COVID-19 on spot detection as a service (COSDaaS) – A cloud-based pandemic service approach by means of a smart screening device for mass screening to minimize the spread of infection efficiently.

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Abstract. The planet is now suffering from the fever of Corona Virus Disease 2019 (COVID-19) since December 2019, a human health fatality, education and the global economy, and we don't know how to cope with this deadly environment and what will happen in the immediate future. First thing is stop transmitting this pandemic disease as a cross-infection so long as there is no discovered antidote to cope with this worrying situation. As a result, a certain number of citizens in all countries must be considered for a mandatory test that may not be available by all individuals or may not be supported by the government due to the availability and expense of the test kit or any other testing tool or procedures that require time to install and use it for community use. Here we have proposed a smart screening device focused on a new cloud-oriented platform "COVID-19 on spot detection as a service (COSDaaS)" – for early screening of infected populations, deploying at low cost in various heavy public transition areas with less effort to protect non-infected people from cross-infection.

Keywords: Smart Screening Device (SSD), COVID-19 on spot detection as a service (COSDaaS), COVID Service Provider (COSP), Smart COVID Analyzer (SCA), cloud Service Provider (CSP).

1. Introduction
The world has seen a variety of catastrophic events at various times from a historical point of view, some with unprecedented impacts. One of the worst cases where an estimated 100-200 million people [1] was killed in the 14th century due to Black Death. Key influenza outbreaks (Flu) have occurred in recent years, including Spanish Flu (H1N1 influenza virus) recorded in 1918 where about 500 million deaths and which originating in Etapes, France [2]; 'Asian Flu' (influenza A subtype H2N2) recorded in 1957–58, originating in China where around 1 million deaths; again influenza A (H3N2) originating in China in 1968 where 1 million deaths; Swine flu (H1N1 influenza) originating in United States in 2009 where 12,469 were deaths [3]; [4] In Zaire (now the Democratic Republic of Congo) 11,315
The novel corona virus (COVID-19) of respiratory disease - an outbreak was closely targeted worldwide which is transmitted mainly through droplets formed when a person is infected with cough, sneezing, or exhales [5][6][7]. One can get infected with breathing in the virus if he or she is close to someone affected by COVID-19 or touches a contaminated surface by eyes, nose or mouth. The common symptoms including cough, Fever, shortness of breath, fatigue, smell, taste and loss of sense [8][5][9], but some patients often suffer from anxiety and discomfort, inflammation of the nose, runny nose, sore throat or diarrhea. Some individuals affected with COVID-19 have mild symptoms breathing problems, and they live without medication but elderly people and those with ongoing health issues such as heart disease, diabetes, chronic disease and cancer are also more likely to develop serious medical condition. Within the first three days of symptom onset, it is most contagious but it can widen even from people who have no symptoms before symptoms start [5][6]. COVID 19 length of the incubation (time from symptoms to infection) varies between 1 and 14 days. According to WHO, almost 80 per cent of confirmed patients recover from the disease without significant complications, but one in six users of COVID-19 will get critically ill and encounter breathing difficulties. In more serious cases, disease can lead to acute pneumonia and other complications which can be handled only in higher-degree facilities (District Hospitals and above). In a few cases, this can also cause death.

One approach proposed in our paper would prevent and slow down transmission for mass people on the spot by smart screening devices that can help diagnose this disease early on. Since we know a wide range of sensors such as temperature, cameras, inertial, proximity, microphones, colour, humidity, and many others available on the market, these sensors, combined with cloud environment, can be converted into a smarter portable system to gain more access and analyse power for COVID-19 like pandemic detection.

In our AI enabled Cloud computing based proposed framework, the Smart COVID Analyzer (SCA) under COVID Service Provider (COSP) expertise not only from sample collection to detection phase based on the available resources provided by the respective Cloud Service Provider (CSP), and finally take the responsibility to send the result to the Government Health Management System (GHMS) through nearest Hospital or Health Centre (HHC) for preventive measure.

