service performance and the accessibility of preventive medicine.

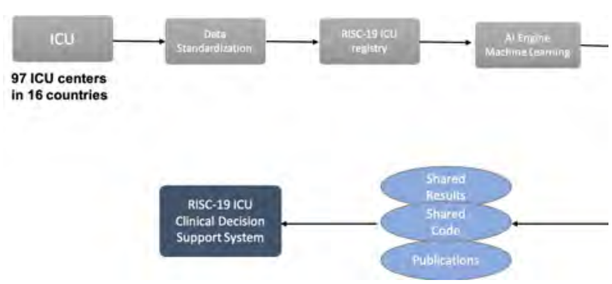


Fig. 13: Framework of the proposed risk prediction approach.

F. Voice-based Diagnosis of COVID-19

Multiple voice detection applications have been created to assist with COVID-19 screening. These applications analyze a users voice sample to detect virus infection symptoms. The

Corona Voice Detect app utilizes forensic voice technology and AI to identify patterns in voice, tone, and speaking sounds related to illness.

G. Respondent-Driven Sampling (RDS)

In the SNOWBALL study, which is a CDC-funded contract (BAA 75D301-20-R-68024), we investigate the potential of respondent-driven sampling (RDS) to fill gaps in understanding SARS-CoV-2 and COVID-19 by relying on respondents active engagement of their own close-contact networks to build a self-generating contact trace from persons who test positive for SARS-CoV-2. Key components of the proposed approach include:

- **Building a rapid-deployment RDS platform to detect active, undiagnosed cases and determine the spread or distribution of active infection in the community.** By developing the capability for rapidly deploying targeted testing into NC communities, we can provide early, high-impact data for public health management of future influenza-like illnesses such as COVID-19, leveraging transmission pathways to systematically recruit community members to complete electronic surveys and present for testing.
- **Testing the effectiveness of RDS sampling in identifying novel positive cases and reaching otherwise under-represented populations and assessing differential social contact patterns via personal network surveys to evaluate the social determinants of infection risk.** We will test whether the RDS platform yields a substantively different population of the epidemic by reacting rapidly with multiple testing modalities and by reaching more distal network contacts than are typically accessed through traditional contact tracing channels.
- **Using RDS to inform and direct molecular epidemiology studies that are representative of the local population.** Combining detailed contact patterns with transmission patterns assessed through molecular epidemiology will permit estimation of secondary attack rates in multiple settings. Identifying contact patterns with higher transmission likelihood protects health workers in hospital and other care settings.

Network-targeted sampling can efficiently sample the community, starting with Duke University Health System (DUHS) patients as COVID-19+ seeds (index cases). Its benefits include 1) locating cases where they are most likely to occur, 2) assessing community spread/distribution, and 3) interrupting transmission by diagnosing cases before they are infectious to others in the community. SNOWBALL offers a translational toolset combining social-structural insights about how community structure channels infectivity with clinical expertise that can detect, treat, and monitor populations.

1) Rationale and Research Strategy: In order to ”reopen” North Carolina to typical activities, we must develop efficient surveillance designs to understand how widespread SARS-CoV-2 is, where and how people are most at risk of acquiring or transmitting it, and whether recovered individuals are immune and prevented from transmitting the virus. Contact patterns and underlying comorbidities are likely different for the most vulnerable groups, putting them at risk biologically and socially (COVID-19 cases are quickly climbing in NCs Hispanic/Latinx population, a group that has poor access to care). However, a network-targeted community sampling design can also direct testing to yield a higher proportion of results that indicate active infection and potentially differentiate venues or communities where transmission is active and undiagnosed. Network-targeted methods do not require intensive contact tracing to achieve a robust, representative sample, nor require personnel to circulate through the community to collect samples. Instead, this approach passively recruits community members to complete electronic surveys and present for testing.

We propose a network-targeted, short-term sampling strategy to efficiently identify active cases and reduce SARS-CoV-2 transmission in NC. With the end of statewide shelter-in-place orders, any new COVID-19 case indicates that the case has had sufficient contact to acquire the infection and is likely continuing to have the same types of contacts, which can further spread the infection. Surveying the cases contact patterns can locate where to deploy testing where such testing is still limited. This social network-targeted sampling creates an efficient sample to identify and diagnosis additional infections. Building on the model of public health contact tracing, a network-targeted method focused on an infected cases whole network will also include the weaker or incidental contacts often responsible for epidemic spread.

