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Artificial Intelligence and Internet of Things (AI-IoT) Technologies in Response to COVID-19 Pandemic: A Systematic Review

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ABSTRACT The origin of the COVID-19 pandemic has given overture to redirection, as well as innovation to many digital technologies. Even after the progression of vaccination efforts across the globe, total eradication of this pandemic is still a distant future due to the evolution of new variants. To proactively deal with the pandemic, the health care service providers and the caretaker organizations require new technologies, alongside improvements in existing related technologies, Internet of Things (IoT), Artificial Intelligence (AI), and Machine Learning in terms of infrastructure, efficiency, privacy, and security. This paper provides an overview of current theoretical and application prospects of IoT, AI, cloud computing, edge computing, deep learning techniques, blockchain technologies, social networks, robots, machines, privacy, and security techniques. In consideration of these prospects in intersection with the COVID-19 pandemic, we reviewed the technologies within the broad umbrella of AI-IoT technologies in the most concise classification scheme. In this review, we illustrated that AI-IoT technological applications and innovations have most impacted the field of healthcare. The essential AI-IoT technologies found for healthcare were fog computing in IoT, deep learning, and blockchain. Furthermore, we highlighted several aspects of these technologies and their future impact with a novel methodology of using techniques from image processing, machine learning, and differential system modeling.

INDEX TERMS Artificial intelligence, compartment model, COVID-19, internet of things, image processing.

I. INTRODUCTION

Internet of things (IoT) technologies can be defined as an amalgam of software and hardware products that can generate, gather and compute data, fundamentally in the form of binary digits. On the other hand, artificial intelligence (AI) is the underlying automation mechanism behind these IoT technologies driving its applications and can be regarded as a distinguished field from IoT due to its intrinsic importance. The union of these two technologies is referred to as AI-IoT. Since the overture of the COVID-19 pandemic, the top priority ever has been to control and contain the pandemic through principles like social distancing and quarantine enforcement [1]. Failure to take action may lead to surges of infectious cases, causing overburden of hospitals [2]. While the efforts in vaccination development have been fruitful, the rate of transmission of the virus is the same as before, and so are the efforts to control its spread.

Identification of a COVID-19 patient is an important strategic approach in controlling the pandemic [3], and its significance became prominent when countries such as South Korea and Israel utilized it for tracking people with COVID-19 symptoms right from the beginning, and infection spread was greatly controlled [4]. The identification approach consists of diagnostic tests, contact tracing, quarantine, isolation, and treatment [3], [5].

In this course, the above approaches can be laborious and perhaps inefficient. Henceforth, the imposition of digital

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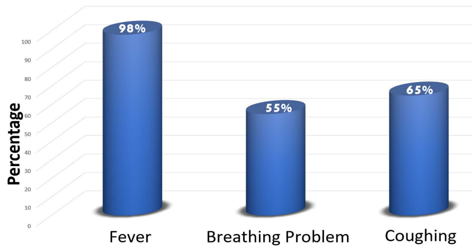

FIGURE 1. Percentage distribution of major symptoms associated with COVID-19.

technologies as an aiding tool is not only the next logical move but has been consistently verified to be beneficial. For example, the infected number can be controlled with low quarantine efforts when accurate tracking technologies like GPS, Bluetooth, etc., are adopted [6].

Many countries attempted to contain the COVID-19 outbreak through different lines of action with varying degrees of results, but the guiding examples have been South Korea and Israel, which took action immediately as the initial infected cases appeared, followed by the extensive utility of information and communication technologies in harmony with voluntary public participation [4], [7]. Such strategies are a ramification of lessons learned from previous epidemics. For example, [8] showed that lack of communication between regional healthcare agencies, invites variable transmission rates over the country, as happened in the 2003 SARS outbreak in Canada [7]. Similarly, during the 2009 influenza pandemic, Switzerland used medical teleconsultations to manage suspected cases in addition to its existing reporting system [9].

The distribution of symptoms of patient infected with COVID-19 [10], [11] is documented in figure 1. Recognizing these symptoms right from the onset is instrumental in flattening the infected number curve. Since smartphones are widely accessible in current times, their embedded sensors have been studied and implemented to detect the symptoms early and provide an immediate diagnosis from imaging techniques, which can take days for final screening.

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), the principal cause of the current pandemic, is known to be highly prone to mutations [12], [13], and thus may penetrate the effectiveness of the current vaccines and antibody drugs [12]. Even most promising vaccines like mRNA-based Pfizer and Moderna [14] are known to be 95 percent effective, leaving out 5 percent of the vaccinated population prone to the infection. While the maturation of broad-spectrum drugs and vaccines is underway [13], the maximum utility of current digital technological tools is the need of time. Additionally, it is worth mentioning how the pandemic is directly affecting the development of many technological trends as well, with notable examples being the deep surge of videoconferencing platforms and the deployment of robots and drones for delivery purposes. In the context of COVID-19, pertaining to AI-IoT technologies, most of the reviews or surveys are either standalone specific to a particular domain of AI-IoT [15], [16] or slightly augmented [17] with other fields, but do not span all associated fields in general. Another problem with such review articles is the inefficiency in classification schemes embedded in such reviews, where overlapping classes of technologies are considered separate, for example, the field of AI and blockchain or IoT and 5G being dealt with as separate classifications, while one class engulfs the other [18]. Besides in prior review articles, conventional techniques of tabulation, charts, and color maps are used to provide a comparison between different aspects, limited by author's knowledge and understanding. This provides an invitation to systematic data-driven techniques to draw more profound insights. Further, text mining [19] techniques have been applied to produce a review of COVID-19 references and determine insight into challenges and future trends, but the proposed method itself was intended as the primary goal of the article. Even generally in review and survey articles, an overview of several classifications associated with a particular domain has been provided with techniques like SWOT analysis [20], Network analysis [21], and machine learning methods [22], [23], but they are more polarized towards application perspective.

In the light of above mentioned drawbacks, the main aim of this review paper is to provide a concise and comprehensive review of several AI-IoT technologies from both technical and application perspectives in a minimum classification scheme, followed by recommendations by authors for possible future works. To provide resolution into some aspects of these technologies and associated comparisons, not only conventional methods like pie charts, bar charts, color maps, and tabulations were utilized. We also proposed and utilized novel interpretable techniques from machine learning, image processing, and mathematical modeling to aid in the insights and comparisons.

The key contributions of this review are summarized as follows:

- The review presents the AI-IoT technologies impact in the COVID-19 context, under a compact taxonomy, comprehensive in engulfing key concepts such as their architecture, availability, theoretical significance, research interest and practical applications. In this respect, their trends and challenges are highlighted and based on them possible future works and trends like the infrastructure of deployment of these technologies, as well as research directions are recommended. The IoT Technologies help to remote monitor the COVID-19 health, Breathing difficulty level, Temperature, and Geo-fencing. The AI helps to predict various COVID-19 factors such as the Oxygen saturation level in the blood based on the IoT sensors data, COVID-19 spread estimation, and automation control for non-contact to minimize the spread.
- To emphasize the significance of several technologies like sensing devices, cloud and fog computing, blockchain, deep learning, machines, etc., that are most inclusive in dealing with the current pandemic

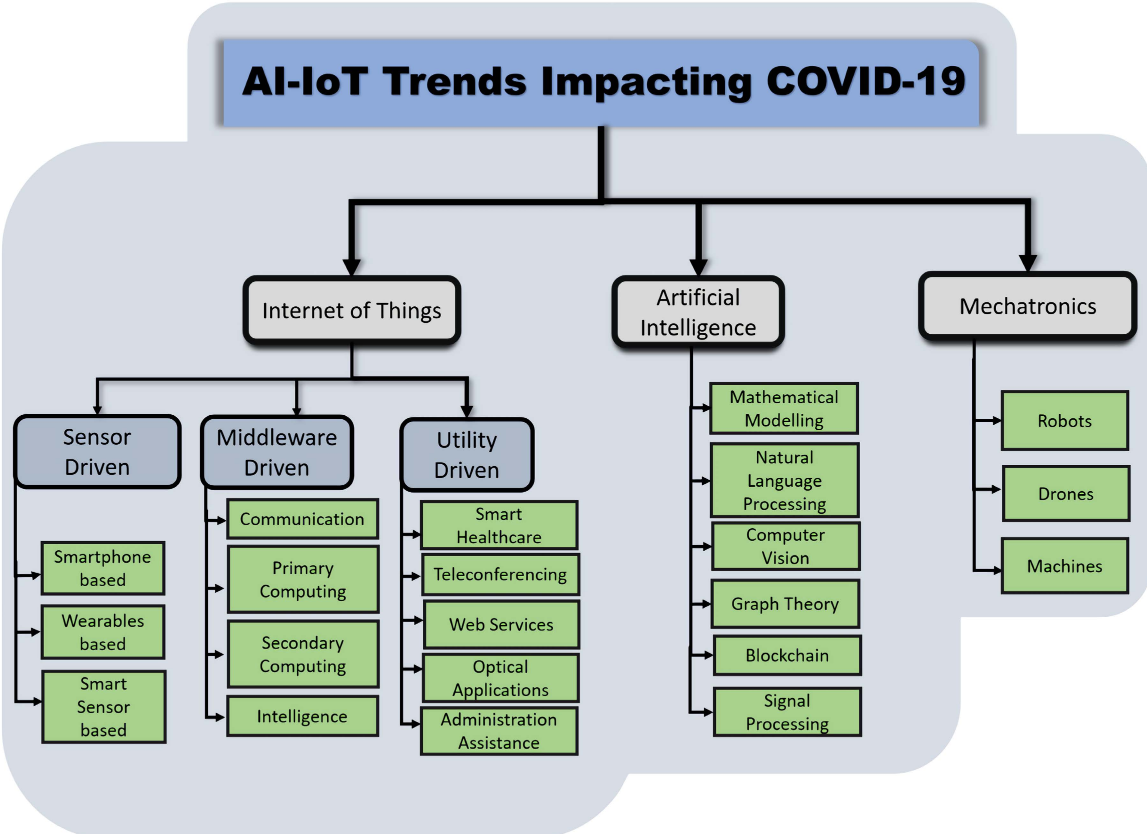

FIGURE 2. Flow diagram presenting classification of AI-IoT technologies entailing the response to COVID-19.

in healthcare, governmental and public sectors. The non-contact sensors specifically and also wearable sensors help to monitor the patients health and movement and contribute more to reducing the COVID-19 spread.
- To propose and utilize novel techniques from machine learning, image processing, and differential system modeling in this review to extract compact and interpretable features from literature data reviewed and present them into meaningful plots and tables.

In the next section, the novel review methodologies are described in detail. In later sections, the review is provided as an expansion of three main classifications of AI-IoT technologies in the COVID-19 context, i.e. Internet of things (IoT), AI, and mechatronics, where these methodologies are applied in different contexts in the review, including the "Future Works" section.

II. ANALYSIS METHODOLOGIES

This section introduces three different data driven AI techniques with their associated theoretical backgrounds. While many aspects of these techniques are novel, they are intended to provide deeper insight into several classification schemes and recommendations by the authors. The corresponding methodologies are described as follows.

A. GRAPH FEATURES BASED INSIGHT

The site "Connected Papers" [24] was considered for this methodology, which can render a graph of an academic paper, where the focussed paper is connected to several other papers based on contextual similarity. In this regard, similar papers are closer (forming clusters) with more bold edges. The nodes represent individual papers with their size signifying the number of citations. The strategy to develop an effective, compact, and interpretable understanding of these graphs is to transform the node, edge, and cluster information into features.

On the contrary, this site does not provide parameters of this graph, which are to be transformed into appropriate interpretable features. To systematically extract information about nodes, edges, and clusters from the rendered graph image, an array of image processing techniques are systematically employed, whose logical flow is represented in figure 3.

Since nodes, edges, and clusters of the graph can be identified as circular objects, lines, and connected components in an image respectively, detection of these becomes a collection of standard image processing problems [25]. In this continuation, the process of node, edge, and cluster number identification is described below:

- ∗ **Node number:** Although there exist many variants of Hough Transform [26] for circular object detection,

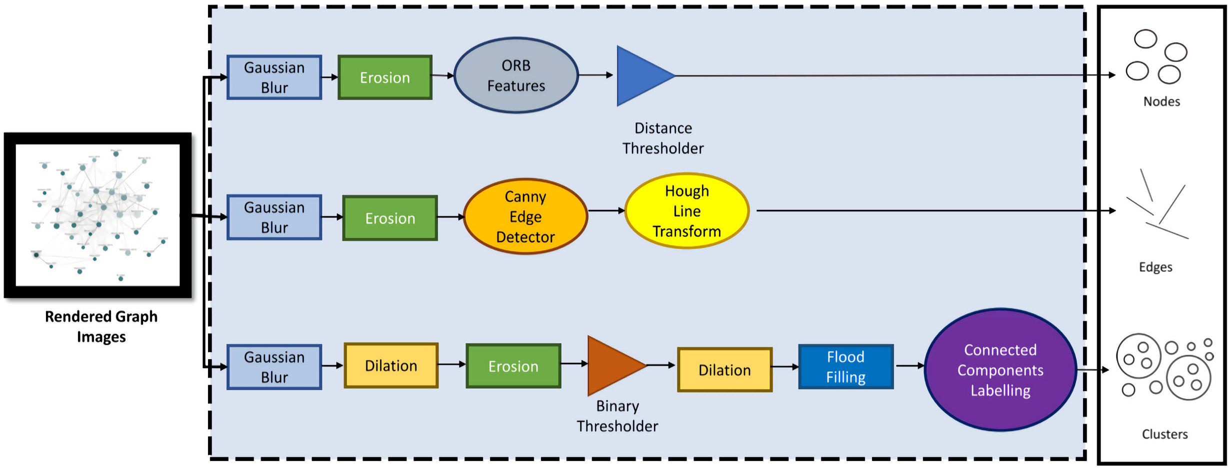

FIGURE 3. Flow diagram of employment of image processing techniques to extract nodes, edges and cluster information from a rendered graph image.

our approach took advantage of the presence of only circles and edges within the image vicinity with a sharp variance of pixels between them, and employed Oriented FAST and rotated BRIEF (ORB) based feature detection [27] to count the total number of nodes. This is done after an erosion operation [25] upon a Gaussian blurred image [25] to nullify the presence of edges. The detected ORB features are thresholded by the minimum distance between two feature positions to lead toward the total count of actual nodes.

∗ **Edge number:** Likewise to circular object detection, an abundant literature is present in line detection context [28], [29]. In this regard, our methodology relies first on an erosion operation upon a Gaussian blurred graph image to refine the thickness of lines for later edge detection by a Canny Edge detector [25] to produce an edge map. Later Hough line transform [25] is performed upon this to detect and count the number of original edges in the graph image.

∗ **Cluster number:** Connected component labeling could be an excellent way to identify the clusters in a graph, from the image representation, but this would work only for appropriate binary images [30]. To tackle this, first, the Gaussian blurred image of the graph is transformed into an image comprising of several blob-like areas, through a sequence of operations like erosion, dilation and flood filling [25]. Later, the clusters are identified and counted with connected components labeling [25].

A demonstration of the above graph attributes identification is represented in figure 4(a), (b), (c) and (d). After extraction of the above information, features for decision trees are constructed through table 1. While on the contrary graph-based techniques have been employed in image processing, to the best of the author's knowledge, this is an original approach to extract features from graph, based on image processing of its rendered image. This provides not only an effective new way to extract necessary information from graphs but also more computationally feasible solutions, where complex networks can be represented by images with a lesser number of pixels.

Reduced Citation (c') is an effective representation of cumulative citations per year normalized over the year (y) to show the relevancy of comparison between two papers published in different years. Entropy (S) metricizes the different active research directions within the same literature domain. Here entropy takes its relevance from the Boltzmann equation of thermodynamics, where entropy represents the number of states, in which the gas molecules can arrange themselves in [31]. Interest index (I) reflects the research interest in terms of active research contributors within the area, while research index (r) describes the rigor in the corresponding research. The associated formulas for the calculation of these features are described by equations (1), (2), (3) and (4).

$$c' = \frac{cy}{2022} \tag{1}$$
$$S = log(C) \tag{2}$$
$$I = 1/(1+n) \tag{3}$$
$$r = 1/(1+E) \tag{4}$$

In our case, these features (as described in table 1) describe several characteristics of research trends and their properties are the range of the feature values.

B. COMPARTMENT MODEL BASED INSIGHT

Compartment models are an abstract representation of the mathematical model that can be represented as a system of unique information entities that can exchange information among themselves. While prior Literature upon them focused on their applications in modeling biochemical, engineering, economic and social processes. We intend to utilize compartment models to model variation of Literature in specific interest domains across time. More precisely, the Literature

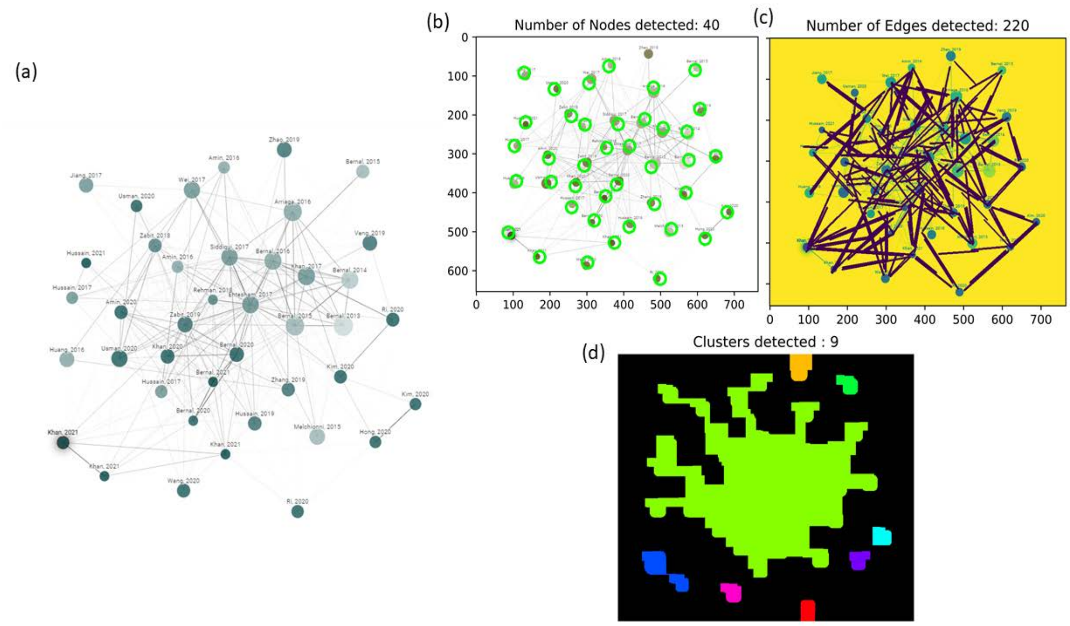

FIGURE 4. **(a) Rendered graph obtained from https://www.connectedpapers.com/ for a random research paper (b) Application of proposed algorithm to detect graph nodes (c) Detection of graph edges (d) Detection of graph clusters.**

TABLE 1. **Tabulation of parameters extracted from graph images and corresponding feature extracted for decision trees.**

Parameter	Feature
Cumulative Citations per year (c), year(y)	Reduced Citation (c')
Clusters (C)	Entropy (S)
Nodes (n)	Interest Index (I)
Edges(E)	Research Index(r)

in a domain is bound to evolve as a redirection from another field. This phenomenon has been very prominent in COVID-19-based Literature, and the prominent example is the reuse of existing smartphone technology to aid contact tracing at a national level.

