

Blockchain-Federated-Learning and Deep Learning Models for COVID-19 detection using CT Imaging

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Abstract—With the increase of COVID-19 cases worldwide, an effective way is required to diagnose COVID-19 patients. The primary problem in diagnosing COVID-19 patients is the shortage of testing kits, due to the quick spread of the virus, medical practitioners are facing difficulty identifying the positive cases. The second real-world problem is to share the data among the hospitals globally while keeping in view the privacy concern of the organizations. To address the problem of building a collaborative network model without leakage privacy of data are major concerns for training the deep learning model, this paper proposes a framework that collects a huge amount of data from different sources (various hospitals) and to train the deep learning model over a decentralized network for the newest information about COVID-19 patients. The main goal of this paper is to improve the recognition of a global deep learning model using, novel and up-to-date data, and learn itself from such data to improve recognition of COVID-19 patients based on computed tomography (CT) slices. Moreover, the integration of blockchain and federated-learning technology collects the data from different hospitals without leakage the privacy of the data. Firstly, we collect real-life COVID-19 patients data open to the research community. Secondly, we use various deep learning models (VGG, DenseNet, AlexNet, MobileNet, ResNet, and Capsule Network) to recognize the patterns via COVID-19 patients' lung screening. Thirdly, securely share the data among various hospitals with the integration of federated learning and blockchain. Finally, our results demonstrate a better performance to detect COVID-19 patients.

Index Terms—COVID-19, Privacy-Preserved Data Sharing , Deep Learning, Federated-Learning, Blockchain

I. INTRODUCTION

A. Background

A new type of Coronavirus emerged in the city of Wuhan in China. Unfortunately, within weeks this coronavirus (COVID-19) spread to several countries and it has been proven fatal. With an estimated 325,000 deaths in 4 months, COVID-19 virus is considered as one of the most deadly viruses [1]. The first confirmed death from COVID-19 infection was recorded in early January this year. The Coronavirus family is categorized into 7 categories i.e. Human Coronavirus 229e (HCoV -229e), Human Coronavirus OC43 (hCoV-OC43), SARS-CoV, Human Coronavirus NL63 (HCoV-NL63, New Haven Coronavirus), Human Coronavirus HKU1, Middle

East Respiratory Syndrome Coronavirus (MERS-Cov), and Wuhan Coronavirus. This novel coronavirus is the seventh type (COVID-19). Some coronavirus has mild symptoms while others such as SARS (severe acute respiratory or syndrome-related Coronavirus), and MERS (middle east respiratory) are much more dangerous. Coronavirus can be easily transmitted between humans mainly through social interaction with an active patient or direct contact with an infected animal.

Without any warning, the number of COVID-19 patients suddenly started to increase leaving the governments and medical practitioners unprepared to handle such a situation. Consequently, there is a shortage of testing kit supplies, and many hospitals worldwide are facing a challenge in identifying COVID-19 positive patients. The following criteria are used to diagnose COVID-19 patients: Clinical symptoms, Epidemiological history, and Positive CT and Pathogenic Testing. Radiological imaging is also one of the COVID-19s major diagnosis method. Most COVID-19 cases exhibit common features (visual symptoms) on CT images, including early ground-glass opacity, and late-stage pulmonary consolidation. There is also a rounded morphology and a peripheral lung distribution [2], [3]. While typical CT images may help to screen suspected COVID-19 cases at an early stage, CT images of various viral pneumonia are similar and overlap with other infectious and inflammatory lung diseases [4], [5], [6], [7]. It is worth noting that radiologists distinguish between COVID-19 and other viral pneumonia. The previous work focus on to diagnose the COVID-19 patients using computed tomography [8], [9], [10], [11], [12]. Therefore, this paper collects lung screening data to diagnose the COVID-19 using computed tomography.

B. Motivations

The motivation of our study is inspired by some fundamental problems. COVID-19 is spreading rapidly and the detection of the positive cases, without leakage the privacy of users, is a challenging task. Moreover, the existing studies are not capable enough to share the data collaboratively and train the model accurately. Collecting data from various sources is a big challenge and a bottleneck in the advancement of AI-based techniques. Furthermore, to train the deep learning model collaboratively, over a public network, is another challenge. Medical practitioners diagnose the patients through the gene sequencing for respiratory or reverse transcription-polymerase chain reaction. Instead of patients waiting for positive virus results, treatments now include those disclosing COVID-19 suspects chest CT scans. Using this approach, authorities and

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medical practitioners can identify and treat patients faster and accurately. Even after recovering from COVID-19, some patients have to live with permanent lung damage [13]. The latest report of the World Health Organization reveals that COVID-19 is an infectious disease that primarily affects the lungs such as SARS, giving them a honeycomb-like appearance [14]. Secondly, some small infected areas in the lungs by COVID-19 has the potential to be missed even by professional radiologists, and thus it is feasible to develop a deep learning-based model for automatic detection of COVID-19. Thirdly, to share the data to train a better deep learning model, while keeping in view the privacy concern of the data providers, is the motivation of our work.

- The first challenge is to share the patients' data from different hospitals without violation of organizations' privacy and train a collaborative model automatically. Data privacy is the main concern and challenge in sharing medical data.
- The second challenge is the unavailability of a dataset, it is quite challenging to collect enough amount of training data and make it open source.
- Finally, to recognize the patterns of the lung screening of COVID-19 is also a challenging task.

C. Our approach

In this paper, we propose a framework to recognize CT scans of COVID-19 patients and collect the data from the multiple hospitals. This article introduces a new dataset, named CC-19, related to the latest family of coronavirus i.e. COVID-19. The dataset contains the Computed Tomography scan (CT) slices for 89 subjects. Out of these 89 subjects, 68 were confirmed patients (positive cases) of the COVID-19 virus, and the rest 21 were found to be negative cases. The dataset contains 34,006 CT scan slices (images) belonging to 89 subjects. Further details of the dataset are provided in Section 4.1. We employ various deep learning models to recognize the COVID-19 patterns of lung CT scans. Moreover, we employ Googles Inception V3 network [15] for feature extraction. We modify the Google Inception for feature extraction and further train the obtained features on a Capsule Network [16] for better generalization. We found the capsule network achieved better performance as compared to other learning models. Additionally, we solve the privacy issue using the federated learning technique. It collaboratively collects the data and trains an intelligent model then shares this intelligent model in a decentralized approach over the public network. In federated learning, the hospitals keep their data private and share only weights and gradients while blockchain technology is used to distribute the data among the hospitals. Instead of directly sharing patients' private data, share the weights of the model, and train the global model to collect weights of the local models in the decentralized network. The decentralized architecture for data sharing among multiple hospitals shares the data securely without leakage the privacy of the hospitals.

