Intelligent Mobile Cloud Platform for Monitoring Patients of COVID-19 in Their Home-Quarantines

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ABSTRACT

Currently the world is going through a pandemic caused by Covid-19, the World Health Organization recommends to stay isolated from the rest of the people. This research shows the development of a prototype based on the intelligent mobile cloud computing (MCC), which aims to measure three very important aspects: heart rate, blood oxygen saturation and body temperature, these will be measured through sensors that will be connected to a NodeMCU module that integrates a Wi-Fi and Bluetooth module, which will transmit the data by using (MQTT) protocol to an IoT platform (Ubidots) through which the data can be displayed, achieving real-time monitoring of the vital signs of the patient Confirmedof Covid-19 in home quarantine and sending alerts to health centers for critical cases,In addition to monitor the treatment response of those who have already recovered from the virus, and to understand the nature of the virus by collecting and analyzing relevant data. The framework consists of five main components: Symptom Data Collection and Uploading (using wearable sensors), Quarantine/Isolation Center, Telemedicine center (that uses machine learning algorithms), Health physicians (doctor), and Mobile Cloud Computing infrastructure. To quickly classifyConfirmed coronaviruses cases and predict critical cases from this real-time symptom data, this work proposes eight machine learning algorithms, namely Support Vector Machine (SVM), Neural Network, Naïve Bayes, K-Nearest Neighbor (K-NN), Decision Table, Decision Stump, OneR, and ZeroR. An experiment was conducted to test these eight algorithms on a real COVID-19 symptom dataset, after selecting the relevant symptoms. The results show that five of these eight algorithms achieved an accuracy of more than 90 %. Based on these results we believe that real-time symptom data would allow these five algorithms to provide effective and accurate classification of Confirmed cases of COVID-19 to Stable and critical situations, and the framework would then document the treatment response for each patient who has contracted the virus .

KEYWORDS (COVID-19, Real-time monitoring, Mobile Cloud Computing, biomedical sensors, machine learning)

INTRODUCTION

Currently, the outbreak of the new coronavirus Covid-19, the first case of which was seen in the city of Wuhan, capital of Hubei province (China) [1]. By the end of 2019, it has become a public health problem for the entire globe, since according to data provided by the World Health Organization (WHO), the pandemic is currently present in more than 224 countries, with more than 99,638,000 positive cases and more than 2,140,000 confirmed deaths. The author in [2], increasing by leaps and bounds, thus setting negative records worldwide, due to its high rate of contagion. The health system in Peru is currently going through a very serious problem, according to the latest reports, there are more than 1,102,000 positive cases and more than 39,800 deaths due to Covid, with a 3.62% lethality rate, with only 11,200 hospitalized patients, 1,892 ICU beds, of which only 7 ventilators are available nationwide. [3], Hospitals and health centers do not have the resources to attend all suspected cases and positive patients. The most recent study on human resources in the health sector indicates that in Peru there are 13.6 physicians for every 10,000 inhabitants, i.e., only 1 physician for 1,000 patients, in addition to an inadequate distribution of medical personnel at the national level. Making the healthcare system totally deficient and inadequate to deal with the increasing number of patients caused by Covid-19. As a result of the aforementioned data, the following question arises: What happens to the people who tested positive for Covid-19, because although Covid-19 cases are classified into five stages: asymptomatic, mild, moderate, severe and critical? [4]. It is those in serious and critical condition that are treated in health centers. Once the patient has been diagnosed with Covid-19, he/she is obliged to remain isolated in his/her home until the incubation and infection stage has passed, which can last between 12 to 15 days. in addition to maintaining distance from family members to reduce the likelihood of contagion. A new question arises: What happens to patients who are isolated in their homes, because they suffer the risk that the disease caused by Covid-19 worsens, and if they are not administered the necessary drugs, they may die, to perform this follow-up they would normally have to be taken to the hospital, where they will undergo various tests to identify the heart rate, respiratory rate, blood oxygen saturation, blood pressure and body temperature, because Covid-19 to develop in the body [5], the health system carries out patient follow-ups by medical personnel, who go to the homes of positive or suspected Covid cases, where the lives of medical personnel are exposed to contracting the disease, in addition to generating effort and expense in the process. Given the current situation in the world, many of the medical centers inthe whole worldare full of patients, exceeding their capacity of care, in these circumstances the medical centers do not attend in the right way, so people have to opt for private health services, as is the case of clinics, However, low-income people cannot have access to this service, neither to health services, nor to a Covid screening, having to spend the incubation stage in their homes, keeping home isolation, increasing the number of people vulnerable to contracting Covid-19, exposing the family of the infected or suspected case, if the necessary measures are not taken such as: isolating the infected person, keeping a distance of at least 2 meters and controlling symptoms on a daily basis. Faced with this situation that the world is going through, it is necessary to resort to innovative and outstanding ideas for the solution of the different problems that this pandemic has generated in society. As we know, the internet of things has been developed even in the health sector, called telemedicine [6], but it can also be applied in the same homes for medical and health purposes. That is why an internet of things system based intelligent mobile cloud computing will be developed to monitor vital signs in patients or suspected cases of Covid-19, this is done with the help of different specialized sensors. The internet of things (IoT) is the interconnection of devices (sensors and actuators) or objects (everyday objects with internet access) through a network, in order to communicate and transfer information, without the need for human presence to do so, this is called machine-machine communication (M2M), for the development of an IoT system protocols, communication technologies, domains and applications are established [7]. The proposed intelligent mobile cloud computing and biomedical sensors system aims to measure certain vital signs in order to provide prompt help in case of any drastic change in their health, reducing the effort of medical staff [8], also avoiding that the patient goes through stress, produced when a person is hospitalized, in the same way, reducing stress in medical personnel, according to a study done in China, cases of 1257 workers are reported, 50% began to feel symptoms of depression and more than 70% presented symptoms of psychological distress [9] thus generating a high risk for those who face this pandemic in the first row, with this proposed solution, the time to obtain vital signs, the time of medical care of home visits and the response time to an anomaly in the vital signs are reduced .

Problem statement

Coronavirus caused many problems in hospitals, where these are no longer able to accommodate a large number of patients. This virus has also begun to spread between medical and paramedical teams, and this causes a major risk to the health of patients staying in hospitals. To reduce the spread of the virus and maintain the health of patients who need a hospital stay, Home-Quarantines and Remote Patient Monitoring (RPM) is one of the best possible solutions .

Significance of study

This study proposes a real-time COVID-19 monitoring system. The proposed system would employ an Internet of Things (IoTs) framework to monitor the vital signs of the injured in real time and determine their health status through the use of intelligent platform that responds to patients in cases where a health care provider is not present .

Remote Patient Monitoring (RPM) of COVID-19: objectives & motivation

Objectives:

1. deploying readily available technology for continuous real-time remote monitoring of patient vitals singes with the help of biosensors on a large scale.

2. effective and safe remote large-scale communitywide care (mass health monitoring with intelligent mobile cloud platform) of low-severity cases as a buffer against surges in covid-19 hospitalizations to reduce strain on critical care services and emergency hospitals.

3. improving the patient, their family, and their community's sense of control and morale.

4. proposing a clear technology and medical definition of remote patient monitoring for covid-19 to address an urgent technology need; address obfuscated, narrow, and erroneous information and provide examples; and urge publishers to be clear and complete in their disclosures.

5. leveraging the cloud-based distributed cognitive rpm platform for community leaders and decision makers to enable planning and resource management, pandemic research, damage prevention and containment, and receiving feedback on their strategies and executions .

Motivation:

The motivation comes from the pandemic currently ravaging the globe. Social distancing, less physical contact and staying at home orders are issued by the government to control the spread of the virus. People who have been in contact with positively tested individuals, but who are not showing symptoms, are also counselled to self-isolate or self-quarantine for some days. Positive patients with mild symptoms are advised to observe quarantine. The self-isolation or quarantine can be observed from home while the affected person sends signs or symptoms of any ailment observed to the doctor at regular intervals. To this end, we are motivated to broaden the scope of the smart home healthcare system to accommodate the upload of symptoms affected by COVID-19 from the comfort of their respective homes .

