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PAPER

FLPanGuard a Conceptual FL-Based Framework to Detect and Fight New Pandemics: Case of COVID-19 Pandemic

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ABSTRACT

The COVID-19 pandemic has highlighted the importance of artificial intelligence (AI) and data-driven solutions in enabling rapid response and decision-making support. To contain the pandemic, medical professionals must collaborate with experts in other fields, such as data scientists, to analyze medical data, including electronic health records (EHR), and to find solutions as fast as possible. However, within a sensitive industry such as healthcare, significant challenges related to data access persist due to privacy concerns and regulations. To solve these challenges, federated learning (FL) provides a novel approach to pandemic response by enabling the use of decentralized private data while maintaining data privacy. This paper provides an overview of FL and explores its application in healthcare during the COVID-19 pandemic. It also introduces FLPanGuard, a conceptual framework that focuses on detecting and fighting a pandemic using FL and other technologies to enhance data collection and security. This framework provides a global response to pandemics starting in the pre-pandemic phase by predicting potential outbreaks using social media content and EHR. It is also expanding into the pandemic phase by assisting medical professionals in diagnosis and treatment. Finally, we explore the limitations of FL to highlight areas where further research is required.

KEYWORDS

federated learning (FL), electronic health records (EHR), pandemic, COVID-19, artificial intelligence (AI)

1 INTRODUCTION

The COVID-19 pandemic has disrupted the world and caused damage in various aspects, including health. The surge in cases has overwhelmed the healthcare system around the globe, and the situation was exacerbated by the closure of the major provider's factories of active ingredients used for drug production

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in 2020. This pandemic was the first in the era of artificial intelligence (AI), so many studies have leveraged AI to manage the outbreak and provide solutions for COVID-19 response components, such as managing the lockdown [1], diagnosing the disease [2], predicting severity [3]–[4], monitoring patients [5], advancing drugs and vaccine development [6], and controlling the fake news propagation [7]. The ongoing pandemic served as a case study to assess the effectiveness of AI-driven solutions in healthcare. In general, AI has revolutionized medicine by proving its ability to assist in public health emergencies and completely transform the healthcare industry.

Artificial intelligence requires sharing data to train the model on a central server and to enhance the model's generalizability. However, the healthcare sector is highly regulated, which means that there are some challenges and ethical concerns that AI-enabled solutions should consider, such as adhering to strict regulations such as CPDR and HIPAA. Most of these regulation concerns are related to data privacy, which minimizes the performance of AI-based solutions due to data scarcity. This obliges the conception of data-robust architectures that enhance the security of patients' data using techniques such as blockchain [8].

Additionally, federated learning (FL) has gained traction as a viable solution that allows harnessing the power of AI in solving complex problems while preserving data privacy through collaborative and decentralized learning. The FL approach consists of training a global model among different participants without sharing their data to preserve data privacy.

In this paper, we present the different applications of FL during the COVID-19 pandemic, the opportunities of using FL to advance the use of AI in healthcare emergencies, as well as the challenges faced. We also propose a global conceptual framework that uses multimodal data to detect a pandemic earlier as well as assisting healthcare professionals in their mission to fight a new pandemic. Finally, we explore the limitations of FL to highlight areas where further research is required.

2 COMPREHENSIVE ANALYSIS OF LITERATURE

2.1 Overview of traditional machine learning

Traditional machine learning (ML) lies in a centralized approach where the training is performed on a single server using data collected from various participants. This approach is efficient for some cases where data privacy is not a critical concern and for participants needing more computational power to perform tasks. This approach has some limitations related to communication overhead and data privacy, as the participants should share their data with a server that can be either malicious or infer to cyber-attacks.

2.2 Distributed machine learning

The distributed ML approach uses multiple machines to train a model jointly in parallel, enabling efficient and fast processing. This approach is helpful for complex ML tasks that require high computational power to handle and analyze large amounts of data. Distributed training can be achieved through data parallelism or model parallelism. The first type consists of dividing data into subsets shared among multiple machines to perform the training models separately. The latter divides the model into parts trained simultaneously across different machines. However, this approach may have significant computational costs.

