FAST CONTAINMENT OF INFECTIOUS DISEASES WITH E-HEALTHCARE MOBILE SOCIAL INTERNET OF THINGS

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ABSTRACT

Because of their high infectiousness and propensity for causing death, contagious diseases pose significant threats to the health of the general population. Vaccination is one of the efficient strategies that may be used to slow or stop the spread of infectious diseases. However, as a result of limited resources and a restricted budget for medical care, it is not possible to vaccinate each and every individual. In addition, it might be challenging to monitor the effects of vaccination in a timely manner using conventional methods, such as outpatient services. We propose an e-healthcare mobile social Internet of Things (MSIoTs)-based targeted vaccination strategy to quickly restrict the spread of the infectious illness in order to address the issues that have been outlined above. To be more specific, we first design an e-healthcare MSIoT architecture by combining the e-healthcare system and MSIoTs. This allows for the timely collection of information about the state of the transmission of the infectious illness. In addition, a network colouring and spreading centrality-based optional candidate searching method has been developed in order to search for candidates that have the potential to effectively prevent infectious illness. In particular, we develop an optimum vaccinated target selection algorithm in order to identify a minimal number of targets whose locations are unevenly distributed. This is done with the intention of lowering the cost of the vaccination process. Extensive simulations show that the suggested method may be an effective alternative to standard schemes in terms of preventing the spread of infectious illness.

I INTRODUCTION

Since about the beginning of civilization, communicable diseases have posed a significant danger to the human race's ability to exist. An epidemic of an infectious illness may result in significant casualties and damage to property, and it can even set the stage for social unrest and a riot [1]. According to accounts from the past, the so-called "Black Death" swept throughout Europe in the 14th century and was responsible for the deaths of more than 25 percent of the continent's population [2]. During the years 1918–1919, the Spanish flu caused around 20–50 million fatalities throughout the globe within a single year. This number is more than the number of people killed in World War I [3]. In recent years, the epidemic of Ebola in 2014 produced significant mortalities in several countries, with a fatality rate of 70% according to the study published by the World Health Organization (WHO) [4]. The prevention and control of infectious diseases is unquestionably one of the most important things that can be done to save lives and maintain societal order. The most efficient and appropriate measure to reduce the

amount of casualties and costs associated with fighting disease is to timely detect the outbreak of the communicable diseases and conduct vaccinations in the critical, preliminary phase of something like the virus spreading. This will allow for the most proper and effective fighting of the disease. For instance, thanks to real-time surveillance and a massive vaccination effort, smallpox has been completely wiped from the globe [5].

However, the conventional methods of containing infectious diseases have a few flaws that prevent them from effectively regulating the spread of infectious diseases. On the one hand, the identification of an infectious illness is often accomplished by patients consulting with medical professionals in hospitals for procedures and treatments; nevertheless, it is impossible to forecast the spread of the infection in these settings. On the other hand, isolating sensitive individuals not only results in financial losses for the susceptible individuals as well as a significant increase in the government's health care costs and labour resources, but it also poses a public health risk. Recently, a promising electronic healthcare system that is based on wearable Internet of Things (IoTs) [6] has been proposed to address the aforementioned public health crisis. This system is designed to address the problem by continuously sensors to detect users' actual health information, such as temperature, heart rate, blood pressure, electrocardiogram, and other similar measurements.

A server is used in the e-healthcare system to gather health data, identify aberrant events, and provide diagnostic assistance [7, 8]. This server is also responsible for supplying information to support diagnoses. The medical centre is able to monitor the users' health status by doing an analysis on the data pertaining to their health. When it becomes clear via an assessment of the users' health some of of them are affected with an infectious illness, the medical centre will implement immunological tactics in order to prevent the disease from spreading further.

Vaccinating those who are at risk of contracting an illness is, in most cases, the least complicated method of disease prevention. Nevertheless, there are constraints on resources and expenses, such as the availability of vaccines, which may make immunisation of all vulnerable persons challenging in many circumstances, particularly during outbreaks of newly discovered infectious diseases.

