CTChain: Blockchain Platform for Contact Tracing and Mapping Active Infections

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Abstract

Despite the effectiveness of social isolation and, in particular, contact tracing for infection management, there are a number of drawbacks, including that it is time-consuming, labor-intensive, and adhoc. Following the COVID-19 outbreak, a number of mobile technologies are emerging to combat the inefficiencies of human contact tracing. However, there is a lack of actual, transparent platform design, and the production of maps for active infection, particularly in the state-of-the-art Blockchain technology. In this paper we introduce CTChain, a blockchain-based tool that collects, organizes, and generates maps of active infections to assist public health officials in their work. Utilizing a hierarchical network architecture, a regional map for active infection is built by navigating via a cache memory-stored blockchain. Our architecture continuously filters out outdated infections to produce batches of the most pertinent dynamic regional data, which may be utilized to issue timely health recommendations and temporarily seal off high-infection areas. CTChain's platform can map the active infections across three different parameters: sparse vs densely populated region, number of people in each location, and initial infection rate. We can examine infection transmission and region "popularity" on a per-region basis because of our region handler capabilities. Due to the network's widespread storage of many copies of the chain, our model is safeguarded against single points of failure.

Key Words: Infection containment; blockchain; contact tracing; network design; client-server; active notification; *

1 Introduction

The health and welfare of the global population was severely debilitated with widespread pandemic outbreaks [37] especially due to COVID-19. It began with less than 30 active infections in Wuhan, China in late 2019 due to the new coronavirus SARS-CoV-2. Since then it has spread to 623 million people on a global basis, and 6.5 million have died as a result [7]. The World Health Organization (WHO) designated COVID-19 as a global public health emergency in January 2020, just a few months after the initial outbreak. Highly contagious diseases such as SARS-CoV-2 is typically spread through personal contact between an infected person and a healthy person [3]. According to several studies, the illness is also extremely contagious and can spread through airborne particles, which only accelerates its unchecked spread. Both symptomatic and asymptomatic infected individuals have the potential to spread the virus. According to one study done in Wuhan [26], the incubation period extends from one to fourteen days, therefore the only option to restrict the spread is to quarantine sick people to a single location during that period. Overall, the healthcare system across the entire world has been over-stretched beyond limits to address the extremely precarious aftermaths of the pandemic.

Many nations have implemented Non-Pharmaceutical Intervention (NPI) [19] to stop the spread of the virus in response to this unprecedented global disaster. These measures include closing offices and schools, and even enforcing countrywide lock-downs. Governments throughout the world have been enforcing several drastic measures to prevent any form of social interaction that limits the infection spread. To minimize human contact, complete worldwide lock-downs has been imposed that includes closing statewide and international borders, closing schools and universities, requesting that employees work from home, closing malls and markets, and suspending public gatherings. These preventative measures caused a downward spiralling effect on the economy, which has led to the search for better public health solutions. Health professionals, scientists, engineers, and administrators are compelled to design easy-to-adapt solutions as the entire world is struggling through this "new normal".

Popular NPI technique for social isolation technique called *contact tracing* seeks to locate and monitor individuals who have come in contact with another infected person. To break the chain of transmission, early screening, diagnosis, and treatment is administered to the identified close contacts. To relieve the severe social distancing limits explained earlier most countries have adopted this tracking approach. In particular, the experience in Hong Kong has shown that contact tracing can successfully prevent the spread of COVID-19 by lowering community transmission from undiagnosed cases [21]. However, typical manual contact tracing is completely dependent on one's memory of remembering and sorting the daily (infection) contacts, which can lead to inconsistent data reporting. Moreover, it does not scale effectively once the pandemic has progressed past its early stages owing to the limited number of employees necessary to carry out the operation. Therefore, designing an efficient and secure digital solution is essential for collecting and managing such high volume dynamic data. Using this information public health professionals can effectively handle active cases by

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avoiding crowded settings and socially isolating the patients. Additionally, the town/city/state administration can utilize this data to pinpoint the locations of current active infections and provide public advisories to combat false information.

In this paper, our main objective is to develop an end-to-end complete blockchain based solution that can collect, sort and generate active infection maps to support the work of health officials. Our solution is termed as ***CTChain: Contact Tracing Chain***, as it uses the inherent *Proof of Authority (PoA)* properties of blockchain to process the dynamic infection contact data. It uses several inbuilt smartphone technologies such as Bluetooth and Global Positioning Systems (GPS) to estimate the closeness and length of a person's exposure to others. The *hierarchical network architecture* comprises of three node types: client, hospital and city. The blocks from each node needs are validated by its parent-level as per inherent PoA characteristics. The regional map for active infection is built by traversing through the chain stored in cache memory pool at the hospital node. Our framework continually prunes the outdated infections to create batches of most relevant dynamic regional data, which can be used by health officials to issue timely health advisories.

We are evaluating capability of CTChain to effectively map the active infections across three different parameters: sparse vs densely populated region, number of people in each region, and initial infection rate. We use grid-view to present nine different combinations, which can be used by health officials to model potential scenarios and plan accordingly. We show concrete results that our platform can handle wide variation of infection rates ranging from mild to complex cases in sparsely and densely populated regions. Our 'region handler' allows us to comb through infection spread and region "popularity" on per-region basis. Although past work has showcased the blockchain architecture for privacy needs without meaningful implementation details, *CTChain presents realistic multi-level platform design with the emphasis on region handler for localized infection maps*. Our model is protected from single point of failure as multiple copies of the chain is stored throughout the network. Its open public architecture makes it relevant for multi-modal data storage and sorting for realistic contact tracing.

There are four main sections in this paper. Section 2 discusses the summary of state-of-art about blockchain-based contact tracing solutions. In Section 3, we describe the proposed framework of the hierarchical network design. Section 4 discusses the performance of the proposed method. The research highlights with concluding remarks and future work are presented in Section 5.

2 Related Work

2.1 Contact Tracing Mobile Apps

By expediting disclosure and contact tracing procedures through efficient digital data flow, connectivity tracing, and location monitoring, contact tracing applications can assist with test findings, locating, distancing, and quarantining steps in an effort to stop and halt the spread of the Covid virus. Given the extensive usage of web-based devices, it may be essential to speed up the monitoring of a large population of smartphone users in order to find infectious disease hot-spots practically and immediately [7].

