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iWorkSafe: Towards Healthy Workplaces during COVID-19 with an Intelligent pHealth App for Industrial Settings

M. Shamim Kaiser[1,*], Mufti Mahmud[2,3,*], Manan Binth Taj Noor[1], Nusrat Zerin Zenia[1], Shamim Al Mamun[1], K.M. Abir Mahmud[4], Saiful Azad[5], V.N. Manjunath Aradhya[6], S. Punitha[7], Thomson Stephan[8], Ramani Kannan[9], Mohammed Hanif[10], Tamanna Sharmeen[11], Tianhua Chen[12], and Amir Hussain[13]

[1] Institute of Information Technology, Jahangirnagar University, Dhaka – 1342, Bangladesh. (e-mail: mskaiser@juniv.edu)
[2] Dept. of Computer Science, Nottingham Trent University, Nottingham – NG11 8NS, UK. (e-mail: muftimahmud@gmail.com, mufti.mahmud@ntu.ac.uk)
[3] Medical Technology Innovation Facility, Nottingham Trent University, Nottingham – NG11 8NS, UK.
[4] Skoder Technologies, Dhaka-1216, Bangladesh.
[5] Faculty of Computing, University Malaysia Pahang, Gambang – 26300, Kuantan, Malaysia.
[6] Dept. of Computer Applications, JSS Science and Technology University, Mysuru–570006, India.
[7] Dept. of CS, Pondicherry University, Puducherry – 60514, India.
[8] Dept. of CSE, M. S. Ramaiah University of Applied Sciences, Bangalore – 560 054, India.
[9] Dept. of Electrical and Electronics Engineering, Universiti Teknologi PETRONAS, Seri Iskandar – 32160, Malaysia.
[10] Bangladesh Institute of Child Health, Dhaka Shishu Hospital, Dhaka – 1207, Bangladesh.
[11] Women Immigrant in Economic Growth, Nottingham, NG2 7JZ, UK.
[12] Dept. of Computer Science, University of Huddersfield, Huddersfield – HD1 3DH, UK.
[13] School of Computing, Edinburgh Napier University, Edinburgh – EH10 5DT, UK.

[*] Co-corresponding authors. Emails: mskaiser@juniv.edu (M.S. Kaiser); mufti.mahmud@ntu.ac.uk, muftimahmud@gmail.com (M. Mahmud)

Abstract

The recent outbreak of the novel Coronavirus Disease (COVID-19) has given rise to diverse health issues due to its high transmission rate and limited treatment options. Almost the whole world, at some point of time, was placed in lock-down in an attempt to stop the spread of the virus, with resulting psychological and economic sequela. As countries start to ease lock-down measures and reopen industries, ensuring a healthy workplace for employees has become imperative. Thus, this paper presents a mobile app-based intelligent portable healthcare (pHealth) tool, called iWorkSafe, to assist industries in detecting possible suspects for COVID-19 infection among their employees who may need primary care. Developed mainly for low-end Android devices, the iWorkSafe app hosts a fuzzy neural network model that integrates data of employees' health status from the industry's database, proximity and contact tracing data from the mobile devices, and user-reported COVID-19 self-test data. Using the built-in Bluetooth low energy sensing technology and K Nearest Neighbor and K-means techniques, the app is capable of tracking users' proximity and trace contact with other employees. Additionally, it uses a logistic regression model to calculate the COVID-19 self-test score and a Bayesian Decision Tree model for checking real-time health condition from intelligent e-health platform for further clinical attention of the employees. Rolled out in an apparel factory on 12 employees as a test case, the pHealth tool generates an alert to maintain social distancing among employees inside the industry. In addition, the app helps employee to estimate risk with possible COVID-19 infection based on the collected data and found that the score is effective in estimating personal health condition of the app user.

Keywords: Industry 4.0; artificial intelligence; machine learning; mobile app; digital health; safe workplace; worker safety; Coronavirus.

1 Introduction

The novel Coronavirus Disease 2019 (COVID-19) is caused by a newly found positive-sense single-stranded ribonucleic acid (+ssRNA) virus pathogen which is known as Severe Acute Respiratory Syndrome CoronaVirus–2 (SARS-CoV-2) and matches closely to bat coronaviruses [1, 2]. In the late of December 2019 the first human case of COVID-19 was reported in Wuhan, China which then spread to the rest of the world by the first quarter of 2020. Due to the soaring infection and mortality rates, the World Health Organization (WHO) declared the disease as a pandemic calling for a global Public Health Emergency on January 2020 [3].

An infectious disease may turn into a pandemic by rapid spread of the pathogen through human mobility between areas of active transmission and disease-free areas [4]. Fig. 1 reports a comparative account on three WHO declared global pandemics (SARS-CoV-2, SARS-CoV, and MARS-CoV) in terms of total cases and deaths. As of 27 October 2020, the virus has spread globally affecting 217 Countries and Territories around the world [5]. This has led to a number of strict measures (e.g., social distancing, self-quarantining and isolation, and restricted mobility etc.) employed by individual countries to tackle the situation in minimizing the spread of the virus and therefore resulted in massive external pressure on global economics, resources and citizens [6–8].

Currently, COVID-19 has caused a social and economical paradigm shift affecting billions of people worldwide across different domains and disciplines. This public health emergency has resulted in embracing severe social and economic measures to conserve health and safety of mass population of individual countries. As lockdown in many countries are being relaxed and industries are starting to operate, ensuring worker safety in this post-lockdown period is very crucial for smooth operation of the supply chain. This situation is even more grave in the developing nations, such as Bangladesh, where a large number of the population survives on meagre daily wages [9].

According to a recent research conducted by the South Asian Network on Economic Modeling (SANEM) on the post-COVID-19 situation of Bangladesh, it has been predicted that a negative income shock of 25.0% would turn the overall poverty rate to 40.9% which ultimately results in another 20.4% or 33.0 million of the population to directly plunge into poverty [10]. Thus, to hold onto and maintain a sustainable economic condition and avoid the possibility of greater economic catastrophe, from the perspective of a developing country like Bangladesh, certain industrial sectors are in the process of reopening and some others have already reopened. But, these industrial sites may serve as the hot-spot of the next disease cluster due to the lack of facilities to ensure social distancing during the working hours. This is even more aggravated due to the crowded nature of industrial factories, specially the apparel industry in Bangladesh,

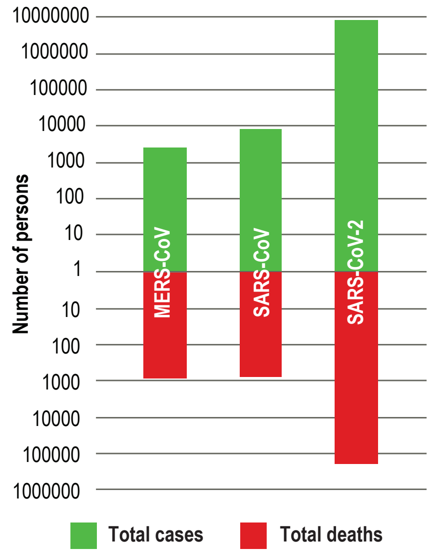

Figure 1. Comparison of SARS-COV-2 with SARS-COV and MARS-COV in terms of number of infected people and number of death.

with a higher possibility of exposure to the infectious disease. One of the findings of [11] characterized workplace as a potential source of COVID-19 infection transmission as well. This stipulates the exigency of timely efforts by responsible authorities to ensure proper health services access to industrial workers with a view to establishing pertinent and effective COVID-19 control measures through continuous monitoring of health related behaviour, health status and smart tracking of them to trace their travel and contacts regularly. Control measures require inclusion of retaliation plans to respond accordingly with integration of infectious disease control training strategy to the workers; ultimately developing a workplace policy which would support the creation of a work environment taking into consideration the health concerns of the workforce who have potentially been exposed to COVID-19.