One alternate strategy for preventing the contagious illness from spreading across a community is to provide vaccinations to certain groups of individuals within that community. Despite this, there are a few obstacles that need to be overcome in order to find the best vaccinated targets. To begin, the uneven geographical extent of infectious sources makes it difficult to identify vaccine targets. This is a problem for two reasons. Second, because the social contacts and relationships of mobile users are so varied, so are their abilities to prevent infectious disease.

This presents a new challenge for public health officials, who must now determine how to select the appropriate vaccinated targets due to the information they obtain from social networks. Third, the dynamic of the network has an influence on the selection of vaccination targets. This can be seen in things like the movement of mobile users, changes in contact frequency, and so on.

We are fortunate that an e-healthcare system that is coupled with the mobile

social Internet of Things (MSIoTs) [9], [10] is being developed with the goal of realising resource-constrained targeted vaccination.

The health information of mobile users that has been acquired by the electronic healthcare system may be evaluated to trace the spread of an infectious illness.

MSIoTs, which are built using mobile users and contact information, give information on the social relationships of mobile users by mining the social data of mobile users [11–13]. The combination of health data and social data may be used to identify a particular set of users who would benefit most from targeted vaccination. Take, for instance, the case of Bob and Alice, two mobile users who are being continually monitored during an outbreak of an infectious disease from both the social and the medical point of view. As a result of the social data analysis, Bob maintains consistent communication with a variety of different mobile users, including Alice. As soon as the health data allow for the conclusion that Alice is an infected patient, Bob should be vaccinated as quickly as possible in order to halt the progression of the infectious illness in its early stages.

There has been a significant amount of research done on targeted vaccination [14–22].

For instance, the use of artificial intelligence in conjunction with simulation techniques is used in order to locate mobile users who have the most effect for the purpose of monitoring the progression of a disease [21]. In [22], the wireless sensor system is used to contain the infectious illness. Connectivity centrality is taken into consideration in order to identify the most significant mobile users. On the other hand, the vast majority of the already available efforts are still unable to quickly prevent infectious illness using ehealthcareMSIoTs. In the first place, the majority of the currently available publications do not give enough consideration to the geographical distribution of infection sources. In point of fact, the infectious agents tend to be found in various parts of the world; hence, the vaccinated targets with varying geographic locations will likely have varying degrees of success in warding off the infectious illness. Second, the majority of the previously published research [19, 23] use the implicit premise that all mobile users are free of infection throughout the process of searching for vaccinated targets, in which infection sources may be chosen to serve as vaccinated targets.

Third, the overlapping preventative effects of vaccinated targets are not taken into account in some of the related works, which means that some vaccinated targets have the same effects on controlling the spread of the infectious disease. This is something that is not taken into account in some of the related works. As a result, there is a pressing need for an innovative, effective, and targeted vaccination strategy to be developed for the purpose of avoiding infectious diseases.

In this work, we expand on our earlier conference version on the creation of e-healthcare MSIoTs [19] and suggest an unique targeted vaccination plan to restrict the spread of the infectious illness. Our goal is to prevent the disease from becoming more widespread. By fusing together and analysing both health data and social data, the suggested system is able to identify an infectious disease epidemic in a timely manner and quickly locate the ideal targets for vaccination. As a result, the infectious ratio as well as the casualty ratio are dramatically reduced,

which results in a situation in which people's properties and a stable social condition may both be jointly guaranteed. To be more specific, we begin by integrating the electronic healthcare system and MSIoTs in order to construct the architecture of e-healthcare MSIoTs for the purpose of accelerating the tracking of the infectious disease's spread. Then, in order to discover the most widely dispersed vaccinated candidates, we make use of a method that is based on graph colouring and an optional candidate search. For the purpose of accurate candidate selection, a brand-new measure known as spreading centrality has been introduced. This metric takes into consideration mobile users' infecting capacities as well as the possibilities of being infected. In conclusion, using the infectious disease spreading analysis model as a foundation, we developed an optimum vaccinated target selection algorithm with the goal of preventing overlapping containment effects. The primary contributions of this essay may be broken down into three categories.