To help public health organizations throughout the world create digital contact tracking tools, Apple and Google together unveiled a new breakthrough for third-party applications for iOS and Android devices[39].The concept is to employ Bluetooth low-energy beaconing technology to keep track of when a device approaches someone using the app to locate and find infections[55]. Given that Google Android and Apple iOS together have the greatest smartphone operating system user base, it is probable that one's approach will be key in how the bulk of contact-tracing applications perform[23]. Since the implementation of lockdown safety measures, many applications, including Healthcode, Covidsafe, Coronawarn, Aarogya setu, and NHS, have been developed to reduce the danger of SARS-CoV-2 transmission. We have compiled information about the different apps that have been used for the cause in the following subsections, organized by country.

2.1.1 United States of America (USA):

The computerized contact tracking project in Virginia comprises 2 million users. One-fourth of the populace has downloaded the state's "Covidwise" app or signed in to get alerts about hazards on their smartphones [6]. Almost 26,000 warnings have been sent out warning people that they were likely exposed to someone possessing COVID-19[53]. COVID Alert NY" offers voluntary, anonymous exposure notifications. You would be notified if you had any kind of close contact with someone who tested positive for COVID-19. Knowing that you could have been exposed allows you to immediately isolate yourself, get checked out, and lower the danger of exposure.[5]. These two programs were among the first contact tracking methods to become well-known in the US [4].

2.1.2 United Kingdom (UK):

Along with the United Kingdom (UK) [22] and the 27 other participating nations that make up the European Union (EU), the European Commission (EC) offered a number of solutions to the COVID contact tracing issue. The most well-known programs among them are "Coronalert" from Belgium, "CoronaMelder" from the Netherlands, "VirusRadar" from Hungary, and "Immuni" from Italy [30].

Notably, "NHS COVID 19" from the UK National Health Services received a ton of favorable feedback from users in the relevant app stores (Apple App Store and Google Play Store)[2].

2.1.3 India:

The "Aarogya Setu" system in India uses contact tracing to keep tabs on everyone you connect with while going about your daily activities[29]. The appropriate parties would be informed and assertive medical care would be arranged for you if one of them later tested positive for COVID-19 [29].

2.1.4 New Zealand and Australia:

New Zealand's success against COVID-19 at the national level is a fascinating issue for researchers studying pandemic prevention. [12] Prior to officially declaring the pandemic finished in June 2020, New Zealand had just 1,569 cases that had been registered and 22 fatalities, which was the best worldwide epidemic outcome of any nation in the globe. The "NZ COVID Tracer" app offers live statistical data that is considered superior to the competitors, as well as on-location QR codes [8]. Australia's "COVIDSafe" has become an appealing option despite the app's poor performance because of the country's generally low number of instances well before the start of 2022. Their iOS app's ineffective design on occasion resulted in service outages and false positive alarms when requirements were not satisfied [44] .

2.1.5 Singapore and France:

Singapore's contact-tracing app, "Trace-Together" had about one million downloads (20 % of the population), and 16 people were active users at the time of launch. The French contact tracing software Stop-Covid has received 1.9 million downloads across the App Store and the Play Store, and it alone has issued 14 alerts in the first few days of operation.

2.1.6 South Korea and Hong Kong:

The use of contact tracing apps, like the "Corona 100" which seem to be widespread in South Korea, enables public health professionals to reduce the time needed to track a person's movement patterns from roughly 24 hours to roughly 10 minutes, helping the general public stay away from contagious areas. The Hong Kong government required the download of the "StayHomeSafe" app and provided armbands with geo-location automated tracking services that alert agents if wearers violated exclusion zones.

Manufacturing scholars and specialists in Liberal nations have questioned the effectiveness of contact tracing applications in finding and following persons infected with the novel COVID virus. [16]. Technical, privacy and security difficulties have made the applications difficult to use, and it is uncertain whether any of them have had an impact on the global COVID-19 pandemic.

Authors examined an organized mapping of global implementation frameworks and advances, along with a comprehensive study of flaws for each circumstance [34]. In order to support healthcare information decision-making with reference to the UK's current position in COVID-19, the major issues facing Bluetooth-based solutions are clearly identified [14]. Rolling Proximity Identifiers (RPI), which are regularly changing spontaneous pseudonyms, are used in the GAP contact tracking method. A GAP architecture is extremely vulnerable to relay-based wormhole attacks, which may produce bogus contacts and potentially compromise the accuracy of only an app-based contact tracking structure, as well as profiling and potentially de-anonymizing infected individuals. [1]. The results show that the mobile apps [28] were used to monitor self-isolated participants, spot those who weren't wearing masks, determine if they had close contact with an infected person, provide precise time and location of the contact, and evaluate the risk of contracting the disease [41].

Contact tracing is indeed the method of recognizing people who may have been in contact with the infected individual and then gathering additional details about such contacts.[50] Contact tracing, in addition to testing, is a useful technique for decelerating the expansion of COVID-19. It's a basic medical investigator tool designed to keep your family, friends, and local residents safe if you've subjected them to the virus.[20]

Effectiveness-wise, it is yet to be proven that Bluetooth can provide an accurate estimate of range while avoiding a high false alarm rate [33]. The secrecy of those who have been infected is at risk due to the updated decentralized techniques used by several nations, [46]. The privacy of those users is in jeopardy when centralized techniques are used, such as those in France used with ROBERT, especially when a malicious centralized power or a hacker is attempting to attack this control. Furthermore, the centralized method seems to be a preferable option if privacy with reference to authority isn't a concern because it seems to permit the establishment of a system that is more beneficial for epidemiologists and that can safeguard privacy from outside attacks, [11]. Choosing between the centralized and decentralized systems is just as challenging as employing automated contact tracking in the first place because neither strategy offers appropriate privacy protection [54].

