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PPChain: A Blockchain for Pandemic Prevention and Control Assisted by Federated Learning

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Abstract: A pandemic can have a huge impact on normal human life and the economy, taking COVID-19 as an example. While the population flow between countries and regions is the main factor affecting the change of a pandemic, exactly as the airline network. Therefore, realizing the overall control of airports is an effective way to control a pandemic. However, restricted to the differences in prevention and control policies in different areas and privacy issues, the patients' personal data of the medical center cannot be effectively combined with the passengers' personal data. This prevents more precise airport control decisions from being made. To the end, this paper designs a novel data sharing framework (i.e., PPChain) based on blockchain and federated learning. The experiment shows that the relationship between the epidemic and aircraft transport can be effectively explored by PPChain, without sharing raw data. This approach does not require centralized trust and improves the security of the shareing process.The scheme can help formulate more scientific and rational prevention and control policies on airports' control. And it can use aerial data to predict pandemics more accurately.

Keywords: blockchain; federated learning; pandemic prevention and control; privacy-preserving

1. Introduction

Since the outbreak of Corona Virus Disease (COVID-19)in 2019, it has had a huge impact on the world economy and people's lives. It is in the interests of all mankind to contain the pandemic at an early date. However, the spread of the pandemic is affected by many factors. Pandemic prevention policies and people's pandemic prevention psychology in different countries will have different effects [1], and have a significant impact on the model parameters of virus transmission. Raffetti et al. [2] further demonstrate that national policies are the most important factor affecting the spread of the pandemic. Sweden has adopted a "natural" herd immunity strategy to deal with the pandemic, but this model has resulted in a COVID-19 death rate 10 times higher in Sweden than in neighbouring Norway [3]. Mishra et al. [4] compare Denmark, Britain and Sweden under different policy models. They conclude that domestic policy effects are affected by inter-country population flows, and even similar policies may produce different effects.

Therefore, it's necessary to include population flow between countries and regions into the prevention and control of pandemic, as well as develop effective policies about population flows, in order to contain the outbreak. This paper aims to study the impact of air network transmission on the pandemic, and how to formulate shipping policies to contain the pandemic. However, at present, most national medical centers are often unable to know the flight status of confirmed patients, and most airline companies cannot know the illness status of passengers due to different national policies. While federated learning [5] can realize multi-party data integration without sharing data. In this paper, federated learning is chosen instead of other distributed learning frameworks.

The main reason is that the compute nodes have absolute control over the data in federated learning, and the central server cannot directly or indirectly operate the data of the compute nodes. The compute nodes can stop computing and communication at any time and exit the learning process. However, in other distributed machine learning frame- works (such as MapReduce, etc.), the central server has a high control over the compute nodes and the data of them. The compute nodes are completely controlled by the central server and receive instructions from the central server. For instance, MapReduce's central server can issue an instruction to compute nodes to exchange data with each other. This can potentially compromise the privacy of user data and may add additional communication overhead. Therefore, the raw data of federated learning can be kept locally, which is an advantage over other distributed machine learning.

The traditional federated learning model often requires an aggregator. It will lead to privacy and the model failure problems [6] if the center aggregator is attacked. Therefore, the paper designs an pandemic prevention and control model based on blockchain. The characteristics of blockchain such as decentralization and security ensure the reliability and effectiveness of the learning process. It makes federated learning not depend on the third party central server, but depends on the consensus mechanism to better protect the data security. The scheme implements the integration of pandemic data and airline data through federated learning. Moreover, the impact of aviation network transmission on pandemic prevention and control is obtained, thus providing support for scientific prediction of pandemic changes and auxiliary policy making.

The rest of this article is organized as follows. Section 2 investigates the current situation of federated learning for pandemic prevention and control. Section 3 mainly elaborates the main architecture of the model. Section 4 introduces the experiment and analysis. Section 5 summarizes the main work of this paper.