1) Here, we present an algorithm for optional candidate searching that is based on network colouring and spreading centrality. The graph colouring theory is used in order to locate the mobile users who have the broadest possible distribution in order to expand the range of immunity. In addition, we propose a unique idea that we call spreading centrality. This idea takes into account the mobile user's capacity to infect others as well as their likelihood of being infected. This allows for the appropriate candidates to be sought after.

2) We construct a dynamic equation-based analytic model to watch the spread of the infectious illness by taking into consideration both the social data and the health data of mobile users. This allows us to observe the spread of the disease more accurately. We are able to quickly see the amount of patients who are infected with time thanks to the analysis model. After that, we will be able to determine the contribution of each mobile user who has been immunised to the overall effort to control the infectious illness.

3) A comprehensive set of simulations are run in order to assess the effectiveness of the suggested method. We begin by analysing the progression of the infection ratio through time using a variety of indicators, such as the number of mobile users who have been vaccinated, the pace at which the illness is spreading, and the rate at which patients are recovering. After that, we compare the performance of the suggested system with that of other, more traditional schemes to demonstrate that the new plan is superior.

II RELATED WORK

We take a look at the works that are relevant to this topic, such as the examination of social data using MSIoTs, the assessment of healthcare information using an electronic medical system, and the management of contagious diseases using wireless networks.

1. An Examination of Social Data Using MSIoTs

Recent years have seen a proliferation of research papers that have focused heavily on social data analysis using MSIoTs. Meng et al. [24] suggested a non-Bayesian social learning-based high-level distributional state inference strategy for use in cooperative contexts while performing a variety of crowdsensing tasks.

Li et al. [25] developed a system for social-based routing in MSIoTs. In

addition, they established a unique metric to measure the node's competence of forwarding packets to other nodes in the network.

Wang et al. [26] proposed a diffusion and manoeuvrability content replication strategy for perimeter network area based on the social graph, content sharing of information, and user mobility to assign mobile users with social content in the edge network region. Their strategy assigned mobile users with social content based on the social graph, content dissemination, and user mobility. He and his colleagues [27] came up with the idea of a handshake agreements generally for cryptography that is predicated on hierarchical identity. Within this paradigm, an efficient cross-domain handshake solution is also created to achieve symptom matching. Xiao et al. [28] suggested two online job assignment algorithms, each of which takes into account the crowdsensing in MSIoTs's average makespan, as well as the biggest makespan, in their own unique way. However, how to exploit the MSIoTs for monitoring the spread of the infectious illness is not well addressed in these studies. In this article, we assemble a prototype system of e-healthcare MSIoT by integrating the mobile social networks (MSNs) and e-healthcare system, whereby the social data and health data are fused to timely detect the emergence and spread of the bacterial infection and effectively contain the infectious disease at the early stage.

The research of health data analysis using the e-healthcare system has attracted the growing interest of specialists in a variety of sectors that are connected to it. Zhou et al. [29] presented a privacy-preserving holomorphic database aggregation for use in cloud-assisted electronic healthcare systems. The holomorphic database would be used for medical picture analysis. Lee et al. [30] developed a healthcare-grade wireless local area network architecture that was specified for a medical institute. This design allows the medical institution to prioritise medical situations in line with the degree of urgency they present. A method for collecting healthcare data from a wireless body area network was suggested by Huang et al. [31]. With this system, healthcare data may be communicated across a wireless network in a safe and secure manner. Lomotey et al. [32] conducted research to find an effective way to maintain synchrony throughout faulty mobile networks in order to keep patients' electronic health information intact.

Even while these works concentrate on some elements of ehealthcare, the vast majority of them do not take into account the ways in which e-healthcare might be used to the prevention of infectious diseases.

In the publications that were already published, the containment of infectious diseases via wireless networks received a significant amount of attention.

A unique measure was developed in order to locate crucial nodes of disease containment, and Sun et al. [22] developed a system that uses wireless sensors to collect information about people's social connections in order to create a model of the progression of the illness. Lu et al. [33] introduced a Markov switching model to predict infectious disease outbreak patterns in syndromic counting time series. In this model, the disease outbreak statuses were treated as hidden state variables. Zhou et al. [34] developed a monitoring system of symptoms to anticipate the epidemic trends connected to the Google search algorithm for the early detection of

epidemic outbreaks. A person-to-person tracking scheme for infections was proposed by Zhang et al. [35] by combining the analysis of social network data and health data from the perspectives of social networks and e-health, respectively. This was done in order to determine how infections are passed from one person to another.

