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COVID-19 Contact Tracing and Detection-Based on Blockchain Technology

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Abstract: The fight against the COVID-19 pandemic still involves many struggles and challenges. The greatest challenge that most governments are currently facing is the lack of a precise, accurate, and automated mechanism for detecting and tracking new COVID-19 cases. In response to this challenge, this study proposes the first blockchain-based system, called the COVID-19 contact tracing system (CCTS), to verify, track, and detect new cases of COVID-19. The proposed system consists of four integrated components: an infection verifier subsystem, a mass surveillance subsystem, a P2P mobile application, and a blockchain platform for managing all transactions between the three subsystem models. To investigate the performance of the proposed system, CCTS has been simulated and tested against a created dataset consisting of 300 confirmed cases and 2539 contacts. Based on the metrics of the confusion matrix (i.e., recall, precision, accuracy, and F1 Score), the detection evaluation results proved that the proposed blockchain-based system achieved an average of accuracy of 75.79% and a false discovery rate (FDR) of 0.004 in recognizing persons in contact with COVID-19 patients within two different areas of infection covered by GPS. Moreover, the simulation results also demonstrated the success of the proposed system in performing self-estimation of infection probabilities and sending and receiving infection alerts in P2P communications in crowds of people by users. The infection probability results have been calculated using the binomial distribution function technique. This result can be considered unique compared with other similar systems in the literature. The new system could support governments, health authorities, and citizens in making critical decisions regarding infection detection, prediction, tracking, and avoiding the COVID-19 outbreak. Moreover, the functionality of the proposed CCTS can be adapted to work against any other similar pandemics in the future.

Keywords: blockchain technology; COVID-19 pandemic; infection data communication; ubiquitous computing

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1. Introduction

The world is currently witnessing a dangerous transformation of the COVID-19 pandemic, rapidly threatening peoples' lives and the global economy amid fears of sequential waves and genetic mutations of this pandemic. According to the last update of the World Health Organization (WHO), there have been 224,372,380 confirmed cases of COVID-19, including 4,625,006 deaths [1]. There is widespread agreement among economists that this pandemic will have substantial negative impacts on the global economy that extend to 2022. According to Statista, the global economy lost at least 2.4% of its gross domestic product (GDP) in 2020. For more clarification, in 2019, the global GDP was estimated at approximately 86.6 trillion US dollars, meaning that just a 6% drop in economic growth amounts to almost 3.5 trillion US dollars in lost economic output [2].

Despite the small increase in optimism with the decrease in the number of infected people in some countries and the approach of vaccine production, a resurgence of COVID-19 in 2021 could leave economies suffering in subsequent years and negate all efforts made to fight against its spread.

Much medical and preventive effort is still being made by health authorities and governments to fight the ongoing COVID-19 pandemic. Moreover, a variety of digital technologies are being used and are playing significant roles in controlling the spread of this pandemic and detecting the virus [3–5].

Artificial intelligence (AI) has many critical applications for fighting against the COVID-19 pandemic [6], including tracking, screening, and predicting current and future infected cases [7], early detection and diagnosis of infection [8], drug and vaccine development [9], and reducing the workload of healthcare workers [10,11].

The spread of COVID-19 can also be addressed as a data science issue [12]. Manipulating COVID-19 infection dynamics requires non-traditional techniques for processing COVID-19 data such as data collection and interpretation, modeling, prediction [13,14], and data visualization and communication.

The internet of things (IoT) is another technology that can be utilized for managing information transmission and monitoring healthcare systems during the COVID-19 epidemic [15,16]. The IoT is a helpful technology for customizing smart applications to monitor patients in quarantine with real-time information processing; this technology is called the cognitive internet of medical things (CIoMT) [17]. In addition to remote health monitoring, the CIoMT can help with diagnosis and dynamic tracking to control the disease growth. It can also assist in contact tracing, clustering, and mitigating the workload of the medical industry.

Blockchain is not neglected in this fight, as it now plays a pivotal role in assisting health authorities [18] and governments around the world to address many challenges of COVID-19 [19,20]. In the COVID-19 epidemic, it is necessary to think of non-traditional solutions for controlling the spread of COVID-19 using blockchain as a critical emerging technology. The unique features of blockchain, such as P2P communication, time stamping, data transparency, trusted and secure transactions, and real-time processing, make it a superior technology for many healthcare system services, especially with the recent COVID-19 pandemic. Blockchain can provide several services compared to traditional and similar techniques, such as databases or cloud computing. For instance, health data security and privacy in patient monitoring provide a single source of truth about the infected cases in real-time, infection data screening and tracking, and significant recommendations for the decision support systems (DSSs) of governments and health authorities.

The greatest challenge that most governments are currently facing is the lack of a precise and automated mechanism for detecting infected cases and identifying the related contact cases of COVID-19. Moreover, people lack a system that can provide P2P alerts about nearby infected persons or public places that infected persons have accessed. The large population increase and the spread of overcrowding in countries make it an urgent need for such a proposed system. Moreover, most hospitals and health authorities in most countries lack a digital system that can monitor the spread of infection in real-time and obtain real statistics regarding the number of infected people. This problem is called COVID-19 contact tracing [19]. These limitations make the proposed system in this study an important solution to fight against COVID-19 growth.

Little research effort has been made, and immature and incomplete systems have been used to solve this problem. All current methods introduced for solving this problem depend on developing mobile applications based on Bluetooth technology. The purpose of these apps is to notify persons when they may have come in contact with an infected person or allow the local health authority to give persons timely care and guidance to protect them and those around them when they are in close contact with others in the same area [21–24]. However, there are some critical limitations of Bluetooth technology used in the recent COVID-19 Apps. Most of these limits are related to security and communication bandwidth, which means that the Bluetooth apps are not the most optimal ones to solve the COVID-19 contact-tracing problem.

In response to the problem, and due to the detected limitations of recent COVID-19 mobile applications, this study aims to introduce the first blockchain system that can be used through a novel P2P mobile application to solve this problem. The proposed system is called the COVID-19 contact tracing system (CCTS). The proposed system consists of four integrated components:

(1) Blockchain platform: used to digitally store the confirmed COVID-19 cases in a sequence of secured blocks in real-time.
(2) Mass surveillance subsystem: used to track all citizens' behavior and motion patterns in crowded regions.
(3) Infection verifier subsystem: used to verify COVID-19 infection instances
(4) P2P mobile application: used by users to estimate infection probability, and for detecting unknown infected cases in crowded regions.

The back end of CCTS includes a blockchain platform, the infection verification system, and the mass surveillance system. The front end involves the P2P mobile application. These components work together in a coherent and automated fashion to achieve the following objectives:

(1) Self-estimation of the COVID-19 infection probability by end users.
(2) Detection of new COVID-19 cases.
(3) Sending and receiving infection alerts in P2P communications within crowds.

The rest of this paper is organized as follows. Section 2 presents a literature review. Section 3 discusses the proposed blockchain system, the COVID-19 contact tracing system (CCTS). Section 4 presents the design and implementation features. Section 5 presents the evaluation and experimental results. Section 6 discusses the obtained results and clarifies the proposed system's strengths and weaknesses compared with other systems in the literature. Section 7 presents the conclusion of this study.

2. Literature Review

The literature on detecting and tracking cases of the COVID has highlighted various techniques that depend on different digital technologies. However, a relatively small body of literature focuses on automatically detecting and tracking cases of COVID-19 using blockchain technology [25]. The literature has introduced some AI algorithms for detecting infected cases based only on deep learning algorithms and lung-X-ray image processing [26–28]. Many studies have used deep convolutional neural networks to detect COVID-19 from chest X-ray images [27,29].

Other studies have used capsule networks and hierarchal learning to develop new artificial neural network algorithms for detecting the COVID-19 virus from chest X-ray images [30,31]. Although these studies achieved promising results regarding the detection accuracy, sensitivity, and specificity, the dependence on lung X-ray images for detecting the COVID-19 virus means that these studies are not useful in the early detection of COVID-19 before it infects the lungs of the patient. Moreover, these studies are not adequate for precisely tracking the actual spread and infection dynamics. Therefore, early detection of infected cases and contacts needs other technologies instead of depending on X-ray chest image processing techniques to detect COVID-19 patients.

An exciting solution for this challenge is to develop smartphone apps or portable medical apps to detect and monitor infected patients in the early stages of infection. Imran et al. [32] developed an AI application called AI4COVID-19 for preliminary diagnosis of COVID-19 from cough samples. The authors addressed this challenge by studying the differences in pathomorphological alterations in the respiratory system created by COVID-19 infection compared to other respiratory infections. This provided a screening and testing tool that is deployable anytime, anywhere, and by anyone. It can also be used as a clinical decision assistance tool. However, this app is not sufficiently mature due to some limitations regarding the quantity and quality of the training and testing data and the difficulty of extracting cough samples' valid features. This issue can cause some overlaps and invalid diagnoses of COVID-19

Other smartphone applications have been developed for early detection and tracking of infected persons based on smartphone communications between the individuals and other citizens [33,34], as well as monitoring the effects of human mobility restrictions on the infection dynamics of COVID-19 [35]. Most of the mobile apps developed for detecting and tracking infected persons depend on using Bluetooth technology to notify users when they have contacted an infected person. Google and Apple cooperated in deploying a new service that would let users know when they have come into contact with someone who has COVID-19 based on smartphone communications [36]. This new technology would depend on the "exposure notification" tool and Bluetooth radios within smartphones to notify the public when they contact an infected person. If a confirmed case tests positive for COVID-19, public health authorities could be alerted through the new mobile service. Public health apps would notify anyone whose smartphones had come close to the infected person's phone in the previous 14 days.

The Singapore Trace Together app [22] is another Bluetooth-based contact tracing application that has been launched by the Singapore government [37]. This application notifies a person quickly if they have been exposed to COVID-19 through close contact with other Trace Together users by exchanging short-distance Bluetooth signals between phones. A similar Bluetooth-based application in the UK, UK NHS Contact Tracing was planned to be used in England after initial trials on the Isle of Wight [38]. Unfortunately, this App has not yet been completed since it has many major technical flaws that mean it does not work correctly. However, the government has said it would pivot to using Apple and Google's code to rebuild it [39].