Literature is a dynamic process in which the content evolves over time but in a specific pattern. Concerning a redirection approach, the Literature can be divided into the interest domain, in which the Literature is of interest, and the new domain, with well-established Literature, whose studies or results can be redirected towards the interest domain context. This leads to the creation of a third field, composed of new Literature in the interest domain, that acts as an intersection of interest field and new field. In the context of COVID-19 based Literature, this is depicted in figure 5(a) as a Venn diagram, where new literature and interest domain as COVID-19 Literature intersect to produce new Literature in COVID-19 domain, represented by a yellow area.

We can infer yearly cumulative citations of literature in a particular domain as a measure of literature in that domain, since our focus is to model the evolution of new literature in COVID-19 context. We can proceed with the modeling, by assuming that the change of yearly citations in new literature in the COVID-19 context is proportional simultaneously to its current citations as well as year citations in the new literature in general (depicting how lucrative this field has been to influence another field). Lastly, this change in new COVID-19 literature should directly affect the already present COVID-19 literature. With these considerations, we model the corresponding compartment model, as shown in figure 5(b). The corresponding differential system [32] of the compartment model is defined below.

$$\dot{N}(t) = -\alpha N(t)C(t) \tag{5}$$

$$\dot{C}(t) = \alpha N(t)C(t) - \beta C(t) \tag{6}$$

$$\dot{R}(t) = \beta C(t) - \tau \tag{7}$$

In equations (5), (6) and (7), 'N', 'C' and 'R' are the cumulative citation numbers on research papers related to purely new fields within the COVID-19 context, the intersection of new Literature and COVID-19 context and established COVID-19 Literature respectively. It is represented as a Venn diagram in figure 5(a). The associated parameters τ, α, and β are constants (whose description is mentioned in figure 5(b)), intuitively depicting a qualitative description of the dynamics. Equations (5), (6), and (7) have a high resemblance to the SIR model of epidemic [32], due to high correlation in their internal structure and dynamics of how infected people number and new Literature on interest domain evolves.

Our goal is to estimate the parameters τ, α, and β in equations (5), (6), and (7), which can provide qualitative insight into an infusion of new Literature into the COVID-19 domain. We can achieve this by considering the above system into a convex optimization procedure by transforming the

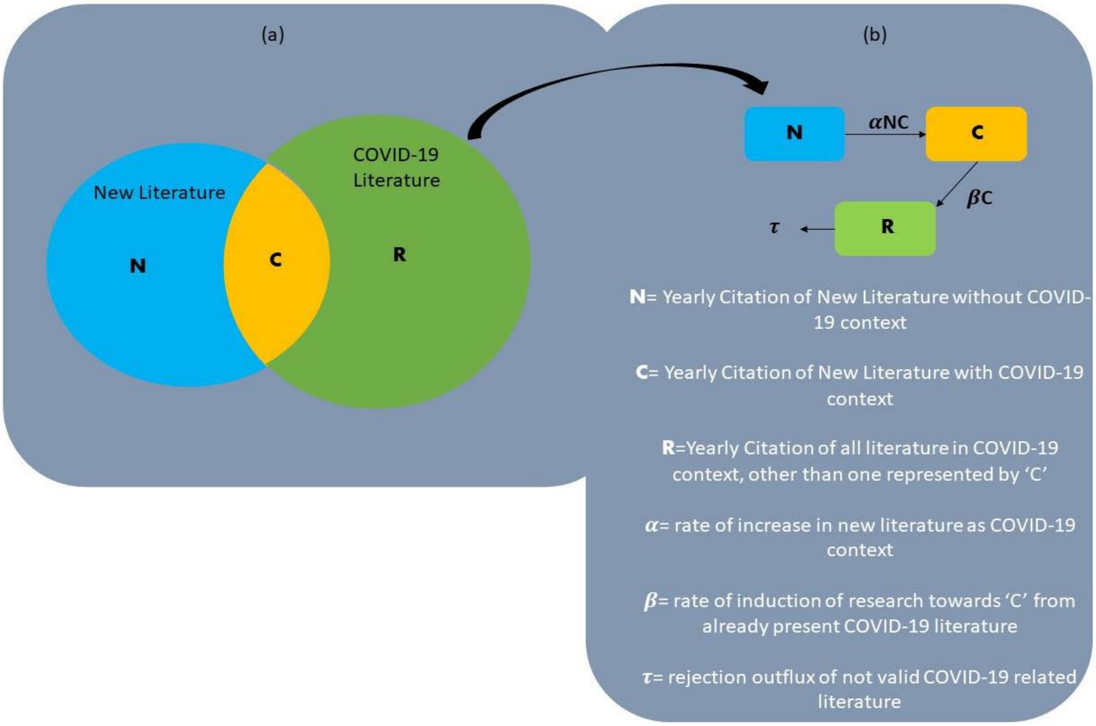

FIGURE 5. (a) Venn diagram representing relationship between N, C and R as the intersection of new literature and COVID-19 literature (b) Compartment Model based Visualization of Induction of new literature into COVID-19 domain.

equality into finding roots of the equality and finally squaring that equality into finding minima. Through simple calculations, we can form the following objective function from equations (5), (6), and (7).

$$\begin{aligned}\mathscr{O}(\tau,\alpha,\beta) = \sum_{\omega} &|j\omega n(\omega) - N(0) + \alpha I_{NC}(\omega)|^2 \\ &+ |j\omega c(\omega) - C(0) - \alpha I_{NC}(\omega) - \beta c(\omega)|^2 \\ &+ |j\omega r(\omega) - R(0) - \beta r(\omega) + \tau\delta(\omega)|^2 + \lambda\mathscr{L}\end{aligned} \tag{8}$$

In the above, $n(\omega)$,$c(\omega)$, $r(\omega)$ and $I_{NC}(\omega)$ stand for Fast Fourier transform (FFT) of functions $N(t)$, $C(t)$, $R(t)$ and $N(t)C(t)$ respectively. The FFT allows the above differential system to transform into an algebraic equation, as otherwise, the derivative on real data might not be well-defined, and techniques of curve fitting would have to be applied which only would lead to additional computational cost. It can be noted that while FFT may lead to complex outputs, the objective function defined by equation (8) is itself real due to the modulus argument '||'. Addition term '$\lambda\mathscr{L}$' in (8) is the regularization term, with λ as Lagrange multiplier, which enforces positive definiteness of states represented in equations (5), (6), and (7) as citations itself cannot be negative. To this end, $\mathscr{L}$ can be defined as,

$$\mathscr{L} = \sum_{t}(N(t) - |N(t)|)^2 + (C(t) - |C(t)|)^2 + (R(t) - |R(t)|)^2 \tag{9}$$

Henceforth, we can estimate parameters by minimization of the objective function in (9), as τ^*, α^* and β^*.

$$(\tau^*, \alpha^*, \beta^*, \lambda^*) = argmin\ (\mathscr{O}) \tag{10}$$

The choice convex optimization procedure chosen is Nelder-Mead Simplex method [33]. The estimation of these parameters would not only provide quantification of the qualitative behavior of citation trends but also allow us to estimate the future trend by solving the differential system (5), (6) and (7) by a Runge-Kutta Integrator.

C. Word2Vec BASED 3D VISUALIZATION

Word2Vec [34] is a family of word embedding algorithms that can translate words and sentences into vectors in the real domain. These real vectors have a 'distance' notion defined on them, which is not possible for standard words and sentences. Therefore, this technique can allow systematic calculation of similarity between two words based on the distance between their associated vectors.

A pre-trained Google's Word2Vec model [35] is considered in our paper, which is already trained on about 100 billion words from the Google News dataset and produces a 300-dimensional vector representation of words. The distance between these vectors directly implies how closely related the two words are. This representation would allow an interpretable visual demonstration of how closely related different sub-domain classifications of the digital trend are. Since 300 dimensions cannot be represented well

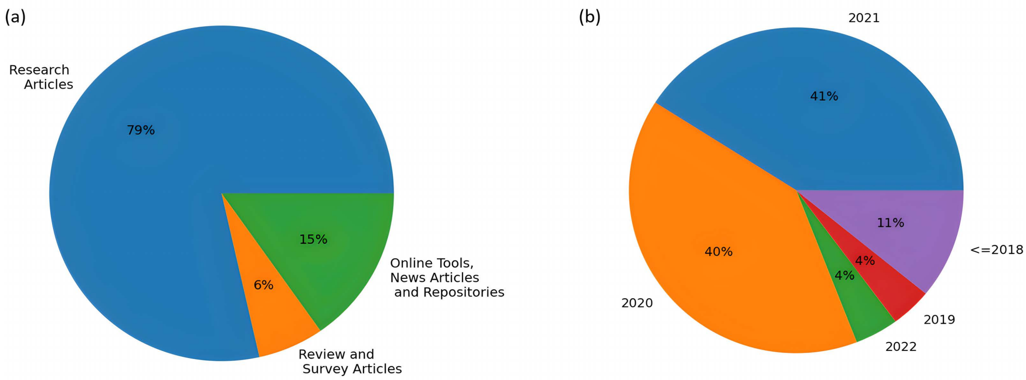

FIGURE 6. (a) Distribution of categories of sampled references for review paper (b) Distribution of year of publication of selected references.

for possible human interpretation, therefore to reduce the dimensionality of these representations to 2 dimensions, Principal Component Analysis (PCA) [36] is performed, followed by extraction of the first and second principal components as a two-dimensional vector. To allow a three-dimensional representation, more attributes are collected like the frequency of occurrence of particular classification in the COVID-19 context, and how often the particular topic is considered both research and implementation-wise. After the collection of this information, a 3D representation of several topics (in pertinence to a specific context) can be constructed, consisting of balls of a specific radius embedded in a 3-D Cartesian plane, the parameters of which are provided in table 2. This visualization can be interpreted as the relative distance of topics (described by balls) in the x-y plane describing their relative general contextual similarity. The positing of balls along the z-axis describes, how frequently the topic has been used in the COVID-19 context, thus implying its relative significance. Lastly, the size of balls would conclude the overall research and implementation contributions imparted on that particular topic. The size of the balls is determined by radius, which is calculated as $(c + exp(i)$, where 'c' is cumulative citation numbers and implementation and 'i' is cumulative articles number.

III. REVIEW OF AI-IoT TECHNOLOGIES

After an explanation of analysis methodologies, the review is organized as an expansion of three main classifications of AI-IoT technologies, namely IoT, AI, and mechatronics.

While the literature produced on the COVID-19 topic has been tremendous, a total of 625 references were selected for this review article, which is in the form of peer-reviewed or pre-print research, review, and survey papers, as well as news articles, online tools, and repositories. The distribution of these references in terms of source and year of the update is provided in figure 6. The sampling criteria for the corresponding references were based on relevance, from the viewpoint of theoretical aspects and significance, practical aspects and applications, alongside research interest

TABLE 2. Tabulation of attributes of three dimensional Word2Vec based representation and corresponding description.

Attribute	Description
x-axis	First PCA component of word embedding
y-axis	Second PCA component of word embedding
z-axis	Frequency of occurence in literature of COVID-19
radius of balls	collective research contribution

of AI-IoT-related technology in intersection with terms like "COVID-19" or "Coronavirus". Furthermore, several challenges of these technologies were highlighted, as well as future works were elucidated upon in light of the selected references. As represented in figure 2, these categories are expanded and covered in detail in the sequent sections. Later the review is completed with a conclusion and future works section. In this course, the analysis methodologies have been applied to different contexts, including the "Future Works" section.

IV. INTERNET OF THINGS

IoT is basically a collection of interconnected devices, whose high-level goal is to provide services through intelligent means [37]. IoT has been declared as a direct intersection of three broad visions of technologies: Things oriented (concerning electronics or mechatronics products), Internet-oriented (concerning communication and internet protocols) and Semantic oriented (concerning the utilization of gathered data) [38]. With the official advent of IoT in 2002 [39], the concept of connecting devices with computing dates back to the 1980s [38].

IoT is in itself a very active field, and with the current pandemic, its value has boomed and is estimated to be valued at around 1.3 trillion dollars by 2026 [40]. In order to make applications of IoT more accessible globally [41], it is important that the solutions are cost and energy effective. Furthermore, open-source solutions are also important as they might be more available to developing countries, besides the

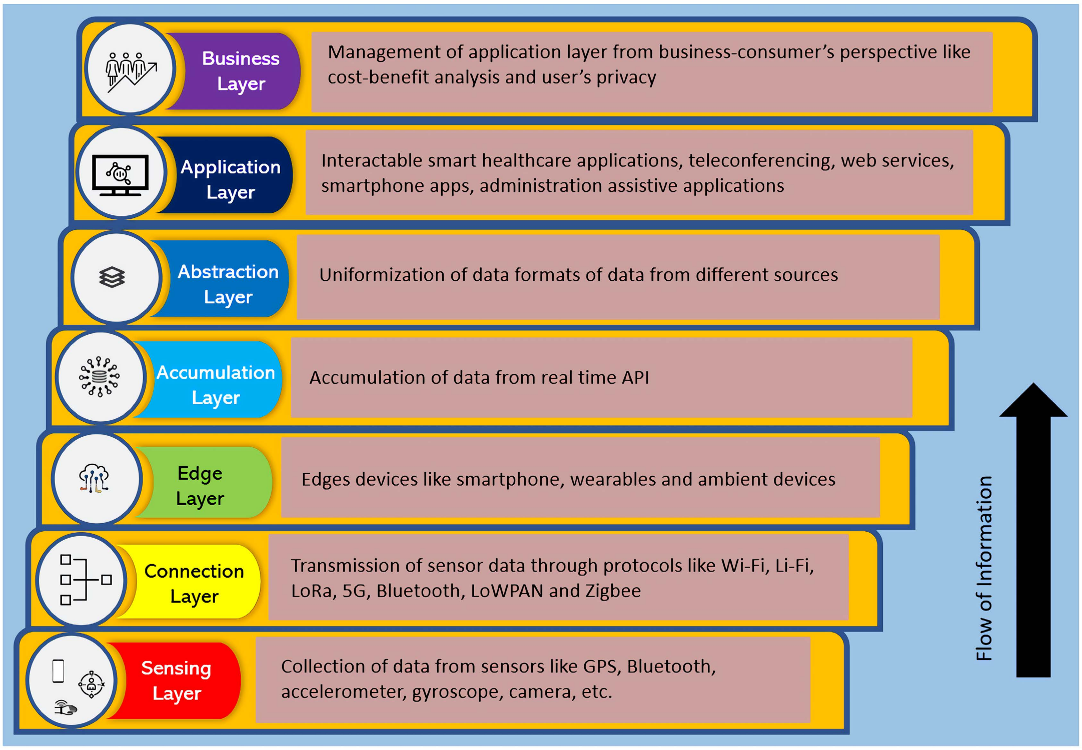

FIGURE 7. Stages of IoT Solution in controlling the epidemic of COVID 19.

characteristic of total community-driven development and maintenance.

While IoT has enabled automation, elimination of human error, and improved cost-effectiveness possible, industrial-scale IoT systems are known to be complicated and require sophisticated maintenance. Furthermore, they create risks to security, privacy, and loss of human jobs. Despite the significant importance of IoT to the modern era, there is no agreed-upon standard upon which several characteristics of its structure can be defined [42]. This vagueness has permitted researchers to impose the IoT architecture to be compromised of 3 to 7 layers. However, since the IoT can be visualized as a network of smart things that can generate, store and exhaust information [43], the following features remain invariant characteristics that IoT has to deliver [43]:

- **Network Invariant Functionality** → management of dataflow from sensors as well as integration of different platform of hardwares and protocols
- **Efficieny** → maintenance of performance with increases is the number of devices
- **Security** → ensuring security regarding flow and data as well as maintaining privacy of users

While technologies like WoT (Web of Things) [44], WSN (Wireless Sensor Networks) [45], CPS (Cyber Physical Systems) [46], M2M (Machine-Machine) [47] and embedded systems [48], [49] have been utilized in COVID-19 application, they somewhat differ from IoT with considerable principle similarities to the point that the prior terms are interchangeably referred to as IoT [38].

1) ARCHITECTURE OF IoT SOLUTION IN COVID-19

The application and advantage of IoT in tackling COVID-19 epidemic have been immense with its operational architecture described by 7 layers. The simplicity [38] of these respective layers provides versatility in the general description of COVID-19 related IoT applications. This architecture is briefly presented in figure 7, and is further briefly layer-wise explained below:

* **Sensing Layer** is responsible for collection of data from different sensors
* **Connection Layer** aims to deal with wireless networks and associated protocols for timely transmission of collected data from sensing layer
* **Edge Layer** transforms the data from several heterogeneous sources into standard form feasible for storage, and includes processes like data formatting, reduction and decoding. This layer may also allow fog computing, i.e. limited processing of received data.
* **Accumulation Layer** converts real time data into query-based data while accompanying methods like filtering and selective storage.
* **Abstraction Layer** stores the data in such a way that different types of data can be reused by a single application
* **Application Layer** basically converts the gathered data into some lucrative result utilized by consumer market in the form of smart cities, smart healthcare etc.

