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Pandemic as a Service (PNDaaS) – A Cloud-Based Approach for Early Detection of Pandemic Diseases (like COVID-19) Through Smart Phone Sensors

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Abstract: Since December 2019 an unbroken pandemic due to the Corona virus disease 2019 (COVID-19) caused by the severe respiratory disease corona virus 2 (SARS-CoV-2), leading in millions of deaths across worldwide. On 30 January 2020 WHO (World Health Organization) proclaimed COVID 19 a "Public Health Emergency of International Concern (PHEIC)" and a pandemic on 11 March 2020. According to WHO, COVID-19 has little or no specific vaccines or antiviral treatments till now, so, the first task is to identify infected people and isolate them to protect against cross-infection. This paper proposes a new cloud-based "pandemic as a service" framework – for early detection of any pandemic disease (such as COVID-19) through smart phone sensors on individual smart phones from anywhere in the world, i.e., any smart phone user can do their preliminary home pandemic test to protect against cross-infection. The government may therefore take the measures as a mandatory test for all smart phone users with the requisite sensors, not only helping to identify the disease early, but also monitoring the users' current location and taking the protective action.

Keywords: Pandemic as a Service, Pandemic Service Provider, Smart Pandemic Service Analyser, Cloud Service Provider, Mobile Sensors, Mobile Service Provider.

1. Introduction

From some kind of statistical point of view, the nation has seen a lot of disastrous diseases like 'The Black Death' [1], 'Spanish Flu - H1N1 influenza virus' [2] led by 'Asian Flu - a subgroup of H2N2 influenza virus', 'influenza A (H3N2) virus', 'Swine flu - H1N1 influenza virus' [3], 'Severe Acute Respiratory Syndrome - SARS' [4], 'Zaire Ebola Virus', '2015 Zika Virus' and many more causes millions of deaths. Now the most outbreak of this millennium is 'COVID-19', the new corona virus originated in Wuhan, China [5][6][7].

The most recent outbreak of this millennium has been an epidemic of respiratory problems caused by 'COVID-19', a novel corona virus [5][6][7], which has mesmerized the entire world. The suspected to cause COVID-19 is scattered primarily through droplets that are consumed when a person coughs, sneezes, or breathes [8][9][10]. These droplets are too large to float in the air and crash to the ground or other surfaces. When you are exposed to someone who has COVID-19 or contact a tainted surface and then breathe the virus into your eyes, nose, or mouth, you will become sick. Fever, asthma, nausea, breathlessness, and lack of scent and taste [11][8][12] are the most classic symptoms, but certain patients also experience aches and pains, respiratory inflammation, runny nose, sore throat, or indigestion. Numerous patients who are infected with the COVID-19 virus can have mild to moderate breathing problems and heal without the need for medical assistance. Significant illness is most likely to affect the aged and others with ongoing health conditions. This is most infectious during the first three days after symptoms appear, but it can also spread from individuals who don't have any symptoms until they appear [8][9].

The key to preventing and delay spread of the COVID-19 virus is to educate yourself about the virus,

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the illness it causes, and how it transmits. One can also shield himself/herself and others from exposure by cleaning hands frequently and wearing of face masks.

As we know, today's smart phones are powerful enough with processing capability, memory capacity, and a variety of sensors capable of calculating various health issues. As a result, our approach can help to identify infectious diseases early in each person and spot their locations using smart phones, preventing and slowing down transmission. The Smart Pandemic Service Analyzer (SPSA) in our proposed expert cloud structure creates and manages different pandemic services (like COVID, SARS, EBOLA, and others) and that depends upon the resource availability of the associated Cloud Service Providers (CSP). Under the umbrella of PSP (Pandemic Service Provider), the CAVDMS (Collection-Analysis-Verify-Decision-Management System) delivers Pandemic services from sample collection (via smart phone sensors) to decision phase (for forecasting disease outcome) and eventually needs to take liability for sending the outcome to the government via HMS (Health Monitoring System) for precautionary action.

2. Literature Survey

From ancient times to till dates people struggle at different times against the pandemics. The entire earth is now based on a chronic respiratory epidemic sparked by a novel corona virus (COVID-19), that has erupted heavily on human-lives and slaughtered a lot of people. Many countries' Governments have adopted measures to minimize the COVID-19 pandemic impacts. Technological advances have played a major role in the introduction of numerous strategies during this unpredictable and tumultuous era. Researchers suggest that a well-managed vaccine production phase might bring a viable strategy to launch in 12-18 months if everything runs perfectly. COVID-19 clinical trials are currently in phase 1-3 trials, as are leading candidates at pre-clinical growth and testing phases.

In this circumstance, each region in the world is attempting to apply numerous methods for identifying COVID-19 corona virus disease like "Nucleic Acid Test" (NAT), and "Computed Tomography" (CT) [13]. The importance of COVID-19 virus detection kits and NAT methods is increasing, while CT scan images are vital for evaluating the severity of COVID-19 pneumonia. Though the "Ping" (a Smart Healthcare device) method of scanning CT images is good for COVID-19 detection, neither the "RT-PCR" ('Reverse Transcription Polymerase Chain Reaction) nor the 'CT scans' for COVID-19 detection are very well fitted, according to [14].

Growth of technological skill carried about through adoption and massive utilization of Big Data, deep learning [15, 16], Artificial Intelligence [17] and cloud computing, on the other hand, it has allowed large datasets to be gathered and handled in real time from a heterogeneous sources, so, critical evaluations is more important. Using CT images with high-resolution, a deep learning algorithm [18] has been implemented for COVID-19 identification. Their proposed model [18], however, relies exclusively on CT images. COVNet i.e. 'COVID-19 neural net recognition' is a 3D deep learning system [19] which is developed to identify COVID-19 and usually depend on chest's CT images in volumetric. ResNet-50, the convolutional model (COVNet) [20], that accepts the inputs of CT slices in a sequential manner and classifies the CT images based on the results and here the observed AUC value (0.96) shows that the proposed model has a high potential to detect COVID-19 cases. In [21] proposes a deep learning approach which not only focused on the region-based computation technique, but also use the '3D CNN ResNet-18' network [20] to identify instances of corona virus through CT images of respiratory, whereas [22][23] represents various appearances of CT images of COVID-19. Using layered auto-encoder an updated deep-learning model is used in [24] for identification of COVID-19 instances in real time around China. In contrast, [25] proposes an AI-based prototype framework (α-Satellite), to determine the infection risk at the population level for a specified region, here the process gathers a variety of massive and real-time data from a variety of outlets, including case and death counts, survey data, social media data, traffic density, and many more. In order to know the public knowledge of COVID-19, the social media data available for a given field may be restricted to be enriched by the conditional generative adversarial nets [26]. A diverse graph auto encoder model is then programmed to group the data from the specified area's adjacent places in turn to approximate its risk metrics. Such vulnerability awareness enables people to take the necessary precautions to shield themselves from contamination while causing the least amount of disruption to their regular routines. A distinct and agent-based dynamic technique "ACEMod" was first used to model flu epidemics [27][28] and which is updated by Chang et al.[29] and applied in Australia to deal with the COVID-19 pandemic. The ACEMod is calibrated based on key parameters of transmission of the disease to simulate the COVID-19 epidemic's details. In [30], a hybrid model is presented which is based on AI for prediction of infection risks about COVID-19 that combines the idea of deep learning and natural language processing improvements. From another article [31], Allam and Jones suggest that in the COVID-19 epidemics, AI and information sharing interoperability frameworks is being used to help interpret and manage worldwide human health.