2. Related Work

2.1. Application of Federated Learning in Epidemic

Qian et al. [7] describe real-world cases of using federated learning in COVID-19 as well as non-COVID-19 scenarios, and analyze limitations and practical challenges. Literature [8–13] use federated learning to assist the diagnosis and intelligent monitoring of COVID-19. However, the above schemes only improve the accuracy of the diagnosis of suspected patients and do not give how to evaluate the effect of the policy. Chen et al. [14] construct a COVID-19 vulnerability prediction map using federated learning synergy to identify high-risk areas and reduce the spread of the disease. However, the method is mainly oriented to the collaboration of organizations in the same field, without providing a cross-domain collaboration approach. Samuel et al. [15] propose a privacy architecture based on federated learning and blockchain technology to support cross- domain interaction of COVID-19 information and protect the authenticity and privacy of information. Pang et al. [16] fuse urban digital twins between multiple cities through federated learning technology, and construct a collaborative urban crisis management paradigm to explore effective prevention and control policies, so as to formulate efficient prevention and control policies. However, the method lacks the competence to analyze the impact of population movement between regions on pandemic prevention.

2.2. Application of Blockchain in Federated Learning

Chen et al. [17] analyze the privacy and security issues of the learning model and design a federated learning system that supports privacy protection based on block- chain, which replaces the central server for parameter aggregation. Ramanan et al. [18] propose a federated learning environment based on blockchain, which uses blockchain to store and share global models and perform model aggregation tasks through smart contracts. Rehman et al. [19] propose a set of blockchain based federated learning frame- work for mobile edge computing networks, redefining the model's storage mode, training process and consensus mechanism.

To sum up, the current federated learning for pandemic analysis is mainly to integrate knowledge in the field, and relies on blockchain technology to strengthen the robustness and credibility of federal learning. However, the research on the interaction of regional policies is still insufficient. On the other hand, the storage overhead of blockchain is large, which has a great impact on federated learning efficiency with more model parameters. Therefore, it is necessary to study how to integrate

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cross-domain information while protecting the rights and interests of data owners. Through this to identify the impact of inter-regional population flow on pandemic prevention and control, so as to better serve pandemic prediction and policy making.

3. PPChain

In this section, we propose a blockchain for COVID-19 prevention and control based on federated learning. With blockchain technology, data can be trusted and distributed among multiple parties without a third party central authority, reducing the risk of data leakage. There are two main types of participants in the network: regional epidemic management centers and individual airlines. Using federated learning technique, the two groups of entities are able to figure out how the disease is spreading through flights, without sharing raw data, to develop targeted containment policies and make predictions. The system uses smart contracts to act as aggregators. In addition, to ensure the efficiency of the blockchain network, the models are trained locally and the blockchain only flows parameter information. The system architecture is shown as Figure 1.

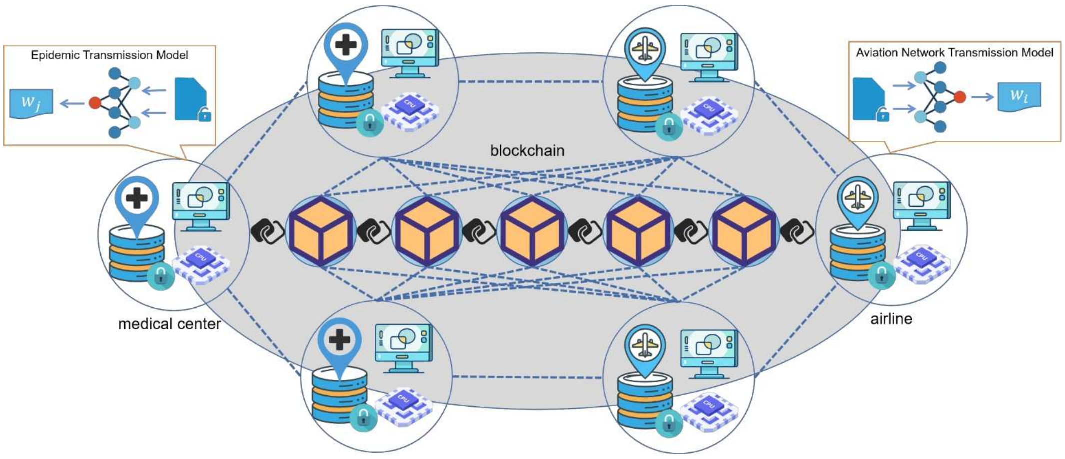

Figure 1. The system architecture.

Using the framework shown in the figure 1, the training process of federated learning is divided into two parts. First, the sample space is aligned, that is, people with the same identity information but distributed in different parties. By using the user ID alignment technique based on encryption, it ensures that the original data of each party does not need to be exposed. In the second phase, the encryption model training is performed based on these aligned entities, as follows.