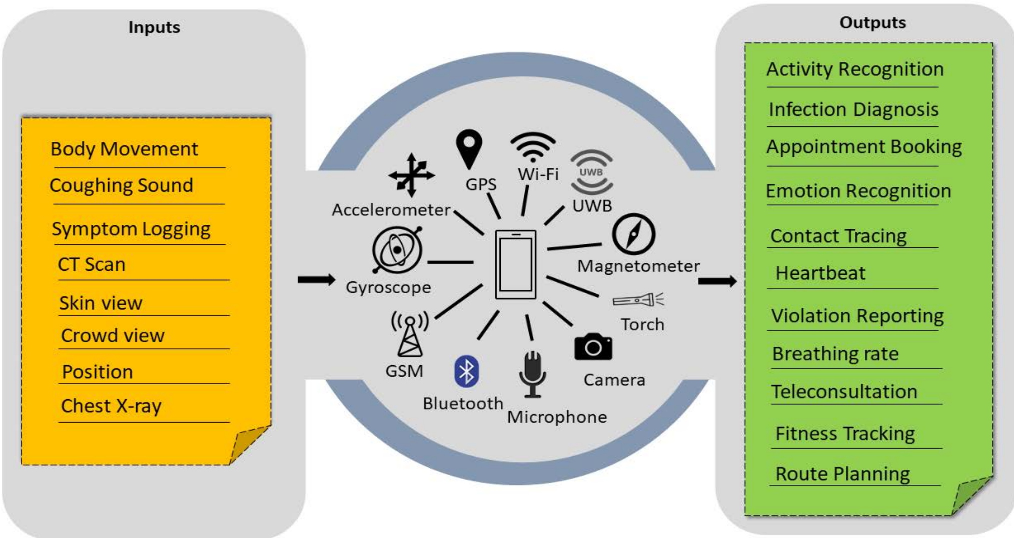

FIGURE 8. Overview of sensor technology utilized in smartphones and corresponding applications during COVID-19 pandemic.

* **Business Layer** engulfs single or multiple IoT application services at a larger scale to design business logistics driven IoT system and services, that is delivered by a business or an organization. This layer involves greater focus on elements like security and privacy

As shown in figure 2, IoT can be divided into three fundamental regimes, i.e. sensor-driven, middleware driven and utility driven. These regimes are discussed further in the context of COVID-19 as follows.

V. SENSOR DRIVEN

This classification observes the IoT applications from the perspective of perception and gives an overview of related technologies in sequent sections.

A. SMARTPHONE

Smartphones are an improvement over previous concepts of mobile phones with extensive computing capabilities to produce functionalities in addition to standard voice calls and text messaging. While primarily a packaged embedded systems, today's smartphones are generally embedded with an array of sensors like camera, accelerometer, gyroscope, proximity sensors, compass and microphones, while supporting several wireless communication protocols like GPS, Bluetooth, Wi-Fi and cellular networks. Smartphone's influence upon COVID-19 is discussed further after discussing its application in previous epidemics, in the following sections.

1) INFLUENCE UPON PRIOR EPIDEMICS

In epidemic control, smartphones provide leverage by possessing the connectivity, computational power with sensors and wireless technologies, in combination with ubiquity to provide extensive data collection and reporting [50]. This utility has been recognized prior to the current pandemic and has been extensively used to deal with previous epidemics. In fact, [51] termed the pairing of a smartphone with healthcare as 'mHealth' providing opportunities like outbreak identification, diagnosis, treatment, patient management, disease control and elimination of the disease. In this regard, [52] surveyed 1332 smartphone apps, relevant to the prevention and treatment of tuberculosis, and identified their functionalities as falling into as being informative, data gathering, alerting and reporting.

Smartphone point of diagnostics can be categorized as: 'colorimetric','electrochemical','fluorescence', and 'microscopy' [53]. On the other hand, the development of mobile phone point-of-care diagnostics is required to be rigorous with its process accompanied by needs and cost-benefit analysis, development of corresponding technology, pre-clinical verification, and then field trials [53]. In this direction, [54] utilized a smartphone application, using Dimagi's CommCare platform, known as the Ebola Contact Tracing application (ECT app), which reported 63% contacts as compared to 39% from paper-based contract tracing. [55] developed an app attending to point-of-care tests for Ebola diagnosis (100% sensitivity and 98% specificity), patient management and surveillance. [56] validated the use of smartphones accompanied by forward-looking infrared radar (FLIR) for the thermal detection of body temperature.

While this procedural limitation might put constraints upon whether smartphones should be extensively utilized in dealing with the current pandemic rigorously, we can deduce from the described literature that the utilization of smartphones in pandemic dealing is well-established.

2) POST-COVID-19 INFLUENCE

Since the current pandemic, smartphones have been utilized to aid primary care [57]–[60], and have proven to

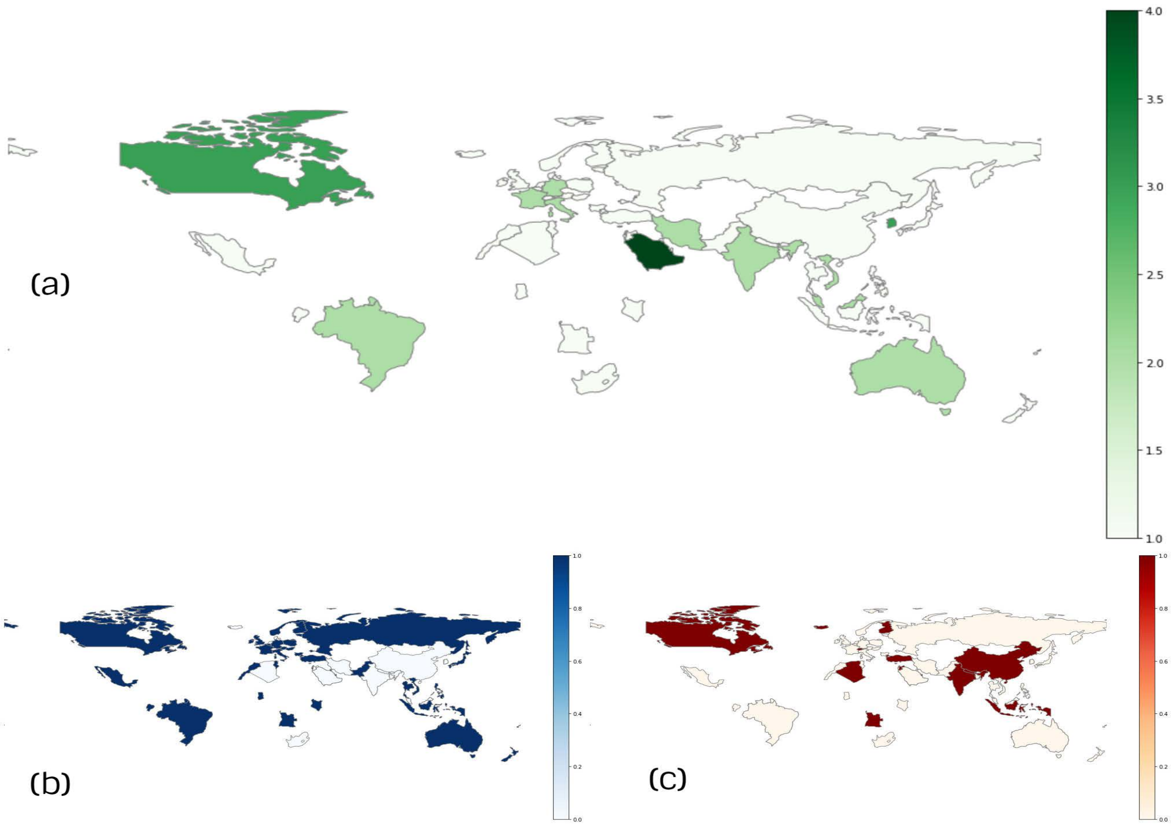

FIGURE 9. (a) Overall distribution of identified 98 COVID-19 related apps across globe (b) Distribution of Bluetooth based contact tracing apps across globe (c) Distribution of GPS based contact tracing apps across globe.

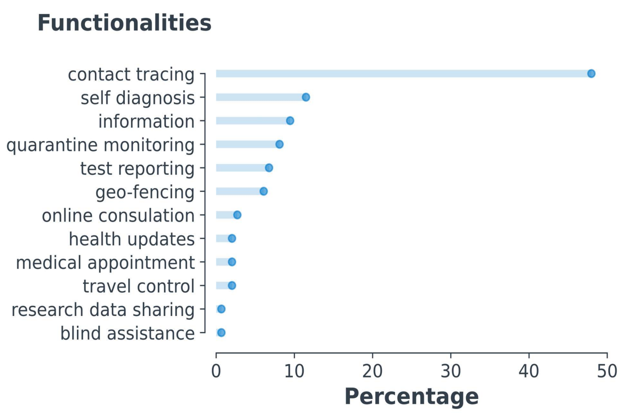

FIGURE 10. Distribution of functionalities in the identified 98 COVID-19 related smartphone apps.

be effective in extending towards affairs of health care like tele-consultations [61], tele-diagnosis [62]–[64], tele-surgery [65], [66] and tele-counselling [67].

Smartphones are frequently used for contact tracing through the deployment of dedicated smartphone apps. Manual tracing of contacts of an infected person may take up to 24 hours of labor, while automated systems leveraging smartphones can reduce this duration to 10 minutes [68]. Furthermore, the data from these contact tracing apps can be systematically integrated with data from police records, telecommunication companies, CCTV recordings and banks to produce more effective contact tracing. In order to ensure the effectiveness of smartphone-based contact tracing, an uptake of at least 56 percent [69] by the public is required, alongside effective detection of less than 15-minute duration presence in proximity of an infected person [70].

In the COVID-19 context, a smartphone's computational and sensor leverage in combination with their ubiquity has allowed much input to output capabilities, allowing applications as represented in figure 8. In this scenario, the sensor availability is most critical, with the most significant categories being GPS, Bluetooth, accelerometer, gyroscope, camera, and microphone, with corresponding literature upon their COVID-19 application considerably exhausted. On the other hand utilization of ambient light sensors and magnetometers in the COVID-19 context has been nearly absent in the literature. While there exist a few studies on estimation of the distance between devices based on magnetic measurements, there are only a few utilization of magnetometers in COVID-19 reference, utilizing smartphones [71].

3) SMARTPHONE APPS

With significant applications realized through the hardware of a smartphone, the next step is to design of the app to

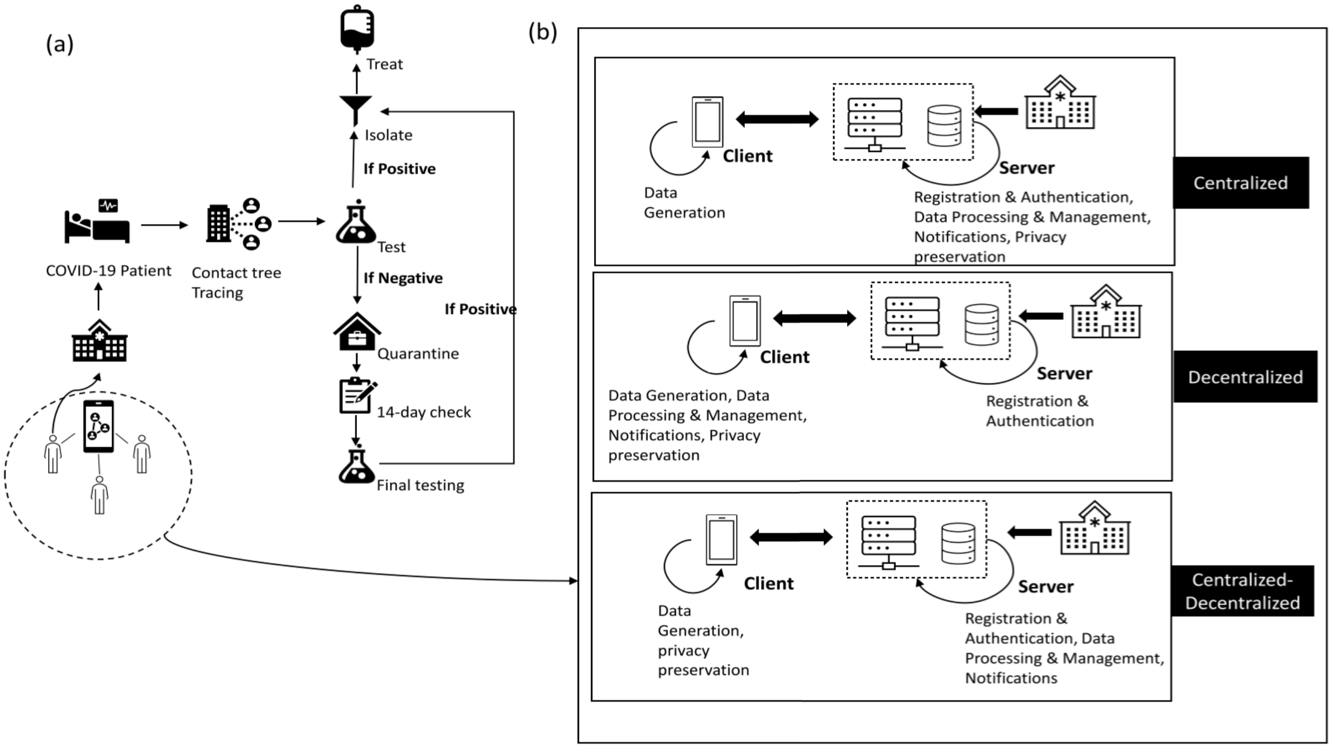

FIGURE 11. (a) Typical digital contact tracing scheme via smartphones (b) Data collection architecture of smartphones in contact tracing aspect.

interface those functionalities for a general user. In this respect, many apps have been deployed both at national and international levels, with their efficacy estimated to be up to 80% [72] upon early adoption by the general public. While preferences of users may define over adaptability of such apps, a study [73] revealed that app design and marketing strategies may also be critical in this respect. On the other hand, the general public opinion of these apps has generally been mixed [74] with critical factors as a guarantee of health and privacy as the main characteristics of these apps.

A study [74] suggested that the majority of the population demand health and privacy as the main characteristics of contact tracing apps, with as much early detection as possible, and its early adoption can lead to the reduction of infection rates by up to 80% [72].

With the sudden overture of the novel pandemic, the main strategy ever has been the cooperation between government and technology-based companies to redirect already present digital solutions to contain the pandemic. An initial example of this process in the case of the Chinese government utilizing platforms of Alipay and WeChat.

This trend quickly became systemized with more dedicated apps having applications towards contact tracing, geo-fencing, self-diagnosis, hospital appointments and consultations, routing, and travel control. Even further apps have been extended towards attending to indirectly affected areas by pandemic like online videoconferencing, therapy and assistance to elderly and disabled people. Likewise, some apps have specifically been developed for old people to cope with isolation experienced through lockdown [75].

In order to analyze these smartphone apps from a subjective point of view, a total of 98 apps were identified, on two major smartphone operating system platforms, i.e. Android and iOS (having a market share of 73 and 26 percent respectively [76]), from Google Play Store and Apple Store respectively. The application stores from these platforms strictly control the COVID-19 apps and condition them to be either affiliated with government or health organizations [77]. Therefore, the apps are expected to be majorly unique to a specific country, and the distribution of our sampled apps across the globe is presented in figure 9(a). It can be observed that apps are widespread across the globe, with some countries implementing more than one app to assist the public and control the pandemic.

The functionality distribution among these apps is plotted in figure 10. With contact tracing being the dominant functionality, the underlying technology can be classified into Bluetooth, GPS, Wi-Fi, towers and smartphone sensors [78]. Among the apps, Bluetooth was identified as the most dominant technology mode for contact tracing, due to its high accuracy, relative greater privacy preservation [79], cost and energy efficiency [80], with its distribution represented in figure 9(b) and distribution of other technologies in figure 9(c). These apps mainly utilize either GPS or Bluetooth signals to pursue contact tracing. Bluetooth is the most frequently used mode of contact tracing.

TABLE 3. Bluetooth based contact tracing protocols.

Name	Architecture	License	Ref
ViraTrace	partially Centralized	Restrcited Public Source License(VIRATRACE PUBLIC SOURCE LICENSE Version 1.0.)	[82]
Pan-European Privacy Preserving Proximity Tracing (PEPP-PT)	partially Centralized	Mozilla Public License Version 2.0	[83]
Exposure Notification System	decentralized	Apple Developer Program License	[84]
Whisper Protocol	decentralized	General Public License 3	[85]
Decentralized Privacy-Preserving Proximity Tracing(DP-3T)	decentralized	publicly-developed Apache 2.0, Mozilla Public License Version 2.0	[86]
OpenTrace	partially centralized	General Public License 3	[87]
Privacy Automatic Contact Tracing (PACT)	decentralized	MIT License	[88]
Herald Protocol	centralized and decentralized	Apache-2.0 license	[89]
Temporary Contact Numbers (TCN) protocol	decentralized	MIT License	
OpenCovidTrace	decentralized	GNU Lesser General Public License v3.0	[90]
Robust and Privacy Preserving Proximity Tracing (ROBERT)	centralized-decentralized	Attribution-ShareAlike 3.0	[91]
DESIRE	centralized-decentralized	Attribution-ShareAlike 3.0	[92], [93]
EpiOne	centralized-decentralized	-	[94]
SpreadMeNot	decentralized	Creative Commons Attribution 4.0	[95]
ConTra Corona	centralized-decentralized	-	[96]

In Bluetooth-based smartphone contact tracing, BLE packets advertising UUID can be of both static and dynamic nature [81]. There have been several contact tracing protocols studied and implemented over this technology, of which some are mentioned in table 3.

In a typical smartphone-based contact tracing scheme, a smartphone of a person records traces of its surroundings, either in the form of contacts coming in the proximity of a person or location. Later if a person is diagnosed by health authorities as being infected with the COVID-19 virus, the contacts from the person's database are contacted to test them for possible infection. In the case of a positive result, the contacts are isolated and treated, otherwise, they are quarantined for 14 to 21 days, until another check is performed on them. This scheme is demonstrated in figure 11(a).

The architecture of how smartphones collect data has been a research focus with consideration of two pillars,i.e. efficient data collection and privacy/ security. In this respect, the architecture of the contact tracing app operation can be classified as centralized, decentralized or a combination of both, depending upon how information is generated at the client (smartphone) and server-side and what information is exchanged between them. Centralized architectures shift core data processing to server-side, in contrast to a decentralized architecture where the main data generation and processing are allocated on a smartphone, at the cost of privacy concerns. On the other hand, decentralized architecture may exhibit a security risk like personalization attacks [17]. The third category, namely hybrid architecture, ameliorates the negative aspects of centralized and decentralized architecture by asserting data generation and management on the smartphone side, while the corresponding data processing and notification generation are managed by the server side. The overview of these architectures is presented in figure 11(b).

B. WEARABLES

Ultrasound-based technology has shown considerable success to provide a safer, cheaper and more convenient alternative to chest tomography (CT) scan and X-ray scan counterparts. A report [97] showed sufficient capabilities of lung ultrasound imaging for fast identification of COVID-19 pneumonia, in parallel with chest radiograph and CT scan counterparts.

Terahertz sensing (utilizing electromagnetic beams in the terahertz range), while being a non-contact method can achieve high resolution and greater penetration [98]. This characteristic has made it suggested for COVID-19 diagnosis [99].

Wearables like smartwatches have been used either towards diagnosis [100] or monitoring of COVID-19 patients [101], [102]. Usage of existing smartwatch brands like Apple watch or Fitbit [103] to detect possible COVID-19 possibility from heartbeat or activity patterns has been performed in literature. In similar direction, products like WHOOP Strap 3.0 and Biosensor Patch1AX [18] collect physiological signals like respiratory or ECG signals in real time to infer correlation with having COVID-19 infection [18].

