Secure Collaborative Augmented Reality Framework for Biomedical Informatics

Youcef Djenouri, Asma Belhadi, Gautam Srivastava, Jerry Chun-Wei Lin*

***Abstract*—Augmented reality is currently a great interest in biomedical health informatics. At the same time, several challenges have been appeared, in particular with the rapid progress of smart sensors technologies, and medical artificial intelligence. This yields the necessity of new needs in biomedical health informatics. Collaborative learning and privacy are some of the challenges of augmented reality technology in biomedical health informatics. This paper introduces a novel secure collaborative augmented reality framework for biomedical health informatics-based applications. Distributed deep learning is first performed across a multi-agent system platform. The privacy strategy is developed for ensuring better communications of the different intelligent agents in the system. In this research work, a system of multiple agents is created for the simulation of the collective behaviours of the smart components of biomedical health informatics. Augmented reality is also incorporated for better visualization of the resulted medical patterns. A novel privacy strategy based on blockchain is investigated for ensuring the confidentiality of the learning process. Experiments are conducted on the real use case of the biomedical segmentation process. Our strong experimental analysis reveals the strength of the proposed framework when directly compared to state-of-the-art biomedical health informatics solutions.**

***Index Terms*—Biomedical Health Informatics, Augmented Reality, Distributed Deep Learning, Multi-Agent System, Privacy.**

I. Introduction

In medicine, sensors and smart devices are deployed widely to not only retrieve as well as collect medical data related to patients but also to detect and diagnose diseases in distributed environment [1], [2]. With the current push in medical industries, exploring sophisticated deep learning architectures for processing smart sensors medical data became a requirement. The primary reason is that companies such as GE Healthcare, Optum, and Cerner are not only analyzing medical data but learning from such data to extract valuable knowledge and decision of future medical cases. Although the existing technologies and platforms provide tools for use with medical data, the exponentially increasing of attacks, and the need of identifying new patterns from medical data will be two hot challenges in medical industries of the future. With the lack of strong intelligent techniques used in learning from medical traces as well as accurately handling sensitive data, serious degradation in terms of systems performances may be lead.

Y. Djenouri is with the SINTEF Digital, Oslo, Norway
A. Belhadi is with the Kristiania University College, Oslo, Norway.
G. Srivastava is with Brandon University, Brandon, Canada and China Medical University, Taiwan.
J. C. W. Lin is with the Western Norway University of Applied Sciences, Norway. (*Corresponding author)

Various Artificial Intelligence (AI) is widely applied to solve complex problems in medical applications. Privacy deep learning, multi-agent systems are just examples of such methods that prove their success in the recent decade. Privacy deep learning [3], [4] are used to learn from the previous examples of medical sensitive data. Kumar et al. [3] developed a secure framework to handle heterogeneous data retrieved from different hospitals, where global deep learning architecture is used with the integration of federated learning technologies. MAS (Multi-Agent Systems) [5], [6] are also been largely investigated in the last years for addressing the challenges of the medical applications. For instance, Bennai et al. [5] developed a multi-agent system for 3D medical segmentation. The intelligent agents used an extended region growing algorithm with a merging strategy to identify and refine the regions of the tumours in brain image data. Allioui et al. [6] presented a diagnose system based on multi-agent technology, where all agents cooperated for executing the segmentation process. It also provides an end-to-end solution by connecting domain experts with data scientist knowledge. This paper proposes a collaborative framework for solving medical applications, the main contributions of this research work are threefold as follows:

1) We propose a new intelligent collaborative framework to deal with medical data in real-time processing. The proposed framework explores privacy deep learning with the combination of convolution neural networks and blockchain technology. It also integrates the multi-agents system with reinforcement learning for designing automated models learned from complex medical data.
2) We adopt the convolution neural network already developed in the literature. Thus, the convolution neural network proposed in this research work communicates with blockchain technology to ensure the full confidentiality of the medical sensitive data in the learning phase, as well as, in the inference phase.
3) We adopt the ARAM library (Augmented Reality Applications Medical) to better visualize the resulting medical patterns. We also analyze the proposed framework on a well-known medical case which is image segmentation. We used six different datasets largely used by the medical community. The results reveal the usefulness of our framework compared to two baseline medical segmentation methods UNET, and FC-DenseNet in terms of accuracy, and very competitive in terms of runtime computation. The results also reveal the effectiveness of SCF-BHI in detecting attacks when exploring the

blockchain strategy.

The rest of this paper is organized as follows: Related work is summarized in Section 2. The proposed framework and designed algorithm are discussed in Section 3. We report our experimental results in Section 4. Section 5 presents the main finding of the application of SCF-BHI in medical industries. Section 6 concludes the paper.

II. Literature Review

We discuss briefly the three main bodies in augmented reality distributed deep learning applications in this section: one on intelligent medical analysis, one on deep learning, one on multi-agent systems.

A. Medical Analysis Intelligence

Nicolau et al. [7] took a look at many interactive solutions that were primarily reality-based in surgical oncology. The authors systematically discussed both the merit and limitations of every system. Wu et al. [8] created a strategy for alignment of surgery images. The authors made use of both RBG-depth and cloud points to make more in-depth knowledge of head surface. Gonzalez et al. [9] gave a medical image-based 3D reconstruction/visualization technique. Making use of both Augmented Reality (AR) and Virtual Reality (VR), their solution was end-to-end as well as modular. Wang et al. [10] build a system for detecting COVID-19 infection regions. The framework can deal with the discrepancy, testing the time-effectiveness of a model, and data security. Ma et al. [11] provide a better understanding of the use of the generative adversarial network in medical systems. It also gives a detailed explanation of why are medical image DNN models easy to attack. Wu et al. [12] explained how medical AI devices are evaluated, and suggested some recommendations from an analysis of the food and drug administration.