With the recent advancement of computing and better understanding of artificial intelligence (AI), various types of rule base [12–15], bio/brain-inspired [16] and machine learning (ML) approaches [17, 18] have acquired unrivalled concentration of the researchers in the last decade for the biological and healthcare big data mining [17], disease prediction and detection [19–23], anomaly detection [24–27], personalized treatment planning for risk prediction [28–30], clinical decision support system [31, 32], text processing [33, 34], disease management [14, 35] and mobile health based app [36–38]. During this COVID-19 outbreak, AI and ML have also been used in infection detection, self-testing and spread prevention in home, clinic and office settings.

A COVID-19 outbreak in an industrial setting might lead to disastrous consequences. If such an outbreak can be prevented through the use of cutting-edge technology, the supply chain can be kept intact to facilitate a steady economic situation in a country. Considering this as a high priority, a large number of COVID-19 related research and development efforts have been conducted globally [21, 39]. Towards that goal, the proposed mobile app based solution uses an intelligent portable health (pHealth) provision for industrial settings. This solution supports instantaneous identification of possible COVID-19 infection using self-test and regular health checkup data, and provides appropriate alert for meticulous tracking based on proximity detection of the workers. All these data are fused and analysed using intelligent analytics and packaged in a mobile app known as '*i*WorkSafe' which ultimately contributes in identification of

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those workers who are possibly exposed to COVID-19. Also, iWorkSafe facilitates the tracing of those workers who have possibly worked with the supposedly infected carrier to cut the transmission link down. This will subsequently aid in prompting public health risk response and management for COVID-19 outbreak in a workplace leading to healthy work environment.

Table 1. Comparison of SARS-CoV-2 with SARS-CoV and MARS-CoV [1, 6]

Factor	MERS-CoV	SARS-CoV	SARS-CoV-2*
CoO	Saudi Arabia	China	China
InfCountr	27	29	217
ConInf	2521	8098	>84,349K
Deaths	866	774	>1,834K
MoR (%)	35.0	9.6	2.2
R_o	< 1	2-4	1.8-3.6 [40]

Legend: CoO–Country of Origin; InfCountr–Number of affected countries; ConInf–Confirmed Infections; MoR–Mortality Rate; * as of 1 Jan 2021.

Addressing the important issue of workplace safety during this challenging time, the following contributions are put forward in the current work:

- A privacy-preserving mobile application for intelligent proximity/contact tracing and COVID-19 screening for industrial settings has been proposed which ensures a healthy workplace for the employee;
- Along with the regular health checkup data inputted by the medical/test centre, an e-health sensor shield is used to collect physiological conditions of each employee and the data are stored in a local database;
- A fuzzy neural network algorithm is used for fusing all these data (i.e., health condition, proximity detection, contact tracing, and COVID-19 self-test information) in the proposed iWorkSafe app and provides a novel metric to determine the healthiness of the workers.

As for the rest of the article, section 2 points out the related works while section 3 describes the possible data sources to detect COVID-19 and the development of the mobile app. The sections 4, 5 and 6 describe the experimentaton and validation of the mobile app, the challenges and future scopes of the current work, and some concluding remarks about it, respectively.

2 Related Work

The scale and spread of COVID-19 pandemic call for a synchronized approach to help the common people in a rather simple way. Harnessing the popularity of mobile computing technologies might be a way to raise awareness among people regarding mechanisms of disease spread, perform self-tests and ways to stay safe [39]. This can also be extended to estimate the future spread of the disease through predictive analysis and decide on pandemic retaliation strategies to minimize the infection transmission leading to reduced death tolls.

Several mobile applications have been released already for automated management of COVID-19 infection. These applications mainly contain features to provide

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Table 2. Apps for the self assessment and management of COVID-19 in industrial setting.

Ref.	Apps	Self-test	SD	CT	Security	Privacy
[41]	Apple COVID-19	✓			✓	✓
[42]	HealthCheck .	✓			✓	✓
[43]	ProtectWell	✓				
[44]	COVID19Tracker	✓		✓		
[46]	AlightWell	✓				
[45]	Social Distancing Tracker		✓			
[47]	SoCo COVID-19 Check	✓				
[48]	Screening Log	✓				
–	*i*WorkSafe	✓	✓	✓	✓	✓

Legend: SD–Social distancing; CT–Contact tracing; Screening Log–The Daily Employee Screening Log.

COVID-19 related information, checking symptoms as well as tracking confirmed and possible infected people to monitor and limit the spread of the infection. Some apps are specially tailored to ensure and protect the safety of the employees returning to the workplace [41–48]. The main features of such apps mainly include a self-screening tool for identifying COVID-19 symptoms or exposure. These regular health screening, proactive measures, and associated data points allow the authority of the business organizations to advance the facilities to protect employee health more efficiently. Besides, employees feel positive returning to work knowing the administration is taking steps to prevent the epidemic and promote wellness.

Apple COVID-19 [41] aids people with up-to-date information about COVID-19 and advises on the dos and don'ts. HealthCheck [42], launched by Stratum Technology, is a secure cloud-based platform that employed data analytics to track and assess the health status of a company's workforce. Cloud-based solutions have previously been employed to different applications for healthcare management and delivery [36, 49]. The HealthCheck app looks for COVID-19 related symptoms to better prepare for future pandemic outbreaks while safeguarding the overall well being of the organization. Employees partake in a self-health-assessment method every day before entering their job premises where they answer a series of health-related questions and receives real-time feedback on matters such as whether they are eligible to work, should they consult their respective supervisor, or stay home. The employers receive alerts when an employee is being suspected with COVID-19 symptoms and get access to employees' unique dashboard. The separate Managerial dashboard feature of HealthCheck enables the employers to identify hot-spots within industry proximity and address staffing needs accordingly. ProtectWell [43], launched by United Health Group and Microsoft Corporation, includes an AI-powered healthcare screening tool for regular screening of employees for COVID-19 symptoms or exposure. If the risk of infection is identified, employees are directed to the COVID-19 testing process and test results are reported to the employers. COVID19Tracker [44], launched by KOKOMO24/7, associates employees with regular self-screening and provide color-coded badge (e.g., Red, green) indicating the employees health status. The app also incorporates contact tracing that stores information like contact identification, contact listing, and contact follow ups. The managerial section of the app facilitates case management through alert, notification, and workflow analysis. AlightWell [46], launched by Alight, provides health screening tools and suspected COVID-19 patients will be connected to healthcare resources for additional screening. SoCo COVID-19 Check [47], launched by County of Sonoma, includes a self-assessment tool and a newsfeed with the latest COVID-19 information. The employer version of the app verifies that employees do not have high temperatures and are wearing face masks. Moreover, The Daily Employee Screening Log [48], launched by Go Canvas, facilitates employees with health screening tool and provides health status report. Social Distancing Tracker [45], launched by DROR, introduces a variant approach where the app mainly focuses on social distancing rather than checking for symptoms and assign the user with daily, weekly and last 14 days of social distancing score.