The authors Fan et al. [36] suggested a lightweight strategy for the protection of radio-frequency identification medical privacy in the Internet of Things. This scheme ensures both the security and privacy of the data that is acquired. However, further research is required to determine the most effective ways to employ both social data and health data in concert with one another in order to prevent the continued spread of an infectious illness.

All of the aforementioned works have made some kind of attempt toward the goal of controlling infections caused by e-healthcare MSIoTs. However, the emphasis of these studies is on infectious diseases that are confined to limited regions, which means that social data and health data are not being used to their maximum potential in order to gather information about infectious diseases.

In contrast to those other articles, this one conducts an exhaustive investigation of the features of e-healthcare MSIoTs and then proposes a revolutionary targeted vaccination scheme by making use of both social data and health data in order to effectively prevent the spread of infectious diseases.

III PROPOSED SYSTEM

We begin by presenting the system model, which is shown in Figure 1 and includes the social graph and the network model. After that, we determine the objectives of the design.

A. Model of a Network

Mobile users, a social server, and an e-healthcare server are the three components that make up the e-healthcare MSIoT.

1) Mobile Users: Let's indicate the set of mobile users in the system using the notation I = "1, 2,..., I I." There may be an existing social link between every pair of mobile users, such as between classmates, family, coworkers, and so on. According to [37], the interactions that mobile users have with one another may be broken down into five distinct categories: a) family ties; b) friendships; c) neighbour relationships; d) professional relationships; and e) weirdness.

The family connection identifies two mobile users who are related to one another in some way, such as a father and a son, a husband and wife, or any other similar pair. The term "friendship" refers to the relationship that exists between two mobile users who often share interests. The term "neighborship" refers to the fact that two mobile users share the same home address, whether it the same room, the same building, or something else entirely. When we talk about mobile users having a colleague connection, we mean those who work at the same firm or attend the same school. The fact that two users are completely unrelated to one another is really strange. Without sacrificing any sense of generality, the social strengths of the aforementioned five connections are distinct, and the order of their relative importance is as follows: 1 > 2 > 3 > 4 > 5.

In this context, the qualities of family relationships, friendships, neighbour relationships, professional relationships, and strangeness are referred to as 1, 2, 3, 4, and 5, respectively. For mobile user I and

mobile user j, we designate a relationship vector ri,j = (r1 i,j ,r2 i,j ,r3 i,j ,r4 i,j ,r5 i,j), where rki,j∈ {0, 1}, k ∈ {1, 2, 3, 4, 5}. rki,j = 1 if there is a connection k between mobile user I and mobile user j and if there is such a relationship. Otherwise, rki,j = 0. It should come as no surprise that the peculiarity cannot coexist with other connections; for example, if r5 i,j = 1, 4 k=1, then rki,j = 0. In addition to this, we have 5 k=1 rki,j> 0 for any two users of mobile devices.

2) The E-Healthcare Server: This server may be found in the cloud and has tremendous computing and storage capabilities.

There are three different capabilities offered by the e-healthcare server. To begin, the server for electronic healthcare may gather users' health data from mobile devices. Second, the e-healthcare server is able to analyse the health data of mobile users with the assistance of the medical centre in order to identify infectious diseases. Thirdly, the ehealthcare server sends notifications to mobile users reminding them to be vaccinated against infectious diseases.

3) Social Server: The social server is installed in the cloud server and is responsible for storing the contact information of mobile users as well as analysing the social characteristics of each mobile user.

Smartphones get the contact information in a variety of different methods. Users of mobile devices, for instance, are able to look for other nearby users of mobile devices within a certain range by using the Bluetooth discovery programme on their cellphones. The length of time spent in touch may also be easily documented by cellphones. Some sort of wireless communication technology, such as cellular, Wi-Fi, or another similar technology, is used to transmit the contact information of each mobile user to the social server. The social connections are derived from the accounts that mobile users have created on various social networking platforms, including as WeChat, Facebook, Twitter, and others. The social server then communicates with the e-healthcare server to share the social information of mobile users in an effort to reduce the risk of infectious illness.