The "Contra Corona" methodology provides a cutting-edge, "hybrid" approach to digital contact tracing that protects both the history of the interaction chart and the presence or absence of infectious diseases. By giving away the server's essential tasks to multiple organizations, it may be possible to reduce the degree of confidence in the server-based components[17].

2.2 Contact Tracing with Blockchain

Until a vaccine is created and made accessible for usage, policymakers and governments are having a tough time attempting to stop the rapid spread of the pandemic Covid-19 [43]. Blockchain technology will be used in this situation to securely record every transaction correspondence between users who have networked devices that can access the cloud. In order to use contact tracings, health professionals and the relevant government immediately seek just the blockchain transactional data corresponding to the infected individuals. A crucial public health strategy to stop the spread of the COVID-19 pandemic and other emerging infectious illnesses is contact tracing, according to [28]. However, care is advised when generalizing app usability, particularly in lower middle-income countries, and when addressing issues with data anonymity, privacy, usage, and rights [10].

Because blockchain technologies are decentralized, safe, and highly regulated, many industries have profited from them [38]. They have enormous potential in epidemic circumstances as well. By notifying those who may have been exposed so they may take the necessary measures, contact tracing aids in the prevention of disease spread. Contact tracing systems have some issues with data security, medical privacy, and transparency. Contact tracing hinders patients from getting medicine because they are afraid of data loss and subsequent shame, marginalization, or abuse, according to several research studies[35].

2.2.1 CovidBloc:

The COVID 19 exposure database is implemented by CovidBloc, a contact tracking system that utilizes the Hyperledger Fabric Blockchain Network [42]. A mobile application operating on a Bluetooth-enabled mobile phone, an internet software platform for health authorities, and a backend web service attempting to serve as a storage site for data being gathered make up the CovidBloc, like other decentralized contact tracking programs. Value Focused Thinking (VFT) is used to examine the effectiveness of blockchain-based decentralized apps in crowd management and contact tracking for the Tokyo Olympics. A VFT structure helps to reduce the number of fundamental and strategic goals that need to be considered for effective contact tracing and crowd control by taking stakeholder viewpoints into account. In [48], the authors have made a comparison between the goals specified by VFT and the characteristics of blockchain technology.

2.2.2 Connect:

The virus's spread appears to be too quick for laborious and ineffectual human contact tracking measures to halt it. "Connect", a blockchain-enabled digital contact tracking system that may use information on verified samples and alert people in their close vicinity, was developed by the authors to solve this problem and slow the rate at which the virus spreads [13]. If many individuals used the platform and profited from the targeted ideas, this would be very beneficial.

2.2.3 Blockchain-Driven Contact Tracing System (BDCT) and P2B-Trace:

The majority of current approaches appear to be elevated designs with little opposition, and they view blockchain as just a completely separate storage solution that aids third-party central data centers, ignoring the importance and potential of the consensus protocol and incentive mechanism [32]. Few writers offered a simple, free Blockchain-Driven Contact Tracing system (BDCT) to close the gap. The BDCT framework suggests an RSA encryption-based transaction verification method (RSA-TVM) to guarantee contact tracing correctness. This method has achieved more than 96 percent contact instance trying to record accuracy even though each person has a 60% chance of failing to verify the contact details [40]. Additionally suggested is P2B-Trace, a blockchain-based project for contact tracking that protects user privacy [45]. In order to prevent data modification, a decentralized architecture is meant to capture the ADS of contact record maintenance. The authors then suggested a zero-knowledge presence categorization algorithm as a way to validate proximity claims while maintaining privacy.

2.2.4 BeepTrace:

With the aim of decreasing the epidemic and resolving privacy concerns associated with contact tracking, unique contact tracing mobile software called "BeepTrace" was created by authors of [31]. The software has two modes: passive and active. Passive mode uses GPS to locate contacts; active mode uses Bluetooth Low Energy (BLE) technology. Based on the communications network they employ, contact tracing techniques might be categorized as follows: BLE is largely used by location-based solutions, whereas RFID is mostly used by proximity-based solutions [47].

2.2.5 BlueTrace:

An application protocol called "BlueTrace" enables people to track their online relationships in an effort to stop the COVID-19 epidemic from spreading [15] . The Singaporean government's BlueTrace authorized the contact tracing once again for the TraceTogether app. The authors of [56] proposed a low-fidelity virtual computer prototype that aids in the transmission of infections through interactions with humans at points of contact throughout time, particularly the transmitting graph structure. Using this disease dissemination model, we could then compare outbreak trajectories with or without peer-to-peer contact tracking.

2.2.6 Automated and Manual Contact Tracing:

The authors of [24] have presented a decentralized blockchain-based contact tracing solution and shown how blockchain-based immutable records might in fact enhance the trustworthiness, transparency, and accountability of COVID-19 contact tracking programs. In their study, they have protected user data through contact tracing solutions by utilizing built-in blockchain characteristics. User's privacy is protected by their suggested solution since it gives them the option to decide how and with whom their data will be shared. More distant users approaches are anticipated to be utilized for the purpose of contact tracing and appear to be on the market as a result of the development of 5G- and beyond-5G-positioning research, according to [49].

Automated contact tracing applications can offer quick and accurate tracing services compared to the more expensive human tracing method; nevertheless, excessive efficiency may cause privacy problems for app users. In an automated tracing situation, an efficient confidentiality solution is developed using the beneficial properties of blockchain [27]. One common technique combines multi-signature with public key clustering, non-interactive zero-knowledge evidence, or both. The work of recognizing connections by many alternative signatures from various contacts at the collaborative engagement stage can be completed with zero knowledge verified proof [35, 51].

However, even on a large scale, manual contact tracing is likely to be required in most cases, and additional study is unquestionably required to strengthen the scientific foundation for autonomous vehicle contact tracing [18]. Future research should evaluate the effects of infection transmission based on the available evidence, as well as the technical aspects of contact-tracing apps (efficiency and absorption), as well as the application interactions with manual contact-tracing systems and the ethical and equitable considerations that they raise [9].