- After identifying the shared entity, the blockchain triggers the smart contract to create the key pair and send the public key to regional pandemic management centers and individual airlines.
- Regional pandemic management centers and individual airlines encrypt and exchange intermediate results, which are used to help calculate gradients and loss values.
- Regional pandemic management centers and individual airlines calculate the encryption gradient and add additional masks respectively. Regional pandemic management centers also calculate the encryption loss. The two kinds of parties then write the encrypted result into the blockchain's ledger through the SDK.
- Smart contracts on the blockchain decrypt the gradients and losses newly written into the ledger and send the results back to both parties. Regional pandemic management centers and individual airlines unmask the gradient information and update the model parameters according to the gradient information.
- Meanwhile, the parameters trained by the model will be written into the blockchain. Then the parameters can be read for better pandemic prediction and prevention and control policy formulation.

Through the above process, the infection caused by the flight flow between different regions can be calculated. We use SIR Model(susceptible-infected-removed) as the model to be trained.

3.1. Pandemic Transmission Model Based on SIR

The SIR model mainly simulates the evolution of susceptible population S, infected population I, and removed population R(with immunity, who is no longer infected or has died after being cured). The key parameters of the model are shown in the table below, where effective reproduction number R is the core parameter trained by federated learning.

Table 1. This is a table caption. Tables should be placed in the main text near to the first time they are cited.

Symbol	**Meaning**
R	Effective reproduction number(=$\frac{\beta}{\gamma}(1-\frac{C}{N})$), the average number of infections per patient
R_0	Basic reproduction number(=$\frac{\beta}{\gamma}$)
β	Average frequency of exposure (per day)
γ	Average removal frequency (per day)
N	Total population (also used as initial susceptible population)
R_{all}	Final outbreak size (replaced by final recovery)
S_{last}	The rest of the uninfected population
$RMSE$	Root-mean-square error

The SIR model is as follows:

$$\frac{dS}{dt} = -\frac{\beta}{N}IS \tag{1}$$

$$\frac{dS}{dt} = \frac{\beta}{N}IS - \gamma I \tag{2}$$

$$\frac{dR}{dt} = \gamma I \tag{3}$$

t is time, $S(t)$ is the number of susceptible persons at t, $I(t)$ is the number of infected persons at t, and $R(t)$ is the number of cured persons at t.

$$N = S + I + R \tag{4}$$

In the initial state, $S(0) = S_0$, $I(0) = I_0$, $R(0) = R_0$. According to the formula (1) and (3):

$$S = S_0 e^{[\frac{\beta}{N\gamma}(R-R_0)]} \tag{5}$$

Because eventually I(t) approaches to zero, according to formula (4) and (5), it can be figured out:

$$R_{all} = N - S_0 e^{[\frac{\beta}{N\gamma}(R_{all}-R_0)]} \tag{6}$$

We have accumulated the time series $C(t)$ that is formed by the daily data, as shown in formula (7).

$$C(t) = I(t) + R(t) = N - S_0 e^{[\frac{\beta}{N\gamma}(R-R_0)]} \tag{7}$$

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Therefore, the least square method was used to conduct regression analysis on the time series formed by the confirmed data and obtain the estimation of each parameter, as shown in formula (8).

$$\underset{\beta,\gamma}{argmin}(\| C_t - \hat{C}_t(\beta, \gamma, S_0) \|) \tag{8}$$

In order to protect the patient privacy information in the electronic medical record data, we adopt the federal learning method to fine-tune the model training. The formula (8) is the objective function of federated learning.

3.2. Aviation Network Transmission Model

For the influence of air traffic network propagation, the probability of cities being affected by diffusion is calculated according to the parameters transmitted by federated learning. The susceptibility probability of flights taking off from each city is approximately as follows.

$$P_{plane} = R_{plane} \cdot \frac{I_{plane}}{N_{plane}} \tag{9}$$

R_{plane} is the effective reproduction number of the flight, I_{plane} represents the presence of cases on the flight, N_{plane} is the total number of people on the flight. Thus, the probability of city k being affected by the imported spread of the epidemic can be calculated, as is shown in formula (10).

$$P_k = 1 - P_k = 1 - \prod_{n=1}^{num_k} [\prod_{m=1}^{f_n} (1 - P_m)] \tag{10}$$

num_k represents the number of cities which have flights to city k, f_n represents the number of flights from city n, P_m is the susceptibility probability of flight m.