B. Social Networking Graph

As can be seen in Figure 2, the social graph is represented by the equation G = 'I, E, W', where 'E' refers to the collection of edges. When there is at least one interaction between mobile users I and j, the graph G will have an edge labelled ei,j = I j) E. This will indicate that the edge exists. G is an example of an undirected graph since the infectious illness may go in any direction.

We define the potential for disease transmission between mobile users I and j by assigning a weight to each edge ei,j in the social graph G. The weights range from 0 to 1. When determining the edge weight, both the frequency of contact and the length of contact are taken into consideration. If one of two mobile users who are often in touch with one another and frequently in the same location becomes a patient, the likelihood of the other mobile user also being infected is quite high. Therefore, the weight of the related edge should be increased according to the frequency with which two nodes interact with one another. And the longer the contact period that they spend, the greater the edge weight that should be applied to the edge that corresponds to that contact length. The setting in which an individual is exposed to a disease is another component that plays a role in that

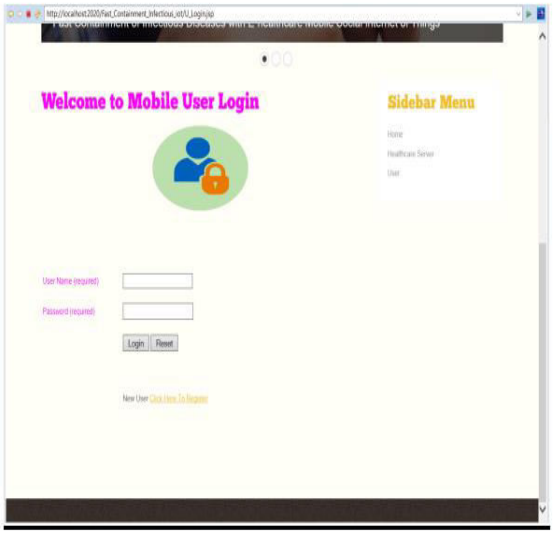
condition's transmissibility. Infectious illnesses like the flu may spread more quickly inside of a building than they do outside [38]. In a similar vein, the contacts that take place inside should be given a greater weight than the ones that take place outside. In addition to this, the social connections that mobile users have with one another are also a factor in the transmission of infectious diseases. If one of two mobile users who are intimately connected with one another contracts an illness, there is a significant risk that the other may also get ill. Therefore, if the connection between two mobile users is stronger, the weight on the edge that corresponds to that connection should be increased. For the purpose of this discussion, we will refer to the total number of interactions that took place between mobile user I and mobile user j over the time interval [0, T]. In this case, the determination of the time scale for the period [0, T] focuses primarily on taking into consideration the two aspects that have been presented here. To begin, the time period should be sufficiently broad to ensure that the statistical data can include an adequate amount of information about significant social contacts. Second, the statistical data may be continually updated to reflect the dynamism and adaptability of social contact information, with the caveat that the time period in question should not be very extensive. As a consequence of this, the time scale of period [0, T] can either be one day or half a day. It follows that since I and j equal one another, the duration of the nth contact is denoted as i,j,n, and T is greater than this value.

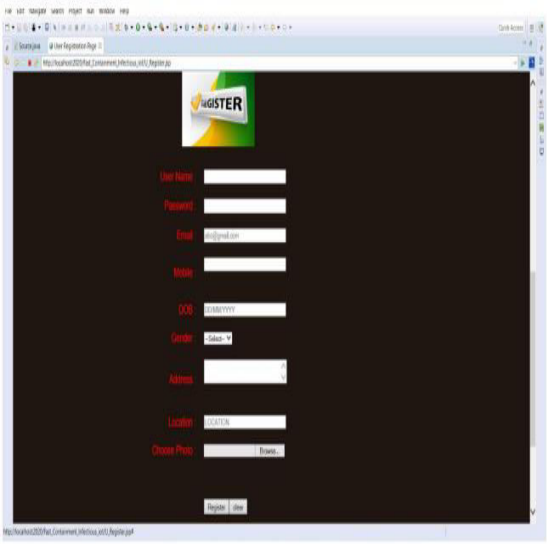
The following elements are a part of the network dynamic that the proposed scheme takes into consideration. First, the mobility of each mobile user is taken into consideration, and the locations of mobile users' contacts at various time slots are gathered. These places might be either inside or outdoors. In addition to this, the malleable nature of the contact that exists between two mobile users over the course of a certain time period is taken into account. To be more specific, the number of contacts as well as the total amount of time spent on each contact is tallied by the cellphones that are carried about.

