Managing COVID-19 Global Pandemic With High-Tech Consumer Wearables: A Comprehensive Review

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***Abstract*—The novel corona virus (COVID-19) created a havoc all around the globe without any prediction of its eradication. All the previous methods seemed to fail and exceptional considerations are now required to be deployed in order to deal with this pandemic. The aim of this retrospective study is to highlight the new solutions to manage and deal with the pandemic. This study discusses different e-health wearable devices that help in early diagnosis of COVID-19 symptoms and also presents an overview of some artificial intelligence and machine learning techniques applied on CT-scan or Chest X-ray images to refine the correct diagnosis of patients. Finally, this work addresses the importance of smart chat-bots that provides assistance to the people suffering from stress and anxiety during quarantine. These chat-bots can offer psychological therapies in isolation and can be very useful.**

***Index Terms*—artificial intelligence, COVID-19, chatbots, e-health, pandemic, physiological monitoring, wearables.**

I. Introduction

The novel coronavirus, officially known as COVID-19, immediately spread all through the world and has changed our day by day lives and the manner in which we communicate. According to [1], 213 countries and territories around the globe have detailed and aggregate of 29,609,173 affirmed instances of the corona virus. COVID-19 has started from Wuhan, China, and has determined a loss of life of 935,916 death toll as per worldometer record on 15 Sept.2020. Taking into account the likely danger of a pandemic, researchers and doctors are hustling to comprehend this new deadly virus and the pathophysiology of this disease to reveal conceivable treatment regimens and find viable vaccine and antibodies as in [2–5].

A few countries have started taking a short on introducing vaccine, however it will take a long time before one can be circulated worldwide. With passage of time, COVID-19 has triggered enormous human losses eventually it is dire necessary to comprehend the ongoing circumtances and to build strategies to control the viral spread. Several research studies have been conducted to forecast the epidemics trend of COVID-19 as shown in [6–10]. This forecasting provides the latest data to setup an efficient and highly suitable epidemic analysis and prediction model based on the actual situation, that aids in allocation of medical resources, the arrangement of production activities, and even the domestic economic development throughout the world. These prediction models also gave pivotal information and an important reference for the government to formulate crisis macroeconomic decisions and medical resources allocation. However even with the lock down and restrictions being imposed, this pandemic is still rising and the situation is going out of hands. So now the healthcare practitioners and worldwide researchers have consented to initiate the use of digital health platforms not just to cease the spread of the virus but also for monitoring, analyzing and diagnosing this pandemic [11].

The main objective of this study is to provide an insight contribution of e-health wearable devices and high tech research and consumer devices to tackle with COVID-19 pandemic. This paper is divided into three sections. Section II deals with the role of wearable sensors and devices in COVID-19 pandemic, section III illustrates the adoption of early detection by means of applying machine learning algorithms on medical imaging data for diagnosis and progression of COVID-19 infected patients and the last section explains the role of smart chatbots in COVID-19 pandemic.

II. Role of Wearables in COVID-19 pandemic

The main function of wearables is to sense, process (analyze), store, transmit and utilize (apply) [13] depending on the application domain, wearer and the processing of data collected from wearables. With the on growing popularity and implementation of wearables in sensing the physiological signs, many devices have been introduced in healthcare system that provides more robust results. For example in [14], it used the wearable device named Fitbit that collects resting heart rate (RHR) and sleep data and successfully evaluates if subject has influenza - a respiratory infection. Similarly in [15], a