Related works

Advances in the development of smart home automation technologies and e-healthcare systems allow people to enjoy in-home medical services without staying in hospitals. Remote health monitoring of patients through home health care technologies assists healthcare givers, medical personnel and physicians to reach out to patients without physical contact or presence of patients at clinics or hospitals. Healthcare technologies also save cost, expenditure and stress for patients as they do not need to travel before seeing their healthcare givers or medical personnel. There have been many published articles in the area of smart health care system, e-health and remote healthcare. Authors inRef:

In the investigation[10]proposed an e-health care system for monitoring patients' vitalphysiological parameters by doctors from any location. The proposed system is capable of collecting the required data from the patient andmaking it available and visible to the doctor for action. The web applicationis a feature of the system that allows the doctor to record thepatient's information, input notes for advice, prescription and dosage ofdrugs while also allowing the patient to key in measured psychologicalparameter values and display of information received from the doctor.Smart TV application was used for reminding patients daily about theiractivities, medications and other events. Lastly, the system has the feature of a mobile application with the same functionality as the webapplication but with an added advantage of access from anywhere and at any time.

In the investigation[11]The proposed platform aims to provide help to the patient'sin formal caregivers and support network. the generalarchitecture of the CMS, separating its functionality into three basic concerns: (a) cloud-based backend services for computationand data storage, (b) mobile and web applications to enhance collaborationand analysis among patients, caregivers, and medicalproviders and (c) embedded and mobile applications to supportthe vital signs monitoring and improve the communication channelin the family caregiver support network. The basic sequenceflow starts when adding a new patient to the system, where multipleusers can get the patient's information locally or remotely. The backend behind the platform gathers the data fromsensors used by patients and builds Personal Health Records (PHR)for each user.

In this paper [12], Authors propose a home hospitalization system based on theIot, Fog computing, and Cloud computing, whereby in this proposed system the environment of the hospitalization room is monitored in addition to monitoring patient health remotely to ensure a good hospitalization process.

In the investigation [13]The architecture includes the home appliances, smartphone, sensors, actuators, Wi-Fi module, and an Arduino board, which serves as the microcontroller. In the system, sensors are installed for measurement of the indoor temperature or humidity levels, and detection of motion and smoke. In our work, communication between the user and the home is wireless. The Arduino microcontroller collects data from various sensors, home appliances and physiological devices through the ESP8266wireless module and transmits it over the internet to the user. The user receives and sends commands to the home through the developed Android mobile application to the microcontroller for necessary actions.

The proposed system in this paper [14] provides a secure and real-time solution for private health data records stored in the cloud. IoT biosensors are used to capture key biological parameters (Heart rate, Oxygen saturation, and Body temperature) from a patient at comfort home. Then, an IoT based microcontroller bears the stuff of processing, encryption, and delivering of secured health parameters to the public cloud. Securing patient data is achieved by using the AES algorithm. The AES is employed in the proposed system to secure patient data prior to storing it into the cloud. This ensures data privacy and the secure distribution of patient data in public networks. In addition, the proposed system provides an alert system by sending an email to some patient relatives or coordinating specialist if vital signs are outside of normal rates.

The core objective of this project [15] is the design and implementation of a smart patient health tracking system. The sensors are embedded on the patient body to sense the temperature and heartbeat of the patient. Two more sensors are place at home to sense the humidity and the temperature of the room where the patient is staying. These sensors are connected to a control unit, which calculates the values of all the four sensors. These calculated values are then transmitted through a IoT cloud to the base station. From the base station the values are then accessed by the doctor at any other location. Thus, based on the temperature and heart beat values and the room sensor values, the doctor can decide the state of the patient and appropriate measures can be taken.

In the investigation [16]The proposed IHCAM-PUSH enables smart hospitals to monitor patients in their homes instead of sacrificing limited hos- pital beds. Smart hospitals are hospitals that have adopted new technologies such as IoT, cloud computing, and cloud stor- age, to improve patient care procedures and facilitate new capabilities, such as monitoring patients remotely in their homes. The proposed model facilitates the acquisition, storage, processing, analysis, and visualization of big data collected by AAL systems and the contextual information that is associated with it.

In the investigation [17]The Architecture Shows four major components of the system namely: (1) Data Gathering or Acquisition via wearable sensors on the patient. (2) Aggregators or concentrator devices such as a Smartphone. (3) Data storage in the cloud. (4) Clinician's application providing necessary interface to interact with the analyzed and visualized information already stored in the cloud.

This paper [18] proposes a real-time COVID-19 detection and monitoring system. The proposed system would employ an Internet of Things (IoTs) framework to collect real-time symptom data from users to early identify suspected coronaviruses cases, to monitor the treatment response of those who have already recovered from the virus, and to understand the nature of the virus by collecting and analyzing relevant data. The framework consists of five main components: Symptom Data Collection and Uploading (using wearable sensors), Quarantine/Isolation Center, Data Analysis Center (that uses machine learning algorithms), Health Physicians, and Cloud Infrastructure.

In the investigation [19]presented a cloud-based smart home environmentnamed CoSHE for a home healthcare wearable unit, a private cloudand robot assistant. The CoSHE system collects physiological, motion and audio signals from residents thorough non-invasive wearable sensorsand thus provides information about the daily activities and location of residents in the home. Comprehensive health data are providedto caregivers and caretakers through a web application built on the cloud server of the system. The system also has a hydration monitoringapplication for continuous monitoring of water consumption levels and daily fluid requirements of the patient. Hydration monitoring is achieved by the use of acoustic data collected from microphones and body activity context derived from a smartwatch accelerometer in the system.

In the investigation [20]A smart home integrated system that runs on an Android operating system, for ambient assisted living for people living with dementia. The design of the system allows the collection, recording and transmission of data through cloud application. The system involves seven types of sensors to detect a person's position, whether standing or sitting, flame detection and use of specified appliances in the home. Also, the sensors remind or alert the patient if he or she forgets to carry out specific tasks in time. A switch is also installed in the system to detect if the light is on or off. The system is also designed to identify the activities of patients and send information to the doctor or caregiver. Data are retrieved from different sensors placed in specific locations in the home for processing.

In the investigation [21]proposed a smart sensing technique based on an integrated sensor network for monitoring the user's home and environment in order to derive information about the user's health status andbehavior. The authors' proposed platform includes sensors that are biomedical, wearable and unobtrusive for monitoring physiological parameters such as ECG, heart rate, breathing waveform, breathing rate, blood pressure and so on. An application on a smart device such as a tablet was proposed for the user's interaction with the sensors. Data collected through the application are further sent to the cloud for storage and data analytics towards services for the elderly.

In the investigation [22]proposed a smart home health monitoring system for remote monitoring of diabetes and blood pressure in patients. The system assists in analyzing the patient's blood pressure and glucose readings from home, sending a notification to the caregiver or healthcare provider if an abnormality is detected and also predicting the status of hypertension and diabetes in patients by training results obtained from the readings. For the model training, support vector machine classification was employed to provide effective and efficient training task. Also, the system is capable of sending alerts and real-time notifications from home about the patient's health to a registered physician or clinic.

In this paper [23], Author portray an experimental model designed for monitoring and checking the health condition of the patients based on sensors. The framework depends on e-health sensor shield associated with a cloud platform which gathers the data from the sensors. The sensors measure various parameters, such as a glucometer, airflow and patient position which are transmitted via microcontroller by a gateway to a cloud storage platform. The data collected in the cloud platform is accessible for further handling, for the investigation of some correlations among measured parameters and health state of the patients.

This paper [24] proposes a multi-physical parameter wireless telemedicine health monitoring system solution, and analyzes the overall structure and functional requirements of the system. Human physiological parameters of the wireless remote medical system for health monitoring include body temperature, respiration, blood oxygen saturation, pulse, blood pressure, and electrocardiogram. In this paper, fabric electrodes are used to extract human bioimpedance signals, discrete Fourier transform algorithm is used to detect human respiratory signals, and respiratory rate is detected based on dynamic differential threshold peak detection technology. The reflection type photoelectric sensor is used to realize the reflection of the human pulse signal, and the continuous measurement of the cuff-free blood pressure based on the pulse wave conduction time is combined with the ECG (Electrocardiogram) data. A self-learning threshold algorithm based on near-infrared photo plethysmography signal trough detection is designed on the reflective blood oxygen saturation calculation algorithm. The difference threshold method is used to extract the QRS band feature points.

In the investigation [25]The system consists of a microcontroller, medical sensors and communication module that are used to collect the patients' information and send it to the cloud for further processing and analysis. Furthermore, a fall detection system that utilizes wearable sensors is proposed where it can detect unpredicted fall. One unique feature in this system that it utilizes voice recognition technology to interact with the patient after detecting a fall, thus verifying if the patient needs an assistant or not, which in turn reduces the false alarms and improves the system accuracy.

