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An Integration of blockchain and AI for secure data sharing and detection of CT images for the hospitals

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ABSTRACT

Deep learning, for image data processing, has been widely used to solve a variety of problems related to medical practices. However, researchers are constantly struggling to introduce ever efficient classification models. Recent studies show that deep learning can perform better and generalize well when trained using a large amount of data. Organizations such as hospitals, testing labs, research centers, etc. can share their data and collaboratively build a better learning model. Every organization wants to retain the privacy of their data, while on the other hand, these organizations want accurate and efficient learning models for various applications. The concern for privacy in medical data limits the sharing of data among multiple organizations due to some ethical and legal issues. To retain privacy and enable data sharing, we present a unique method that combines locally learned deep learning models over the blockchain to improve the prediction of lung cancer in health-care systems by filling the defined gap. There are several challenges involved in sharing that data while maintaining privacy. In this paper, we identify and address such challenges. The contribution of our work is four-fold: (i) We propose a method to secure medical data by only sharing the weights of the trained deep learning model via smart contract. (ii) To deal with different sized computed tomography (CT) images from various sources, we adopted the Bat algorithm and data augmentation to reduce the noise and overfitting for the global learning model. (iii) We distribute the local deep learning model wights to the blockchain decentralized network to train a global model. iv) We propose a recurrent convolutional neural network (RCNN) to estimate the region of interest (ROI) in theCT images. An extensive empirical study has been conducted to verify the significance of our proposed method for better prediction of cancer in the early stage. Experimental results of the proposed model can show that our proposed technique can detect the lung cancer nodules and also achieve better performance.

1. Introduction

Artificial intelligence (AI) and blockchain (BC) based technologies have earned a good reputation among the research community over the past few years. AI is now capable of processing huge anount of data, whereas blockchain provides a decentralized and secure data access (Tanwar et al., 2019, 2020; Bodkhe et al., 2020a, b; ALzubi et al., 2019; Gupta et al., 2020a,b,c; Hathaliya and Tanwar, 2020; Mehta et al., 2020; Ali et al., 2019; Afzal et al., 2020). AI has already achieved great success in various fields such as speech recognition (Zhang et al., 2018; Fahad and Yahya, 2018; Bhattarai et al., 2016; Schroff et al., 2015), face recognition (Ranjan et al., 2019; Zhang et al., 2018; Bianco et al., 2018), fine-grained image recognition (Zhang et al., 2018; Seo and Shin, 2019), and visual search (Cha et al., 2018; Han et al., 2015). Other than these areas of studies, AI, especially deep learning, has proven its worth by achieving outstanding performance. Deep learning-based and medical imaging applications include histology tissue segmentation (Wang et al., 2017a,b,c), brain magnetic resonance imaging (MRI) analysis (Yoo et al., 2018), blood cell analysis, and many more (Zhou et al., 2018). Deep learning-based frameworks allow researchers to design better detection models capable of detecting all kinds of diseases especially

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Abbreviation table

Abbreviation	Description
CT	Computed tomography
MRI	Magnetic resonance imaging
RCNN	Regions with convolutional neural networks
ROI	Region of Interest
IPFS	Interplanetary File System
CNN	Convolutional neural networks
RGI	Radial Gradient Index
IADLT	Image Data Augmentation
BAT	Bat Algorithm for Data Equalization

perilous diseases at early stages. Blockchain technology can assist in collecting data over the decentralized network to train a large number of high-quality images (i.e., radiology scans, MRIs, CT scans). Besides, a trained model based on clinical records of diseases, obtained from global organizations, can help to achieve better performance for early treatment of many diseases. Cancer detection is also one of the most important use-case of this approach.

Lung cancer is the most common type of cancer found in human beings. According to amyotrophic lateral sclerosis (ALS), an estimated 160,000 new cases of lung cancer were reported in the USA in the year 2018 alone. Currently, more than 3 million women are suffering from lung cancer in the USA. This year alone, lung cancer was held responsible for 41,400 deaths (40,920 women and 480 men). Therefore, early cancer detection and treatment are vital for the prevention of high mortality. To diagnose lung cancer, the most common type of medical technologies include ultrasound, X-rays, and computerized tomography (CT) scans that produce a multi-dimensional image that helps in better understanding of damaged tissues' properties. A CT scan based screening is one of the most effective and commonly adopted technique specifically for lung cancer detection (Akin et al., 2012; Stavros et al., 1995). However, diagnosing lung cancer at the early stage is a non-trivial task even for the specialists as well. Therefore, an image processing approach can play a vital role in diagnosing cancer at the early stage by providing the detailed characteristics of healthy and damaged tissue properties.

Recently, several researchers have proposed deep learning-based models for cancer detection (American Lung Association, 2020; Ardila et al., 2019; Singh et al., 2011; De Koning et al., 2018; Ozdemir et al., 2019; Zhang et al., 2019). However, most of them are not sufficient to analyze important features related to lung cancer (Zhao et al., 2019; Ardila et al., 2019). Additionally, deep learning approaches need high computational resources and time to achieve high performance due to the complex nature of image textures and feature extraction process (Miao et al., 2015; Ahn et al., 2017; Shelhamer et al., 2017; Shan et al., 2012; Du and Yeo, 2001; Chen et al., 2003; Yap et al., 2008). Due to the lack of availability of medical data (mainly due to privacy concerns), it is difficult to squeeze the true potential of deep learning techniques. A large amount of training data is required to exploit the true potential of deep learning-based techniques, realize a robust and accurate model. Therefore, addressing these issues in a single model capable of efficient lung cancer detection is a challenging task. It is a known fact that diseases can evolve by changing their physical properties, shape, appearance, symptoms, etc. In other words, to find the updated evolving properties regarding lung cancer requires storing and sharing data over a commonly accessible network for multiple organization. In this way, multiple organizations can share their data to solve a common problem based on the latest available information. One of the solutions is to store and share data over a decentralized network such as blockchain. By sharing data over the distributed ledger leads to the following challenges: i) Violation of organizations data privacy and to share the organizations' data in such a manner that the ethics of data privacy are observed ii) Collect a large amount of data from different organizations and to construct a collaborative deep learning model.

To tackle the mentioned challenges, we propose a novel multi-model method that combines deep learning and blockchain technology to diagnose early-stage cancer from CT images. The blockchain-based network can exchange data between different organizations while observing legal obligations. Data sharing between organizations enables the model to train on a large amount of data from different sources. To diagnose early-stage cancer from the CT images based on shared data raise some concerns: (i) How to secure medical data exchange i.e., the privacy of the data is observed (ii) How to deal with different sized CT images from different sources to train the deep learning model (iii) How to distribute the weights of the pretrained deep learning model over the decentralized network.

The smart contract ensures a secure data exchange by authorizing the uploading of the medical images automatically. It generates parameters based on conditions and terms associated with data-sharing agreements. The smart contract can track and collect the data from the original destination. Some parameters such as data provider name, address of the hospital, use condition, and the description of the data are required to share the data through the smart contract. We briefly discussed the smart contract in Section 4.1.

Usually, deep learning models require to have the same size of images. Dealing with CT images of different sizes and from various sources is not a trivial task. For this reason, we adopted the Bat algorithm and data augmentation for the transformation of data to feed into the neural network. The Bat algorithm reduces noise and also tackles the overfitting problem for the neural network (Cui et al., 2018). Further details and information can be found in Section 4.2.

To distribute the deep learning model over the decentralized network, we follow some significant steps for constructing the global model of deep learning: (i) Participants locally compute training gradients. (ii) The blockchain secure aggregate local weights without leakage the private information. iii) The local weights are passed through the IPFS and hashes are stored over the blockchain decentralized network, and after processing the input, the output is shared over the decentralized network. (iv) Updated weights of neural networks are again stored in IPFS via blockchain to reduce the computational power. Therefore, the distribution of the training task reduces time and utilize decentralized resources over the network. We briefly explained all the steps in Section 4.1.

In summary, we propose a novel method that combines various deep learning models (specifically the RCNN) over the blockchain to improve lung cancer detection and learn itself through the decentralized network. By employing blockchain, one can synchronize distributed information to improve classification performance by making use of the evolving data. Each health-care system contributes a part of significant learning data for high performance. It can help to predict cancer at early stages, thus saving millions of cancer patients' lives. The overall contributions of this paper can be summarized as follows:

1. We propose a novel framework that combines deep learning with blockchain to provide learning over decentralized data sources.
2. We design a customized smart contract to establish a secure large-scale real-time data sharing among different data providers.
3. We modify the RCNN by integrating the Region of Interest (ROI) pooling layer to detect the region of interest and train in a decentralized manner.
4. Finally, an intensive empirical study is conducted to validate our proposed method through the blockchain and deep neural network.

In this paper, we utilize blockchain and artificial intelligence to distribute data over a decentralized network. This enables organizations to make the best use of novel symptoms and cases for lung cancer patients without compromising the organizations' privacy concerns. The proposed approach distributes a locally trained model to collaboratively train a global model for big data analytics i.e. lung cancer CT scans. Further, this new technology can extract new patterns for the new cases of lung cancer over the decentralized network. The proposed framework collects a huge amount of data (pre-trained weights) from different sources and to train a collaborative deep learning model over a decentralized network to make use of the most novel information about lung cancer. The main goal of this paper is to improve the deep learning model and learn itself from the data for better prediction. In this way, medical practitioners can understand and diagnose new cases and symptoms in a better way.