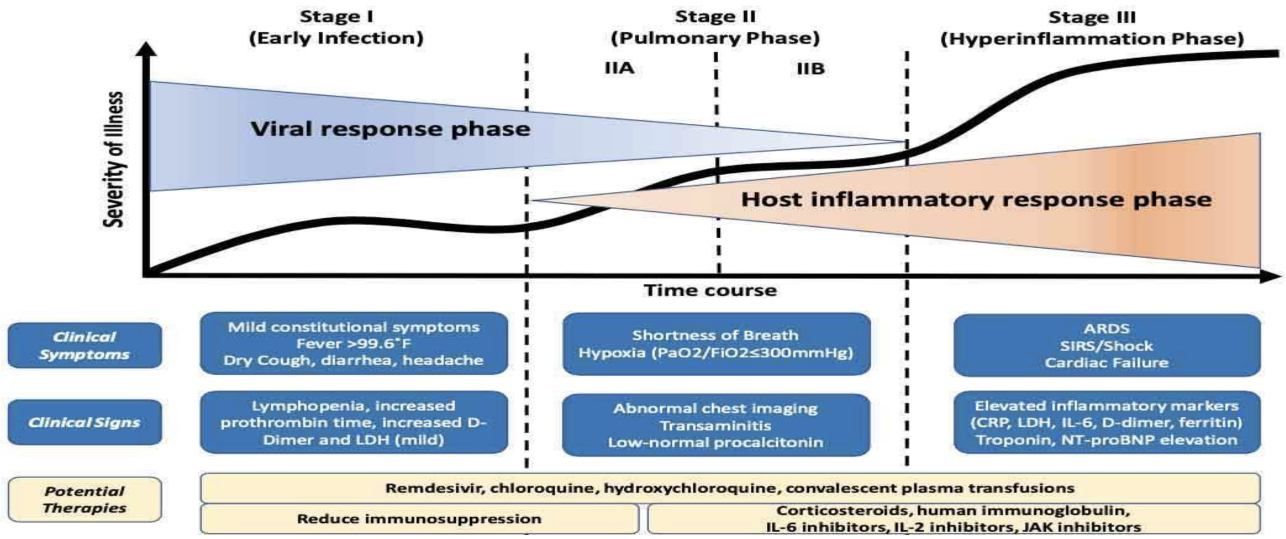

Fig. 1: Phases of COVID-19 virus progression as depicted by [12]

real time monitoring system is developed for cardiac patients using wearable sensors that aids in using the most recent healthcare services which probably will not be possible in any case due to the low doctor to patient ratio. The developed monitoring framework is then assessed for 40 individuals. The researchers in [16] come up with the conclusion that wearables can identify the abnormal physical signs e.g., neurocognitive disorders and parkinson disease, from the data collected by sensors attached to the body. All these studies referenced above edify the way for the adoption of e-health wearable devices in form of a new perspective for the precaution of this deadly infectious virus i.e. COVID-19.

According to the research studies, the physiological anomaly detection strategy is created. It can distinguish the odd signs reflected by the physiological information gathered from wearables. According to the latest studies developed by [12], the clinical symptoms as illustrated in Fig 1. are well defined in the form of three phases. The common physiological symptoms at the onset of COVID-19, the sensor modalities implemented to measure them and the changes in those metrics are listed in Table 1. Today, the newest wearables serving as tipping point to fight with this pandemic are Apple Watch, WHOOP, Gramin, Huawei Smart watch Strap, Fitbit, Zephyr BioHarness, or VivaLNK Vital Scout and many more [17–44] as listed in Table 2. These have the ability to track the RHR, Electrocardiogram (ECG), sleep duration, core temperature (CT) and other physiological symptoms of COVID-19 virus. Studies in [45] have revealed that the fundamental clinical presentations of COVID-19 are fever (90% of cases or above), cough (around 75%) and dyspnea (up to 50%). There are many clinical trials correlating with these basic symptoms that propose more reliable and accurate wearables for COVID-19. Some of the trails are mentioned in Table 3.

III. Role of early detection algorithm technology on medical images for COVID-19 monitoring

With the increasing number of cases of COVID-19 pandemic, it is highly crucial to move for contactless and automated image acquisition workflow to avoid the severe risks of infection. Medical data in the form of ultrasound, X-ray, computed tomography (CT scan) and Magnetic resonance imaging (MRI) images can be very helpful in disease diagnosis, tracking, and prognosis. This process will eventually reduces the risk of incorrect diagnosis of virus and also reduce the risk of spread of virus especially to healthcare workers.

The Early Detection Algorithm (EDA) has been proposed in [51] to detect and alert the users before the appearance of the clinical symptoms through the use of wearable devices. When using wearable devices for detection of early infections, EDA gives the opportunity of self-isolation, adoption of care or diagnostic testings and the possible way outs to further diffuse the infection. Furthermore, the use of wearables can also be extended to the distance diagnosis in mild cases by distance vitals collection resulting in the conservation of sensitive hospital resources and simultaneously minimize the probability of further diffusion to front end health workers as an alternative method of face to face diagnosis. Therefore, the aggregation of the enlisted metrics could lead to higher signal to noise ratio (SNR) to be utilized as a predictor of COVID-19 risk. Hence, development of EDA with higher true positive and true negative rate is of utmost importance for distance monitoring. The intensive care unit (ICU) nurses adopt the necessary early warning indicators of the system to sense the verge of complications for a specific case. Therefore, wearable sensors utilized by distance patient observation relate to platforms for development of feasible patient interventions, stabilize patient-nurse caution ratio and become a cost effective way-out in terms of medical care and readmission rates. In the context