In another direction, Apple's AirTag and similar technologies, while being very popular today for tracking purposes are not considered for purpose of contact tracing. Although, there exists some literature on tracking of lost things, as well as pets [104].

C. SMART SENSING TECHNOLOGY

The smart sensing innovations in current technologies, while primarily targeted at the reduction of contact possibilities, is leading to cost-effective, scalable and fast solutions.

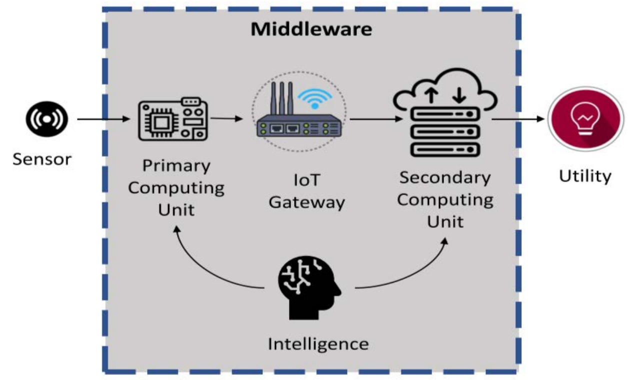

FIGURE 12. Middleware conception in IoT.

However, the progress towards robustness and data efficiency has become rapid due to integration of AI. Smart sensors are sensors connected with microprocessors or digital signal processors to perform real-time filtering operations. These sensors can range from biosensing to ambiance based and their application in the context of aiding counter COVID-19 efforts are summarized in table 4.

TABLE 4. Summarization of applications of Smart Sensing during COVID-19.

Applications	Approach	Ref
Sanitization	Utilization of wireless sensor technology, like infrared. ultrasonic etc. to extend functionality of hand sanitizers and washers, in order to reduce contact	[48], [116], [117]
Biosensors	Non-contact based approach towards sensing of biological characteristics like thermometery, cough detection, breathing rate, ECG, EEG, glucose monitoring, oximetery and heartbeat, which may or may not be IoT focussed	[118]–[125]
Screening	Utilizing of electromagnetic (UWB and Doppler radar, radio-frequency, terahertz) or acoustic beams (ultrasonic) and X-ray spectrum (X-ray and CT-scans), and ultrasonic beams for detection of COVID-19 either at micro-level (blood tests, hyperspectral imaging) or macro-level (organ scan or physical manifestation), providing fast, low cost and non-invasive diagnosis as compared to well established methods like PCR and RT-PCR	[?], [126]–[128], [128]–[138]
Ambience	usage of cameras either as CCTV or robots (in combination with LiDAR) monitoring social distance, followed by estimated air quality and weather conditions for resource planning	[139]–[142]

VI. MIDDLEWARE DRIVEN

Within framework of IoT, middleware can thought of as a black box whose input is raw sensor data and output is the utility formularized from processed data, as depicted in figure 2, thus performing as the union of 5 layers between sensing layer and business layer, as shown in figure 11.

A. COMMUNICATION TECHNOLOGY

The main principle of IoT is to send sensed data to the cloud through some IoT gateway [105]. The IoT gateway serves the purpose of edge layer in 7 layered IoT architecture [105] providing secure [106], efficient and robust transport [107] of data provided between sensor devices and cloud. Its fundamental building blocks consist of hardware (embedded systems coupled with wireless modules) and software (operating system) [38].

Radio-based wireless networks can be classified into four categories: WLANs (Wireless Local Area Networks), WMANs (Wireless Metropolitan Area Networks), WPANs (Wireless Personal Area Networks), and WWANs (Wireless Wide Area Networks).

WWANs cover larger areas and are further classified as cellular and satellite networks [108]. Regarding cellular networks, 5G is the current state of the art and thus most important, permitting high data rate (up to 10 Gbps [109]), capacity and lower delay [110] as compared to it predecessor 4G [111]. This technology is in competition with current WLAN technologies like Wi-Fi 6 which is relatively cheap but has a lesser range. However, research is being done on the next generations Beyond 5G (B5G) [112] and 6G [113], with applications in the COVID-19 pandemic, to improve security, energy efficiency, and area traffic capacity. In this scenario, increasing the traffic capacity of the communication should be of vital importance, since a pandemic usually leads to a significant jump in traffic in communication between patients and healthcare [112].

On the other hand, WPANs are low-powered and medium data rate networks, covering lesser areas, and include popular wireless technologies like ZigBee, Bluetooth, Wi-Fi, and Ultra-wideband (UWB), in the order of increasing data rate. Li-Fi, being less popular than WPAN, is characterized by higher capacity and security, suitable for hospitals and public places. Recently Li-Fi technology has recently been discussed for COVID-19 patient monitoring [114] and surveillance [115].

Generally IoT gateways use WPANs to acquire data packets from sensors augmented with primary computing units and use WWANs to transmit data to secondary computing units [105].

B. PRIMARY COMPUTING

Primary computing unit is an abstraction over a compact sized embedded systems package that performs relatively less computing upon sensor data. This category includes ubiquitous smart gadgets like smartphones, tablets and smartwatches, as well as wearables and equipment composed of specialized embedded systems.

With reference to the current COVID-19 era, popular operating systems of these primary processing unit include

Linux or UNIX-like systems e.g. Android, Ubuntu, Core, Xinu, Linux4Tegra etc. [107] alongside with RTOS (Real-Time Operating Systems). Within this competition, Python has been recently gaining fame due to a single-board computer family called Raspberry Pi [143], [144]. Other popular single-board computer families finding their application during pandemic include Arduino [48], [145], Jetson Nano [146] and Xilinx FPGAs [147].

C. SECONDARY COMPUTING

This abstraction engulfs the large-scale computing functionality upon gathering data from individual primary computing modules. This massive data is separately dealt with the technology of 'Big Data' to systematically analyze management, refinement, and security associated with data. This technology holds immense significance in the COVID-19 context since the data used for systematic outbreak prediction, tracking, and control, as well as diagnosis, treatment, vaccine, and drug discovery is in the form of big data. On the other hand, the services produced from this data are produced through scalable computing systems. Cloud computing has become a popular trend in this domain through the virtual allocation of scalable computer resources [148] on demand [149], excelling previous technologies like network computing, internet computing, and grid computing [150] offering services like software, platform, infrastructure, virtualization, and data storage [149]. These attributes have allowed cloud services to find applications in business, governmental, education, and health sectors [151]. These computing services are further developed as Software as a Service (SaaS), Infrastructure as a Service (IaaS), and Platform as a Service (PaaS).

D. INTELLIGENCE

Artificial intelligence (AI) engulfs the software part of primary and secondary computing and processes the sensor data to produce the utility. Majorly this AI has been centric upon secondary computing units (usually in the form of a cloud) with major applications being thermal imaging-based early COVID-19 detection [152] and monitoring [153]. While it allows versatility in the utility of the IoT system, it is prone to latency, privacy, and security attacks.

Machine learning (ML) and deep learning (DL) intelligence is generally more robust than conventional AI, and the research upon it has been exceptionally active in the context of IoT. However, due to ethical conflicts and lack of explainability from health care providers leaves them less credible for stakeholders in the health industry to adopt them maturely [112]. Furthermore, to resource constraints of IoT systems, scalability of these ML models is essential to conform to the speed, size, and complexity of the mission. However, this is expected to be solvable with the advent of 6G technology that would be readily available by 2030 [113].

With the ubiquity of Ml and DL-driven intelligence, it is the time of need to bring this intelligence directly to IoT devices to reduce the latency of processing and security loopholes. In this respect, work is being done to deploy compact versions of large parameter set DL models onto IoT devices' microprocessors, despite limited computing and memory capabilities. While quantization of these models [154] and prunning [155] are common approaches, new research like [156] and [157] is being done to optimize the architecture of these models for resource-constrained environments like microcontroller's limited SRAM. Such approaches have reportedly allowed more than 32 times memory savings, 58 percent lower latency, and 70 percent accuracy on benchmark deep learning models. Even further, the limitation of Moore's law on semi-conductor has been proposed to pave towards deployment of these AI models on promising emerging technologies like photonics [158] and quantum-based embedded systems [159] to achieve new horizons of computation by harnessing much more freedom of parallelism, not possible on semi-conductor based embedded systems. Furthermore, ML-based intelligence has also paved its way toward IoT security by providing new solutions for network intrusion attacks [160], spoofing attacks [161], large scale attacks and malicious traffic [162] thus reducing additional security cost in the expansion of IoT systems both at hardware and software level.

The intelligence can be considered as an abstraction over primary and secondary computing in either a centralized or distributed manner as discussed in following sections.

1) CENTRALIZED APPROACH

In this approach, the AI mainly operates at the secondary computing level upon the data collected from the sensor. This approach is also termed as Cloud computing approach, and its efficacy is dominant when the IoT devices do not have sufficient computing and/or storage capabilities. In this scenario, the costs associated with data handling and processing is reduced, thus suitable for healthcare services. However, this approach has drawbacks in terms of privacy, security, energy efficiency, bandwidth and latency [163].

2) DISTRIBUTED APPROACH

IoT devices, that can be considered as a composite of sensor and primary computing unit can produce a large amount of data in certain real-time applications while having limited computing capabilities. In this scenario, Cloud computing is not the best choice due to inclusive inevitable latency in data transfer and bandwidth saturation [164]. To this extent, an alternative methodology is to shift the envelope of AI processing over to primary computing units, which would improve latency, privacy, and security issues, and reduce traffic at secondary computing unit side, thus improving reliability in overburden situations as is the case of the initial phase of COVID-19 pandemic.

Despite its benefits, distributed approach, also termed fog or edge computing, can be considered as a replacement for the centralized approach due to the limitation of computation to primary computing units or edge devices and thus cannot provoke power computing tasks. To this end, work is being done to propose hybridized centralized-distributing approaches that can lead to scalable AI implementation with flexible computation resources [165] that would prove monumental in COVID-19 applications with a much larger pool of stakeholders like monitoring of safety measures in public places, mass vaccination, etc.

VII. UTILITY DRIVEN

This section classifies the IoT influence upon COVID-19 from application perspective, with inherent characterization described below.

A. SMART HEALTH CARE

The enforcement of social distancing during the still active pandemic has allowed the general practice of IoT influenced health care, termed as telehealth, e-health or smart health care, thus allowed lesser hospital visits, reduction of burden on hospital resources, and timely and remote care. Even before the current pandemic, the global telehealth sector is estimated to be over 0.3 trillion dollars by 2025 [166]. The use of smart health care could also be prophylactic in dealing with COVID-19 asymptomatic patients by early detection with possible effective treatment. In this regard, a guiding case could be South Korea [167], where around 2 percent of the population went into intensive care for COVID-19 infection when treated for minor symptoms.

The concept of smart health care can be extended into a generic framework, smart cities, through its main core i.e. IoT automation. This would allow more versatile applications beyond health care, like automated COVID-19 guidelines monitoring and even education system [168]. Due to the increasing market of IoT and the huge popularity of 5G, smart cities propose an effective system to not only efficiently handle the challenges of the current pandemic but also future national and global disasters as well.

Irrespectively, smart health care has been effective in the current pandemic situation in the following areas.

1) PRIMARY CARE

Amid the fear of contracting the COVID-19 infection, even many individuals avoided primary and event urgent medical care by not going to the hospital, although the chance of catching the COVID-19 infection is less than 1 percent [169]. With the additional overburden of consumption of hospital resources upon COVID-19 patients, remote primary care consultation has come into play as an effective substitute. UK's National Health Service (NHS) initially responded to COVID-19 management with telephonic services, but this quickly systematically evolved by focusing primarily on tele-primary care. With versatility of smartphones, they have proven to be effective from automated diagnosis and monitoring perspective [57]–[60], [170]. Not only IoT systems are deployed to be dealt with COVID-19 infected patients but also provide support to another category of patients, like diabetic [171] who do not have readily accessible primary healthcare.

2) AUTOMATED DIAGNOSIS

The infusion of AI and medical equipment has allowed new and redirection of several medical equipment technologies. Several new temperature screening solutions, which have been aided with AI techniques to further enhance automation, have been developed [172] to detect temperatures related to COVID-19 infection. Likewise, AI algorithms are being used in the automated diagnosis of COVID-19 cases from radiological imaging scans [173], as well respiratory systems [174]. In this regard, there have been techniques for synthetic augmentation of data sets produced that not only prevent over-fitting but also produce superior accuracy [175]. Although the influence of this technique has not been found in the COVID-19 reference, some efforts have been made to improve CT-scan-based COVID-19 diagnosis [176]. Furthermore, there has been some work done on the diagnosis of diseases using deep learning, from a pathological point of view, by the generation of virtual stains [177], [178]. In another direction, smartphones are being integrated with medical instruments wirelessly, enabling human-interpretable visualization. For example, otoscopes can be wirelessly linked with smartphones to provide a view of the internal of the ear.

3) AUTOMATED MONITORING

Likewise to the theme of automated diagnosis,i.e. the reduction of contact between patients and health care professionals, monitoring in health care facilities is also being automated and work has been done to monitor sound levels in intensive care units [179] and secretion management [180]. Intensive care units have been complimented with IoT to allow remote monitoring of patients by taking advantage of the camera, microphones, and smart alarms to allow communication between patients and healthcare professionals [103].

B. OPTICAL APPLICATIONS

Many optical fields, pertaining to the visible light spectrum, have paved their way in processing several aspects of the global pandemic. With applications spanning contact tracing and diagnostics fields, the following trends have been the most imminent.

1) CCTV CAMERAS

Cameras being the most versatile and popular optical application, came into action as surveillance tools during the COVID-19 pandemic. Closed-circuit television cameras (CCTV) have been finding direct applications in social distance monitoring, contact tracing, policy planning, and safety measure adherence. These applications have been further improved by augmenting the RGB data with data from additional sensors like infrared [181], depth [182] or ultraviolet sensors [139] to produce more sensitive technologies. These technologies have been well complemented with state-of-the-art computer vision and machine learning models like CNN, RCNN, SSD, and YOLO [183] for crowd monitoring and violation zone detection.

2) 3D PRINTING

3D printing has proven to be an extremely versatile and flexible solution for manufacturing protection equipment for medical devices [184]. This technology has allowed providing alternatives to already scarce ventilator machines, and reusable and efficient masks. testing devices and isolation wards [184].

3) VIRTUAL REALITY

The field of virtual reality has been greatly affected by the pandemic due to its utility while enduring lockdown. Its global market is estimated to be around 62 billion dollars by 2027. Virtual reality, while affecting the fields of entertainment, gaming, sports, and simulation [185], is also transforming the traditional way of medical training [186]. Not only this but also virtual reality has proven to increase patient satisfaction by providing a visual aid for diagnosis reporting, as well as supplying therapeutic media to patients recovering from physical [187] or emotional injury [188].

4) HOLOGRAPHY

Holography is a branch of optics that generates a view of an object in 3D space. While telecommunication software's usability has boomed in the lockdown due to COVID-19, as seen with the case of Zoom, Skype, and Microsoft Teams, virtual perception of real events has become prone to acceptability [122]. Furthermore, holography has been combined with digital microscopy [189] and mixed reality [190] towards rapid screening of COVID-19 and a better understanding of the damage caused by COVID-19. Although, these directions are so far relatively in the initial stages.

5) OPTICAL SENSORS

Optical sensors provide a rapid alternative to time costly diagnosis tests of COVID-19 like RT-PCR. Recently optical fiber-based sensors for the screening of COVID-19 [191]. [192] reported work being done on laser nano-interferometric lasers for non-contact screening of COVID-19. In this direction, a more simplistic technique, in terms of apparatus cost, namely self-mixing interferometry [193]–[195] can allow economical non-contact screening solutions with sufficient accuracy and resolution, but so far no work has been reported on this. Utilization of these techniques might prove fruitful for innovation in future smart sensing technologies. In a similar fashion, spectroscopic techniques like Fourier, Raman [196], [197], Fluorescence and Surface Plasmon Resonance spectroscopy [198] have found applications in early diagnosis from swab samples.

C. WEB SERVICES

With web browsing as a common necessity and luxury in the modern era, several web-based services have been developed and even reshaped, targeting tasks ranging from assisting and informing the general public to communication between the public and institutions during lockdown policies, through blogging, messaging, video calling, networking, and software sharing platforms. These trends are further elaborated on in the following sections.

1) CHAT SERVICES

A study in 2021 [199] analyzed calls that occurred on the national crisis hotline regarding the topic of suicide, during the pandemic and deduced that elderly people were most impacted by the lockdown. Not only this but also related chats rose to almost 50 percent as compared to the pre-epidemic routine. Therefore, the availabilty of chat services with either human personnel or bots could help people face the lockdown during the pandemic period.

Since controlling the pandemic demands social distancing, thus minimum interaction between health care professionals and patients could reduce the possible number of risks. One such strategy is the utilization of mobile and web-based bots to assist the patients in their time of need. Furthermore, they can be monitored through technologies like robots [200] and smart health care units [179].

2) INFORMATION MEDIA

Many digital solutions, focusing on mobile technology, are putting efforts to provide the most accurate COVID-19 related and health information to the general public [201]. With massive amounts of information produced and exchanged on social media and websites, with its intensity overshot in the current pandemic, the associated demerit, i.e. false information, has also become significant and its solutions to tackle this becomes necessary since they may lead to deviation of political, social and health education correctness of a large portion of the society, which can indirectly affect the efforts against containing the pandemic.

In order to detect misinformation online, several datasets have been developed [202]. Several news mining tools are available online with the ability to analyze and classify a large portion of information online as big data.

On the contrary, news and information from credible information have been made publically available through interactive dashboards [203]. Some AI-enabled information platforms are being proposed that use natural language processing techniques to translate information media content into the native language from reliable sources [204], as well as use social media activity to warn the general public about pandemic activity [205].

3) CHATBOTS

AI chatbots are gaining popularity due to their effectiveness both from a business and utility point of view [206]. AI chatbots can not only provide an informative and therapeutic resource during lockdown amid COVID-19 but also help in diagnostic evaluation and recommending measures to individuals recently identified at-risk [207]. Likewise, some chatbots are being developed to imitate health care professionals [208] to meet the supply and demand of medical consultations.

4) VIDEO CONFERENCING

While pandemic has generally brought negative impacts on people's well-being and their daily schedule, video conferencing has proven an influential factor Videoconferencing platforms have been used to help common public and mentally ill patients [209] deal with symptoms of anxiety, depression and stress during the lockdown. A study [210] found a positive correlation between less loneliness and videoconferencing among older people. Furthermore, video-based primary and specialist care has proven to be effective to overburdened hospital schedules and has reportedly been providing a satisfactory substitute for both patients and doctors [211].