D. Contributions

The main contributions of the paper are not limited to:

- 1) This paper introduces a new dataset that consists of 89 subjects out of which 68 subjects are confirmed COVID-19 patients. The dataset contains 34,006 CT scan slices (images) belonging to 89 subjects.
- 2) This paper proposed a blockchain empowered technique to collect the dataset collaboratively from different sources while keeping in view the organizations privacy concerns. Federated learning employed is to protect the organizations data privacy and train the global deep learning model using less accurate local models.
- 3) Thirdly, we detect the patterns of COVID-19 from the lung CT scans using deep learning models (VGG16, VGG19, DenseNet, AlexNet, and MobileNet, ResNet, and Capsule Network).
- 4) Finally, we compare the state-of-art local model (i.e., ResNet, Capsule Network, etc.) with the federated learning model and the results clearly show the superiority of our proposed method.

E. Applications

The proposed approach is practical for big data analytical (i.e., lung CT scans), and it also efficiently process the data using the blockchain and deep learning model. Let's take a scenario of the real-time use case of a hospital having some new symptoms of the COVID-19 virus. To find out new symptoms or new information regarding COVID-19, the data needs to stored on a decentralized network without leakage of the privacy of the patients and securely share the knowledge of the latest patients. The federated learning secure data through the decentralized network and distribute the training task to train a better model from the latest available patient data.

The proposed framework collects a huge amount of data from different sources and to train the deep learning model over a decentralized network for the newest information about COVID-19 treatments.

F. Structure of paper

The rest of this paper is organized as follows: In Section II, we present an overview of the studies related to deep learning, COVID-19, and federated learning. In Section III, This paper proposed the capsule network and federated-learning-blockchain for secure data sharing without leakage the privacy. In Section IV, we describe dataset and experiment results for our proposed scheme. Finally, Section V concludes this paper.

II. RELATED WORK

A. AI in Covid-19

Artificial Intelligence (AI) based techniques have played an essential role in the domain of medical image processing, computer-aided diagnosis, image interpretation, image fusion, image registration, image segmentation, image-guided therapy, image retrieval, and analysis techniques. Artificial Intelligence aids in extracting information from the images and represent information effectively and efficiently. Artificial Intelligence facilitates and assists doctors and other medical practitioners to diagnose various diseases while eliminating human error

and increasing the speed and accuracy of detection. These techniques enhance the abilities of doctors and researchers to understand how to analyze the generic variations which cause the disease in the first place. Deep learning is the core technology of the rising artificial intelligence and has reported significantly diagnostic accuracy in medical imaging for automatic detection of lung diseases [17], [18], [19]. Deep learning surpassed human- performance on the ImageNet image classification task, with one million images for training in 2015 [20], which showed dermatologist-level performance on classifying skin lesions in 2017 [21] and obtained remarkable results for lung cancer screening in 2019 [17]. Pneumonia can be diagnosed using Computed Tomography (CT) scans of the chest of the subject. Artificial Intelligence (AI) based automated CT image analysis tools for the detection, quantification, and monitoring of coronavirus and to distinguish patients with coronavirus from disease-free have been developed [6]. In a study by Fei et al., they developed a deep learning-based system for automatic segmentation of all lung and infection sites using chest CT [7]. Xiaowei et al. aimed to establish an early screening model to distinguish COVID-19 pneumonia and Influenza-A viral pneumonia from healthy cases using pulmonary CT images and deep learning techniques [13]. In Shuai et al. study, based on the COVID-19 radiographic changes from CT images, they have developed a deep learning method that can extract the graphical features of COVID-19 to provide a clinical diagnosis before pathogenic testing and thus save critical time for the disease diagnosis [22]. Recently, C. Zheng et al. [11] developed a deep learning-based model for automatic COVID-19 detector using 3D CT volumes.

B. Federated Learning

Federated learning was proposed by McMahan et al. [23] to learn from the shared model while protecting the privacy of data. In this context, the federated learning is used to secure data and aggregates the parameters for the multiple organizations[24], [25], [26], [27], [28]. The hospitals can share the dataset during training and information about their dataset is revealed through analyzing the distributed model [29], [30], [31], [32], [33], [34], [35], [36], [37]. This decentralized approach to train models preserves privacy and security. A lot of research has been done in federated learning for transferring the matrices of weights of deep neural networks. The previous studies do not consider to share the medical data without compromising the privacy of organizations[38], [39]. In this article, we simulate our model to collect the data from different sources using federated learning combined with blockchain technology while sharing data without privacy leakage.

III. PROPOSED MODEL

This article considers a common pattern recognition in the CT scans of COVID-19 suspects and decentralized data sharing for the multiple hospitals. Each hospital shares its data to build a robust and collaborative model. Our goal is to design a framework capable of recognizing the pattern of

COVID-19 from lungs CT scans in collaboration with multiple hospitals. In this paper, we consider multiple hospitals share their private data and the local deep learning model such as VGG, Resnet, MobileNet, and Capsule network shares the weights. The global model federated learning combines the weights and makes it a more intelligent and robust model. We divided the methodology into two parts i) Capsule Network ii) Federated Learning. Firstly we focus on recognizing the pattern of COVID-19 using different deep learning models. Then we use federated learning for sharing the data among the hospitals to diagnose COVID-19 patients in a fast and accurate manner.