Modern smart phones combine a wide number of sensors and have strong computing capabilities. Using smart phones, information on everyday activities can be sensed and even visual data captured [32]. 'Temperature fingerprint sensor', for instance, could also be used to measure the severity of a fever [33]. On the other hand, human exhaustion may be detected using videos and images captured by smart phone camera sensors or ‘onboard inertial sensors’ [34][35]. Story et al.[36] use mobile phone videos to recognize nausea, whereas Lawanont et al.[37] track neck positioning and recognize health migraine levels using camera photos and inertial sensor readings. Consequently, voice evidence gathered from the smart phone's microphone sensor is being used to diagnose coughing [38][39]. In [40] suggests using an online survey through telephone to capture simple travel information of human beings and their typical depictions. This information is useful for training algorithms of machine learning to train and forecast almost every person's infection risk, allowing high-risk instances to be managed effectively for confinement.

In particular, unless the initial phase of a susceptible individual of acquiring COVID-19 is separated from serious patients with high fever and shortness of breath in order to avoid overloading medical systems and physicians, otherwise the diagnosis and quarantine of infected patients would be delayed and the care of patients less effective [41].

After reviewing all of the cases we recommend an approach based on smart phone that allows people checking at home to avoid crowding in clinics or testing centers, which also lower the impact of cross-infection with others and saves money on testing kits, and also to see where the infected individual is moving-around. As a result, our priority is to halt the spread of the disease as rapidly as possible and here, the Pandemic Service Provider (PSP) plays the major role to control the whole thing and that may be instructed by the Health Monitoring System of the government to detect any pandemic disease early.

3. OVERVIEW AND RATIONALE

A. Smart Phone Sensors:

TABLE I. SMART PHONE SENSORS USED FOR HEALTH MONITORING

Typical Smart Phone 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 Metal health Assessment
Motion sensors (Accelerometer, Gyroscope)	Sleep
GPS	Track Location

Now a day, sensors [42] plays an important role for measuring different health parameters. Moreover, today’s mobile phones come with a range of sensing devices which is used to monitor a variety of health indicators. Table I shows some inbuilt smart-phone sensors and their usefulness in different health issues.

Some Smart phone sensors are utilized to predict the common symptoms are as follows –

a) Body Temperature Measurement using Temperature or Thermal Camera sensor:

In [43], the 'temperature-fingerprint sensor', which is situated beneath the smart phone's touch interface, is being used to measure the degree of temperature. Another temperature sensors like LM35 and LM358 is used for measuring body temperature and pulse rate respectively and those are controlled by the microcontroller [44] ATmega328.

The idea of an integrated unit in [45] that measures the body temperatures and pulse rates. The aim of this work [46] is to compare temperature readings from a silicon band gap temperature sensor integrated in a smart phone (the Sensation SHTC1) with temperature sensors from a Met One 064-2 thermostat. Furthermore, the application "Weather Station Pro" was used to take data readings with this sensor. The reference point temperature is calculated by 'Thermal Wrist' [47] through mobile phone's 'thermal camera' with a 'wristband sensor' from the heat calculation of the wristband. Utilizing ‘Thermal IR Camera’ (a non-contact temperature sensors) on eye glasses to detect facial temperatures in variations [48] introduce a method for measuring optimistic emotional and intellectual states for stress detection.

b) Determine heart rhythm (pulse rate) and heart rate variability Using a camera and microphone sensor:

In case of measuring Heart Rate and its Variability, Smart phone’s Microphone and Camera sensors are jointly being used. By using the inbuilt light absorption properties of haemoglobin in the blood, the sensors record a video or photograph of naked skin in the form of a ‘PPG’ (photoplethysmogram) signal. Actually, PPG recognizes volumetric variations [49][50] by observing reflected light differences with pulmonary stimulation via the blood vessels, and then ‘FFT’ (Fast Fourier Transform) processing is applied to this PPG signal, yielding the success rate of refractive index is about 98 percent.

c) Diagnose severe respiratory conditions like coughing, pneumonia, breathlessness, and lung cancer through microphone sensor :

Coughing and breathing noises are evaluated for quicker respiratory health evaluation [51][52][53][54][55][56][57] using different methodologies such as 'Flappy Breath' [51] or 'PCA' analysis [52] for determining the volume of the sound inputted based on a certain volume of air blowing during quiet, ingestion, and exertion.

d) Diagnose Nose related complaints through Microphone Sensor:

An audio-based smart phone technology- 'Listen-to-Nose' [53] is for detecting nose related disorders including soupy nose, blocked nose, and snoring. The system detects sound signals that are appropriate for breathing or snoring in order to determine which symptoms the user is feeling. The system captures sounds using a computer's microphone on the client side and uses an acoustic recognition model to identify audio data periodically. Other acoustic input, such as voice and non-voice, are discarded by the 'acoustic recognition model', which categorizes input sounds as rubbing the nose or snoring.

e) Diagnose Lung disorders through Microphone Sensor:

Various methodologies for assessing lung dysfunction using microphone-based detection analysis are already being developed. "Spiro Smart" [54] is a famous piece of software. A standard 'spirometer' measures the respiration air velocity as air is passing via a mouthpiece to measure lung functional ability. A number of things can be decided by using some plots [54] like- Forced Vital Capacity (FVC), Forced Expiratory Volume in one Second (FEV1), FEV1 / FVC and Peak Expiratory Flow (PEF). In FVC, the full volume emitted during the expiration period; in FEV1, the volume emitted during the first second; whereas FEV1 / FVC is the ratio of the two measures and PEF is the maximum flow rate received as during survey. The separate Flow vs. Volume curves are used to assess mild, moderate and severe lung dysfunctions i.e. 60-79%, 40-59% & less than 40% respectively.

f) Judgements of Physical & Psychological fitness and movement through smart-phone sensors like GPS, light, gyroscopes, microphone, accelerometers & magnetometers :

A smart phone based 'Acceleration-based Detection System' [58] is developed to analyze fatigue with surface electromyography as the criterion during the 30-STS test. The stress level or psychological state of an individual can be inferred from their expression while spoken over the mobile and tracking the dialogue through the microphone of the Smartphone [59][60][61]. The GPS provides positioning information, while the accelerometer sensor monitors information about physical fitness and orientation while sleeping. Smart-phone evidence, on the other hand, is critical for assessing mental health conditions such as anxiety [62], emotions [63][64], and daily anxiety levels [65]. In recent years, motion detectors (such as gyroscopes, proximity sensors, magnetometers, and GPS sensors) embedded in cell phones have become increasingly important for real-time tracking [66-72] of daily activities.

g) Skin health monitoring using camera sensor:

To assess the effectiveness of smart phone imagery in assessing skin lesions, a reference [73] was a cross-sectional study of skin disease. The majority of today's skin disease identification systems use advanced methods of image processing in conjunction with standard imagery [74][75]. To explore the effectiveness that use mobile devices for skin chromophore mapping, a ring-shaped beam of energy for the mobile phone camera was used [76]. Basically, red, green, and blue emission spectrum LEDs, one white LED and two orthogonally guided polarizers make up the ring.