2. Literature Survey

People fight the pandemics at different times from ancient times to dates. Recently, the entire world has concentrated closely on an epidemic of respiratory disease triggered by a novel corona virus (COVID-19), get troubled worldwide, and kill the lives of people. Governments in a number of countries have taken measures to reduce the COVID-19 pandemic effect. During this immense and chaotic time, globally, scientists are working relentlessly to find a vaccine. Candidates for the COVID-19 vaccine, as well as other candidates for preclinical production and testing are currently in step 1-3 studies. In this circumstance almost all countries around the world are struggling together just to monitor the corona virus outbreak COVID-19. So many techniques such as “NAT (Nucleic Acid Test)”, and “CT (Computed Tomography)” [10] are available to diagnose COVID-19 corona virus disease, where NAT is used to classify various sequences of nucleic acid and organism types, specifically blood, tissue, or urine related diseases caused by a virus or bacteria. On the other hand, CT scanning is the most efficient and realistic way to detect the extent and degree of inflammation of the lung [10], whereas detection kits and NAT technique are becoming critical to detect COVID-19 virus. The inclusion of regular clinical diagnostic presentations for radiographic pneumonia in the province of Hubei reported by National Health Commission of China [11] as to diagnosis the severity of COVID-19 pneumonia by the key images of CT scan. The pandemic COVID-19 and the resulting enormous demand for treatment have inspired companies, academics and researchers to develop methods of detection that are highly efficient, smarter, and more reliable. A smart method of CT image reading system for the COVID-19 revealed by Ping, a Smart Healthcare device that can interpret findings at a precision rate above 90 percent in around 15 seconds [12]. On the other side, of
course neither the 'Reverse Transcription Polymerase Chain Reaction (RT-PCR)' nor the COVID-19 'CT scans' diagnosis are well suited [12]. In fact, with advances in computational capabilities and widespread use of AI [13], machine learning, big data[14, 15] like technologies embedded with cloud computing, it has become possible to collect and analyse vast amounts of data from various sources in real time, and to make informative predictions of it. A deep learning based AI algorithm with high resolution CT images [16] has developed for detection of COVID-19. For detection of COVID-19, CT images of the volumetric chest analysed by ‘COVNet (COVID-19 neural network detection)’, the three-dimensional deep learning technique [17] has been used. A convolutionary ResNet-50 model called COVNet [18] which takes its inputs as a sequence of CT segments and the CT image class labels determines its output and demands the proposed model is more capable to detect COVID-19 due to its AUC value 0.96. To detect cases of corona virus using pulmonary CT images another location-attention system concatenation with the three-dimensional CNN ResNet-18 network [18]- a deep learning method is proposed in [19]. Various types of COVID-19 CT imaging were found in [20, 21]. Another deep learning model [22] derived from customized stacked auto encoder is used to guess COVID-19 cases throughout China. For assessing the risk of infection at the community level for a given geographic area, α-Satellite - another AI-based prototype system is proposed [23]. Social media data for a specified region could be inadequate to being enriched by the conditional adversarial generative networks [24] for knowing COVID-19's public awareness. To estimate the risk indexes aggregate information from the given city's locality areas, an auto encoder model of a heterogeneous graph is then configured. Again, a stochastic agent-based discrete model called “ACEMod (Australian Census-based Epidemic Model)” [25] is used to model the COVID-19 pandemic, previously used for influenza pandemic simulation, based on main disease transmission parameters across Australia [26, 27]. The best solution the model suggests is to incorporate foreign entry, case separation and social distancing constraints with 80 percent or higher enforcement in at least 13 weeks. For COVID-19 infection risk prediction, incorporating the concept of susceptible infected disease a hybrid AI model is proposed [28]. For better understanding and manage the worldwide public health during the COVID-19 pandemic, another AI model based upon some standardisation protocols and data sharing techniques is proposed [29]. In addition the COVID-19 is detected by means of medical detection kits. But that method is expensive, requiring a diagnosis to be installed. Now a day, a lot of sensors on the market with strong computing capabilities can be constantly sensed awareness of day-to-day activities. For instance, the temperature-fingerprint sensor can be used to sense the body temperature to predict fever level [30]. On the other hand, inertial sensors can be used to detect human fatigue level [31] where Images and videos taken from the camera or data taken from on board inertial sensors. Similarly, Story et al. [32] use Smartphone videos to predict nausea, while use camera images and measurements of inertial sensors used by Lawanont et al. [33] to monitor neck location and predict headache rates in humans. Audio data obtained from the microphone sensor is also used for detecting the form of cough [34]. There is very little literature regarding the COVID-19 syndrome, due to its recent emergence. Considering all the scenarios we recommend a smart screening system that will allow people to check in different heavy public transition areas to avoid gathering in hospitals or test centers that not only reduce the risk of cross-infection with others, save the cost of test kits, and also identify the places where the infected person travels. So our aim is to avoid the spread of the disease as soon as possible and the whole thing will be managed through cloud computing by the COVID service provider (COSP).