A. Capsule Networks for Detection of COVID-19

After the introduction of deep learning, some deep learning frameworks gained popularity among the AI community because of their robust and generalized behavior. Many corporate sectors such as Google have launched various deep learning frameworks such as Inception, VGG, Resnet, ImageNet Desnet, MobileNet and Capsule Network, etc. for image classification. A deep learning framework usually has a feature extraction pipeline that estimates and extracts prominent features. Afterward, a learning process such as MLP (multi-layer perceptron) is applied to learn the appropriate class on the extracted features. Over the past few years, researchers have used and fine-tuned the feature extraction pipeline of these robust deep learning frameworks. However, this article trains and test each model to compare with the capsule network. We design a Capsule Network because it achieves high performance in detecting diseases in the medical images. The previous technique needs lots of data to train a more accurate model. The Capsule Network improves the deep learning models performance inside the internal layers of the deep learning models. The architecture of our modified Capsule Network shown in Figure 1, which is similar to Hinton's Capsule Network. Capsule network contains four layers: i)convolutional layer, ii) hidden layer, iii) PrimaryCaps layer, and iv) DigitCaps layer.

A capsule is created when input features are in the lower layer. Each layer of the Capsule Network contains many capsules. To train the capsule network, the activation layer represents instantiate parameters of the entity and compute the length of the capsule network to re-compute the scores for the feature part. Capsule Networks is a better replacement for Artificial Neural Network (ANN). Here, the capsule acts as a neuron. Unlike ANN where a neuron outputs a scalar value, capsule networks tend to describe an image at a component level and associate a vector with each component. The probability of the existence of a component is represented by this vectors length and replaces max-pooling with "routing by agreement". As capsules are independents the probability of correct classification increases when multiple capsules agree on the same parameters. Every component can be represented by a pose vector U_i rotated and translated by a weighted matrix $W_{i,j}$ to a vector $\hat{u}_{i|j}$. Moreover, the prediction vector can be calculated as:

$$\hat{u}_{i|j} = W_{i,j}u_i \quad (1)$$

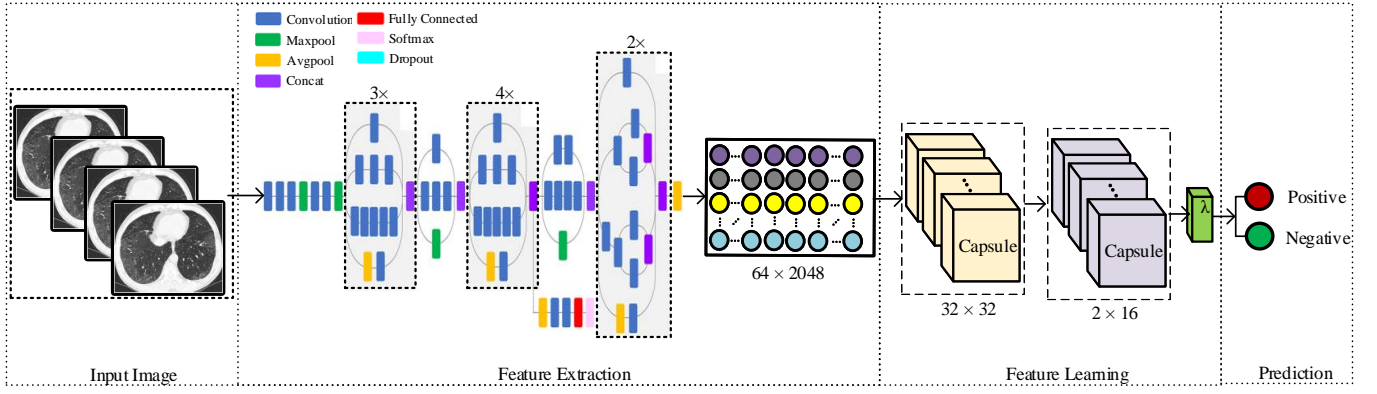


Fig. 1: Deep Learning Model for COVID-19. We employ a modified version of inception V3 (IV3*) deep learning model as a feature extraction pipeline. Further, we train the extracted features using to layers of the capsule network.

The next higher level capsule i.e. s_j processes the sum of predictions from all the lower level capsules with $c_{i,j}$ as a coupling coefficient. Capsules s_j can be represented as:

$$S_j = \sum_i c_{i,j} \hat{u}_{i|j} \quad (2)$$

where $c_{i,j}$ can be represented as a routing softmax function given as:

$$c_{i,j} = \frac{e^{b_{i,j}}}{\sum_k e^{b_{i,k}}} \quad (3)$$

As can be seen from the Figure 1, the parameter c , A squashing function is applied to scale the output probabilities between 0 and 1 which can be represented as:

$$a = \frac{\|a\|^2}{1 + \|a\|^2} \frac{a}{\|a\|} \quad (4)$$

For further details, refer to the original study [16]. We perform the routing by agreement using the Algorithm 1

Algorithm 1 Routing algorithm.

- 1: For all capsules i in layer l and capsule in layer $l+1$ do $b_{i,j} \leftarrow 0$
- 2: For k iterations do
- 3: For all capsule i in layer l do $c_{i,j}$
- 4: For all capsule j in layer $l+1$ do S_j
- 5: For all capsule j in layer $l+1$ do S_j State For all capsule i in layer l , j in layer $l+1$ do $b_{i,j} \leftarrow b_{i,j} + \hat{u}_{i|j} \cdot v_j$
- 6: Return v_j

C is an array after softmax, and it can be determined by dynamic routing by agreement. There are quite a few introductions to this method, the main meaning is that through several iterations, the distribution of the output of the low-level capsule to the high-level the capsule is gradually adjusted according to the output of the high-level capsule, and finally an ideal distribution will be reached. The detailed training algorithm is shown in the paper [40]. We use the capsule network to train the model and compare it with the state of art deep learning networks. Table 1 shows the difference between traditional and capsule network. In section 4.3, we compare traditional deep learning with the capsule network classifiers.

TABLE I: A comparison between capsule and traditional neural network.