Interactive web-based self-screening tools have also been developed by organizations such as, SafetyTek [50], NetHealth [51], Appian [52], PEGA [53], and Ceridian [54] to manage the safety of their workforce during the pandemic. Employees use a simple web or mobile interface to report their health status and based on the data the companies can track and manage current and future health exposure risks. Along with self screening ClearPass [55] developed by Red Level Group ensures social distance through pre-registration and queuing for accessing specific locations within the company. Besides Tsingoal introduces localSense [56] to ensure social distance using tags which trigger alarms if social safe zone violates (tags distance is less than 6ft.). The system also store incident information including ID, time and duration.

Table 2 reports the existing apps and their major features and a comparison with the iWorkSafe app. As seen in the table, the developed mobile apps and web-based systems considering the industrial and co-working settings mainly concentrate on self screening tool where employees need to input their health related information. But in developing countries like Bangladesh, most of the workers in industrial sectors lack proper educational background and training to effectively use this kind of interactive tools. Hence, only self screening can provide mislead data which in turn can be a great risk for the workforce health and company well-being. Features of iWorkSafe are mainly designed by keeping those complications in mind and rather than self screening we introduces screening with sensor to collect employees' vital signs and to ensure data integrity. Besides, our app takes social distance into account while generating health score for individual employees. Thus, iWorkSafe, being an AI and cloud based intelligent app, could be proved as an emerging solution to ensure safe workplace.

3 Proximity, Tracing and COVID-19 Detection

COVID-19 has a huge impact on socio-economic status after its outbreak. To keep the economic sector steady, it is essential to estimate the health condition of employees, maintain safe distance among staff at the industry, and track contacts of all staff to isolate them if anyone is infected with the SARS-COV-2. Figure 2 illustrates the functional block diagram of a system that fused multi-modal data such as physiological, p-health mobile app, and clinical data from the medical center. The mobile app uses Bluetooth low energy, wifi, interface to detect the social distancing among staff and track contacts. Based on these collected data, the system generates a risk score that categorized employees into three groups such as Green–Fit to work, Orange–Observe the symptom, Red–clinical attention required. The app can surmise the possibility of COVID-19 infection in an individual and instruct the user for contacting with a nearby hospital for the COVID-19 test.

Table 3. Data Sources for various application used in industry setting

Application	e-Health	B/W/C/N	Camera	App
Attendance		✓		✓
Vital Signs	✓			✓
Social distance		✓	✓	
EHS				✓
Contact Tracing		✓		
COVID-19 Selftest		✓	✓	✓

Legend: B/W/C/N–Bluetooth/Wifi/Cellular/NFC; e-Health– e-Health sensor; App– Mobile Application; EHS–Emergency Health Services

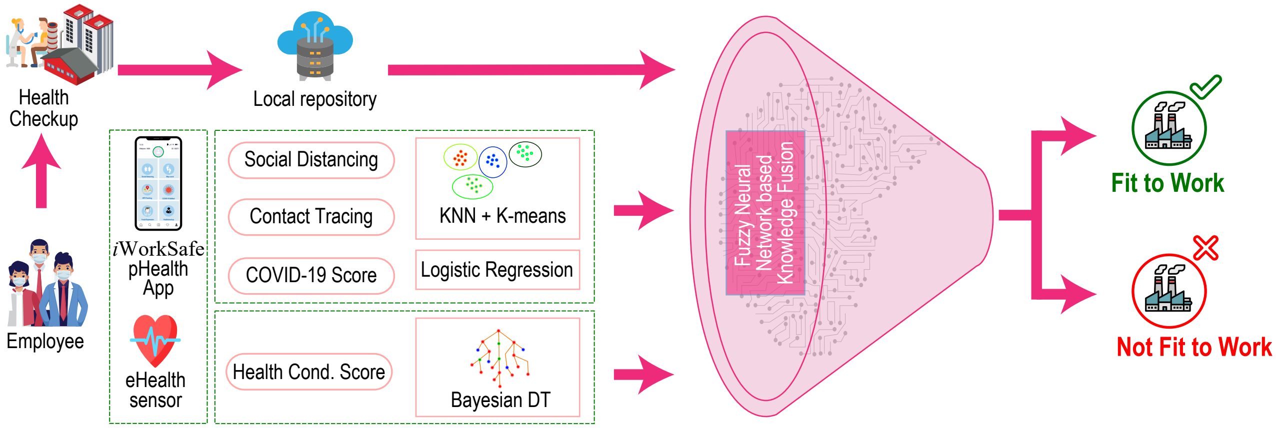

Figure 2. Functional block diagram of the *i*WorkSafe app. The app collects mutimodal data and identifies if an employee is fit for work or not by applying artificial intelligence based techniques such as machine learning and fuzzy neural network based inference systems.

3.1 Data Sources

As the number of smartphone users is rising and expected to reach more than 3.5 billion by 2020, and 4.54 billion active internet users found on January 2020, most of the companies/countries are employing mobile phone sensors (such as GPS, Bluetooth, WiFi, etc.) and smartphone app for controlling the disease spread of COVID-19. The real-time data generated by these sensors can be collected, anonymized, analyzed for ensuring social distance, contact tracing of close contacts with infected staffs, screening COVID-19 at office/home, assessing the physical condition of the healthy and infected person. Table 3 lists the various data sources and possible applications for combating the spread of the COVID-19 virus.

Broadly, three types of data, such as health condition data, user proximity and contact tracing data, user-provided COVID-19 self-test data through mobile app, which will be employed for safeguarding that an employee in the industry has less risk of getting infected by COVID-19 virus which refers the physical fitness of the employee. Figure 2 shows a functional block diagram in which along with these three types of data, routine health checkup data will also be integrated to ensure all the employees in the industry are healthy and provides their best effort. The data can be stored in the local repository for further testing and training purpose of the system.