The rest of the paper is organized as follows: In Section 2, we discuss recent relevant studies. The proposed framework is described in Section 4, where we discuss each component in detail. Section 4.1 discusses the data sharing techniques between different health-care systems. Whereas, a comprehensive analysis of the proposed model including competitiveness and complexity can be found in Section 5. Finally, we conclude our research contribution in Section 6 including some future directions.

2. Related work

Over the last decade, many studies were conducted to identify cancer by analyzing the different types of medical image data. Initially, (Chen et al., 2003) proposed a contour filter model to deal with the natural texture of ultrasound images, that can help to draw breast tumor boundary. It uses a hybrid filtering model that can partially process the image and improve the accuracy by using the active contour model technique. Later, Drukker et al. (Drukker et al., 2004) proposed a model to identify lesion characteristics in breast ultrasound images (BUIs) using the Bayesian neural net. The lesion characteristics are distinguished based on a radial gradient index filtering technique. While five hidden layers of Bayesian neural network are constructed for the classification of breast cancer and normal patient. However, both techniques have no automatic procedure to identify the region of interest (ROI) in the BUIs. Their approaches mainly focused on the performance evaluation of lesion detection, which only analyzes the position of the lesion. Furthermore, Yap et al. (Yap et al., 2008) proposed a new lesion detection method based on hybrid filtering, multifractal processing, and threshold-based segmentation. Histogram equalization is adopted to ensure the uniformity of the BUIs. Shan et al. (Shan et al., 2012) also proposed a lesion detection technique by exploiting speckle reduction and considering the combination of max-energy orientation and radial distance in texture features of the BUI. The speckle reduction for the anisotropic diffusion (SRAD) helps to automate the region of interest selection. But these techniques cannot be perfectly recognized a small number of segments and do not automatically detect the ROI from the CT scan images. Our proposed deep neural network finds the ROI automatically and identifies a small number of segmentations.

In (Zhao et al., 2019) and (Zhang et al., 2019), a deep convolutional neural network approach was used to detect the region-of-interest of lung cancer images. Singh et al. (Singh et al., 2011) emphasis on bio-inspired parallel applications to explore subsequent screening examinations for the lung cancer detection. Similarly, Nasser and Abu-Naser (2019) used an artificial neural network to find the symptoms (fingers, chronic disease, anxiety, and etc) of lung cancer. The model is able to find lung cancer from the symptom of human body. Furthermore, Bhatia et al. (2019) used the deep residual learning technique to detect the cancer from the CT scan images. Yang at el. (2019) highlights the main challenges of cancer detection and marks the tumor inside the lung cancer cells. However, aforementioned methods are not sufficient to analyze the important features and often limited regarding feature extraction process. Therefore, this paper proposes the CNN based model to learn the characteristics of lung cancer detection due to its strong ability to learn features. Therefore, we focus on the Radial Gradient Index (RGI) filtering method based on lesion detection method for the lung cancer.

2.1. Cancer detection based on CNN reorganization

Generally, the most advanced methods contain some important constraints (De Koning et al., 2018; Smith et al., 2018; Ozdemir et al., 2019; Zhang et al., 2019), especially image processing methods, which rely on rule-based methods and specific assumptions such as edges, homogeneity in images. In the absence of such strong assumptions, deep learning models demonstrated high accuracy in object detection. This which ensures that the status of lung CT scan lesion detection can also be improved. Deep learning and CNNs, according to their training procedure, can be categorized as follows:

1. **Patch-based CNN's approach:** This method trains the CNNs for image patching and sliding window testing methods (Kooi et al., 2017; American Lung Association, 2020; Ardila et al., 2019; De Koning et al., 2018; Singh et al., 2011; Zhang et al., 2019). However, among thousands of patches and each one involves a time-consuming and patch overlap that generates a lot of redundancy.
2. **Fully convolutional approach:** It avoids the computational redundancy. In (Long et al., 2015) and (Shelhamer et al., 2017), a fully convolution method is proposed to improve efficiency by training the entire image. It performs pixel-wise segmentation instead of a single probability distribution in the classification task of each image.
3. **Transfer learning approach:** The transfer learning approach (Ravishankar et al., 2016; Shelhamer et al., 2017) has recently been widely used in biomedical research. This method uses a pre-trained model of non-medical images to overcome data deficiency limitations in medical imaging.

For most of the lung related CT scan images, existing studies focus on utilizing CNN for mammography (Mordang et al., 2016; Ahn et al., 2017). Dungal et al. (2015) applied a deep learning model for the segmentation of masses for mammography. Furthermore, Mordang et al. (2016) used the CNNs for micro-calcification detection. Recently, Ahn et al. (2017) proposed the use of the CNNs in breast density estimation. For lung CT scan imaging, Zhang et al. (2019) and Zakria et al. (2019, 2020) used a deep convolutional neural network algorithm for the images classification. The limitation of the study carried out by Zhang et al. (2019) was heterogeneity in image quality. Moreover, it uses the multitask learning in which the model loses important features. Our proposed technique deals with such problems during the data pre-processing stage.

2.2. Block-chain based previous models

In this section, we discuss the proposed methodology, for health care domains, that adopt the blockchain to share the data between the organizations. There are various challenges such as data privacy and secure exchange of data among the organizations. However, (Downing et al., 2017) exchanged the information across the organization based on external and internal policy. Furthermore, some other interesting research focuses on secure healthcare data (Zhang et al., 2016; Azaria et al., 2016), brain simulation (Angraal et al., 2017), biomedical (Kuo et al., 2017; Hathaliya et al., 2019; Akram et al., 2020; Kumari et al., 2020; Bodkhe et al., 2019, Bodkhe et al., 2020a, b; Gupta et al., 2019, 2020a,2020b; Vora et al., 2018; Bhattacharya et al., 2019), and e-health data sharing (Angraal et al., 2017; Wang et al., 2020; Kumar et al., 2019; Kumar et al., 2020). Yue et al. (2016) focused on authorized users for the central database, which is based on the private blockchain. Besides, Griffs et al. (2018) used ethereum protocol for the remote patient monitoring system for minimizing risk. Similarly, Some authors (Ivan, 2016; Gupta et al., 2020a,2020b; Benzaid et al., 2016) proposed an encryption-based mechanism to store publicly organization data. Later, some authors (Chen et al., 2018; Alazab et al., 2013; Pham et al., 2020; Farivar et al., 2019; Vinayakumar et al., 2020) designed a blockchain-based framework to share data on the cloud storage without any involvement of a third party. Recent studies (Wang et al., 2018; Jiang et al., 2018; Shubbar et al., 2017) focus on the diagnosis of the patient condition and treatment for real-time healthcare systems. Therefore, we design a blockchain-based mechanism for the lung cancer image (weights) sharing scheme to predict cancer in the early stage.

2.3. Overview of combining the AI and blockchain

This section discusses the advantages of utilizing blockchain and artificial intelligence. First, we discuss some studies related to healthcare and other domains that adopted blockchain and artificial intelligence to secure data sharing and automatically train the deep learning models. There exist various challenges, such as the concern for data privacy and secure exchange of data between the organizations (Tanwar et al., 2019). However, Sudeep Tanwar et al. (2020), exchanged the information for the healthcare record system by combining the AI and blockchain across the organization. Moreover, they discuss the application of the blockchain in the health care systems in detail. Some other studies focus on the AI-based smart contract that enables data sharing along with policy control (Mehta et al., 2020; ALzubi et al., 2019). Kumar et al. (2019) combined the machine learning and blockchain for android devices that focus on sharing malware-related information to a decentralized network. Besides, Salah et al. (2019), focused on smart contract for privacy protection using the AI in cyber-physical systems. These studies do not focus on distributing the deep learning model to the decentralized network and combine the local model to create the global model. Our proposed method focuses on sharing the local model over the blockchain network later used to collaboratively build a new global deep learning model for better prediction. In this way, the collaboratively updated model helps in effective diagnosis of the patients' condition and thus leading to better treatment.

3. Preliminaries

In this section, we review the background of the blockchain, smart contract, and deep learning foundation related to the proposed method.

3.1. Smart contract

A Smart Contract is a kind of a digital contract, based on certain rules, between different organizations in the form of executable code. The Blockchain network uses smart contracts to take action based on a smart contract. The smart contract allows an organization to keep a record of all the transactions, without the intervention of the third party, which are traceable and irreversible. The main goal of a smart contract is to provide a secure method and reduce the cost. Moreover, the smart contract is publicly available across the network for interaction among the users. The rules of a smart contract are recognized by multiple organizations that run over the decentralized blockchain network and can run automatically according to the user conditions. The smart contract has three characteristics i.e., the information is: (i) immutable, (ii) transparent and (iii) permanently operational.

3.2. Interplanetary file system (IPFS)

IPFS is a peer-to-peer distributed file system for accessing and sorting data, files, images, websites, etc. The design of the protocol provides historic versioning of the Internet similar to repository versioning maintained by GitHub. Each file and all the blocks within are given a unique identifier based on a cryptographic hash. Duplicates are removed across the network and version history is tracked for every file. The working flow of IPFS shown in Fig. 1.