Operation	Neuron (scalar)	Capsule (vector)
Affine transformation	NA	$\hat{u}_{i j} = W_{i,j} u_i$
Weighted sum	$a_j = \sum_{i=1}^3 W_i x_i + b$	$S_j = \sum_i c_{i,j} \hat{u}_{i j}$
Activation	$h_{w,b}(x) = f(a_j)$	$a_j = \frac{\ a_j\ ^2}{1 + \ a_j\ ^2} \frac{a_j}{\ a_j\ }$
Output	scalar	vector(a_j)
Graphical representation		

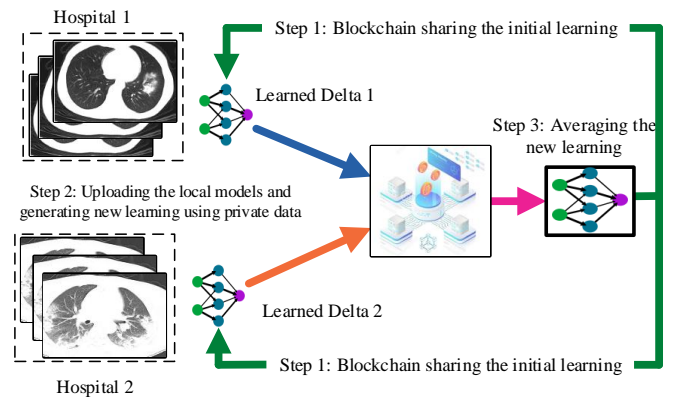


Fig. 2: Overview of the Federated Learning process.

B. Federated Learning to Secure the Privacy of the Data

In this section, we considered a decentralized data sharing scenario with multiple hospitals for the COVID-19. Each hospital is willing to share its model, our proposed method assists in hiding the user data and share the model in the decentralized network. The process of the data to train the model on a decentralized node without compromising user privacy. The base architecture of federal learning is shown in Figure 2. Figure 2 Combines the models from different

hospitals with a collaborative task. Our main goal is to utilize federated learning to share the data among the hospitals without leakage of privacy. We consider H is the hospitals and d is the union dataset. Each of Hospitals' H agrees to share the data without leakage of the private information. First, we train the Global Model M , without the leaking private data then we alter a small part of the randomized mechanism through the 1) Random sub-sampling, 2) Distorting. The random sub-sampling model can get final weights $R(M)$ and share the data locally. 1) Random sub-sampling: Let H be the number of hospitals. In every round of the communication is subset of X_t of size $m_t \leq H$ is sampled. Then distribute the weights (w_t) among the hospitals. The blockchain stores the local hospitals models $\{w^H\}_{H=0}^{m_t}$. The difference among the local and distributed model is referred to hospitals as H 's update $\Delta w^k = w^k - w_t$. The updated weights send to the decentralized network of every round.

2) Distorting: A Gaussian method was utilized to disorder the sum of updates. It required the information about the sensitivity information to sum all operation. The sensitivity of the updated version is measure by $\Delta w^h = \Delta w^h / \max\left(1, \frac{\|\Delta w^h\|_2}{S}\right)$. Scaling helps to ensure limited second standard $\forall H, \|\Delta \bar{w}^H\|_2 < S$. Sensitivity of the update bound operation by S . The updated model is defined as:

$$w_{t+1} = w_t + \frac{1}{m_t} \underbrace{\sum_{H=0}^{m_t} \Delta w^H / \max\left(1, \frac{\|\Delta w^H\|_2}{S}\right)}_{\text{Gaussian mechanism approximation sum of updates}} + \underbrace{\mathcal{N}\left(0, \sigma^2 S^2\right)}_{\text{Sum of update clipped at } S} \quad (5)$$

We noticed that the distortion of $1/m_t$ in the Gaussian process is regulated by the $S^2\sigma^2/m$ noise variance. But this distortion shouldn't surpass a certain amount. Otherwise, the additional noise removes too much detail from the sub-sampled average and no learning improvement can arise. Gaussian mechanism and sub-sampling are distributed processes. Nevertheless, it is used for gradient averaging, covering a single data point gradient at each iteration. This m and σ often describes the lack of privacy suffered when the randomized process produces an average estimate.

Choosing m and σ is specific S , distortion and lack of privacy are calculated by the rate $r = \mu/2m$. The greater σ and smaller m , the loss if the privacy is higher. The Privacy Accountant tells us that for fixed $r = \pi/2m$, i.e. with the same amount of distortion, privacy loss is smaller for both π and m . The preference will then be based on an upper limit at the r -distortion rate and a lower limit on the number of consumer sub-samples. Therefore describe the V_c variance between customers as a measure of similarity among hospital updates shown in the below equation. The parameters (x, y) is the throughout of H hospitals is defined as:

$$VAR[\Delta w_{x,y}] = \frac{1}{H} \sum_{H=0}^H \left(\Delta w_{x,y}^H - \mu_{x,y}\right)^2 \quad (6)$$

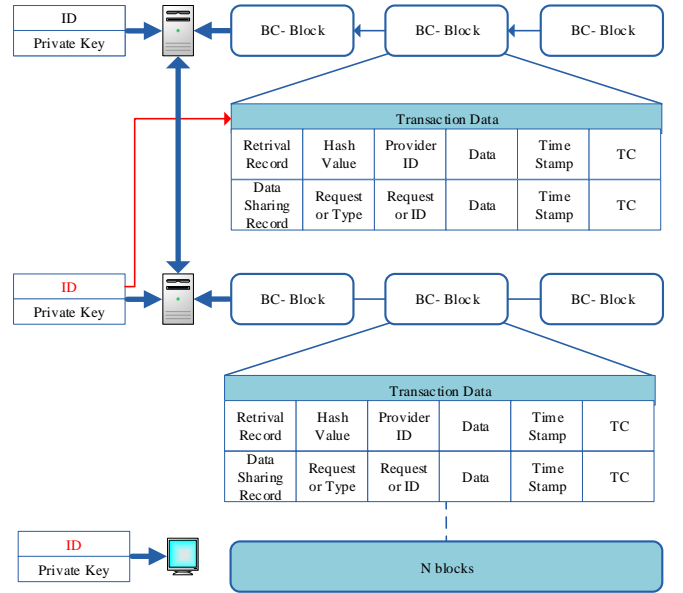


Fig. 3: Overview of the Blockchain record storing process. TC represents the transaction count.

where $\mu_{x,y} = \frac{1}{H} \sum_{H=1}^H \Delta w_{x,y}^H$

V_c is defined as the sum of all variances in the update matrix:

$$V_c = \frac{1}{b \times a} \sum_{x=0}^q \sum_{y=0}^p VAR[\Delta w_{x,y}] \quad (7)$$

Finally, the U_s update can be expressed as:

$$U_s = \frac{1}{b \times a} \sum_{x=0}^q \sum_{y=0}^p \mu_{x,y}^2 \quad (8)$$

$\Delta w_{x,y}$ describes the (x, y) -th parameters of the updates from $\Delta w \in \mathbb{R}^{b \times a}$ for the communication round. Moreover, S defines trade-off. If S has a smaller value then the noise will be smaller.