3.2 Health Condition Detection

Daily health condition recording using e-Health Sensor is essential for early detection of medical conditions. In the proposed system, an e-Health sensor platform is used in the industrial setting which would be able to record body temperature, blood pressure, electrocardiography, oxygen saturation level, pulse rate, airflow of every employee. In this regards, the proposed e-health sensor platform used heartbeat, blood pressure, oximeter, spirometer and temperature sensors to accumulate multi-modal data for analysis in different aspect of healthiness of the employees. Regular health checkup by the in-house doctor of the industrial setting will examine employee's health and commit the data into the local repository for further real time health testing of the employees. Moreover, in entry level of the industry, e-health sensors will gather all sensors data which will used for training our system. In our proposed system, a probabilistic model called Bayesian Decision Tree [57,58] has been used for training and validation to get the health condition score for fitness of the employee. We have used this mixture model of decision tree and Bayesian theory to handle categorical variables and missing data in principled way to get better performance. Decision have been made in the non-terminals and leaves level to get the total probability of the model. Suppose, $\omega_1, \omega_2, \omega_3, \ldots, \omega_m$ represent multinomial decision variables of the tree branch with $m-1$ nodes, then the output of the leaves will be:

$$P(Y|X, \omega_1, \omega_2, \omega_3, \ldots, \omega_m)$$

where X and Y is the inputs and outputs respectively. Furthermore, the portable monitoring system stores these physiological data in the local health register database for every employee. These stored data can be employed to detect vital signs using artificial intelligence-based reasoning and generate an alert if clinical attention is required. In addition, in-house doctors examination is also stored in the local repository for the further decision of taking action related to COVID-19 score. The computational complexity of the health condition detection process is estimated as $O(m \cdot n)$.

3.3 Proximity Detection and Contact Tracing

Social distancing or minimizing physical connection is one of the indispensable steps to impede the spread of COVID-19 which is at least 6 feet between individuals as per WHO [3]. Users' proximity and position detection by a smartphone can ensure the social distancing among individuals. The various interfaces such as Bluetooth, WiFi, near-far communication (NFC), and Global Positioning System (GPS) of smartphones can help to obtain proximity and contact tracing data of users [59]. However, the coverage areas of Bluetooth, WiFi, and Cellular network are about 2 meters, 15 meters, and 1000 meters respectively, and thus, Bluetooth low energy can be used for maintaining social distancing in the industry setup. The contact tracing can detect possible exposure to a worker who has been diagnosed with the COVID-19 virus.

Figure 3 shows proximity detection and contact tracing among the employee in the industry. Each employee requires to install an application (in short, app) using the office ID, the system sends one-time password (OTP) to the official mobile number which is registered to an employee, the app user will then input the OTP in the app then the registration of the app is completed to the server. The service will then send an encrypted temporary ID (in short TID) from a trusted cloud and/or the server of the industry [16] (Figure 3 (A)). The system releases application programming interfaces for connecting the system to the national contact tracing database and electronic healthcare record database (see Figure 3 (B)). The system is integrated into the healthcare system or test center where regular/routine health checkups of the employee will be performed (Figure 3 (C)). COVID-19 self-test feature of the app which takes a survey about the current symptoms from the user. The app will also take e-health, facial expression, proximity detection data, and then generates an employee's health status score (Figure 3 (D)). The calculated health status/COVID-19 score will be sent to the Industry database which can be integrated with health care systems. The system also generates a referral pathway for the employee if any medical support or attention is essential. App users use Bluetooth low energy radio signals to track users' proximity (Figure 3 (E)). In addition, the system takes contact tracing TIDs from each employee after a periodic interval or when the app is syncing with the server. After the syncing period, the app will receive another TID which replaces the old TID. The contact tracing flow diagram is illustrated in Figure 3 (F). If a person found in contact with the COVID-19 patient then the concerned will be notified and take necessary measures. GPS based location-based tracking can ensure infected or individual (i.e.,

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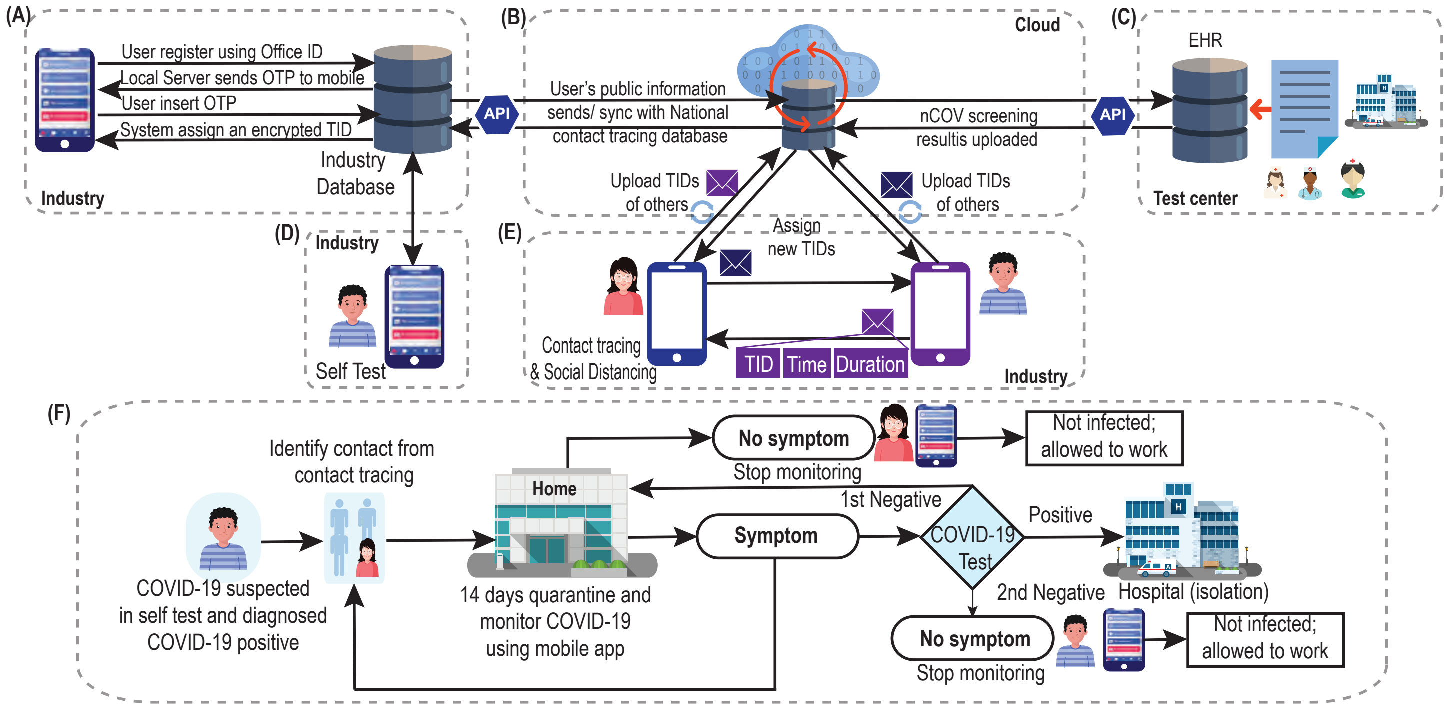