3. Overview and Rationale

3.1. Sensors:
To calculate different health issues, such as respiratory rate, heart rate, heart rate variability and health issues like skin & eye disease advanced day-to-day sensors can be used. Typical health monitoring sensors are shown in Table 1.

Table 1. Typical Health Monitoring Sensors
| Typical Sensors                  | Health Issues                                                                 |
|---------------------------------|-------------------------------------------------------------------------------|
| Microphone                      | Nasal symptoms (Blowing the nose, Sneezing and Runny Nose), Lung Functions, Ear health, chronic pulmonary diseases such as cough, asthma, shortness of breath, Fatigue level |
| Image Sensor (Camera), Microphone| Cardiovascular activity – Heart Rate, Heart Rate Variability, Respiratory and Lung Health |
| Image Sensor (Camera)            | Eye Health, Skin Health                                                        |
| Temperature, Thermal Camera      | Body Temperature Measurement                                                   |
| Motion sensors (Accelerometer, Gyroscope, Proximity), GPS | Physical Activity and Movements                                               |
| Motion sensors (Accelerometer, Gyroscope), Camera, Light Sensor, GPS | Cognitive function and Mental health Assessment                               |
| Motion sensors (Accelerometer, Gyroscope) | Sleep                                                                       |
| GPS                             | Track Location                                                                |

Utilization of some typical sensors to detect the common symptoms of the diseases, like COVID-19:

3.1.1. Camera sensor: Heart Rate (HR) & Rate of Respiration (RR) assessment
Both front and rear camera sensors of smart phone were used to track both the ‘heart rate’ and the ‘rate of Respiration’ [35], where ‘photoplethysmogram (PPG) fingertip signal’ (from the top of the ‘rear-facing camera’) used to achieve the HR, In which RR is measured from the front camera by tracking chest and abdominal motions. Another way to obtain HR and RR Welch’s power spectral density is required by prevailing intensity in the frequency-domain of images. On the other hand to gain 6–60 breaths (wide dynamic range) per minute as an automated selection protocol for Region-of-Interest (ROI)’ was used. Above mentioned contact based HR monitoring systems enabling the user to direct contact through the smart phone’s camera lens holding the fingertip tightly, otherwise erroneous result will obtained due to any change in finger position [36]. At the other hand, contactless monitoring systems measure HR from the face-video-derived PPG signal. In reference [37], such a contactless cardiac pulse monitoring device, called ‘Face Beat’, was introduced. ‘Face Beat’ measures the heart rhythms and determines HR from the face video taken by a user using the front camera of the smart phone. Reflected light of the increasing blood flow in the facial blood vessels on a specific section of face is detected by the photo-detector image sensor device to calculate the difference and simultaneously captured Green Channel footage data is securitized. Another proposed method [38] that the colour of the reflected light is identified from the face and make the difference to obtain both RR and HR.