In the investigation [26]The architecture of IoMT applications is segregated into the (three) layers: detecting, the transport, and the application. In the Detecting layer they make use of many sensors to record the various parameters used for calculating the various Health Indexes. In the Transport layer, the calculated data (Health Indexes) is sent to the cloud by using a Wi-Fi Module ESP8266 or an Ethernet shield with the Arduino Uno. they make use of the open-cloud server, Thing Speak, in order to make the data available on the cloud, so that the information can be retrieved by healthcare providers anywhere on the globe. In the Thing Speak server it is possible to make a unique account and to create an exclusive channel for project. Such that, when they make the required channel, they acquire the unique Identification in the form of an API key to transfer the data onto the cloud. The API-key is used whilst working on Arduino Uno with the aim of accessing the data put in server and in the third layer of abstraction i.e., the application layer by usage of the unique API key by the respective healthcare providers so that the relevant data can be obtained from the server in real-time.

In this work [27], they present an affordable home telemonitoring system for patients with idiopathic pulmonary fibrosis (IPF), based on an application for mobile devices and Bluetooth-enabled sensors for pulse oximetry and blood pressure measurements. Besides monitoring of vital signs, the system incorporates communication via videoconferencing and emergency response, with support from a helpdesk service.

In all the mentioned works is present the importance of monitoring vital signs, focused on different types of diseases, the research work developed, focuses on the monitoring of Covid-19, establishing the different levels of severity of the different signs, has the minimum number of sensors to capture the signs that vary in that disease, In addition to having a web system, in which the doctor can view statistics and graphs of the different vital signs, managing to send alerts to an email or a mobile device, in this way, this research unifies different technological aspects of the antecedents and seeks better alternatives to focus on monitoring patientsInfected andsuspected of Covid-19 in home quarantine .To our knowledge, no one has developed a complete framework forusing Intelligent Mobile Cloud Platform for Monitoring Patients of COVID-19 .

THEORETICAL FRAMEWORK

E- health systems

Electronic Health (E-Health) refers to the use of electronic communication within health care sector. The technical progress in mobile communications and networking technologies has led to the development of specific systems in e-health labeled as tele-health. Tele-health refers to the remote clinical and non-clinical services (e.g., provide training and medical educations). Tele-medicine is more specific term refers to remote clinical services for patients on remote areas. With the increasing prevalence of mobiles and tablets, it extensively used to support the practice of health care which known as mobile health (m-health). For more clarification. Figure 1, show the relation the relation between e-health systems .

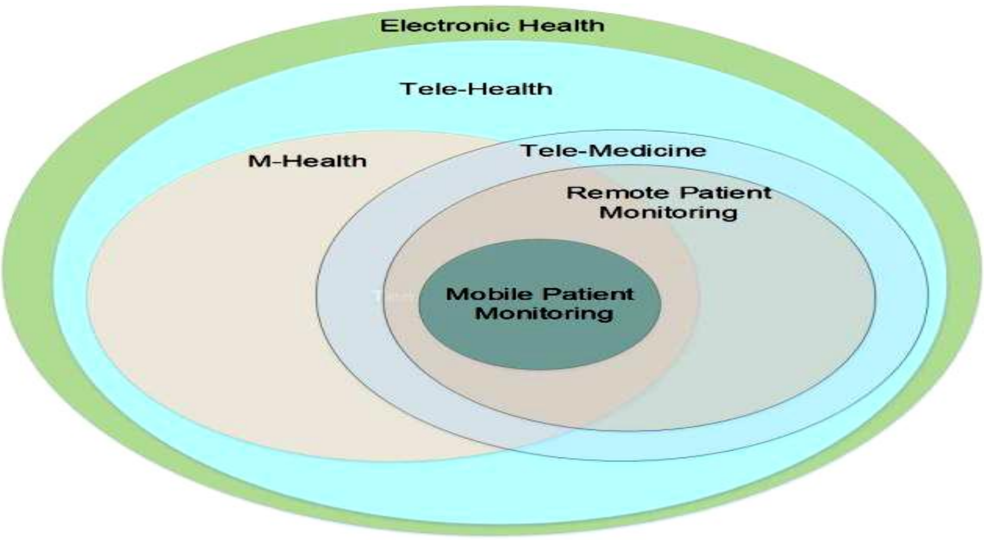

Fig 1: Relations between E- health systems[28]

Developing e-health systems (e.g., remote patient monitoring (RPM), mobile health (m-health), telemedicine, e-visits, e-consultations, etc.) are an increasing need. Such systems are used for continuous monitoring, diagnosis, prediction, and treatment. Consequently, they contribute to reducing healthcare costs. Patient monitoring systems considered one of the most important services in mobile health. It helps patients to perform daily activities while their vital signs are fully monitored. Several technologies integrated to provide real time PMs such as Internet of Things (IoT), cloud computing, fog computing clinical decision support systems, etc. Internet of things (IoT) application contribute in enriching business and address various challenges in the health care sector. It facilitates the sensing, processing, and communication of physical and biomedical parameters [29]. The IoT-based wireless body area network (WBAN) is a wireless sensor network between wireless devices that enable remote monitoring for different environments Medical environment is one of the promising fields of WBAN for remote, continuous, and real-time patient monitoring using wearable and implantable sensors. S. Ullah et al in [30] surveyed WBAN in medical environments The sensor nodes can be placed either on the patient‘s body or under his skin to collect certain body parameters or vital signs (e.g., electro cardiogram (ECG), electroencephalogram (EEG), body movement, temperature, blood pressure, blood glucose, heartbeat, and respiration rate levels) The collected data are used for different purposes, such as in-hospital monitoring, remote diagnosis, ambulatory patient monitoring, and trigger emergency services. Every WBAN node has a way for implementation within the body and a role in the network as suggested by IEEE 802.15.6 taxonomy WBAN has a significant role in improving the quality of life, decreasing healthcare costs, and reduction in the workload of medical professions .

Telemedicine

Telemedicine is an assuring method, which provides healthcare by combining both it and telecommunication. It grants better healthcare without any social and economical constrains. Telemedicine is a service among the remote patients and physicians. In this system, the patient's health data automation is an important feature. Achieving this function makes telemedicine system very reliable. Data management in healthcare management system improves with the advent of increasing reputation in cloud computing. It presents leasing standards, scalability and data access capacity without geographical conditions .

There are three common types of telemedicine:

- Interactive medicine: Also called “live telemedicine,” this is when physicians and patients communicate in real time.
- Remote patient monitoring: This allows caregivers to monitor patients who use mobile medical equipment to collect data on things like blood pressure, blood sugar levels, etc.
- Store and forward: Providers can share a patient’s health information with other healthcare professionals or specialists .

Keyword in Telemedicine

- Cloud Computing (CC)

  it makes smartphones scalable in terms of storage and processing capability. shared resources, storage, hardware and software are the peculiar characteristics of cloud computing, which makes the smartphone motto work anywhere anytime.

- Mobile healthcare (M-healthcare)

  enables patients to be monitored at any time, any place through wireless technology. mobile computing devices create more free space, less clutter and lower costs, while delivering more services more efficiently.

- Mobile Cloud Computing (MCC)

  applying mobile cloud computing (MCC) in medical applications could minimize the limitations of traditional medical treatment (e.g., small physical storage, security and privacy, and medical errors) .

Real-time Remote Patient Monitoring (RRPM)

Continuous real-time patient monitoring by a scalable, distributed, AI-based system. Multiple patients can be accommodated simultaneously. The doctor is proactively alerted to patients who may require attention .

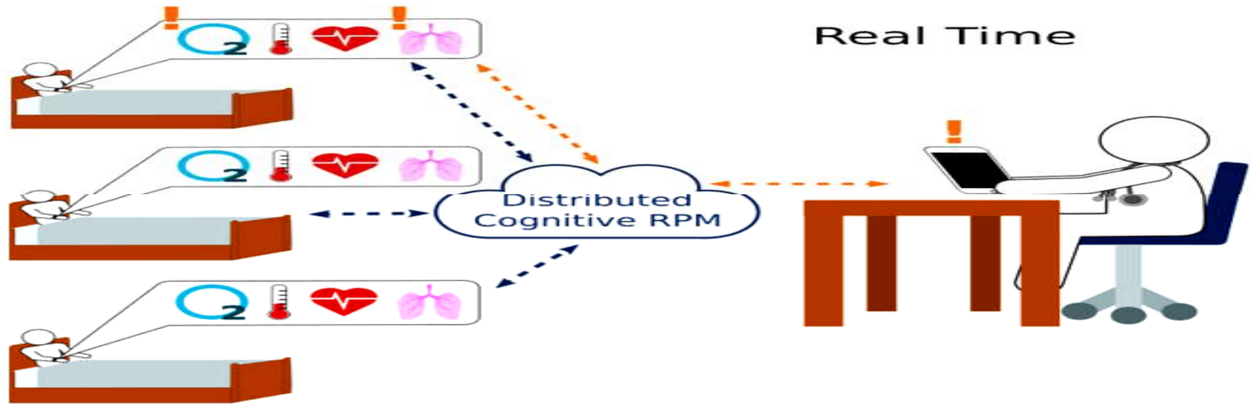

Fig 2: The framework of Real-time Remote Patient Monitoring (RRPM) system.[31]

THE PROPOSED FRAMEWORK

This section depicts and discusses our envisioned intelligent mobile cloud computing (MCC) -based framework, which could be used to monitor and identify (or classified) potential coronaviruses cases, in real time. Equally important, this framework could be used to predict the treatment response of confirmed cases, as well as to better understand the nature of the COVID-19 disease. Fig. 3 shows the framework of our proposed architecture. It consists of five main components: Symptom Data Collection and Uploading (patient side), a Quarantine/Isolation Center, a Data Analysis Center, an interface to Health Physicians, all of which are interconnected through a Cloud Infrastructure .