B. Deep Learning Distribution

Dai et al. [13] gave rise to using reinforcement learning alongside next-gen wireless networks for the processing of distributed data. A function wad proposed that was shown to maximize the utility of the shared data. Weng et al. [14] created an FL-based distributed framework for solving conflicts from a group of distinct behaviours that could occur in crowdsourcing platforms. Liu et al. [15] presented an intelligent learning approach to ensure evaluation of distributed platforms focusing on accuracy and latency. Dai et al. [16] used deep learning and the Genetic algorithm to try and solve online offloading issues. Luo et al. [17] initiated advanced technologies for the reduction of computational resources with sensor data while maintaining the number of hidden features analyzed.

C. Multi-Agent Systems

Cicirelli et al. [18] investigated using cognitive agents in distributed models. The authors also exploit many of the well-known properties of intelligent agents like proactivity, reactivity, and cognitive to boost performance. Casado et al. [19] discussed intelligent systems for use in supply chains. The authors also made use of blockchain technology in their framework design. Ciatoo et al. [20] used autonomy in intelligent systems to be able to analyze social features independently. Alqahtani et al. [21] investigated a framework with multiple agents to improve security in any distributed platform. The authors build a layer between the applications and use the hardware layer to fix conflicts among users. Alsboui et al. [22] created improvements in data distribution scalability in mobile apps. The authors also created integration efforts of mobile agents at the communication level. It should also be clear that most of the AR papers combined with distributed DL applications are not in the realm of use in the medical domain. In this research work, a novel dedicated framework is proposed that is complete and combines AR, DL, security, privacy, in a multi-agent system. The main focus of this work is to solve known issues in distributed medical data platforms. Details are described below.

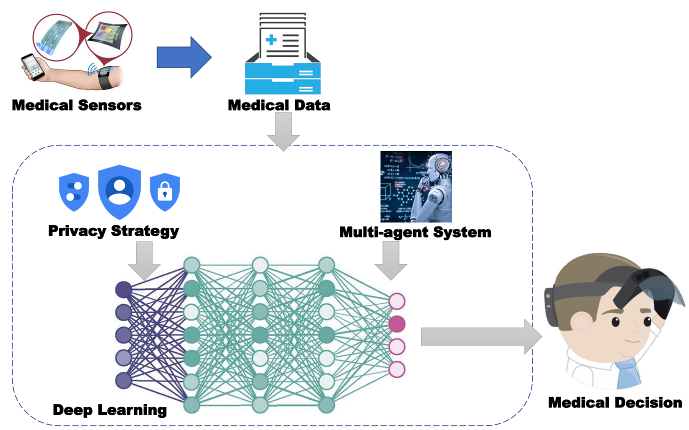


Fig. 1. SCF-BHI Framework

III. Secure Collaborative Augmented Reality Framework for Biomedical Health Informatics

A. Principle

Let us begin by introducing the main components of the SCF-BHI (Secure Collaborative augmented reality Framework for Biomedical Health Informatics). Fig. 1 illustrates the designed framework which is based on different smart technologies such as privacy deep learning and multi-agent system for dealing with the medical sensor data. The medical data is extracted first from the medical sensors. The deep learning with a multi-agent system is then executed to derive the medical decisions. In particular, DL is used for the creation of model automation from medical data. Multi-agent systems can then be used to handle heterogeneous and distributed data simultaneously. Augmented reality is incorporated to visualize the resulting medical patterns. In this context, the doctors used hololens to well interpret the outputs of the deep learning models and efficiently provide medical decisions. Privacy strategy is used to secure the learning process. SCF-BHI components are described in detail throughout this section.

B. Multi-Agent Systems

Multi-agent systems can be defined as a tuple $< \mathcal{A}, \mathcal{S}, \mathcal{U}, \mathcal{R} >$. We can say that $\mathcal{A}$ is a set of agents, where each agent in itself is a Markov decision process, we also say that $\mathcal{S}$ can be defined as a finite set of environment states, where $\mathcal{U}$ can be defined as a set of actions as well as define $\mathcal{R}$ as a reward function. When focusing on behaviour for each and every agent that exists in $\mathcal{A}$, we represent this with a policy that will specify how agents choose their specific action when only the state is given. Each agent's purpose is to find a policy that will allow the maximization of the objective functions. For example, for prediction, each agent's policy is for the maximization of predicted objects. Different components are given next in detail:

1) **State**: Previous states' decisions are dependant upon for next actions. Each agent's state, therefore, consists of two parts, a set of previous actions as well as current handled data. We define $\mathcal{S}$ as the size of state space measured in observation number.
2) **Action**: It is the assignment of the decision behaviour of each observation in the database. For instance, in the case of prediction task, it is the assignment of the class of each object.
3) **Reward**: Reward function determination is crucial. A better learning process is instantiated this way for each agent in $\mathcal{A}$. Ground truth is used in this setting. The reward function is given in Eq. 1.

$$R(\mathcal{A}_i, \mathcal{U}_j) = \begin{cases} 1, & \text{if } \mathcal{A}_i(\mathcal{U}_j, O_j) = \mathcal{G}(O_j) \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where $\mathcal{A}_i(\mathcal{U}_j, O_j)$ is decision of agent $\mathcal{A}_i$, whether observation O_j has correct action or not. $\mathcal{L}(O_j)$ is ground-truth for observation O_j.
4) **Environment**: Set of databases that contain a large population of smart sensor data. This will then allow the environment to be able to generate particular states for training agents and the estimation of the best actions to take.