Although these applications have tried to utilize the advantages of Bluetooth technology to perform contact tracing of COVID-19, some Bluetooth technology limitations mean that it is not the optimal solution for solving this problem. These limitations can be categorized as follows:

- Bluetooth allows mobile phones to lose connection in certain conditions.
- Bluetooth has a lower bandwidth than WiFi.
- Bluetooth allows only short-range communication between devices.
- Security of Bluetooth is a key challenge, and Bluetooth connections can be hacked.

Quick response (QR) code-based applications are another technology that has been used in China. The idea behind this app is to determine whether citizens should be quarantined or allowed into subways, malls, and other public spaces based on relational cross-matching by scanning the QR code [40]. However, the QR code may become distorted, which can lead to improper reading by devices. Additionally, inappropriate designs and formatting can make QR codes un-scannable.

Some studies have started to use blockchain to develop new applications for addressing the contact-tracing problem for the COVID-19 pandemic. BeepTrace [41] is an initial blockchain scheme proposed for addressing the critical privacy-preserving challenge in digital contact tracing for the COVID-19 epidemic. BeepTrace also depends on Bluetooth technology, GPS, and WiFi for better tracing performance, maximizing privacy preservation [42], and making an efficient network for contact tracing. However, this scheme focuses only on solving the privacy-preservation problem in previous contact tracing apps by integrating blockchain with those applications. Moreover, it is still in its early stages of development and has not yet been peer-reviewed.

3. The Proposed COVID-19-Contact Tracing System (CCTS)

As a response to the limitations stated previously in developed mobile apps for addressing the COVID-19 contact tracing problem [36,37,39–41], this study introduces the first blockchain system for solving this problem, the COVID-19 Contact Tracing System (CCTS). The proposed system can be developed based on four subsystem models as we proposed in our initial work [25]:

- Blockchain platform: used to digitally store the confirmed COVID-19 cases in a sequence of secured blocks in real-time.
- Mass surveillance subsystem: used to track all citizens' behavior and motion patterns in crowded regions to detect the contacts in the last 14 days.
- Infection verifier subsystem: used to verify the infection instances (i.e., contact persons) to confirm the infection transferee from a confirmed COVID-19 case to a contact person.
- P2P mobile application: used by citizens to perform two tasks: (1) self-estimation of infection probability, and (2) detection of unknown infected cases in crowd regions.

The four subsystems work together in an integrated, coherent, and automated fashion. The general architectural model of the proposed system, CCTS, is described in Figure 1. The back end of CCTS includes a blockchain platform, a mass surveillance subsystem, and an infection verifier. The front end includes a P2P mobile application.

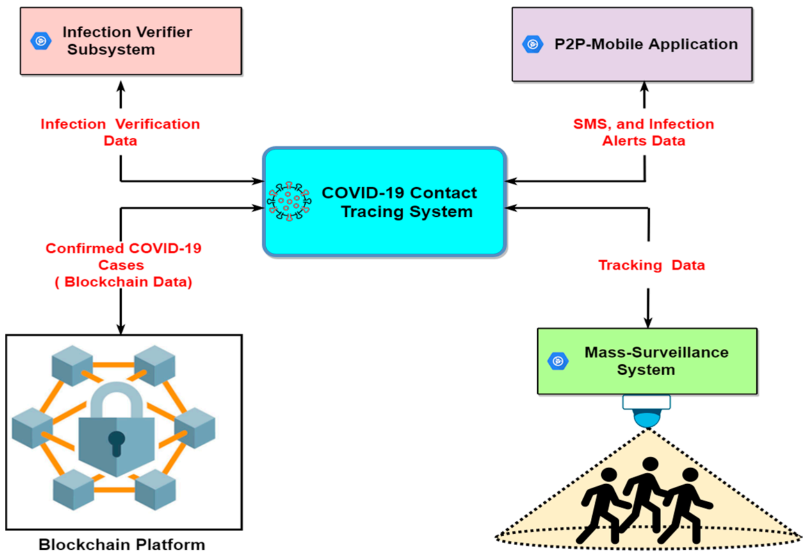

Figure 1. The proposed COVID-19 contact tracing system (CCTS) model.

3.1. The Blockchain Platform

A blockchain platform can operate as a decentralized warehouse to digitally store confirmed COVID-19-cases in a sequence of blocks in real-time. The time stamping, P2P design, and real-time tracking properties of blockchain make it an effective technique for digitally saving and monitoring confirmed COVID-19 cases. These important features of blockchain make it a better solution for detecting and tracking infected cases of COVID-19 than the traditional techniques such as database and cloud computing that depend on a centralized design and low transactions. In the proposed CCTS model, blockchain works as a key player that manages, stores, monitors, secures, and authenticates all transactions in real-time between the blockchain and the mass surveillance subsystem, infection verifier subsystem, and P2P mobile app. To store confirmed cases of COVID-19 in blockchain, we propose digitally representing the confirmed cases (i.e., the infection sources) using regular expressions. Each case is associated with an ID called an infection pattern. In addition, the contact persons and the infected places (e.g., markets, stations, shops, schools, etc.) accessed by a confirmed case can be digitally represented as infection instances. The basic advantage of using a regular expression for specifying the infection patterns is the possibility of deriving a wide range of instances for each pattern. Hence, this feature is an excellent motivation to specify the unknown COVID-19 cases (i.e., contacts). For instance, in Figure 2, the regular expression $P|Bab*+c$ can be used to specify the infection pattern of a confirmed case of COVID-19. This pattern can yield many infection instances that digitally represent the infected persons and infected places in the form "Pabc", "Pabbc", "Pabbbc", "Pabbbbc", ... , "Babc", "Babbc", "Babbbc", "Babbbbc", ... etc. The infection instances that start with 'P 'represent infected persons, while those that begin with 'B' represent infected places.

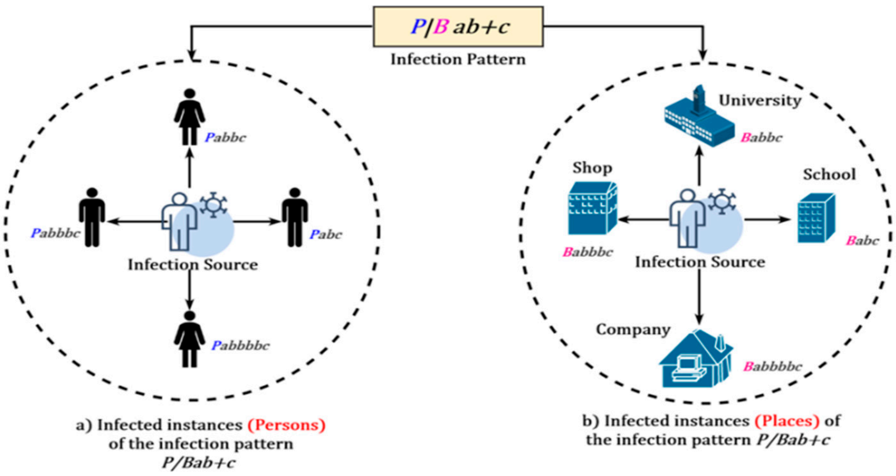

Figure 2. A proposed model representing the infection patterns and the corresponding infection. Instances using the regular expression technique: (**a**) infected persons and (**b**) infected buildings.

The confirmed cases of COVID-19 can be stored in the blockchain as a sequence of secured blocks. These blocks can be created according to the following steps:

- Step 0: The initial block, Block 0 (called a genesis block), is created by default to store the first confirmed COVID-19 cases that have been recognized in the pandemic. Each case is stored using a unique infection pattern (see Figure 2). The blockchain then asks the mass surveillance system to return the contacts, and infected places related to the detected confirmed cases within the last 14 days. The returned data is represented in a set of infection instances for each infection pattern stored in the genesis block.
- Step 1: The set of detected contacts and infected places (i.e., infection instances) are then encapsulated to store them in a new block. This block must be verified firstly by the blockchain administrator staff (called miners). The miners execute some verification trials according to the blockchain algorithm to obtain the valid block-hash code (BHC) as formulated in Equation (1):

$$\text{BHC} = \text{Hash}(\text{MR} + \text{P} + \text{IS Code}) \tag{1}$$

  where BHC is the block hash code, MR is the Merkle root value (i.e., a unique fingerprint for all inserted data into the block in the form of Merkle root code), P is the previous block's hash code, and IS Code is a random value representing an arbitrary value of an infection code (the infection code is a random value generated by the blockchain system to notify the contacts with the infection details by sending SMS messages to their P2P mobile apps contain the infection codes).
- Step 2: The IS Code (i.e., infection code) is then tested many times (one test for each code) by the miners to obtain the valid hash code of that block (i.e., BHC). The Miners repeat this process by trying new infection codes—many times until they obtain the IS Code that meets the target block hash code BHC.
- Step 3: Once a specific miner has succeeded in obtaining the valid block's hash code (i.e., BHC), he broadcasts this block and its hash code (BHC value) to the rest of the miners to verify its validity by performing a reverse hashing calculation as in Equation (2). If the remaining miners confirm the new block's validity, all peers will

be notified that a new block has been added to the blockchain. Then, the blockchain state is updated with the added block at all nodes in the network.

$$\text{IS Code} = \text{Hash}^{-1}(\text{MR} + \text{P} + \text{BHC}) \quad (2)$$

Figure 3 depicts how blockchain is constructed as a sequence of new hash blocks. Each block includes a new set of detected confirmed cases of COVID-19. Each block is specified using the Merkle root (MR), previous block hash code (P), IS-Code, and the block hash code (BHC).