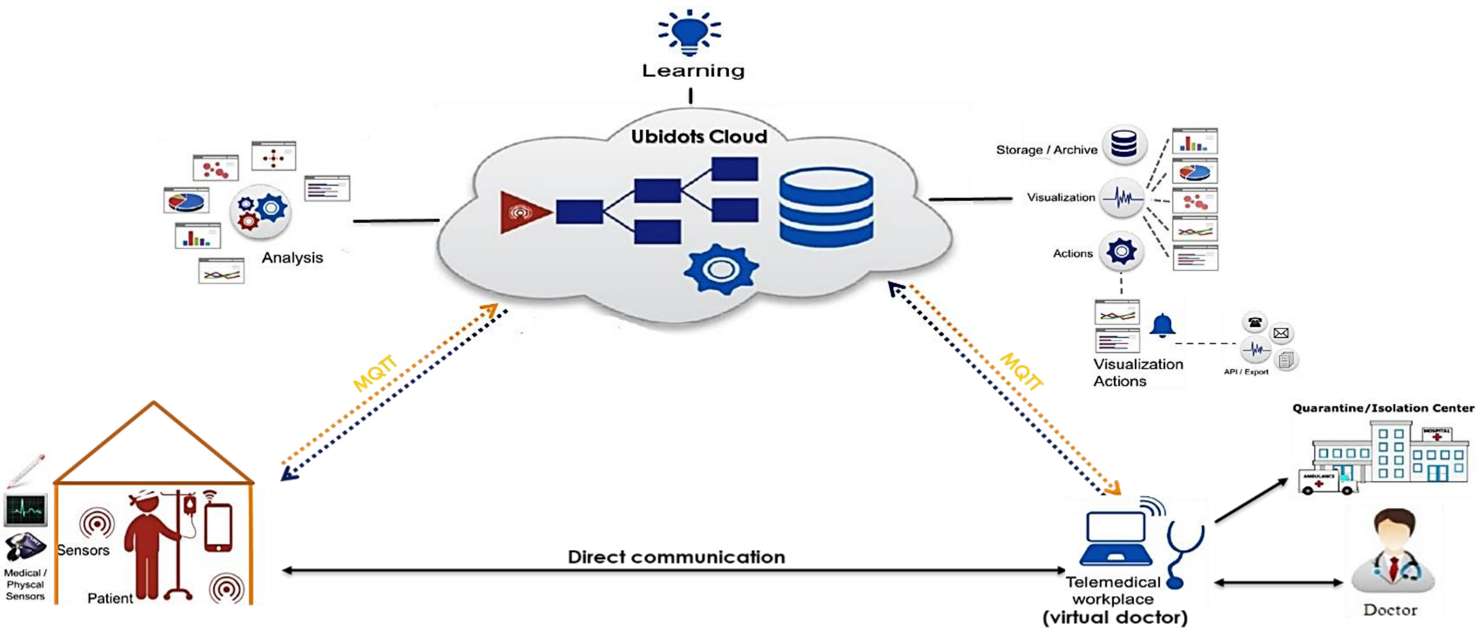

Fig. 3. The framework of our proposed architecture for Monitoring of covid-19 patients in home quarantined.

Symptom data collection and uploading (patient side)

The aim of this component is to collect real-time symptom data through a set of wearable sensors on the user's body. The most relevant COVID-19 symptoms were identified, based on a real COVID-19 patient dataset. These identified symptoms were: Fever, Fatigue, and Shortness of Breath. There are several biosensors available to detect these symptoms. For instance, temperature-based sensors can be used for the detection of Fever. heart-rate sensors can be used to detect Fatigue. Finally,oxygen-based sensors can be used to detect Shortness of Breath .

Telemedicine center (virtual doctor)

The Telemedicine center hosts data analysis and machine learning algorithms. These algorithms are used to build a model for COVID-19 patients' classification and upload this model on the cloud after that, and to provide a real-time dashboard of the processed data. The model could then be used to quickly identify or classify potential COVID-19 patients' cases, based on real-time data collected and uploaded from patients. The model can also predict the patient's treatment response. Over time, the disease models developed from this data will provide useful information about the nature of the disease .

Health physicians (doctor)

Physicians will monitor Confirmed and suspected cases whose real-time uploaded symptom data indicates a Critical or possible infection by our proposed machine learning based classification/prediction model. The physicians will then be able to respond swiftly to these cases by following up with any further clinical investigation needed to confirm the case. This allows the Critical confirmed cases to be isolated in Quarantine/isolation center and given appropriate health care .

Quarantine/isolation center

Patients whose health condition worsens during surveillance at home quarantine are sent to this center in order to receive the necessary health care, as well as that collects data records from Patients who have been home quarantined or isolated in a health care center. These records include both health (or technical) and non-technical data. For health (or technical) data, each record includes time-series data of the abovementioned symptoms, while for non-technical data, each record includes travel and contact history during the past 3–4 weeks, chronic diseases, age, gender, and any other relevant information, such as family history of illness. Each record would eventually also include the treatment response for each case .

Mobile Cloud Computing infrastructure

The MCC infrastructure is interconnected through the Internet, and (1) allows upload of real-time symptom data from each patient, (2)Analysis and visualization of the patient's vital signs, (3) maintains personal health records, (4) communicates classification results, (5) Sending alerts for critical cases via e-mail, SMS, or calls ... etc., (6) communicates physician recommendations, and (7) provides for storage of information

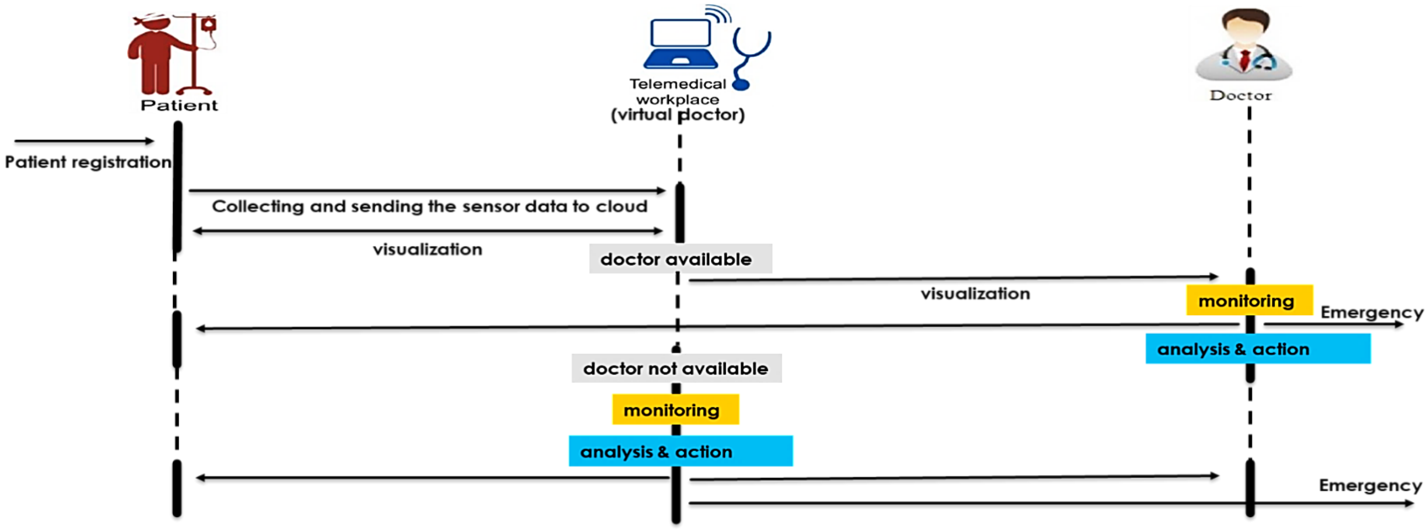

Fig. 4. Sequence diagram showing flow of communication between the different components of the architecture.