The existing contact tracking method has three shortcomings. User's very sensitive personal information may be revealed to a third party or organization and it is held in a central database that might be accused of theft and tampering with [52]. The effectiveness of established contact tracing procedures is highly constrained since they primarily focus on data exchange through a single dimension, such as location-based tracing. It is essential to create a blockchain-based digital contact tracing method that delivers contact tracing effectively without endangering the privacy or confidentiality of users [26]. People may withdraw their information at any time using blockchain, which gives them full access to it at all times during its existence [25].

3 CTChain: Platform Design

Our suggested design uses blockchain technology and a well defined network hierarchy to gather and handle connections between users for contact tracing. User identification, region mempool, region handler, and result analytics make up its four main building blocks. These blocks are connected to a number of other entities, such as the city node, hospital node, event verification, region risk calculation, blockchain processing, and broadcasting results.

3.1 CTChain Architecture Overview

The proposed CTChain structure makes use of specialized nodes to meet the demanding requirements of the *hospital, city, and user activities* as shown in Figure 1. From the user's localized chains, the hospital node constructs and bundles them to be delivered to the city-level nodes. Once the users 'at-risk' have been located, the mobile client transmits a transaction block to the hospital node as shown in (Table 1). The user's personal ID and the time of contact are hashed information in this block, which is necessary to build the ultimate city/regional blockchain. The information about the infection is given to the *region handler* through the mempool after being first checked for data validity by the second-level city node. The infection will be added to the region-specific cache *only if* it is pertinent in terms of risk level or time of encounter. Otherwise, it will be eliminated as a past-due event. The map shown in Figure 1 is divided into specific zones based on risk statistics (low, medium and high) to illustrate the gradations of severely infectious to safe regions.

3.2 Client Node

The mobile client that collects user information and transmits transactions between users makes up the user identification block. The procedure begins with the gathering of user data, which is then packaged into transactions or events. The client then sends this data to a hospital node using infection or recovery values that have been established. People's user-Ids, geolocation, timestamps, and a flag indicating whether or not they are infected with COVID are all collected by our system. Additionally, since Bluetooth is used to identify and communicate a user's position, anonymization can only occur when an ID is provided to the user in place of a name or other identifier. Data that enters the network is first transmitted to the client node for ultimate archival and processing. When new clients want to join the network, the client node serves as the network manager. The user handshakes with the client node at a known IP address after becoming a member of the network and seeks a parent node by submitting their current information (location mainly).

The user's whole profile, including name, user ID, demographic data, and history of interaction with the pathogen, is kept in a separate block. In order to re-verify the transactions, update the block, and the mempool, the acquired data is updated every five minutes. Multiple mini-mempools that are specific to each newly constructed area are produced once the transactions have been updated in the region mempool. After this, it will continue to add blocks to the chain. Each block in a blockchain is given a distinct nonce and hash, but it also refers to the hash of a previous block in the chain, which makes mining blocks challenging, especially on big networks.

3.3 Hospital Node

A key component of our design is the hospital node, which enables medical personnel to immediately acquire infection information for an area and send infection alarms to the network while also dividing the responsibility of the nodes into smaller entities. These hospital nodes learn about a client and their shared certificates, and they use that information to approve incoming transactions from a particular client. Through an infection occurrence or transaction, it can also get direct infection information. If the hospital node traces out a certain individual as infected during a given time period, it will result in a change in the user's status and return all prospective users who are also at risk. Additionally, the parent city-level node can provide risk region changes to the hospital node. The existing list of risky or dangerous zones are simply updated by this new infection information.

Every block that the hospital node adds to its blockchain is copied and sent to another node. These blocks include a list of events that the city node subsequently unpacks, analyzes, and prepares a chain to upload the data for the city-level regional infection map. This saves memory by providing the

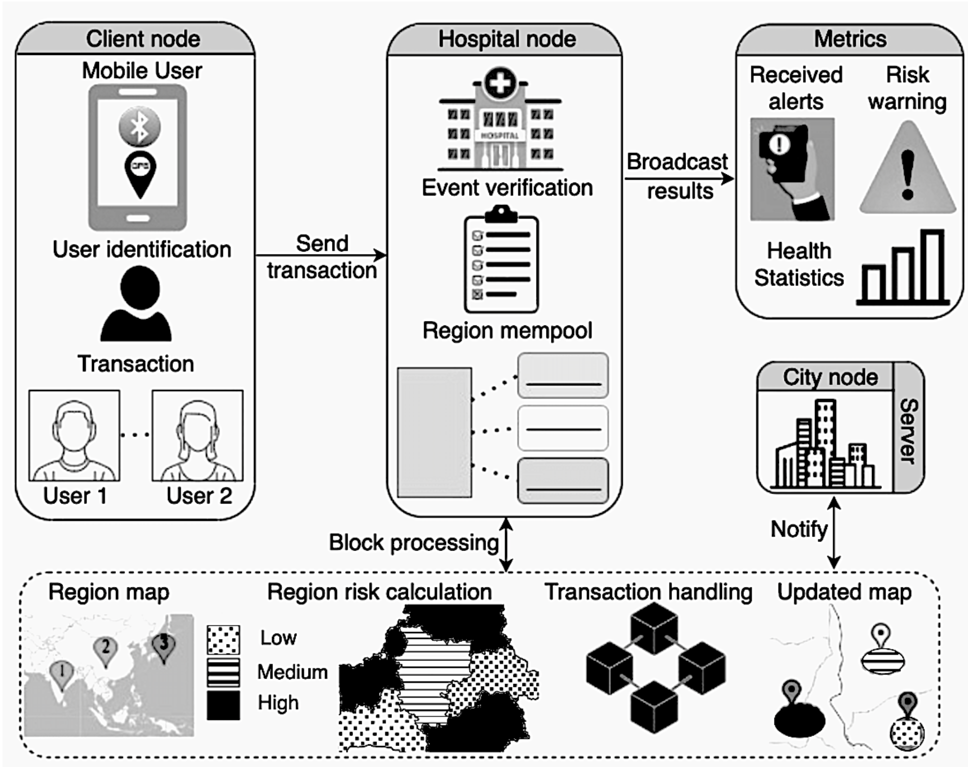

Figure 1: This is our hierarchical architecture for contact tracing. This framework consists of client node, hospital node, local mempool, region handler, city node and result broadcast

city node with its own region handler. It takes the current legitimate "events" that include information that complies with the requirements of python dictionaries. These occurrences are recorded in a list known as a "block" which is added to the collection of blocks that makes up the blockchain and is signed to be processed further. The hospital node just verifies that each event contains the necessary keys and values for the purposes for which it is required. For instance, a location event requires current location coordinates, while a new illness event requires the infection state. On the blockchain, verification also takes place, although this largely only entails making sure that all hashes and blocks are congruent.