TABLE I: physiological metrics relevant to COVID-19

Index	Physiological metrics	Sensor modalities	Changes in physiological metrics
1	Temperature	Temperature	Increase in temperature
2	Heart rate (HR)	ECG, Pulse plethysmography (PPG)	Decrease in heart rate
3	Heart rate variability (HRV)	ECG, PPG	Paradoxical decline in HRV
4	Blood pressure	PPG	High blood pressure
5	Heart rhythm	ECG, PPG	Atrial fibrillation and non-sustained ventricular tachycardia
6	Respiratory rate	ECG, PPG, accelerometer	Increase respiratory rate
7	Oxygen saturation (SpO2)	PPG	Decrease in SpO2
8	Sleep	accelerometer	Improper sleep status
9	Cough	Mechanical or piezoelectric sensing	Increase in dry cough

TABLE II: Available commercial wearable devices for COVID-19 detection.

Index	Company/Device name [Reference]	Form factor	Physiological parameters	Price
1	Fitbit charge 4 [17]	wrist monitor	SpO2, HR, activity, sleep	150$
2	Fitbit Ionic [18]	Wrist monitor	SpO2, HR, sleep, activity	250$
3	Fitbit Versa 2 [19]	Wrist monitor	SpO2, HR, activity, sleep	200$
4	AIO Sleeve [20]	Arm sleeve	SpO2, HR, HRV, activity, ECG	169$
5	Apple Watch Series 4/5 [21]	Wrist monitor	Respiratory rate (RR), HR, HRV, activity, ECG	399$
6	Beddit [22]	Contactless In-bed	RR, HR, sleep	150$
7	BioIntellisense [23]	Epidermal patch	Skin temperature (ST), RR, HR, coughing, sneezing	NA
8	Biostrap [24]	Wrist monitor	HRV, HR, SpO2, RR, sleep	175-320
9	Biovotion Everion [25]	Armband	ST, SpO2, RR, HR, HRV, sleep	NA
10	Cosinus Two [26]	In-ear	CT, SpO2, HR, HRV, activity	330$
11	Empatica Embrace [27]	Wrist monitor	ST, HR, HRV, activity	NA$
12	Equivital LifeMonitor [28]	Chest monitor	CT, ST, SpO2, RR, HR, HRV, galvanic skin response	NA$
13	Garmin Fenix 5 [29]	Wrist monitor	SpO2, HR, activity, sleep	500$
14	Garmin Forerunner 945 [30]	Wrist monitor	SpO2, HR, RR, activity, sleep	550$
15	Garmin Venu [31]	Wrist monitor	SpO2, HR, RR, activity, sleep	300$
16	Garmin Vivoactive 4 [32]	Wrist monitor	SpO2, RR, HR, activity, sleep	579$
17	Hexoskin [33]	Compression shirt	SpO2, RR, HR, HRV, activity, sleep	579$
18	Kinsa [34]	Smart Thermometer	ST	50$
19	Oura [35]	Ring	RR, HR, HRV, activity and sleep	299$
20	Spire Health Tag [36]	Tag attached to clothing	RR, HR, activity, sleep	399$
21	VivaLNK Fever Scout [37]	Epidermal patch	ST	60$
22	VivaLNK Vital Scout [38]	Epidermal patch	RR, HR, HRV, activity, sleep	150$
23	WHOOP [39]	Wrist monitor	R, HR, HRV, recovery and sleep	30$
24	Beurer SE80 [40]	contactless in-bed sensor	RR, HR, sleep	500$
25	Fitbit Blaze Smart Fitness Watch [41]	Wrist monitoring	Accelerometer, Vibration sensor Optical HRM, Gyroscope	265$
26	Spire Mindfulness and Activity Tracker [42]	Clipped on belt or bra	Stress and breathing	169$
27	Owlet Smart Sock [43]	socks	Pulse oximetery and HR	249$
28	Huawei Smartwatch [44]	Wrist monitoring	HR and activity	206$

of the pandemic, artificial intelligence (AI) is being applied and brings results in three fields: in virus research and the development of drugs and vaccines, in the management of services and resources at healthcare centers and in the analysis of data to support public policy decisions aimed to manage the crisis, for instance in the confinement measures. The AI-empowered image acquisition and processing techniques can significantly be applied on these medical images. The recent research works and their results are illustrated in Table 4.