2.3 Overview of federated learning

Federated learning is a delocalized approach to learning launched by Google in 2016 to redress the challenge related to data privacy as well as other concerns related to communication overhead and security. FL allows training a global model among different participants without sharing their data to preserve data privacy. The difference between FL and distributed learning lies in the heterogeneous character of training data in FL. In FL, the server sends an initial global model to all participants; this model will be trained collaboratively and independently using the local data of each participant, who will send back the model's updates to the server once the training is performed. The server aggregates the collected updates to create and share an improved version of the models. This process will be repeated until convergence or until a predefined number of iterations is achieved.

There are several types of FL, such as horizontal FL, vertical FL, and federated transfer learning [9].

2.4 Federated learning in healthcare for COVID-19

Federated learning is an effective solution for sensitive fields such as health where data cannot be shared due to ethical and regulatory concerns. During the COVID-19 pandemic, there was a huge need for insights that could be extracted from multiple sources of data to manage the outbreak and tools to fight the pandemic. AI was widely utilized to propose solutions and support medical professionals through their journey to predict and treat patients. However, it could leak efficiency because of data scarcity and heterogeneity. FL can be utilized to redress these problems as it offers the possibility of collaborative learning to diversify the data source, allowing the model to be trained on large amounts of distributed data while preserving its privacy. During the COVID-19 pandemic, FL was utilized for several reasons: drug discovery, contact tracing, COVID-19 detection, vaccination, and surveillance (refer to Table 1).

Drug discovery. AI has become a powerful tool for test diagnostics of drugs and identification of valuable treatments. During the ongoing pandemic, AI can help in discovering the structure of the COVID-19 virus using RNA datasets as well as repurposing an effective treatment using pharmaceutical data. However, this data is restricted and cannot be shared. To redress this problem, FL has been used to perform training on pharmaceutical data without sharing it. For example, [10] proposed FL-DISCO to analyze molecular data using a graph neural network (GNN) to extract properties and propose new drugs for infectious diseases using a generative adversarial network (GAN). ESA-FedGNN proposed a solution for drug discovery that can help propose drugs for new diseases such as COVID-19 [11]. ESA-FedGNN utilizes strategies such as the double-mask strategy and Shamir secret sharing to prevent malicious attacks and enhance data protection.

During the pandemic, the pharmaceutical supply chain was impacted by the closure of the major providers of active ingredients used for drug production in 2020. In this context, [12] proposed FortiRX, a demand forecast model to redress the problems related to the pharmaceutical supply chain. FortiRX leverages blockchain, FL, and CP-ABE access control mechanisms to preserve patients' privacy.

Vaccination. To contain the damages of the lockdown and prevent deaths caused by the spread of SARS-CoV2, we need to develop vaccines immediately and vaccinate over 70% of the population to achieve herd immunity. Developing a vaccine in a short period may also cause some undiscussed side effects, especially long-term effects, and may push people to reject the vaccination.

Artificial intelligence has been used to model the structure of SARS-CoV2, determine potential antigenic targets for vaccine development, identify vaccines with promising results, and predict the side effects of these vaccines before the clinical trial phase.

For example, [13] proposed Fedcovid to predict the side effects of COVID-19 vaccines. The proposed model combined FL with other techniques to lessen challenges related to skewed and imbalanced data due to the scarcity of data representing patients who have experienced severe side effects.

[14] has also implemented FL using social media datasets for opinion mining of COVID-19 vaccination. This kind of research aims to investigate the acceptance of vaccines among a population.

COVID-19 detection. During the ongoing pandemic of COVID-19, AI has addressed problems related to disease identification and classification of cases. It has put forth several suggestions to assist medical practitioners in identifying the disease and predicting its severity. These models helped conceal the lack of medical resources and provided rapid and accurate diagnostics. For instance, [15] and [16] have employed FL to train ensemble deep learning algorithms on CT images for COVID-19 detection.

[17] Build a trust-augmented model for COVID-19 detection using FL with transfer learning and deep reinforcement learning to handle problems related to data scarcity, client selection, and communication cost. While [18] and [19] have chosen to leverage FL and blockchain in their COVID-19 detection models.

A great interest was also given to mortality prediction; thus, [20] proposed an FL-based solution to train EHR using a ML algorithm to forecast mortality within seven days. Furthermore, [21] developed a federated transfer learning for survival detection.