The information about the cities is contrasted with a select group of currently severely affected areas. The user immediately receives a notification to switch to location mode and is informed of any possible risks if the location is in a highly contagious area. The user receives a notice that the data has been "recovered" after it has been placed in the mempool. The extra data is accounted for, verified, and built into a new block using hashlib (which offers a unified interface to all the secured hash), which is then processed through the merkle hash, verified against the rest of the blockchain, and added to the blockchain created when the mempool or cache reaches its capacity (the minimum block size of 100 in testing). The city node then receives a copy of this filled block that will be used for generating health advisories.

3.4 Region Handler

Any node that monitors specific 'regions' in an area is operated by the Region Handler module. As shown in Figure 2 it verifies the transactions as the gathered events are provided to this node to make sure whether the user is in its region-of-interest. If they are, the region handler adds their event to a temporary list of events associated to that particular region to check its risk, and then sends the results back to the node, passing the warning to the user. Any node can query the region handler for statistics such the percent people infected per unit area per hour (PPH). The health administrators are responsible for identifying regions based on the geography of the area since the region handler can add/remove regions at the request of its node.

The areas are classified into three groups based on the infection rate in Figure 1. The area highlighted in black is deemed to be at high risk of infection if the infection rate is more than 50%. Similarly, the region with dot pattern has a low infection rate with less than 20% of the people affected, while the region with line pattern has a moderate infection rate between 20 and 50 percent. The major goal is to situate the regions in locations with more human activity, such as malls, companies, or restaurants. Each region is manually specified by an administrator. Every time the node receives a request to add a new region, it sends the region's name and coordinates to the region handler, which adds the new region to its list of managed

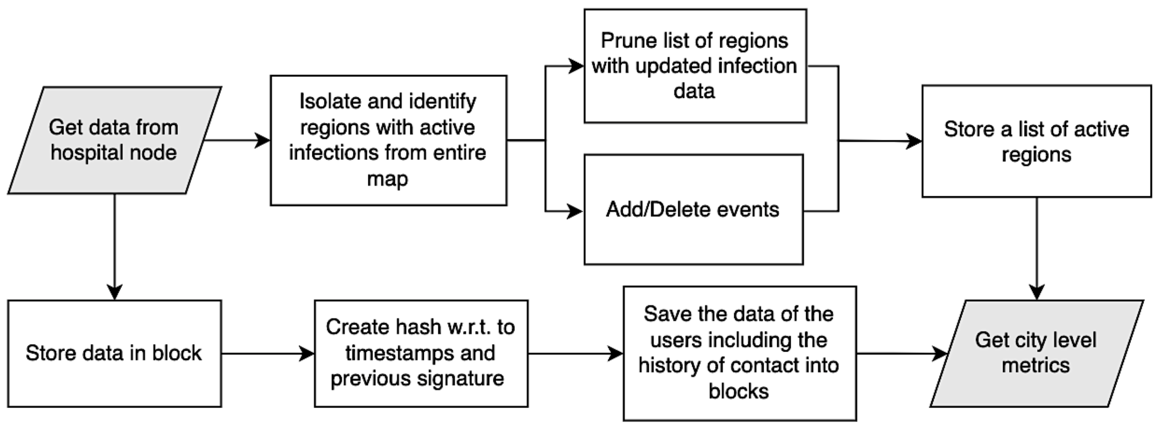

Figure 2: Processing through region handler in blockchain

Table 1: Sample block data

Sample Block Data	
Name of Entities	**Sample Data**
Index number of block	001032
Current Block Signature (32-byte)	ahK4CTbkjwbxg6HVH...
Previous Block Signature (32-byte)	oBHBuns3nxsyim4k...
Public key of creator (64-byte)	MMGvigqkagd9d8...
Creator Name of the block	Heart 'Medical Center'
ID of creator	VMAC007
Node type of creator	'Client node'
Timestamp of creator	84432214770.69
IP of creator node	127.0.0.1:295
Block events at city node	
Node Id	I-0010046828592
Type of event	"Contact Event"
User ID's	*userA*: "O-001...", *userB*: "O-002..."
Status of user	*statusA*: "At-Risk", *statusB*: "Infected"

regions and, if required, extends the "primary region box" to incorporate it. The map is updated and the areas are defined in this way.

The region handler stores each region as a separate python dictionary. Each one of them includes the region's name and latitude and longitude coordinates. Additionally, a list for recent events is given to each area. For testing purposes, additional lists are also provided for metric data storage; however, in the final product, the metrics would likely be handled by a distinct entity. The information about an incoming event is added to the region's list of recent events if it occurs inside that region. The region handler will delete any obsolete transactions from each area after the processing is finished (such as determining PPH or the percentage of infected files where in our case this is any transaction over 1 day old).The whole list of all the regions is kept in a JSON file and may be reloaded, deleted, or both (still keeping the collection of regions, just without recent events).

3.5 City Node

The city node serves as the primary data processor, where we establish the areas and carry out computations based on those regions. These nodes have the ability to transmit a group of "high risk users" and "high risk locations" to their child hospital nodes (this is done as a response to the hospital node sending up a block). The city node transmits the necessary metrics to the client and the hospital node by relying on the data that is processed from the region handler. The city node processes all "transactions" by passing them via the Region Handler, which explicitly examines the "transaction location" using the regions set up on the global map.