Within the education sector, the shift of physical learning towards e-learning while producing its challenges, in terms of proper accountability of students and fairness of the testing, has allowed accessibility of education to a broader audience who cannot afford education. In mitigating the challenges of e-learning, some solutions have been produced [212]. Nevertheless, some studies [213] suggest the potential of video-based social media platforms to produce engagements, questioning ability, and collaborative learning capabilities in education institutions.

D. ADMINISTRATION

Since the global pandemic outreach necessitates spread prevention and disease eradication strategies, the associated administrative actions are critical to producing sufficient efficiency. This gives room for the inclusion of many AI-based technologies to not only aid the associate officials in decision making but also automate the process or policy and resource planning.

1) POLICY PLANNING

With many stakeholders involved, policy planning is of critical importance in the COVID-19 era and digital technology has played a pivotal role in improving the accuracy and effectiveness of planning. In this regard, work has been done that utilized AI, parallel computing, and network science to address planning lines of action in response to epidemic [214]. Basically, the steps include modeling of agents representing individuals, followed by generation of time-varying interaction networks, simulating the corresponding epidemic process, and modeling the evaluation of several interventions and public policies [215].

Autonomous policy enforcement systems are being proposed, fundamentally based on IoT, that can gather data from different sources like from public contact-based to hospital-based data to allow data-driven decisions that can control the spread of pandemic [216]. One of the important AI's considered in these autonomous systems is reinforcement learning [217], [218], which has proven to be state of the art in providing effective data-driven policies in cost reduction, spread minimization, and lockdown optimization.

Satellite imagery-driven machine learning has been gathering recent research attention, particularly due to the fact that such data provides a birds-eye view to allow guided implementation of suitable preventive strategies [219]. But such literature is mostly about COVID-19 crises like flood and weather disasters. In this direction, [220] provided a generalizable and accessible approach towards this direction, and it certainly shows promise in shedding light on policy making, resource allocation, and spread prevention of COVID-19.

2) RESOURCE PLANNING

While lockdowns and other preventive measures have greatly impacted the financial status of society as a whole, the prior development phase of vaccination programs has become ripe enough for mass distribution and administration. In this respect, the mathematical supply chains frameworks [221] are being developed to minimize the cumulative costs and lost doses [221] in terms of transportation and capacity.

Even still, the vaccination and drug research and development is still at large, due to the introduction of many variants of the original virus-like Alpha, Beta, Gamma, Delta and even strong variants like Omicron [222]. On the contrary, the parallel efforts in prevention and hospitalizations are still as critical. In order to deal with the burden over hospital resources like ventilators and beds, an open-source tool was developed for optimized planning of needed hospital resources to handle future load [223]. Machine learning-based targeted testing has been implemented along the Greek border to allocate limited tests for traveling across borders (an estimate of 18.4 percent capacity of performing tests on travelers was recorded during the peak of summer tourism in Greece), by deducing which travelers are likely to be testing positive [224].

VIII. PRIVACY AND SECURITY

Privacy and security features are an essential demand of IoT, and this trend has been greatly amplified since the pandemic due to the involvement of a greater pool of stakeholders like the governmental organizations, health care, and educational sectors [225]. Since IoT-based systems are usually resource-constrained, therefore, the installment of sophisticated security and privacy features is itself a challenge and produces a greater probability of cyberattack targets in this sector. Furthermore with data collection, ensuring privacy and security in handling of that data becomes mandatory, which may be guided by regulations like GDPR or data protection impact assessment (DPIA), in terms of what information can be stored and shared [79]. Violations of these guidelines can lead to serious penalties, as happened with the case of a major platform like Whatsapp for being charged 225 million euros by the Irish Data Protection Commission, for violation of privacy regulations, the second-highest fine under EU domain [226]. However, they might be overwhelmed by an opaque chain of sub-contracts in the process of outsourcing to private firms. This lack of transparency may lead to an invasion of privacy and trust, as happened with the case of the NHS app, where ID checks of users on this app were performed by facial recognition on more than 16 million UK citizens by a private subcontractor [227].

According to a talk [225] by a cyber security-based company 'Tide', the investment in IoT suffered as much as 2360 percent losses to data breaches in 2021. Likewise, recent estimates show that costs of malicious cyber attacks would be over 10 trillion dollars per year by 2025 [228]. In response to this, they developed a blockchain-based zero-trust protocol to encrypt sensitive information within IoT-based systems.

In this regard, [229], there are 14 privacy and security requirements that should be adhered to when implementing IoT-based systems, which can be further classified into long-term (LT) and short-term (ST) requirements based on the duration of their impact. This classification is elaborated in table 5.

To provide resolution to the classifications of privacy and security requirements, they are further compared with their overall graph features, as discussed in 'Analysis Methodologies' section, by considering their arithmetic mean. It is evident that while the interest index and research index are balanced for both short-term and long-term privacy requirements, the average reduced citations and entropy of research in long-term privacy requirements in prevalent.

Based upon these requirements, the security solutions can be categorized into key management, intrusion detection, blockchain [229] and anonymization [230]. With anonymization and blockchain techniques as standard choices, they ensure data availability, data unchangeability, data authenticity and data encryption [231] through sophisticated employment of cryptographic methods like hashing (irreversible perturbation) and encryption (controlled reversible perturbation) [230]. These solutions are meant to either prevent or deal with cyberattacks which can be phishing, malware and DDoS (distributed denial of service) [232] in nature. Among these, DDoS is considered the most serious to mitigate [232]. On the other hand, malware types attacks are the most transmissible that can affect up to four layers of the IoT architecture [233].

With COVID-19 smartphone apps being one of the most active digital actors during pandemic, they are prone to likewise privacy and security risks. For example, there has been work done in extracting geolocation information from mobile apps [234], [235]. Similarly, a study [236] outlined transparency and necessity in data collection, retainment and sharing as the main privacy concern related to contact tracing. On the contrary, possible security risks associated to contact tracing related system may include bluesnarfing, playback attack, wireless device tracking, denial of service, enumeration and carryover attack [236].

Generally, smartphone apps are prone to replay/relay attacks, device tracking, location tracking, enumeration attack, denial of service, linkage attacks, carryover attacks and disclosure of social graph [17]. The essence of these security threats is to either track user's location or ID, or perturb the functionality of device. These apps are required to request permission from users to gain access to specific functionality of smartphones, of which about one third are known to invade user's privacy [237] and even starts logging location without formal registration to the app by user. According to a study [237], EU based apps are comparatively privacy preserving, as compared to non-EU based apps due to conformity of GDPR regulations, yet pertinent to security vulnerabilities.

With smartphone apps being deployed over Android and iOS platforms, these platforms are themselves vulnerable to cyber attacks like Gain information, Bypass, Overflow, Memory corruption, Denial of Service (DoS), SQL injection, Cross site scripting, HTTP response splitting [76] and malwares. While iOS platform's security is more restrictive and robust, they are still known to be prone to malware attacks [76].

In order to deal with privacy related issues, the architecture of flow of information between smartphone app and a global server comes into play. With such architectures classifiable into centralized, decentralized or centralized-decentralized, centralization is often easier to implement as compared to a decentralized counterpart [238] but at the cost of lesser privacy, more security risks and additional processing and storage requirements. Usually privacy risks are invoked due to control power of health authorities and governments over user's personal information from the central server, and by nefarious entities that may systematically hack into local device or a back-end server to extract sensitive information [239]. Possible security risks to contact tracing systems may include data leaks from the server and user side [239], in centralized systems. Other attacks include false positive claims and relay attacks [239].

Amongst technologies adopted by COVID-19 contact tracing apps, GPS-based contact tracing apps are known to be less privacy-preserving due to the collection of location data like longitude-latitude data. Such schemes are prone to security risks like spoofing attacks [240], where false detections are induced by fake GPS signals. Additionally, GPS-based contact tracing creates trust issues from the user side. On the other hand, GPS-based contact tracing can allow the capture of additional information about epidemic like environmental contamination [79]. It has been advised that utilization of location data is prone to security risks like differential privacy attacks [238], [241], even when such data is anonymized.

On the other hand, while BLE-based contact tracing apps are known to be privacy-preserving, especially in the decentralized scenario, still the data collected from them are known to be de-anonymized [242]–[244]. Not only this, but also there have been studies demonstrating the trackability of device's fingerprint around the internet [245], [246] or through, geo-localization [247], eavesdropping attack [248], trolling attack [249], and identity tracking [250] using BLE. Even GDPR-certified BLE decentralized protocols like Exposure Notification and Decentralized Privacy-preserving Proximity Tracing protocol are known to be prone towards Linkage attacks where recorded beacon traffic can be interpolated towards location estimation. Furthermore, there have been studies analyzing criticizing the precision and authenticity of the BLE protocols [251], [252].

Other methods like use of surveillance cameras, QR codes, mobile operator etc can record places-based data. Although

TABLE 5. Classification of 14 main privacy and security requirements and their comparison based on mean of their graph features: reduced citations (c'), interest index (I), research index (r) and entropy (S).

Requirements	Impact Classification	mean(c')	mean(I)	mean(r)	mean(S)
Session key establishment, forward secrecy, session key security, mutual authentication	Short term (ST)	7.48	0.97	0.93	0.38
conditional privacy preserving, differential privacy, patient anonymity, non-repudiation, location privacy, traceability, data authenticity, unforgeability, identity privacy, data integrity	Long term (LT)	19.86	0.98	0.94	0.41

there have been many privacy preserving solutions proposed [229], [236], [253]–[256], but they are at the expense of greater computation [257].

IX. ARTIFICIAL INTELLIGENCE

This section discusses research and application directions of artificial intelligence towards COVID-19 pandemic.

Artificial Intelligence can be characterized into two broad categories depending upon whether preset rules for computation are defined or not:

- Algorithm Driven
- Data Driven

The first category of AI has a concrete assignment of its sub-parts for evaluations of outputs from given inputs, depending upon the problem. However, the latter category utilizes prior data of the problem at hand, to design the sub-parts of AI, which finally is able to consume the input to produce output. These classifications are further described in the below sections.

A. ALGORITHM DRIVEN AI

Artificial intelligence was originally realized as the formulation of algorithms to solve a particular problem. Development of data driven techniques came at a later stage when such technique reportedly gained superior performance against the state of the art algorithms, as happened with the case of AlexNet (a data driven AI algorithm) outperforming other state of the art image processing algorithms [258]. Even still, due to the longer history of algorithm driven AI, its applications are still prevalent in COVID-19 context. To this end, the corresponding AI being deployed is first designed by a professional engineering team, as a raw algorithm composed of certain thresholds, which are determined by empirical evidence gathered and monitored by experts in the field of the problem at hand. After that, rigorous field testing is performed on that algorithm to make it certifiable for industrial applications. This is described in figure 13(a).

B. DATA DRIVEN AI

Data-driven AI, more commonly referred to as machine learning (ML), encompasses an array of techniques that primarily constitute two fundamental structures, namely linear and/or non-linear models. A technical combination of the ramification of these units gives rise to a variety of techniques of both low and high complexity, in terms of a number of free parameters. These free parameters are needed to be adjusted, based on prior data, through mathematical optimization techniques, the most employed ones being the family of gradient descent algorithms (important optimizers being stochastic gradient descent (SGD) and Adaptive Moment Estimation (ADAM)), Levenberg–Marquardt optimizers and nature-inspired algorithms like genetic algorithms, ant colony optimizations, etc. Data-driven AI gained its reputation by providing excellent performance into many AI-related problems, previously handled by algorithm driven AI, including problems belonging to Natural Language Processing (NLP), image processing [258] and game playing, to say the least [259], that could not have been possible with conventional algorithm driven AI.

The low complexity classification includes techniques like linear and LASSO regression, Support vector machines (SVM), k-nearest neighbors (k-NN), k-means clustering, Linear discriminant analysis (LDA), and reinforcement learning (RL). A very important and abstract category of this category is artificial neural networks, also called feedforward networks (FNN), which mimic the structure of biological human brains [260]. Feedforward neural networks are infact an iteration over fundamental units called perceptron, which are inherently a linear system followed by a non-linear system. The architecture of FNN is described in figure 14(a). These models can be interpreted as collection of nodes, connected with edges (commonly referred to as weights). These nodes can be grouped as layers, comprising of input layer, hidden layer and output layer. The input layer interfaces with the inputs, and the output layer interfaces with the output. The hidden layer is sandwitched between input and output layers and can be of arbitrary number with different number of nodes. At each node, the data from previous nodes get multiplied by weights and summed up to produce an output. This is equivalent to a standard linear model. Moreover, at nodes after first layer, the output is further passed through an activation function, which is usually non-linear in nature. The weights of these models are adjusted by optimizing a suitable objective function on inputs and final output towards its minimum. This iteration of the perceptrons increasing fitting capability of the ML model over prior data.

Moreover, it is to be noted that FNNs in their most basic form as perceptrons are equivalent to all low complexity ML models with proper choice of linear, non-linear models and objective function. These FNNs, when increased in depth or

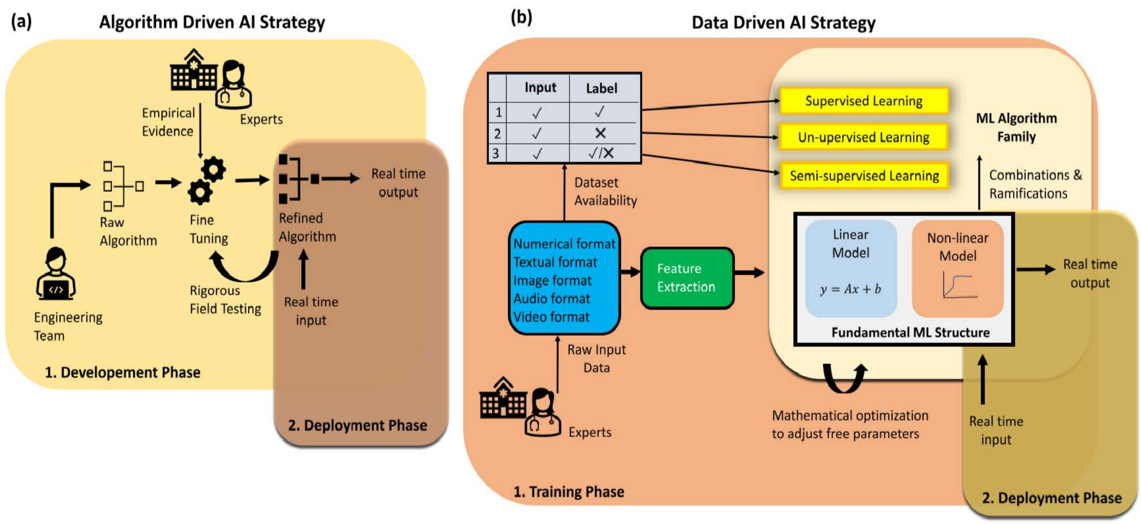

FIGURE 13. (a) and (b) describe functional flow of algorithm driven AI and data driven AI respectively, in application to COVID-19.

number of hidden layers, become an integral part of deep learning and provide basis for further deep learning models, which are high complexity data driven AI techniques. That being said, the topology of several families of these data driven AI models, impacting COVID-19 efforts, are presented in figure 14 (b). While there is significant diversity in such topologies, many topologies have less exhausted but recently gaining attention in COVID-19 context, forexample, less explored Kohonen networks have been finding applications in autonmous unmanned vehicles (UAV) for crowd sensing and detection of COVID-19 cases [261].

These ML models can also be characterized as supervised, unsupervised and semi-supervised depending upon whether the prior dataset contains information of output (commonly referred to as labels), do not contain, and contains information only for some inputs. In any classification scheme, the ML models proceed towards applications as follows: first experts in their respective field produce reliable datasets, that contains information on inputs and outputs related to the field. Next, the training phase takes place, where the parameters of the chosen ML models are optimized with respect to these datasets. After rigorous testing of the accuracy of these models on prior data, they are deployed industrially where they can deal with real-time inputs. This is represented in figure 13 (b).

1) DATASET AVAILABILITY

The research and utilization of deep learning in COVID-19 situations have been very active and several real-world datasets from governmental, private, and public organizations and companies are made open source to aid ML research. Despite this, there is still a significant restraint on not only availability but also the credibility of datasets [262], [263], one main reason being that many organizations generate such datasets for their own applications. Furthermore, since the healthcare professionals, policy and decision-makers do not have technical access to this AI, therefore the translation of these materials towards interactive and interpretable web or platform-based applications is of important value [2]. To this end, several datasets related to COVID-19 were identified and are classified, as per how they relate to AI applications. These categories are computer vision, signal processing, natural language processing, epidemic statistics, graph theory, and meta. These datasets can be readily available to train models upon or requires some additional technical tool to extract the raw useable data. The associated information of these datasets and their distribution is tabulated in table 6 and figure 15 respectively.

AI techniques have been previously employed to contain the previous epidemics, like tuberculosis, in diagnosis [425], detection [426], prediction [427] and tracking [428]. However, with further development of several AI fields along the way, the literature of AI attending to current COVID-19 pandemic has become richer and state of the art.

An overview of several AI applications in COVID-19 topic are concisely tabulated in table 7 and 8. To add resolution, the AI field in COVID-19 context is divided into several regimes and discussed further in the following sections.

2) NATURAL LANGUAGE PROCESSING

Natural language processing has been used in combination with deep learning [429] to make COVID-19 literature, available on sites like ArXiv or PubMed [430], more readable and accessible to scientists, thus boosting research. State of the art NLP-deep learning models like BERT and its variations have been applied to perform tasks like question-answering, semantic search, and summarization of literature [431], [432].