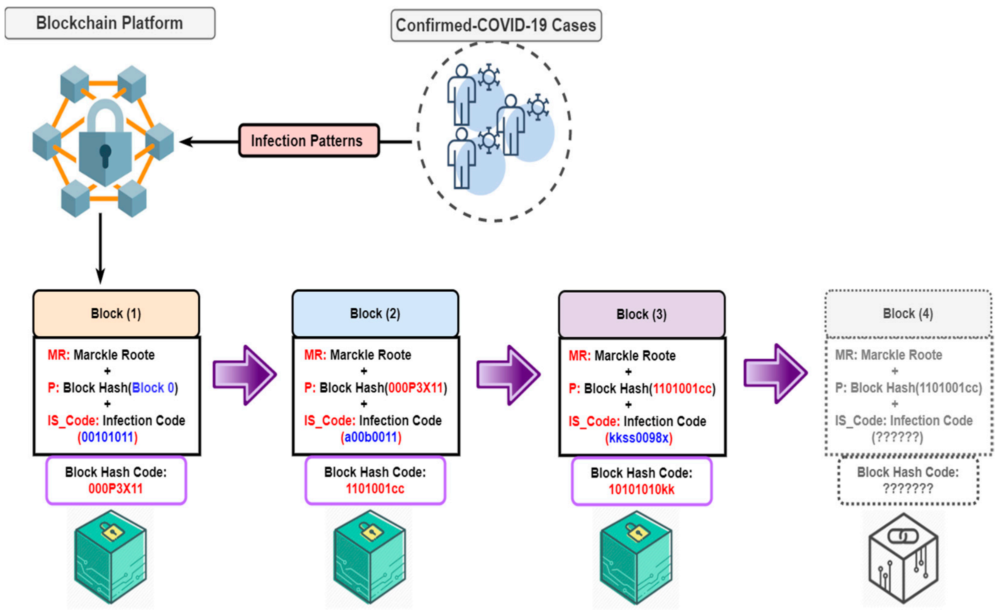

Figure 3. A proposed model of the blockchain as a sequence of blocks. Each block contains an identified number of confirmed COVID-19 cases.

3.2. Mass Surveillance System

The second component in the proposed CCTS is the mass surveillance subsystem. This subsystem can be used to track all citizens' behavior and motion patterns by installing many nodes of the mass surveillance system in all cities, streets, and public places, as depicted in Figure 4. It can be utilized to detect, track, and monitor whether contacts are responding to the blockchain instructions. This can be achieved by performing two essential functions:

(1) *Detecting and tracking function:* This function can be invoked by the mass surveillance subsystem to track the behaviors of the confirmed COVID-19 cases stored in the blockchain during the last 14 days. Therefore, this function can monitor and detect the nearby contacts and the set of infected places that COVID-19 patients accessed.
(2) *Blockchain feedback function:* The mass surveillance system invokes sending the detected set of contacts and infected places to the blockchain (i.e., tracking results). Then, the blockchain engine digitizes the received set in the form of infection instances encapsulated as a new block after verifying its validity by the set of miners.

Figure 5 depicts how the mass surveillance subsystem operates based on the two functions for recognizing the contacts and infected places based on an oriented blockchain request. Blockchain instructs the mass surveillance subsystem to find the contacts and infected places of a specific confirmed COVID-19 case. The mass surveillance subsystem translates this input data into a tracking order forwarded to the detecting and tracking function to process it. After finding the contact persons and infected places within the last 14 days, the tracking results are sent to the blockchain feedback function that translates it as a set of detected infection instances (i.e., contacts and infected places) and forwards them to store them in the blockchain as new probable cases of COVID-19.

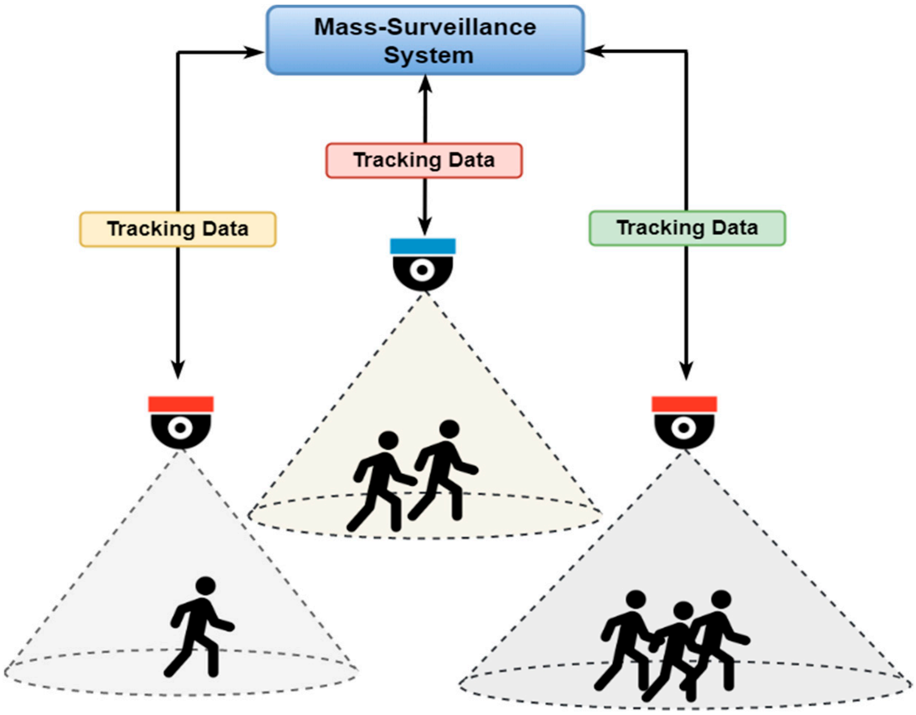

Figure 4. A proposed model of the mass surveillance system.

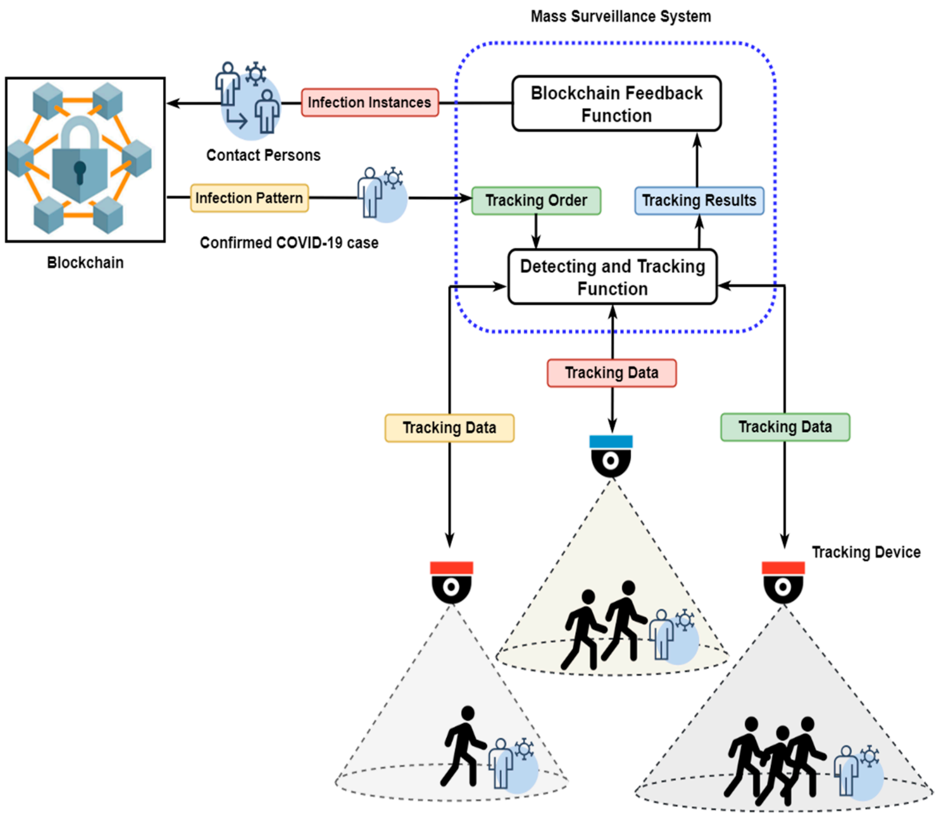

Figure 5. A proposed model of the mass surveillance subsystem functionality for recognizing the contacts relative to confirmed COVID-19 cases stored in the blockchain.

3.3. Infection Verifier Subsystem

Verifying the infection instances to confirm infection transfer from a confirmed COVID-19 case to a contact is an important requirement of the proposed system, CCTS. This requirement can be implemented by a finite automaton model, the best recognition verification technique for recognizing patterns. A unique finite automata model is responsible for verifying all infection instances derived from the corresponding infection pattern (i.e., confirmed COVID-19 case) stored in the blockchain. When new contacts are recognized as new COVID-19 cases, the blockchain engine sends a notification message (i.e., SMS). This message contains an infection code that a person can input to the infection verifier subsystem to verify his infection. If the infection verifier accepts the infection code entered by a person, this person has a high infection probability with COVID-19. Figure 6 shows how the infection verifier recognizes the infected instances (i.e., unknown infected contacts and places) that correspond to the infection pattern, (0* | 1*) 0 (1* | 0) 1 using a finite automata model.

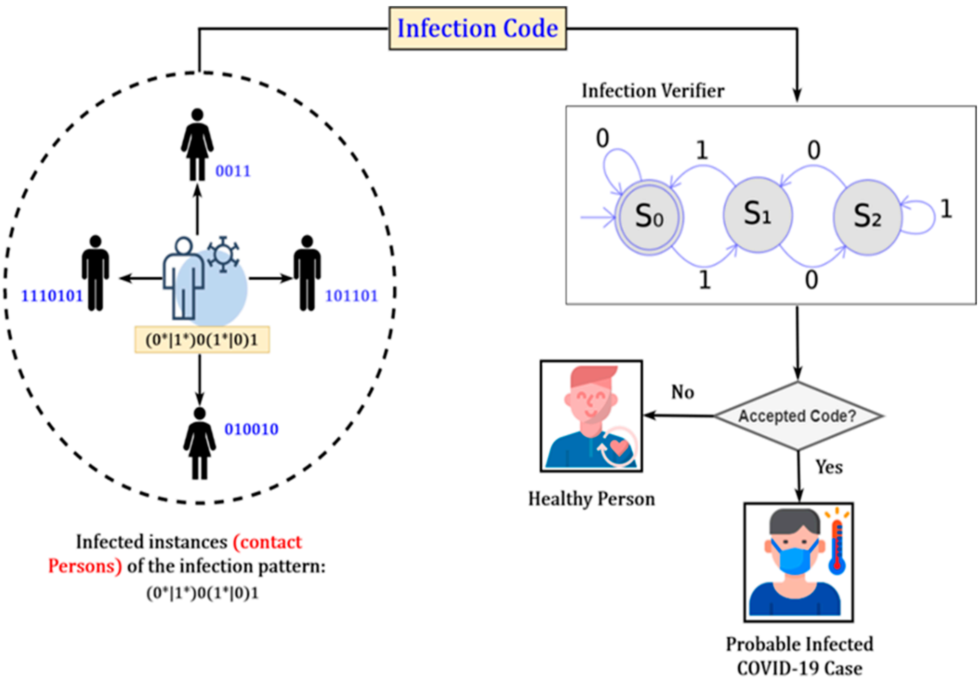

Figure 6. Proposed model of the COVID-19 infection verifier subsystem.