Based on the probability of city k being affected above, the importance of airports is ranked by measuring the location of airport nodes and the airline flow of airports. Weighted proximity algorithm is used to highlight the influence of path distance between nodes on recognition results.

$$P_i^C = P_k \cdot (M - 1/\sum_{j=1}^{M} f(d_{ij})) \tag{11}$$

M represents the number of airports in the network, and d_{ij} represents the minimum number of transit times from airport i to airport j, $f()$ is a logarithmic function. The importance output matrix of adjacent nodes is set for evaluation:

$$H = \begin{bmatrix} 1 & \delta_{12}D_2/k^2 & \dots & \delta_{1M}D_M/k^2 \\ \delta_{12}D_2/k^2 & 1 & \dots & \delta_{2M}D_M/k^2 \\ \vdots & \vdots & \dots & \vdots \\ \delta_{M1}D_1/k^2 & \delta_{M2}D_2/k^2 & \dots & 1 \end{bmatrix} \tag{12}$$

In the matrix, δ_{ij} is the contribution allocation parameter. If two nodes are connected, the value is 1; otherwise, the value is 0. The element on the diagonal is 1, which means that the contribution ratio of the node to itself is 1. D_i is the degree of the airport i, k is the average degree of the node:

$$k = \sum_{i=1}^{M} D_i/M \tag{13}$$

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Calculate the weight S_i of each airport node:

$$S_i = \sum_{j \in N_i} W_{ij} \tag{14}$$

N_i is the neighbor node set of node i, W_{ij} is the weight of the edge directly connected to node i. According to formula (11)-(14), the importance of each airport node is obtained, as C_i.

$$C_i = \sum_{i=1, j \neq i}^{M} P_j^C \delta_{ij} S_j D_j / k^2 \tag{15}$$

3.3. Federated learning training process assisted by blockchain

The workflow of PPChain mainly includes four stages: initializing the collaborative training alliance, writing the encrypted results to the ledger, reading and sending the results, and updating the model parameters.

In the stage of initializing the collaborative training alliance, assume that the participants of N_1 CDC(Centers For Disease Control And Prevention) $p_i, i \in \{1, 2, ..., N_1\}$, and the participants of N_2 airlines $q_i, i \in \{1, 2, ..., N_2\}$, join the blockchain network and obtain a configuration file containing predefined information such as collaboration model and initialization parameters to form a collaborative training alliance. The blockchain network randomly selects $M(M = M_1 + M_2, where M_1 = N_1/2, M_2 = N_2/2)$ participants to form a certification consortium to enable the system's consensus algorithm.

It is a remarkable fact that smart contracts will be deployed on the blockchain to create a key pair for each entity that joins the network, and return the public key as a means of identification and encryption, while the private key will be stored in the blockchain ledger along with the entity's characteristic information. It will be read by the smart contract for decryption during the result reading and sending phase.

In order to ensure communication efficiency and make collaborative training and node identity information easy to maintain, this paper applies the channel mechanism to the blockchain network. The channel is a dedicated subnet for specific members to communicate with each other. Different types of transactions will be executed in different task channels. Therefore a relatively independent ledger will be formed for easy management and maintenance, and finally the communication efficiency could be improved.

In this paper, two types of channels are designed, in which the identity channel is used for the storage of private keys and entity characteristic information. We designed an identity form for the registration of information for nodes joining the network. Forms are normalized data containing entity identity information that circulates in channels in the form of smart contracts. The typical data structure is shown in Table 2.

Table 2. The typical data structure of identity form

Symbol	Explanation
ID	The identity number of the entity
$type$	Categories of entities (medical, aviation)
$name$	Name of entity
$time$	The time that the entity joins the blockchain network
$state$	Whether the entity is incorporated into an authentication consortium
s_k	The entity's private key information

The other channel is used for collaborative training of federated learning, where relevant entities join and complete business on the channel after authentication and authorization. And the channel ledger records the complete process of collaborative training. When the training is completed, the ledger data of the channel is hashed to form a hash value and stored in the system's general ledger. Similarly, collaborative training is also implemented in the form of forms in the channel through smart contracts. Table 3 shows the form structure of co-training.