Deep learning-based NLP models have been used to classify or identify misinformation [433] on social media platforms, which is needed as the spread of false information

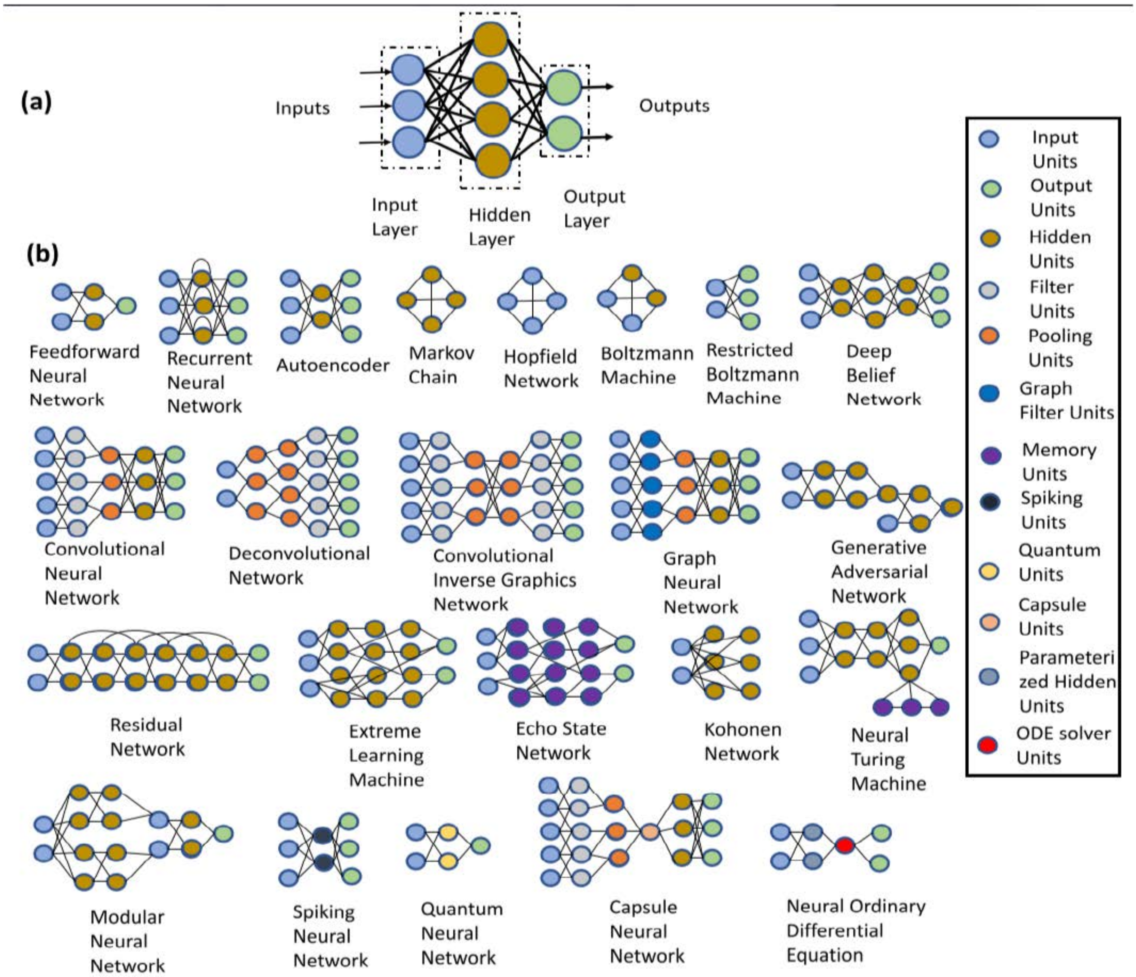

FIGURE 14. (a) Basic architecture of FNN (b) Architectures of several general data driven AI models that have been applied in COVID-19 related research.

can lead to dangerous false opinions like reluctance towards vaccination.

Natural Language Processing Tools have been used to construct knowledge graphs which have been lucrative in the drug discovery domain [434], [435]. Not only this but such knowledge graphs are also useful in aiding researchers and policy makers to analyze through heavy COVID-19 related literature [436]. Such advanced models, including Transformer based models [437], can be useful to further perform sentiment analysis upon social media activity, like on Twitter trending tweets [438], which can provide insight to policy into general public mental state allowing to make more informed decision.

3) BLOCKCHAIN

Blockchain refers to a collection of blocks connected through hashing functions (most notably SHA-256) [439]. Working in a decentralized peer-to-peer network, two neighboring blocks mutually verify the information shared between them. This is contrary to the concept of centralization, which permits the gathering of data into a singular spot and prevents distribution. On the other hand, this trait allows centralization to be prone to data breaches [440]. In 2017 alone, over 0.14 billion customer's data was stolen [441]. [442] reported 2219 data breaches between 2005 and 2010 in US education and health care centers. Originally invented as the underlying principle behind cryptocurrency 'Bitcoin' by Satoshi Nakamoto in 2008, blockchain permits the reduction of unconfirmed transactions while increasing the integrity of the system [443].

While invoking attributes of security, trust, and rapidity, blockchain has found numerous applications in COVID-19 era with the goal of verification, and sharing. These applications may range from contact tracing, to resource allocation and record management. For example, there have been frameworks proposed to allow blockchain-inspired systems for social distance monitoring and contact tracing [444], [445], collection of IoT based data, robots, and drones based surveillance and contactless delivery, as well as sharing of COVID-19 data [446] locally and globally between hospitals and institutions. In terms of record management, which

TABLE 6. Categorization of detected COVID-19 datasets according to the fields of AI with references.

Dataset Category	Ease of Availability	Nature	Ref
Computer Vision	yes	lung CT and X-ray scans, Facemask availability	[264]–[278]
Signal Processing	yes	coughing and breathing sounds, accelerometer and gyroscope data	[279]–[285]
Natural Language Processing	partial	social media texts, bibiliographic data	[275], [286]–[291]
Epidemic Statistics	yes	numbers on states of epidemic like vaccinated, infected, deceased etc.	[292]–[312]
Graph Theory	partial	contact and mobility statistics	[313]–[324]
Meta	yes	contains more than of prior categories	[325]–[328]

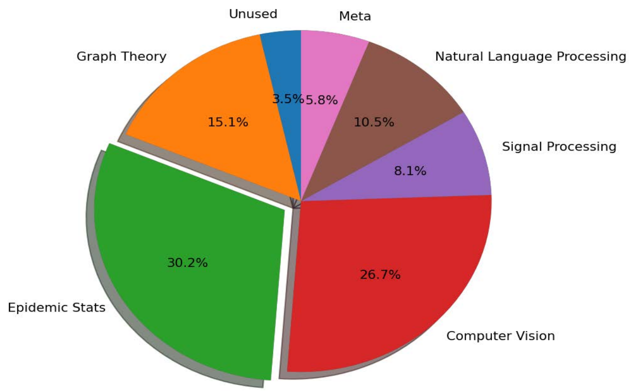

FIGURE 15. Distribution of useful datasets for machine learning applications in COVID-19 context.

essentially demands privacy and security, vaccination, diagnostics, and immunity certificates are made credible with blockchain technology [447] which imposes an efficient and trustable system for registration, distribution, storage, and reporting of negative side effects of vaccine administration [448]. The authentication of vaccination reports becomes important, as, since August 10, 2021 [449], the number of fake vaccination certificate vendors have approached 10,000 in 29 countries on social media platforms, and this may lead to information about the pandemic status and expectations from policies not being credible.

Since blockchain enables seamless, secure, autonomous and decentralized human-to-machine and machine-to-machine data exchange, they are a valid solution, in the form of smart contracts, to aid pandemic affected national sectors like finance and agriculture [450]. The literature on blockchain methodology has been rich for COVID-19 applications in different configurations of blockchain infrastructure [451]–[453], [453]–[455] and have been summarized in figure 16.

4) COMPUTER VISION

Due to situation-wise lack of doctor availability and even false positives from expert diagnosis from medical imaging [456] and RT-PCR tests [457], computer vision is an essential tool to efficiently compensate for this drawback, especially when such technique is able to provide well over 99 percent accuracy [276] over diagnosis from CT-scan based medical imaging. Computer vision influence on medical imaging can be realized as either classification, segmentation, or reconstruction tasks [458] on images or videos. Conventional computer vision has been dominating imaging diagnostics from a segmentation point of view, where the main approach lies in segmentation of the processed image, followed by estimation of the region of interest to estimate severity [459].

For the case of COVID-19 diagnostics, medical imaging can be mainly divided into chest X-ray scans or CT scans, and they have been widely used in this domain [460]. Studies have suggested CT scans to be more sensitive to detection of COVID-19 by 20 percent, as compared to RT-PCR test [461], but this approach may not be economical. This propels some studies to prefer X-ray scans to be a cheaper and less radioactive alternative [462]. Furthermore, these scanning technologies are further automated with AI algorithms that can determine optimal parameters for the highest resolution images based on the patient's pose [463]–[465].

Computer vision has been surpassed through deep learning models ever since AlexNet (a convolutional neural network) surpassed established computer vision algorithms, with manually engineered features, in the 2012 ImageNet Large Scale Visual Recognition Challenge [258].

Computer vision deep learning models are composed of feature extractors augmented with a function approximator, and they have been majorly playing the role of classifiers in COVID-19 imaging diagnostics. What transfer learning does is that it dissociates the feature extractor of a model trained on some other dataset, and then uses that feature extractor as a starting point for training on a new dataset or to use the same feature extractor and augment it with some other kind of function approximators like the same connected layer or some other machine learning model. The lack of datasets for chest X-rays and CT scans for COVID-19 patients makes transfer learning a viable option [466].

a: MEDICAL IMAGING

Artificial intelligence has dominantly been researched in the COVID-19 context in the form deep learning based diagnostic imaging, and has been previously rigorously studied for general diagnostics through clinical trials [467]. This direction

TABLE 7. Summary of applications of AI in COVID-19 era.

Concept	Description	Trends	Techniques	Challenges	Ref
Drug discovery and repurposing	Developement of therapeutic drugs to mitigate the effect of the disease	drug-target interactions (prediction of binding tendency between compounds and COVID-19 infected proteins), drug-drug synergy (analyzing molecular similarity between current viral drugs and second generation drugs) and combination of prior for discovery of new design of COVID-19 inhibiting molecules	Machine Learning (SVR, SVM, Random Forest, feed forward neural network, Hidden Markov Model), Deep Learning (MLP, CNN, LSTM, RNN, GRU, GAN, Autoencoders, Reinforcement Learning, Natural language processing, Baeysian Classifiers, graph attention networks, active learning)	Limited datasets upon novel virus interactions with drugs	[329]–[333]
Viral Study and Vaccine Discovery	Study of viral structure and characteristics of of corresponding disease. Such analysis include genomic and phylogentic analysis which may signify virus origins and accelerate vaccine production.	Prediction of antibodies corresponding to virus.Prediction of protein structure of virus	Supervised Learning (Decision Trees, SVM, recurrent geometrical network, LSTM, transformers,Random Forests, MLP, Logistic Regression, Reinforcement learning), Digital Signal Processing, Molecular Dynamics Simulation	Bias and imbalance in datasets	[334]–[342]
Social Media Analysis	deduction of lucrative results from information shared on social media platforms	infodemic (spread of misinformation), Sentiment Analysis on platform like Youtube, Twitter, Instagram, Gab and Reddit, Distance learning, Characterizing self-reporting of symptoms into epidemic statistics and diagnosis, experiences with testing, and mentions of recovery	Supervised learning (linear and logistic regression, naive Bayes classification, decision trees, support vector machine, autoregressive neural networks, LSTM, transformers), unsupervised (Latent Dirichlet Allocation)	Data available may be noisy and insufficient, systematic scalable deployment of analysis tools, privacy concerns	[343]–[354]
Epidemic Modelling and Forecasting	Modelling of states of real epidemic (usually numbers) as differential or stochastic system	Model based Curve Fitting, Parameter Estimation, Forecasting. Dataset based forecasting	Deterministic and Stochastic versions of compartment models(Logistic, SIR, modified SIR), Deep Learning (LSTM, RNN, GRU, CNN-RNN,CNN-LSTM, Prophet, Transformers), linear regression, LASSO, Support vector regression	limited and incomplete datasets with lack of geo-spatial, social, political and statistical information, parameters of epidemic model vary over time inducing uncertainity, imperfection in assumptions underlying epidemic models,	[355]–[369]
Quarantine Monitoring	Validating if susceptible population is properly isolating themselves with precautionary measures like mask wearing	Smartphone biometric(face image, GPS) identification, utilization of social media apps like WeChat, IoT driven quarantine monitoring and reporting of abnormalities in biosignals, Drone based monitoring	Deep Learning models (Facenet), Utilization of sensors like ear, blood, motion sensors etc to monitor biosignals (temperature,blood pressure, respiration rate), Computer vision and machine learning techniques like SVM, HOG etc	Privacy preservation	[370]–[374]
Contact Tracing	Identification and containment of contacts of an infected person	Both forward (looking for post-contacts) and bidirectional (looking for both pre- and post-contacts) contact tracing through digital tools like Smartphone Apps and Blockchain Technology. Privacy Preservation on data collection like GPS, Bluetooth, Wi-Fi, UWB, in either centralized or decentralized manner. Applying ML and AI techniques on collection data, human activity recognition to scrutinize contact tracing	Imposition of centralization, decentralization and their combination as architectural theme for data sharing between client and server. Hashing and cryptographic based generation of BT's ID, Usage of blockchains with and without combination with cryptographic protocols like Diffie-Hellman, zero knowledge, blind signatures and proxy re-encryption	GPS performs poorly in heavily built up outdoor and indoor areas. Different phones transmit bluetooth at different strength, as well as orientation variant transmission, affecting distance estimation. Different app architectures are prone to security risks like replay/relay attack, device tracking, enumeration attack, denial of service, de-anonymizing the users, carryover attack, disclosure of social graph, lack of transparency of data for researchers, false positives, trust issues, malicious vulnerability	[17], [257], [375]–[387]

TABLE 8. Summary of applications of AI in COVID-19 era (continued).

Concept	Description	Trends	Techniques	Challenges	Ref
Policy Enforcement	Developing policies like assigning hospital resources, planned lockdowns etc. that minimize the spread of infection	AI based decisions are employed after analysis of social distance monitoring, contact tracing, drug discovery, vaccine production, intelligent transportation. traffic monitoring etc. in combination with availability of resources	Integration of IoT with health and transport sectors, Deep Learning(reinforcement learning, transfer learning techniques), Network Analysis, Epidemic Models, Agent based simulations	Privacy and security in data collection in sharing, data availability, operational costs	[216], [388]–[392], [392], [393]
Patient Monitoring	Monitoring of patient's vital and reception of corresponding prescriptions	remote monitoring of COVID-19 infected as well as other ill patient's biosignals via smartphone apps, web apps, IoT, CCTV, signal processing, machine learning models to determine the need to be hospitalized	geofencing, time frequency analysis, machine learning (logistic regression)	Operational and energy costs, availability of sensors, acceptability of such technology	[394]–[401]
Automated Diagnosis	digital diagnosis of COVID-19 based on symptoms which may allow timely treatment and prevent spread	utilization of IoT and deep learning models to monitor breathing patterns, oxygen saturation level, temperature, detection from lung ultrasound, CT and X-ray scans	utilization of sensors like accelerometer, microphone, camera, WiFi etc. either self-workable or as a contactless system , Deep learning models like variations of CNN, GRU, RNN, LSTM, Vision Transformers etc.	While such methods are fast and convenient they are less reliable and accurate as compared to well established methods like PCR test.	[152], [394], [395], [402]–[406]
AI Assistants	Automated software products to assist health care workers and general public	Screening and rehabilitation of COVID-19 patients, accessibility of health related knowledge, inquiry, update of health records, for general public, either through dedicated platforms, already present platforms like Siri and Alexa or as chatbots on social media platforms like Whatsapp, radiologist assistants to diagnose from imaging like CT scans, help people deal with anxiety during lockdown	NLP, deep learning techniques(particularly CNN)	Public adaptability as people prefer real humans, need of internet connection	[407]–[413]
Social Distance Monitoring	Detection of people and relative distance between them beyond 6m threshold	Utilization of IoT devices, drones and unmanned aerial vehicles to ensure social distancing, mask wearing, computer vision, human mobility monitoring through activity recognition	Machine Learning (SVM), Deep Learning (CNN,YOLOv3, HOG, SSD, YOLO-tiny, DeepSORT)	Faulty camera calibration and occlusion in computer vision models, Privacy concerns, Trust evasion due to lack of transparency	[146], [183], [414]–[424]

provides an alternative route to RT-PCR based diagnostics, which is prone to high false-negative rates [405]. In some studies, CT-scan imaging based diagnosis is considered a better option than RT-PCR based diagnosis [468], but this is challenged by its poor specificity due to the lack of differentiation between pneumonia or adenovirus infections [469]. From deep learning perspective, despite the challenges of lack of transparency, explainability, and expert inclusion, significant work has been to done to overcome these challenges, which has recently led to the first industrial AI for autonomous diagnostic imaging in clinical use [470].

In deep learning framework for diagnostic imaging, datasets from two major imaging technologies: chest CT and X-ray scans are usually studied upon, while other notable technologies include lung ultrasound scans, that relatively more safe and convenient at the cost of reduced sensitivity [406]. A common framework for the application of deep learning in this scenario is discussed in figure 17, where CT-scan based dataset is considered as an example, however same is the case for X-ray scan-based deep learning methodology.

It can be noted from figure 17 that another class 'Other Disease' is added as many characteristics of effects of other lung related diseases like pneumonia is similar to that of COVID-19, therefore a misdiagnosis is possible from the lung scans [471], [472]. The purpose of the intermediate data augmentation step is to increase the classification accuracy and reduce the over-fitting capacity of deep learning models by increasing the size of the original dataset, usually achieved through GANs [473]. It is followed by the image pre-processing step whose aim to denoise images and extract useful features to be fed into a deep learning model, that does not only improve classification accuracy but also reduces the training time of the associated deep learning

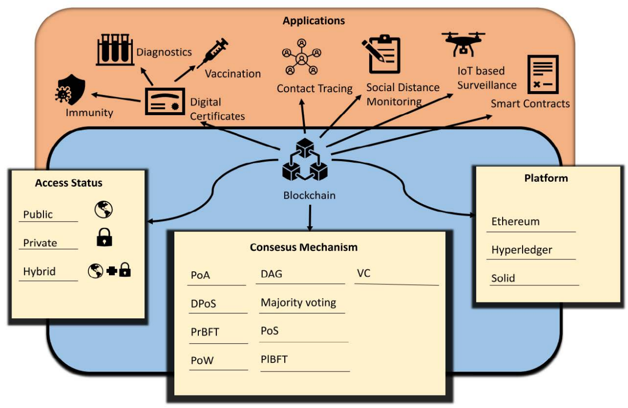

FIGURE 16. Blockchain applications and configurations in counter COVID-19 efforts.

model. Additionally, the last layer in figure 17 is intended to represent a 'softmax' layer [472], which is a class of activation functions suitable for multi-class classification.

While a multitude of deep learning architectures have been researched upon for medical imaging-based COVID-19 diagnosis, the configuration of common models [474], [475] is described in table 9. It is empirically evident from attributes of a number of parameters and accuracy density of these models that the depth of the models while leading to overall greater accuracy are negatively correlated with the individual parameters towards the accuracy of the model. For case of CT scans, the main trend has been either to construct architecture of a new model that can appropriately capture features, or to transfer the features learned from other well-trained and established models. Notable examples of dedicated models include spiking neural networks (SNN) [476], DenseNet-169 [134], VGG-16 [134], VGG-19 [134], ResNet-50 [134], InceptionV3 [134], Ensemble Deep Classifiers (EDL-COVID) [477] with maximum reported accuracy of about 99 percent. On the contrary, transfer learning approaches comprise of ensemble transfer learning techniques [478] (where as much as 15 pre-trained models have been reportedly compared), as well as complimenting transfer learning with generative models like CycleGAN [479], which have pushed the maximum accuracy towards 99.6 percent. Furthermore, works on ResNet-101 and Xception deep learning models have report an accuracy around 99.9 percent [456].