3.1.2. Microphone and camera sensor: HR and HR Variability (HRV) assessment
Camera and microphone are mutually being used for estimation of HR and HRV through bare skin visual ‘photoplethysmogram (PPG) signal’, such as the face or fingertip. The properties of haemoglobin light absorption in the blood vary from those of other body tissues including flesh and bone. PPG measures volumetric fluctuations by detecting refractive variations and/or light reflectivity with arterial pulsation through the tissue [39, 40]; whereas red light sources near-infrared (NIR) are used in most commercial devices [39, 40]. Some researchers used an embedded smart phone with a white flashlight to illuminate the PPG tissue. In reference [41] a flashlight and camera sensor from the PPG signal obtained from the fingertips were used to test the HR and HRV. The pulsing signal was extracted from the green channel of the video data after a low-frequency band-pass filtering. In [42] corrupt video data commonly recognized by movable objects is identified and discarded. The PPG signal was extracted from all three channels (red, blue and gray) from the index fingertip video, make the difference of maximum and minimal intensity to derive the threshold then based on the threshold value aggregates the pixel values with higher intensity than the threshold. The PPG signal achieved via the red channel other than two channels the regular increase in blood flow rates during the cardiac cycles was reflected and finally applying ‘Fast Fourier Transform (FFT)’ analysis on this PPG signal the pulse rate was obtained at an accuracy rate about 98 percent.

3.1.3. Temperature or Thermal Camera sensor: Measure the Body Temperature
The sensor temperature-fingerprint, used to predict fever rates [43]. Additional ‘ATmega328’ microcontroller for tracking patient body temperature (LM35 Temperature Sensor) and pulse (LM358 Heart Beat Sensor) [44] is used as a CPU. In [45] the definition of an embedded system is demonstrated for calculating heart rate and body temperature. Another temperature monitoring sensor the thermal camera embedded with a wristband [46] calculates the reference point temperature. In [47] an eye glass tracking system is implemented to follow optimistic cognitive and impulsive conditions for sentimental computing using ‘Thermal IR Camera’ (contactless temperature sensors) which follows changes in facial temperature.

3.1.4. Microphone Sensor: Detect Nasal symptoms (Blowing the nose, Sneezing and Runny Nose)
The application software Listen-to-Nose [48] detects nasal symptoms that decisive on audio. The application detects sound patterns through a microphone sensor by using acoustic recognition algorithm that match blowing or sneezing (discards other audio information like speech and silence), to identify the symptoms the user has.

3.1.5. Microphone Sensor: Measure Lung Function using

"SpiroSmart" is microphone based application software [49] that sends the recorded audio data of exhalation to a server for calculating the flow rate of exhalation to test the lung function. A typical spirometer calculates the air flow rate when going through a mouthpiece. Such mouthpiece flow can be combined to achieve Flow vs. Time (FT), Volume vs. Time (VT), or Flow vs. Volume (FV) expiry plots. Different amounts are determined from the plot: (1) ‘FVC’ (Forced Vital Capacity) - During the expiry period entire volume expelled; (2) ‘FEV1’ (Forced Expiratory Volume) - In the first second the amount expired; (3) The ratio of FVC & and FEV1 (4) ‘PEF’ (Peak Expiratory Flow) - The best flow rate obtained for the period of the test. Different lung dysfunctions [49] like Mild (60-79%), Moderate (40-59%) and Severe (<40%) are obtained from the combination of flow vs. volume curves.