Figurer 4 presents the scenario (or workflow) employed by the Sequence diagram, which can be described as follows:

1) The system non-invasively collects real-time patient's symptom data through wearable devices and sensors in home quarantine and upload to the mobile cloud. Again, these symptoms are: Fever(temperature), Fatigue (Heart rate), and Shortness of Breath (Spo2). Further, Personal information, medical history and geographical location of the patient. The Quarantine/Isolation Center also periodically submits data from their isolated and quarantined patients who are housed in the center. The content of that data is similar to the real-time data collected from patients.
2) The sensed symptom data are Analysis and visualize to the system component through the Cloud Infrastructure. Vital Signs patient's,Textual and Digital records from the health care center are also regularly sent to the Telemedicine center (virtual doctor) through the Cloud Infrastructure foranalysis and construction of classification models.Telemedicine center hosts machine learning algorithms, which use the data received from the mobile cloud computing to continuously update its models. The models are then used to classifyConfirmedand potential cases, based on the real-time symptom data from each patient. Telemedicine center also analyzes all its data, and presents the results on a real-time dashboard. That dashboard can be informative to physicians about the nature of the virus.

3) If a critical case is identified, it will be sent to the relevant physician to follow up with the patient.In the event that a doctor is not available,virtual doctorwill take his turn and respond to the patient.The suspected patient will then be called and encouraged to visit the health care center for clinical tests, such as the Polymerase Chain Reaction (PCR) test, which is used to identify positive cases. If the confirmed case is critical, the emergency will be called and the patient will be transferred toQuarantine/isolation centerfor more monitoring and health care services .

SYSTEM IMPLEMENTATION

Hardware tools:

- ESP32-WiFi-Bluetooth-Development-Board.
- LLC I2C Logic Level Converter module.
- Low-Power-MAX30102-Heart-Rate-Oximeter-SPO2-Sensor.
- Infrared-Thermometer-Sensor-MLX90614.
- Medium 400P Breadboard & Breadboard Jumper Wires.

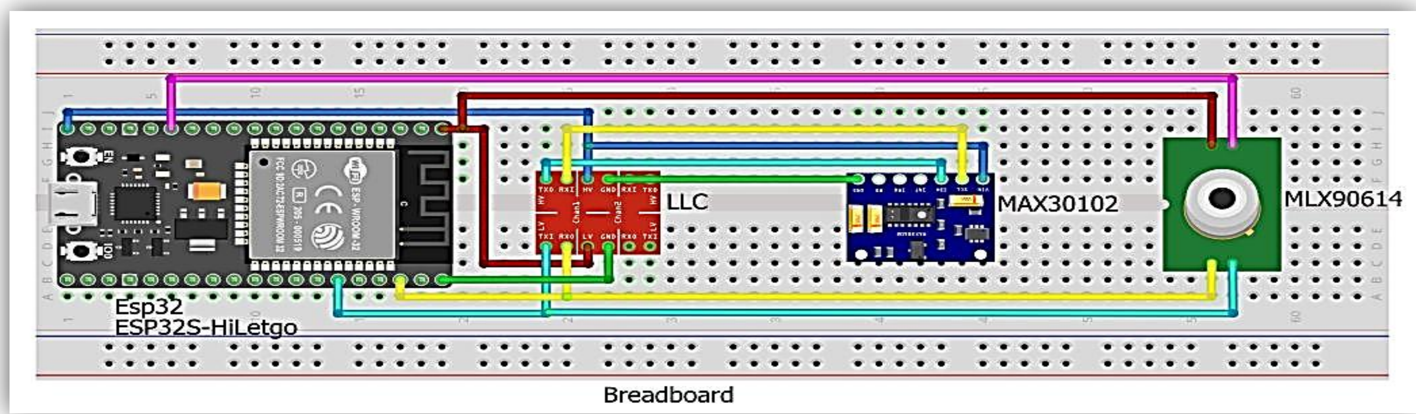

Fig. 5. Show the component of the hardware architecture.

Software tools:

- (**Arduino IDE 1.8.13**) is an open-source electronics platform based on easy-to-use hardware and software.
- (**Ubidots**) is an IoT application development platform with data analytics and visualization tools to rapidly construct and deploy data-driven solutions.
- Waikato Environment for Knowledge Analysis (**Weka**), is tried and tested open-source machine learning software that can be accessed through a graphical user interface, standard terminal applications, or a Java API.
- (**MQTT**) is an OASIS standard messaging protocol, publish/subscribe messages between sensors and clouds.
- (**Fritzing**) is an open-source hardware initiative that makes electronics accessible as a creative material for anyone.
- Computer devise (**windows 10 + chrome explorer**), mobile phone (**android + ubidots explorer**).

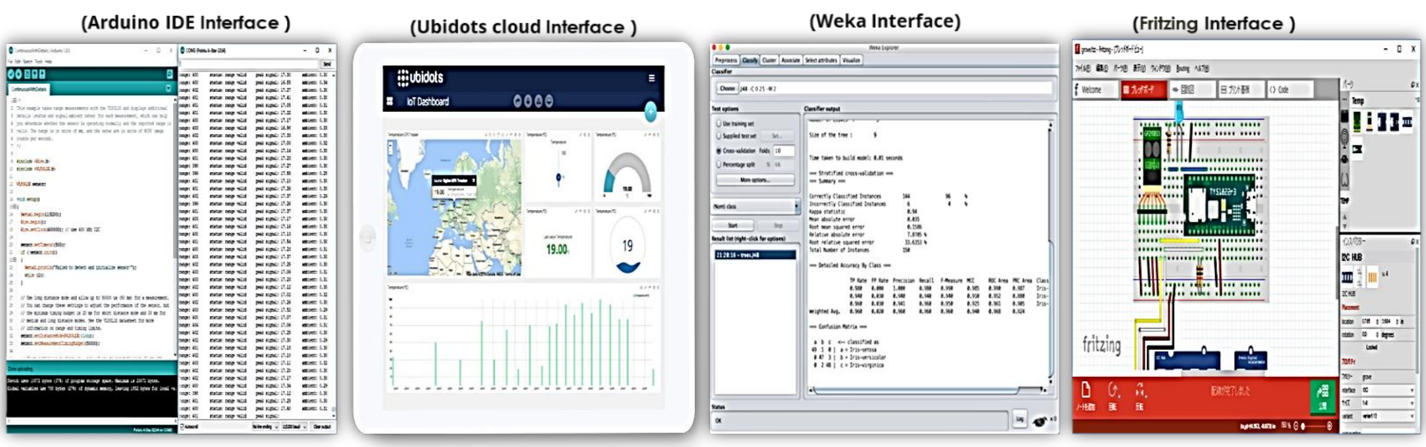

Fig. 6. Show the component of the software architecture.

Our monitoringsystem allows physicians or patient-supervising professionals to take physiological measurements and remotely analyze their patients, always know their health conditions, and determine the necessary medical characteristics without any physical and direct contact with them. The system is accompanied by a web application to remotely follow and determine the covid-19 patient's health condition if he/she is critical or normal case in a combination of the data from the sensors, as shown in Figure 7. Using patterns from visualization concepts, we use different widgets and different colors to display the results of the sensors as well as the diagnosis, based on data from the sensors. The system uses amachine learning algorithm to decide on the status of the patient as without any symptoms or having mild, moderate, or severe symptoms along with individual sensor reading for explanation and evaluation .

