



INTERNET OF MEDICAL THINGS (IOMT) ENABLED THIRD-PARTY MONITORING MODEL FOR INFECTIOUS DISEASES CONTROL DURING EPIDEMICS

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Abstract

Infectious diseases pose a very significant threat to development of the society and the world at large. With several outbreaks of diseases like Monkeypox, Lassa fever, SARS, COVID-19, etc, the global economy was grossly affected. The rate of transfer and mortality associated with similar outbreaks is alarming. This research presents a novel approach utilizing the Internet of Medical Things (IoMT) to develop a third-party notification model. This model uses IoMT's ubiquitous connectivity to notify even ordinary individuals of the presence of an infectious disease vector within a specified range. A four-tier architecture, including cloud and web API blocks, healthcare provider management, IoT sensory, and notification blocks forms the bedrock of the model. The research focuses on developing a Location Tracking Device (LTD) prototype that incorporates the Haversine formula for real-time distance calculation between individuals performed at the edge using the location data supplied by the LTDs as input parameters. The optimization of data reception rates was based on the average human walking speed in order to enhance response time of the system. Results from testing the prototype demonstrate an average of 4.68s response delay which corresponds to an offset of about 6.85m from the real vector distance calculation. The research implementation challenges include the internet connection speed, network availability, and topography. Despite these challenges, the IoMT-enabled model introduces a promising approach to infectious disease-carrier monitoring, integrating personalized carrier/vector-presence awareness with associated risks within the disease control ecosystem. Hence, every user can use the LTD during an epidemic to help track the user's nearness to a symptomatic person thereby helping to control the spread of infectious diseases during epidemics.

1.0 INTRODUCTION

Infectious diseases have long been one of the challenges against societal developments. The global history of epidemic outbreaks and several other unanticipated pandemics in humans found their roots in zoonotic sources [1]. Some of these diseases have been successfully passed from these vectors to humans in the forms of Monkey pox, Lassa fever, Ebola virus disease EVD, Severe Acute Respiratory Syndrome SARS, COVID-19 and so on.

The transfer and mortality rates associated with infectious diseases are things of utmost concern to all nations. For instance, Lassa fever situation report for week 30 in Nigeria revealed a cumulative 5990 suspected cases, 867 confirmed cases, 37 probable cases, 164 deaths (confirmed cases) and case fatality

ratio (CFR) of 18.9% [2]. Just before the COVID-19 pandemic, the overall regional TB incidence trended slightly upwards from 27.6 cases per 100,000 population in 2015 to 28.4 cases in 2020 [3]. In 2015, Indian National Centre for Disease Control, NCDC reported Ebola Virus Disease (EVD) as the deadliest epidemic [4]. However, as of 17 December 2014, the World Health Organization (WHO) according to Indian NCDC newsletter reported that 18,603 confirmed, probable, and suspected cases of EVD have been reported in eight countries, with a total of 6915 deaths [4]. The outbreak of COVID-19 virus however was first announced by WHO in China on December 30, 2019 but the virus was isolated from a clinical sample on 7 January 2020 by the China CDC [5]. As at April 2022, over 489 million cases and over 6 million deaths have been reported globally [6]. In the same April 3, 2022, after an increase in the cases observed during the first half of March 2022, the new cases identified the next two weeks following decreased by 16% [6]. Over 9 million new cases with over 26000 new deaths were reported across the six WHO regions [6]. All these show that responding to infectious disease outbreak is a thing of urgent concern.

In addition, while the economic crisis experienced in sub-Saharan countries like Nigeria, reflecting in the fall in oil price was probably occasioned by the pandemic [7]. Another study on the impact of COVID-19 on economic growth in Nigeria identified that 157.3% increase in infectious diseases observed in the country led to 182.76% increase in death rate within a space of two weeks [8]. This negative trend if not checked will certainly lead to a prolonged lockdown of persons and businesses which invariably leads to economic inactivity and attending economic recession. Since the outbreak of the COVID-19 pandemic, a lot of researches have established the menace of the pandemic and its attaining consequences. Different efforts were made as a result to tackle the spread through vaccine development with medical associations further encouraging contact with patients which placed the medical personnel at a higher risk of contracting the virus [9], [10]. Many technological solutions and models [11] were proposed for remote diagnosis, automated diagnosis, automated care and remote monitoring of patients by medical personnel and professionals, and control by monitoring the spread level.