Two advantages of verifying the COVID-19 infections based on the infection code are:

(1) A specific person can verify his infection by themselves using an infection verification model implemented in the system's back end.

(2) The infection codes used in P2P communications among all citizens using the P2P-mobile application subsystem are used to identify the probably infected persons and estimate the infection probabilities of others.

3.4. P2P Mobile Application

The P2P mobile application is utilized in the proposed CCTS to work as the front end of this system. The novel design of the P2P-mobile app can provide the citizens with two significant services:

(1) *Self-estimation of infection probability*: This service enables persons to evaluate their COVID-19 infection probability by themselves digitally. This objective can be achieved by built-in communication between P2P mobile applications, the blockchain platform, the mass surveillance subsystem, and the infection verifier subsystem. The process of how a person can digitally evaluate the infection probability is depicted in Figure 7.

When a newly confirmed COVID-19 case is registered as a new infection pattern in the blockchain, the mass-surveillance subsystem detects all the corresponding infection instances (i.e., contacts), and the blockchain platform sends streams of infection codes (in the form of SMS messages) to all detected persons (i.e., contacts). Using the P2P mobile application, each person may receive many infection codes in his inbox from the blockchain. The person can verify these codes by the automated connection with the infection verifier subsystem. If it accepts the infection code, this means that the person has a high infection probability, and the Infection verifier returns detailed information about the infection (i.e., date and time, location, source of infection, etc.) to the user. This scenario is executed through the hidden communication between the mass surveillance and the infection verifier subsystem. Using the P2P-Mobile App, each person may receive many infection codes in their inbox from the blockchain. The more infection codes they receive, the more COVID-19 cases they have contracted with. For example, if they receive 10 infection codes in their inbox, this means that 10 confirmed COVID-19 cases have probably infected them. Using this feature of the P2P mobile application, the infection probability of each user can be estimated automatically using the binomial distribution function. This technique specifies the number of times (x) that an event occurs in independent trials, where p is the probability of occurring in a single trial. Hence, the binomial distribution function is an appropriate technique that can be used to estimate the infection probability as formulated in Equation (3):

$$\mathrm{P(X)} = \frac{\mathrm{N!}}{\mathrm{X!} \times (\mathrm{N}-\mathrm{X})!} \times \mathrm{P^X} \times \mathrm{Q^{N-X}} \tag{3}$$

where, $\mathrm{P(X)}$ is the infection probability function, and N is the total number of infection codes in the inbox of each user. X is the number of infections that occur, where $\mathrm{X} = 0, 1, 2, 3, \ldots\ldots \mathrm{N}$. $\mathrm{P^X}$ is the probability of successful infection occurrences, and $\mathrm{Q^{N-X}}$ is the probability of unsuccessful infection occurrences.

(2) *Detection of newly infected cases within a crowd*: The peer-to-peer communication of the P2P mobile app with the back-end subsystems can also enable persons to detect and predict newly infected cases within crowded regions. This goal can be achieved by exchanging the infection probability rates between persons using the P2P mobile app. In other words, when a user enters a crowded area of people, or a specific person is close to him, his P2P mobile App will automatically receive a set of warning messages from the set of all nearby person(s). The received warning messages contain the infection probability percentages of all nearby persons in the same domain. In this way, a person can check all received warning messages (i.e., infection probability rates) and use his P2P mobile app to arrange them according to the highest infection probability rate automatically. Hence, the person can take the required precautions against highly probable infected cases detected in the same domain. This scenario is depicted in Figure 8 that explains how users can detect probable infected cases within a crowded area of people using his P2P mobile application through hidden communication established with the blockchain system.

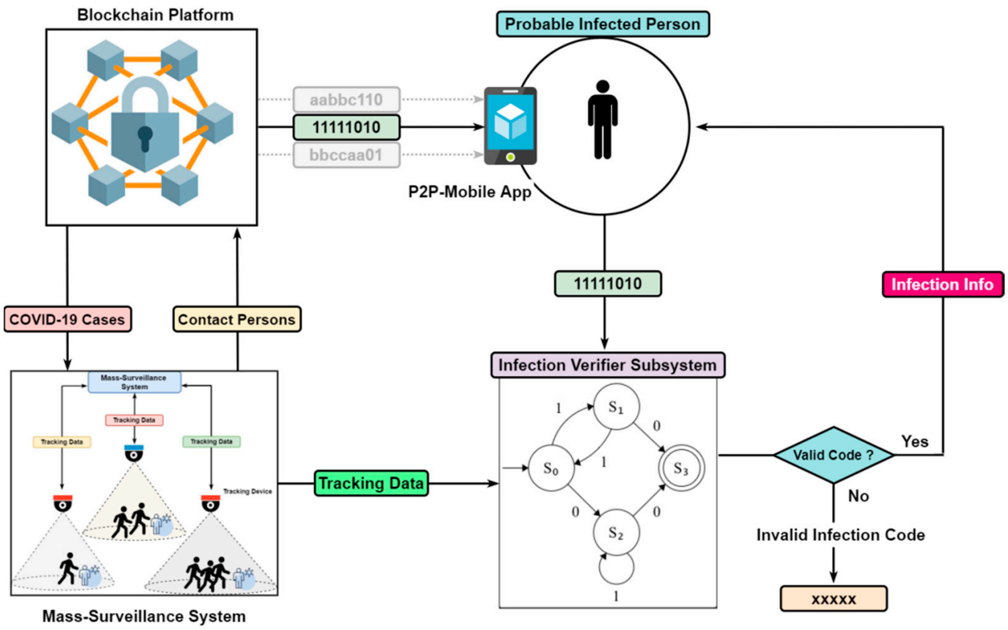

Figure 7. A proposed model depicting the self-infection verification process using a P2P mobile application.

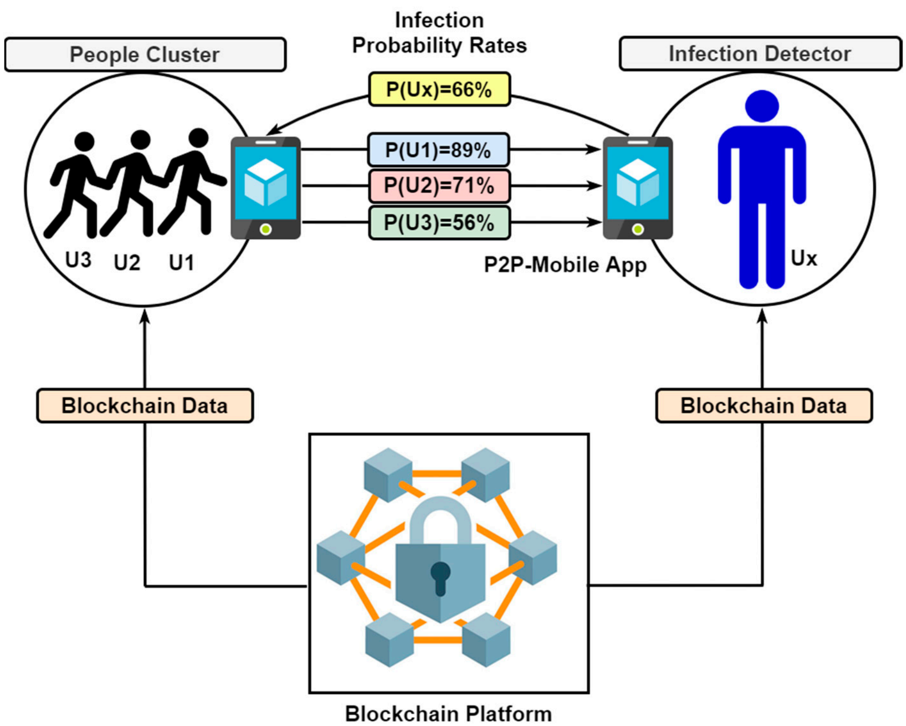

Figure 8. A proposed model depicting the detection of probable COVID-19 cases within a cluster of people.

4. CCTS Implementation

To implement the proposed CCTS subsystems, we use various software tools:

(1) Ethereum is used for developing the blockchain subsystem in the proposed CCTS. Ethereum is an open-source, globally decentralized blockchain computing platform that can implement and execute programs in smart contracts. It uses blockchain to store and synchronize the system's state changes (i.e., blocks), along with a cryptocurrency called ether. The main advantages of Ethereum are that it enables developers to

build powerful blockchain applications with high availability, suitability, neutrality, transparency, and security.

(2) Java and Firebase were used to develop the P2P mobile App and store and sync COVID-19 data between different users in real-time. Firebase is Google's mobile platform that helps developers quickly develop high-quality apps and grow their business. The main advantages of using the Firebase tool are its ability to implement server-side apps, save/read files to/from the cloud, secure data, build big databases, and send notifications and alerts in real-time communication.

(3) Python and Mongo DB were used for simulating COVID-19 data and analyzing GPS data.

Figure 9 shows three screens of the main interface of the developed P2P mobile app. The Home screen in Figure 9b prompts the user with real-time COVID-19 spread status statistics. The Inbox screen in Figure 9c prompts the user to list all received infection codes used to estimate the infection probability. The Alerts screen in Figure 9e alerts the user with infection probability values of the nearby persons in the same area where the user is found. This screen prompts the user with four types of information, the identity of the nearby infected persons in the same area (e.g., national ID, personal photo, address, phone number, etc.), their infection probability, and a GPS map of the place of infection with dots representing the infected persons in the same area. The Infection Detail screen in Figure 9f prompts the user with all the information and details of infection, such as the source of infection, date, and place of infection on a GPS map.