B. Cloud Service Models

Proposed Cloud Service Model along with the default Cloud Service Models are depicted in figure 1. In general the models of cloud computing operation are-

a) Software as a Service (SaaS):

Along with the required hardware and network facilities, a pre-built program as well as the necessary applications and system software's are supplied by this framework.

b) Platform as a Service (PaaS):

Along with the required hardware, network and operating system facilities the users can get the benefits of installing or developing their own applications and software's by this framework.

c) Infrastructure as a Service (IaaS):

Only the network and hardware are supplied by this framework, but the clients can develop their own applications and system software's.

C. Pandemic as a Service (PNDaaS) - The Proposed Service Model

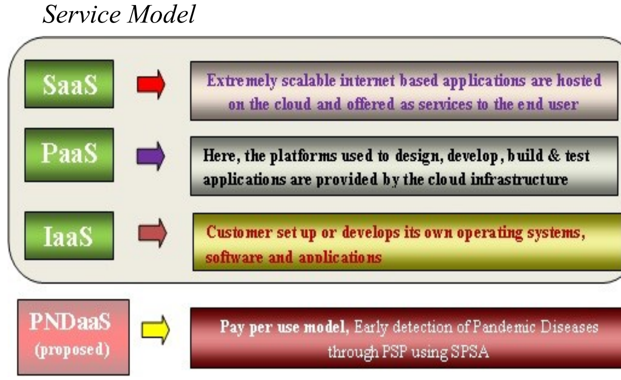

Figure 1. Cloud Service Models and Proposed Service Model

Figure 1 represents the existing service models including our proposed model (PNDaaS). In cloud environment, PNDaaS offers early warning capabilities for COVID-19 like pandemics through smart phone sensors with much less way to lower cross-infection. On the other hand, this model plays the vital role to link the VM's (Virtual Machine) to the actual physical server without favoring user's side or the provider's side as there is no direct interaction between consumers and Service Providers. So, when a user or a cloud service provider enrolls in the PNDaaS model, they all have to go through it.

D. Cloud Service Provider (CSP)

Basically a company that is able to create public clouds, maintain private clouds, or deliver on-demand cloud computing services such as SaaS, IaaS and PaaS are known as Cloud Service Providers.

E. Mobile Service Provider (MSP)

A MSP is a company that provides mobile communication services to mobile device users such as smart phones and tablet PCS is known as Mobile Service Providers.

F. Health Monitoring System (HMS)

A special division could set up by the government to monitor and respond to the pandemic.

G. Pandemic Service Provider (PSP)

PSP is important in providing pandemic services to all consumers and HMS as part of PNDaaS. It also plays a vital role in ensuring that users and CSPs connect efficiently. To avoid future clashes, PSP signed the Users and CSPs before resource allocation on the cloud server. As a result, PSP keeps track of all user identity keys and their CSPs in a log table.

H. Smart Pandemic Service Analyser (SPSA):

SPSA can develop, maintain, and deliver on-demand Pandemic Cloud Services (PCS) such as COVID-19, SERS, EBOLA, and other diseases to the PSP after obtaining periodic signals from the CSPs and SPSA keeps a record of PSPs and their corresponding CSPs.

4. Proposed Work

All of we know that the whole world is now suffering the fever of COVID-19 a fatality on human lives. To deal with this troubling situation the first thing should stop to spread among others.

The increasing demand of smart phones with a variety of sensing devices, combined with the emergence of cloud computing services, can be an enticing technology for constant and remote supervision of the health of a person at a marginal extra cost.

Take into account the present situation, and experienced in our previous findings on different cloud management services [77-81], we propose a new cloud based "Pandemic as a Service" model that satisfies smart phone clients and their allies for testing early basis as timely identification of infectious diseases using smart phone's sensing devices to mitigate cross-infection.

Our proposed architecture of "PNDaaS" model is depicted in figure 2, in which PSP plays the crucial role from sample collection to detection process by using cloud infrastructure, and finally sends feedback to the HMS for action.

Our goal is to provide a trustable cloud platform to the society where the government can take initiative for all smart phone users to go through this model to gain the benefit of preliminary testing as soon as any pandemic disease is detected.

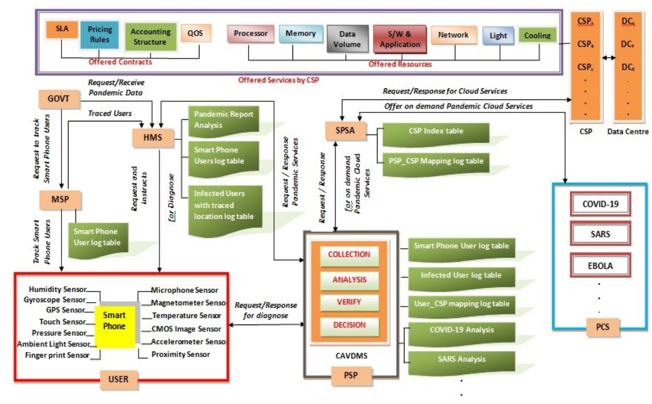

Figure 2. Proposed Architecture of Pandemic as a Service (PNDaaS) Model

A. Working procedure of PNDaaS Model

The working model of PNDaaS is represented in figure 2, where the CSPs are sending periodic signals, recording details and available resources to SPSA following successful contract agreements and offering resources. Upon receiving details from the CSP, SPSA creates the Pandemic Cloud Services such as COVID-19, SARS, EBOLA or any other and also maintains the log table of CSPs' for any future reference. SPSA, on the other hand, offers Pandemic Cloud Services to PSPs after getting on-demand service requests from PSPs, and also preserves a mapping log table of PSP-CSP as a future reference. As per our proposal, the government should make the initiation a mandatory search for all Smart Phone users in order to detect any epidemic outbreaks as soon as possible so that the virus does not spread to others. The government will have to ask MSPs to monitor all Smart Phone users at first and instruct to its own HMS where each smart phone user is compelled to perform their preliminary testing. After receiving instructions from the government request for pandemic services, HMS forwards the requests to the PSP. PSP either makes a Service Level Agreement (SLA) as a new customer or checks as an existing customer upon receipt of the request from the HMS. HMS sends the information of all smart phone users to the PSP after obtaining permission from the PSP and simultaneously demands and instructs smart phone users to perform diagnosis with the contact of PSP. PSP verifies the authentication of all users from its Smart Phone User log table after receiving the request from the users, and provides the specific "Pandemic App" with the necessary guidelines to diagnose their tests. The CAVDMS (Collection-Analysis-Verify-Decision Management System) under PSP now periodically collects the required symptoms through its COLLECTION module via Smart Phone Sensors. On the other hand, after receiving SPSA's on-demand pandemic cloud service, ANALYSIS Module is now engaged in figuring out the correct tools for measuring the samples collected. VERIFY module checks the computed data within specified pandemic disease threshold value. After testing, the DICISION module makes a decision — "Infected" or "Not Infected" and returns to the Users as well as the HMS, along with the user's current location. Now the HMS prepares and provides the Pandemic reports to the Government for taking necessary actions.

Our new "SEAP (Sensor-based Early Auto-Detection Pandemic)" algorithm automatically handles all processes automatically as well as assigning VMs to PMs with the basic minimum of resources and SPSA does the mapping of VMs to PMs under PNDaaS. As a consequence, it's obvious that no one (i.e. Customers, PSPs, or CSPs) can communicate directly with each other to obtain this service without the SPSA's approval. In the event of any dispute, SPSA will obtain records in detail of the alleged CSPs', Users or PSPs' from its own PSP-CSP Mapping log table if required. Thus there is no risk that the PSPs or the CSPs could confuse or deceive the Cloud users.