The city node determines the precise region where the "transaction" is recorded by checking each established region one at a time. If the "transaction" is possibly in a specified region, we add that transaction to the region's current "mempool" and delete any existing old data (a period of 1 day). In order to estimate the risk calculation measure, we later compute the population density and the proportion of affected people. If a transaction is not in a designated region, it is placed in the "mempool" and handled on a much bigger scale in the same manner as the hospital node. These areas can provide a list of non-infected ("at risk") travelers who have visited there. The city node may take transactions originating from new areas and provide risk estimations for all regions, just like hospital nodes, which can also accept transactions related to infection. The blocks passed or registered by the child hospital nodes provide the transaction information to these city nodes. Following the unpacking of these blocks, the city node's mempool cache are used to hold all of the transactions. The hospital node and the users at the client level are also recipients of the city node's

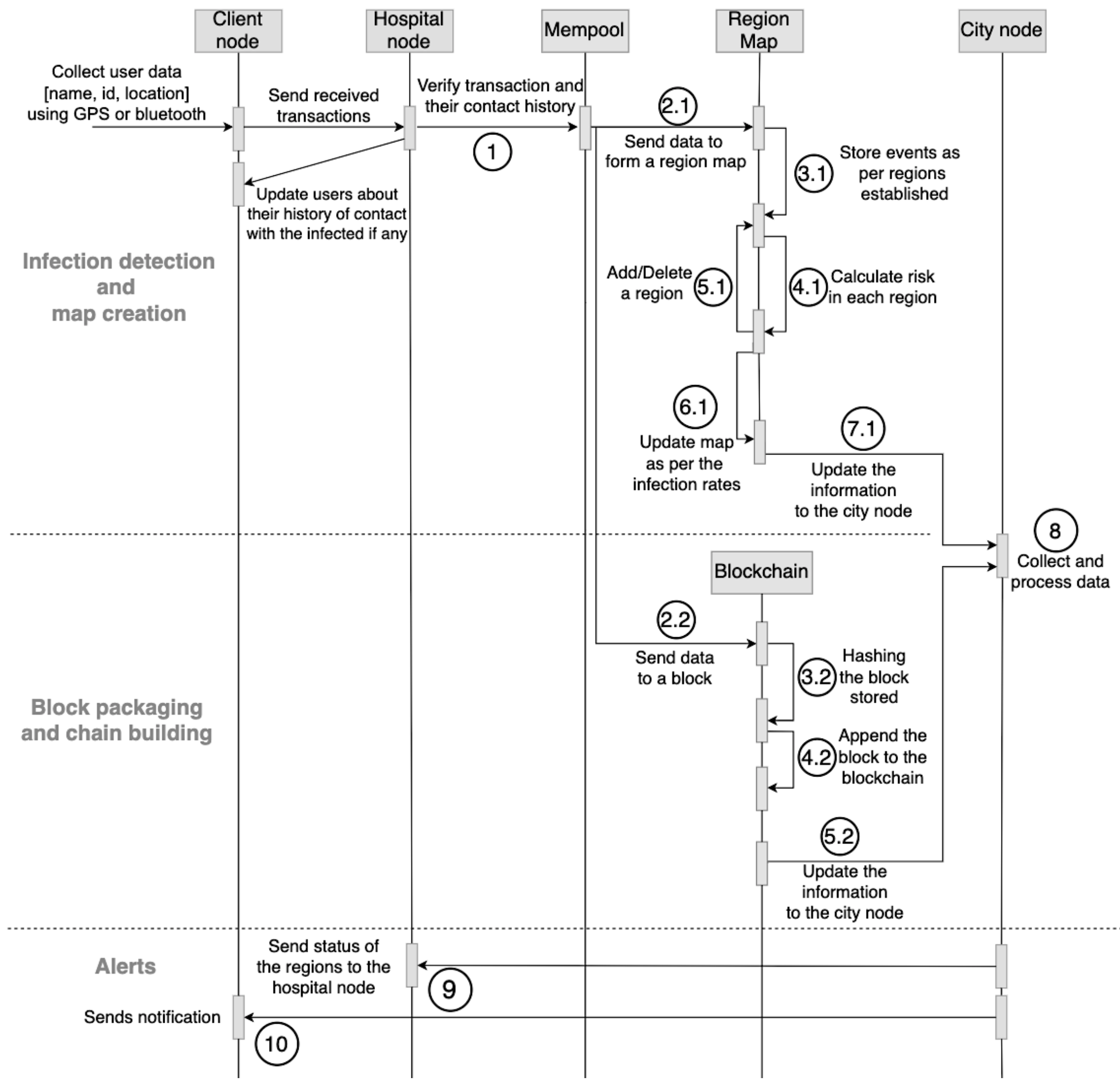

Figure 3: This is the sequence diagram for our hierarchical framework. The core process happens at the blue blocks in the processing detection level. It has 15 steps that shows how the data is carried out to the framework and back to the client

results.

3.6 CTChain Sequence

The framework's sequence diagram is shown in Figure 3. At the beginning, client node gathers user information and transmits the transaction to the hospital node. Verification of transactions, contact history checks, and storage in the mempool comes into action. The infection detection and map-creation level, which is the initial component of the architecture helps in performing the actions on the established map, where it stores events, calculates the risk of a region and updates the map. This aids in drawing the boundaries of a territory on the existing map and the event is recorded in a blockchain. The data is hashed and then used to estimate risk in various places, updating the map of those regions in line with the most recent infection rates and this process takes place in the block packaging and chain building level. In every cycle, the danger is continually computed, allowing the map's areas to be added or removed depending on the rate of infection. The new information entered into the blockchain and the updated region map data is forwarded to the city node where it informs the hospital node of the condition of various regions and sends messages or alerts to the client node's users.