3.1.6. Microphone Sensor: Detect chronic respiratory conditions (like cough, asthma, shortness of breath), pulmonary disruption and lung cancer
For faster pulmonary health assessment many researchers used a microphone sensor to detect a coughing and respiratory sound, and analysed the captured audio signals. Using built-in microphone of a smart phone based interactive game ‘Flappy Breath’ [50] was developed where the users play by inhaling and exhaling to detect breathing. The game measures the occurrence and intensity of the sound inputted when playing using the microphone, determines the typical amount of air flowing referring to silence, inhalation and exhalation. To detect the coughing situation, the audio signal recorded by the smart phone's microphone was analyzed using a cough detection algorithm ‘PCA’ (Principal Component Analysis) [51], where the cough sound spectrogram was separated, normalised and analysed on the basis of the distinct pattern and after re-generate the signal of coughing identify the coughing occurrences finally.

3.1.7. Accelerometer, gyroscopes, magnetometers, GPS, Light & Microphone Sensors: Assessment of Mental Health and Physical Activity & Movement
Due to variety of inbuilt embedded sensors (like accelerometer, light, GPS, microphone etc.) of today's smart phones, data such as call history, SMS history and system utilisation to track a person's behaviour remotely and determine their mental health or fatigue level [52]; the accelerometer may provide information on movement and physical activity during sleep.

3.2. Proposed Service Model- COVID-19 on spot detection as a service (COSDaaS)
Figure 1 represents our proposed service model (COSDaaS) and basic cloud service models. COSDaaS under Private Cloud offers low-cost, early detection services for COVID-19 like pandemic disease with less effort to reduce cross-infection through the Smart Screening Tool. From data collection phase to decision phase the actual physical resources invoked by the Virtual Machines in such a way that once the COSDaaS model is enrolled by a customer or cloud service provider, no possibility of direct interference between users and Cloud Service Providers (CSP), as a result to avoid being partial either or both sides.

3.3. Cloud Service Provider (CSP)
A service provider that provides some storage or software or hardware or network infrastructure to the customers through SaaS or IaaS or PaaS is called a cloud service provider which not only offers services to companies or individuals, but also ensures that it takes responsibility for anything relevant to the customers’ applications.

3.4. Government Health Management System (GHMS)
The Government can create a special unit to track and deal with the pandemic situation.

3.5. Smart Screening Device (SSD)
For spot diagnosis of the disease, a small device made by sensors connected to the cloud environment can be used to sense data.

3.6. COVID Service Provider (COSP)
For maintaining a smooth contact between SSD and CSP, COSP plays a major role as it compelled to register SSD and CSPs before assigning resources to the cloud server and to avoid potential conflict.

3.7. Smart COVID Analyzer (SCA)
After receiving the periodic signals from the CSPs, SCA will use the available cloud resources and will be able to collect data from SSD, analyze it and eventually identify the disease itself. SCA therefore maintains a mapping table of COSP to its respective CSPs’, as well as a log table of SSDs’ connected to it.

4. Proposed Work
The increasing demand for embedded sensors coupled with pay-based infrastructures and services from Evolving Cloud Computing would make it a better technology for consistent and remote
monitoring of a person’s health with minimal extra costs. Consider the current scenario and based on our previous observations on various cloud management services [53-57] we are proposing a cloud computing-based "COVID-19 on spot detection as a service" that accommodates people for preliminary testing as an early detection of any pandemic diseases by means of low-cost sensors with less effort to mitigate cross-infection.

Figure 2. Proposed Architecture of COVID-19 on spot detection as a service (COSDaaS) Model

Figure 2 represents our proposed "COSDaaS" service model, where COSP provides users with the services from sample selection to testing phase with proper use of cloud resources and finally submits the reports to the GHMS to take the required steps.