All these efforts have contributed largely towards controlling the menace of the infectious diseases within their limited contexts of applications; however, these researches were focused mainly on two parties:

the patient and the care giver. The research question is: Can a third-party be involved in the control of infectious diseases? If yes, how? Hence, the aim of this research is to develop a third-party model for infectious disease monitoring and control using the ubiquitous internet of medical things (IoMT). The proposed solution to the control of the spread of infectious diseases focus on maintaining a specific range of distance from an infected person. The system notifies the third-party of the presence of and infected person within a particular range of distance.

The rest of the work is organized as follows: section two is a review of related literatures, while section three is the research methodology. Section four presents the results of the work and recommendations for future work while section five concludes the work.

1.1 Related Works

A lot of works have been done on the subject pertaining to infectious diseases ranging from remote monitoring [12]–[15], diagnosis [16], pattern detection [17], prediction [17], [18], and applications [19], [20]. The works of Jabbar et al and Swayam siddha et al proposed the application of cognitive radio (CR) based IoT specific for the medical domain as a viable tool to battle infectious diseases, vis-à-vis COVID-19 [21], [22]. The Cognitive Internet of Medical Things model has five distinct steps – Self quarantine, self-test, upload test-result to IoMT cloud for medical record storage and analysis, online health consultation, and medical devices and service delivery. Taiwo and Ezeugwu proposed a mobile application-based smart home healthcare system for effective monitoring of the elderly and the disabled while at home. The system used a monitoring framework based on hyperspace analogue to context methodology for service discovery and context change in the home environment towards reading of the physiological parameters through the sensor nodes for improved system performance [13]. The system helps in minimizing the personal contacts between the patients and care givers.

To solve the problem of asymptomatic carriers in transmitting a disease, a secure remote health monitoring model for early disease diagnosis in cloud-based IoT environment was proposed by S. Akhbarifar [14]. The model utilizes the lightweight block encryption methodology to forward the collected patient's critical data to ensure privacy and confidentiality of patient's medical record which is then subjected to computational analysis using some data mining approaches like J48, Support vector machine SVM, multi-layer perceptron MLP, K-star,



random forest RF and so on. Experimental outcomes show that K-star classification method with 95% accuracy, 94.5% precision, 93.5% recall, and 93.99% f-score provides the best results among RF MLP, SVM, and J48 classifiers for 10-fold cross-validation. Also, for producing dynamic results, S-Boxes may be categorized as a robust cryptographic technique based on the evaluation factors that includes bijection, strict avalanche criterion, nonlinearity, and algebraic degree.

Roy and Kumar employed a deep ensemble framework of transfer learning models for early prediction of COVID-19 from the respective chest X-ray images of the patients [23]. The dataset was used with seven different transfer learning models in an experimental set up, and all the predictions were found to be false-positive. Then, the ensemble learning-based framework was developed that utilizes the predictions of individual seven transfer learning models to make the final prediction. The prediction result was found to be 100% true and can be used for early detection of COVID-19.

A combined approach using point-of-care diagnostics and Internet of Medical Things (IoMT) to Combat the COVID-19 Pandemic was proposed by [15], [16]. Here, the vital signs of patients are collected via wearable sensors [24] and are submitted to clinical cloud storage through the internets and their information transferred to nearby hospitals. The data gathered through the IoT sensor nodes are aggregated for analysis and machine learning operations and auto-recommendation of the patient for emergency medical support [15]. Singh proposed a fog-assisted and the Internet of Things-based quality of service framework to prevent and protect from COVID-19 [18]. The system involves the real-time processing of user's data by observing their symptoms and immediately generating an emergency alert, medical reports, and significant precautions to the user, their guardian as well as doctors/experts. The healthcare application that can make initial decisions for COVID-19 detection based on symptoms and to provide the affected individual with the location of the nearest health facility for assistance was developed. The design outcome of Yang et al's research serves as an essential platform that defines the measured readings of COVID-19 symptoms for monitoring, management, and analysis [24].