Each agent $\mathcal{A}_i$ begins by scanning observations of i^{th} smart sensor, next computes first observation, remaining observations of i^{th} smart sensor are computed next. The reward function is calculated for decision using the ground truth of the initial observation. The process is then repeated for the entire observation set for the i^{th} smart sensor. This results in a local decision set denoted as LD_i derived for each and every agent $\mathcal{A}_i$.

C. Deep Learning Privacy

In this work, a convolution neural network is used with a privacy strategy to train the biomedical data securely.

1) **Convolution Neural Network (CNN)**: CNN is defined as a class in deep architectures that can be applied to computer vision applications like visual recognition as well as to object detection. Recently we have seen CNN be applied in various scenarios of data representation like textual data as well as time-series data. CNN's primary idea is in the realm of feature extraction in matrices using convolutional filters (CF). CF is defined as a weight set that can be applied to each and every element in a data pixel matrix. Weights can be adjusted as well as learned making use of back-propagation methods. We make use of VGG16 here, a well-known CNN architecture.
2) **Privacy Strategy**: We proposed a new strategy to ensure privacy during the learning process. We used Ethereum as a system to save the different models learned from the different agents. It can secure the data communication among the different agents by building a blockchain system. The blocks are first generated, each of which contains the models trained by each agent. After creating the blocks, a hash function is determined to protect the created models by the agents. The hash function is used to easily detect the different changes by the hackers. Formally speaking, a hash function is defined as follows:

$$\mathcal{H}(M_i) = V_i, \quad (2)$$

where M_i is the model generated by the agent $\mathcal{A}_i$, and v_i is a unique code represented by 32 bits.
Another mechanism is also explored based on proof of work, which helps mitigate detecting the hashes. All agents have access to the proof of work and agree to the way of creating new blocks in the system. The encryption system is also needed to be used for ensuring the privacy of data transportation across the different agents.

D. Augmented Reality

To ensure better visualization of the resulted medical patterns, we used augmented reality techniques. We were inspired by ARAM (Augmented Reality Applications Medical) library [23], where the main purpose is to automatically identify markers. It provides different functionalities such as intensity image analysis, marker corner position estimation, line fitting, markers generation and pruning. This library is shown great interest in the medical domain, in particular for segmentation-based applications, where markers and pose estimation of the objects are crucial for a better understanding of the results. Fig. 3 illustrated the augmented reality results by the output of the brain tumour detector proposed in [24]. The encoder-decoder deep learning architecture is first used to identify the tumour regions of the brain. The input of the model is the brain image, and the output will be the different regions of the tumours. The ARAM is then adopted and used to visualize the tumours and mark the whole tumour as the main red rectangular and the enhancing tumour core illustrated by yellow color.

Algorithm 1 presents the pseudo-code of the SCF-BHI algorithm. The input data is the set of n medical data used in the training, the set of k new medical data used in the inference, and the set of k agents. The process starts by collecting the medical data from the sensors. The collected medical data are trained using the deep learning models, where each agent is responsible to learn one model, the security strategy is used to secure the training procedure. The

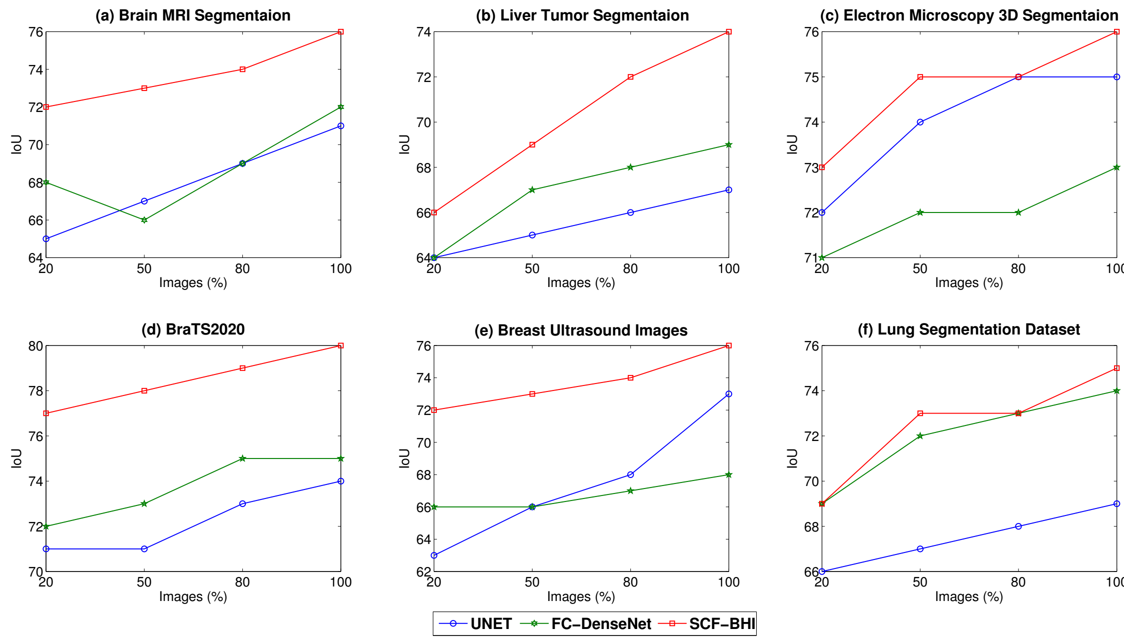


Fig. 2. Accuracy of the SCF-BHI compared to the state-of-the-art image segmentation solutions.

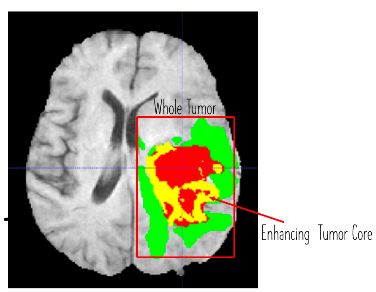


Fig. 3. Augmented reality illustration.