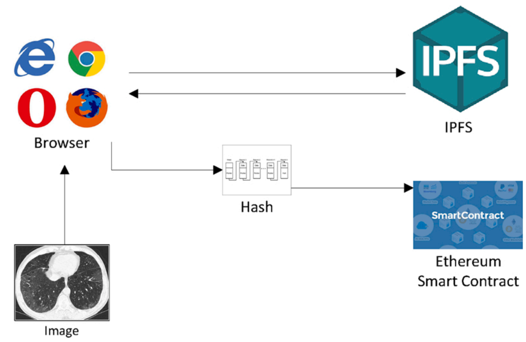

Fig. 1. Working flow of IPFS.

3.3. Background of deep learning global model

Neural networks can be trained using forward propagation and backward propagation. These methods calculate and update the neuron weights present in various neural network layers'. For a forward propagation method, the input is passed through $F = f(x, w) = \bar{y}$, and for processing the input code x and w parameter vector, the trained dataset $D = (x_i, y_i); i\varepsilon I$ for each hospital (x_i, y_i). The learned weights are shared over the decentralized network. The loss function of training dataset is defined as $L(D, w) = \text{loss}$. D is defined as dataset and l is the loss function., $\text{loss} = \frac{1}{D}\sum_{(x_i, y_i)\in D} l(y_i, f(x_i, w))$. For backward propagation, the weights of the neural networks are updated using stochastic gradient descent (SGD) defined as below equation:

$$w^{t+1} \longleftarrow w^t - \eta \nabla_w L(D^t, w^t) \tag{1}$$

It can be seen in Equation (1), the learning rate is η, and the i^{th} is the iteration of the w^t parameters. $D^t \subseteq D$ is the hospital mini-batch training dataset. The above equation is used for a single user. To learn a local model and collaboratively create a global model for the private dataset for each hospital $v \in V$ shown in Equation (2)

$$w^{t+1} \longleftarrow w^t - \eta \frac{\sum_{v\in V} \nabla_w L(D_v^t, w^t)}{|V|} \tag{2}$$

3.4. Classification of lung cancer images based on CNN

The weight sharing, for deep learning networks, can drastically decrease the number of parameters and reduce the training complexity. Comparatively, Convolutional Neural Network (CNN) based architectures can have such advantages for multidimensional data. In general, the CNN is composed of several feature extraction layers, as shown in Fig. 2. Usually, the first layer is an image input layer followed by a combination of various convolutional filter, downsizing, normalizing layers, etc. A combination of these layers help in extracting the strongest features. And at the end, a learnable such as neural network is employed to learn based on the extracted strongest features. Related details are shown in Fig. 2.

1) Convolution Layers: Parameter sharing scheme is used in convolutional layers to control the number of parameters while retaining the strongest features, including scale invariance, rotation invariance, and translation invariance. The simplest way to prevent overfitting is to reduce the size of the model. This model can effectively avoid overfitting and improve CNNs' generalization. The input maps the dataset and the output reduces the dimensionality. The combinations of each mapping from the upper layer can be expressed by Equation (4):

$$x_j^l = f\left(\sum_{i\in M_j} x_j^{l-1} * k_{ij}^l + b_j^l\right) \tag{3}$$

where, M_j is the set of input mapping, k_{ij}^l is the convolution kernel which

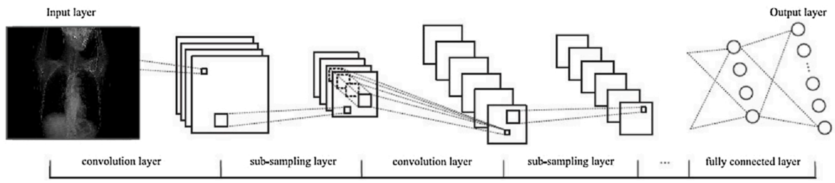

Fig. 2. Cancer detection based on CNN.

represents the association between output feature mapping j^{th} and input feature mapping i^{th}, b_j^l is the bias corresponding to j^{th} graph features, activation function (f) to produce the final output of the neuron.

$$\delta_j^l = \delta_j^{l+1} W_j^{l+1} \circ f'(u^l) = \beta_j^{l+1} \text{up}(\delta_j^{l+1}) \circ f'(u^l) \tag{4}$$

where $l+1$ defines the sampling layer, weight W is the convolution kernel, and the value of the up-sampling operation can be expressed by: $B_j^{l+1} \circ \text{up}(.)$. The partial derivative of the cost function, respect to convolution kernel k with bias b can be expressed as:

$$\frac{\partial E}{\partial b_j} = \sum_{u,v} (\delta_j^l)_{u,v} \tag{5}$$

$$\frac{\partial E}{\partial k_{\text{ij}}^l} = \sum_{u,v} (\delta_j^l)_{u,v} (p_i^{l-1})_{u,v} \tag{6}$$

where $(p_i^{l-1})_{u,v}$ are the patches of convolution $x_i^{l-1} i$ and k_{ij}^1, the center of each patch is represented by (u, v), k_{ij}^1. Convolution kernel extracts patches from the input feature maps.

2) Sub-sampling Layers: The pooling layers reduce the number of parameters, spatial pooling is also known as sub-sampling or down-sampling. Image deformation influence could be reduced by this layer (e.g., translation, scale, and rotation). It decreases the number of parameters and avoids overfitting, and improves the model's accuracy. In the convolution layer, each linear map is associated with the learnable filter, which is expressed as:

$$x_j^l = f(\text{down}(x_j^{l-1}) + b_j^l) \tag{7}$$

where $f(\text{down}(x_j^{l-1}) + b_j^l)$ shows the sub-sampling function of bias b.

$$\delta_j^l = \delta_j^{l+1} W_j^{l+1} \circ f'(u^l). \tag{8}$$

Equation (9) shows that minimizing such bias b improves the overall estimator performance with respect to error cost function.

$$\frac{\partial E}{\partial b_j} = \sum_{u,v} (\delta_j^l)_{u,v}. \tag{9}$$

4. Proposed model

In this section, we elaborate on the proposed cancer detection technique which consists of three phases: (i) blockchain-based data sharing (ii) smart contract creates trust between the organizations (iii) AI-based deep neural network model. The hospitals share the weights of the locally learned neural network trained using images such as MRI, CT-SCAN, etc. The local model weights are stores in the IPFS (interplanetary file system) along with the authentication details of the hospitals. The hashes of the IPFS are stored in the blockchain ledger. The global deep learning model computes and combines the local model weights using the blockchain nodes. Furthermore, deep neural network process the data, and the updated weights are stored in the IPFS, and hashes of updated weights are stored in a permission blockchain ledger to achieve better performance. Fig. 3 shows the architecture of the proposed framework to combine the blockchain and deep learning model. Firstly, all hospitals upload the local model weights to the IPFS with the legal retractions and fix the amount to get the data. The IPFS store the local model weights and hashes are stored in the blockchain ledger to reduce the cost. A client can request permission for accessing the shared data according to the hospital policy. Because of the heterogeneous nature of data from different sources, we utilized the bat algorithm and data augmentation for training the collaborative global model. The collaborative deep learning model can help in better detection of cancer, and blockchain-based network can exchange information between organizations with different legal restrictions. Through the exchange of information between different organizations, a better AI learning model Is trained.

4.1. Data sharing using blockchain technology

The smart contract provides security and privacy to exchange data among the hospitals. The smart contract is used for a secure data exchange to authorize the uploading of the medical images automatically. It generates parameters based on conditions and terms associated with the data-sharing agreements.

A smart contract is used to exchange the images data among the hospitals. The IPFS stores all local model weights with hashes (reference id) are stored in the blockchain database. Registered/authorized hospitals share the locally trained deep learning models weights through the smart contract. A smart contract grants access to share the model on the blockchain network. Since the blockchain network is fully distributed and multiple party's data collection environment, only a registered organization can access the shared weights (data). The smart contract guarantees the transparency and reliability of the blockchain across

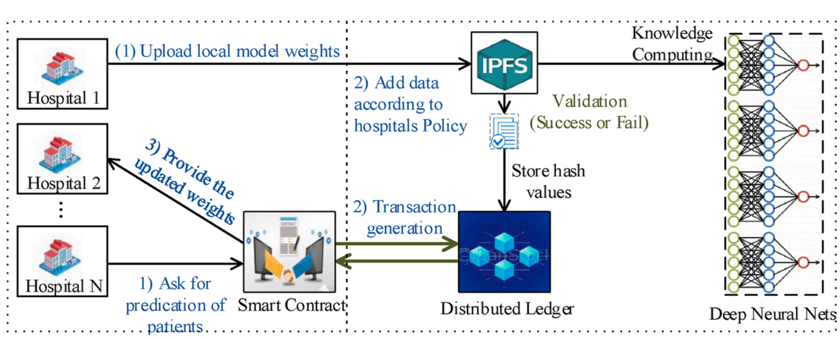

Fig. 3. Proposed model for data sharing and lung cancer detection.

geographically distributed nodes. This revitalizes the idea and facilitated the design of smart contract. Algorithm 1 and 2 shows a smart contract for the registration of the hospitals and share the hospital data with the access control rules. The organization registers its data with the function of RegisterData. The hash, address, description, and price attributes are used to fetch the data. After uploading the data in the blockchain network, all hospitals access the data with the permission of other organizations. The access token permits data access. Organizations may share a series of medical data, and authorized clients access the data.