Surveillance. By leveraging the power of IoT, AI has been deployed to help authorities monitor public spaces to ensure compliance with protection measures, clustering individuals and identifying those that have been close to confirmed cases and have a high risk of contamination. FL and AI contributed to developing surveillance systems to monitor the spread of the virus and predict the number of cases and deaths. The surveillance systems allow tracking transmission dynamics and predicting future trends by analyzing vast amounts of data from different sources such as epidemiological data, social media, travel patterns, EHR, and environmental factors, etc. Using human mobility data, including geographical locations, [22] proposed FMTL, a FL-based model to predict the number of infections.

It was also important to ensure the well-being of people during and after the pandemic. To this end, [23] predicted the mental health in the work environment post-pandemic by analyzing facial emotions and speech.

Table 1. Summary table of FL applications for COVID-19

Ref	Year	Data Type	Output	Models	Evaluation
[10]	2021	Not available	Drug discovery	GAN + GNN	Not available
[11]	2023	Not available	Drug discovery	ESA-FedGNN	Not available
[13]	2023	EHR	Vaccine side effects	Neural network	F1 score
[12]	2023	Pharma sales data	Pharmaceutical product demand forecasting	FortiRX, XGBoost	MSE: [7.84–1346.83] Loss: [0.133–22.76]
[14]	2022	Tweets	Sentiment analysis about COVID-19 vaccination	RNN	Val acc: [82.62%–92.28%]
[24]	2021	Face dataset	Masked faces detection	DRFL	Accuracy: [84.2%–94.7%]
[23]	2021	Images, audios	Mental health in work environment post-pandemic	XGB, MLP, RF	• Facial recognition accuracy 71.64% • Speech recognition accuracy 85.04%
[22]	2022	Human mobility data	Infection rates under mobility constraints	FMTL, SEIR	RMSPE: 2.10% MAPE: 4.4%
[25]	2022	Caught records	COVID-19 detection	CNN	Accuracy: 93%
[15]	2022	Lung CT images	COVID-19 detection	Ensemble deep learning	Accuracy: 98.2%
[16]	2022	CT images	COVID-19 detection	Deep learning	AUC: 98%
[19]	2023	CT scans	COVID-19 detection	Deep learning + incremental learning	Accuracy: 98.99%
[20]	2021	EHR	Mortality detection	ML models	AUROC: 78.6%–83.6%
[17]	2022	X-ray images	COVID-19 detection	Reinforcement learning + transfer learning	F1 score of 95.8%
[21]	2022	EHR	Survival detection	SurvMaximin	Not mentioned
[26]	2021	Patient's health data + real time mobile diagnostic	Diagnosis, treatment, rehabilitation, post COVID complications	Neural networks	Not available
[27]	2021	cough sounds and chest X-rays	COVID-19 diagnosis	ResNet50, ResNet101, and InceptionV3	Accuracy: Cough: 95% X-ray: 98%
[28]	2021	Blood data	Severity classification	Neural network	Accuracy: 95.3, 79.4, and 97.7% for each node
[29]	2023	EHR	COVID-19 detection	SVM, LR, DT, Catboost, Random Forest, Extra Trees, and Ada Boost	F1: 87% Precision: 78% AUC: 91%
[18]	2021	Not implemented	COVID-19 detection	Not implemented	Not implemented

3 FL AND NEW TECHNOLOGIES

Combining FL with other technologies such as IoMT, 5G, and blockchain can improve security, reduce communication costs, and improve performance. Here are a few instances of works that combine FL with other technologies to get around FL's restrictions.

IoMT: It is a network of interrelated medical applications and wearable devices, such as smartwatches and sensors, connected via the Internet to collect and transmit healthcare data, enabling remote patient monitoring. The IoT is beneficial to FL and AI in improving medical procedures. In the context of the pandemic, [26] proposed an FL-based platform that aims to address every facet of the COVID-19 epidemic, from infection detection and treatment to rehabilitation of sequelae following the illness, as COVID-19 convalescents may develop post-morbid complications. This platform is addressed to medical specialists to help them diagnose and identify effective therapy. Another solution that uses AIoMT and FL was presented by [25] to provide offline and remote real-time COVID-19 detection using Caught records. The approach addresses latency and data privacy issues because of the combination of AIoMT and federated learning.

5G: To cover the problem of data scarcity, some research has utilized the 5G technology either to collect data [27] automatically or to faster communication [28] in a FL-based architecture for COVID-19 detection.