Algorithm 1 SCF-BHI Algorithm

Input: $D = \{D_1, D_2, \ldots, D_n\}$: the set of n medical data used in the training. $D_{new} = \{D^1_{new}, D^2_{new}, \ldots, D^k_{new}\}$: the set of k medical data used in the inference. A: the set of k agents.
Output: $R(D_{new})$, decision rules of new medical data.
*************Training*****************
for each agent A_i **do**
    $M_i \leftarrow$ DeepLearning(D, A_i);
    Security(M_i, A_i);
end for
$M \leftarrow$ Combining(M_i);
*************Inference*****************
$R(D_{new}) \leftarrow \emptyset$;
for $D^i_{new} \in D_{new}$ **do**
    $R(D^i_{new}) \leftarrow M(D^i_{new}, A_i)$;
    $R(D_{new}) \leftarrow R(D_{new}) \cup R(D^i_{new})$;
end for
$R(D_{new}) \leftarrow AR(R(D_{new}))$;
return $R(D_{new})$.

combination of the model trained is performed to obtain the global model. As a result of the training phase, the weights of the global models are adjusted. In the inference step, the propagation of weights of the global model is performed for each new medical data, and this is performed by each agent. Augmented reality is performed to derive valuable medical decisions, easily interpretable by doctors. We remark that the training phase, performed only once independently from the number of medical data in the inference, is a high time-consuming task that includes several training models, and processing. However, the inference step contains only one loop and needs simple propagation of the learned models in the training phase.

IV. Performance Evaluation

In this section, we compare the proposed SCF-BHI and compare it with state-of-the-art solutions. In particular, six medical segmentation datasets are used for the evaluation. The detailed description of these datasets is given in the following:

1) Brain MRI segmentation[1]: It contains brain magnetic resources images (MRI) together with manual FLAIR abnormality segmentation masks. The images were obtained from The Cancer Imaging Archive (TCIA). They correspond to 110 patients included in The Cancer Genome Atlas (TCGA) lower-grade glioma collection with at least fluid-attenuated inversion recovery (FLAIR) sequence and genomic cluster data available.
2) Liver Tumor Segmentation[2]: It contains 130 computed tomography (CT) scans for segmentation of the liver as well as tumour lesions. This dataset was extracted from LiTS – Liver Tumor Segmentation Challenge (LiTS17) organized in conjunction with ISBI 2017 and MICCAI 2017.
3) Electron Microscopy 3D Segmentation [25]: It represents a $5x5x5\ m$ section taken from the CA1 hippocampus region of the brain, corresponding to a $1065x2048x1536$ volume. The resolution of each voxel is approximately $5x5x5\ nm$.

[1]https://www.kaggle.com/mateuszbuda/lgg-mri-segmentation
[2]https://www.kaggle.com/andrewmvd/liver-tumor-segmentation

4) BraTS2020 [26]: It utilizes multi-institutional pre-operative MRI scans and primarily focuses on the segmentation of intrinsically heterogeneous (in appearance, shape, and histology) brain tumours, namely gliomas.
5) Breast Ultrasound Images [27]: It is categorized into three classes: normal, benign, and malignant images. The data collected at baseline include breast ultrasound images among women between ages between 25 and 75 years old. This data was collected in 2018. The number of patients is 600, female patients. The dataset consists of 780 images with an average image size of $500 * 500$ pixels.
6) Lung Segmentation Dataset SIIM COVID [3]: It contains the masked lungs from the SIIM-FISABIO-RSNA COVID-19 detection competition. The resolution of all images is $512x512$.

To evaluate the proposed framework, the IoU (Intersection Over Union) is used as metric of comparison. IoU is largely used to test image segmentation algorithms, which can be defined by,

$$IoU = \frac{Intersection(R, G)}{Union(R, G)}, \tag{3}$$

where $Intersection(R, G)$ is the intersection of the region R found by the trained model, and the ground truth G. $Union(R, G)$ is the union of the region R found by the trained model, and the ground truth G.

The experimental evaluation of the implementation has been performed on a computer with a 64-bit core i7 processor running Windows 10 and 16 GB of RAM. The CPU host is a 64-bit quad-core Intel Xeon E5520 with a clock speed of 2.27 GHz. The GPU device is an Nvidia Tesla C2075 with 448 CUDA cores (14 multiprocessors with 32 cores each) and a clock speed of 1.15 GHz. It has 2.8 GB of global memory, 49.15 KB of shared memory, and a warp size of 32. Both the CPU and GPU are used in single precision. In our implementation scenario, we used the GPU blocks to simulate the multi-agent system environment. Each agent is allocated to one GPU block, where a shared memory of each block is allocated to the corresponding agent. The communication among agents is done using global and constant memories of the GPU host.

We compare the SCF-BHI framework, with the following baseline image segmentation solutions:

1) UNET [28]: It is a state-of-the-art biomedical image segmentation model, it is based on encoder-decoder deep learning architecture. It considers an image as input and another image as the output of the same dimension. The output is the label or the class of each pixel in the input data. The encoder is composed of a convolution layer followed by Relu function and max-pooling operators. The decoder is also composed of a convolution layer followed by the Relu function but will be followed by up-convolution.
2) FC-DenseNet (Fully Convolutional Dense Connection Network) [29]: It is also considered as state-of-the-art biomedical image segmentation models. It considers an image as input and another image as the output of the same dimension. The output is the label or the class of each pixel in the input data. It is composed of several dense layers. Each dense layer is connected not only with previous and next layers but with other layers.