An integrated disease control system that oversees detection, analysis, and response was proposed by [25]. The convergence model collects data from IoT sources in a central server, runs analysis on the

collected data and then performs a prediction. The convergence model has five components: data collection, data processing, and abbreviation, AI analysis, service matching by classification, and prevention matching. The control system based on the convergence model is based on the matching result and AI analysis done on the bedrock of the data collected through the IoT nodes and agent monitoring information. The target parameter here is the disease information as a tool for future prediction. Still in control, Saleh et al proposed an IoT enabled smart queuing model to support massive safe crowd at Ka'aba [26]. The study employs formal methods and the attending governing equations to implement multi-entry and multi-exit points in performing safe and smooth circumambulation of the Ka'aba. The simulation result shows that while maintaining as safe distance among the pilgrims, circumambulation time was reduced to about 20.53 minutes.

While all these scholarly works are very much valid and useful, the third person has no way of getting involved in the control of the spread. This work however focuses on developing an IoT-based model for notifying an ordinary person (a public user) about the presence of an infectious disease vector around a public domain. The significance of this research lies in its capacity to increase the scope of infectious disease control efforts by involving third parties in monitoring and prevention activities. It leverages the ubiquitous IoMT technology to develop a model that offers a novel approach to disease control that complements existing strategies that were focused on patient-caregiver interactions. Engaging public users in disease monitoring and control would not only enhance the effectiveness of existing efforts, but it also promotes community participation and awareness. In addition, the development of a third-party model for infectious disease control has wider implications for public health, healthcare delivery, and pandemic preparedness, particularly as it concerns emerging infectious diseases like COVID-19.

2.0 METHODOLOGY AND ANALYSIS

The system model follows a four-tier architecture that comprises the cloud and web API block, the healthcare provider and the caregiver's management block, the IoT sensory block and notification block as depicted in Figure 1. The research assumes that there is a central database that is constantly being monitored and managed by the Centre for Diseases Control out of which analysis and decisions are made based on the data supplied by the system. In addition, the system monitors the real-time spread of a disease by tracking the real-time location of symptomatic patients and



their interaction with unflagged patients. It is assumed that there is a public access to the Diseases Control Management System, where each person can register a prototype real-time location tracking device (LTD) for personal use. Just like the use of some medically approved nose masks was enforced during the time of the COVID-19 pandemic, the research assumes that having a tracking device maybe enforced as the only condition for one to move about during the time of pandemic.

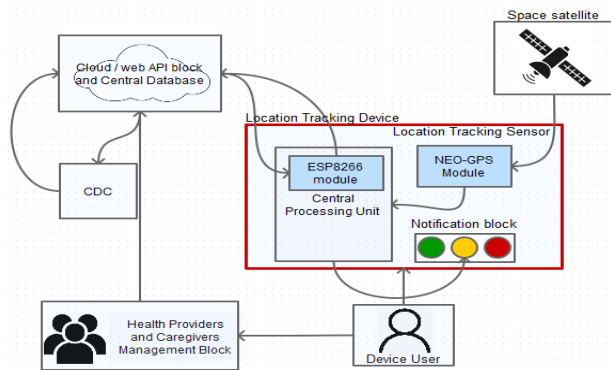


Figure 1: A four-tier architecture of the third-party enabled infectious disease control monitoring model

i. Location Tracking Device - IoT Sensory and Notification Block

The functionality of this block is to constantly send the real-time location of both symptomatic and asymptomatic users to the cloud repository through the internet, and also receive information from the cloud storage based on the data that is processed at the edge. The LTD containing the sensory and notification node is used by users (both infectious disease positive patients and negative persons) as seen in the diagram of Figure 1. The research used the NodeMCU v3.0 development board as the base board for developing an LTD prototype for users. The NodeMCU board has in-built connectivity to the internet powered by ESP8266 WIFI module attached to it. The NEO—GPS module alongside its antenna was used for constantly getting the real-time location of the LTD from space satellite.

The GPS module among other things returns the longitude, the latitude, and the altitude of the device at every point in time to the microcontroller unit. The location data alongside the device data is sent to the remote repository through the Wi-Fi module. Light emitting diodes, LEDs were used to send notification to the user based on information delivered to it as a result of the edge processing of the supplied location data per time. The NodeMCU v3.0 was powered by a 5V supply through a cable while the Vcc supply from

the NodeMCU averages to 3.3V. The prototype setup is depicted in Figure 2.