We need an approach that can quickly identify and contain new COVID-19 cases to prevent the second wave from overwhelming NCs state health system. Network-targeted sampling can identify where in the community undiagnosed infections might be present, confirmed by RT-PCR to diagnosis active infections. This scalable sampling strategy would be useful for capturing asymptomatic or lowly-symptomatic cases or close network contacts not within the same household. This approach improves on public health contact tracing in 3 important ways:

- First, we will leverage the social contact network of those diagnosed with COVID-19 to identify the epidemics periphery. Social contact networks comprise multiple ties between people, with strong ties reflecting intensive interaction that is clearly a risk for transmission, and weak ties representing incidental contact through common daily activities. Although weak ties are less likely to pass infection per tie, their much larger number means that people are likely passing infection through these ties. Importantly, because index patients will be largely aware of their strong-tie contacts symptoms and recent activities, they are best positioned to understand where they acquired the disease or whom they may have infected, helping to guide targeted recruitment and sampling.
- Second, to broaden participation, we will use both in-clinic and at-home testing. We have multiple teams of testers, including at least one with Spanish fluency, who can be mobilized to collect appropriate respiratory samples

(nasopharyngeal) for RT-PCR testing for active infection and venous blood for antibody and serologic testing.

- Third, testing for both active infection with RT-PCR and for convalescence with serology, combined with a symptom diary, will provide key knowledge about infection course, symptom prevalence in conjunction with infection prevalence, and transmission related to behavior and contact patterns.

2) Approach: Transmission of SARS-CoV-2 is most likely to occur with repeated, prolonged, or invasive contact, meaning that close contacts, people in congregate living situations, and healthcare workers are most likely to become infected. Thus, targeting social contacts is likely to yield higher numbers of undiagnosed but positive cases than random sampling would. Index cases (seeds) for these link-sampling designs would be patients from Durham County who test positive for SARS-CoV-2 at DUHS. We will also trace weaker contacts who might be the source of the index cases infection, or someone to whom the index spread the infection.

Our goal is to work closely with DUHS to develop a workflow whereby index cases will be sampled from anyone testing positive for SARS-CoV-2. Once a case is enrolled, we will administer a survey that elicits general information about activities and symptoms and includes a social network module to capture details about social networks, living situations, and activities/venues. Building this capability will create a SNOWBALL Platform allowing public health departments and/or epidemiologic researchers to quickly deploy an easy-to-use platform for physical and electronic coupons and surveys in future pandemics. The platform will employ the Fast Healthcare Interoperability Resources (FHIR) standard to facilitate access to electronic health record and public health surveillance systems.

Respondent-driven sampling leverages cases to identify testing candidates. Each index will be given 3-5 unique electronic codes to invite peers, together with recommendations to guide their selection, based on survey information about seed-peer contact patterns, peer risk, and sample diversity to achieve representativeness. We will exclude peers known by the seed to have been diagnosed with COVID-19. We will aim for 1 close contacts likely to be infected based on index-peer interactions; 1 contacts at risk due to his/her close interactions; and 1 contacts constituting a central figure at a venue frequented by the index. Indexes in congregate living situations will receive 1-2 additional coupons for co-residents. Indexes whose samples required fewer than 10 RT-PCR cycles until detection will receive 1-2 additional coupons for people with whom they had sufficient contact in the 48 hours prior to sampling. We will also aim to maximize diversity in the sample through venue-targeted sampling. Contacts with coupons who complete the survey will be given an appointment for testing (in-clinic or at home). Recruited contacts who test positive on RT-PCR will be given coupons to elicit their own set of contacts, following the same protocols as the seeds.