Figure 3. Mobile app to trace contact and COVID-19 exposure among the workforce inside the industry. (A) App user registers to the system with the office ID, the system sends one-time password (OTP) to the registered mobile number which requires to be inputted in the app, and after the registration, the app will receive an Encrypted temporary ID (in short TID); (B)The system releases application programming interfaces which can connect the national contact tracing database (if any). Also, the system takes input from a hospital/test center where regular/routine health checkup of the employee will be performed. (C) A test center that generates employee health status; (D) COVID-19 self-test using the app which takes survey symptoms from the user. The app also takes e-health, facial expression, proximity detection data, and then generates a score. Finally, the calculated COVID-19 score will be sent to the Industry database; (E) App users use Bluetooth low energy radio signals to track users' proximity; and (F) Contact tracing flow diagram.

isolated person) an individual who came close contact with the infected person (i.e., quarantine person) to stay their home. If these persons leave the place or turn off the smartphone interface, it will be reported to the government agencies. Also, GPS based location tracking guides a user to avoid the infected area. The resolution of GPS is also low (>10 meters) compared to Bluetooth [59]. In short, the geo-location and proximity data collected using Bluetooth, WiFi, Cellular network and GPS interface of a smartphone can assist the app to detect users' proximity and position precisely. For tracing proximity and tracking contact, we have employed K Nearest Neighbor and threshold-based algorithm. The computational complexity of the proximity detection process is $O(n^2)$ and contact tracing process is $O(log_2 n)$.

3.4 COVID-19 Self-test

Self-Screening feature of the *i*WorkSafe pHealth mobile app allows industry staff to assess their selftest using questionnaires in compliance with WHO guidelines, and the score indicates the possibility of COVID-19 infection. However, the self-screening is not

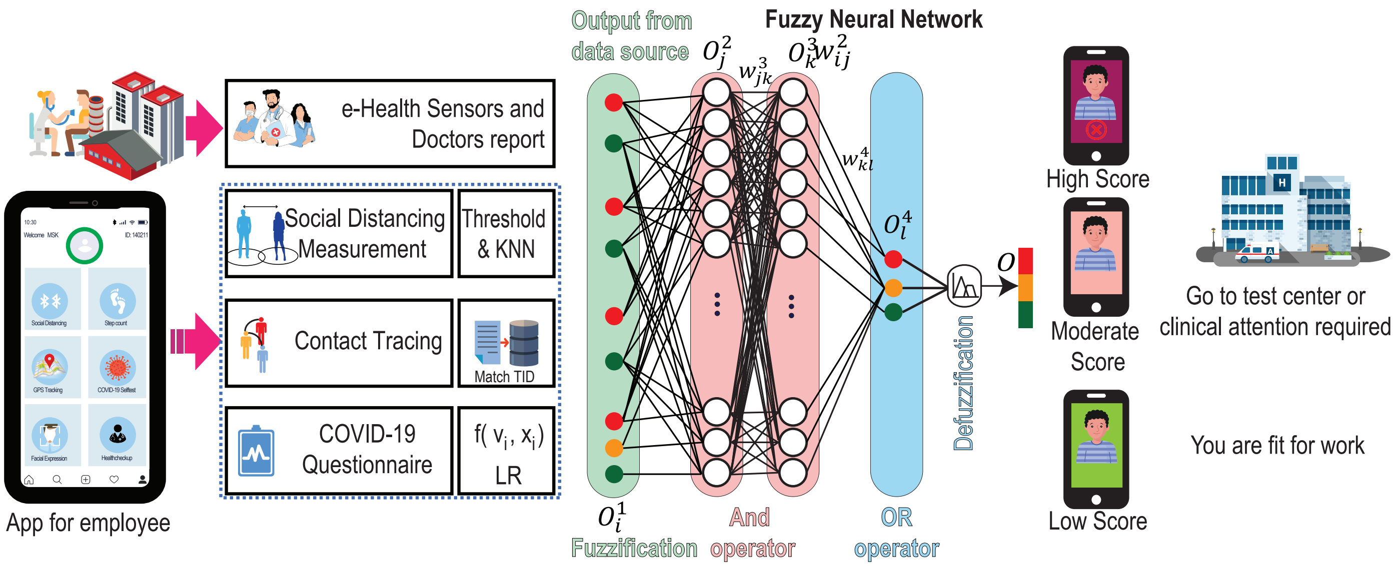

Figure 4. Fuzzy Neural Network based COVID-19 self screening and check employee eligibility to attend the workplace. Here red, orange and green refer Sad/Not fit/low/Yes/High, medium and Happy/ fit/High/No/Low respectively.

a gold standard and may give false negatives. The score of COVID-19 Self-test (θ), calculated by:

$$\theta = f(v_k, x_k) = \sum_k v_k x_k, \tag{1}$$

where x_k is the k-th question of the questionnaire and v_k is the corresponding weight. Therefore, the likelihood, $p(\theta)$ of logistic regression model is expressed in Equation 2.

$$p(\theta) = \frac{1}{1 + e^{(-\theta)}} \tag{2}$$

The COVID-19 self-test process has a computational complexity of $O(n^2)$. The model is trained by COVID-19 Open Research Dataset Challenge (CORD-19) and dataset discussed in Section 4.2.

3.5 Fuzzy Neural Network based Fusion

In order to reduce this high false negative, along with the questionnaires, we have fused health status data, social distancing, and contact tracing information. The Fuzzy Neural Network (FNN) [60] controller is employed to fuse the knowledge acquired from these data [59, 61]. Figure 4 shows a functional diagram of FNN based COVID-19 self screening system which can be employed to check employee eligibility to attend the workplace. The FNN based fusion process has a maximum computational complexity of $O(n^k)$ where n is the input and k is the number of membership functions. It should be noted that, as a whole, the computational complexity of the iWorkSafe app depends on complexity of each of the processes employed in the app which in turn depends on specific methods used in those processes.

The proposed FNN includes five layers with layer 1 for fuzzification, layer 2 for rules, layer 3 for implication, layer 4 for aggregation and layer 5 for defuzzification.