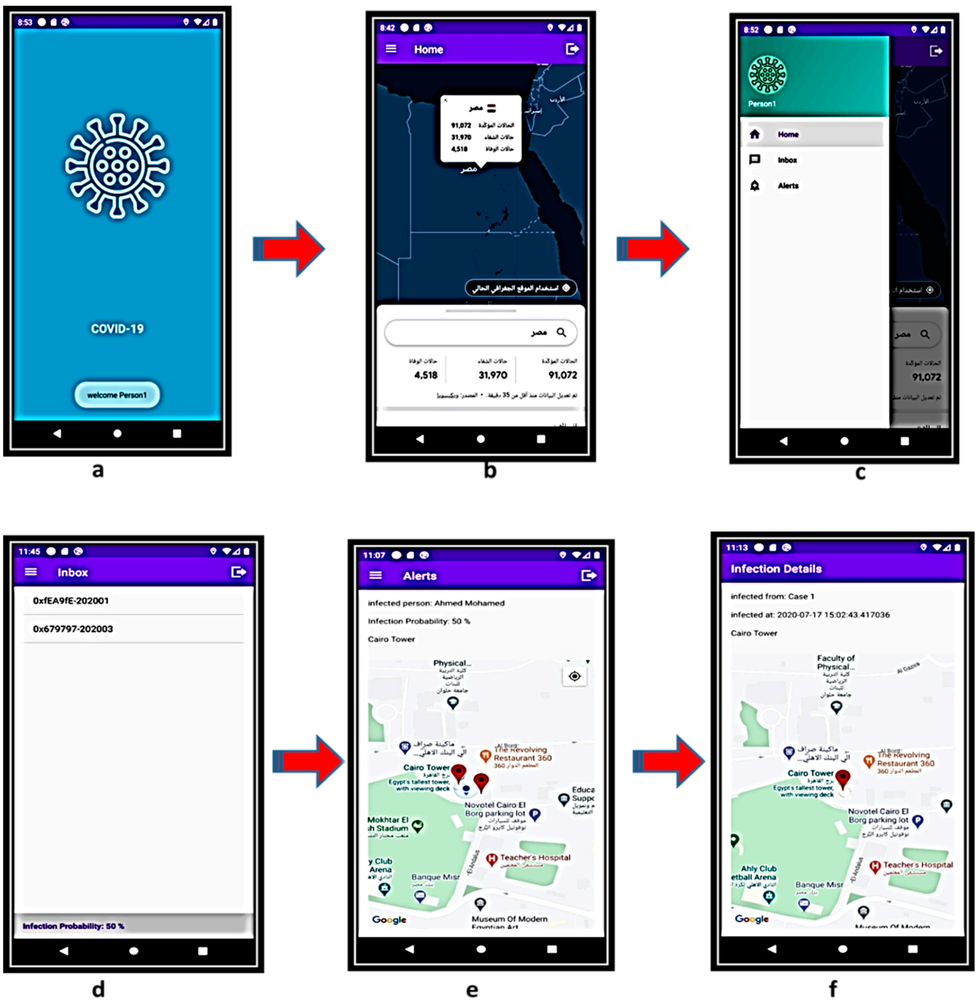

Figure 9. A COVID-19 contact tracing system (CCTS) app: (**a**) Open screen, (**b**) Home screen, (**c**) Menu screen, (**d**) Inbox screen, (**e**) Alerts screen, and (**f**) Infection Details screen.

5. Evaluation and Experimental Results

To evaluate the efficiency of the proposed system, CTSS, we simulated its functionality on a created dataset consisting of 300 cases labeled as confirmed COVID-19 cases and 300 cases labeled as contacts (without consideration of contact duplication). Each confirmed case has a different set of contacts who were met in the last 14 days. Therefore, the total number of contacts is 2539 (with consideration of contact duplication). We had to use created data because we could not find a benchmark dataset suitable for the functionality of the proposed system. The created dataset involves 300 confirmed cases of COVID-19, which have been organized into 10 Excel sheets. Each sheet involves 30 cases. The rows represent the number of contacts for each confirmed case of COVID-19, and the column represents the set of confirmed cases for each contact person. Cell values represent a specific person's infection day within the last 14 days (all values are between 1 to 14). For example, Case ij = 10 means that the confirmed case i has met the contact person j on the 10th day within the last 14 days. Also, there is a location history for each person to track infection among all users. The set of contacts and their location history data are presented in two excel files: dataset and location history.

The performance of the proposed system was evaluated against a set of metrics that measure the efficiency of the proposed CCTS in recognizing the unknown infected COVID-19 cases and estimating persons' infection probabilities. The selected metrics depend on a set of variables, true positive (TP), true negative (TN), false positive (FP), and false-negative (FN). According to the results obtained for these variables, the evaluation metrics of CCTS can be calculated as depicted in Equations (4)–(12). These metrics evaluate the recall (or sensitivity), precision, specificity, negative predictive value (NPV), false-negative rate (FNR), false-positive rate (FPR), false discovery rate (FDR), accuracy, and F1-score, respectively.

$$\text{Recall (TPR)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5}$$

$$\text{Specificity (TNR)} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{6}$$

$$\text{NPV} = \frac{\text{TN}}{\text{TN} + \text{FN}} \tag{7}$$

$$\text{FNR} = \frac{\text{FN}}{\text{FN} + \text{TP}} \tag{8}$$

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} \tag{9}$$

$$\text{FDR} = \frac{\text{FP}}{\text{FP} + \text{TP}} \tag{10}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{11}$$

$$\text{F1} - \text{Score} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}} \tag{12}$$

5.1. Results of Detecting Contacts within a 2 m^2 Area of Infection by GPS

After simulating the proposed CCTS's functionality on 2539 contacts distributed evenly across each confirmed COVID-19-case, each confirmed case has n contact persons within a 2 m^2 area covered by the GPS. Table 1 presents the evaluation results of calculating the metrics formulated in Equations (4)–(12). These results are calculated for the first 150 contacts portioned into five groups of confirmed cases (i.e., from Case 1 to Case 150). Table 2 presents the simulation results of the second 150 contacts distributed across another five groups of confirmed cases (i.e., from Case 151 to Case 300). Table 3 summarizes the averages of the obtained results of simulating the proposed CCTS on all contacts.

Table 1. Evaluation results of simulating the CCTS to detect the first 150 contacts within a 2 m^2 area of infection by GPS according to five groups of confirmed cases: Cases 1–150.

	Cases 1–30	Cases 31–60	Cases 61–90	Cases 91–120	Cases 121–150
#Contacts	140	192	228	247	240
TP	83	102	110	124	124
FP	0	0	0	0	0
TN	0	0	0	0	0
FN	57	90	109	123	116
Recall (TPR)	0.574219577	0.53771164	0.515137085	0.511530229	0.523119288
Precision	0.933333333	0.966666667	0.966666667	1	1
Specificity (TNR)	0	0	0	0	0
NPV	0	0	0	0	0
FNR	0.425780423	0.46228836	0.484862915	0.488469771	0.476880712
FPR	0	0	0	0	0
FDR	0	0	0	0	0
F1-Score	0.69262506	0.678011803	0.66355998	0.666114028	0.668974179
Accuracy	0.574219577	0.53771164	0.515137085	0.511530229	0.523119288

Table 2. Evaluation results of simulating the CCTS to detect the second 150 contacts within a 2 m^2 area of infection by GPS according to five groups of confirmed cases: Cases 151–300.

	Cases 151–180	Cases 181–210	Cases 211–240	Cases 241–270	Cases 271–300
#Contacts	270	299	299	311	313
TP	140	157	146	155	156
FP	0	0	0	0	0
TN	0	0	0	0	0
FN	130	142	153	156	157
Recall (TPR)	0.516268639	0.522883043	0.491568154	0.505067988	0.501076794
Precision	1	1	1	1	1
Specificity(TNR)	0	0	0	0	0
NPV	0	0	0	0	0
FNR	0.483731361	0.477116957	0.508431846	0.494932012	0.498923206
FPR	0	0	0	0	0
FDR	0	0	0	0	0
F1-Score	0.666292581	0.66641158	0.641815703	0.660956388	0.648153216
Accuracy	0.516268639	0.522883043	0.491568154	0.505067988	0.501076794

Table 3. Results summary of simulating the proposed CCTS on the used data set within A 2 m^2 area of infection by GPS.

Metrics	Cases 1–300
#Contacts	2539 (repeated cases are considered)
SUM(TP)	1306
SUM (FP)	0
SUM (TN)	0
SUM (FN)	1233
AVG (TPR)	0.519858244
AVG(Precision)	0.986666667
AVG (TNR)	0
AVG (NPV)	0
AVG (FNR)	0.480141756
AVG (FPR)	0
AVG (FDR)	0
AVG (F1-Score)	0.665291452
AVG(Accuracy)	0.519858244

5.2. Results of Detecting Contacts within a 5 m^2 Area of Infection by GPS

To improve the detection of the set of contacts for each confirmed COVID-19 case, we updated the GPS settings in the proposed CCTS to cover a 5 m^2 area of search instead of only 2 m^2. Then the simulation process is repeated with the same dataset. The goal of this update is to increase the TP and decrease the FN of the proposed system. This will lead to more efficiency and accuracy in detecting the set of contacts within a contagion region of COVID-19. Table 4 presents the simulation results of the second round of the experiment for detecting the first 150 contacts (i.e., Cases 1–150) within a 5 m^2 area by GPS. Similarly, Table 5 shows the simulation results of detecting the second 150 contacts (i.e., Cases 151–300). Table 6 summarizes the averages of the obtained results of simulating the proposed CCTS on the total contacts in the dataset within a 5 m^2 area by GPS. Figure 10 compares the recall, precision, F1-score, and accuracy of the proposed CCTS when simulated within a 2 m^2 area and a 5 m^2 area of infection by GPS.