Table 3. The form structure of co-training

Symbol	Explanation
$MissionID$	Serial number of the cooperative training task
$Owner$	The entity that provides the gradient
$epoch$	The number of rounds iterated by cooperative training
$param$	Encrypted gradient information
$timestamp$	The timestamp of the gradient write to the ledger
$collaborators$	A collection of entities that participate in the corresponding collaboration
$mask$	Mask information

In the stage of writing the encryption result to the ledger, the entity that uploads the model fills in the corresponding form information, and iteratively updates the epoch field. The form is broadcast in the channel. The certification consortium verifies and signs transactions. Transactions are handed over to channel members for consensus. If the consensus is successful, the transaction commit channel is packaged into transaction blocks.

After above steps, smart contracts on the blockchain decrypt the gradients and losses newly written to the ledger and send the results back to both parties, which is the result reading and sending phase. The epidemic control center and airlines will uncover the gradient information. In the model parameter update stage, the model parameters are updated according to the gradient information, and the above process can be summarized as the collaborative training step in Table 4.

Table 4. The proceedings of collaborative training

step	CDC	airport	Smart contracts on blockchain
1	initialize β, γ	initialize R_{plane}	Create an encryption key pair and send the public key to both parties
2	calculate $\parallel \Gamma_A \parallel = \parallel C_t - \hat{C}_t(\beta, \gamma, S_0) \parallel$ and send it to the blockchain	calculate $\parallel \Gamma_B \parallel = \parallel C_t - \hat{C}_t(R_{plane}, S_0) \parallel$ and send it to the blockchain	Create the collaboration form and write $\parallel \Gamma \parallel = \parallel \Gamma_A \parallel + \parallel \Gamma_B \parallel$
3	calculate $\frac{\partial \Gamma}{\partial R_0}$, then encrypt it and write it to the blockchain	calculate $\frac{\partial \Gamma}{\partial R_{plane}}$, then encrypt it and write it to the blockchain	read the contents of the ledger, decrypt and send to both parties
4	update β, γ	update R_{plane}	update block
$Obtainedcontent$	β, γ	R_{plane}	the ledger of co-training

4. Experiment and Analysis

This section introduces the experimental environment of PPChain and evaluates the system performance from three aspects: training accuracy, time cost, transaction processing efficiency and transaction latency.

Hyperledger Fabric was used to build the blockchain network in the system, and the federated learning parameters were trans- mitted through smart contracts. The main body of the system model was realized under the chain, and SDK was used to read and write the data on the chain.

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4.1. Experiment Settings

To evaluate the system performance of the proposed PPChain, experiments are run on real datasets.Global epidemic data published by Hopkins University were used for epidemic data, and public data sets of FlightConnections were used for inter-regional flight information.

In this experiment, the two types of datasets are randomly divided into 10 subsets with equal numbers and assigned to 20 participants as local datasets.

The experiment was run on a laptop equipped with a 4-core, 8-thread Intel CPU i7-7700HQ and 16 GB of memory. Use the Python programming language to develop SDKs to implement the business logic of the system. Smart contracts are written in the Go language. The learning model is written using Python 3.9 and Pytorch 1.4.0 and executed on the NVIDIA Geforce GTX 1050M GPU.

4.2. Performance Evaluation

The Table 5 describes the parameters for co-training.

Table 5. The parameters for co-training

Parameter	Value
$numberofepochs$	10
$nmberofiterations$	1500
$learningrate$	0.015
$batchsize$	64

After collaborative training, the training obtained R_0 is fitted with the actual infection curve, and the accuracy of the training is judged by $RSME$. As shown in the Figure 2. It can be seen that the system can better implement collaborative training.