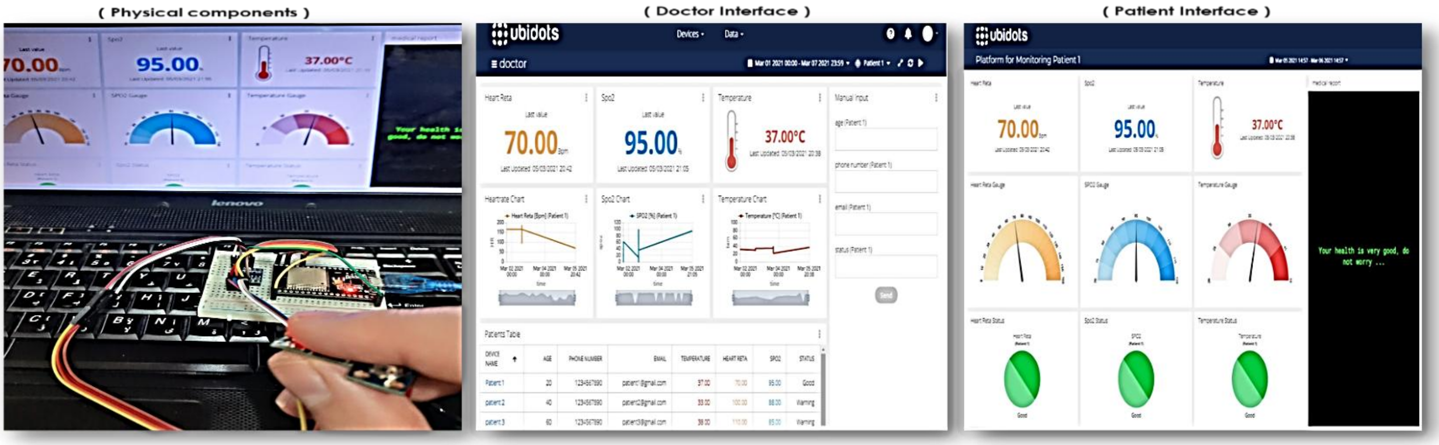

Fig 7. The sensors and the web application in our prototype implementation: (a) first part (b) Sconed part (c) Third part.

Figure 7 shows the prototype implementation of the COVID-19 patients monitoringsystem. The system contains medical sensors connected with a processor and aWi-Fi module for data processing and transfer to the cloud for analysis and visualize. The system has threeMain parts: firstpart consists of two sensors placed on the finger of the hand connected to NodeMCU, its purpose is to identify the symptoms of the critical covid-19 patients by measuring the temperature, oxygen level in the blood, and the heartbeat rate. The on-board process is programmed using Arduino to combine the data and send it to a cloud-storage platform using the Wi-Fi module.Sconed partis a physician interface for monitor patients' vital signs, respond quickly to critical cases, as well as update patient information. Third part is the patient interface to see his vital signs and communicate with the medical staff as well as receive alerts about his health status .

Classification of confirmed cases

This section further discusses the Classification models, and the machine learning algorithms that will be employed in the Telemedicine center (virtual doctor) component of the proposed MCC-based framework. In particular, an experiment was conducted to investigate the possibility of using rule based and machine learning algorithms for quick identification (or Classification) of COVID-19 patients cases in home quarantine. The rest of this section describes that experimental setup, and presents and discusses the results .

A. The rule-based system for decision-making

An important part of our framework is the rule-based system for decision-making. While there have been many approaches that utilize machine learning or neural networks to predict or classify various diseases, they work on the availability of a large set of data and then identifying patterns in the data for classification or prediction tasks. These approaches cannot be used if very limited data is available or there is no data at all. In such cases, rule-based approaches are a preferred way to perform classification tasks.as show in figure 8, The basic idea in a rule-based system is to have a rule-base that contains a set of rules. These rules have been learnt from the domain experts or adopted from clinical guidelines and research findings. In the simplest case, rules work on the principles of matching various conditions of the symptoms of a patient with the existing knowledge in the rule-base. The rules in our case relate to the absence or presence of a symptom or the range of sensor value above or below a certain threshold value for covid-19 patients. For rules definition, we consulted two experts specialized in infectious disease. The consulted doctors identified that SpO2 measurement is a key and essential determinant of COVID-19. If the SpO2 is > 95% with a normal temperature, the patient's condition is not criticaland the patient should not go to the COVID-19 center. However, if the SpO2 is between 93% and 94% with enough high temperature (>38), then it is important to call the doctor to look into the patient's condition and transfer him to health isolation centers, if required, to take additional measures. In addition, we also extracted some rules from the existing literature as discussed in related work. This allowed us to define four classes of screening results. Each class meets a specific set of rules. A patient is evaluated against the rules and is assigned a class based on the conditions stated in each class. These classes as defined as below:

• Class 0: Non-symptomatic

– SpO2 ≥ 95%;

– Heartbeat Rate ≤ 100 bpm;

– Temperature ≤37.2 _C;

– No headache and pains.

– No comorbidities.

• Class 1: Mild symptoms

– SpO2 ≥ 95%;

– Heartbeat Rate ≤ 100 bpm;

– 36 ^{o}C ≤ Temperature ≤ 38 ^{o}C;

– No shortness of breath.

– No comorbidities

• Class 2: Moderate clinical symptoms

– 93% ≤ SpO2 ≤ 94%;

– Heartbeat Rate > 100 bpm;

– Temperature ≥ 38 ^{o}C.

• Class 3: Serious clinical symptoms

– SpO2 ≤ 92%;

– Heartbeat Rate > 120 bpm;

– Temperature > 38 ^{o}C.

– Occurrence of comorbidities

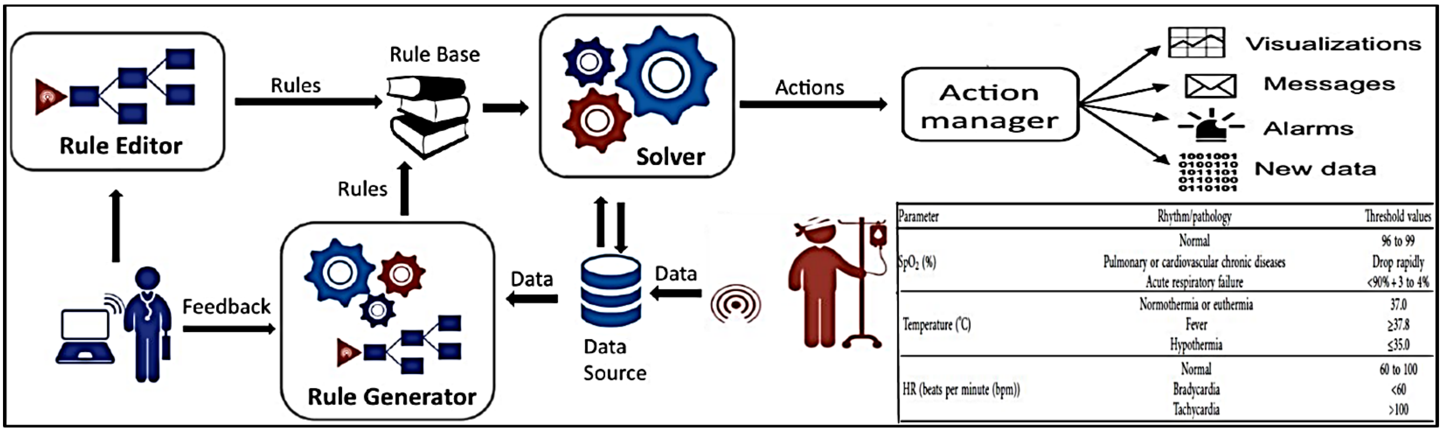

Fig 8, the framework of rule-based system for decision-making

While the sensors are useful for detection of vital signs, we have also additional parameters of shortness of breath, headache, and occurrence of any comorbidity (diabetes, heart disease, hypertension, etc.) in our rules. At the moment these parameters are assessed from visual inspection and through question-answering. In the current version, and for classification purposes, it is sufficient to have the confirmation from the patient. In the diagnosis stage, further devices can be used to determine these symptoms. For example, the expert or physician can carry out measurement of glucose level, blood pressure, or performing an ECG for a conclusive outcome. This will only be needed in the case of serious clinical symptoms (class 3). For screening purposes, verbal confirmation of a patient may require several additional questions depending upon the regional guidelines for COVID-19 patients casesclassification .

B. The machine learning algorithms for decision-making

Use when data is abundant or when a dataset of covid-19 patients is available to build classification models.

1. Dataset

A dataset of 14251 confirmed COVID-19 cases from the COVID-19 Open Research Dataset (CORD-19) repository [32] was used. The data contains different types of information about each case. Our work focused on symptoms, and some information about the patient. However, some of this information was missing for many of the cases documented within the database. Moreover, the data was not well structured for use by machine learning algorithms .

2. Data preprocessing

The data are preprocessing and structure to be better suited for machine learning. The cases with documented symptoms were collected. This resulted in a list of 80 symptoms. However, many of these symptoms were judged to be synonyms. Thus, the number of symptoms was reduced to 20. This merging of synonymous symptoms was done in an ad-hoc manner by two medical doctors, who are co-authors of this work. we also determined the relative importance of these 20 symptoms. The following six different statistically-based feature selection algorithms were employed in that work, to rank the 20 symptoms, based on their importance: Spectral Score, Information Score, Pearson Correlation, Intra-Class Distance, Interquartile Range, and our Variance Based Feature Weighting. The first five of these methods had been proposed earlier in the literature [33]. The sixth method was a new one. It not only ranks the symptoms, but also assigns importance weights to each of them. It was found that the most important five symptoms (ordered from most important to least important) are: Fever(temperature), Fatigue (Heart rate), and Shortness of Breath (Spo2). This resulted in a preprocessed dataset of 1476 × 7 data records. Among which 854 of those records were from criticalCOVID-19 cases, and 622 records were for non-critical cases .