3.6.1 Advisory and Alert Handling:

A city official can track the spread of an infection within a given area (a hospital, a city, or an entire region) and base decisions on this information. For example, the official might pass ordinances requiring people to wear masks or to stay at

Algorithm 1 Client level transaction workflow

1: Client: *C*
2: Transaction: *t*
3: Region handler: *R*
4: Region specific risk of infection: *r*
5: Mempool Cache: *cache*
6: **Begin**
7: **while** Incoming '*t*' == true: **do**
8:     Validate and verify '*t*'
9:     **if** '*t*' is valid: **then**
10:         Verify identity of *C*
11:         Send verified '*t*' to *cache*
12:         Send '*t*' to *R*
13:         **if** '*t*' falls in valid region: **then**
14:             Alert '*C*' about current *r*
15:             Request '*C*' to shift to send GPS data
16:             Backtrack every 5 minutes to get recent contacts
17:         **else**
18:             **if** '*t*' is not in valid region: **then**
19:                 Request '*C*' to send Bluetooth data
20:                 Repeat the process from line 7
21:     **while** '*t*' is stored: **do**
22:         Add '*t*' to region-specific cache
23:         Clean outdated '*t*'
24:         Retrieve *r*
25:         Alert '*C*' about the region's *r*
26: **if** *cache* is full: **then**
27:     Package all *t* in *cache* into a block
28:     Append block to the blockchain
29:     Push block up to parent City node
30:     Clear the *cache*
31: **End**

home, depending on how widely the infection gets spread and how many people are getting ill. They can also make a decision to isolate a certain area based on regional considerations (like a mall that has high infection risk). The program now only notifies users of potential risks based on their most recent interaction history. For example, if an individual comes in contact with a sick person, or enter a high-risk region, he/she will receive alerts accordingly.

4 Evaluation Results

4.1 Tools and Platform

This project uses several tools to construct CTChain application, and perform simulation for user movement through the regions. Before writing the software, we looked for a realistic simulator to give us user data that we could run with the software. For this simulation, we are using an open-source GitHub project called "trip-simulator" made by SharedStreets[36]. This trip simulator is ran through NPM, and constructs a JSON file of vehicles (users), and the paths

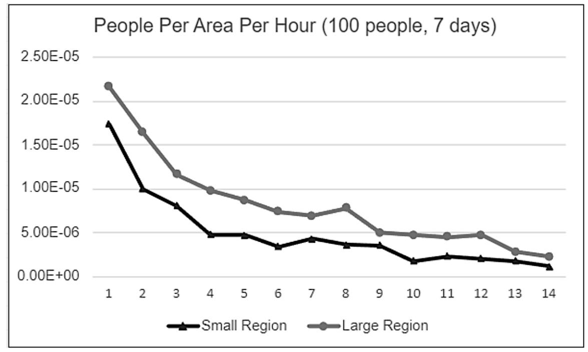

Figure 4: PPH for 100 people

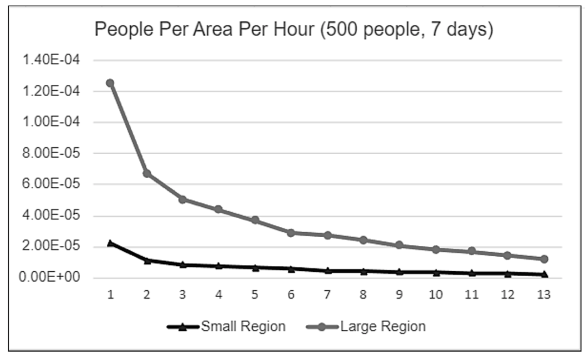

Figure 5: PPH for 500 people

that they have travelled over a given period of time. These simulations were ran for groups of 100, 200, and 500 users; and the simulated times included 1 day, 7 days, 14 days, 21 days, and 28 days. With the output JSON files, we ran a Python script to remove excess identifier data, and converted the collection of paths into a collection of points and timestamps.

Our software is written in Python 3.0 and uses several libraries for additional functionalities. These libraries include the following: 'flask' allows nodes to host their own servers and receive requests using the HTTPS protocol. These 'requests' allow both clients and nodes to send the different types of data (transactions, blocks, and statistics) back and forth. We also used 'pycryptodome' and 'ssl' for certificates and cryptographic hashing to make sure that all data being sent over the network is secure and verifiable. Python libraries 'pandas' and 'numpy' are used together to process large data sets and give us easy-to work with results data. Aside from these software tools, we also made use of the Microsoft suite, mainly Excel, to view and graph our collected results. Running simulations took between 15 minutes to a few hours depending on the average size of the incoming data. These simulations were ran on a AMD CPU with 16 GB of RAM.

4.2 Result Discussion

We are evaluating CTChain capability to map out the active infections in terms of three different parameters: sparse vs