Table 4. Second round of the experiment. Evaluation results of simulating the CCTS to detect the first 150 contacts within a 5 m^2 area of infection by GPS according to the five groups of confirmed cases: cases 1–150.

	Cases 1–30	**Cases 31–60**	**Cases 61–90**	**Cases 91–120**	**Cases 121–150**
#Contacts	140	192	228	247	241
TP	140	192	228	247	241
FP	0	0	0	0	0
TN	0	0	0	0	0
FN	0	0	0	0	0
Recall (TPR)	1	1	1	1	1
Precision	1	1	1	1	1
Specificity (TNR)	0	0	0	0	0
NPV	0	0	0	0	0
FNR	0	0	0	0	0
FPR	0	0	0	0	0
FDR	0	0	0	0	0
F1-Score	1	1	1	1	1
Accuracy	1	1	1	1	1

Table 5. Second round of the experiment. Evaluation results of simulating the CCTS to detect the second 150 contacts within a 5 m^2 area of infection by GPS according to the five groups of confirmed cases: cases 151–300.

	Cases 151–180	**Cases 181–210**	**Cases 211–240**	**Cases 241–270**	**Cases 271–300**
#Contacts	270	300	299	311	313
TP	270	300	299	311	313
FP	2	3	3	0	1
TN	0	0	0	0	0
FN	0	0	0	0	0
Recall (TPR)	1	1	1	1	1
Precision	0.994444444	0.991841492	0.992024642	1	0.997222222
Specificity(TNR)	0	0	0	0	0
NPV	0	0	0	0	0
FNR	0	0	0	0	0
FPR	0	0	0	0	0
FDR	0.005555556	0.008158508	0.007975358	0	0.002777778
F1-Score	0.996969697	0.995634921	0.995844797	1	0.998550725
Accuracy	0.994444444	0.991841492	0.992024642	1	0.997222222

Table 6. Results summary of simulating the proposed CCTS on the used dataset within a 5 m^2 area of infection by GPS.

Metrics	Cases 1–300
#Contacts	2539 (repeated cases are considered)
SUM(TP)	1800
SUM (FP)	9
SUM (TN)	0
SUM (FN)	0
AVG (TPR)	1.0
AVG(Precision)	0.995952381
AVG (TNR)	0
AVG (NPV)	0
AVG (FNR)	0
AVG (FPR)	0
AVG (FDR)	0.004047619
AVG (F1-Score)	0.997765568
AVG(Accuracy)	**0.995952381**

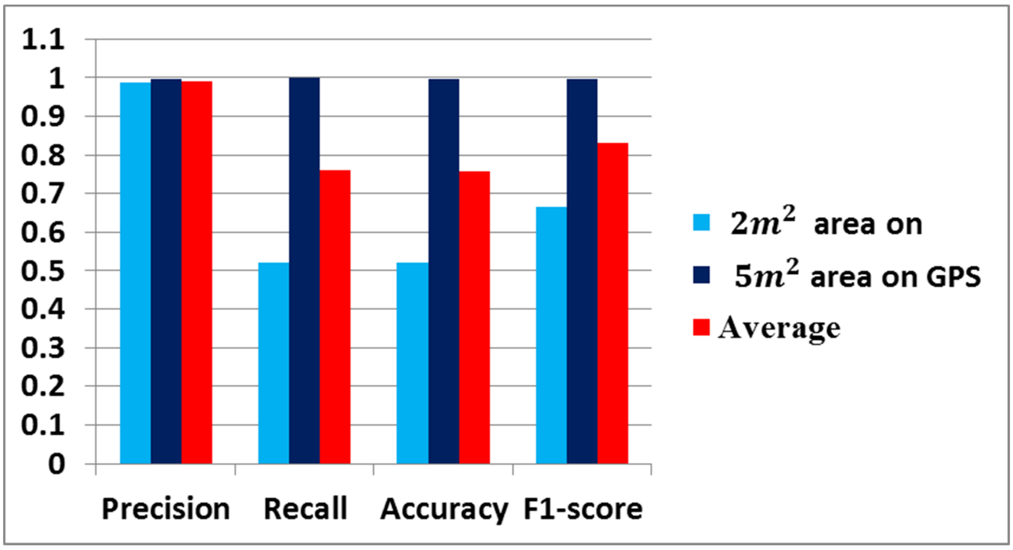

Figure 10. Comparison result of precision, recall, accuracy, and F1-score of the proposed CCTS in recognizing the contacts of COVID-19 within a 2 m^2 area and a 5 m^2 area of infection by GPS.

5.3. Infection Probability Evaluation of Contacts

One of the interesting features of the proposed CCTS is its ability to automatically evaluate the infection probability of a contact covered by the GPS in an infected area. Figures 11–20 depict the average infection probability of 300 contacts according to the detected number of confirmed cases of COVID-19 existing around each person within the last 14 days. The 300 contacts are divided into ten groups, and each group has 30 persons in the dataset.

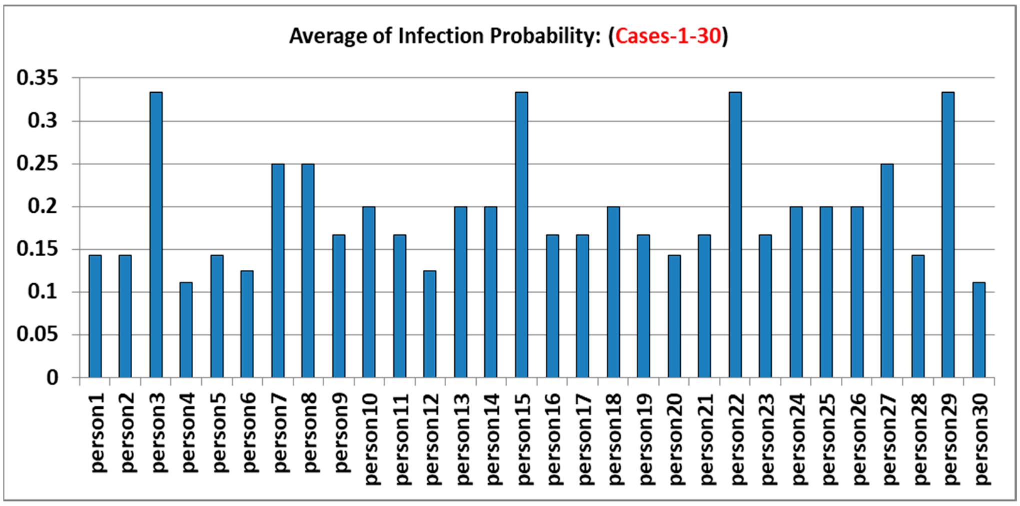

Figure 11. Results of estimating the infection probability of contacts 1–30.

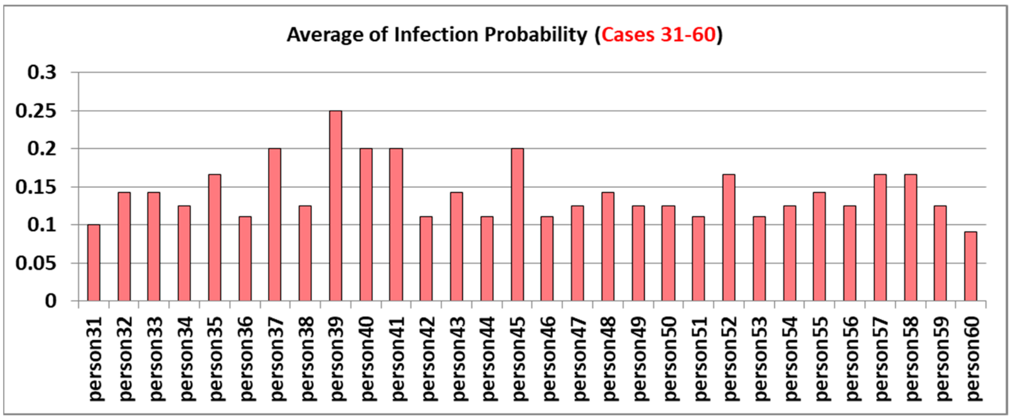

Figure 12. Results of estimating the infection probability of contacts 31–60.

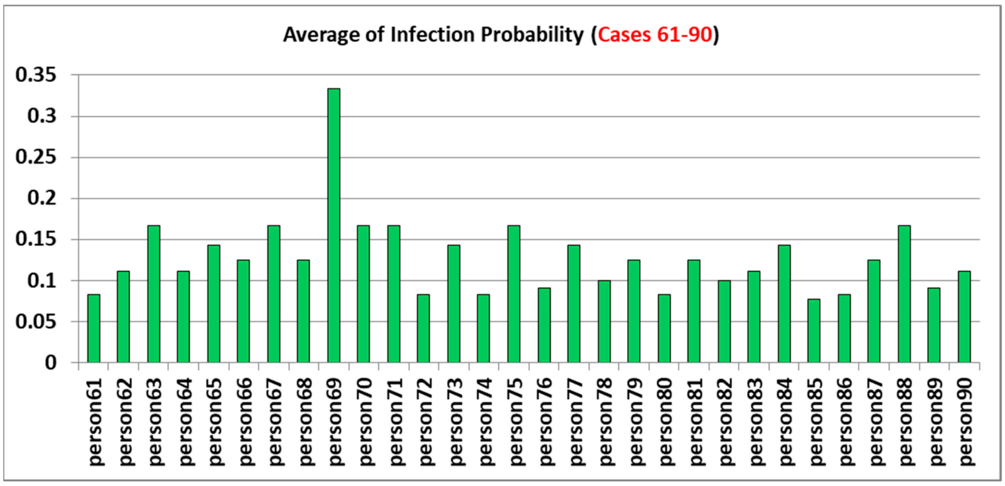

Figure 13. Results of estimating the infection probability of contacts 61–90.