Algorithm 2 shows a sample smart contract for data sharing. In this scenario, the smart contract provides the rules to share the data among organizations. The owner of the Register Hospitals (H) the ownership of data and provides a digital signature on the data. The token is generated in the blockchain ledger. The process of a smart contract guarantees that the shared images come from an authenticated source. The smart contract uploads the data in the blockchain network with the signature of the registered hospitals. Furthermore, it helps in providing more accurate prediction and decision support keeping in view the security concerns.

Algorithm 1. Hospital registrations smart contract.

ContractState⟵1 created
HospitalSatate⟵ ReadyToUploadImages
h⟵ is the set of: Registor Hospitals(H)
$h1$⟵ belongs to list of hospitals
Restricted access to only $h \in H$
if Hospital is registed & IPFS hash == true **then**
  ContractState⟵1 sucessSign
  HospitalSatate⟵ sucessApproved
  create a validation message for all hospitals
end if
if Hospital is registed & IPFS hash ! = true **then**
  Revert contractState show an error
end if

Algorithm 2. Uploading data using smart contract.

function REGISTERDATA(hash h, address ad, description des,price p)
  Data[h].owner⟵ msgSender
  Data[h].address⟵ ad
  Data[h].description⟵ des
  Data[h].price⟵ p
  Data[h].subscribers⟵ []
  Data[h].owner⟵ hash
  return true
end function
function REQUESTDATAWITHADDRESSANDHASH(address ad, hash h)
  require (reverseIndex[address] <> NULL or require(Data[hash].subscribers))
  ad⟵ Data[h].address
  h⟵ reverseIndex[ad]
  return AccessTokenfor address
end function
function SUBSCRIBEDATA(hash h, price p)
  require (balance[msg.sender] >= Data[h].p)
  balance[msg.sender] − = Data[h].p
  Data[h].subscribers + = msg.sender
end function

4.2. Combining the blockchain and deep learning model

Each hospital shares the local model weights and can download the updated weights for the collaboratively built model. The shared weights are trained through the vital parts of the deep learning model shown in Algorithm 3. The hospitals locally compute the gradients and send the weights to the global blockchain network. The blockchain computes the nodes and aggregates the models. The smart contract shares the aggregated results to the hospitals without revealing the original information of the images. Moreover, the input of the local model weights is passed through the blockchain decentralized network, and after processing the input, the updated model output is shared in the decentralized network. Therefore, gathering all new cases of lung cancer through the smart contract for training a collaborative deep learning model is an effective method. Additionally, we simulate the training outputs in the decentralized network through the proof-of-work, proof-of-stake and delegated-of-work reduce the training computations of the deep learning model. Delegated-Proof-of-Stake is used to vote the hash as it avoids the complex hash operation. The state information of each node in a distributed network is taken as the dataset. The dimensional matrix (M) is the input of the deep neural network, and the average number of becoming the mining node in a term is the capacity label. After training our network, we get the average transaction number of the i_{th} node as long as M_i is input. Furthermore, the states of the i_{th} node by falling the output of the matrix M_i is computed as: M={computing power ratio, online time, payoff, hop, connection number, latency}. To compute the node capability based on neural network, the function is expressed as: AverageTransactionRate= f(computing power ratio, online time, payof, hop, connection number, latency)= f(M). Additionally, to check the fairness of the permissioned blockchain, first, we calculate the average transaction number, second assign the maximum number of capacity in a node pool (MaxNP). Thirdly, generate a random number and compare the random number less than MaxNP, fourth generate the threshold to measure the number of super nodes. Finally, pick all random nodes through the super nodes. In this way, the average number of transaction values train the deep learning model. More precisely, the deep learning model selects the nodes to create the commit block, then calculate the score of each node creating the block.

For a better understanding, take an example of two hospitals (organizations). These two hospitals contribute their data to the blockchain network. Suppose, there are n hospitals $H_i, i = 1, ..., N$, and hospitals agree to share the weight of the locally trained model. The data is attached to a transaction $\mathrm{Tx}^0_{\mathrm{co}}$ signed by hospitals. Data is used to generate a private key and to learn the model. The hashes are stored in the distributed blockchain ledger. The secure data sharing scheme is shown in Fig. 5. Step 1: initialize the key generation process for the asymmetric key generation for authentication. Step 2: uploading the private data into the authenticated blockchain network also verifies the sender and receiver request and then upload the data. Step 3: generate the data blocks to broadcast the data over the network. Step 4 and 5: collect all the hospitals' records and generate the Merkle hash value of records linked to the blockchain. Step 6: broadcast all results. Furthermore, In this scheme, the generator tries to generate different solutions from the noise that is similar to the real input, and the discriminator tries to detect if the generated solution is cancer or not. The network will always have a decent knowledge, so it will be able to check the submissions with some accuracy. For example, if we are requesting images of bridges, we can easily discriminate fake objects, unauthorized nodes, and promote trustworthy ones. Finally, implementation of the deep neural network is aimed to learn itself from the huge volumes of data resources through the blockchain technology. It proves that the blockchain technology is used to train the model form the different sources which can achieve better performance.

Blockchain technology provides a new paradigm for processing health data through which medical practitioners can benefit from efficient and automated predictions.

Algorithm 3. Training process of global model.

function GLOBALMODELTRANING(Hospitals H, Dataset $\{D_n\}^{n\in[N]}$, global weights w^0, Loss $L(w,x)$, iteration I, clip bound θ)
  for i $\in [I]$ **do**
    for h $\in [H]$ **do**
      sample dataset with probability $\frac{|D^i_h|}{|D_h|}$
      for x $\in D^t_h$ **do**
        $gd^i_h(\mathrm{x}) \longleftarrow \nabla_{\mathrm{w}^i} L(\mathrm{w}^i, \mathrm{x})$

(continued on next page)

(*continued*)

$$gd_h^i(x) \leftarrow gd_h^i(x)/max\left(1, \frac{\|gd_i^2(x)\|}{\theta}\right)$$

end for

$$gd_h^i \leftarrow \sum_{x\in D_h^i} gd_h^i(x) + \mathcal{H}\left(0, \frac{\theta^2\rho^2}{H}\right)$$

end for
end for

$$gd_h^i \leftarrow \frac{1}{H}\left(\sum_{n\in[H]} gd_h^i\right)$$

$w^{i+1} \leftarrow w^i - \eta \cdot gd^i$

end function

4.3. Deep learning based model

The proposed cancer detection technique consists of three phases: (i) data processing (ii) CNN based cancer detection (iii) train the deep neural network based on distributed ledger (blockchain) data sharing in Fig. 4. The proposed data preprocessing techniques include Bat algorithm and data augmentation technique. By using Bat algorithm, the resolution of the images is improved along with some noise reduction. Additionally, the data augmentation improves the computational efficiency of the model and increases the sample size. A CNN model is developed for the detection and characterization of cancer tissues. The blockchain network stores and exchanges the trained model results throughout the network for spreading the information regarding the new cancer patients. Our proposed framework stores and updates information about the new types of patients. It helps to increase cancer detection accuracy by providing a dynamic way of sharing information about the new cases of cancer. Moreover, the decentralized blockchain keeps a record for all types of patients history.

4.3.1. Data processing techniques

To train a predictive model, image data must meet high-quality standards. An invalid data sample can jeopardize the classification accuracy of a model. High-quality datasets can help in avoiding overfitting, and reduce the time of model training. Cancer can be divided into several families. Generally, samples vary dominantly in terms of numbers from a particular cancer family to a household. This change of numbers in sample data results in poor robustness and low accuracy while training. To solve the mentioned problem, we have adopted data enhancement techniques to improve the quality of samples in data. We use an intelligent optimization algorithm based method called the Bat algorithm that helps to solve the imbalance sample data problem.

4.3.2. Image data augmentation (IADLT)

Data augmentation is used to increase the sample's size of data for increasing the performance of the deep learning models. Thereby, relatively neglected is the effect of imbalanced data for action unit

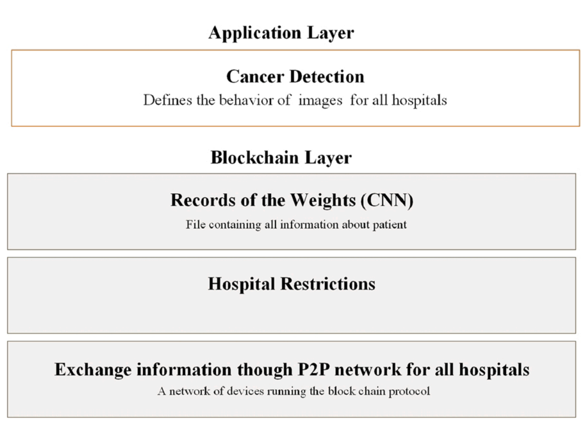

Fig. 4. Blockchain based framework.