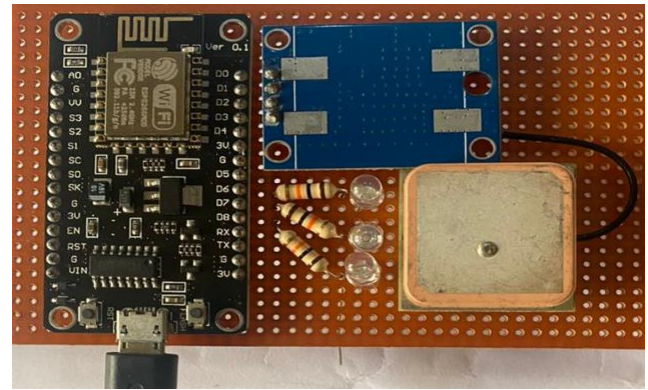


Figure 2: The location tracking device prototype

ii. Cloud And Web API Block

The central database is developed on top of MySQL database management system (DMBS). The API is written using PHP scripting language for the purpose of sharing data between the application written in different languages. For each data sent to the central database via the API, a processing is triggered at the edge of the cloud to compute the status of the requesting device and then, the status is communicated to the requesting device through API also. This communication is performed through an HTTP request sent back and forth from the server. The details of the computation are done in Section 2.1 of this article following the haversine equation.

iii. Healthcare Provider's Management (HPM) Block

The HPM block is designed such that each healthcare provider will have their management system linked to the central repository through an application programming interface, API. Upon diagnosis of an infectious disease on a person, the healthcare provider tags a patient's LTD as positive such that upon detection of such device by other members of the public's LTDs, the system flags a signal indicating the presence of a symptomatic patient.

The HPM block is a web-based interface that has the functionality of interacting with the central database through an API. The moment the healthcare system's diagnosis of a patient reads positive for an infectious disease, the symptomatic patient's data is updated to the central system based on the patient's identity number. The patient's interaction with other people is beyond the monitoring of the healthcare provider. Instead, they are able to monitor only the present location of the patient who has registered with them at any particular point through the location data sent to



her system in response to an HTTP request initiated as a result of tagging a patient to be symptomatic.

2.1 Calculating Device Social Distance

The distance between two devices was calculated using the popular Haversine formular used in calculating the great circle distance between two geo-points. Equation 1 is the Haversine equation. The equation takes into consideration, the longitude, and the latitudes of the device under consideration.

$$hav\sin(\theta) = \sin^2(2\Delta\phi) + \cos(\phi_1) \cdot \cos(\phi_2) \cdot \sin^2(2\Delta\lambda) \tag{1}$$

Where, $hav\sin(\theta)$ is the haversine of the central angle θ ; $\Delta\phi$ is the latitudinal difference between the two points; ϕ_1 and ϕ_2 are the latitudes of the two points in radians; $\Delta\lambda$ is the longitudinal difference between the two points; The Earth’s radius is also factored into the formula.

The above formula is factored into the code used to calculate the haversine of the central angle between two points on the surface of earth. From the foregoing, central angle (θ) can be found using the inverse of the haversine function:

$$\theta = 2 \cdot \arcsine(\sqrt{hav\sin(\theta)}) \tag{2}$$

From the foregoing, the great-circle distance (D) between the two points is given by multiplying the central angle by the radius of the Earth:

$$D = R \cdot \theta \tag{3}$$

Where, D represents the great-circle distance between the two points; R is the radius of the Earth.