TABLE I
RESULTS OF SCF-BHI WITH DIFFERENT NUMBER OF AGENTS.

Dataset	# of Agents:1		# of Agents:2		# of Agents:5	
	CPU	Acc.	CPU	Acc.	CPU	Acc.
Brain MRI Segmentation	94	75	95	78	97	81
Liver Tumor Segmentation	92	68	93	72	95	73
Electron Microscopy 3D Segmentation	92	73	94	74	95	75
BraTS2020	90	77	92	78	94	79
Breast Ultrasound Images	93	72	94	73	96	76
Lung Segmentation Dataset SIIM COVID	94	70	102	72	106	75

A. *Accuracy Performance*

The first experiments aim to evaluate the accuracy of the SCF-BHI compared to the baseline image segmentation solutions, the UNET [28], and the FC-DenseNet [29] using the six datasets mentioned above. By varying the percentage of the number of images used as input from 20% to 100%, Fig. 2 shows that SCF-BHI outperforms the two baseline algorithms in terms of the union over intersection metric. Thus, the IoU of the SCF-BHI reached 80% for handling 100% of the BraTS2020 dataset. Whereas the IoU for the other models goes under 75% for dealing with the same configuration. These results are obtained thanks to the distributed deep learning simulated by the multi-agent system.

B. *Runtime Performance*

The second experiments aim to evaluate the runtime of the SCF-BHI compared to the baseline image segmentation solutions, the UNET [28], and the FC-DenseNet [29] using the six datasets mentioned above. By varying the percentage of the number of images used as input from 20% to100%, Fig. 4 shows that SCF-BHI needs more time compared to the two baseline models. However, the gap among the three models are too small, whatever the percentage of the number of images used as input. These results are explained by the fact that SCF-BHI is a collaborative framework where communication among the different agents in the system is needed which yields the inference process high time-consuming.

C. *Privacy Performance*

The third experiments aim to evaluate the privacy strategy of the SCF-BHI on the six different datasets described above. By varying the number of attacks from 10 to $10,000$ attacks, the SCF-BHI with the blockchain strategy can identify a high number of attacks compared to the SCF-BHI without blockchain technology. Thus, the percentage of attacks detected by our framework is 72% for handling 10,000 attacks on the BraTS2020 dataset. However, the percentage of attacks detected without blockchain technology does not exceed 61%

[3]https://www.kaggle.com/farhanhaikhan/unet-lung-segmentation-dataset-siim-covid

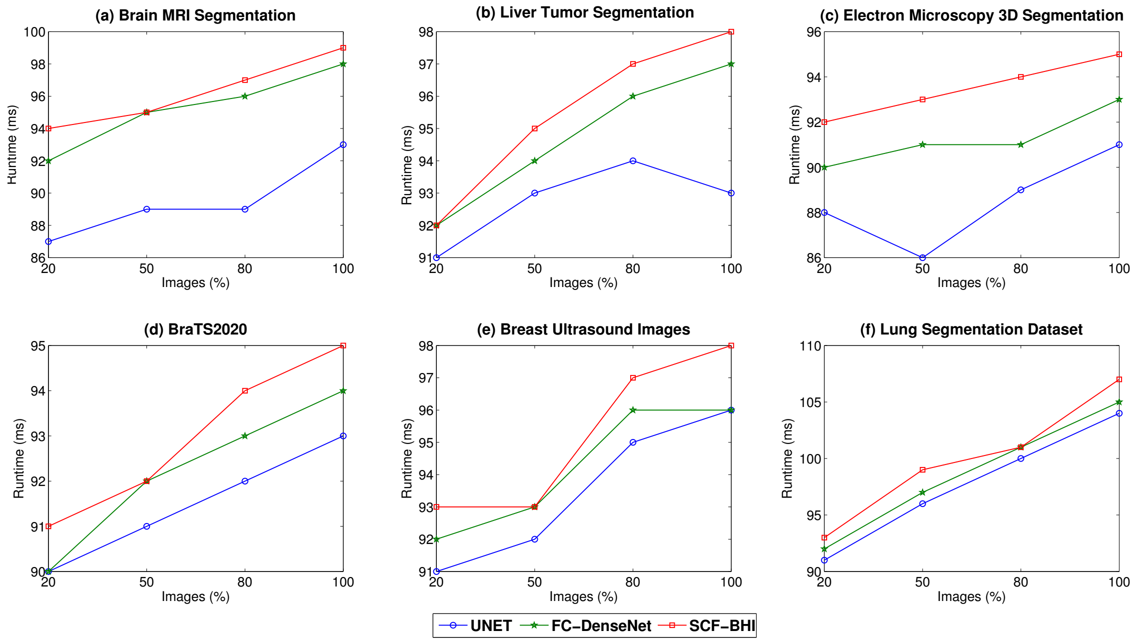


Fig. 4. Runtime of the SCF-BHI compared to the state-of-the-art image segmentation solutions.