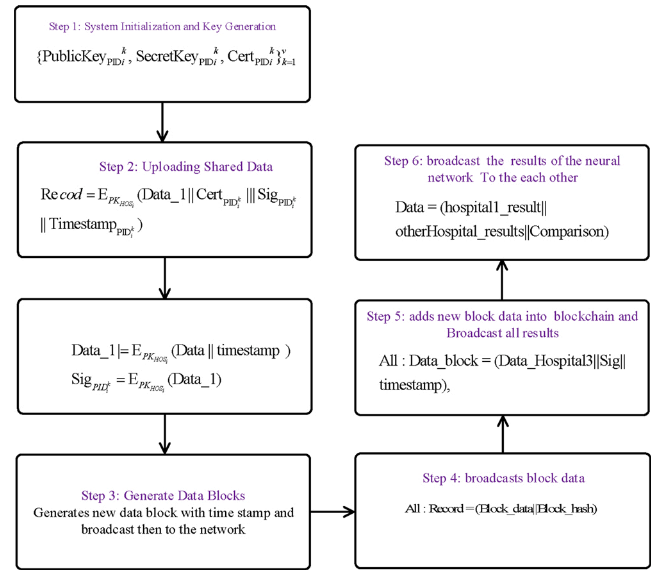

Fig. 5. Secure data sharing scheme.

detection. Our proposed augmentation in the deep learning model helps to reduce the overfitting and improve the generalizability.

The effectiveness of data augmentation in an image transformation changes the location of the pixel but does not change the features of images and it also generates new data. Data augmentation techniques in image processing use various kinds of methods, for instance, scale, contrast, zoom, reflection/rotation, flip, shift, color, noise and transformation.

Let $A = [a1, a2, \ldots, a8]$ be an accumulation of these procedures. $Mi = am, \ldots, an$ is the order of operations, and i is the length of M. $M2 = a1, a2$ that represents the transforming, rotation, and flip of data by using augmentation.

For each data augmentation technique, λi shows the weight of augmentation technique, this operation sequence can be represented as:

$$M_i = \lambda_m a_m, \ldots, \lambda_n a_n \tag{10}$$

The weights of the image augmentation technique describe λm and $am \subseteq A$. To perform multiple data augmentations is necessary to use this step in the whole process. For a CT scan image matrix m, $Mk(m)$ shows the k augmentations. Fig. 7 shows a few samples of data, which is generated by data augmentation technology. It can be observed that original texture features are still retained by most of the newly generated images.

4.3.3. Bat algorithm for data equalization (IBA)

Imbalance data is one of the challenges of machine learning, that effects the accuracy of the classifiers. In this paper, to deal with the different sized CT images from various sources, we adopted Bat algorithm for the transformation of data, fed to the neural network, to tackle the problem of heterogeneous network medical data. The Bat algorithm reduces noise and also tackles the overfitting problem for the neural network. For instance, one class has 5,842 images, while the second class has 9,012 images. This difference has a great impact on the performance of CNN for image classification.

Algorithm 4. Bat Algorthim for CT Scan Image.

input⟵1 cancer Dataset
input⟵ bats: bat
input⟵ population
$(a, b) \leftarrow$ getState(bats)
for t <MaxItration **do**
  for $bat_i \subset bats$ **do**

(*continued on next page*)

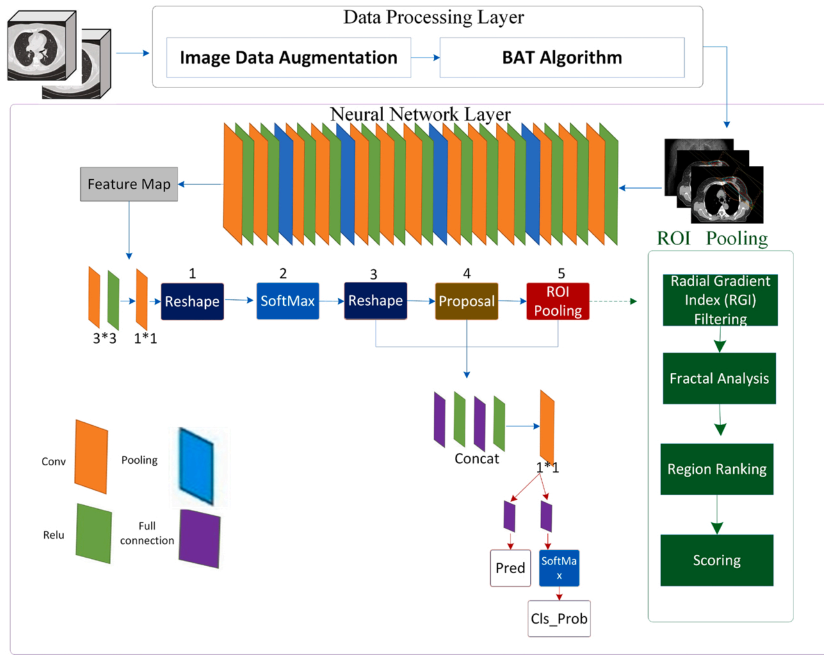

Fig. 6. Proposed model for lung cancer detection.

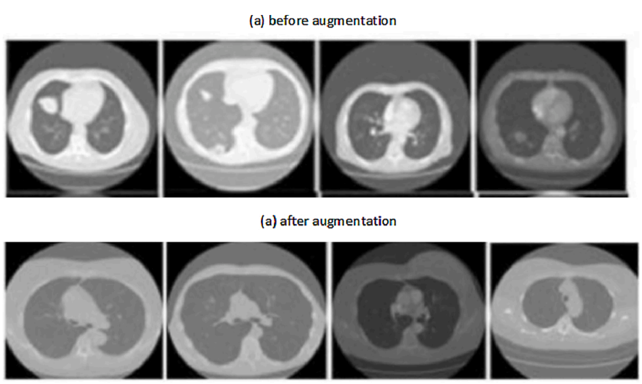

Fig. 7. Cancer dataset using IADLT.

(*continued*)

7:	$(a_i^{t+1}, b_i^{t+1}) \longleftarrow$ updateState (a_i^{t}, b_i^{t})
8:	(templeset)$\longleftarrow$ resample (dataset, a_i^{t+1})
9:	accuracy$_i^{t+1} \longleftarrow$ trainmodel (templeset)
10:	**end for**
11:	(bats)$\longleftarrow$ localsearch(bats)
12:	$x^* \longleftarrow$ getbest(bats)
13:	$s = s + 1$
14:	**end for**
15:	trainset$\longleftarrow$ resample(dataset)

We used the resampling method to deal with imbalanced. The resampling method provides a way to convert "imbalanced"to "balanced"the data. There are generally two methods of dealing with imbalanced datasets i) undersampling and ii) oversampling. Therefore, both techniques have different usage, undersampling removes some samples from the original subset, and oversampling creates multiple copies of a subset. The main reason for oversampling is to correct for bias in the original dataset.

Swarm intelligence algorithms is an efficient solution of a general interval optimization problem. Many scientists have conducted several in-depth studies on group intelligence and its applications (Gao et al., 2017; Li et al., 2017; Wang et al., 2017a,b,c). Wang et al. (2017a,b,c) using an evolutionary multi-objective optimization algorithm to deal with networks - floor plan problems in physical social systems.

To solve the issue of weight combination, our approach presents the dynamic resampling scheme based on a bat algorithm. Due to the characteristics of the potential parallelism and rapidness, some researchers have used this technique for optimization-based practical applications/problems (Cai et al., 2016, 2018; Cui et al., 2019, 2018). We have used the technique to optimize the sampling weights of multiple classes of medical images. In the process of model training, to maintain the balance of datasets samples properly, every class is resampled based on the weight of the corresponding epoch. Assuming N defines the number of cancer disease images class, the number of cancer image families is N, whereas $I \subset N$ defines the resampling weights. Because of the optimization, the position of every bat is considered as an arrangement of multiple sampling weights that can be represented as below:

$$\text{position} = w_1, \ldots, w_n.$$

Our goal is to improve the accuracy of the training images. To represent the best position for the Bat optimizing threshold, Algorithm 4 defines the detailed process of resampling. The updateState function (line 7) updates the speed and position of the bat as reported by Cai et al. (2016) rules. Apply a local search algorithm (LocalSearch) for the bat population. Resample (Line 8) and trainModel (Line 9) methods can be obtained precision and accuracy.

This section describes our improved CNN-based cancer image detection methods, including (1) classification of chest and lung cancer pixels as grayscale images; (2) CNN design for the detection of the CT scan images. Fig. 8 shows the deep learning process. Deep neural

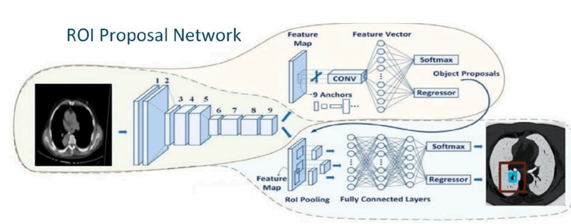

Fig. 8. Overview of the neural network.

networks detect and classify the images properly. Based on the image results, we achieved automatic prediction and identification of cancer disease.