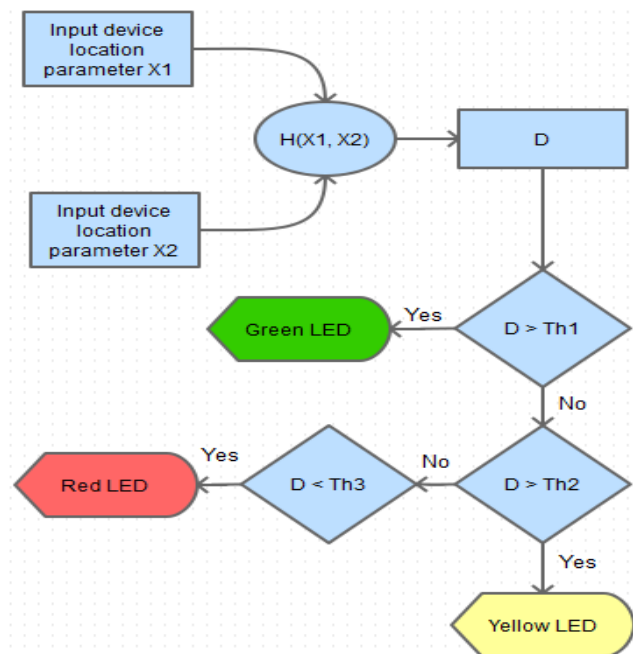


Figure 3: The operational process of the IoMT system

2.2 The Operational Process of the IoMT System

The input wearable IoT devices are designated as X_1 and X_2 . The device location data (longitude and latitude) sent to the cloud is passed to the haversine function at the edge of the cloud to compute the distance D between the devices on the earth plane. This is done following a continuous querying model. The calculated distance D is passed to the location status checking method which checks the threshold value Th_1 , Th_2 and Th_3 to detect the current location state of the individual. The threshold statuses are designated as normal for Th_1 , warning for Th_2 and danger for Th_3 . These are programmed to output different output signals. If the distance D falls below a specified threshold value, a corresponding alarm signal is triggered as indicated in Figure 3.

2.3 Geo-Location Data Reception Rate Versus Average Human Walking Speed

If left unmanaged, the data payload sent to the remote repository has the potential to become excessive, making real-time distance computation between the LTD’s geographical points practically unattainable. Therefore, various strategies were employed to regulate the remote sensing process and the transmission of sensed data to cloud storage through the API. An experimental approach was utilized to measure the time it typically took for the LTD to acquire and send location data to the cloud. This was determined across multiple trials, involving the resetting of the serial terminal in the Arduino IDE to obtain fresh satellite data. Table 1 shows the reception time for various trial attempts for receiving satellite data.

Table 1: LTD’s data reception time from remote satellite

S/N	Reception time (s)
1	11.08
2	19.45
3	29.54
4	9.5
5	23.86
6	8.38
7	17.87
8	1.99
9	23.36
10	3.69
11	32.64
12	20.65
13	1.79
14	28.38
15	2.88
Average	15.67067

From the data collected, it took an average of about 15.67s for the GPS module to receive satellite data. Hence, the reception rate was averaged to 15s.

The average walking speed of human beings according to Christopher McCrum is 1.3m/s [27]. This then entails that on the average, before the GPS sensor sends location data from the remote satellite to the cloud, an average human being must have covered an average distance of 20m. This parameter helps in tuning the device for different response categories. 45s interval was chosen for the alarm signal to commence. Since the continuous querying approach for the database updates the device’s geo point location on the database every 15s, indicating a 20m distance covered by a human before the next data is sent to the database, the system is designed to start beeping the moment the distance observed between a user and a symptomatic person drops from 60m. As the next data enters the database, the calculated distance now drops to 40m if the patient is working in the same direction of an infected person, thereby causing the controller to beep faster until it gets to a less than 20m distance from the infected person, triggering a continuous beep on the device. This signifies an unacceptable distance.

In another case, if the symptomatic person is coming in the direction opposite to the non-infected person, the algorithm may quickly jump the warning stage designated by threshold Th_2 on to Th_3 thereby altering the sequence of the normal alarm triggering.

3.0 RESULTS AND DISCUSSION

The device was tested at the Federal University of Technology, Owerri, specifically at the School of Information and Communication Technology. Two of the IoT nodes (devices) were used for the testing, originating from two different points and arriving at a point. The location data collected from the device are as stated in the Tables 1 and 2. The system was tested under the sun at its full strength with the devices having a clear view of the sky. Tables 1 and 2 show the individual data collected from the two IoT nodes moving from points A and B respectively to point C, the convergence point.