Fuzzification converts crisp inputs into linguistic variables. In this papers, health status detection (HSD), social distancing (SD), contact tracing (CT), COVID-19

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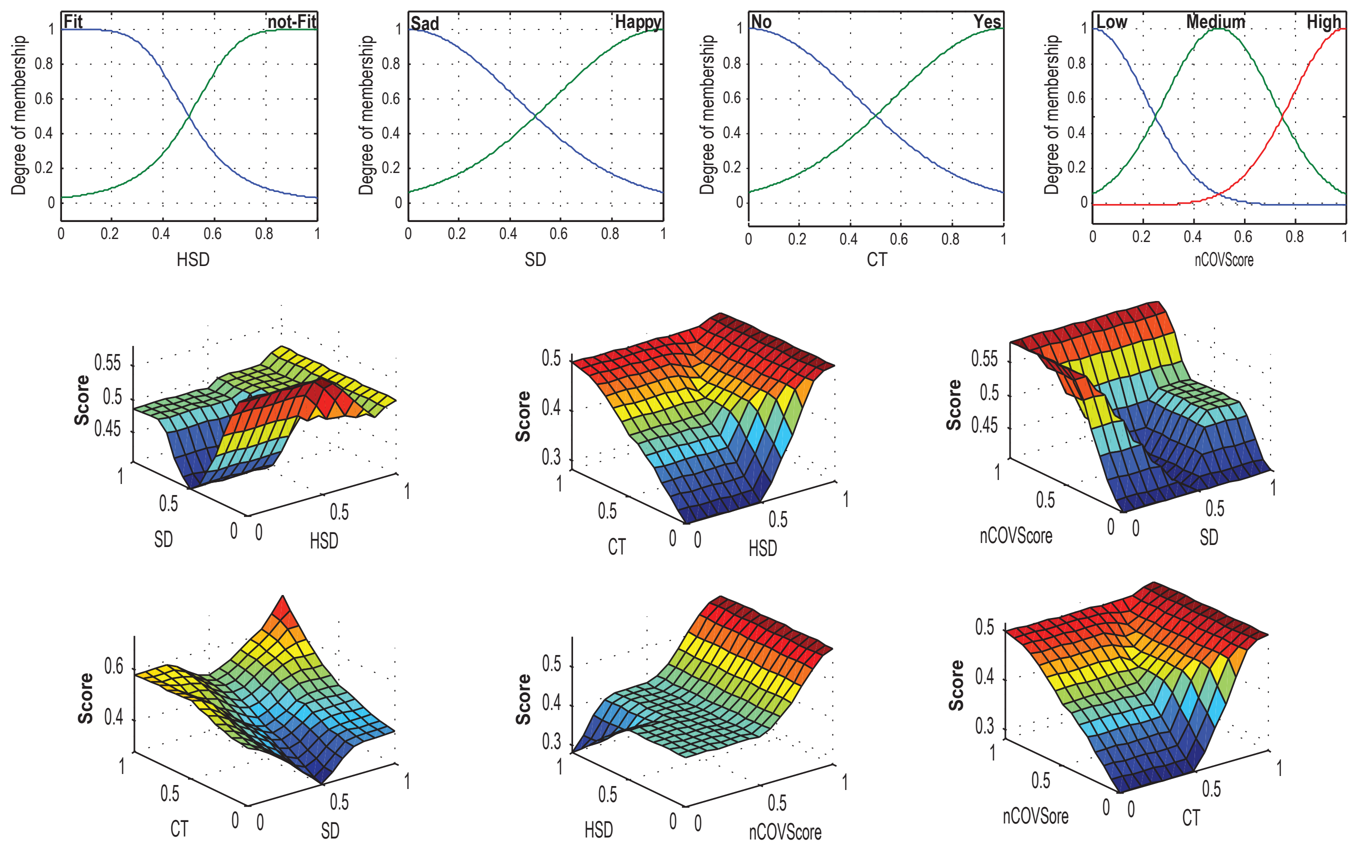

Figure 5. The membership functions and linguistic terms of the input and output variables, and the surf plot shows the relationship between input and output variables.

questionnaire ($nCOVScore$) are crisp inputs collected using e-health sensor shield and clinical staff, as well as the mobile app are converted into linguistic variables using the fuzzification process. The considered linguistic variables for each of these inputs are: $\mathcal{B}$:{Fit or Not-fit} for health condition detection; $\mathcal{C}$:{Low, Medium, High}; $\mathcal{D}$:{No, Yes} for contact tracing; $\mathcal{E}$:{Low, Medium and High} for COVID-19 questionnaire (see Figure 5). The outputs of the fuzzification layer are the degree of membership (value lies between 0 and 1) for each of these inputs. In this case, the Gaussian membership function is chosen for the linguistic terms mentioned above as it produces smooth output and has less computational complexity.

The rules interconnect input and output linguistic variables using conjunction ('and'), disjunction ('or') and negation ('not') procedures. The inference sub-system employs fuzzy reasoning and generates fuzzy output from the fuzzy inputs. In this case, the Mamdani fuzzy inference system is utilized which takes HSD, SD, CT, and $nCOVScore$ as inputs and produces the required linguistic terms (low, Moderate and High) for COVID-19 score following fuzzy rules.

The defuzzification layer converts fuzzy value to a crisp value. In this paper the center of gravity defuzzification method is considered.

The output of various layers can be written as:

$$\text{Layer 1: } O_1 = \mu_{I_{ip}}(X_p) = \exp\left[-\frac{(c_{ip} - X_{ip})^2}{2\sigma_{ip}^2}\right] \tag{3}$$

$$\text{Layer 2: } O_2 = w_j = \prod_p \mu_{I_{ip}}(X_p) \tag{4}$$

$$\text{Layer 3: } O_3 = w_j \circ F_j \tag{5}$$

$$\text{Layer 4: } O_4 = \sum_i w_j \circ F_j \tag{6}$$

$$\text{Layer 5: } O_5 = D \circ O_4 \tag{7}$$

where, X_p refers to inputs p (HSD, SD, CT, $nCOVScore$) $\mu_{I_{ip}}(X_p) \in [0, 1]$ is the membership function for the linguistic variable I_{ip} ($\mathcal{B}$,$\mathcal{C}$,$\mathcal{D}$,$\mathcal{E}$); c_i and σ_i are centre and width (also called premise parameters) of the ith linguistic variables; w_i and is the firing strength of rules; $\circ$ is called implication operator which is product; $F \in \{Low, Medium, High\}$ is linguistic term; $\mu_F(Z_j)$ is the membership function of Z_j. The premise and consequent parameters can be adjusted using gradient decent algorithm. If the defuzzification value O, given by equation 8, lies in the 1st-2nd quartiles, then the employee is fit to work, else clinical attention is required. Here, the clinical attention could be in the form of performing further clinical investigation or observing self-isolation as per government regulations.

$$O = \frac{\int \mu_F(z) z dz}{\int \mu_F(z) dz} \tag{8}$$

$$= \frac{\sum_j w_j m_j z_j}{\sum_j w_j m_j} \tag{9}$$

where m_j and z_j are consequent parameters, and $\mu_F(Z_j)$ is the membership function of linguistic term F ($F \in (\text{Low}, \text{Medium}, \text{High})$).

Figure 5 shows membership functions and linguistic terms of the input and output variables, and the relationship between input and output variables (that is, HSD, SD, CT, and $nCOVScore$) are illustrated using surf plot.

4 Experimentation and Validation

4.1 App Description

Developed in Java, the android mobile app-based intelligent pHealth tool, "iWorkSafe", is capable of integrating data on employee health status, proximity and contact tracing, and user-provided COVID-19 self-screening and allow employees to estimate the risk of possible COVID-19 infection. The Bluetooth low energy sensing and K Nearest Neighbor model have been used to track users' proximity and trace contact with other employees and a logistic regression model have been used to calculate the COVID-19 self-test score. The fuzzy neural network model fused information from these data and created risk score that can be used to measure an employee's fitness.