Likewise, X-ray scans tend to follow the same trend with constructed deep learning models like ResNet-50 [480], ResNet50V2 [278], XGBoost [481], VGG [480], Covid-Net [480], Covidx-Net [482], DarkNet [265], U-net [483], COVID-caps [484], EfficientNet-B7 [485] and OptCoNet [486] with accuracy of detecting COVID-19 reportedly maximum 98 percent [265]. On the other hand, inclusion of transfer learning has known to exceed this 98 percent accuracy barrier where the feature extractor from previous model like ResNet [487], SqueezeNet [487], DenseNet [487], VGG [488] is augmented with other

TABLE 9. Configuration of common deep computer vision models in terms of number of parameters in units of million (M), input dimensions (pixelsxpixels), Number of operations in units of Giga operations per second (GOPs), inference time per batch (s) and Accuracy density percentage per million parameters (signifies the contribution of parameters towards accuracy of model).

Architecture	Num. of Parameters (M)	Input Dimensions	Num. of Operations (GOPs)	Inf. time per unit batch (s)	Acc. Density (%/M par)
Squeezenet	1.31	224x224	0.84	1.53	46
mobileNet	4.19	224x224	0.58	3.34	21
Resnet-18	11.79	224x224	2	1.79	6
Densenet-201	20.18	224x224	4	17.15	3.9
Inception-V3	23.85	229x229	6	10.1	3.5
Resnet-101	44.5	224x224	8	8.9	1.9
Resnet-152	60.3	224x224	11	14.31	1.5
AlexNet	61.07	227x227	0.73	1.28	0.9
VGG-16	138.4	224x224	16	5.17	0.55
VGG-19	143.6	224x224	20	5.5	0.5

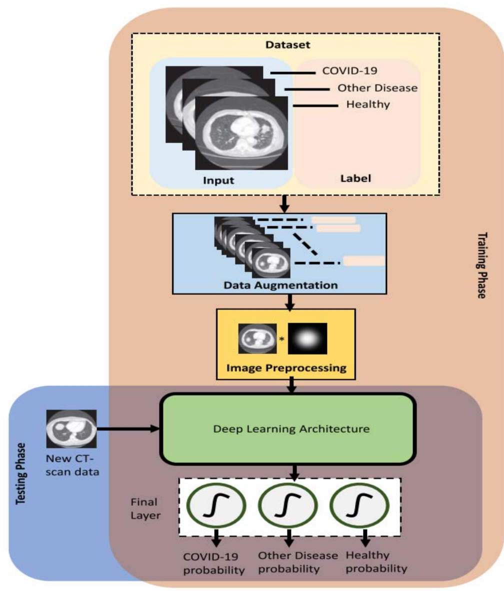

FIGURE 17. General deep learning based computer vision framework for COVID-19 diagnosis from medical imaging with CT-scan imaging taken as example.

machine learning models like SVM [489], MLP [489], etc. or the same model is trained upon the COVID-19 dataset. Inclusion of ensemble reinforcement learning techniques [490] has provided satisfactory results in X-ray based COVID-19 detection with accuracy ranging between 98 to 99.1 percent over different datasets. Similarly, some sophisticated models are also being developed to enable COVID-19 diagnosis from lung ultrasound imaging [491], [492].

b: HUMAN ACTIVITY RECOGNITION

Human activity recognition (HAR) is the characterization of different activities like walking, sitting, standing, etc. In the

COVID-19 context, human activity recognition may not only provide an alternative to GPS or Bluetooth-based contact tracing but also allow efficient surveillance for social distance monitoring and hospital places during the COVID-19 pandemic.

Computer vision-based human activity recognition for social distance monitoring may prevail in technologies like Bluetooth or GPS where their signals are not reliable like in crowded places, dense cities, etc. This leads the way toward state-of-the-art variations of CNN to classify human activities, and thus identify social distancing. [386]. In order to detect face masks, there is considerable literature from conventional computer vision algorithms like the Viola-Jones algorithm and SIFT feature-based detection to ResNet-50, MobileNetV2, VGG-16, YOLOv2, and FacemaskNet [277].

Other method of human activity recognition include through accelerometer data and/or gyroscope [387] attained either through wearables [493] or smartphones [494], further processess through signal processing algorithms like repetition spikes counter [493], machine learning models like Generalized Linear Model [387], Random Forest [387], AdaBoost [387], etc. and deep learning models like deep CNNs [387], attention based CNNs [495], federated learning models [496], etc. CNNs are employable after collecting 2D time-frequency representations through techniques like wavelet transform [497].

Deep learning-based projection of 2-D movement data into 3-D could have an advantageous application on accelerometer data for activity recognition, but currently, such scheme has been only adapted to animal poses [118].

5) MATHEMATICAL MODELING

Mathematical modeling is the representation of real-life processes, and corresponding processing upon those representations, through mathematical tools from functional analysis, dynamical systems, and optimization theory. In this respect, mathematical models dealing with COVID-19 can be contextualized in the following domains.

a: EPIDEMIC MODELS

Epidemic models, are an important tool to model not only several states that can be associated with pandemics like the number of infected and recovered, etc., but also allow assessment of economic outcomes of pandemic and evaluation of policies to contain the pandemic.

Epidemic models are majorly modelled as differential equation systems, formally conceptualized through compartment models [498]. In this respect, SIR [355] and logistic [357] models are one of the simplest models. With the SIR model being more important, is composed of states like susceptible number, infected number and recovered number. The fundamental goal of these models is to monitor metrics like reproduction numbers and fatality rates, alongside with parameters of these models (that can possible be time varying). SIR model has been extended into many other models like GSIR [499], SEIR [499], SEIRD [500], SIQR [33], SIPHERD [501], SIDARTHE [502], $\theta-$SEIHRD model [503], SE(Is)(Ih)AR [504] and the list goes on. In the same direction, fractional order models [505], [506] are gaining popularity. Contrary to differential systems, another trend in epidemic modeling is stochastic based [507]–[510] mainly utilizing Markov or Bayesian-based techniques. These models can be further improved by the imposition of knowledge of physics associated with the epidemic [511]. In course of improvement, recently sparse identification-based methods are gaining popularity for modeling dynamics and prediction of parameters and states of these models [512]–[514].

In order to make the above models work with real-life data, they are usually complemented with curve fitting techniques. Furthermore, the accuracy of these models is further increased by the addition of data driven techniques [515], or metaheuristic optimization techniques [515] and can be extended to forecasting context [516]. Another practical application of these models is towards the determination of optimal vaccination policies amongst alternatives for minimization of spread, with consideration of demographic and sociological information like age [517].

b: FORECASTING

Real world data associated with several states associated with COVID-19 pandemic, which can be realized through epidemic models, can be independently forecasting by considering them as time series [518], [519]. Techniques involved are standard time series analytic methods like ARIMA [520], auto-correlative models [521], SVR [522], genetic programming [523], Gaussian process regression [524], wavelet decomposition [525], logistics regression [526]. Further approaches include data driven based like LSTM [527], GRU, Bi-LSTM, Variational Autoencoders [528], nonlinear autoregressive neural networks [529], Generative Adversarial Networks (GAN) [530]. Main drawbacks of these models is lack of interpretability, but encoder [531] and attention [531] based mechanism based forecasting approach has shown promise in ramifying this aspect. Forecasting can be useful to keep track of time series associated with other areas that are directly or indirectly affected by pandemic like agriculture [532], vaccine efficacy [533] and weather [534] forecasts.

c: CONTROL THEORY

Control theory is naturally embedded in the concept of enforcing policies, distribution of critical resources like ventilators, beds, and vaccines to minimize the spread of COVID-19,i.e to being the reproduction number within certain desired bounds [2], which might directly reduce the exhaustion of precious resources. But at the end of the day, delivery of the produced results into an intuitive web or computer application accessible to health or policy maker might be a challenge [2]. In this regard, control theory has been primarily complemented with epidemic models [535], using techniques from linear [536], non-linear [537] and optimal control theory [538], in order to deduce control strategies [539] as well as governmental intervention paths [540] and public awareness strategies [541] to minimize critical metrics like mortality rate [535], reproduction number [538].

6) GRAPH THEORY

Many real-life problems can be divided into independent components, symbolized as nodes, which have some relationship, symbolized by an edge. These structures are well known in mathematics as graphs, the theory of which is still an active area of research today. In the context of COVID-19, when it comes to modeling of epidemic systems, social networks, supply chain, and drug discovery problems, graph theory comes into play naturally or unexpectedly while also presenting its solutions to its problems from its repository of graph analytic techniques.

a: ONLINE SOCIAL NETWORKS

Despite the development of vaccines and effective inoculation progress all over the world, community cooperation in previous transmission preventive schemes is still very much important, partly due to mutations of the virus as well as residue vulnerability after inoculation. Particularly, the first governmental level lockdowns in the initial phase of the pandemic lead to an increment of around 70 percent on social media sites like Facebook, Whatsapp, Instagram [542] and Twitter [543], thus providing a readily available platform to users for sharing their personal experiences regarding physical symptoms, opinion on vaccines and public health intervention policies [353]. Furthermore, generally, anxiety and depression levels overshoot after retrieval of Covid-19 news on social media [354].

Popular social network platforms like Twitter and Facebook's data can be crawled and the tweets or posts shared surrounding sensitive topics, as well as related user information. The textual datasets are usually dealt with natural language processing and machine learning techniques and the resultant sentimental or authenticity of information evaluated is complimented with its distribution across networks using standard graph analytic techniques like cluster, partition, centrality, betweenness, connected components, and path-based analysis [544], [545].

Online social networks are an indirect way of addressing the status of a pandemic and its possible mitigation strategies, since social networks, engulf almost every member of a particular community, producing content regarding the progression of particular news (authentic or false), vaccination status, mental health statuses, public opinion, medical supplies, and employment rates. Utilization of this information would be helpful in effective health intervention schemes by policy makers and improve general public sentiment [354], [546]. Furthermore, the lexical [353] analysis of social media content containing symptoms reported by users, like from Twitter tweets, forms an effective way to diagnose in comparison with laboratory tests.

The inclusion of news can be from various sources like news outlets or even political and state leaders [543]. The latency in the spread and exchange of information to the current situation can be sufficiently low to provide a metric on the status of the pandemic, by analyzing the sentiment and emotion associated with exchanged information content and filtering based on it, in the context of the respective situation like increased infected numbers of vaccination status. While this approach is dominantly studied through data science means, there is an absence of literature on employing control theoretical treatment to this theory. For example, if the vaccinated numbers can be represented by state $u(t)$ as a function of time t, and the status of vaccination as being active and passive can be classified as determining whether $u(t)$ is stable or unstable. The determination of the density of data exchanged, e.g. tweets with positive sentiment to vaccination, around the time t, acts as a positive definite function $L(u(t))$ on it since the information exchanged with positive sentiment is proportional to the number of people with positive vaccination status. Under the language of Lyapunov control theory [537], this can act as a Lyapunov function, that can determine the stability of state $u(t)$ through the following conditions.

$$\dot{L}(u(t)) <= 0 \tag{11}$$

$$\dot{L}(u(t)) \ > \ 0 \tag{12}$$

If equation (11) holds then the overall public opinion on vaccination is passive, otherwise equation (12) would imply that the public is actively engaged in the vaccination schemes. This control theoretical treatment would pave bridge between online social networks and epidemic statistics, the literature on which is relatively sparse in COIVD-19 context. For example, [351] proposed supervised learning models to determine confirmed deaths, recovered and suspected categories from Twitter tweets, which would compensate for the inaccuracies in epidemic statistic records due to lack of access to testing facilities or recording constraints. These studies become more relevant for smart city citizens, who are more adhered to the latest technology and social media [547], and some studies have been able to produce a prediction of the outbreak of confirmed cases seven days prior, with more than 98 percent certainty [548].

b: EPIDEMIOLOGY

Network analysis comes into usefulness in the application of contact tracing, where the point of action is following graphs of contacts. Whilst such graphs can be simple, a study [549] suggested that tracing contacts of contacts can significantly reduce transmission rates as compared to the simple tracing of direct contacts. Therefore, the employment of sophisticated graph-based analytic techniques is needed. Therefore, the study of social networks as a whole is crucial to monitor the spread of an epidemic, where each node-edge pair is formed when two contacts come in proximity of 5m or less from each other [549].

While routine techniques associated with these social networks comprise sensitivity, network structure correlation, degree correlation, degree distribution, clustering coefficient, betweenness, and eigenvector centrality analysis, these techniques are associated with the static network. Since real-life networks are temporal-wise dynamic, these networks are subdivided into static social networks. An important technique named null networks that have proven useful in studying COVID-19 which can demonstrate link between transmission rate and different network priorities (different geographical societies) [549] as well as estimate the extent of effectiveness of imposed policy [550] as well as travel restrictions [551] upon pandemic.

Furthermore, network-based models can provide additional insights into trends of the epidemic which cannot be possible through other mathematical or deep learning models. For instance, the apparent linear curves of COVID-19 infected numbers as compared to mathematical models predicted non-linear curves were explained through network-based analysis [552].

Stochastic simulation models [553] and epidemic models augmented graphs [554] have been employed that can effectively estimate the percentage of contacts traced given the reproduction number of the COVID-19 epidemic. These models have been instrumental in the assignment of public policy like imposition like social distancing, case isolation, etc. which are predicted to be enough to contain the epidemic. Additionally, network-based techniques [555] have been used for determination of effective strategies for distribution of vaccines.

The data-driven analogue of network analysis techniques is graph neural networks. Graph-based data, containing information on location and time, has been utilized using graph neural networks to forecast the spread of infection [556]. Traffic revitalization can be important in urban management and policy-making considerations and has been tackled through convolutional-recurrent neural network architectures [557] on graph-based data. Additionally, the problems of optimization can be converted to graph embeddings, complimented with reinforcement learning to identify the allocation of crucial resources for containment of the pandemic [392].

c: SUPPLY CHAIN

The current pandemic has been a source of perturbations in supply chain networks, primarily due to labor shortages [558]. Such labor shortages have been so serious that even franchises like McDonald's started hiring 14-year-old workers to compensate for the shortage. The cause of the shortage may be linked to deaths from the pandemic, illness, depression (due to lockdown restrictions), or the risk of infection. Network analysis becomes a useful tool as the supply chains are itself networks with edges representing price and product flow. A promising trend in this regard has been game-theoretical supply chain networks [558] that can take into account the competition between businesses constraint with labor shortages, which can help identify profit-maximizing businesses. Furthermore, as vaccination distribution is as important as its research and development, many mathematical optimization-based solutions are developed for effective cost and dose control [221], [559].

d: DRUG DISCOVERY

Drugs in the category of antiviral and immunomodulators have been targeted against treatment of COVID-19 [560]. In this respect, supervised and supervised ML techniques have been complimented with graph theory to screen virtual drugs for their efficacy, sensitivity and toxicity in drug-target interaction, alongside with biomarker identification. In this respect, fully connected neural networks [561] and Bayesian network analysis techniques [21] have been employed for comparison of effects of different treatments available for COVID-19 infection. Other popular techniques include knowledge graphs [562] and graph neural networks [563], the later of which have proven to be state of the art in drug-target interaction framework. Likewise, network medicine framework [564], [565] have been adopted for drug repurposing to treat respiratory symptoms of coronavirus infection with positive results [565]. Network-based techniques have been used for the exploitation of disease-gene drug interactions for the identification of repurposable drugs [566].

7) SIGNAL PROCESSING

Signal processing deals with the extraction of lucrative information from arbitrary functions (signals), that can be continuous or discrete, whose domain lies in one dimension. In the COVID-19 pandemic, these one-dimensional signals may be dispersed in the environment, in the form of audio, infrared or bio signals, and the processing of these signals becomes the matter for creating an application.

Some signal processing fields like compressed sensing have shown versatility in its techniques and cross boundaries of many domains like reduction of CT and X-ray scan doses and minimum scanning points for mobile location estimation [567], but void of COVID-19 context. Although, some effort has been made in this respect to introduce literature in COVID-19 context [568], yet the effort is in the early stage.

Irrespectively, the applications of signal processing in COVID-19 context have been practically significant, and are described below.

a: HUMAN ACTIVITY RECOGNITION

Whilst both video (4D signal) and 1D signal-based HAR have been active in COVID-19 related research, 1D signals may be of practical consideration due to corresponding low cost and power considerations. The most popular sensor for extracting these 1D signals are accelerometer and gyroscope, and these 1D signals can be augmented with other biosignals like temperature and heart rate to add resolution and accuracy of the HAR task. The algorithms considering the morphology of the signals like repetition spikes counter [493] have been easy to implement and easy to use for HAR tasks, machine learning has been paving way for more accuracy and robustness in this direction, with popular techniques tackling applications to COVID-19 include generalized linear regression [387], logistic regression, random forest [387], AdaBoost [387], non-linear kernel discriminant analysis, Naive Bayes and SVM.

b: MEDICAL EQUIPMENTS

In the current pandemic, not only new equipments have been explored for dedicated processing of biomedical signals for diagnosis, but also improvement of current medical equipment to assist COVID-19 patients. An example of this is the control of oxygen flow from ventilators can be optimized in relationship with a patient's health status, and a study [569] utilized reinforcement learning under the Markov decision process to accomplish this.

Since coughing and breathing problems are one of the most eminent symptoms of COVID-19 infection, therefore efforts are being made to sense the associated signals and perform an automated diagnosis. In order to make machine learning over these signals possible, [570] produced a cough, breathing and voice sound dataset to distinguish between infected and normal individuals. However, real-world data may not be enough to make the most accurate model, therefore [404] proposed respiratory simulation model to compensate for the sparsity of data, based on the latest clinical research.

Methods in feature extraction from audio signals include segmentation and normalization [571], harmonic to noise ratio [571], Variable Markov Oracle Method [572], empirical mode decomposition [573], Mel Spectrograms [574]. On the other hand, classifier methods include state vector machines [571], XGBoost [572], convolution deep neural network [573], transfer convolution neural network [574], LSTM [575], ResNet50 [575] with maximum accuracy achieved as 99 percent.