B. *Process Flow Diagram of PNDaaS*

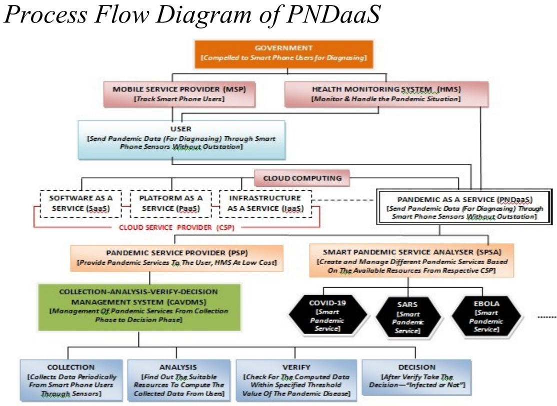

Figure 3. Process Flow Diagram of Pandemic as a Service (PNDaaS) Model

5. Algorithm and Flowchart

A. *SEAP (Sensor-based Early Auto-Detection Pandemic) Algorithm*

1. Government requests to MSP for tracking Smart Phone Users.
   - 1.1 MSP tracks the Smart Phone Users
   - 1.2 MSP prepares the list of Users Zone-wise.
   - 1.3 MSP sends the traced User's lists to HMS.
   - 1.4 HMS maintains a User Log Table for Smart Phone Users.
2. Government requests to HMS for monitoring the pandemic
   - 2.1 HMS requests tor pandemic services to PSP
   - 2.2 PSP checks for HMS's authentication and SLA
   - 2.3 If Authentic –
     - 2.3.1 Acknowledgement (for Service granted) sent to HMS
     - 2.3.2 HMS sends the user details to PSP
     - 2.3.3 HMS requests and provide guidelines to the Users through SMS for diagnosing the disease over Smart Phone.
     - 2.3.4 User requests for diagnosing to the PSP
     - 2.3.5 PSP checks for User's authentication from its User Index table provided by the HMS
     - 2.3.6 If authentic –
       - 2.3.6.1 Acknowledgement (for Service granted) sent to the users.
       - 2.3.6.2 User sends the periodic records to the PSP over Smart Phone.
     - 2.3.7 Else
       - 2.3.7.1 "User not accepted for services" – The user receives a reply.
       - 2.3.7.2 Go to step 2.3.4
   - 2.4 Else
     - 2.4.1 "Not accepted " –The HMS receives a reply
     - 2.4.2 Go to step 2.1
3. PSP collects the periodic data from the users through Smart Phone
4. PSP requests for on demand pandemic cloud services to its own SPSA
   - 4.1 SPSA requests to its CSP for getting the cloud services.
   - 4.2 SLA and verification of PSP is checked by CSP
   - 4.3 If authentic –
     - 4.3.1 Acknowledgement (for Service granted) sent to PSA

4.3.2 SPSA map the PSP to its CSP and maintain a PSP-CSP mapping log table.

4.4 Else

4.4.1 "Not accepted for services"— The SPSA receives a reply

4.4.2 Go to step 4.1

5. SPSA provide the on demand pandemic service (like COVID-19) to the PSP
6. PSP evaluates on the collected data
7. PSP checks for the specific pandemic category by its Verify Module.
8. If within threshold –

8.1 PSP sends a message – "Not infected" to the users as well as to the HMS.

8.2 Go to step 2.3.4

9. Else –

9.1 PSP sends a message – "Infected" to the users as well as to the HMS.

9.2 PSP locates the infected people's location information.

9.3 PSP locates the infected people's location(s) about last few days.

9.4 PSP compares between the traced location(s)

9.5 If same –

9.5.1 PSP sends the "current location of the infected person" to the HMS

9.5.2 Go to step 10.

9.6 Else –

9.6.1 PSP sends the "traced locations travelled by the infected person" to the HMS.

9.6.2 Go to step 10.

10. HMS sends the pandemic reports to the Government.
11. Government takes necessary actions.
12. End.

B. Flowchart

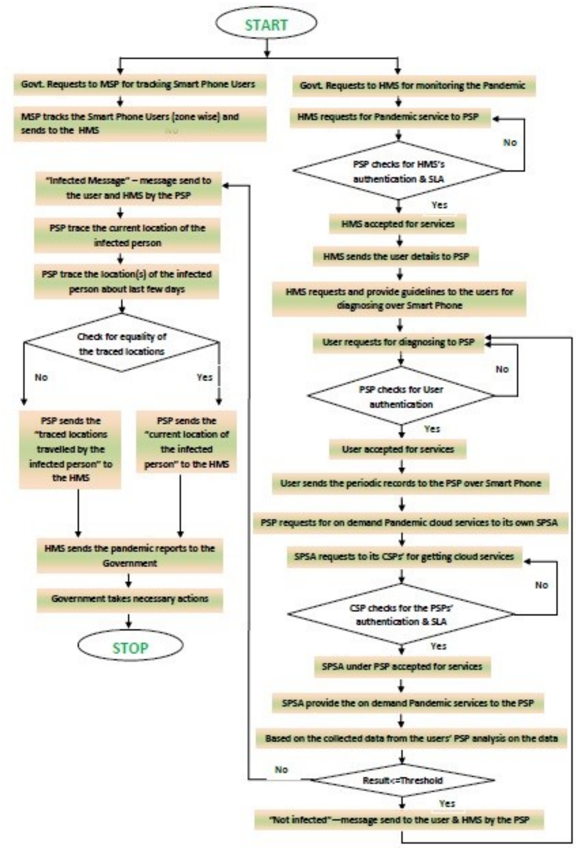

Figure 4. Flowchart of PNDaaS Model

6. DETAILED ANALYSIS OF PNDAAS MODEL (A CASE STUDY)

As so many research works done on sensor based health monitoring system, but all sensor based devices are committed to detect a particular category of symptom. Our proposed model also inspired from previous works except that multiple inbuilt sensors of smart phone can be utilized for the detection of multiple symptoms at a time to diagnose a disease. In order to improve our proposed framework here we mention the analysis part of some previous works to achieve a predicted result through cloud computing.

A. Detection of Nasal symptoms (Sneezing, coughing, blowing the nose) by Microphone Sensor

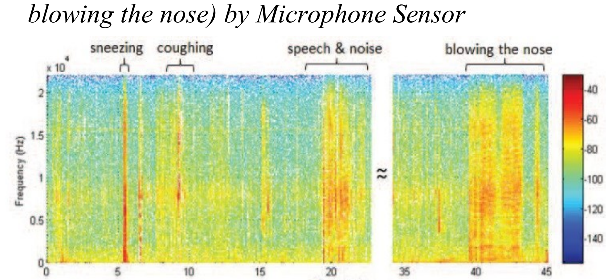

Figure 5. Spectrogram image of the acoustic data [53]

Preliminary research [53] reveals the ability to establish an audio-based model of identification that recognizes nose-related incidents. The spectrogram of a single audio sample is shown in Figure 5, where red and blue reflect values of high and low amplitude correspondingly. Other audio events, such as coughing, silent and voice can be distinguished from nostrils and snoring events. Sneezing has specific amplitude duration of about 500 milliseconds. Furthermore, Nose-blowing, for instance, has less amplitude and a longer period than coughing.