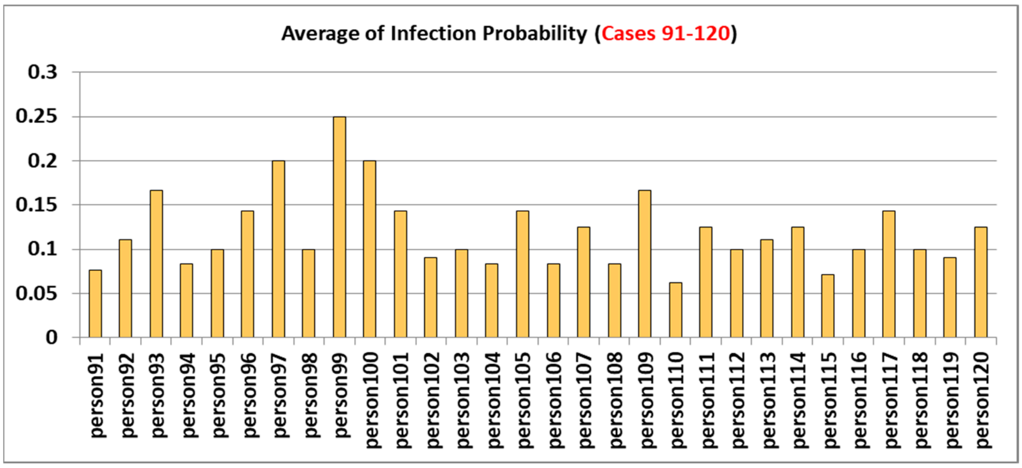

Figure 14. Results of estimating the infection probability of contacts 91–120.

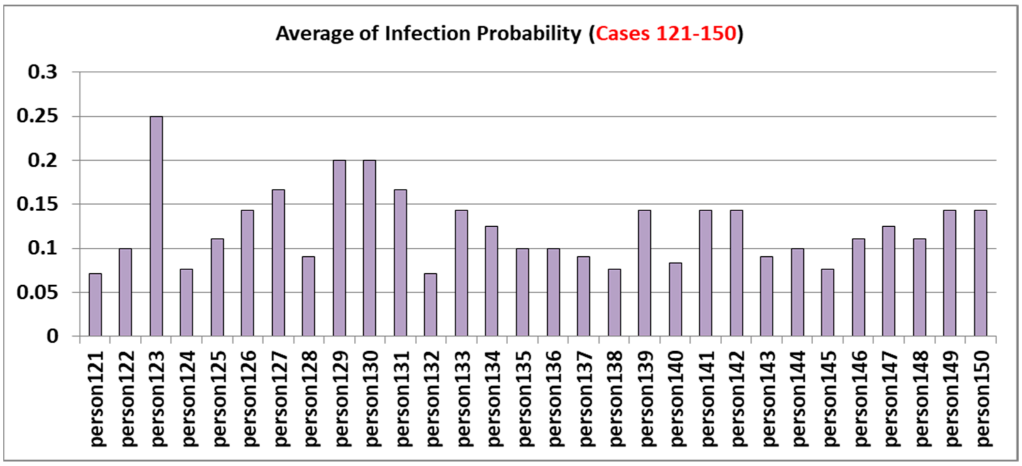

Figure 15. Results of estimating the infection probability of contacts 121–150.

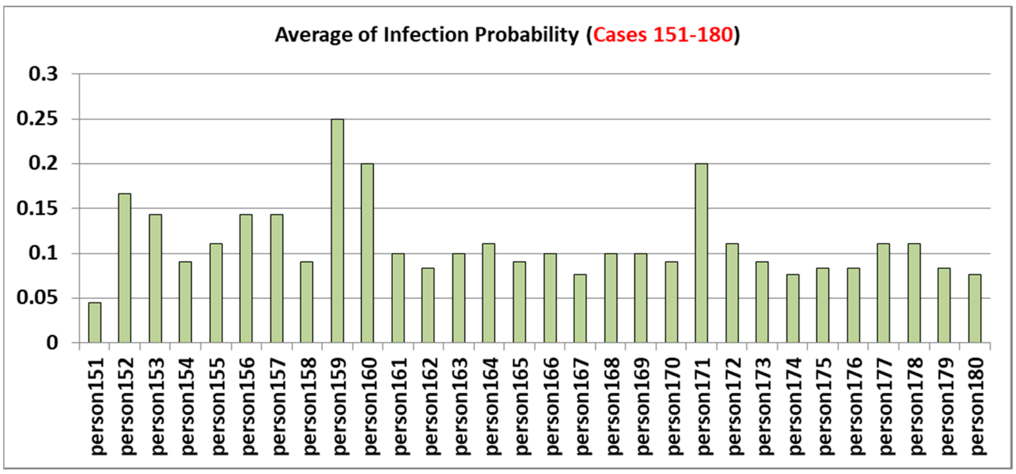

Figure 16. Results of estimating the infection probability of contacts 151–180.

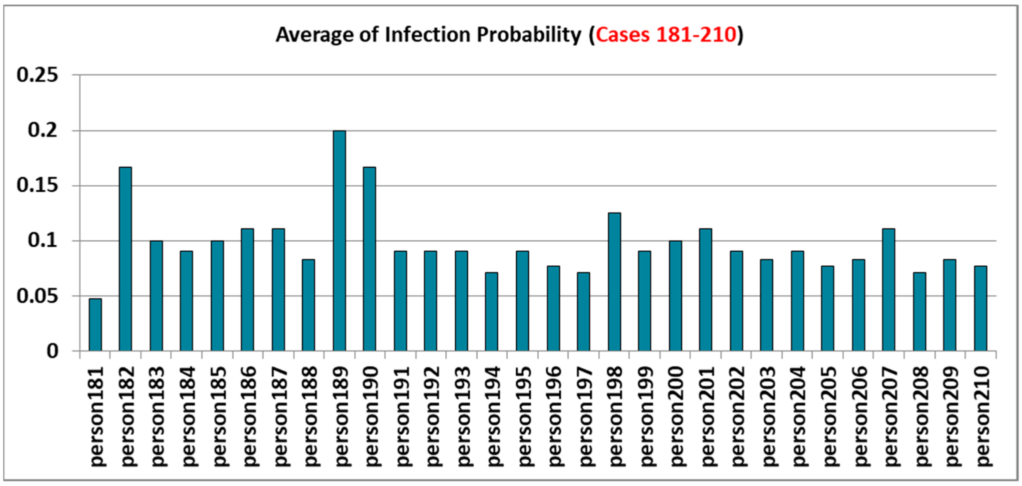

Figure 17. Results of estimating the infection probability of contacts 181–210.

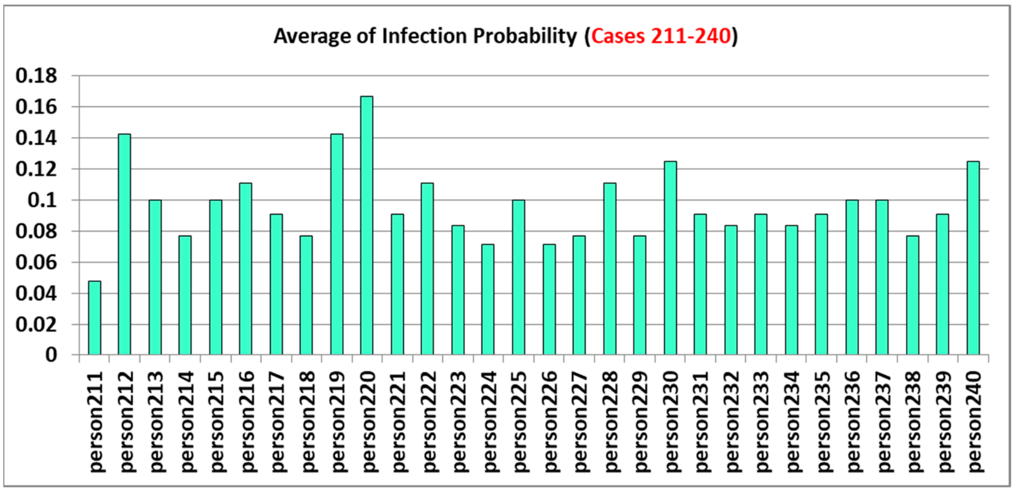

Figure 18. Results of estimating the infection probability of contacts 211–240.

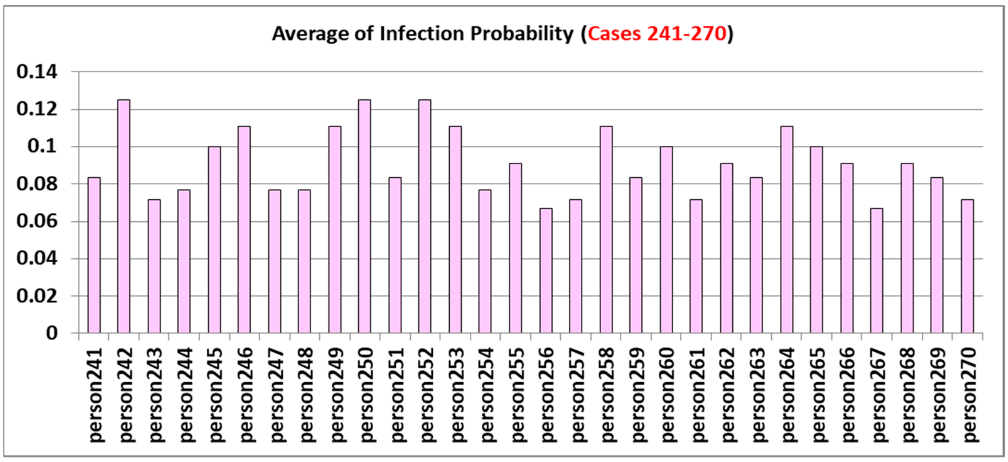

Figure 19. Results of estimating the infection probability of contacts 241–270.