IV. Role of Smart Chatbots in COVID-19 pandemic

During the pandemic of the coronavirus disease, people manifest in two ways: the first one includes people that are obviously afraid of the contagious disaster this disease is causing and the other one regards those that suffer of a turbulent behavior as fear and anxiety because of the panic and confinement caused all around the globe. Regularly we are besieged by reports about the loss of lives, this COVID-19 turning as a suicide epidemic. Hence, the COVID-19 also created mental health crisis and brings long-term consequences to our mental health [62]. Considering all the ongoing business terminations, lost positions, just as a shutdown of most public occasions or the dread of economic recession because of second wave of this pandemic, the depressions seem to be very real and can determine eventually an increase of the suicide risk in future. The solution lies in improving the social connections and thus helping people to overcome depression and suicidal thoughts keeping in mind the idea of physical distancing. With the on growing use of wearable devices in this havoc of COVID-19, the use of chatbots with the help of artificial intelligence can manage different situations caused by the mental health crisis. For example in [63] the authors

TABLE III: Current clinical trials using wearable sensors to monitor and measure physiological metrics relevant to COVID-19

Study name [Ref]	Functions	Communication mode	Target subjects	Hardware	COVID-19 application scenario
In-ear SpO2 [46]	Monitoring of Hypoxaemia in COVID-19	SpO2 recording following the breath hold protocol	14 healthy subjects	Two PPG sensors were used per subject, one made sure about inside attached to desired ear channel and the other to the correct forefinger; the two sensors recorded at the sametime	Improved non-meddlesome wearable SpO2 observing is attractive especially in COVID-19 outpatients with a risk of respiratory crumbling
IoT-Q-Band [47] 2018	Detect and track absconding COVID-19 quarantine subjects	Wi-Fi, LTE, GPRS	4 subjects	ESP32 Kit	Provides three indicators. If the IoT-Q-Band has tampered with the leading indicator changes its color from green to red also performs the geofencing task, and the middle indicator changes its color IF a quarantine subject is 50 m away from the quarantine location; the same location status change is pushed to the cloud server as well. The third indicator indicates the days left in the quarantine
Headset like wearable device [48]	Track key sypmtoms of COVID-19	NA	NA	Temperature sensors (thermistor), PPG, MIC, arduino, mobile phone	Measure respiratory rate, rapid or shorten breathing and cough
Mechano-acoustic sensing [49]	Track physiological symptoms and full range of natural motions of the neck	NA	50 subjects	Accelerometer and a precision temperature sensor	Attached at neck; it provides interface to the intrathoracic cavity for recordings of respiratory activity. The same data streams include information on HR, heart sounds and cardiac amplitude. A thermally insulating pocket around the temperature sensor enables measurements of ST, with robust correlations to core body values
Sticker-like medical device streams symptom data to physicians [50]	Continuous monitoring for COVID-19	NA	NA	Temperature and pulse oximetry	The device is placed at the base of the throat to pick up vibratory signatures of breathing, coughing and swallowing.

developed a chatbot named “Aapka Chikitsak” on Google Cloud Platform (GCP) using a natural language processing (NLP) to give free basic information without physical visits to doctors. This virtual doctor suggests preventive measures, intuitive advising meetings, interactive counseling sessions, healthcare tips, and side effects covering the most pervasive infections in India. In [64], the authors introduced a chatbot that helps the patients to answer questions regarding COVID-19.

Similarly the researchers in [65] launched another specialized chatbot named Symptoma to distinguish COVID-19 utilizing a lot of different clinical cases joined with case reports of COVID-19. The outcomes show that Symptoma can precisely recognize COVID-19 in 96.32% of clinical cases. While considering just COVID-19 indications and hazard factors, Symptoma distinguished 100% of those tainted when presented with just three signs. Chatbots offer solid potential for curated data. The data can be customized to the necessities and indications of the person. When the user asks some questions, the answer can be given in an interactive manner, faster than traditional online searching methods. Based on the user location, the provided information is adapted and respects local regulations and guidelines. WHO and CDC, are also using chatbots in their website to update the users about the increase in number of cases. Everybody that have access to smart phones or online computers can get access to chatbots. In fact, the expansion in number of chatbots for COVID-19 can diminish the load on call centres of hospitals. Likewise, the chatbots interactive manifestation checking highlights can possibly bring down the volume of cases in urgent care and emergency care.

V. Conclusion

In this comprehensive review study, an overview of high-tech consumer wearables are discussed which can possibly measure physiological symptoms remotely. The scope of wearables against COVID-19 is very broad. Wearables can also be used to monitor the condition of patients under quarantine. Not just the wearables were discussed, but we also commented on the role of AI combined with medical imaging technologies i.e. X-rays, CT scan, ultrasound and MRI. The use of machine learning or deep learning algorithms on real time images provides more accurate results instantly and reveals the severity and urgency of patients need to be addressed. In last, we depicted the solutions for the people who are under stress and facing mental health issues because of this pandemic, the chatbots seeming to be very attractive and efficient when they correlate with their virtual therapists or virtual doctor. This might be helpful to control their mental stress and depression.