Figure 6(A) shows the initial screen of the iWorkSafe app where the user interface design (UI) is based on user experiences (UX) and human interaction of mobile screen as most of the industry workers are not that much tech-friendly compared to the other desk job service holders. This intelligent pHealth app tracks the proximity and traces the contact of employee when they come with in the distance of 1 meter and spend

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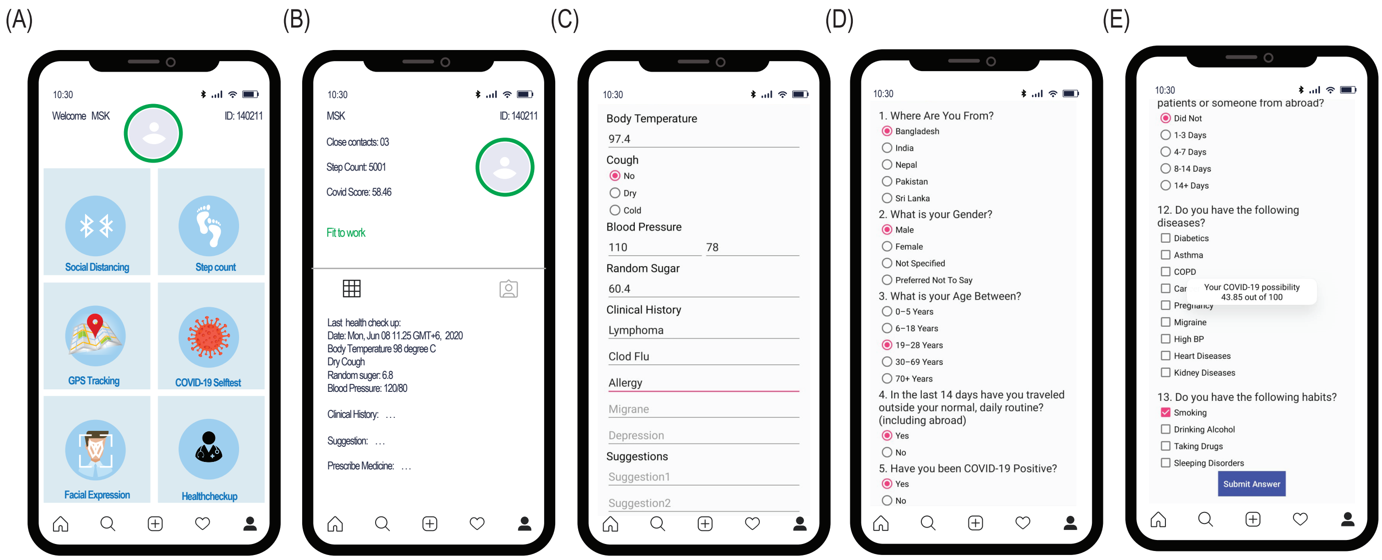

Figure 6. *i*WorkSafe app user interface (A) App launching frame; (B) Proximity and Contact tracing; (C) Health checkup; (D)-(E) COVID-19 self-screening.

more than 15 minutes. During this duration, the app exchanges encrypted asynchronous key and then count number of tracked employee (see Figure 7) using thresholding and K-nearest neighbors algorithm. Figure 6 (C) shows UI of the app when doctor has inputted health status of an employee after face to face meeting, COVID-19 self screening questionnaires are shown in Figures 6 (D) and (E). The COVID-19 self score is generated by a weighted summation based on logistic regression. In addition, the app is developed with laravel PHP framework and uses Google firebase real-time database at the back-end to enable app uses to perform real-time contact tracing among the industry employees.

Role-based access control (RBAC) is applied for authorization and authentication process of different roles. In *i*WorkSafe, three distinct roles are implemented (Admin, Client and doctor). For each role there exists a different panel of maneuver for setting permission level for data security and integrity of passing information from client and doctor's input to the server. Seamlessly, APP database is connected to the local e-health register for storing worker's health data from e-health sensors and doctor's input after physical investigation upon self COVID-19 test score of the app. Moreover, an unique generated value is created after every REST API connection over the HTTPS (SSL) for bearer authentication of uploading the COVID-19 statistics of the industry to the government Health Information System (HIS).

4.2 Data Generation

The data has been collected from RBS Fashion, a local garment of Bangladesh from 12 July 2020 to 13 July 2020 after the approval from the ethical committee of the Jahangirnagar University, Dhaka, Bangladesh. Out of 158 employees, only 20 employees of RBS Fashion participated with the informed consent in the study. The participants were aware of the study and switched on the Bluetooth interface. The identity of the app users was anonymized and 12 individuals were working on the same floor for considering the social distancing information. Noteworthy, on 12 July 2020, data of the

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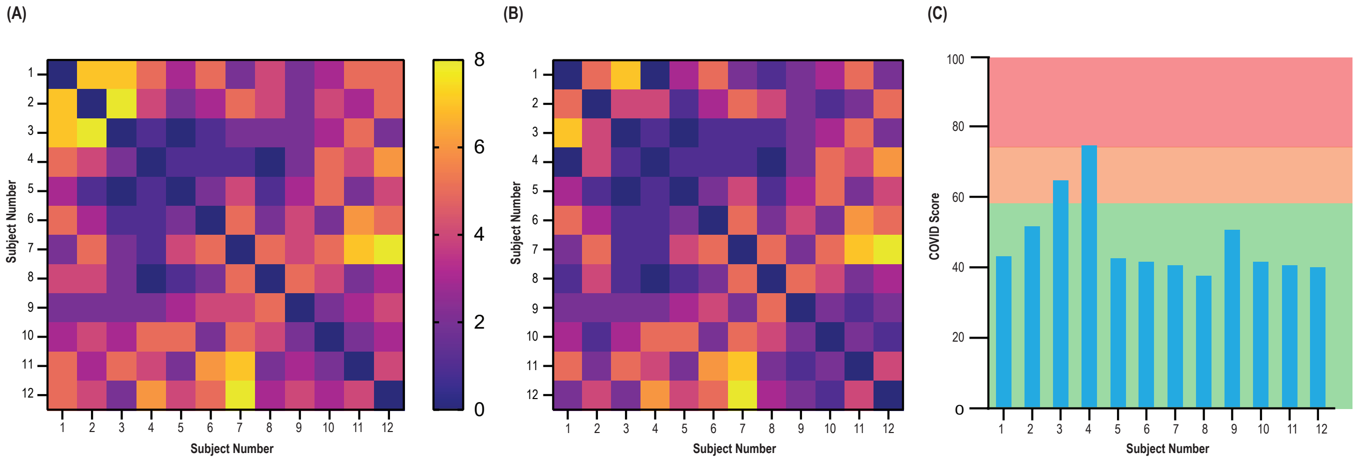

Figure 7. Proximity tracing and COVID-19 score calculation for office workers. (A) Proximity tracing for twelve employees, (B) Proximity tracing for twelve employee when the alert feature of the app is activated and (C) the corresponding COVID-19 score of the employees.

anonymous app user's has been collected and no alert was generated if social distancing rule violates whereas on 13 July 2020, alert feature of the app was activated and observance of the transmissive alert was shown on app frame when two employees got closer physically to each other for 4 minutes.