Blockchain: Traditional healthcare systems face various risks such as single-point failure, centralized authority, data alterations, high risk of inference attacks, and communication costs. One solution for those problems is implementing a blockchain-based architecture that can address privacy and security concerns [15], [18].

4 CONCEPTUAL FL-BASED FRAMEWORK FOR COVID-19 FIGHT

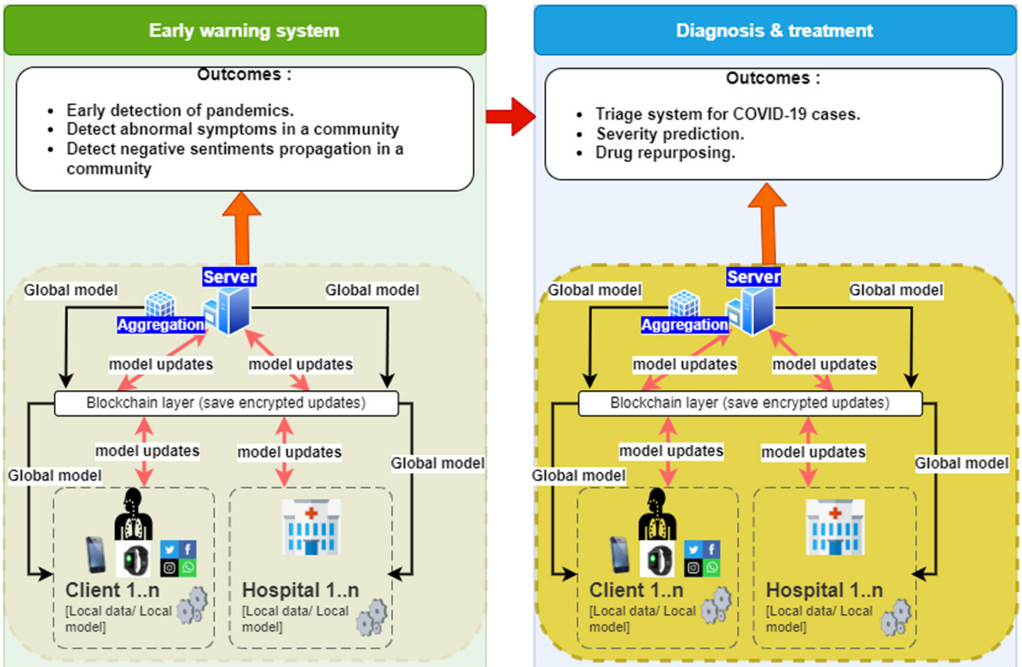

Fig. 1. FLPanGuard, a conceptual FL-based framework to control and fight pandemics

In Figure 1, we propose a conceptual FL-based framework called FLPanGuard to control and fight pandemics such as the COVID-19 pandemic. The previous works predominantly focused on responses during and post-pandemic. However, FLPanGuard targets the pre-pandemic phase, which is rarely discussed, through an early warning system that leverages both social media and medical data to predict potential outbreaks. Furthermore, the framework offers solutions during the pandemic via the diagnosis and treatment phase:

Early warning system: It is the first stage of our conceptual framework; it consists of providing an early warning system for the COVID-19 pandemic using different types of data, such as social media content, data collected from wearable devices and sensors, EHR, biological data, mHealth data, and so on. This phase aims to detect a pandemic earlier by detecting the spread of abnormal symptoms in a community that can be described as a new disease and can lead to a new epidemic or pandemic.

On the other hand, analyzing social media content can help understand a community's global sentiment and awareness about an abnormal change in their health state, which can help detect new pandemics earlier.

At this stage, data collected from social media and medical forums, as well as medical data provided by hospitals and medical devices, will be analyzed to extract the symptoms in specific communities during a given period, and then a score will be calculated for each symptom. This score will be used to detect medical abnormalities and predict the potential risk of a pandemic. Once the risk is detected, a trigger will be launched to inform epidemiologists, stakeholders, and medical professionals about it.

This process is described in Figure 2. The second stage of this framework will be initiated if experts prove this risk.