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TABLE IV: Medical imaging technique for correct diagnosis and monitoring of COVID-19 patients

[Ref]	**Medical images technique**	**Dataset details**	**COVID-19 Application Scenarios**	**AI technique**	**Results**
[52]	X-ray images	224 images of affirmed Covid-19 patients, 700 images with regular bacterial pneumonia, and 504 images of normal conditions, another dataset tallies 224 images with affirmed Covid-19 cases, 714 images with affirmed bacterial and viral pneumonia, and 504 images of normal conditions	DL with X-ray imaging may extract significant biomarkers related to the Covid-19 disease	transfer learning with CNN	The accuracy, the sensitivity, and the obtained specificity is 96.78%, 98.66%, and 96.46%
[53]	CT scan images	There are 742 CT images and 2 categories (COVID/NonCOVID)	to detect the coronavirus infected patient	five different deep CNN-based models (AlexNet, VGGNet16, VGGNet19, GoogleNet, and ResNet50) have been selected for the investigation	ResNet50 proved to be as the most appropriate DL model from limited chest CT dataset using the classical data augmentation with testing accuracy of 82.91%
[54]	Brain MRI images	Data collected from thirty men (81%) and 7 women (19%)	brain abnormality in severe COVID infection	signal abnormalities located in the medial temporal lobe in 16/37 (43%, 95%IC 27-59%) patients	Eight distinctive neuroradiologic patterns (excluding ischemic infarcts) were identified in patients with severe COVID-19 infection with abnormal brain MRIs.
[55]	chest computed tomography (CT) imaging	NA	early classification of COVID-19 patients	CNN with initial parameters are tuned using multiobjective differential evolution (MODE).	The proposed model achieves significantly more Kappa statistics and outperforms competitive models by 1.9276%
[56]	Lung Ultrasound images	Around 60,000 ultrasound images of confirmed COVID-19 cases	helped in quick clinical decision making	use of pattern recognition algorithm	clinical scoring is set: A = 0 point, B1 = 1 point, B2 = 2 points, C = 3 points. Thus, a LUS of 0 is normal, and 36 would be the worst. This method reduced the use of both chest x-rays and computed tomography (CT)
[57]	lung ultrasonography (LUS) images	277 lung ultrasound (LUS) videos from 35 patients, corresponding to 58,924 frames	DL with X-ray imaging extracted signifcant biomarkers linked to the Covid-19 disease	novel deep network, derived from Spatial Transformer Networks, which predicted the disease severity score associated to a input frame and provides localization of pathological artefacts in a weakly-supervised way	DL for the assisted diagnosis of COVID-19 from LUS data
[58]	X-ray images (JPEG)	Total 307 images categorized into four classes i.e. normal, pneumonia bacterial, and pneumonia virus	coronavirus detection using chest X-ray images	three deep transfer models are selected in this study for investigation which are the Alexnet, Googlenet, and Restnet18	Googlenet resulted to be the main deep transfer model as it achieves 100% in testing accuracy and 99.9% in the validation accuracy
[59]	Chest X-ray images	320 images in total, classed in two categorize: 160 images for patients affected by COVID-19 and 160 Normal images	classifier for COVID-19 using chest X-ray images	Deep Transfer Learning (DTL) method using CNN based models InceptionV3 and ResNet50 with Apache Spark framework	High accuracy was obtained by the proposed model i.e. 99.01% by the pre-trained InceptionV3 model and 98.03% for the ResNet50 model
[60]	Chest CT scans	1014 images	COVID-19 detection in epidemic areas.	statistical analysis was performed with software (SPSS, version 21.0; SPSS, Chicago, Ill)	The sensitivity of chest CT in suggesting COVID-19 was 97% (95% confidence interval: 95%, 98%; 580 of 601 patients) based on positive RT-PCR results
[61]	lung ultrasonography (LUS) images	A dataset named POCUS contains 1103 images of which 654 COVID-19, 277 bacterial pneumonia and 172 sound subjects, extracted from 64 videos	assist physicians in diagnosing COVID-19	developed and trained POCOVID-Net (deep CNN)	The model shows sensitivity of 0.96, specificity of 0.79 and F1-score of 0.92 in a 5-fold cross validation

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