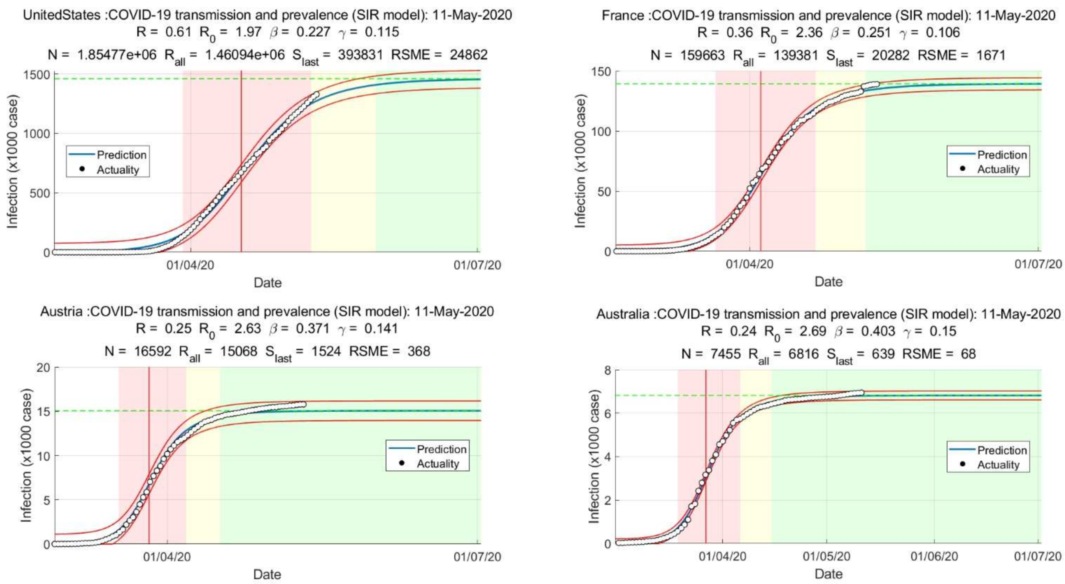

Figure 2. Infection curve fitting graph.

In this paper, a more accurate impact of the aviation network on the spread of the epidemic is obtained through collaborative training, because it realizes the data alignment between common entities without exposing privacy. According to the R_{plane}, we apply it into the designed aviation network propagation model to obtain a directed network diagram of the epidemic propagation through the aviation network, as shown in Figure 3.

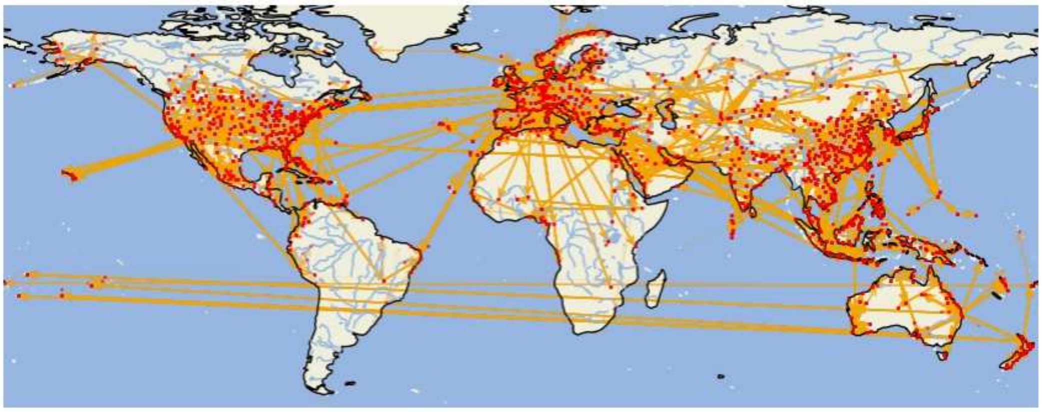

Figure 3. Directed network of epidemic transmission in aviation network.

This paper explores the impact of aviation network on the epidemic, so as to assist the formulation of effective prevention and control policies. In this paper, the top 20 airports with the highest importance and 20 airports with the median importance are selected for comparison.

Apply the data after the airport closure back into the model that has been trained for calculation. With closing these airports, the number of cities daily affected by the imported spread of the epidemic are as Figure 4. As is shown in the results, it can be seen that the effect of closing 20 general important airports is small, but closing the top 20 important airports will significantly reduce the number of affected cities.