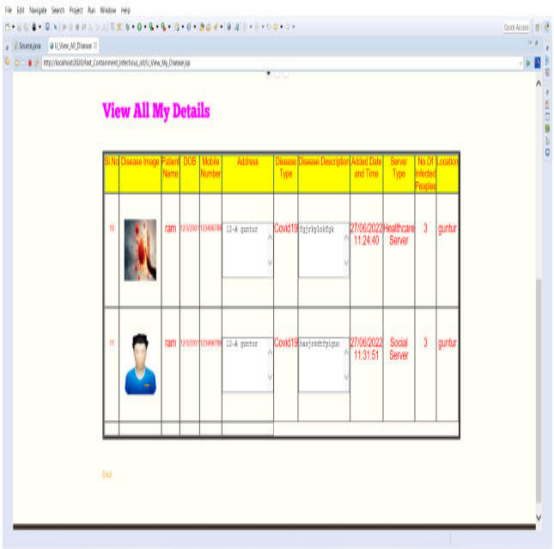
In addition, the social data that is used to create the social graph is continuously recollected and analysed in order to show the dynamic of contacts and social relationships among mobile users. This is done so in order to indicate how the social graph is constructed. The e-healthcare and MSIoTs-based targeted vaccination plan that has been presented ought to accomplish two objectives. To begin, the system has the potential to reduce the overall number of people who get infected during an epidemic of an infectious illness. Second, there is a minimal resource overhead required to actualize the green system (for example, consumptions of labour and electrical resource, etc.). This is due to the fact that the green system is more efficient.

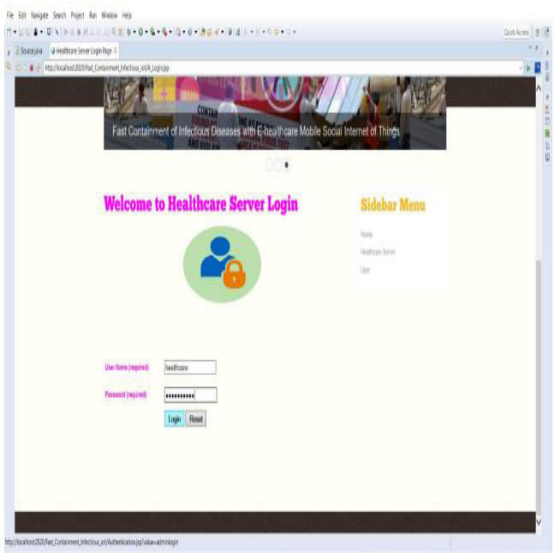
IV RESULTS

User login









V CONCLUSION

In order to prevent the contagious illness from spreading further, we have suggested a revolutionary vaccine strategy that is based on e-healthcare and MSIoTs. In order to establish the architecture of e-healthcare MSIoTs, the e-healthcare system and MSIoTs had to be integrated with one another. As a result of this integration, health data and social data may now be gathered together. The infectious disease spreading analysis model that has been developed in order to monitor the process of the infectious disease spreading has been established with the help of health data and social data.

In addition, we have developed a graph colouring and spreading centrality-based vaccinated candidate finding method in order to locate the candidates who have the greatest potential to have an impact on a large number of people.

We have designed an algorithm for selecting vaccinated targets so that we may identify those individuals who are most effective in warding off infectious diseases while keeping the expense of vaccination to a minimum. The findings of the simulation demonstrate that the suggested method is superior than other traditional methods. As part of our ongoing research, we will investigate the mechanisms that protect individuals' privacy during the interchange of health data as well as the building of e-healthcare fog using social IoTs.

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