The primary purpose of selecting network contacts for serological testing is efficiency and sample diversity. Each respondent will provide information on close contacts and venues frequented, acting as key informants for likelihood of infection risk at each place/type. We will conduct a network analysis of contact patterns and venue-based behaviors aimed at evaluating population diversity and spatial heterogeneity. We anticipate collecting samples for 100 serological tests drawn from persons who tested positive for SARS-CoV-2 at a DUHS clinic. Although this does not provide sufficient power to fully test effectiveness, this pilot will provide information on feasibility and population diversity. Peers will be asked to consent to nasopharyngeal swabbing to diagnose active COVID-19 infection and to consent to blood draws for a serological test.

Serology test results provide us with an assessment of previously infected but recovered cases to help map the extent of infection within the network neighborhood of each RT-PCR+ positive SNOWBALL participant. Our goal is to use the network contacts and contact patterns described above to develop our understanding of SARS-CoV-2 transmission, including asymptomatic and pre-symptomatic transmission likelihood among diverse contacts and with detailed information about previous symptoms, mitigating or exacerbating behaviors, and the social and spatial ranges of Durham County residents.

H. Early Warnings and Alerts: Face Recognition and Body Temperature Scanning

AI is transforming COVID-19 diagnosis and screening. Infrared temperature scanners have been used to screen for fever in public places. However, the technology requires personnel to complete the scanning. In order to limit the potential exposure of frontline staff in airports, hospitals, or healthcare facilities some have begun using cameras with multisensory technology based on AI. These enhanced cameras can recognize individuals with elevated body temperatures, recognize corresponding faces, and trace the individual's movement. During the COVID-19 pandemic several states have begun using facial recognition to fight the virus spread. This technology assists in monitoring those who disregard quarantine guidelines or assessing the body temperature of infected people in a crowd. Facial recognition and AI provide unparalleled control for quarantine scenarios by using facial recognition in collaboration with other technology. For example, the FindFace system combined with CCTV cameras can identify individuals in real-time, facilitating prompt response even as AI assesses that individuals social network.

- **Social Interaction Analysis**: Uses complex recognition and searches of historical data to assess the number of likely infected individuals.
- **Real-time Violation Monitoring**: Identifies quarantined individuals and notifies authorities if they are recognized on camera, even if wearing a mask or facial covering.
- **Tracking Quarantine Compliance**: Algorithms that recognize silhouettes make it possible to monitor individuals using multiple cameras even if facial imaging is not available.
- **Age Detection**: AI is highly useful in assessing age, which is helpful in monitoring those age 60 and over who are

encouraged to remain at home during the COVID-19 pandemic because they are more susceptible to infection.

I. Social Control and Fake News Detection

While fighting the actual pandemic, science and medicine must also battle the dissemination of incorrect information online. Throughout the COVID-19 pandemic, inaccurate information spread quickly. Overcoming misinformation requires the integration of various tools in the arenas of information technology, law, and education. Previously, news was spread by a limited number of organizations, but today news is spread via social media and the internet. Fake news can be defined as deliberately inaccurate information that is disseminated through traditional or social media. Unfortunately, fake news can seriously mislead or harm individuals and organizations. Fake news is sometimes aimed at profiting from the promotion of specific treatments, supplements, or products. Stressful situations, like a pandemic, are often linked to an influx of information or misinformation. When COVID-19 was designated as a global public health emergency, the WHO Information Network for Epidemics (EPI-WIN), a platform for sharing specific information with targeted groups, was created. In the context of misinformation, AI tools can recognize and monitor incorrect information from questionable sources. Doing so helps to keep the focus on fighting the coronavirus, which is vital to an effective response. For example, the JRC created an AI-based Classifier capable of identifying misinformation by evaluating the news article language. While a 100% detection rate is not possible, the JRC machine learning algorithm offers an 80% rate of success.

J. Communication and Chatbot

Using triage systems based on AI may reduce the load on physicians. Medical chatbots could assist patients with identifying symptoms, provide vital education around hand hygiene, and refer individuals for treatment if symptoms worsen. In addition, phone software capable of recognizing and recording patient data such as temperature and advancing symptoms could prevent patients from seeking unnecessary hospital care if they have mild symptoms. This additional data could also be used with AI algorithms to monitor COVID-19.