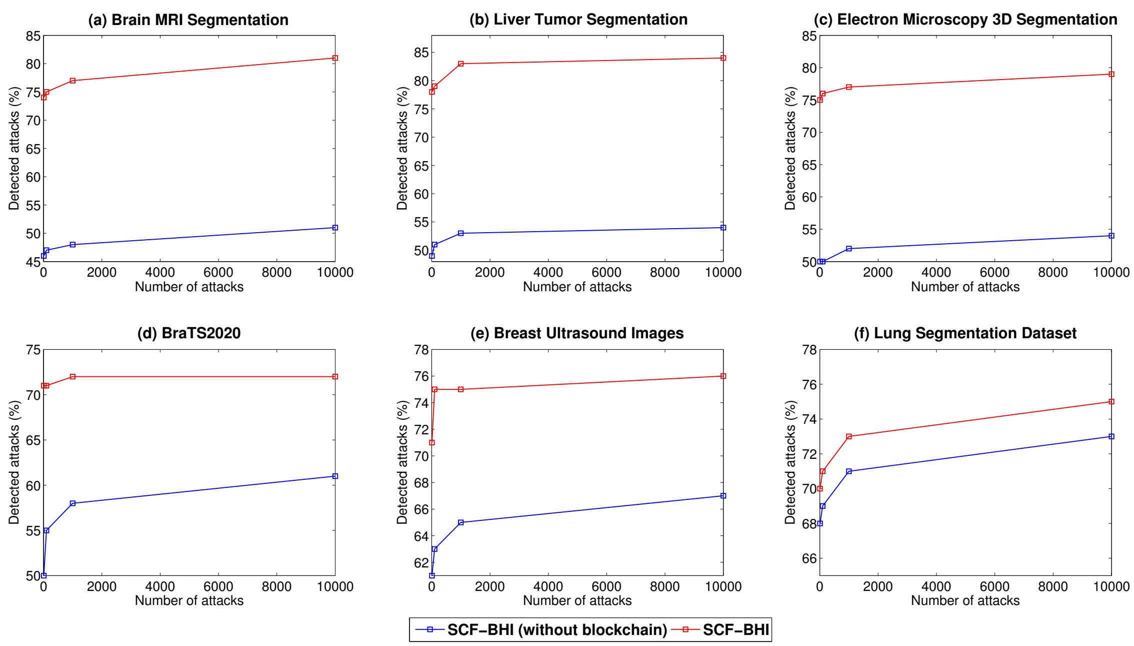
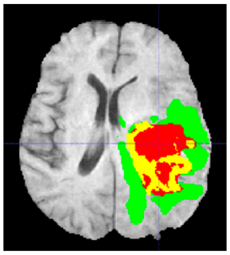


Fig. 5. Percentage of detected attacks of the SCF-BHI with and without using the blockchain strategy.

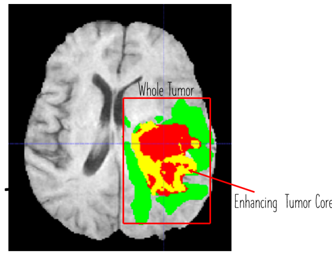
for handling the same configurations as input. These attacks are related to data acquisition, where hackers attempt to update the medical data. This yields that the deep learning model infer wrong results, and this can infect the medical decision. These results are obtained thanks to the efficient blockchain strategy by SCF-BHI which can identify the different types of attacks.

D. Multi-Agent Performance

The next experiments aim to compare the performance of the SCF-BHI solution with a different number of agents. Table I shows both the runtime in mile seconds and the intersection over union value of the SCF-BHI using a different number of agents. By varying the number of agents from 1 to 5, the results reveal the clear improvement of accuracy but also increasing of runtime performance. This performance is explained by the fact that the knowledge sharing among the different agents in SCF-BHI helps in accurately handling biomedical data, however, this process is highly time-consuming due to the communication cost among the different agents.



(a) Without augmented reality



(b) With augmented reality

Fig. 6. Case Study on Brain Tumor Segmentation: The figure in left is the results of the SCF-BHI without introducing augmented reality concept, where the second one is the results of the SCF-BHI by incorporating the augmented reality.

E. Case Study on Brain Tumor Segmentation

Fig. 6 presents the case study of the application of the SCF-BHI on brain tumour segmentation. The figure on left is the results of the SCF-BHI without introducing the augmented reality concept, where the second one is the results of the SCF-BHI by incorporating the augmented reality. From both figures, we can see the impact of augmented reality in helping doctors accurately provide medical decisions. Thus, with hololens, the doctor can easily select the different parts having tumours, and therefore better understand the tumour cause, and also better identify the tumour distribution in the body.

V. Discussions and Future Perspectives

This section discusses the main findings from the application of the SCF-BHI framework to handle biomedical applications.

- The first finding of this study is that the proposed framework can efficiently deal with biomedical data by incorporating a convolution neural network, and multi-agent system. The convolution neural network has the goal to identify the relevant features in the medical data. In addition, the communication among intelligent agents in the system allows reaching better accuracy.
- From an artificial intelligence standpoint, the proposed framework is an example of combining different artificial intelligence technologies for boosting the performances of biomedical solutions. In our specific context, deep learning, and artificial intelligence meet the biomedical informatics for handling biomedical data.
- Another finding of this study is that multi-agent system benefits from blockchain technology. Thus, each agent can securely communicate with the other agents by generating a chain of blocks semantically known to each other.
- The last observation is that the framework is generic and can be applied in any biomedical application, which necessitates smart collaborations via medical entities. This scenario reflects well the current needs in biomedical informatics.

Motivated by the promising results shown in this paper, different directions may be investigated:

1) **Improving the learning step.** Privacy deep learning is used in this research work. In particular, the combination between the convolution neural network and blockchain technology is explored to handle medical data in a confidential way. Additional deep learning models may be investigated for reducing the error learning rate, and other privacy technologies should be exploited for enhancing the confidentiality of sensitive medical data, especially for data related to patients. In addition, the deep learning architectures allow solving different data representations collected from different kinds of medical devices. Convolution neural networks allow dealing with matrix data such as images, and transactions, where the recurrent neural networks perform very well on time series data such as vital signs of patients. Therefore, an interesting topic for future work is to integrate other deep learning models into the proposed framework, such as recurrent neural network [30]. transfer learning [31], active learning [32], and reinforcement learning [33].
2) **Improving the runtime processing.** Real-time processing is a critical issue for medical deep learning. Large companies such as GE Healthcare, Optum, and Cerner require processing time in a few milliseconds per frame. Even the medical data is not very large, where few numbers of layers are needed in the learning, the runtime processing is one of the most challenging issues for data scientists working on medical data. Therefore, the interesting direction of this research is to explore both optimization methods [34] and high-performance computing [35] for boosting the performance of the proposed framework without loss of quality of returned outputs.
3) **Case studies.** We already show in this paper one of the exciting applications of the proposed framework in the medical domain which is image segmentation. Motivated by the promising results shown in this research work, we plan to extend the suggested framework for addressing other challenges in medical applications such as tumour detection [36], automatic disease diagnosis [37], epidemic outbreak prediction [38], and drug discovery [39]. In this context, several research questions need to be addressed, e.g how can make the proposed framework more generic for handling these applications, what are the challenges faced to the proposed framework for better processing the target applications, and which data augmentation techniques need for reaching successful training process.

VI. Conclusion

This paper introduced a new secure collaborative augmented reality framework for biomedical health informatics by incorporating distributed deep learning, multi-agent system, augmented reality, and privacy strategy. The medical data is first collected from smart sensors. The distributed deep learning is then performed to efficiently learn from medical data. To simulate the intelligence of the different medical entities, the multi-agent system is investigated. Augmented reality is incorporated to better visualize the resulting medical patterns. In addition, to ensure better collaboration among the agents in the system, a privacy strategy based on blockchain is developed. To validate the performance of the proposed framework several experiments have been carried out on the real use case of the biomedical segmentation process. The obtained results demonstrate the validity of our suggested methodology in biomedical health informatics settings.

References

[1] G. Manogaran, M. Alazab, H. Song, and N. Kumar, "Cdp-ua: cognitive data processing method wearable sensor data uncertainty analysis in the internet of things assisted smart medical healthcare systems," *IEEE Journal of Biomedical and Health Informatics*, 2021.

[2] A. A. Abdellatif, L. Samara, A. Mohamed, A. Erbad, C. F. Chiasserini, M. Guizani, M. D. O'Connor, and J. Laughton, "Medge-chain: Leveraging edge computing and blockchain for efficient medical data exchange," *IEEE Internet of Things Journal*, 2021.

[3] R. Kumar, A. A. Khan, J. Kumar, A. Zakria, N. A. Golilarz, S. Zhang, Y. Ting, C. Zheng, and W. Wang, "Blockchain-federated-learning and deep learning models for covid-19 detection using ct imaging," *IEEE Sensors Journal*, 2021.

[4] F. Isensee, P. F. Jaeger, S. A. Kohl, J. Petersen, and K. H. Maier-Hein, "nnu-net: a self-configuring method for deep learning-based biomedical image segmentation," *Nature Methods*, vol. 18, no. 2, pp. 203–211, 2021.

[5] M. T. Bennai, Z. Guessoum, S. Mazouzi, S. Cormier, and M. Mezghiche, "A stochastic multi-agent approach for medical-image segmentation: Application to tumor segmentation in brain mr images," *Artificial Intelligence in Medicine*, vol. 110, p. 101980, 2020.

[6] H. Allioui, M. Sadgal, and A. Elfazziki, "Intelligent environment for advanced brain imaging: multi-agent system for an automated alzheimer diagnosis," *Evolutionary Intelligence*, pp. 1–16, 2020.

[7] S. Nicolau, L. Soler, D. Mutter, and J. Marescaux, "Augmented reality in laparoscopic surgical oncology," *Surgical oncology*, vol. 20, no. 3, pp. 189–201, 2011.

[8] M.-L. Wu, J.-C. Chien, C.-T. Wu, and J.-D. Lee, "An augmented reality system using improved-iterative closest point algorithm for on-patient medical image visualization," *Sensors*, vol. 18, no. 8, p. 2505, 2018.

[9] S. González Izard, R. Sánchez Torres, O. Alonso Plaza, J. A. Juanes Mendez, and F. J. García-Peñalvo, "Nextmed: automatic imaging segmentation, 3d reconstruction, and 3d model visualization platform using augmented and virtual reality," *Sensors*, vol. 20, no. 10, p. 2962, 2020.

[10] B. Wang, S. Jin, Q. Yan, H. Xu, C. Luo, L. Wei, W. Zhao, X. Hou, W. Ma, Z. Xu *et al.*, "Ai-assisted ct imaging analysis for covid-19 screening: Building and deploying a medical ai system," *Applied Soft Computing*, vol. 98, p. 106897, 2021.

[11] X. Ma, Y. Niu, L. Gu, Y. Wang, Y. Zhao, J. Bailey, and F. Lu, "Understanding adversarial attacks on deep learning based medical image analysis systems," *Pattern Recognition*, vol. 110, p. 107332, 2021.

[12] E. Wu, K. Wu, R. Daneshjou, D. Ouyang, D. E. Ho, and J. Zou, "How medical ai devices are evaluated: limitations and recommendations from an analysis of fda approvals," *Nature Medicine*, vol. 27, no. 4, pp. 582–584, 2021.

[13] Y. Dai, D. Xu, S. Maharjan, Z. Chen, Q. He, and Y. Zhang, "Blockchain and deep reinforcement learning empowered intelligent 5g beyond," *IEEE Network*, vol. 33, no. 3, pp. 10–17, 2019.

[14] J. Weng, J. Weng, J. Zhang, M. Li, Y. Zhang, and W. Luo, "Deepchain: Auditable and privacy-preserving deep learning with blockchain-based incentive," *IEEE Transactions on Dependable and Secure Computing*, 2019.

[15] M. Liu, F. R. Yu, Y. Teng, V. C. Leung, and M. Song, "Performance optimization for blockchain-enabled industrial internet of things (iiot) systems: A deep reinforcement learning approach," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 6, pp. 3559–3570, 2019.