B. Detection of Lung Function by Microphone Sensor

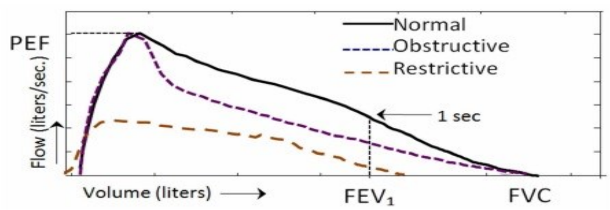

Figure 6. Different Flow Vs. Volume Curves [54]

A pulmonologist examines the flow curve's structure (Figure 6) qualitatively, who tests the downward limb of the flow-versus-volume curve from the point of PEF generation [54]. The solid line or a linear slope demonstrates the normal lung activity i.e. absence of restriction of airflow, whereas, the purple dotted line indicates asthma or COPD like lung dysfunctions i.e. restriction of airflow due to varying exhaled air time constants in various lung parts and finally, permissive lung infections, such as breathing tiredness or pulmonary fibrosis, is represented by the orange dashed line.

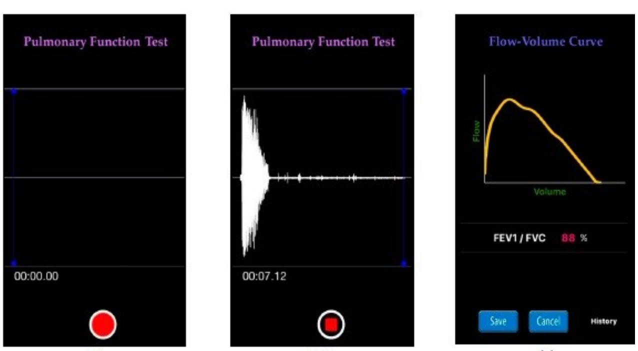

Figure 7. FEV1 Vs. FVC ratio evaluation through mobile phone (a) prior to recording (b) registration of forced exhalation (c) curve of flow volume and approximate FEV1 Vs. FVC ratio [54]

Figure 7 calculates the ratio of FEV1 and FVC through a smart phone based application [54].

C. Detection of Body Temperature through Camera sensor

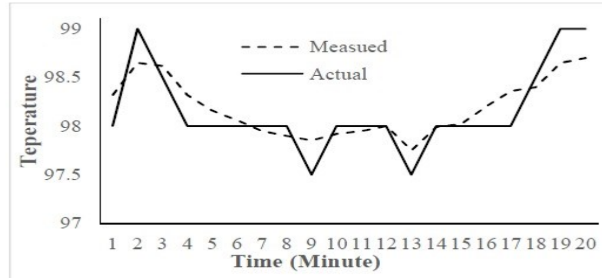

Figure 8. Actual Vs. Measured body temperature for 20 minutes [45]

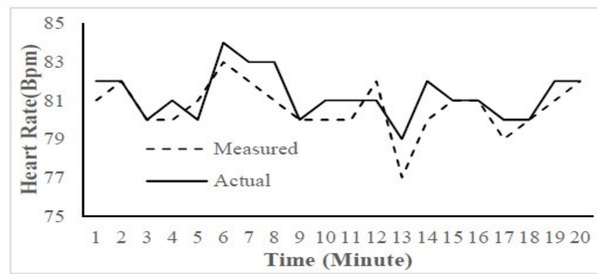

Figure 9. Actual Vs. Measured Heart Rate for 20 minutes [45]

Body temperature and heart rate are measured for a person for 20 minutes for performance control of the system [45], and the result is shown in Figures 8 and 9, respectively. There may be a little bit difference between the actual body temperature (measured through clinical thermometer) and the sensor based measured body temperature, as well as the actual heart rate (measured through Sphygmomanometer) and the sensor based measured heart rate because of a little movement of the finger touched on the surface of the sensor device, as a result, noise has an impact on the analog value for the associated blood flow.

7. Results and Discussion

A. Experimentation

TABLE II. WORLDWIDE DATA ON COVID-19

TEST CASES	No. OF TEST CASES (millions)
World Populations	7800
Total COVID-19 Tests	339.305827
Total cases	17.758804
Total Deaths	0.682999
Total Recovered	11.16152
Total Active Cases	5.914285
Total Smart phone users	3500
Possibility of tests	3160.69417
15% of Possibility test	474.104126

Since reaching cloud infrastructures or real data centers is challenging, we used simulation-based experiments which may be easily simulated to equate the recommended algorithm's credibility to past efforts that is actually in use by various cloud providers.

Given the overall scenario, we use the COVID-19 Pandemic data sets for our part of the analysis. Pandemic service provider of our proposed model (PNDaaS) can easily track the total number of tests, people infected along with their locations and how many people are left to test among all smartphone users worldwide. Table II characterizes the COVID-19 data in millions around the world[82].

B. Discussion

Table II represents the statistics about populations throughout the world, number of COVID tests were performed worldwide, and overall COVID Cases (i.e. overall Deaths + Recovered + Active Cases). According to the August 1, 2020, 06:22 GMT revised report [82], 339.305827 millions COVID-19 tests were performed worldwide; while the estimated number of smart phone users worldwide is 3500 million [83]. So, according to our proposed work if all the tests can be done by the active smart phone sensors in a cloud based network, then further 3160.69417 millions of tests (i.e. “total number of COVID-19 tests” is subtracted from the “total number of Smart Phone users”) can be performed up to the date [82].

From the analysis part (Figure 10) it is realized that the possibility of tests is much higher than the Total COVID-19 tests till now. Even if we consider the 15 percent chance test (through individual smart phones), then the number 474.104126 is also higher than the Total COVID-19 tests (339.305827) so far [82]. As a result, if 15-20% of smart phone users perform their test on their mobile, the risk of cross-infection can be reduced.

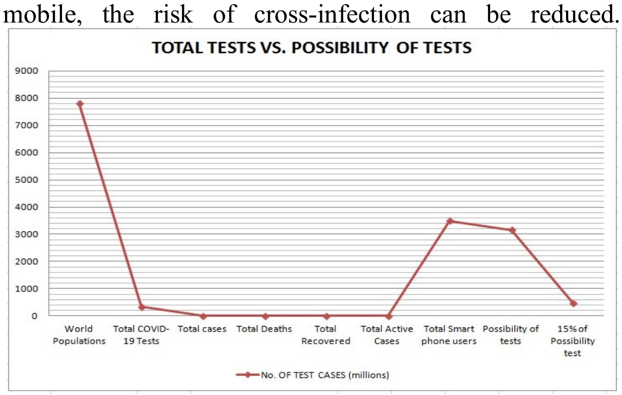

Figure 10. Total COVID-19 Tests (As on August 1, 2020, 06:22 GMT, Ref [82]) Vs. Possibility of Tests (By Smart Phone Sensors)

8. CONCLUSION

Focused on our results, we conclude that more screening should be performed at house through smart phone with a minimum cost, reducing the possibility of cross-infection. Our solution can result in a comprehensive cloud-based handheld research platform with a user-friendly atmosphere that can be embedded into a medical system as part of a public health action plan. As we believe that this is a "cloud-based pandemic service" that mostly functions like a timely identification of disease outbreak to prevent cross-infection. Here, the "Pandemic Service Provider" also acts as a broker among patient’s (who are willing to test the pandemic disease on a pay-as-you-use basis) and the Cloud Service Provider's (who have resources on a rent basis) to prevent each other from claiming any fictitious acquisitions and that would remove injustice between the actual use of services for testing purposes by consumers and the bill provided by vendors.