K. Vaccine and Drug Development

Fighting COVID-19 effectively over the long term requires the development of vaccines. AI can be utilized to facilitate vaccine production. Emerging studies using the Vaxign-ML tool to forecast two dozen COVID-19 vaccine options using five non-structural proteins and the S protein focuses on exploring the whole proteome of COV-2. Using machine learning in conjunction with reverse vaccinology allows researchers to predict vaccine targets. Another vaccine trial is using HLA-binding prediction tools that require peptide stability assays. 777 peptides were evaluated and predicted as acceptable binders for 11 MHC allotypes with elevated prediction binding scores. Initial results will make key contributions to the creation of an effective COVID-19 vaccine. Another study utilizes DL to create a drug-target interaction model known as the Molecule Transformer-Drug Target Interaction (MT-DTI). It recognizes available drugs capable of acting on COVID-19 viral proteins. This model suggests that atazanavir, an antiretroviral drug typically used to treat HIV, may be beneficial in developing a drug aimed specifically at COVID-19. The drug must pass through the trial stage before possibly being used to treat coronavirus patients. The study creates a data-driven drug utilization framework using statistical analysis and machine learning methods to mine large transcriptome data and knowledge graphs. The data supporting analytics to identify antivirals and vaccines rests upon an understanding of the genomic content of SARS-CoV-2 which contains the necessary molecular targets for these health interventions. To support this research, the IBM Functional Genomics Platform has analyzed over 60,000 SARS-CoV-2 genomes and pre-computed all gene, protein, functional domains, and biochemical pathways for this virus surfacing the data as an open research asset to aid in the pandemic. This data resource provides important ground truth data to aid in controlling this global health crisis. Trial results indicate that machine learning is able to effectively predict drug SARS candidates, making it a possible means of reframing drugs to combat the global COVID-19 pandemic.

IV. The Role of Robotics in Managing COVID-19

As the COVID-19 pandemic grows, the potential uses for robotics become clear. Robotics can be utilized during a pandemic to disinfect, deliver food or medication, monitor vital signs, or assist with border control. Generally, robots have been created to handle dangerous, tedious, or dirty jobs. They were initially used industrially. In similar a fashion, an infectious disease can result in environments that are unsafe for human interaction. The recent Ebola outbreak pointed out a variety of use cases, but interdisciplinary research funding in collaborations with government agencies and industries is still limited. However, the far-reaching impacts of the COVID-19 pandemic may facilitate more expansive research into the use of robotics to mitigate infectious disease risks [42].

- **Disease Prevention**: Currently, robotic ultraviolet (UV) disinfection of surfaces is in use because COVID-19 spreads through respiratory droplets and contaminated surfaces. The virus can live on surfaces such as glass, plastic, or metal for days, but UV light is effective in lessening contamination of high-touch surfaces in hospital settings. While disinfection would normally require manual work by humans, which increases exposure risks for workers, remote-controlled or autonomous robots may provide effective, fast, low-cost disinfection. Additional opportunities remain in the sensing of high-touch areas and intelligent navigation. There is potential for the next generation of robots to traverse high-risk areas and constantly sanitize all high traffic areas.
- **Crowd Surveillance**: Containing COVID-19 requires that governments enforce social distancing mandates. Some countries, including India and China, have utilized drones to monitor crowds and gatherings.

- **Public Announcements**: Drones are capable of broadcasting vital information, especially in locations without open communication channels.
- **Mass Screening**: Drones can utilize thermal cameras, night vision, computer vision systems, or specialized sensors to monitor crowds and screen groups using body temperature and heart rate data.
- **Essential Supply Delivery**: Drone technology can quickly deliver medical or other essential supplies, reducing strain on healthcare institutions and staff. During pandemics and outbreaks, it can be difficult to maintain sufficient staffing to test individuals and process samples. Automated oral or nasal swabbing may accelerate the process, lessen the chance of infection, and allow staff to undertake more complex tasks.
- **Screening and Diagnosis**: Mobile robots may be utilized to measure body temperate in public spaces. Already, automated camera systems are often used to screen crowds in expansive areas. Integrating vision algorithms and thermal sensors with autonomous or remote-controlled robots may enhance screening coverage and efficiency. Mobile robots could also be utilized for monitoring body temperature for hospitalized individuals or outpatients with data automatically linked with healthcare IT systems. It is possible that linking facial recognition software and security systems would enable faster contact tracing; however, appropriate guidelines would be required to respect privacy.
- **Drones and UAVs**: These technologies offer clear advantages during public health emergencies. These devices are capable of reaching remote areas or reducing human interaction. China has successfully utilized drone technology to combat the COVID-19 pandemic. In light of this, many countries are collaborating with researchers to drive innovative drone use in the fight against the coronavirus. Drones offer many benefits toward mitigating pandemic effects and stopping further outbreaks.