4.3 Proximity Tracing and COVID-19 Detection

The Proximity tracing and health status score (COVID-19 score) for 12 employee are shown in Figure 7. The one-to-one proximity data of these employee was recorded without (7 (A)) and with an alert which was generated by app when two employees were came within 1 meter for more than 4 minutes (7 (B)). It has been observed that the alert feature of the app can help in maintaining required social distance among employees. On the other hand the fitness score also shows the effectiveness of the app which is shown in the figure 7 (C). Here the score of the worker 3 and 4 lie in the Orange portion it means these workers are not fit for work and would require further clinical investigation.

5 Discussion

An intelligent pHealth app such as iWorkSafe can provide a healthy workplace for the workers in an industrial setting during the COVID-19 pandemic. With the view to ensure safety of industrial workforce through the usage of technology during this challenging time, the iWorkSafe app paves the way towards reestablishing operation of these industries by preventing the spread of the virus, to reinstantiate the economic sustainability of countries fighting the COVID-19 pandemic. The iWorkSafe pHealth app, capable of intelligent proximity detection, secure contact tracing, health condition detection and COVID-19 screening at an industrial settings, has been designed to safeguard employees in a workplace with large number of workers and where it is difficult to ensure their safety during a pandemic situation. Along with the regular health checkup data inputted by the medical/test centre, an e-health sensor shield is used to collect physiological conditions of each employee and the data are stored in a local database. An intelligent technique, a fuzzy neural network algorithm, is used for fusing the health condition, proximity detection, contact tracing and COVID-19 self-test information in the proposed *i*WorkSafe app and provides a novel metric, called *COVID score*, to determine the fitness of the workers. As this app uses machine learning techniques, collection of training data emerged to be the main challenge during the development of this app. The process of accessing relevant COVID-19 data suitable for the app involved lengthy and time demanding bureaucratic procedures related to agreements, compliance and precautions, and has been a very difficult task. Additionally, to ensure high accuracy in estimating the *COVID score* by the app, reducing false positive and false negative rates have been very challenging aspect of this work.

Now, given the recent approval of COVID-19 vaccines, the *i*WorkSafe app still holds the competence in stopping the spread of the virus and ensures a safe workplace. According to a report published in [?],it has been projected that the maximum production capability of 10 leading vaccine candidates will be around 10 billion vials by the end of 2021. To vaccinate 7.5 billion individuals on the planet, it will require 15 billion vials (two dosages for every individual) of vaccines. Although majority of the high- and middle-income nations have affirmed the necessary sum through a pre-request to the vaccine manufacturers, still people have to wait for their turn to come to get vaccinated as the whole lot of ordered doses are not immediately available. Moreover, as in the UK, the delivery of the immunization has been prioritized from more vulnerable individuals to lesser ones [?]. This delivery scheme has been adopted throughout the world. Most importantly, in a research directed by the Duke Global Health Innovation Center, low-middle and low-income nations may need to wait until 2023-2024 for immunizations. Considering this, until the immunization consignments reach the developing nations, the *i*WorkSafe app will be able to combat this emergency situations. It should also be noted that the *i*WorkSafe app is not restricted to COVID-19, but will be able to encounter the spread of any infectious disease if the neural network model used in *i*WorkSafe is trained and tuned accordingly with appropriate data.

While admiring the benefits provided by *i*WorkSafe, the challenges must be discussed as well. Conventional clinical and fitness mobile apps use electronic medical records (EMR) and personal health records (PHR) extracted and prepared from corporate health systems. For *i*WorkSafe the EMR are created by means of a clinical record, while PHR – an EMR subset – are provided by the app user. The credibility and quality of health data cannot be guaranteed in all situations and this poses a great challenge in developing clinical/wellbeing apps. The *i*WorkSafe app uses GPS and Bluetooth to ensure social distancing, and geo-location and personal information of the app user for tracking. Usage of such data raises privacy concerns which need to be satisfied in the app. High-quality data is essential for proper functioning of *i*WorkSafe. The characteristics of such high-quality data may include precision, credibility, completeness, relevance, interpretability, timeliness, representational consistency, etc. The quality data collection using heterogeneous and resource constraint sensors is also intriguingly challenging.

There are also aspects of the *i*WorkSafe app, as listed below, which can be further improved in future releases.

Smart Devices and Setup The contact and proximity tracing features of *i*WorkSafe require Bluetooth and Wi-Fi interfaces to be switched on to allow data transfer between devices when workers come in close proximity with each other. Also, a cloud-based framework is required to analyze the data to gain actionable insights. Interface to these can be simplified in the future releases of the app.

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Multimodal Data Fusion When multimodal data are collected using heterogeneous sensors, inconsistency may be found in the data. Thus, raw data fusion at low-level will be useful to deal with the inconsistency in the data. Also, knowledge extracted from these data can also be fused at high-level, and analyzed by selecting appropriate fusion rules based on AI/ML.

Privacy and Data Protection As iWorkSafe collects and transfers personal data to a cloud infrastructure for further analysis. Here, user privacy and data security may be of concern and might require employing robust encryption techniques which need to be tailored for low resource settings.

Asymptomatic COVID-19 Asymptomatic COVID-19 virus carriers have transmission potential among close contacts [62]. However such asymptomatic COVID-19 carriers can not be identified with traditional COVID-19 self-screening apps and this needs to be considered in the future release of the app to secure a healthy workplace.

6 Conclusion

An intelligent mobile app, called iWorkSafe, has been proposed in this work which checks for the risk of COVID-19 infection among employees to ensure a healthy workplace. The app can collect multimodal data such as health condition, proximity, contact tracing and COVID-19 self-screening data. The risk estimation process is done through a number of steps which include– 1) analysing the acquired data using different machine learning approaches, 2) fusing the generated knowledge using fuzzy neural network approach, and 3) estimate the risk score which denote the health status of an employee. This will assist industries in predicting possible COVID-19 among employees and maintain business continuity. A low value of the score denote an employee's fitness to work (i.e., low risk of COVID-19 infection) whereas medium and high values of the score indicate the necessity of clinical attention. The viability of iWorkSafe app has been demonstrated using data collected from an industry. This representative case study has been performed by collecting data from 12 employees of that industry and revealed that iWorkSafe can help in ensuring social distancing measure with final scores reflecting the health condition of the employees. This work can be extended by integrating machine learning based approach in detecting the status of mental health and thereby predicts the physical and mental fitness of employees before joining the work.

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Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Authors and Contributors

This work was carried out in close collaboration between all co-authors. All authors have contributed to, seen and approved the final manuscript.

Ethical Approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent

Informed consent was obtained from all individual participants included in the study.

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