More extensive result analysis will be possible whenever the device and the cloud framework are developed applying our research.

9. FUTURE SCOPE

About the fact that we live in a modern age, the current urgent crisis (COVID-19) encourages us to access the digital world and do more of our job from home through the internet. So, why not take our medical test online from the comfort of our own home? We have already shown it by our proposed work based on previous research and review. Our goal is to increase service quality and throughput, as well as patient’s satisfaction, to the point that low capital expenditures are possible, and to continue to use cloud services to detect any kind of diseases as effectively as possible in the future.

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CONFLICT OF INTEREST

No funding agencies and no conflicts of interest.

REFERENCES

[1] Duncan, C.J.; Scott, S. What caused the black death? Postgrad. Med. J. 2005, 81, 315. [CrossRef] [PubMed]

[2] Martini, M.; Gazzaniga, V.; Bragazzi, N.L.; Barberis, I. The spanish influenza pandemic: A lesson from history 100 years after 1918. J. Prev. Med. Hyg. 2019, 60, E64–E67.

[3] CDC. Influenza (flu). Available online: https://www.cdc.gov/flu/pandemic-resources/2009-h1n1-pandemic. html (accessed on 30 January 2020).

[4] Song, Z.; Xu, Y.; Bao, L.; Zhang, L.; Yu, P.; Qu, Y.; Zhu, H.; Zhao, W.; Han, Y.; Qin, C. From sars to mers, thrusting coronaviruses into the spotlight. Viruses 2019, 11, 59. [CrossRef]

[5] "Coronavirus disease 2019 (COVID-19)—Symptoms and causes". Mayo Clinic. Retrieved 14 April 2020

[6] Hui DS, I Azhar E, Madani TA, Ntoumi F, Kock R, Dar O, et al. (February 2020). "The continuing 2019-nCoV epidemic threat of novel coronaviruses to global health—The latest 2019 novel coronavirus outbreak in Wuhan, China". International Journal of Infectious Diseases. 91: 264–266. doi:10.1016/j.ijid.2020.01.009. PMC 7128332. PMID 31953166.

[7] "WHO Director-General's opening remarks at the media briefing on COVID-19". World Health Organization (WHO) (Press release). 11 March 2020. Archived from the original on 11 March 2020. Retrieved 12 March 2020.

[8] "Q&A on coronaviruses (COVID-19)". World Health Organization. 17 April 2020. Archived from the original on 14 May 2020. Retrieved 14 May 2020.

[9] "How COVID-19 Spreads". Centers for Disease Control and Prevention (CDC). 2 April 2020. Archived from the original on 3 April 2020. Retrieved 3 April 2020.

[10] "Q & A on COVID-19". European Centre for Disease Prevention and Control. Retrieved 30 April 2020.

[11] "Symptoms of Coronavirus". U.S. Centers for Disease Control and Prevention (CDC). 20 March 2020. Archived from the original on 30 January 2020.

[12] Hopkins C. "Loss of sense of smell as marker of COVID-19 infection". Ear, Nose and Throat surgery body of United Kingdom. Retrieved 28 March 2020.

[13] D. Wang, B. Hu, C. Hu, F. Zhu, X. Liu, J. Zhang, B. Wang, H. Xiang, Z. Cheng, Y. Xiong et al., "Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus–infected pneumonia in wuhan, china," Jama, 2020.

[14] Bioworld. (2020, March). [Online]. Available: https://www.bioworld.com/articles/ 433530-china-uses-ai-in-medical-imaging-to-speed-up-covid-19-diagnosis.

[15] Wang, S.J.; Moriarty, P. Big data for urban health and well-being. In Big Data for Urban Sustainability; Springer: Berlin, Germany, 2018; pp. 119–140.

[16] Azmak, O.; Bayer, H.; Caplin, A.; Glimcher, P.; Koonin, S.; Patrinos, A. Using big data to understand the human condition: The kavli human project. Big Data 2015, 3, 173–188. [CrossRef].

[17] Bini, S.A. Artificial intelligence, machine learning, deep learning, and cognitive computing: What do these terms mean and how will they impact health care? J. Arthroplasty 2018, 33, 2358–2361. [CrossRef].

[18] J. Chen, L. Wu, J. Zhang, L. Zhang, D. Gong, Y. Zhao, S. Hu, Y. Wang, X. Hu, B. Zheng et al., "Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography: a prospective study," medRxiv, 2020.

[19] Li, L., Qin, L., Xu, Z., Yin, Y., Wang, X., Kong, B., ... and Cao, K. (2020). Artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT. Radiology, 200905.

[20] He, K., Zhang, X., Ren, S., and Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 770-778).

[21] Xu, X., Jiang, X., Ma, C., Du, P., Li, X., Lv, S., ... and Li, Y. (2020). Deep learning system to screen coronavirus disease 2019 pneumonia. arXiv preprint arXiv:2002.09334.

[22] Kanne, J. P. (2020). Chest CT findings in 2019 novel coronavirus (2019-nCoV) infections from Wuhan, China: key points for the radiologist. Radiology, 200241.

[23] Chung, M., Bernheim, A., Mei, X., Zhang, N., Huang, M., Zeng, X., ... and Jacobi, A. (2020). CT imaging features of 2019 novel coronavirus (2019-nCoV). Radiology, 200230.

[24] Hu, Z., Ge, Q., Jin, L., and Xiong, M. (2020). Artificial intelligence forecasting of Covid-19 in China. arXiv preprint arXiv:2002.07112.

[25] Ye, Y., Hou, S., Fan, Y., Qian, Y., Zhang, Y., Sun, S.,and Laparo, K. (2020). _-Satellite: An AI-driven system and benchmark datasets for hierarchical community-level risk assessment to help combat COVID-19. arXiv preprint arXiv:2003.12232.

[26] Mirza, M., and Osindero, S. (2014). Conditional generative adversarial nets. arXiv preprint arXiv:1411.1784.

[27] Zachreson, C., Fair, K. M., Cliff, O. M., Harding, N., Piraveenan, M., and Prokopenko, M. (2018). Urbanization affects peak timing, prevalence, and bimodality of influenza pandemics in Australia: Results of a census-calibrated model. Science Advances, 4(12), eaau5294.

[28] Cliff, O. M., Harding, N., Piraveenan, M., Erten, E. Y., Gambhir, M., and Prokopenko, M. (2018). Investigating spatiotemporal dynamics and synchrony of influenza epidemics in Australia: An agent-based modelling approach. Simulation Modelling Practice and Theory, 87, 412-431.

[29] Chang, S. L., Harding, N., Zachreson, C., Cliff, O. M., and Prokopenko, M. (2020). Modelling transmission and control of the COVID-19 pandemic in Australia. arXiv preprint arXiv:2003.10218.

[30] Du, S., Wang, J., Zhang, H., Cui, W., Kang, Z., Yang, T., ... and Yuan, Q. (2020). Predicting COVID-19 using hybrid AI model. Available at http://dx.doi.org/10.2139/ssrn.3555202.

[31] Allam, Z., and Jones, D. S. (2020, March). On the coronavirus (COVID-19) outbreak and the smart city network: universal data sharing standards coupled with artificial intelligence (AI) to benefit urban health monitoring and management. In Healthcare (vol. 8, no. 1, p. 46). MDPI.