3. Classification model

This work used this preprocessed dataset to build a classifier model for our identification (or Classification) system. The function of this model is to estimate the likelihood Deterioration of health status of covid-19 patientsin home quarantine. Several learning algorithms (i.e., classifiers) could have been used for this purpose. Those classifiers can be categorized into multiple categories. WEKA Software [34], (which we used in this work) categorizes the classifiers into six categories: (1) function-based classifiers, such as Support Vector Machines, (2) lazy classifiers, such K-Nearest Neighbors, (3) Bayes based classifiers, such as Naïve Bayes, (4) rule-based classifiers, such as Decision Tables, ZeroR, and OneR, (5) tree-based classifiers, such as Decision Stump, and (6) meta classifiers, such Neural Networks. In this work, at least one classifier from each category was selected. Specifically, this work compares the performance of eight machine learning algorithms: (1) Support Vector Machine (SVM), using Radial Basis Function (RBF) kernel, (2) Neural Network, (3) Naïve Bayes, (4) KNearest Neighbor (K-NN), (5) Decision Table, (6) Decision Stump, (7) OneR, and (8) ZeroR [35]. This work used WEKA Software to run all of these algorithms on our dataset. The default parameter values were used for each of the eight algorithms. Below is a brief description of the eight algorithms:

3.1. Support Vector Machine (SVM). SVM is a supervised learning method. Given a set of training examples that are labeled (i.e., each instance in the training set either belongs to the positive or negative class), SVM learns the hyperplane that best separates the instances from each class, and maximizes the margin between the data instances and the hyperplane itself. This learnt hyperplane is then used to assign (or classify) a class label for any new test instance.

3.2. Artificial Neural Network (ANN). ANN is a supervised learning method. The learning process tries to mimic the learning that takes place inside the human brain. To do so, multiple layers of nodes are connected through edges. The edges connecting between the nodes are represented as numerical weights. The output of each node is computed as weighted sum of its inputs. Given a set of training examples that are labeled (i.e., each instance either belongs to the positive or negative class), the ANN learns the numerical weights that best classify the instances from each class. This learnt model is then used to assign (or classify) a class label for any given test instance. The test instance drives the inputs to the nodes of the first layer. Then a threshold is applied to the outputs of the final layer, to determine the label for that test instance.

3.3. Naïve Bayes. Naïve Bayes is a supervised learning method. The learning process follows a probabilistic approach. It uses Bayes theorem to compute the model parameters. Given a set of training examples that are labeled (i.e. each instance either belongs to the positive or negative class), Naïve Bayes computes multiple model parameters, such as the probability of each class label to occur. These parameters are then used to assign (or classify) a class label for any given test instance. This is done by computing the probabilities of the test instance to be assigned to each of the possible class labels. The maximum value among these probabilities decides the label of that test instance.

3.4. K-Nearest Neighbors (K-NN). K-NN is a supervised instance-based learning method. The learning process follows a lazy approach. It does not compute a model. Given a set of training examples that are labeled (i.e. each instance either belongs to the positive or negative class), K-NN computes distances between a given test instance and all the training instances. These distances are then used to assign (or classify) a class label for the test instance. This is done by aggregating the class labels of the K closest training instances to the test instance.

3.5. Decision Table. Decision Table is a supervised learning method. Given a set of training examples that are labeled (i.e., each instance either belongs to the positive or negative class), this method computes a model by building a decision table. That table consists of a set of conditions and corresponding actions. The table is complete if it considers every possible combination of input instance for the conditions, and prescribes the corresponding actions for each of them.

3.6. Decision Stump. Decision Stump is a supervised learning method. Given a set of training examples that are labeled (i.e., each instance either belongs to the positive or negative class), this method computes a model by building a decision tree, with only one internal node. In other words, it makes the prediction for any given test instance using only one feature of that instance. This feature is determined by computing the information gain for all features across all training instances, selecting the one with the maximum information gain value.

3.7. One Rule (OneR). OneR is a supervised learning method. Given a set of training examples that are labeled (i.e., each instance either belongs to the positive or negative class), this method computes a model by generating one rule for each feature in the data set. It then selects the one with the minimum total error.

3.8. Zero Rule (ZeroR). ZeroR is a supervised learning method. Given a set of training examples that are labeled (i.e., each instance either belongs to the positive or negative class), this method computes a model by using only the target feature (i.e., class) while ignoring all other features. It is considered the simplest classification method. It assigns any new test instance to the majority class. Usually, it is used as a benchmark to determine baseline performance .

4. Performance evaluation

To evaluate the performance of the eight learning algorithms, four performance measures were used: Accuracy, Root Mean Square Error, Fmeasure, and ROC area. These measures can be computed using a confusion matrix and cross validation methods.

4.1. Confusion matrix. The confusion matrix is used to visualize the performance of a binary (2-class) supervised learning problem by creating a 2-by-2 matrix. Each row in the matrix shows the instances in the predicted (or computed) class, while each column shows the instances in the actual class. The resulting matrix consists of four values (see Table 1).

True Positive **(TP)**	False Negative **(FN)**
False Positive **(FP)**	True Negative **(TN)**

Table1 Confusion Matrix.

o True Positive (TP): are the number of instances that were classified (using the predictive model) as positive, and are actually positive.
o False Positive (FP): are the number of instances that were classified (using the predictive model) as positive, but they are actually negative.
o False Negative (FN): are the number of instances that were classified (using the predictive model) as negative, but they are actually positive.
o True Negative (TN): are the number of instances that were classified (using the predictive model) as negative, and they are actually negative.

4.2. Cross validation. Cross Validation is a statistical method used to measure the performance of learning and classification methods. This is done by splitting the available labeled data instances into k folds. One of these folds is used for testing, and the rest are used for training. This work used 10-fold cross validation. The data instances are divided into 10 folds. For 10 iterations, one-fold was used for testing and 9 folds for training, such that in every iteration a different fold is used for testing.

4.3. Accuracy. The accuracy of a classifier is computed as the number of correctly classified instances to the total number of instances. It is given by:

$$\text{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

4.4. Root mean square error. The Root Mean Square Error (RMSE) is computed as the square root of the average of squared differences between the predicted classes (or labels) and the actual ones. It is given by:

$$\text{RMSE} = \sqrt{\frac{\mathrm{FP} + \mathrm{FN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}}$$

4.5. F-measure. The F-measure is computed by combining the two measures of precision and recall. It is given by:

$$\text{Fmeasure} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

where,

$$\text{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

and

$$\text{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

4.6. ROC area. The Receiver Operating Characteristic (ROC) is another way to measure the performance of a classifier. This is done by plotting the True Positive Rate against the False Positive Rate. The area under the resulting ROC curve is then used to measure the performance of the classifier. The closer the area to 1 is, the better the classifier is. The true/false positive rates are given by :

True Positive Rate = $\frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$

and

False Positive Rate = $\frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}}$

RESULTS AND DISCUSSION

1) Confusion matrices

622	0
104	750

(a)

621	1
104	750

(b)

587	35
104	750

(c)

622	0
105	749

(d)

622	0
104	750

(e)

539	83
349	505

(f)

422	200
267	587

(g)

0	622
0	854

(h)

Fig. 9. Confusion matrices. (a) SVM. (b) Neural Network. (c) Naïve Bayes. (d) K-NN. (e) Decision Table. (f) Decision Stump. (g) OneR. (h) ZeroR.

Fig. 9 shows the confusion matrices that resulted from applying 10- fold cross validation to the eight selected classifiers. (Large numbers in the upper-left and lower right boxes of these matrices represent good scores. Large numbers in the lower-left and upper right boxes of these matrices represent bad scores) .