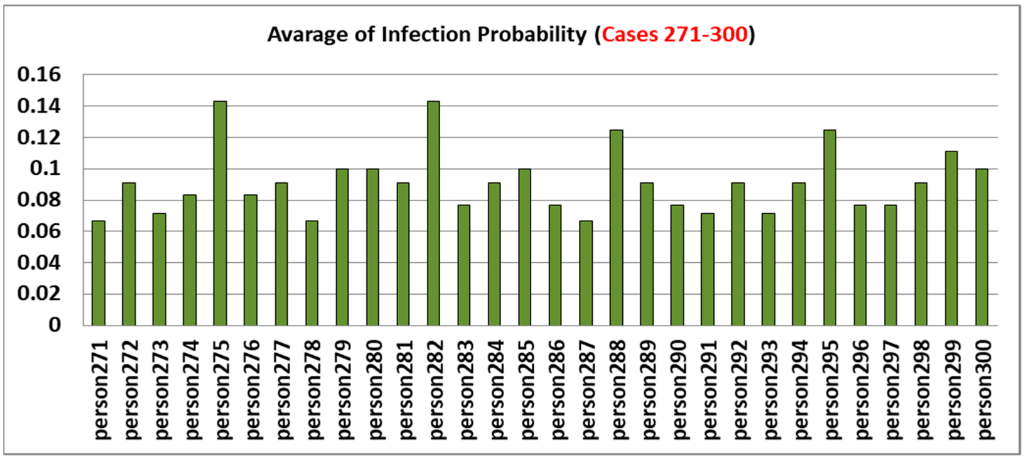

Figure 20. Results of estimating the infection probability of contacts 271–300.

6. Discussion

Prior work has studied the importance of detecting and tracking the infected COVID-19 pandemic cases based on developing mobile application systems. However, these studies did not introduce a complete and mature solution to solve this problem effectively and completely [33–38,41].

Moreover, those studies investigated the possibility of using Bluetooth technology to develop mobile applications able to detect and track COVID-19 cases. However, Bluetooth technology has many weaknesses regarding communication efficiency and security, as mentioned previously in the introduction. Moreover, very little was found in the literature on the question of utilizing blockchain technology to develop new mobile applications able to solve the COVID-19 contact tracing problem better than Bluetooth-based applications [41]. The present study was designed to investigate the feasibility of utilizing blockchain technology to develop a blockchain-based system called COVID-19 Contact Tracing System (CCTS) to detect and track cases of COVID-19 and their contacts. The CCTS consists of four subsystems, a blockchain platform, a mass surveillance subsystem, an infection verifier subsystem, and a P2P mobile application. The four subsystems work together in a coherent and automated way to detect and track cases of the COVID-19 pandemic within an infection region covered by GPS. The major contributions of the proposed CCTS can be categorized as follows:

(1) Enabling self-estimation of COVID-19 infection probability by end-users using a mobile app
(2) Detecting and tracking the unknown cases of COVID-19
(3) Sending and receiving infection alerts among users in P2P communications within crowds for avoiding infection occurrences.

At the decision support level, the proposed system can assist governments and health authorities in making critical decisions based on transparent data provided by the blockchain, such as infection dynamics, infection statistics, and infection growth. The communication between the blockchain and mass surveillance systems results in new infection data of new unknown cases of COVID-19, which are then registered in the blockchain. Moreover, P2P communication established between the blockchain and P2P mobile apps will enable citizens to send and receive messages in the form of infection alerts using their mobile apps. In addition, users can automatically calculate and estimate their infection probability through P2P communication conducted between the P2P mobile apps and the infection verifier system.

The current study found that the proposed CCTS achieved satisfying results when simulating its functionality within a 2 m^2 area of infection covered by GPS, and achieved optimal results when simulated within a 5 m^2 area of infection covered by the GPS, as depicted in Figure 10. This result means that the proposed CCTS achieved greater accuracy, sensitivity, and precision in recognizing the contacts of a COVID-19 case within a 5 m^2 area of infection covered by GPS than a 2 m^2 area.

This also demonstrates that the detection and tracking functions of the proposed CCTS work better within wide areas than they do in narrow ones, based on GPS coverage. However, in general, the proposed CCTS achieved an accuracy of 75.7% in recognizing contacts who are predicted to be infected with COVID-19.

It is also important to demonstrate that, in the two simulation rounds we executed, we observed a clear difference in detecting contacts of COVID-19 within two GPS areas. The results proved that the wider the GPS area is, the more accurate CCTS is in detecting contacts of COVID-19. Therefore, the CCTS achieved good results in detecting contacts of COVID-19 within a 5 m^2 area a 2 m^2 area of infection covered by GPS. This suggests that the proposed CCTS needs more investigation with additional simulation experiments within more areas of infections covered by GPS. This will lead to more data about the system's accuracy in recognizing contacts of COVID-19 in different situations.

Another interesting finding is the effectiveness of the proposed CCTS in enabling the individuals to automatically make a self-estimation of the infection probability based on the number of infection codes received in the inbox of their P2P mobile app. Moreover, it can exchange infection alerts between persons close to each other within a GPS area. Therefore, the results presented in Figures 11–20 show the calculation of the average of infection probability $P(X)$ (see Equation (3)) of the 300 cases of contacts based on the number of infection codes received in their mobile app's inbox. For example, in Figure 20, contact #300 has an average infection probability of 10%. This result is calculated based on nine infection codes received in his/her mobile app's inbox. Hence, the CCTS automatically applies the infection probability formula in Equation (3) and then calculates the average of infection probability based on the number of infection codes, N, as in Equation (13). This means that the CCTS calculates the average value of $P(0)$, $P(1)$, $P(2) -$ to $P(9)$ that equates to 10%. Similarly, the average infection probability of the other contacts in the dataset has been calculated as in Equation (13):

$$\mathrm{AVG}(\mathrm{P}(\mathrm{x})) = \sum_{\mathrm{x}=0}^{\mathrm{x}=\mathrm{N}} \frac{\mathrm{P}(\mathrm{x_i})}{\mathrm{N}} \tag{13}$$

These findings broadly support the work of other studies [33–38] in developing mobile applications that can assist governments and health authorities in detecting and tracking cases of the COVID-19 pandemic. On the other hand, this study may be considered the first work that depends on blockchain technology for solving this problem in a complete and mature scheme. Table 7 compares the proposed CCTS and other competitive applications in the literature.

According to these findings, we can infer that the proposed CCTS is a promising blockchain-based system to fight against the COVID-19 pandemic and other coming outbreaks.

On the other hand, we have to clarify that the proposed system, CCTS has been simulated in-house and has not been certified and deployed to be available with all citizens and decision-makers. Therefore, these findings must be interpreted with caution because they depend on the blockchain network configuration, Wi-Fi communications, mass surveillance systems configuration, and the accuracy of GPS coverage to specific areas of crowds of people. Moreover, it is important to bear in mind the privacy preservation challenge as the motion of citizens is hypothesized to be monitored by a surveillance system and this requires configuring the mass surveillance systems with security and encryption constraints [43].

Despite the mentioned limitations, we can say that the proposed system is expected to be a promising technique to assist governments, health authorities, and citizens to make critical decisions regarding infection detection, prediction, tracking, and avoidance of COVID-19 outbreaks. Moreover, the system can be enhanced to serve additional participants and medical stakeholders if it is augmented with additional technologies such as artificial intelligence and the internet of things (IoT). In addition, since the proposed system is intended to serve the governments and health authorities, it is necessary to admit that it requires more improvements at the level of P2P communications and more dependence on, and utilization of, blockchain technology. However, with the entrance of industry 6-technologies, most countries recently sought to create more smart cities and hospitals that depend on emergent technologies such as AI, IoT, and blockchain technology. This will enhance the benefit opportunities of using the proposed CCTS at all levels.

Table 7. Comparison between the proposed system, CCTS, and other competitive mobile applications.

COVID-19 App	Technology	Function	Maturity Level	Results
Singapore TraceTogether [22]	Bluetooth	contact tracing using *blue trace protocol*	Launched app	**n/a**
Google/Apple Contact Tracing [36]	Bluetooth	contact tracing using *exposure notification technology*	Defined and designed app	**n/a**
UK NHS Contact Tracing [39]	Bluetooth	contact tracing using *self-reporting of symptoms*	Defined app	**n/a**
China Health Code System [40]	GPS/QR-Codes	contact tracing using *colored QR-codes*	Launched app	**n/a**
BeepTrace [41]	GPS, Bluetooth, Cellular, and WiFi	Privacy-preserving of contact tracing using *blockchain and PK encryption*	Theoretical framework	**n/a**
CCTS (The proposed system)	Blockchain/GPS/WiFi	contact tracing using: ▪ Blockchain ▪ Mass surveillance system *Regular expression and finite automata*	Defined, designed, imple mented, and tested App	**Precision = 99.13%** **Recall = 75.79** **F1-Score = 83.15%** **FDR = 0.004** **Accuracy = 75.79%**

7. Conclusions

The purpose of the current study was to investigate the effectiveness of utilizing blockchain technology to develop a new system able to fight against the spread of the COVID-19 pandemic. The study proposed a new system called the COVID-19 Contact Tracing System (CCTS) to address the COVID-19 contact tracing problem. The proposed CCTS can detect and track COVID-19 cases based on integrating four subsystems: a blockchain platform, a mass surveillance subsystem, an infection verifier subsystem, and a P2P mobile application, which work together in a coherent and automated way. The most prominent finding to emerge from this study is the ability of CCTS to recognize unknown cases of COVID-19 (i.e., contacts) with an accuracy of 75.79%, and a false discovery rate (FDR) of 0.004, which represent unique results compared to other systems in the literature.

The second interesting finding of this study is the success of the proposed CCTS in enabling individuals to perform self-estimation of infection probability and sending and receiving infection alerts through P2P communications within crowds of people to avoid the infection risk. The evidence from this study suggests that more blockchain-based applications can be developed to suppress the spread of epidemic diseases and early detection of unknown infected cases through a P2P mobile app.

Several questions remain to be answered regarding the proposed system. The system's functionality requires more simulation in different data patterns for achieving more accuracy in detecting contacts of COVID-19 within different GPS areas. Moreover, preserving people's privacy against mass surveillance subsystem cameras is a significant challenge. In addition, enhancing the CCTS's intelligence using deep learning techniques may increase the efficiency and accuracy in recognizing COVID-19-contacts. These issues will be investigated to produce the next version of this promising blockchain-based system in the future.

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Institutional Review Board Statement: The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Institutional Review Board.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Exclude this statement since the study is supported by a simulated and created dataset. We have not downloaded it from a specific URL.

Conflicts of Interest: The authors declare no conflict of interest.

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