Table 1: Geo-points for device X_1 moving from point A to target C

Geo-points	Latitude L1	Longitudes L1
1	5.382001	6.989589
2	5.381988	6.989522
3	5.381905	6.989488
4	5.381847	6.989398
5	5.381766	6.989331
6	5.381681	6.98926
7	5.381617	6.989178
8	5.381532	6.989091
9	5.381472	6.98903
10	5.381417	6.988968

Table 2: Geo-points for device X_2 moving from point B to target C.

Geo-points	Latitude L2	Longitudes L2
1	5.38197	6.9896982
2	5.38177	6.9896982
3	5.381596	6.9896695
4	5.38137	6.9896398
5	5.381265	6.9895648
6	5.38114	6.9894653
7	5.381102	6.9894462
8	5.380983	6.9893147
9	5.38093	6.9892535
10	5.380807	6.9892005

3.1 Cross-Sectional Detection Using Two Sensor Nodes

Figure 4 shows the path traced by the LTD prototype borne by two individuals during the testing phase. At the onset, the individuals maintained a normal safe distance between each other, and then, at the tail end, they seem to converge. The path traced by the orange line represented that node tagged to a person that tested positive for an infectious disease, while the one that traced blue dots represented an individual that tested negative of infectious disease. The device was internet- powered using an MTN Nigeria 4G MiFi module.

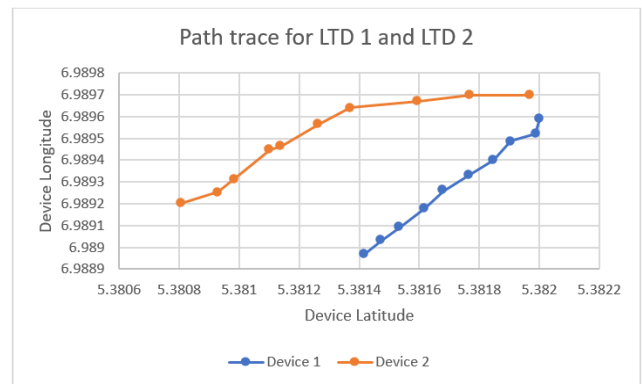


Figure 4: The path-trace of the LTD borne by two individuals

The results showed that there is an average delay of about 4.68s in reporting the presence of a positive person around the carrier indicating an offset of about 6.085m from the calculated distance. Several factors were thought to have contributed to the response time of the system. These include the internet connection speed and the network available for communication between the GPS module and the satellite. Another issue of concern is the topography of the area, including the structures around the area used for device testing.

4.0 LIMITATIONS

While LTD provides an estimated distance between the infected carrier or the disease vector, third parties can only intuitively determine the direction of the distance as to either north, south, east, west, etc directions. This intuitive approach cannot be fully

relied on as that can be perceived largely in the current north direction of the third-party. This research does not provide the direction to which the vector or infected carrier is located.

5.0 CONCLUSION

In conclusion, this research presents a design for infectious disease control during epidemics through the development of an Internet of Medical Things (IoMT) enabled third-party monitoring model. The third-party takes the form of perceived disease vectors and infected humans. The model uses Location Tracking Devices (LTDs) integrated with IoT sensors to provide real-time tracking of individuals' movements in relation to the presence of infectious diseases positive patients. The research proposes a broader approach to disease control by involving not only the infected individuals and healthcare providers but also ordinary individuals as third-party monitors. This is critical considering the ripple effect of infectious disease transmission from one individual to another.

The proposed model is an extension of the traditional focus on patient-caregiver interactions by introducing a third-party, ordinary individuals, into the disease control ecosystem. The IoMT-enabled system solely relies on the Haversine formula for calculating the distance between individuals, ensuring real-time notification to even the third-party when an infected person is within a specified range. The architecture includes cloud and web API blocks, healthcare provider management, and the IoT sensory and notification block. The system's optimization was done by adjusting the data reception rate based on human walking speed to enhance the response time and accuracy.

The research was faced with challenges such as internet speed, network availability, and the nature of the testing environment. These have tangible effects on the response time of the device. The research provides a foundation for a practical, technology-driven solution to infectious disease monitoring. Future work should focus on addressing optimization challenges, data reception and expanding the model's applicability in diverse settings.

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