[32] J. M. Purswani, A. P. Dicker, C. E. Champ, M. Cantor, and N. Ohri, "Big data from small devices: The future of smartphones in oncology," in Seminars in radiation oncology, vol. 29, no. 4. Elsevier, 2019, pp. 338–347.

[33] Maddah, E., and Beigzadeh, B. (2020). Use of a smartphone thermometer to monitor thermal conductivity changes in diabetic foot ulcers: a pilot study. Journal of Wound Care, 29(1), 61-66.

[34] Karvekar, S. B. (2019). Smartphone-based human fatigue detection in an industrial environment using gait analysis. Available at: https://scholarworks.rit.edu/theses/10275/. Accessed on 1 February 2020.

[35] Roldan Jimenez, C., Bennett, P., Ortiz Garcia, A., and Cuesta Vargas, A. I. (2019). Fatigue detection during sit-to-stand test based on surface electromyography and acceleration: a case study. Sensors, 19(19), 4202.

[36] Story, A., Aldridge, R. W., Smith, C. M., Garber, E., Hall, J., Ferenando, G., ... and Abubakar, I. (2019). Smartphone-enabled video-observed versus directly observed treatment for tuberculosis: a multicentre, analyst-blinded, randomised, controlled superiority trial. The Lancet, 393(10177), 1216-1224.

[37] Lawanont,W., Inoue, M., Mongkolnam, P., and Nukoolkit, C. (2018). Neck posture monitoring system based on image detection and smartphone sensors using the prolonged usage classification concept. IEEJ Transactions on Electrical and Electronic Engineering, 13(10), 1501-1510.

[38] Nemati, E., Rahman, M. M., Nathan, V., Vatanparvar, K., and Kuang, J. (2019, September). A comprehensive approach for cough type detection. In 2019 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE) (pp. 15-16). IEEE.

[39] Vhaduri, S., Van Kessel, T., Ko, B.,Wood, D.,Wang, S., and Brunschwiler, T. (2019, June). Nocturnal cough and snore detection in noisy environments using smartphone-microphones. In 2019 IEEE International Conference on Healthcare Informatics (ICHI) (pp. 1-7). IEEE.

[40] Rao, A. S. S., and Vazquez, J. A. (2020). Identification of COVID-19 can be quicker through artificial intelligence framework using a mobile phone-based survey in the populations when cities/towns are under quarantine. Infection Control and Hospital Epidemiology, 1-18. DOI: https://doi.org/10.1017/ice.2020.61.

[41] National health commission of china. (March, 2020). [Online]. Available: http://www.chinadaily.com.cn/m/chinahealth/index.html.

[42] Kooistra, J. Newzoo's 2018 GlobalMobileMarket Report: Insights into theWorld's 3 Billion Smartphone Users. Newzoo. 11 September 2018. Available online: https://newzoo.com/insights/articles/newzoos-2018-globalmobile-market-report-insights-into-the-worlds-3-billion-smartphone-users/ (accessed on 3 January 2019).

[43] E. Maddah and B. Beigzadeh, "Use of a smartphone thermometer to monitor thermal conductivity changes in diabetic foot ulcers: a pilot study," Journal of Wound Care, vol. 29, no. 1, pp. 61–66, 2020.

[44] Vikramsingh R. Parihar, Akesh Y. Tonge, Pooja D. Ganorkar, "Heartbeat and Temperature Monitoring System for Remote Patients using Arduino", International Journal of Advanced Engineering Research and Science (IJAERS), Vol-4, Issue-5, May- 2017, ISSN: 2349-6495(P) | 2456-1908(O)

[45] Md. Asaduzzaman Miah, Mir Hussain Kabir, Siddiqur Rahman Tanveer, M. A. H. Akhand, "Continuous heart rate and body temperature monitoring system using Arduino UNO and Android device", Conference Paper · December 2015 DOI: 10.1109/EICT.2015.7391943.

[46] Sonia Gavin, Bobby Sidhu, "The Effectiveness of Smartphone Temperature Sensors for Ambient Temperature Monitoring", Bcit Environmental Health Journal.

[47] Hiroki Yoshikawa, Akira Uchiyama and Teruo Higashino, "ThermalWrist: Smartphone Thermal Camera Correction Using a Wristband Sensor", Proceedings of the 5th Workshop on Sensing Systems and Applications Using Wrist Worn Smart Devices (WristSense '19), Kyoto, Japan, 11–15 March 2019.

[48] Benjamin Tag, George Chernyshov, Kai Kunze, "Facial Temperature Sensing on Smart Eyewear for Affective Computing", UBICOMP/ISWC '17 ADJUNCT, SEPTEMBER 11-15, 2017, MAUI, HAWAII, USA, https://doi.org/10.1145/3123024.3123084.

[49] Majumder, S.; Mondal, T.; Deen, M.J. Wearable Sensors for Remote Health Monitoring. Sensors 2017, 17, 130. [CrossRef] [PubMed].

[50] Rolfe, P. In Vivo Near-Infrared Spectroscopy. Annu. Rev. Biomed. Eng. 2000, 2, 715–754. [CrossRef].

[51] Sta_ord, M.; Lin, F.; Xu,W. Flappy Breath: A Smartphone-Based Breath Exergame. In Proceedings of the 2016 IEEE First International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE),Washington, DC, USA, 27–29 June 2016; pp. 332–333.

[52] Larson, E.C.; Lee, T.; Liu, S.; Rosenfeld, M.; Patel, S.N. Accurate and privacy preserving cough sensing using a low-cost microphone. In Proceedings of the 13th International Conference on Ubiquitous Computing, Beijing, China, 17–21 September 2011; p. 375.

[53] Chen, N.-C.; Wang, K.-C.; Chu, H.-H. Listen-to-nose: A low-cost system to record nasal symptoms in daily life. In Proceedings of the 2012 ACM Conference on Ubiquitous Computing, Pittsburgh, PA, USA, 5–8 September 2012; pp. 590–591.

[54] Larson, E.C.; Goel, M.; Boriello, G.; Heltshe, S.; Rosenfeld, M.; Patel, S.N. SpiroSmart: Using a microphone to measure lung function on a mobile phone. In Proceedings of the 2012 ACM Conference Ubiquitous Comput.-UbiComp '12, Pittsburgh, PA, USA, 5–8 September 2012; pp. 280–289.

[55] Larson, E.C.; Goel, M.; Redfield, M.; Boriello, G.; Rosenfeld, M.; Patel, S.N. Tracking lung function on any phone. In Proceedings of the 3rd ACM Symposium on Computing for Development, Bangalore, India, 11–12 January 2013; p. 29.

[56] Goel, M.; Saba, E.; Stiber, M.; Whitemire, E.; Fromm, J.; Larson, E.C.; Borriello, G.; Patel, S.N. SpiroCall: Measuring Lung Function over a Phone Call. In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, San Jose, CA, USA, 7–12 May 2016; pp. 5675–5685.

[57] Thap, T.; Chung, H.; Jeong, C.; Hwang, K.-E.; Kim, H.-R.; Yoon, K.-H.; Lee, J.; Chon, K.H. High-Resolution Time-Frequency Spectrum-Based Lung Function Test from a Smartphone Microphone. Sensors 2016, 16, 1305. [CrossRef]

[58] Cristina Roldán Jiménez, Paul Bennett, Andrés Ortiz García and Antonio I. Cuesta Vargas, "Fatigue Detection during Sit-To-Stand Test Based on Surface Electromyography and Acceleration: A Case Study", Sensors 2019, 19, 4202; doi:10.3390/s19194202, www.mdpi.com/journal/sensors.