4.4. Training process of R-CNN

The CNN model proposed by Girshick in 2014 is divided into four sub-processes for target detection. First, the region proposed algorithm is used to obtain 2000 suggested regions in the image. Secondly, the CNN features of 2000 regions are extracted and the fixed dimension features will be the output. Third, the target is classified according to the characteristics. Finally, to get an accurate object bounding box, CNN accurately locates and merges foreground objects through regression operations. To quantify and classify objects accurately, we pay attention to the ROI of the image and combine the different features of the object. Our proposed model scheme recognizes the region of interest for lung cancer based on the following steps:

- The measured feature map conv 5-3 is assigned to all input object anchors. The anchor rating and bounding box (bbox) regression parameters are extracted by the forwarding estimation of the RPN network.
- Proposal bbox positions are determined from the locations of anchors and the parameters of the bbox regression.
- Handling the proposal coordinates beyond the boundaries of the image (making the minimum value of the coordinates 0, the maximum is the width or height).
- Filter out the proposal whose size (width and height) is less than a given threshold.
- Sort the remaining proposals according to the target score from large to small, before extracting pre_nms_topN (e.g. 6000) proposals.
- Perform non-maximum suppression on the extracted proposal, and then filter the previous post_nms_topN (e.g. 300) proposals as the final output according to the foreground score after nms.

Algorithm 5. Input: dataset
Output: Detection model
Step 1: Initialize the training network

1. Initialize pre-training model parameters
2. Initialize the caffe deep learning library
3. Construct for imdb and roidb function which precomputes the maximum overlap.
4. Save only caffe module and define the path of module
5. Training the region proposal network and store the weights in the network

Step 2: Use the trained region proposal network in step 1, sort the regions according to the probability of including the foreground object region

1. Initialize pre-training model parameters
2. Initialize the caffe deep learning library
3. Construct for imdb and roidb function which precomputes the maximum overlap.
4. Save only caffe module and define the path of module
5. Training the region proposal network and store the weights in the network

$$\mathrm{RGI}(j,k)=\frac{\sum_{(j',k')\in C_i}\overrightarrow{g}(j',k')\cdot\widehat{r}(j',k')}{\sum_{(j',k')\in C_i}|\overrightarrow{g}(j',k')|}$$

$$D_q=\begin{cases}\dfrac{1}{q-1}\lim\limits_{\varepsilon\to0}\dfrac{log\left(j_q(\varepsilon)\right)}{log(\varepsilon)} & \text{for } q\in R \text{ and } q\neq1\\ \lim\limits_{\varepsilon\to0}\dfrac{\sum_i\mu_i log\mu_i}{log(\varepsilon)} & \text{for } q=1\end{cases}$$

$$c(q)=\frac{1}{1+[q^2(j,k;t)-q_0^2(t)]/[q_0^2(t)(1+q_0^2(t))]}$$

$$q(x,y;t)=\sqrt{\frac{(1/2)(|\nabla I|/I)^2-(1/4)(\nabla^2 I/I)^2}{[1+(1/4)(\nabla^2 I/I)]^2}}$$

$$q_0(t)=\frac{\sqrt{\mathrm{var}[z(t)]}}{z(t)}$$

$$S_n=\frac{\sqrt{\mathrm{Area}_n}}{\mathrm{dis}(C_n,C_0)\cdot\mathrm{var}(C_n)},n=1,\ldots,k$$

$$\mathrm{score}(p_0,\ldots,p_n)=\sum_{i=0}F_i\cdot\phi(H,p_i)$$
$$-\sum_{i=1}^{m}d_i\left[(\tilde{x}_i,\tilde{y}_i)+\left(\tilde{x}_i^2,\tilde{y}_i^2\right)\right]$$

1. Get step 2 proposal regions and sent to the ROIs
2. Send the sorted regions according to the probability of including the foreground object region to the network as the weight of the objects
3. By comparing the size of caffe blob, regression weights get by all large and small regions.
4. The loss-cls and loss-box loss functions are calculate by

$$L(\{p_i\},\{t_i\})=\frac{1}{N}\sum^{L_{\mathrm{cls}}}\left(p_i,p_i^*\right)+(\lambda)\frac{1}{N}\sum_i^{p}{}^*L_{\mathrm{reg}}\left(t_i,t_i^*\right)$$

5. Experiments

This section consists of the following four parts:
1) Dataset
2) Verify the accuracy and time with image augmentation deep learning technology.
3) Verify the accuracy of the R-CNN-net model.
4) Compare the R-CNN, bat algorithm and image augmentation deep learning technology.
5) Results of combining the deep learning and blockchain technology and data uploading through the IPFS.

5.1. Dataset

For our experiment, we collected the local data of lung cancer from the Sichuan Cancer Hospital. The dataset consists of 5,842 CT cases from 9,012 patients. The number of training samples is 4098, and the number of testing is 1752. The data is labeled with cancer and non-cancer patients. Furthermore, the data includes the patients' thin-slice chest CT scan prior to biopsies.

5.2. Verify the accuracy and time with image augmentation deep learning technology

We have already discussed the need for augmentation and data transformation for training the deep learning models over the decentralized network. The state-of-the-art model includes GoogleNet and Resnet. To compare the model results, we trained four Resnet models having different layer size. Table 1 shows the parameter settings of the image augmentation technology applied to all models. The results and execution time comparison of trained models can be seen in Figs. 9–13, respectively. From the presented graphs, it can be seen that by applying data augmentation and batch algorithm, the trained model takes much less execution time. Among all the models, GoogleNet achieved the best performance concerning accuracy and Resnet-50 achieved concerning execution time. However, the improvement in accuracy between both models is very less. To validate the performance, we increased the layer up to 152 layers. With an increase in accuracy, it also consumes more execution time. Indeed, augmentation does not affect in few models due to less number of layers in the model. Due to this reason, the optimized number of layers in GoogleNet proves the significance of augmentation for our desired task.

5.3. Verify the accuracy of R-CNN-net model

We conduct the experiments on the R-CNN using various cancer images to segement the cancer clusters. Figs. 14 and 15 show the proposed R-CNN scheme detects the region of interest on the cancer slices based on the nodule annotations of the lung-RADS. If the prior CT was not found, then the model of lung center is used to detect the region of interest in the lung-RADS. The proposed method was able to find morphological features such as nodules and scars in the 3D lung cancer screening. It shows that model found the vasculature and parenchyma surrounding the nodule to identify the presence of pulmonary nodules in the analyzed images. Fig. 15 distinguishes true nodules from shades, vessels and ribs. Further, The first 7 nodules are non-cancerous, and the second row shows cancerous nodules. The numbers below this figure are the probability prediction of the R-CNN model. If nodules are large or in irregular shape, the model predicts high chances of the cancerous nodules. The number of the below figure shows the number of possibilities to predict the cancerous nodule. More precisely, Fig. 15 can observe that doctors misdiagnose some nodules. The reason may be that human is not fit for processing the 3D CT scan images. Perchance some doctors can not find irregular boundaries or erroneously consider some normal tissues as nodule boundaries leading to false negatives or false positives. From this perspective, our proposed model can potentially be of great use to doctors in their effort to make a consistent and accurate diagnosis.

5.4. Compare the R-CNN, bat algorithm and image augmentation

We compare the results of the R-CNN, Bat algorithm, and image augmentation schemes. Figs. 16 and 17 show the performance of the different models. All models achieved good results concerning the accuracy. The accuracy of the IBA is the best, when the number of epochs is increased, the accuracy will increase continuously. The accuracy of the IADLT is less than the IBA because it losses some features while imaging transformation. Furthermore, the R-CNN achieved better detection performance in terms of accuracy.

5.5. Blockchain based data uploading IPFS

We use the ganache server for a public blockchain and deploy the smart contract. The truffle framework was used for testing the smart contract in the ganache server. Furthermore, we install node.js and metamask extension for the client-side development. For the IPFS server, we use infura Gateway to store the files in the IPFS. All roles have been tested to ensure that the smart contract worked properly. The hospitals upload images to the blockchain network and store the hash into the smart contract. In ganache, for different role different address are stores such as patient (0 ×

Table 1
Parameters setting of data augmentation.

Parameters	Range	Description
rotation_range	0.2	rotation range
rotation_scale	1/255	ratio of image magnification
horizontal_flip	1	range of horizontal translation
fill_mode	nearest	fill the image when flipping
width_shift	0.2	range of horizontal translation
zoom_range	0.5	ratio of randomly zooming image
height_shift	0.1	range of vertical translation
shear_range	0.1	range of projection transformation

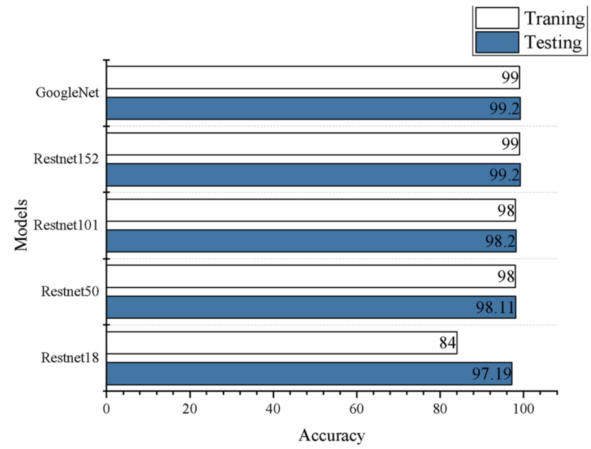

Fig. 9. Cancer data accuracy and loss.