4.1. COSDaaS model (Working Procedure)
The proposed COSDaaS model (see figure 2.), where periodic signals, report information, and available resources sent by the CSP to SCA after effective contracts. Upon acquiring resources, SCA establishes and manages the Pandemic Cloud Service such as COVID-19 or any other, and also retains the CSPs’ log table for any potential reference. At the other hand, SCA provides the Pandemic Cloud Services to the SSD via COSP after receiving requests from SSD for on-demand service, and also maintains an SSD-COSP mapping table as a guide to who and from where the service is intended. According to our suggestion, in order to disperse the infection among others, the government will take the initiation as a compulsive test for mass citizens by installing SSD into public transition areas to detect any disease outbreak stops early. After installing SSD in heavily public transfer areas (such as Railway Station, Airports, Bus Terminals, Supermarket, Shopping Mall, etc.) it must be enabled with Cloud environment through a data processing service provider (here, COSP). When a client goes to a specific place to fulfill his / her requirement, he / she must go through the screening process (by SSD) before entering the location for the preliminary ongoing pandemic detection. After receiving the client’s sample data SSD sends it for analysis to the COSP. At the other hand, SCA collects data from different SSDs regularly through its FETCHING module under COSP, and TESTING module is now engaged in the identification of the appropriate tools for measuring the collected samples. DETECTION module eventually takes the decision based on the evaluated result whether the person is "Infected" or "Not Infected" and sends a message to the individual. For those infected, a message along with the current location will be sent to the nearest HHC. Ultimately, HHC periodically prepares and submits COVID review reports to GHMS for the required action.

Our new SCCD (Smart Cloud COVID Detection) algorithm handles all processes automatically and
also places Virtual Machines (VMs) to the actual Physical Machines (PMs) to assign the minimum amount of resources needed. Mapping the VMs’ to PMs’ performed by SCA under COSDaaS. So it's really clear that no one can communicate directly with each other to access this service without either the users or the CSPs’ permission from the COSP. In the case of any conflict, SCA can obtain the suspected customers' comprehensive records, or CSPs, from its own SSD-COSP as well as from the COSP-CSP Mapping log table if necessary. Thus there is no chance that Cloud users may be confused or deceived by the COSP or the CSP.

4.2. Working procedure of Smart COVID Analyzer (SCA) Module
Figure 3 displays the different SCA sub modules and the movement from one module to another for preliminary COVID-19 pandemic detection. The first module i.e., the FETCHING module collects the Client samples from the SSD via the sensors embedded in it. TESTING module is now engaged for symptom prediction following sensing of the data by the respective sensors. Within this module various algorithms are embedded to evaluate the samples to predict the symptoms. Each colored line uniquely represents the flow from sample collection to the process of symptom prediction.

Let us describe some notations used for symptom prediction by TESTING module —

// For Fever level Detection
Body_Temperature- Temperature of the body

// For Pulse Rate Detection
PPG_Signal – Photoplethysmogram Signal
Figure 3. Process Flow Diagram of Pandemic Smart Covid Analyser (SCA)

VCB – Volumetric Changes in Blood
Pixel_Intensity – Intensity of Pixel for each frame
RGB_Channel – Record video through Red-Blue-Green Channel
SFFT – Simple First Fourier Transform
SFFT_Red_Channel – PPG obtained via Red Channel compared to Blue and Green Channel using Simple Fast Fourier Transform analysis
Threshold – Difference between Maximum and Minimum Intensity

// For Heart rate, Respiratory rate Detection
Image – Captured by Camera Sensor
HR – Heart Rate
RR – Respiration Rate
BloodVessels← Use the Green Channel captured video
P_Array - The camera sensor’s Photo detector Array detects light reflection (in variations) from a Specific section of the face

// For Cough and Breathing Trouble
Audio_Signal ← Sound (Cough, Breathing)
CBT – Cough and Breathing Trouble

// For Cough Analysis
Audio_Signal ← Sound (Cough, Throat_clearing, Speech, Noise)
Spectogram – Contain different audio signals of Cough, Throat Clearing, Speech and Noise
PCA – Principal Component Analysis which isolate spectrogram of the cough sound from other Sound
CA—Cough Analysis

// For Nasal symptoms
Audio_Data – {Blowing the nose, sneezing, runny nose, silence, speech}
ARM – Acoustic Recognition Model
CD – Classified Data
SVM – Support Vector Machine
Nasal- Blowing the nose, sneezing, runny nose