2) ROC curves

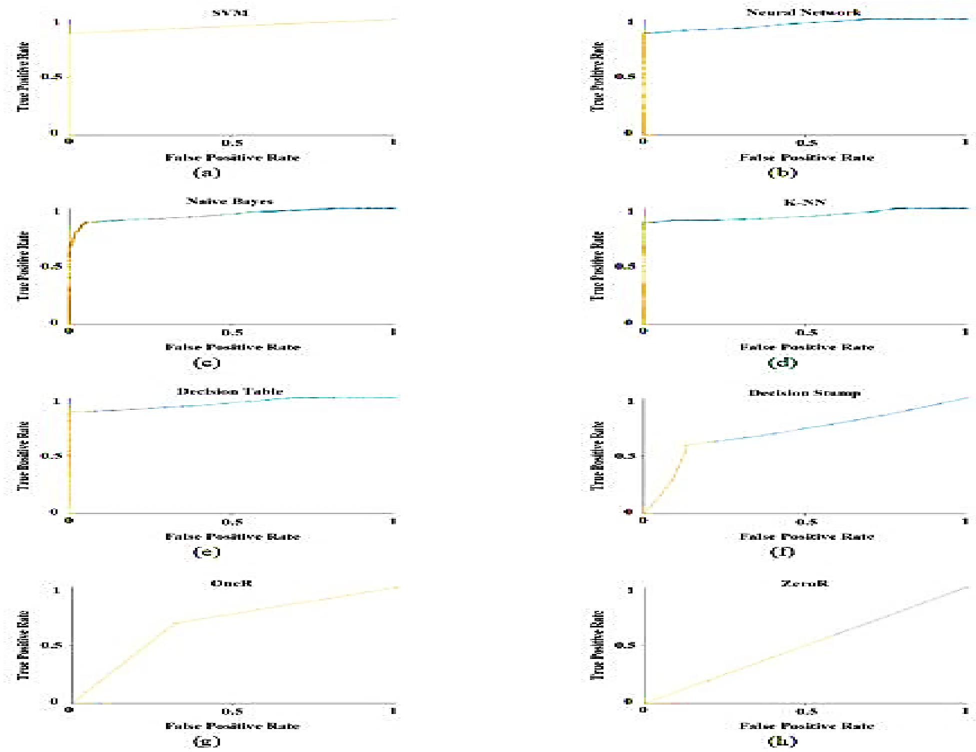

Fig. 10. ROC curves. (a) SVM. (b) Neural Network. (c) Naïve Bayes. (d) K-NN. (e) Decision Table. (f) Decision Stump. (g) OneR. (h) ZeroR.

Fig. 10 shows the ROC curves that resulted from applying 10-fold cross validation to the eight selected classifiers.

3) Performance measures

Fig. 10 shows the ROC curves that resulted from applying 10-fold cross validation to the eight selected classifiers. Table 2 and Fig. 11 compare the performance of the eight algorithms. It shows the Accuracy, Root Mean Square Error, F-measure and ROC Area of each algorithm, which were calculated using the well-known 10- fold cross validation method. The results presented in Table 2 and Fig. 11 suggest that the models built using SVM, Neural Network, Naïve Bayes, K-NN and Decision Table algorithms are effective in classify confirmed cases of COVID-19 patients in home quarantine. Taken together, this suggests that our proposedintelligenceMCC-based framework could use a combination of these five effective models. This could be done by aggregating the results of these five learnt models, based on majority votes .

Algorithm	Accuracy	Root Mean Square Error	F-measure	ROC Area
Support Vector Machine (SVM)	92.95 %	26.54 %	93.0 %	93.9 %
Neural Network	92.89 %	24.23 %	92.9 %	95.5 %
Naïve Bayes	90.58 %	30.99 %	90.6 %	94.2 %
K-Nearest Neighbor (K-NN)	92.89 %	28.06 %	92.9 %	93.9 %
Decision Table	92.95 %	23.97 %	93.0 %	95.0 %
Decision Stump	70.73 %	43.86 %	70.6 %	70.1 %
OneR	68.36 %	56.25 %	68.5 %	68.3 %
ZeroR	57.86 %	49.38 %	57.9 %	49.7 %

Table 2 Summary of performance results .

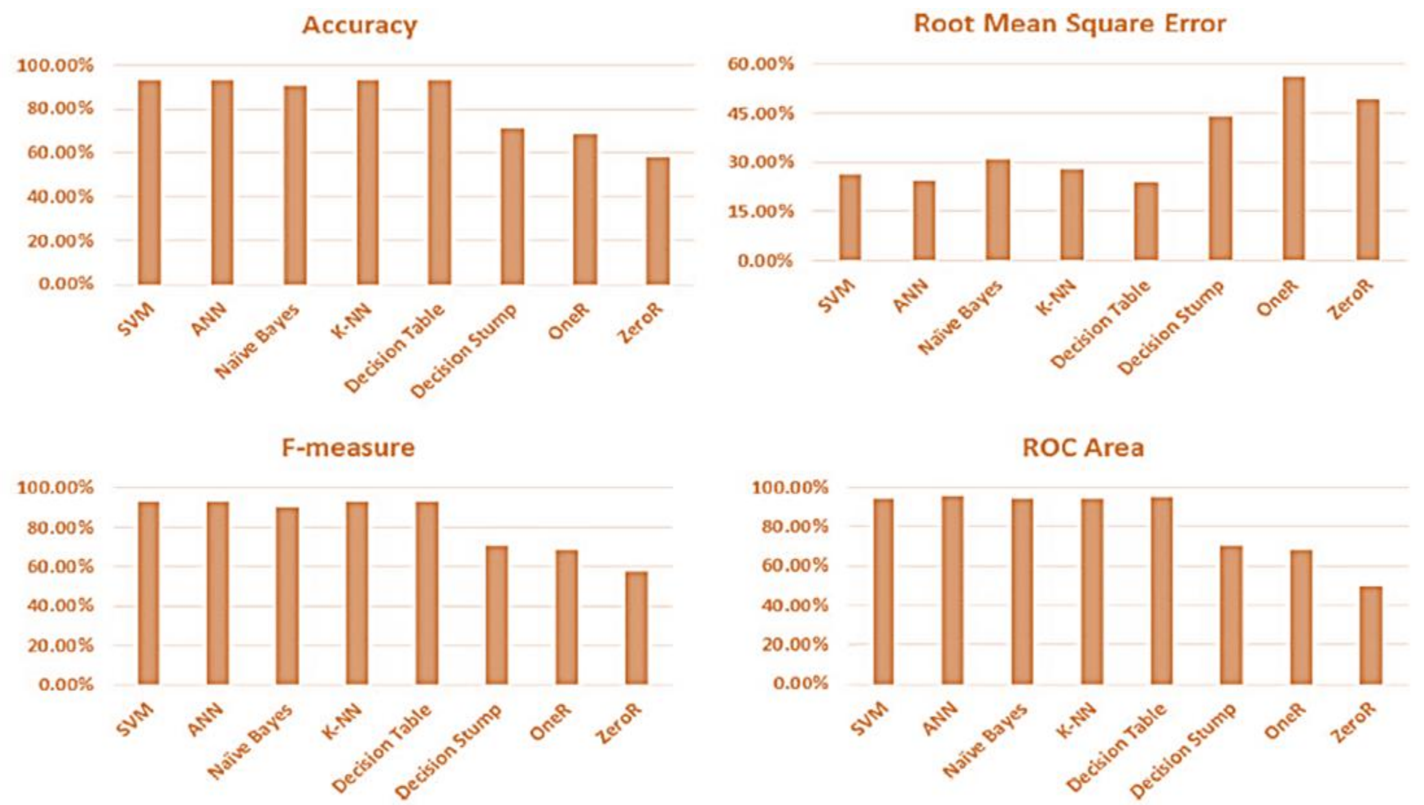

Fig. 11. Performance measures of the eight algorithms. (a) Accuracy. (b) Root Mean Square Error, (c) F-measure. (d) ROC Area .

CONCLUSION

This paper has proposed an intelligent MCC -based framework to reduce the impact of communicable diseases. The proposed framework was used to employ information and vital signs of confirmed COVID-19 cases to develop a machine-learning-based classify model for disease, as well as for analyzing the treatment response. The framework also communicates these results to healthcare physicians, who can then respond swiftly to critical cases identified by the classify model by following up with any further clinical investigation needed to confirm the case. This allows Transferring critical cases to Quarantine/isolation center and given appropriate health care. An experiment was conducted to test eight machine learning algorithms on a real COVID-19 dataset. They are: (1) Support Vector Machine, (2) Neural Network, (3) Naïve Bayes, (4) K-Nearest Neighbor (KNN), (5) Decision Table, (6) Decision Stump, (7) OneR, and (8) ZeroR. The results showed that all these algorithms, except the Decision Stump, OneR, and ZeroR achieved accuracies of more than 90 %. Using the five best algorithms would provide effective and accurate classification of critical cases of COVID-19 patients. Employing the proposed real-time monitoring framework could potentially reduce the impact of communicable diseases on the lives of patients and reducing the momentum taking place in health centers as well as the lack of resources and treatment of cases in which the doctor is not available in order to quickly respond to critical cases, as well as mortality rates through early detection of critical cases. This framework would also provide the ability to follow up on recovered cases, and a better understanding the disease .

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