1) *Blockchain based fast and effective Federated Learning:* As patients data is sensitive and the volume is high, placing data on the blockchain with its limited storage space is very expensive and resource-intensive. Thus, the real data is stored by the hospital, blockchain help to retrieve the data. When a new hospital provides the data, it stores a transaction in the block to verify the owner of the data. The hospital data include the type of data and the size of the data. Each transaction for data sharing and retrieval process is shown in Figure 3. The proposed model solves data-sharing retrieval requests. Multiple hospitals can collaboratively share the data and train the model to predict optimal results. The retrieval mechanism does not disturb the privacy of the hospital. Inspired by Maymounkov et al, [41], we present multi-organization architecture using blockchain technology. All hospitals H are partitioned share data in various categories. Each category has a different community. Each community maintains the log table $Log(n)$. The blockchain stores the all unique IDs for every hospital

Data retrieval into the physically present nodes is expressed by equation 9. We measure the distance between two nodes in the following Equation 9 where H is the data categories to retrieve the data among the hospitals. Moreover, the distance of two nodes $d_i(H_i, H_j)$ measured to the retrieve of data, and $(x_{pq}^{H_i} + x_{pq}^{H_j})$ are the attributes of the weight matrix for the node H_i and H_j , respectively. Every hospital generates its unique ID according to the logic and distance of the nodes.

$$d_i(H_i, H_j) = \frac{\sum_{p,q \in \{H_i \cup H_j - H_i \cap H_j\}} (x_{pq}^{H_i} + x_{pq}^{H_j})}{\sum_{p,q \in H_i \cup H_j} (x_{pq}^{H_i} + x_{pq}^{H_j})} \cdot \log(d_p(H_i, H_j)) \quad (9)$$

Provided two nodes H_i and H_j with unique IDs $H_i(id)$ and $H_j(id)$ shown in the equation 10.

$$d(H_i, H_j) = H_i(id) \oplus H_j(id) \quad (10)$$

To secure the privacy of data in a decentralized manner the randomized method for two hospitals nodes shown in equation 11, where R and R' is the neighboring records of data. O is the outcome set of data. $\mathcal{A}(R) \in S$ achieves the privacy of the data.

$$Hr[\mathcal{A}(R) \in S] \leq \exp(\epsilon) \cdot Hr[\mathcal{A}(R') \in O] \quad (11)$$

However, to achieve data privacy for multiple hospitals, Laplace is applied for the local model training (m_i):

$$\hat{m}_i = m_i + \text{Laplace}(s/\epsilon) \quad (12)$$

where s shows the sensitivity as expressed by equation 13

$$s = \max_{H, H'} \|f(H) - f(H')\|_1 \quad (13)$$

The consensus algorithm is executed to train the global model from the local models. All nodes are collaboratively trained in the model. Therefore, we provide proof of work to share the data between the different nodes. During the training phase, the consensus algorithm checks the quality local models and the accuracy is measured by mean absolute error (MAE). $F(x_i)$ shows predicated data and m_i, y_i is the original data. The high accuracy of m_i shows the low mean absolute error of m_i . The voting process consensus algorithm among the hospitals shown in equation 14 and 15. Where equation 14 $MAE(m_i)$ shows the locally trained model and γ shows the global models weights in equation 15.

$$MAE(m_i) = \frac{1}{n} \sum_{i=1}^n |y_i - f(x_i)| \quad (14)$$

$$MAE(H_j) = \gamma \cdot MAE(m_j) + \frac{1}{n} \sum MAE(m_i) \quad (15)$$

To preserve the hospitals' data privacy, all data is encrypted and signed using public and private keys (PK_i, SK_i), MAE calculates the all transactions and broadcast the (H_j). $MAE(M)$ calculates each transaction of the model. If all

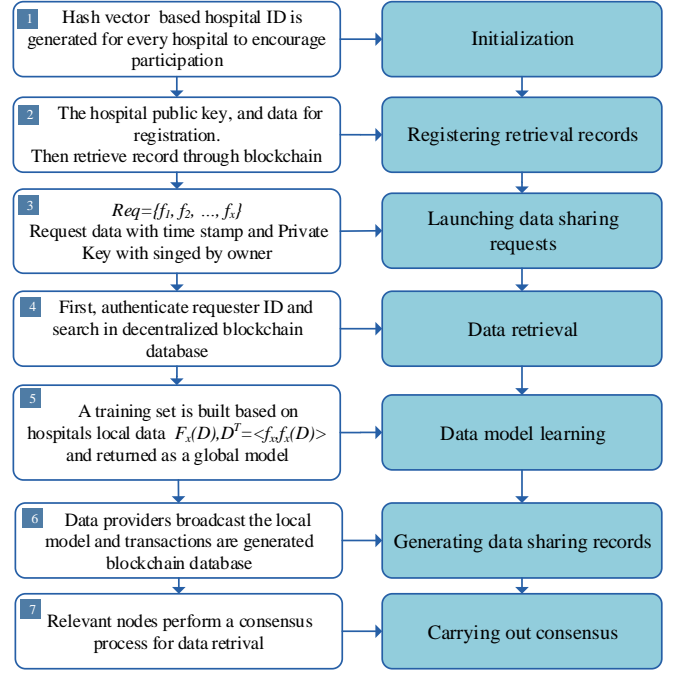


Fig. 4: Data Sharing Process.

transactions are approved then the record is stored in the distributed ledger. More precisely, the training of the consensus algorithm describes as follows:

- 1) Node H_i transfers the local model m_i transaction to the H_j .
- 2) Node H_j transfers the local model m_i to the leader.
- 3) The leader broadcast the block the node to the H_i and H_j .
- 4) Verify the H_i and H_j and wait for the approval.
- 5) Finally, store the blocks in the retrieval blockchain database.