// For Stress level detection
Conversation – Recording the conversation with Microphone
S_Level – Stress Level

// For Lung Dysfunction
FT – Flow_Time Diagram
VT - Volume_Time Diagram
FV - Flow_Volume Diagram
FA – Flow rate of Air
FVC – Forced Vital Capacity i.e., total volume emitted during expiry
FEV1 – Exhaled volume in the first second
R_FVC_FEV1 – Ratio of FVC and FEV1
PEF – Peak Expiratory Flow i.e. maximum speed of flow velocity achieved during the test
D_Airflow – Degree of Airflow
L_Function – Lung Dysfunction i.e., Mild, Moderate or Severe

5. Algorithm, Flowchart
5.1. SCCD (Smart Cloud COVID detection) algorithm
1. COVID Service Provider (COSP) offers preliminary detection of COVID-19 using Smart Screening Device (SSD) through Smart COVID Analyzer (SCA) in cloud environment
2. SSD may be installed in important places
3. SSD collects symptoms from the Clients
4. SSD requests to COSP for diagnosing
5. COSP checks for the SSD’s authentication and Service Level Agreements (SLA)
6. If Authentic—
   6.1 Service accepted and acknowledgement sends to the SSD
   6.2 COSP requests to the intended CSP for getting the on-demand cloud resources
   6.3 CSP checks for the COSP’s authentication and SLA
   6.4 If bona fide –
      6.4.1 Service established and acceptance message sends to COSP
      6.4.2 Based on the agreement CSP sends the periodic signals / resource details to Smart COVID Analyzer (SCA)
      6.4.3 SCA store the record details in a log file
      6.4.4 Go to step 8
   6.5 Else –
      6.5.1 Message - “Not acknowledged for services” back to the COSP
      6.5.2 Go to step 6.2
7. Else –
   7.1 Message - “Not accepted for services” returns to the SSD
   7.2 Go to step 4
8. SCA collects the client’s symptoms from the SSD by its Fetching module
9. SCA fetches the periodic record details about the resources from its log file
10. Based on the collected symptoms SCA analysis on the data by its Testing module
   10.1 If within Threshold –
      10.1.1 “Not Infected” -- message returned to the SSD as well as to the Client
      10.1.2 Go to step 11
   10.2 Else –
      10.2.1 SCA trace the current location of the infected person
      10.2.2 “Infected” -- message returned to the SSD, to the Client, as well as to the nearest Hospital / Health Center (HHC) with details about the Client
11. Check for the availability of the client
12. If client exists—
   12.1 Go to step 3
13. Else—
   13.1 Go to step 14
14. HHC sends the pandemic reports to the Government Health Management System (GHMS)
15. GHMS takes necessary actions
16. End

5.2. Flowchart:
6. Conclusion
The end result of our approach is to create a portable testing device with an efficient interface that can be incorporated as part of the patient safety management system into medical and home equipment. Approach COSDaaS model recognizes actual physical server load next to VM user constraints.
addressing the mapping problem of client’s tasks into actual servers in such a way that not only reduce the number of nodes used, also the physical machines with overuse or underuse can be defined and resolved simultaneously without violating any Service Quality and Service Level Agreements. Since we consider this to be a pandemic tool that not only serves as an early detection of pandemic diseases to prevent cross-infection, also it acts as an intermediary between clients and CSPs’, ensuring that nobody can communicate with each other without COSP’s permission. This will eliminate the inequity between the customers' actual usage of energy with the billing records by the suppliers’, therefore avoiding any fake claims that might be brought against one another in order to get unlawful compensation.

7. Future Scope:
Based on the present critical pandemic situation (COVID-19) much of the work on the COVID-19 analysis of our proposed model has been covered. The result analysis can be performed after implementation of the model. Our target is to increase the QoS with costs savings and in near future our aim is to accomplish more cloud computing capacity to battle other pandemic diseases from home as soon as possible at lower prices, less overheads.

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