V. The Role of Blockchain in Managing COVID-19

While DLT/blockchain and the IoT are distinct forms of technology, the integration of the IoT and blockchain is a massive paradigm shift that will spur the evolution of systems across the health industry. Blockchain has the capability to address IoT vulnerabilities and resolve security issues around the connection of WIoT devices. The way blockchain creates and stores data, consensus mechanism, and decentralized nature resolve issues found in centralized cloud-based IoT systems. Many use cases have illustrated blockchain's applicability to all IoT system aspects. Blockchain can be utilized to manage device identities, store cloud data or that of distributed objects, and confirm and encrypt data within communication networks. It also mitigates risk by using multiple nodes to transmit peer-to-peer data, making it almost impossible for data to be tampered. Blockchains consensus mechanism is also able to prevent a compromised node from contributing data to the chain, which safeguards data integrity [43], [44].

Blockchain offers the ability to create audit trails for healthcare interactions, protect system access, facilitate data sharing, and support healthcare supply chains, as the health industry moves to embrace a patient-centered, IoT-based paradigm. Those healthcare systems created using blockchain technology would benefit from greater data security and accuracy as records could be integrated and patients would have clearer ownership of their health data. In addition, blockchain lessens a systems reliance on a centralized third party to manage the sharing of data, handle transactions, or confirm data accuracy or ownership. Blockchain enables chain participants to directly engage in pseudonymous, secure transactions. Blockchain enables data owners and eHealth service providers to interact without the need for a third party. The kind of data shared and timeframe of use is controlled by the data owner via smart contracts. Blockchains distributed ledger allows data owners to see the transfer of data among chain participants. Cryptocurrencies such as bitcoin also allow for the monetization of eHealth data [4], [44].

Blockchain technology is also capable of aiding in the fight against COVID-19 by providing verifiable blockchain certificates. This technology could secure COVID-19 testing results, providing people with a certificate to confirm if test results are positive or negative. This would be useful for providing proof of immunity based on antibody testing. Blockchain has the capability to help users confirm their health status, which would enable communities to appropriately lift restrictions and better target quarantine guidelines. Blockchain technology also offers the ability to monitor patients infected with contagious viruses including COVID-19. Infected or exposed individuals could wear an IoT device to monitor movements, enabling effective containment and simultaneously protecting privacy. Remote Patient Monitoring can also benefit from blockchain technology. Reviewing the gathered data generates both data privacy and data security issues. Blockchain provides a new means of accessing, storing, and sharing data in compliance with GDPR and HIPPA protocols. Blockchain technology can also be utilized for the supply chain management. For instance, VeChain is a blockchain-based platform created to track Chinas vaccine production. Everything related to vaccine production including codes, materials, packaging, etc. can be documented and maintained via distributed ledgers. This platform provides a dependable method for mitigating risks around alterations to vaccine data because records are permanent, enabling researchers to create a high-quality vaccine during the pandemic [44].

VI. Conclusion

The COVID-19 pandemic has caused extreme strains on healthcare systems and has shut down almost the entire global economy. As the scientific and research community is struggling to find a swift solution and a cure, Smart and Connected Health has become the core technology for fast prediction, modeling, examination, and evaluation of infected patients. In light of the urgent need for SCH solutions, this paper presented a selection of original and innovative techniques in the field to help combat this raging pandemic. We began this paper by proposing a set of complementary techniques and providing a comprehensive overview of the role of (W)IoT. Following this, we discussed how AI, ML, and Big Data can be harnessed to stop the epidemic and minimize the loss of human lives. We also took a broad look on the role of robotics and drone technology in managing public health and pandemics. Finally, we examined how DLT/blockchain can improve the shortcomings of the current SCH solutions and help us in the event of pandemics.

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