[16] Y. Dai, D. Xu, K. Zhang, S. Maharjan, and Y. Zhang, "Deep reinforcement learning and permissioned blockchain for content caching in vehicular edge computing and networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 4, pp. 4312–4324, 2020.

[17] Q. C. F. R. Y. Luo, Jia and L. Tang, "Blockchain-enabled software-defined industrial internet of things with deep reinforcement learning," *IEEE Internet of Things Journal*, 2020.

[18] F. Cicirelli, A. Guerrieri, G. Spezzano, and A. Vinci, "A cognitive enabled, edge-computing architecture for future generation iot environments," in *IEEE World Forum on Internet of Things*, 2019, pp. 35–40.

[19] R. Casado-Vara, J. Prieto, F. De la Prieta, and J. M. Corchado, "How blockchain improves the supply chain: Case study alimentary supply chain," *Procedia Computer Science*, vol. 134, pp. 393–398, 2018.

[20] G. Ciatto, A. Maffi, S. Mariani, and A. Omicini, "Towards agent-oriented blockchains: Autonomous smart contracts," in *International Conference on Practical Applications of Agents and Multi-Agent Systems*, 2019, pp. 29–41.

[21] F. Alqahtani, Z. Al-Makhadmeh, A. Tolba, and O. Said, "Tbm: A trust-based monitoring security scheme to improve the service authentication in the internet of things communications," *Computer Communications*, vol. 150, pp. 216–225, 2020.

[22] T. Alsboui, Y. Qin, R. Hill, and H. Al-Aqrabi, "Enabling distributed intelligence for the internet of things with iota and mobile agents," *Computing*, pp. 1–19, 2020.

[23] A. Belhaoua, A. Kornmann, and J.-P. Radoux, "Accuracy analysis of an augmented reality system," in *The International Conference on Signal Processing*, 2014, pp. 1169–1174.

[24] A. Myronenko, "3d mri brain tumor segmentation using autoencoder regularization," in *International MICCAI Brainlesion Workshop*, 2018, pp. 311–320.

[25] A. Lucchi, K. Smith, R. Achanta, G. Knott, and P. Fua, "Supervoxel-based segmentation of mitochondria in em image stacks with learned shape features," *IEEE Transactions on Medical Imaging*, vol. 31, no. 2, pp. 474–486, 2011.

[26] B. H. Menze, A. Jakab, S. Bauer, J. Kalpathy-Cramer, K. Farahani, J. Kirby, Y. Burren, N. Porz, J. Slotboom, R. Wiest *et al.*, "The multimodal brain tumor image segmentation benchmark (brats)," *IEEE Transactions on Medical Imaging*, vol. 34, no. 10, pp. 1993–2024, 2014.

[27] W. Al-Dhabyani, M. Gomaa, H. Khaled, and A. Fahmy, "Dataset of breast ultrasound images," *Data in Brief*, vol. 28, p. 104863, 2020.

[28] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *International Conference on Medical image computing and computer-assisted intervention*, 2015, pp. 234–241.

[29] X. Duan, L. Nao, G. Mengxiao, D. Yue, Z. Xie, Y. Ma, and C. Qin, "High-capacity image steganography based on improved fc-densenet," *IEEE Access*, vol. 8, pp. 170 174–170 182, 2020.

[30] J. C.-W. Lin, Y. Shao, Y. Djenouri, and U. Yun, "Asrnn: a recurrent neural network with an attention model for sequence labeling," *Knowledge-Based Systems*, vol. 212, p. 106548, 2021.

[31] H. Lin, J. Hu, W. Xiaoding, M. F. Alhamid, and M. J. Piran, "Towards secure data fusion in industrial iot using transfer learning," *IEEE Transactions on Industrial Informatics*, 2020.

[32] H. Deng, K. Yang, Y. Liu, S. Zhang, and Y. Yao, "Actively exploring informative data for smart modeling of industrial multiphase flow processes," *IEEE Transactions on Industrial Informatics*, 2020.

[33] A. Belhadi, Y. Djenouri, G. Srivastava, A. Jolfaei, and J. C.-W. Lin, "Privacy reinforcement learning for faults detection in the smart grid," *Ad Hoc Networks*, p. 102541, 2021.

[34] V. Bharti, B. Biswas, and K. K. Shukla, "A novel multiobjective gdwcn-pso algorithm and its application to medical data security," *ACM Transactions on Internet Technology*, vol. 21, no. 2, pp. 1–28, 2021.

[35] P. Haripriya and R. Porkodi, "Parallel deep convolutional neural network for content based medical image retrieval," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, pp. 781–795, 2021.

[36] D. Ravì, C. Wong, F. Deligianni, M. Berthelot, J. Andreu-Perez, B. Lo, and G.-Z. Yang, "Deep learning for health informatics," *IEEE Journal of Biomedical and Health Informatics*, vol. 21, no. 1, pp. 4–21, 2016.

[37] W. Zhu, L. Sun, J. Huang, L. Han, and D. Zhang, "Dual attention multi-instance deep learning for alzheimer's disease diagnosis with structural mri," *IEEE Transactions on Medical Imaging*, 2021.

[38] D. C. dos Santos Gomes and G. L. de Oliveira Serra, "Machine learning model for computational tracking and forecasting the covid-19 dynamic propagation," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 3, pp. 615–622, 2021.

[39] C. Li, W. Wei, J. Li, J. Yao, X. Zeng, and Z. Lv, "3dmol-net: Learn 3d molecular representation using adaptive graph convolutional network based on rotation invariance," *IEEE Journal of Biomedical and Health Informatics*, 2021.