[59] Cornet, V.P.; Holden, R.J. Systematic review of smartphone-based passive sensing for health and wellbeing. J. Biomed. Inform. 2018, 77, 120–132. [CrossRef].

[60] Lu, H.; Frauendorfer, D.; Rabbi, M.; Mast, M.S.; Chittaranjan, G.T.; Campbell, A.T.; Gatica-Perez, D.; Choudhury, T. StressSense: Detecting stress in unconstrained acoustic environments using smartphones. In Proceedings of the 2012 ACM Conference on Ubiquitous Computing—UbiComp '12, Pittsburgh, PA, USA, 5–8 September 2012; p. 351.

[61] Estevão, M.S.; Duarte, F.J.; Fernandes, E.; Gil Santos, A.; Marques, M.M.B. Unexpected reactivity of trifluoromethylated olefins with indole: A mechanistic investigation. Tetrahedron Lett. 2012, 53, 2132–2136. [CrossRef]

[62] Huang, Y.; Xiong, H.; Leach, K.; Zhang, Y.; Chow, P.; Fua, K.; Teachman, B.A.; Barnes, L.E. Assessing social anxiety using gps trajectories and point-of-interest data. In Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing, Heidelberg, Germany, 12–16 September 2016; pp. 898–903.

[63] Eysenbach, G.; Saeb, S.; Mohr, D.; Reis, D.; Asselbergs, J.; Ruwaard, J.; Ejdys, M.; Schrader, N.; Sijbrandij, M.; Riper, H. Mobile Phone-Based Unobtrusive Ecological Momentary Assessment of Day-to-Day Mood: An Explorative Study. J. Med Internet Res. 2016, 18, e72.

[64] Ma, Y.; Xu, B.; Bai, Y.; Sun, G.; Zhu, R. Infer Daily Mood using Mobile Phone Sensing. Ad Hoc Sens. Wirel. Netw. 2014, 20, 133–152.

[65] Ben-Zeev, D.; Scherer, E.A.; Wang, R.; Xie, H.; Campbell, A.T. Next-Generation Psychiatric Assessment: Using Smartphone Sensors to Monitor Behavior and Mental Health. Psychiatr. Rehabil. J. 2015, 38, 218–226. [CrossRef] [PubMed]

[66] Derawi, M.; Bours, P. Gait and activity recognition using commercial phones. Comput. Secur. 2013, 39, 137–144. [CrossRef] Sensors 2019, 19, 2164 41 of 45

[67] Ronao, C.A.; Cho, S.-B. Human activity recognition using smartphone sensors with two-stage continuous hidden Markov models. In Proceedings of the 2014 10th International Conference on Natural Computation (ICNC), Xiamen, China, 19–21 August 2014; pp. 681–686.

[68] Seera, M.; Loo, C.K.; Lim, C.P. A hybrid FMM-CART model for human activity recognition. In Proceedings of the 2014 IEEE International Conference on Systems, Man and Cybernetics—SMC, San Diego, CA, USA, 5–8 October 2014; pp. 182–187.

[69] Eastwood, M.; Jayne, C. Evaluation of hyperbox neural network learning for classification. Neurocomputing 2014, 133, 249–257. [CrossRef]

[70] Catal, C.; Tufekci, S.; Pirmit, E.; Kocabag, G. O n the use of ensemble of classifiers for accelerometer-based activity recognition. Appl. Soft Comput. 2015, 37, 1018–1022. [CrossRef]

[71] De, D., Bharti, P.; Das, S.; Chellappan, S. Multi-modalWearable Sensing for Fine-grained Activity Recognition in Healthcare. IEEE Comput. Soc. 2015, 19, 1.

[72] Wang, A.; Chen, G.; Yang, J.; Zhao, S.; Chang, C.-Y. A Comparative Study on Human Activity Recognition Using Inertial Sensors in a Smartphone. IEEE Sensors J. 2016, 16, 4566–4578. [CrossRef].

[73] Hubiche, T.; Valério, L.; Boralevi, F.; Mahe, E.; Skandalis, C.B.; Phan, A.; del Giudice, P. for the Research Group of the French Society of Pediatric Dermatology (Groupe de Recherche de la Société Française de Dermatologie Pédiatrique) Visualization of patients' skin lesions on their smartphones: A newstep during dermatology visits. JAMA Dermatol. 2016, 152, 95–97. [CrossRef].

[74] Friedman, R.J.; Rigel, D.S.; Kopf, A.W. Early Detection of Malignant Melanoma: The Role of Physician Examination and Self-Examination of the Skin. CA Cancer. J. Clin. 1985, 35, 130–151. [CrossRef].

[75] Wadhawan, T.; Situ, N.; Lancaster, K.; Yuan, X.; Zouridakis, G. SkinScan©: A Portable Library for Melanoma Detection on Handheld Devices. In Proceedings of the 2011 IEEE International Symposium on Biomedical Imaging: From Nano to Macro, Chicago, IL, USA, 30 March–2 April 2011; pp. 133–136..

[76] Kuzmina, I.; Lacis, M.; Spigulis, J.; Berzina, A.; Valeine, L. Study of smartphone suitability for mapping of skin chromophores. J. Biomed. Opt. 2015, 20, 90503. [CrossRef] [PubMed].

[77] Himadri Biswas, Debabrata Sarddar, "Verification as a Service (VaaS): A Trusted Multipurpose Service for Accounting, Billing Verification and Approval of Consumed Resources at Low Computational Overhead to Enhance the Cloud Usability", International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 19 (2018) pp. 14402-14410 © Research India Publications. http://www.ripublication.com

[78] Debabrata Sarddar, Himadri Biswas and Priyajit Sen, "Safety as a Service (SFaaS) Model - The New Invention in Cloud computing to establish a Secure Logical Communication Channel between Data Owner and the Cloud Service Provider before Storing, Retrieving or Accessing any Data in the Cloud" International Journal of Grid and Distributed Computing, ISSN 2005-4262 Vol. 10, No. 10 (2017), pp.1-20.

[79] Himadri Biswas, Debabrata Sarddar, "Power Management as a Service (Pmaas) – An Energy Saving Service by ―Auto-Fit VM Placement‖ Algorithm in Cloud Computing for Maximum Resource Utilization at Minimum Energy Consumption Without Live-Migrating the Virtual Machines by using the Concept of Virtual-Servers" in International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-2, December 2019.

[80] Himadri Biswas, Debabrata Sarddar, Uddyalok Chakraborty, "Environmental Viability as a Service (Evaas) – An Eco-Friendly Cloud Service for Optimum use of Resources at Low Energy Consumption with Less Carbon Emission", International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-8 Issue-6, March 2020, pp-5193-5202

[81] Rajesh Bose, Himadri Biswas, Debabrata Sarddar , Manas Kumar Sanyal, "Cloud Billing & Verification Of Consumed Resources and Storage Spaces by a Cloud User" in International Journal of Applied Engineering Research ISSN 0973-4562 Volume 11, Number 9 (2016) pp 6568-6576.

[82] COVID-19 Data Worldwide, https://www.worldometers.info/coronavirus/

[83] Total Number of Smart Phone users worldwide, https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/

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