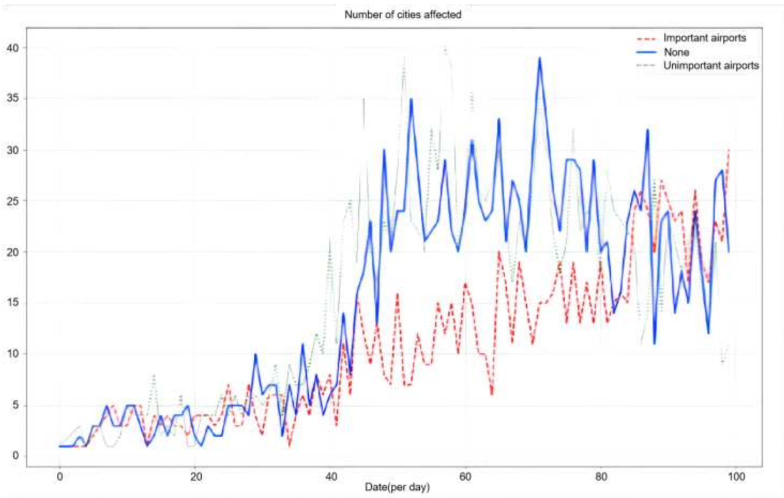

Figure 4. Comparison of the impact of airports on the spread of COVID-19.

Next, the changes of transaction efficiency and transaction latency in the collaborative training process of the system are recorded. And the transaction processing efficiency is reflected by the system running time, including the process of data reading, verifying signatures, completing transactions, consensus and data on-chain. Transaction latency mainly includes consensus delay and communication delay between nodes, and is divided into maximum delay, average delay and minimum delay due to network jitter.

In this paper, the number of network nodes is changed to test the changes in transaction efficiency and transaction latency, as shown in Figure 5 and Figure 6.

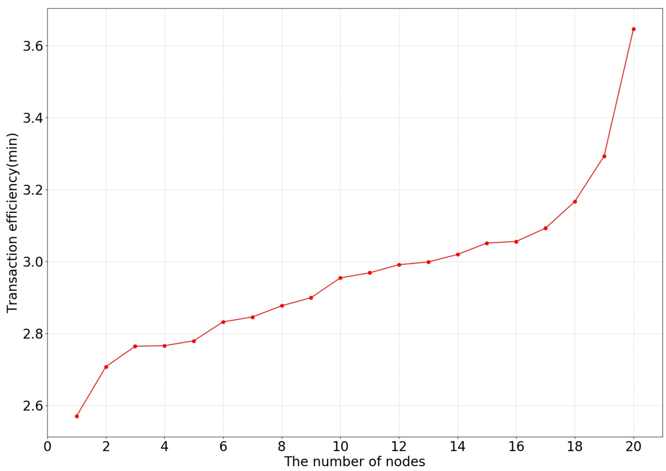

Figure 5. The effect of the number of nodes on transaction efficiency in cooperative training.

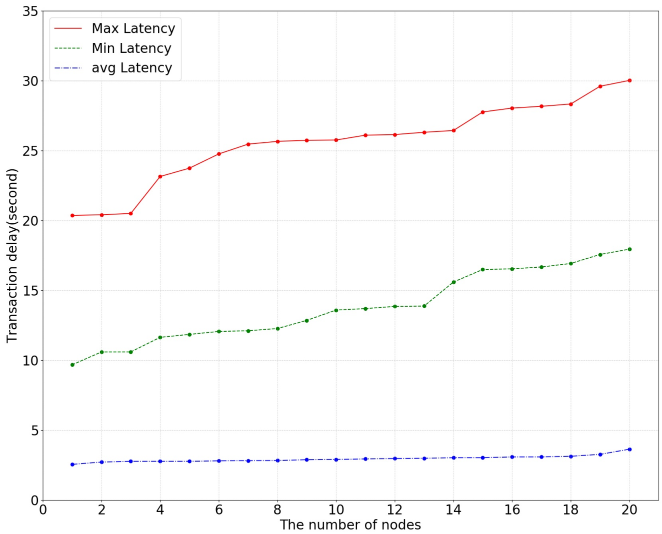

Figure 6. The effect of node number on transaction delay in cooperative training.

5. Conclusions

In this paper, aiming at the problem that medical centers and airlines cannot fully obtain the flight information of confirmed patients or the illness of passengers due to privacy protection, we designed an PPChain without sharing the original data. The system combines federated learning into the blockchain, improving the security of shared processes without the need for centralized trust. Through experiments, we have verified that effective data sharing can be achieved without destroying privacy, and the impact of aviation policy can be simulated, so as to formulate prevention and control policies more scientifically and rationally, and predict the epidemic more accurately.