2) *Data Sharing Process* : Current approaches use encryption to protect the data. And to share data among the hospitals, it is still a risk for data providers to share personal data because of certain security attacks. A simple solution is to transmit the data is to send requester legitimate details and to preserve the data holder's privacy. Instead of the original data, data providers, such as hospitals, exchange only the learned models with the requester. Figure 4 shows the process of data sharing. The nodes are communicating with each other and the consensus process learns from federated data. The provider and requester searches and stores the data into the blockchain nodes. More precisely, the steps of data sharing are shown in Figure 4. To integrate the blockchain with federated learning retrieved data securely for the multiple world-wise hospitals which can provide the effectiveness predication.

To protect the privacy of the data, we share the trained model instead of the original image data. The objective of the proposed architecture is to train the global model from the local models. The secure data sharing illustrates in Figure 5. In the first phase, we select the training data and then use the private federated learning algorithm for collaborative multi-hospital learning. More precisely, the local model share

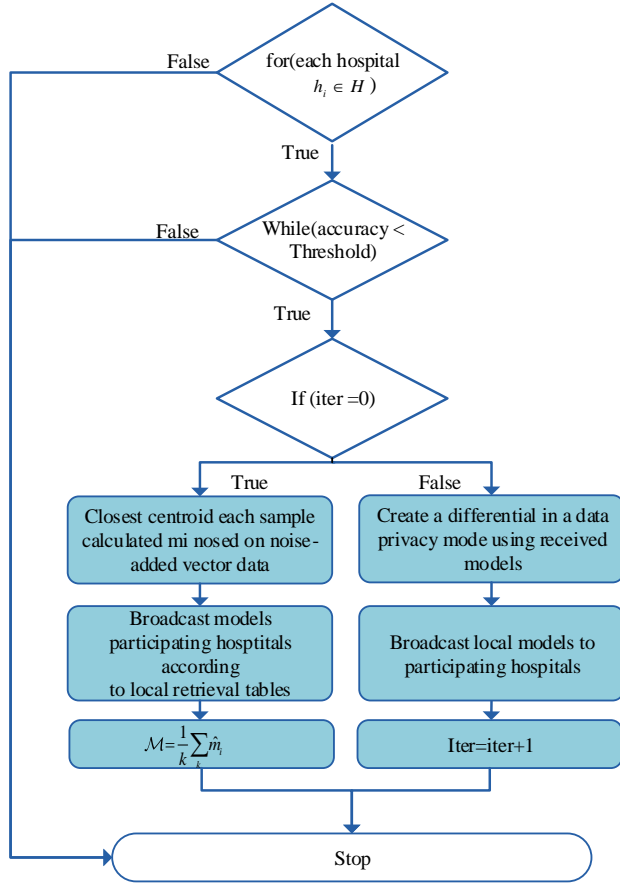


Fig. 5: Private Federated Learning Algorithm.

the weights to the blockchain network and federated learning combines the local model into the global model.

IV. EXPERIMENTS RESULTS

A. CC-19 Dataset

In the past, Artificial intelligence (AI) has gained a reputable position in the field of clinical medicine. And in such chaotic situations, AI can help the medical practitioners to validate the disease detection process, hence increasing the reliability of the diagnosis methods and save precious human lives. Currently, the biggest challenge faced by AI-based methods is the availability of relevant data. AI cannot progress without the availability of abundant and relevant data.

In this paper, we introduce a small new dataset related to the latest family of coronavirus i.e. COVID-19. Such datasets play an important role in the domain of artificial intelligence for clinical medicine related applications. This data set contains the Computed Tomography scan (CT) slices for 89 subjects. Out of these 89 subjects, 68 were confirmed patients (positive cases) of the COVID-19 virus, and the rest 21 were found to be negative cases. The proposed dataset CC-19 contains 34,006 CT scan slices (images) belonging to 89 subjects out of which 28,395 CT scan slices belong to positive COVID-19 patients. This dataset is made publicly available via GitHub (<https://github.com/abdkhanstd/COVID-19>). Figure 6 shows some 2D slices taken from CT scans of

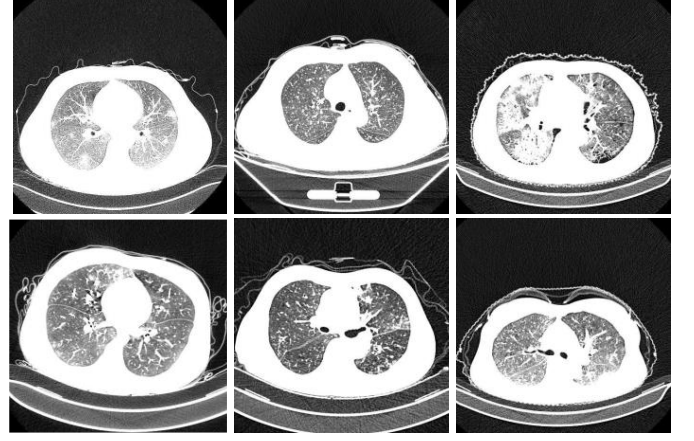


Fig. 6: Some random samples of CT scan 2D slices taken from CC-19 dataset.

the CC-19 dataset. Moreover, some selected 3D samples from the dataset are shown in Figure 7. The Hounsfield unit (HU) is the measurement of CT scans radiodensity as shown in Table II. Usually, CT scanning devices are carefully calibrated to measure the HU units. This unit can be employed to extract the relevant information in CT Scan slices. The CT scan slices have cylindrical scanning bounds. For unknown reasons, the pixel information that lies outside this cylindrical bound was automatically discarded by the CT scanner system. But fortunately, this discarding of outer pixels eliminates some steps for preprocessing.

S/No	Substance	Hounsfield Unit (HU)
1	Air	-1000
2	Bone	+700 to +3000
3	Lungs	-500
4	Water	0
5	Kidney	30
6	Blood	+30 to +45
7	Grey matter	+37 to +45
8	Liver	+40 to +60
9	White matter	+20 to +30
10	Muscle	+10 to +40
11	Soft Tissue	+100 to +300
12	Fat	-100 to -50
13	Cerebrospinal fluid(CSF)	15

TABLE II: Various values of Hounsfield unit (HU) for different substances.