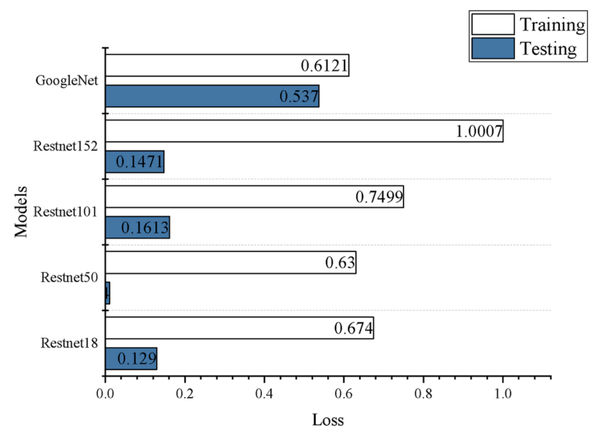

Fig. 10. Cancer data accuracy and loss.

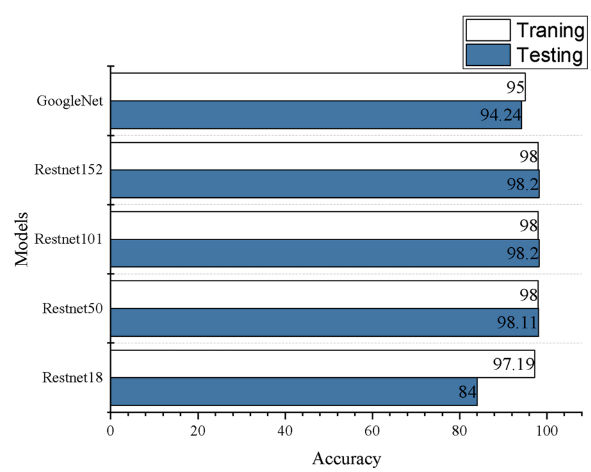

Fig. 11. Cancer data accuracy and loss.

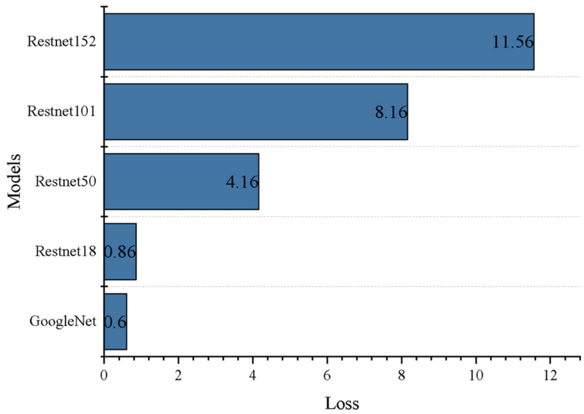

Fig. 12. Cancer data accuracy and loss.

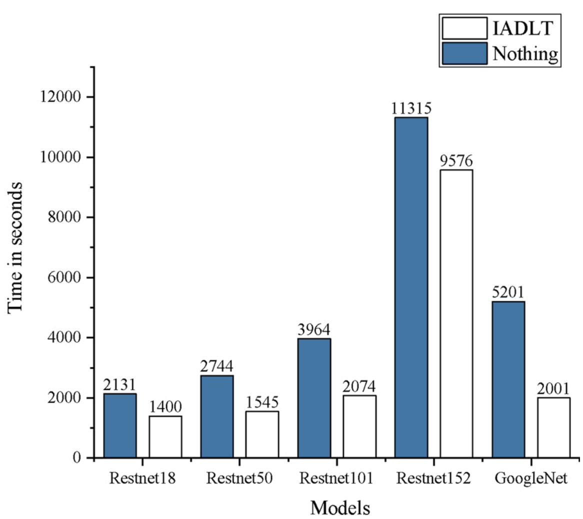

Fig. 13. Cancer data time comparison.

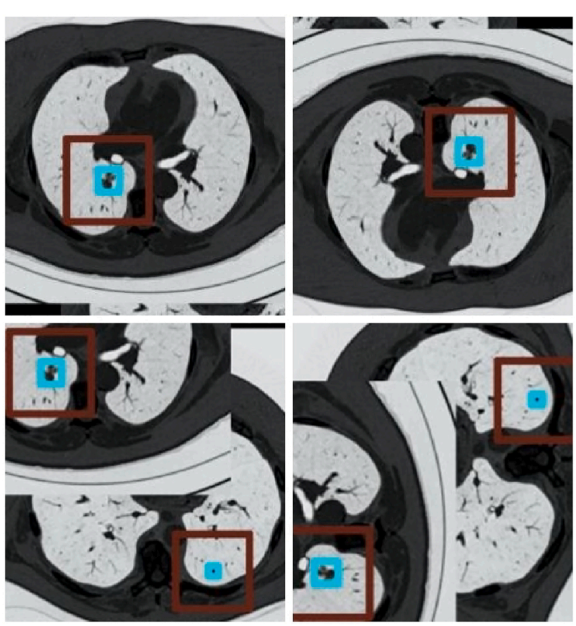

Fig. 14. Sample of cancer detection.

ca35b7d915458ef540ade6d35458dfe2f44e8fa733c) and hospital (0 × 18965a09acff6d2a60dcdf8bb4aff308fddc180c) to test the smart contract code. Functions are designed to approve or deny the permission of the images. Fig. 18 shows the smart contract verifies the application from the blockchain database. It shows that the gas price per transaction and the total cost to run the transaction. Moreover, each transaction creates the block address, shown in the Ethereum platform shown in Fig. 18. More details of each execution cost is the gas required as shown in Table 2.

To deploy any contract, a specific amount of gas is required. The maximum limit of gas is pre-decided by the creator, which is 300,0000. Two types of gas consumption are observed; transaction gas and execution gas. Transaction gas is the amount of gas required to deploy the smart contract on blockchain. While the execution cost is the gas required to execute logical operations in each function.

Figs. 19–22 show the simulation results that prove that the combination of blockchain and deep neural network increases the performance in terms of reducing the computational cost of the neural network. It shows the training labels improved the prediction performance of the deep learning model. Moreover, the blockchain network calculates the value of nodes by using the deep neural network. And then selects the nodes and calculate the threshold value the features of the dataset taken as the input information to the blockchain nodes. The mining pools provide output to the users. The average number of transaction shown in Fig. 19. The blue label defines the real labels and the red provides the prediction. Fig. 19(a) shows the correlation among the computing power ratio and average transaction are defined as the trend of the blue dots and red dots show an increasing pattern of the average transaction with the computing power ratio, which is constant with the real world decentralized network. Fig. 20(b) demonstrates the payoff increases when transactions node are increase. Fig. 21 and 22 (c) and (d) show that the nodes are negatively correlated. Finally, the demonstration shows to share the medical images in the blockchain network effects the performance of the neural network. Furthermore, to share the data in the blockchain network, the deep learning model provides better performance as it is trained using a large amount of data.

5.6. *Comparison and discussions*

. The Table 3 shows the comparison of the different algorithms with the images. As we can see in this table our proposed scheme used blockchain and deep learning model to train the better model than other previous works. Our proposed scheme is able to the real-time deployment of blockchain. Table 4 shows the feature comparative analysis with other approaches to distinguish the lung cancer approaches.

6. Conclusion

A novel multi-model approach is proposed in this paper which combines deep learning and blockchain technology to diagnose early-stage cancer from the CT scan images. The main purpose of the combining the blockchain and deep neural network, the modeltake input data of each patient in the distributed network to diagnose a particular health condition of patient by low-dose CT scan of the images or speculating on radiology images. A deep neural network model diagnoses the report images that contain the information about the cancer nodules, which performed for a patient on the blockchain distributed network. Further, the deep learning models require a large number of resources such as computing power to train the model, To train the model, the blockchain used as a manner to mining the blockchain. The shared blockchain network will address the problem of the computational resources and publish the lung cancer diagnosis output on the blockchain. The smart contract exchanges the data among the hospitals that enable the deep neural network to learn from the huge amount of data with different patient cases to detect cancer symptoms and further characterize the region of interest regarding tissue properties.

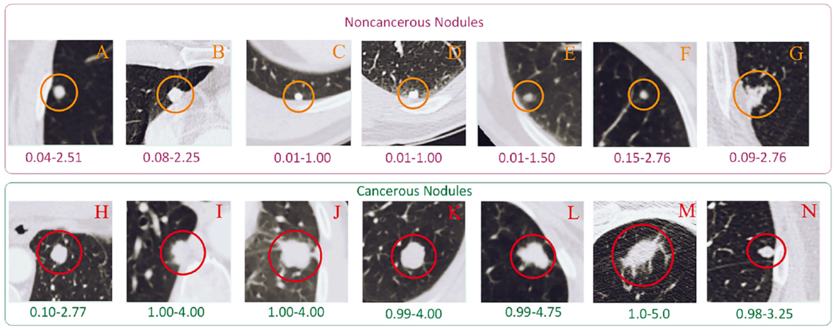

Fig. 15. Sample of cancer detection.