References

1. V. Bavel; A. Cichocka; V. Capraro. National identity predicts public health support during a global pandemic. *Nature Communications* **2022**, *13*, 517.
2. E. Raffetti; E. Mondino; G. Baldassarre. Epidemic risk perceptions in Italy and Sweden driven by authority responses to COVID-19. *Scientific Reports* **2022**, *12*, 9291.

3. N. Brusselaers; D. Steadson; K. Bjorklund. Evaluation of science advice during the COVID-19 pandemic in Sweden. *Humanities and Social Sciences Communications* **2022**, *9*, 91.
4. S. Mishra; J. A. Scott; D. J. Laydon. Comparing the responses of the UK, Sweden and Denmark to COVID-19 using counterfactual modelling. *Scientific Reports* **2021**, *11*, 16342.
5. Q. Yang; Y. Liu; Y. Cheng; et al. Vertical Federated Learning. *Federated Learning*; Synthesis Lectures on Artificial Intelligence and Machine Learning; Springer: Cham, Switzerland, 2020; pp. 69–81.
6. X. Zhou; M. Xu; Y. Wu; N. Zheng. Deep Model Poisoning Attack on Federated Learning. *Future Internet* **2021**, *13*, 73.
7. F. Qian; A. Zhang. The value of federated learning during and post-COVID-19. *International Journal for Quality in Health Care* **2021**, *33*, mzab010.
8. A. Kallel; M. Rekik; M. Khemakhem. Hybrid-based framework for COVID-19 prediction via federated machine learning models. *The Journal of Supercomputing* **2022**, *78*, 7078–7105.
9. M. Salam; S. Taha; M. Ramadan. COVID-19 detection using federated machine learning. *Plos one* **2021**, *16*, e0252573.
10. R. Wang; J. Xu; Y. Ma; et al. Auxiliary Diagnosis of COVID-19 Based on 5G-Enabled Federated Learning. *IEEE Network* **2021**, *35*, 14–20.
11. W. Zhang; T. Zhou; Q. Lu; et al. Dynamic-Fusion-Based Federated Learning for COVID-19 Detection. *IEEE Internet of Things Journal* **2021**, *8*, 15884–15891.
12. K. M. Elshabrawy; M. M. Alfares and M. A. M. Salem. Ensemble Federated Learning for Non-II D COVID-19 Detection. In Proceedings of 2022 5th International Conference on Computing and Informatics (ICCI), Future University, Egypt, 9-10 March 2022 ; 057–063.
13. Alam; U. Mahbub; R. Rahim. Federated Semi-Supervised Multi-Task Learning to Detect COVID-19 and Lungs Segmentation Marking Using Chest Radiography Images and Raspberry Pi Devices: An Internet of Medical Things Application. *Sensors* **2021**, *21*, 5025.
14. J. J. Chen; R. Chen; X. Zhang; M. Pan. A Privacy Preserving Federated Learning Framework for COVID-19 Vulnerability Map Construction. In Proceedings of ICC 2021 - IEEE International Conference on Communications, 14-23 June 2021; 1–6.
15. O. Samuel; A. B. Omojo; A. M. Onuja; et al. IoMT: A COVID-19 Healthcare System driven by Federated Learning and Blockchain. *IEEE Journal of Biomedical and Health Informatics* **2023**, *8*, 823–834.
16. J. Pang; Y. Huang; Z. Xie; et al. Collaborative City Digital Twin for the COVID-19 Pandemic:A Federated Learning Solution. *Tsinghua Science and Technology* **2021**, *26*, 759–771.
17. X. Chen; J. Ji; C. Luo. When machine learning meets blockchain: a decentralized, privacy preserving and secure design. In Proceedings of IEEE International Conference on Big Data, Pisca taway, 10-13 December 2018; 1178–1187.
18. P. Ramanan; K. Nakayama. BAFFLE: blockchain based aggregator free federated learning. In Proceedings of 2020 IEEE International Conference on Blockchain (Blockchain), Rhodes Greece, 2020; 72-81.
19. M. H. Rehman; K. Salah; E. Damiani. Towards blockchain based reputation-aware federated learning. In Proceedings of International Symposium on Edge Computing Security and Blockchain, Toronto Canada, 6 July 2020; 183–188.