Collecting dataset is a challenging task as there are many ethical and privacy concerns observed the hospitals and medical practitioners. Keeping in view these norms, this dataset was collected in the earlier days of the epidemic from various hospitals in Chengdu, the capital city of Sichuan. Initially, the dataset was in an extremely raw form. We preprocessed the data and found many discrepancies with most of the collected CT scans. Finally, the CT scans, with discrepancies, were discarded from the proposed dataset. All the CT scans are different from each other i.e. CT scans have a different number

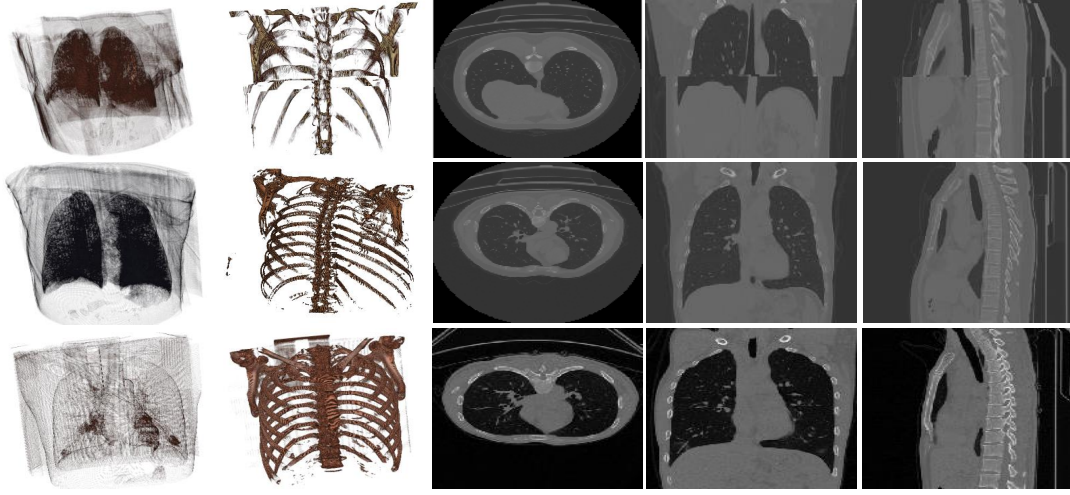


Fig. 7: This figure shows some selected samples from the “CC-19 dataset”. Each row represents different patient samples with various Hounsfield Unit (HU) for CT scans. The first column, from left to right, shows the lungs in the 3D volume metric CT scan sphere. The second column shows the extracted bone structure using various HU values followed by the XY, XZ, and YZ plane view of the subjects’ CT scan. It is worth noting that the 3D volumetric representation is not pre-processed to remove noise and redundant information.

of slices for different patients. We believe that the possible reasons behind the altering number of slices are the difference in height and body structure of the patients. Moreover, upon inspecting various literature, we found that the volume of the lungs of an adult female is, comparatively, ten to twelve percent smaller than a male of the same height and age [42].

B. Evaluation Measures

Specificity and sensitivity are the abilities of a model that how correctly the model identifies a subject with disease and without a disease. In our case, it is critical to detect a COVID-19 patient as missing a COVID-19 patient can have disastrous consequences. The formulas of the measures are given as follows:

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

$$\text{sensitivity} = \text{recall} = \frac{TP}{TP + FN}$$

$$\text{specificity} = \frac{TN}{TN + FP}$$

$$\text{Total accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

A medical diagnosis based system needs to have high sensitivity and recall. We present a comprehensive overview of various famous deep learning frameworks. The results presented in Table III indicate the superiority of our proposed method.

C. Results of the pattern recognition with the benchmark algorithms

This article conduct results from different kinds of deep learning models i.e.,(VGG16, AlexNet, Inception V3, ResNet

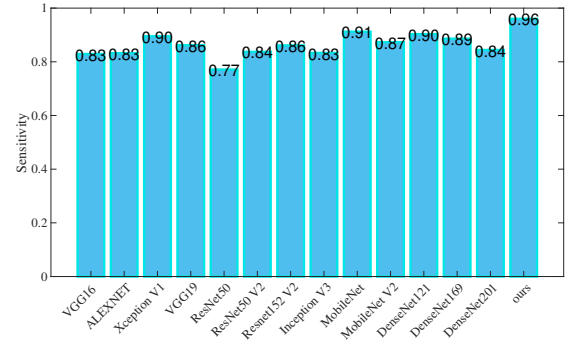


Fig. 8: Sensitivity/Recall of the COVID-19 dataset over the decentralized network.

50-152 layers, MobileNet, DenseNet). We used deep learning models and different layers for comparing the performance models on the COVID-19 dataset, which is shown in Table III. We evaluate the performance of the capsule network for the detection of COVID-19 lung CT image accuracy. Figure 8 shows the deep learning models; the capsule network achieves high sensitivity and less specificity, we achieved high detection performance through the capsule network. Figure 9 shows the Inception V3 capsule network achieved the best performance and provide the highest sensitivity and lowest specificity. These models were tested using three different test lists containing about 11,450 CT scan slices.

D. Federated Learning Security analysis and Results

We test the federated learning using the CC-19 dataset for a secure data sharing scheme for the hospitals. First, we test the three hospitals or providers to share the corona related dataset then we increase up to 9. Figure shows the accuracy of the different Hospitals. The accuracy was changed when the

TABLE III: The performance of some famous deep learning networks. The bold values represent the best performance. It can be seen that the capsule network exhibited the highest sensitivity while ResNet 0.249 has the best specificity.