Chatbots are being deployed that can employ speech recognition and natural language processing upon speech signals and diagnose COVID-19 based on symptoms reported. This technology has removed the burden from the previous screening of potential cases based on phone hotlines [576]. 'Symptoma' [576] is an example of such chatbots that can not only differentiate between 20,000 diseases but also diagnose COVID-19 with more than 96 percent accuracy. Likewise, 'MedBot' is an automated health assistant [408], deployed on Google Cloud Platform (GCP), which provides services like symptoms-based diagnosis, counseling services, and guidance, thus compensating for lockdown restrictions and lengthy doctor appointments. Furthermore, a chatbot named 'Clara' was deployed by a collaboration of Microsoft and CDC with similar functionality.

8) LIMITATIONS OF DATA DRIVEN TECHNIQUES

While the influence of data driven techniques over standard algorithmic applications has been profound, they are prone to the following limitations:

- **Data Quality:** Data available to deep learning models may be sparse, heterogeneous, or noisy in nature. The main reason for data sparsity may include the costs associated with data collection [577] and legal complications in sharing of model [578]. Data collection and labeling, especially for diagnostics, can be challenging and costly to achieve. Furthermore, the data used to train the model may not be gathered from trustable sources [579], leading to unreliable results.
- **Transparency:** The results produced by deep learning models may not be objectively coherent with the theory underlying the problem, thereby making the results uninterpretable. Their action is fundamentally the same to that of a black-box model that can approximate any mapping between two objects [580]. This scenario can be unacceptable in application fields, that may have many stakeholders, like that of health care and policy making. Due to this limitation, GDPR regulates the explainability of algorithms utilized inpatient screening [581].
- **Security and Privacy:** Wherever there is data involved, there is the demand for privacy and security. Such concern comes into action in the case of deep learning models, where the data used to train the models, whether anonymized or not, can be decoupled either directly or indirectly to extract sensitive information. Some examples include the studies where sensitive information like faces of people [462] or records of subscribers [582] have been extracted from weights of the trained models and the data used to train the model respectively. Furthermore, these datasets may become prone to manipulations by attackers to force the learned model to perform additional malicious tasks.
- **Model Limitation:** There are innate limitations to the performance of deep learning techniques. It is a well-known fact deep learning models are known to be biased [583], [584], as they project what they have learned from the data provided. Therefore, it is not expected they would be completely adopted over standard models and adaptive algorithms [585] leading to problems of scalability and generalizability. Other limitations include catastrophic forgetting, a phenomenon associated with transfer learning (a frequently utilized technique in COVID-19 imaging) that can make the model forget the model from the previous task. Furthermore, there are limitations to probabilistic and generative models [586]. A study showed that while transformers are state-of-the-art deep learning models with superior performance, their generalizability to conventional statistics was not promising [587].
  Another important limitation of data driven models include adversarial attacks, where small perturbation in data significantly deviates the predictions of the models, lead to a lack of trustability in such models for industrious adaption.
- **Model Size:** Machine learning models, especially deep learning models, when architected and trained to show superior performance are supposed to be deployed into

real time embedded systems, whose specifications and floating-point precision is going to be much lower than the systems they were originally designed on. Therefore, quantization of these models, as well as their pruning, becomes a requirement for economical deployment [588] and maintenance of the accuracy becomes a challenge.

a: SOME SOLUTIONS TO THE LIMITATIONS

- **Model Size:** Solutions to the problem of model size have been tackled with deep studies of sparse networks and various properties are explored like training quantization error, and comparing performance of training these networks with those of dense models with later pruning [589], [590]. Furthermore, pruning of large deep models has been studied where a study [588] reportedly compressed VGG-16 model by 49 folds with equivalent accuracy. Furthermore, there is growing evidence that while state-of-the-art models consume large amount of power, their computing power may reduce faster than Moore's law [591].
- **Model Limitations and Transparency:** In order to systematically deal with bias in machine learning models, a European Union-driven AI team derived a framework to define AI risk and bias and introduce general principles for robustness, privacy, and transparency [592]. Usage of decentralized training strategies like federated learning has been considered promising to not only produce scalable models but also generalizable performance towards unseen data [593]. Another category of techniques named parsimonious models may not only improve generalizability but also ameliorate transparency of such models to predict physical phenomena by adopting a minimum number of parameters [594]. The explainability of AI models can be further improved by dedication identification of necessary features as well as adjustment of weights and activation functions to convert relevant information into the final output. Additionally, since deep learning models are stochastic in nature, the uncertainty associated with their predictions can be evaluated, which would induce transparency in medical diagnostics like X-ray imaging based COVID-19 diagnosis [580]. In course of attaining generalizability in multi-modal inputs and multi-modal tasks, it appears that transformer architectures are a promising strategy, without resorting to complementary techniques [595].
- **Data Quality:** In order to deal with sparse and unbalanced datasets, a technique called 'Active Learning' has been developed that considers sample diversity and corresponding improves accuracy and decreases bias [596]. Furthermore, bias can be compensated by utilizing multiple independent datasets. Other methods like ensemble techniques, transfer learning, contrastive learning [597], meta-learning and transformers [598] are known to give sufficient accuracy given limited datasets. From a non-technical perspective, there have been proposals for incentive mechanisms in different sectors involved in data collection to improve the quality, as well as quantity of data.
- **Security and Privacy:** In order to bypass the data-sharing challenges across different institutions for model training, federated learning is a primary candidate, where a model takes advantage of the edge layer of IoT and trains a model across different edge devices with no data sharing among these edge devices [593]. Furthermore, datasets can be dealt with differential privacy or homomorphic encryption mechanisms that perturb the data with minimal effect of inferences from it [458]. In addition, dimensionality reduction of these datasets can reduce the possibility of reverse engineering sensitive information from trained AI models.

X. MECHATRONICS

Mechatronics can be considered an interdisciplinary engineering field focussing on both electrical and mechanical aspects. Mechatronics has developed both life-supporting and threat-preventing applications in pandemic times. Owing to their significance, a lot of efforts have been put in reducing the monetary and energy costs of their production, as well as embedding them in the IoT framework with current state-of-the-art 5G communication technology [18]. With reference to COVID-19, mechatronics applications can be divided into the following domains.

A. ROBOTS

Robots as being programmable mechatronic systems capable of interacting with real-world environment, mirror the same functionality as smart sensing by imitating the same principle of reducing the possibilities of contact [599]. Robots, alongside drones, are being used to deliver prescription drugs to patients at home, in order to reduce contact [600]. In another direction, robotic versions of imaging technologies are being deployed that are contactless in nature. Robotic ultrasound systems [601] can automatically adjust probe position for optimal resolution, followed by automated diagnosis through a 3D deep convolution network. These automated equipment systems can be further extrapolated into robotic carts, with a built-in camera and display systems complemented with medical equipment, allowing professional healthcare accessible to any location, especially in quarantined areas to limit exposure [602].

The field of commerce has been greatly affected by the pandemic due to social distancing and lockdown policies. In order to support the local commerce stores, a company named ''Starship Technologies'' released delivery robots [603] to deliver groceries to the consumer's doorstep. These autonomous vehicles provide a contactless driving and delivery option, thus minimizing the spread. Understanding its efficacy, it has been promoted as a clear choice in Germany [604]. This contactless trait has allowed studies on the transportation of goods through autonomous vehicles [605].

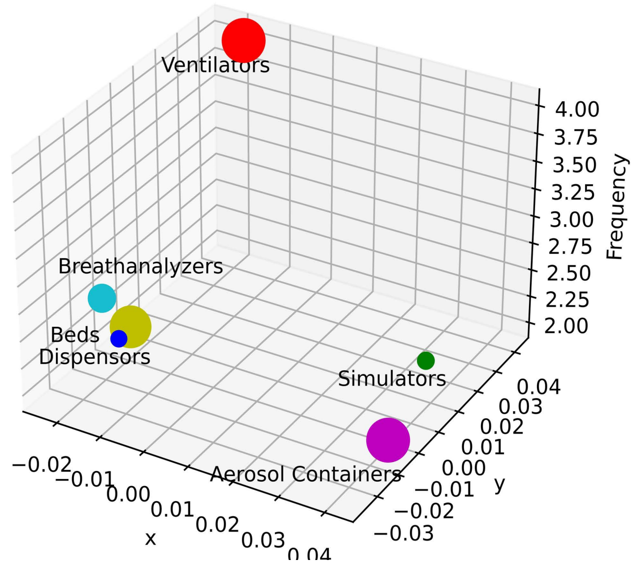

FIGURE 18. Word2Vec based visualization of machine based trends combating COVID-19.

Autonomous robots can be helpful in cleaning and diffusing disinfectants in indoor environments and can reduce the possibility of spreading infection from family interactions [606]. They have been deployed as human interactable robots via gesture and speech recognition to make hand sanitization more accessible to the public passing by [607]. They are being researched to be deployed at UAVs to provide a mobile IoT framework for crowd sensing and COVID-19 detection amongst crowds.

B. DRONES

Since the advancements in computer vision, drones have become a popular trend, as they provide a mobile carrier with inbuilt cameras to proceed the computer vision. They have found a wide range of applications, including agriculture, supply chain, professional photography and surveillance [608]. However, drone technology faces a key challenge of computation limits, as well as limited datasets for its computer vision models which are mostly data-driven [608] for the purpose of object detection and tracking. Edge computing has been thoroughly researched to make it feasible for drone technology to meet the challenges of onsite computation [609]

Drones are being used to aid in sectors that have been indirectly affected by the pandemic. In the agriculture sector, drones are being used for monitoring water resources, agricultural production, and storage facilities thus compensating for lockdown and social distancing restrictions [610].

Drones are being deployed in densely populated areas where wireless connectivity is an issue and this can permit large aerial cover of places, especially in hospitals, with thermal imaging, patient identification, and distance monitoring [611]. Furthermore, these wireless devices can be linked through a drone-based networking system, and thus can elude the limitations of standalone Bluetooth or GPS-based technologies [612] for contact tracing.

Furthermore, drones have been deployed at country scales for social distance monitoring, public announcements, spraying of disinfectants in public places [613], food delivery [614], [615], mass screening [616] and vaccine delivery [617]. Drones have also been studied for the distribution of viral tests to possible infected people, thus reducing transmission rate [618]. Since surveillance naturally demands privacy, work has been done to fuse blockchain with drone's data collection methodology [619]. Blockchain applications to drones have been extended towards contact tracing in combination with 5G [620] and even 6G technology [621].

C. MACHINES

The role of electrical machines in aiding COVID-19 patients and health care workers is trending from both engineering and research points of view. Based on the implementation and research paper-based results from Google search and Google scholar, the further sub-domains of machines are visualized by using Word2Vec of keywords and projecting those sub-domains onto a 2D plane using principal component analysis (PCA). Thereafter, the side of points is decided by the cumulative citations and number of unique implementations. The resultant visualization can be seen in figure 18. Furthermore, these sub-domains are further discussed below.

- **Ventilators:** While COVID-19 is a respiratory tract disease, breathing problems are the most apparent system. In order to deal with that, several ventilators designed have been proposed, whose sole purpose is to automatically inject oxygen into lungs [622]. These ventilators can be classified as invasive and non-invasive [623]. Invasive ones are used for critically ill patients, who cannot breathe on their own, while non-invasive ventilators are meant for assisted breathing.
  Ever since the beginning of the pandemic, many global manufacturers have played their part in mass-producing ventilators to overcome the shortage [624]–[626].
- **Dispensers:** Work is being done to make soap and sanitizer dispensers automated [627] and contactless [48], [116] which would ultimately reduce transmission rates, as well as reduce clustering in public places.
- **Neuro-muscular Electrical Simulators:** Some work is being done to utilize neuro-muscular electrical simulators to improve muscle function of people recovering from COVID-19 [628], as well as elderly people during lockdown [629].
- **Aerosol Containment Devices:** Vacuum based aerosol containment devices, that can extract clean air from virally infected air, may reduce the transmission of droplets from COVID-19 infected patients [630]–[632]
- **Smart Beds:** Smart beds are being developed that can not only perform continuous breathing rate monitoring of COVID-19 patients but also are installed with automatic alarms and user-friendly control and interface to

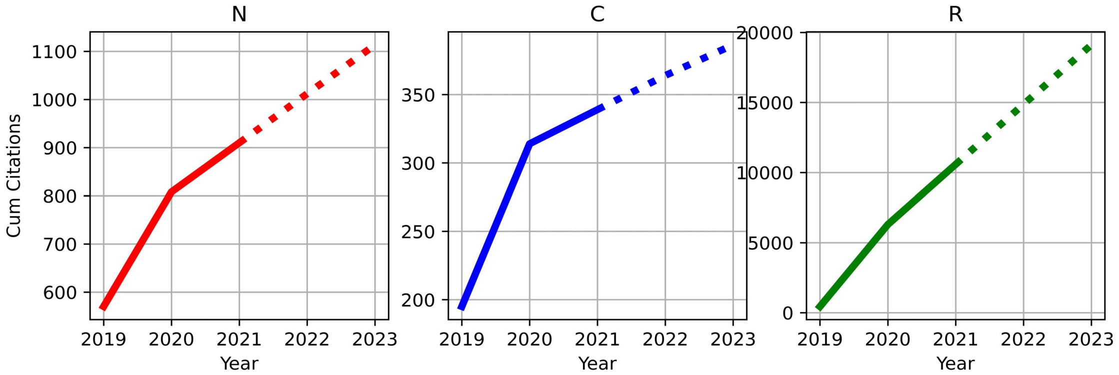

FIGURE 19. Cummulative citation trends of 'N', 'C' and 'R', for the case of compressed sensing literature in relation with COVID-19, where bold curve represents so far trend, and the dotted curves represent future trends.

assist patients in critical conditions [633]. Furthermore, ICU beds can be installed with CCTV cameras that allow better in-depth monitoring of critically ill patients [399]. Additionally, detectors are placed inside patient care beds to detect sleep disturbances in COVID-19 patients in order to evaluate their health status [634].

- **Breathanalyzers:** While breath analyzers are good candidates for rapid testing, they are not yet globally available mainly because their technology is in progress. However, their efficacy has been appreciated and approved in many countries like Singapore, Malaysia and the Netherlands [635]. Breath analyzers can be classified into photonics biosensors, electronic nose, mass spectrometry, terahertz spectrometry, and gas chromatography based [635], among which photonics biosensor is a possible industrial application due to its minimum size and result latency. The inbuilt sensor responses can be further complemented with machine and deep learning methods [636] with promising results and have been reportedly verified for distributions [637].

XI. CONCLUSION

This article presented a systematic overview of an array of AI-IoT technologies like blockchain, cloud computing, fog computing, sensing technologies, machine learning, deep learning techniques, and robots, that have effectively aided COVID-19 efforts, within the proposed taxonomy. In this regard, not only conventional review techniques are used but a novel review methodology is also proposed, where we utilized techniques from image processing, dynamical systems, and machine learning to provide insights into some aspects of particular technologies. Consequently, we provided theoretical and application advantages, disadvantages, trends, and comparisons of these technologies, alongside with proposal of potential future works that have been less explored currently. We discovered that, by far, the field of healthcare has captured the utility of all technologies detected in AI-IoT umbrella. We conclude that the technologies of fog computing and cloud computing hybridization in IoT, deep learning, and blockchain technology will determine the future of COVID-19 related AI-IoT technologies.

XII. FUTURE WORKS

Based on the discussion, as expressed from literature considered in so far review, we highlight the following future trends that are significant from application and research perspective to not only deal with current pandemic, but with infectious diseases in general:

- Development of cost, environment friendly, and energy effective solutions is the main focus with the encouragement of more open-source solutions. Many companies are already leading the work in low cost, high battery life, and global satellite-based connectivity is IoT solutions.
- Amongst many applications of IoT and mechatronics, ventilators and health monitoring systems have proven to be most active in tackling the pandemic, and they are here to stay till the end of the pandemic. In particular, the remote versions of these applications would certainly reduce the burden on hospital resources and allow the care of more critically ill patients to be taken care of.
- The pandemic has heavily influenced the video-conferencing trend, especially in education, where video lectures are recorded contrary to prior real-time lecture trends. Furthermore, these lectures can be in native languages, other than English, making it difficult for foreign students to follow. This provides room for digital solutions towards solving not only this language barrier (through video transcription and language translation-based subtitle embedding), but also improves comprehension of students by providing summary and knowledge graphs of different clips of the video.
- While there exist many tools already that provides an interface to many state-of-the-art COVID-19 related resources, there is still too much literature left in hibernation and there is a need for systematic open source collaboration for making the current state of the arts into interactive user interfaces.

- Utilization of less explored non-contact technologies like self-mixing interferometry would prove fruitful towards innovation into future smart sensing technologies, due to its cost-effective apparatus with sufficient accuracy. This is clearly possible since the literature on the application of radar technology is already in abundance and there is a high degree of correlation in the working principle of both of these technologies.
- Utilization of ambient light sensors and magnetometers in COVID-19 should be focused on, as it has been minimally explored.
- There is a need to consider the tracking devices like Apple Air tags for contact tracing purposes, which will not only reduce inaccuracies produced by smartphone-based contact tracing technologies but can also be linked with drones to allow broader aerial coverage.
- The government-affiliated contact tracing apps should be made open source, which will not only increase the trust of the general public of these apps but also allow continuous improvement from a wider pool of engineers.
- Mapping of 2D movement data into a 3-D environment, using only accelerometer data, while not applied in the COVID-19 context, could have an advantageous application, for increasing robustness of medical imaging, as well as CCTV-based social distance monitoring.
- Needed utilization of a generalizable and accessible approach towards satellite imagery has important applications from both policy design and resource planning perspectives.
- More rigorous study of compressed sensing in reducing radiation doses for COVID-19 diagnosis, as well as imparting efficient minimum sensor scanning location points for mobile phone tracking is required, as it has been absent for application in the COVID-19 pandemic.
- Application of control theory in the social media-based prediction of epidemic statistics is needed to compensate for deficiencies of epidemic data collection processes.
- With the immense importance of hybridization of fog computing and cloud computing technology, followed by anticipation of 6G technology, it is expected that it will produce virtually infinite computing capability with desirable security and latency. In this respect, a unified generalized framework is required to permeate the corresponding constraints as well as improve its infrastructure with deep learning and blockchain technology to manage applications of COVID-19 like diagnostics, quarantine, and social distance monitoring, systemized vaccination, effective policy design, etc.

In fact, in order to show the future inclusion of compressed sensing in the COVID-19 context, we simulated the NCR model (as described in 'Analysis Methodologies' section) to analyze the trend of cumulative citations of literature containing pure compressed sensing content, compressed sensing used as an application to COVID-19 (either directly or indirectly) and COVID-19 literature as a whole without containing compressed sensing-based application as 'N', 'C' and 'R' respectively. The results are depicted in figure 19. It is apparent that while the cumulative citations of general COVID-19 literature is growing at nearly the same rate as in previous years, the growth of literature on the application of compressed sensing techniques, is saturating in later years while overshooting previous research. Therefore, there is a need for further exploration of this technique to produce more beneficial applications in COVID-19 literature.

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