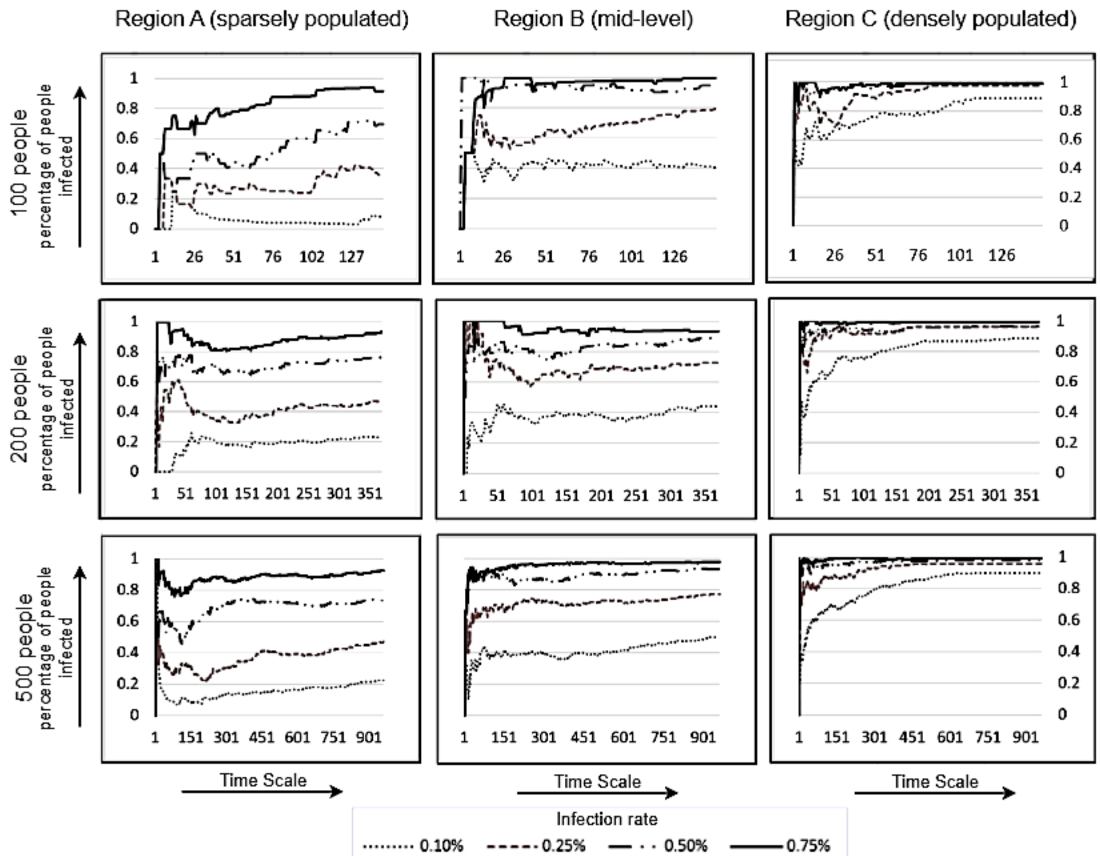

Figure 6: Result graphs

densely populated region, number of people in each region, and initial infection rate. Our goal is to show concrete efficacy results that our platform can scale well through various cases of mild to seriously infectious. To begin, we devised a new metric termed as PPH to determine activity level of specific regions.

PPH itself stands for "people per area per hour." For each region, this metric is calculated by taking the list of events from a regions mempool over the course of the most recent hour, and dividing this number by the area of the region (in square degrees latitude/longitude). The proper formula for this is as follows: $(\,number\,of\,events\,in\,the\,last\,hour)/(\,degree\,latitude * degree\,longitude)$.

The results for the number of active people in each region during a certain period of time are shown in Figures 4 and 5. These graphs visually represent that the densely populated region receives approximately twice the foot-traffic as compared to the sparse one. These visuals are independent of any infection data and present a minimalist view of each region just with the increase in the ongoing traffic.

We have constructed a 3×3 grid in Figure 6 to show the variations of the percentage of population infected w.r.t. independent parameters such as total people passing through the region, population density, initial infection rate, and time. The goal of this grid-view is to depict that the *platform can handle transactions a wide variation from mild to complex infection rates cases in sparsely or densely populated regions*. The first column (leftmost) represents the low population density Region A, whereas the rightmost column is the most popular Region C and Region B is moderately populated. This experiment has been carried out with 100, 200, and 500 people per region which is represented as each row. Within each subplot, the x-axis represents the time scale and the y-axis shows the percentage of people infected w.r.t. entire regional population. Each graph further has four different characteristics to represent initial infection rates ranging from 10% to 75%. For example, in the lowest data point only 1 out of 10 people are COVID-19 positive initially. The rest of x-axis shows the progression of infection through the regional population.

It is evident from each and every graph in Figure 6 that as the initial rates increase, the number of infection cases also increases as expected. We begin the deep-dive by investigating the *first row* of 100 people in the various regions. It is observed that the steady-state values becomes higher from sparse to densely populated areas (left to right), even with low initial infection rate. Moreover, things deteriorate at a faster pace in Region C as compared to Region A. Thus, the population density is the deterministic factor for the probability of contracting infection in comparison to the other initial conditions. This verifies the merits of social distancing directives from Center for Disease Control (CDC) and real-life phenomena where people were migrating away from the cities to escape from the peak of the pandemic.

We next explore the *column-wise* 3×3 grid, beginning with the lowest population density of Region A (1^{st} column). It is observed that the processing time increases with the change in the x-axis scale for the exact same 7-day period. Although the infection trends remain mostly consistent for each region as the population grows, CTChain scales accordingly to accommodate the increased transactions. Our framework limits the number of incoming requests from the client to the hospital node, preventing the server congestion at the higher levels. The most remarkable results are in Region C (last column) when almost the entire population gets infected and thereby will need substantial medical help from the administrators. We are presenting week long data in Figure 6, but the patterns continue to remain consistent for month long simulation as well. Hence, we are skipping them for brevity.

5 Conclusion

The healthcare system across the entire world has been over-stretched beyond limits to address the extremely precarious aftermaths of the Covid-19 pandemic for the past few years. Non-Pharmaceutical Intervention in form of contact tracing for infection containment can be laborious, adhoc and a time-consuming process. Although digital solutions are emerging in the wake of the pandemic, concrete design details especially for linking user information with active infection regional maps are lacking. Our CTChain uses blockchain-based hierarchical node structure to improve the performance and efficacy of this process. The chain model stores transactions in an anonymized and immutable way, allowing for accurate data as well as publicly available statistics. The blockchains work by allowing quick and consistent access to blocks of information, that can be processed for risk calculations, user infection alerts, region/global statistics, and much more.

Through the use of specially designed region handler, we are able to see the infection spread and region "popularity" (PPH) at a per-region level. This allows even faster response times for users entering specific regions, as well as providing metrics that can be used in the future to determine trends in how infections will spread throughout given regions. We show concrete results that our platform can handle wide variation of infection ranging from mild to highly contagious regions. This allows for more specified mandates, such as temporarily shutting down certain unacceptably risky regions, to mitigate the number of users getting sick. Our model is better than state-of-art design as it works on a hierarchical and is more publicly accessible. It is efficient for larger complex systems as it can be scaled on a wider level. Moreover, it has reduced vulnerability to a single point of failure as multiple copies of the chain stored throughout the network. PoA makes it more trustworthy with open public architecture and thus relevant for multi-modal data storage and sorting for contact tracing. In the future, we want to use smart contracts to offload intelligent processing data and issue automated notifications in a refined manner.

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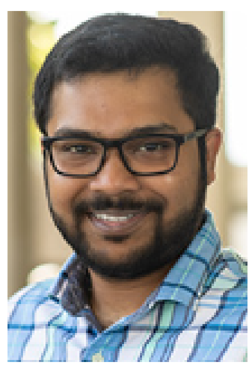

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