Feature extraction network	Learnable node	Pre-trained on	Precision	Sensitivity / Recall	Specicity
VGG16 [43]	MLP	Imagenet	0.8269	0.8294	0.1561
AlexNet [44]	MLP	Scratch	0.833	0.831	0.191
Xception V1 [45]	MLP	Imagenet	0.830	0.894	0.110
VGG19 [43]	MLP	Imagenet	0.827	0.8616	0.128
ResNet50 [46]	MLP	Imagenet	0.833	0.771	0.249
ResNet50 V2 [47]	MLP	Imagenet	0.830	0.837	0.166
Resnet152 V2[47]	MLP	Imagenet	0.828	0.861	0.134
Inception V3 [48]	MLP	Imagenet	0.828	0.833	0.159
MobileNet [49]	MLP	Imagenet	0.830	0.912	0.089
MobileNet V2 [50]	MLP	Imagenet	0.828	0.873	0.118
DenseNet121 [51]	MLP	Imagenet	0.832	0.903	0.113
DenseNet169 [51]	MLP	Imagenet	0.831	0.886	0.126
DenseNet201 [51]	MLP	Imagenet	0.829	0.844	0.152
IV3* (Ours)	Capsule Network	Scratch	0.830	0.967	0.004

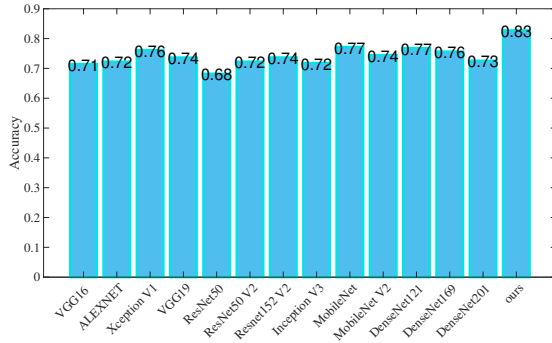


Fig. 9: Accuracy of the COVID-19 3-D Images.

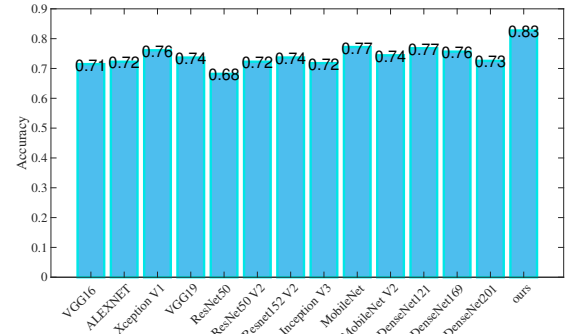


Fig. 10: The Accuracy of dataset COVID-19 for different providers.

hospitals or providers were increases. We can say that it would be better to use more providers to collect data and results will be better. Figure 11 shows that model loss convergence. The Federated learning algorithm is scalable and the global model combines the local models to train the local COVID-19 images. We compare the federated learning with the local model shown in Figure 9. The local model trained in the whole dataset and the federated learning model learn from local models to the global model. Figure 10 and 11 indicates that performance increases significantly when data providers are increasing. However, federated learning does not affect the accuracy but it achieves privacy while sharing the data.

The following points were kept in view to ensure the trust among the parties using the federated learning with blockchain technology:

- **Differences-Privacy:** Figure 5 describes the differences in privacy analysis, where a principled approach that enables organizations to learn from most data while ensuring that these results do not allow data to be

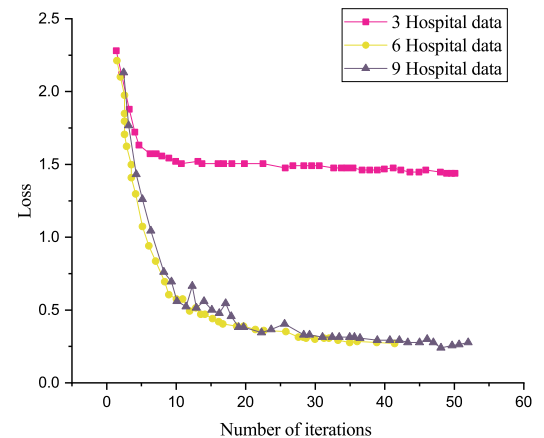


Fig. 11: The Loss of dataset COVID-19 for different providers.

distinguished or re-identified by any individual. On the other hand, equation 11 to obtain the value in the data to ensure strong data security.

- **Trust:** The decentralized trust mechanism of the blockchain allows everything to run automatically through a preset program, which will greatly improve data security. Relying on a strict set of algorithms, the decentralized blockchain technology can ensure that the data is true, accurate, transparent, traceable, and cannot be tampered with.
- **Security of the Data:** Data providers have the authority to control their data. Actual data is uploaded with the signature of the owner in the blockchain database. The owner has the right to control and change the policy of the data using the smart contract. The blockchain uses cryptographic algorithms that enable the security of the data.

E. Compared with Other Methods

There are a lot of previous work has been done for detecting the corona-virus [52], [53], [54], for instance, the GAN algorithm is used to detect the corona-virus. Based on these techniques, we design a secure data sharing technique to distribute the data form the multiple hospitals. However, GAN generates the fake images due to fake data the performance is not reliable in case of medical images. However, due to the small number of data patients [55] the data analytic is difficult. Our proposed model collect a huge amount of real-time data to build a better prediction model. In comparison with the federated learning with the state-of-art deep learning models such as VGG, RESNET, ImageNet, MobileNet, Desnet, Capsule Network. The results show the accuracy is similar to train the local model with the whole dataset or divide data in different model and combine the model with federated learning. We analyse our results by comparing them with the other methods proposed [52], [53], [54] used GAN technique to detect the corona-virus, we use capsule network and federated learning to detect corona-virus scans. Moreover, the use of chest x-ray data, we use CT scanned data for accurate detection. According to a survey of doctors, CT-Scans [56] are more accurate than the X-ray dataset.

Finally, the other authors [52], [53], [54] do not focus on secure data sharing among the various hospitals. We proposed a secure data sharing model, which is the best solution to collect the data a small amount of data and train the global model and predict the patients form the network.

V. CONCLUSION

In this paper, we introduce a new dataset CC-19 that contains 34,006 CT scan slices (images) belonging to 89 subjects. Moreover, we recognize patterns from the CT-scan COVID-19 using the deep convolutional neural networks (CNN). We apply various deep learning models for training and testing the dataset. The Capsule Network achieved the highest accuracy. Additionally, we design the federated learning model to secure sharing the medical data with the privacy-preserved concern. The model is smart as it can learn from data shared among

thousands of hospitals. Moreover, training and testing can be tackled privately and securely with the federated learning and it deals with the risk of model normalization, where shared model parameters might be too influenced by a single contributor. A deep learning model for the analysis of COVID-19 patients through lung screening. We believe that this research can help to detect COVID-19 patients using lung screening as hospitals share their private data to train the model better to help the clinical performance evaluation.

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