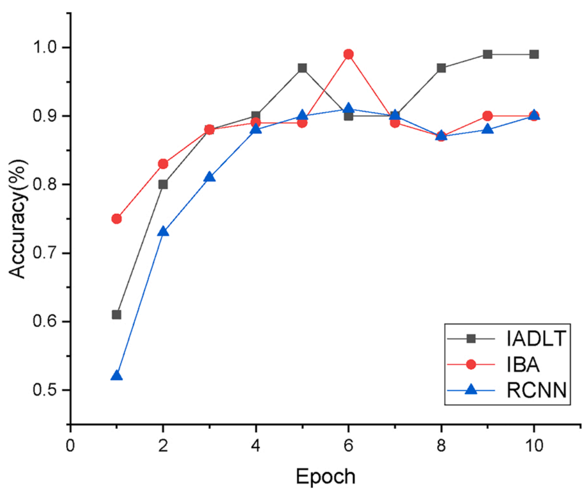

Fig. 16. comparison between the RCNN, Data augmentation, bat algorithm accuracy.

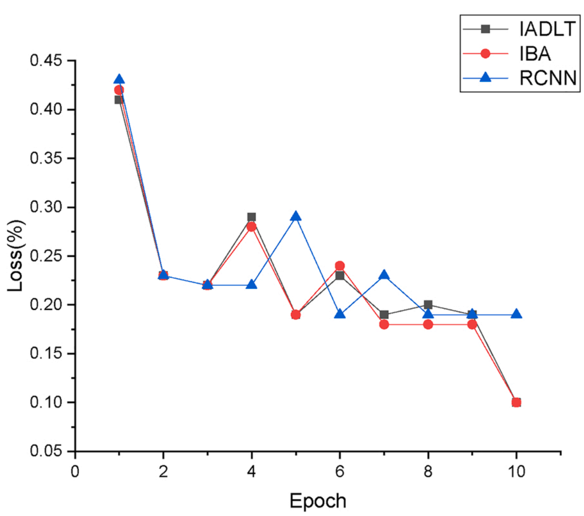

Fig. 17. comparison between the RCNN, Data augmentation, bat algorithm loss.

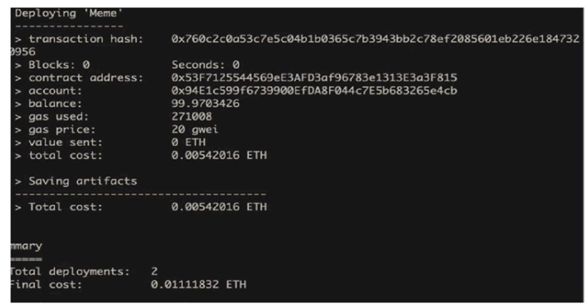

Fig. 18. Blockchain based results.

Table 2
Smart contract cost test (IPFS storage: gas price=2).

Function	Transaction gas	Execution gas	Actual cost
Contract creation	1808235	1338219	0.00361647
Add file	67512	53945	0.000107896
Delete file	29206	19034	0.000058412
Set recipient	340968	30231	0.000060462
Set blacklist	31290	14203	0.000028402

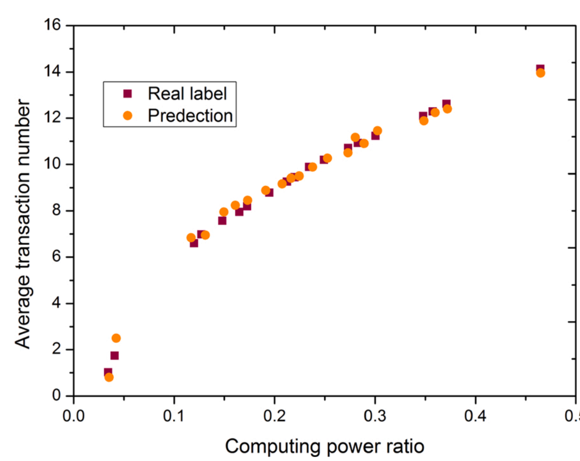

Fig. 19. Computing power ratio and average transaction.

Additionally, dealing with the different sized CT images various sources for training purposes, we adopted bat algorithm and data augmentation for the transformation of data to feed into the neural network to tackle the problem of heterogeneous network medical data. The bat algorithm reduces noise and also tackles the overfitting problem for the neural network. The comparative results indicate that the proposed model can achieve higher detection accuracy over the medical image dataset. We found that our proposed deep learning based model detect the nodules and achieve better performance. Therefore, the proposed model based on deep learning cancer detection in the early stages and further helps in treatment/diagnosis.

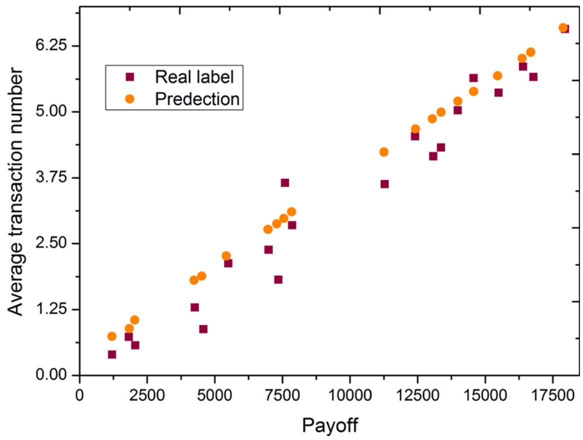

Fig. 20. Pay off of transacation.

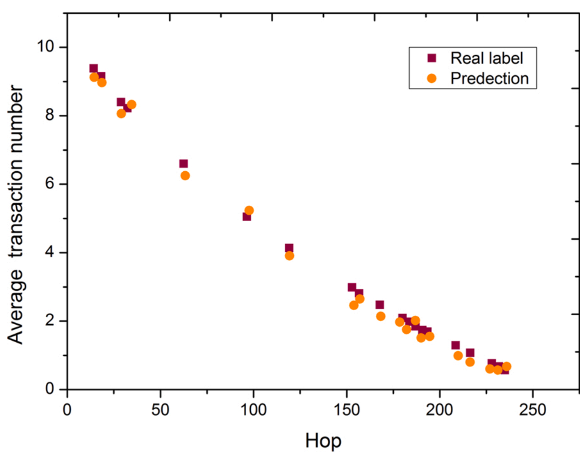

Fig. 21. Hop of blockchain transacation.

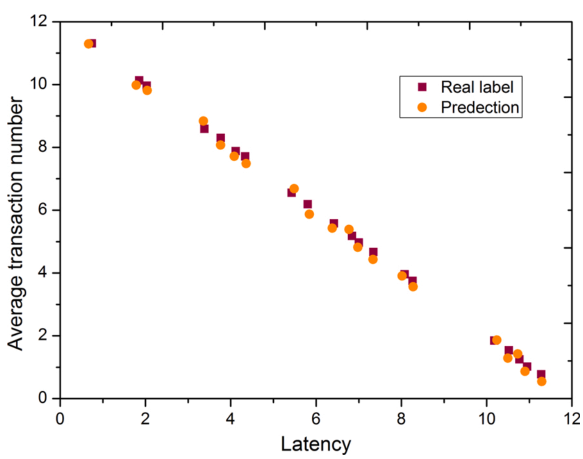

Fig. 22. Latency of blockchain transacation.

Authors' contributions

Rajesh Kumar: Writing – Original draft preparation, Methodology, Conceptualization, Methodology.
WenYong Wang: Supervision.
Jay Kumar: Visualization, Investigation.
Ting Yang: Supervision.
Abdullah Khan: Data curation, Validation.
Wazir Ali: Writing – Reviewing and Editing.
Ikram Ali: writing – Reviewing and Editing.

Table 3
Comparsion with the other models.

Authors	Algorithm	Images	Applications
Zhao et al. (2019)	CNN	CT slices	Survival analysis
Hua et al. (2015)	DBN &CNN	Volumetric CT	Nodule classification
Hussein et al. (2017)	CNN	Volumetric CT	Nodule characterization
Wu et al. (2020)	CNN	Volumetric CT	pulmonary nodules detection
Dou et al. (2020)	CNN	Volumetric CT	pulmonary nodules detection
Shen et al. (2017)	CNN	Volumetric CT	ungnodulemalignancy classification
Paul et al. (2016)	CNN	CT slices	Survival prediction
Wang et al. (2017a,b)	CNN	CT slices	Lung nodule classification
Hirayama et al. (2016)	CNN	CT slices	Extraction of ground glass opacity (GGO) candidate region
Tajbakhsh and Suzuki (2017)	MTANN &CNN	CT slices	Lung nodule detection and classification
Kim et al. (2016)	SSAE	CT slices	pulmonary nodules classification
Ours	CNN + RCNN and Blockchain	CT slices	Lung nodule detection and classification

Table 4
Feature comparative analysis with other approaches for lung cancer.

Primitive	Zhao et al. (2019)	Taher and Sammouda (2011)	ALzubi et al. (2019)	This Work
Blockchain	No	No	No	Yes
Smart contract	No	No	No	Yes
Deep learning classification	Yes	Yes	Yes	Yes
Deep learning detection	Yes	Yes	Yes	Yes

Declaration of Competing Interest

The authors report no declarations of interest.

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