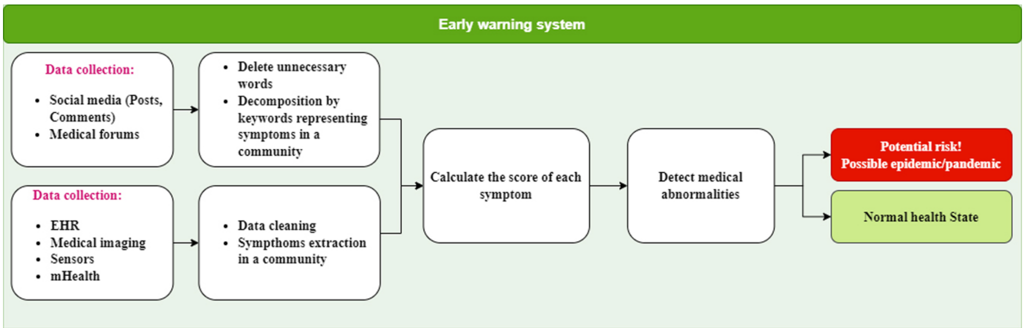

Fig. 2. Phase 1 of FLPanGuard: the early warning system

Diagnosis and treatment: The second phase of this framework consists of providing tools to help medical professionals detect severe cases through a triage system for cases to alleviate hospital stress during a pandemic. The triage system will also help reduce direct contact with the significant number of infected people to protect the limited human resources (HR) and reduce their infection rate. Furthermore, the proposed frameworks can also suggest a treatment for the new disease as an additional model's application (see Figure 3).

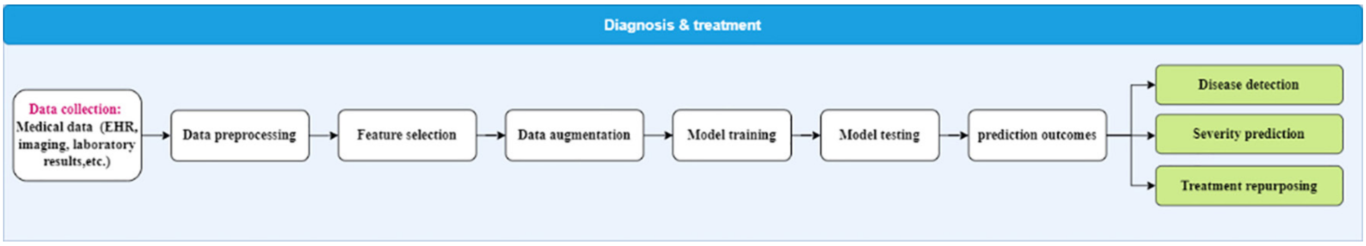

Fig. 3. Phase 2 of FLPanGuard: diagnosis and treatment

Data strategy: High-quality and large-scale medical datasets are crucial for developing robust and generalizable AI solutions. Medical data can be presented in different forms, such as biomedical data, medical images, and EHR. Insight about medical issues can also be captured through information collected using wearable devices or through social media content.

The use of medical datasets in AI solutions is essential and can provide valuable insights into the patient's state and treatment. For instance, COVID-19 patients can be examined from multiple data sources using multimodal data including imaging, sounds, laboratory results, vital signs, mobile data, etc. The severity of COVID-19 was tied to factors such as age, sex, comorbidities, and abnormalities in biomedical results as well as in chest images. The fusion of this multimodal data has been proven to accelerate the study of a patient's state through a transdisciplinary perspective for an efficient and evident prognosis [30].

However, when using data for medical purposes, there are some limitations and concerns that should be considered, such as data privacy and security, data quality, data heterogeneity, and data scarcity. Using traditional ML in this case may not be beneficial as it requires sharing data with a server to train the model. The collaborative aspect of FL addressed the privacy concerns as it offers the possibility of training a model across multiple clients locally without sharing their data, which means access to diverse and heterogeneous data. Thus, training a model across multiple hospitals from multiple regions will help learn diverse patterns to improve both performance and the model's generalizability.

In this context, FLPanGuard focuses on how to exploit AI to fully control and fight a pandemic; it leverages FL's ability to train multiple AI models using a fusion of multimodal and decentralized data while maintaining privacy. For instance, the fusion of symptoms collected from social media content, medical records, and health sensors will help visualize the problem with various features and large datasets, which will improve the accuracy of our early warning system phase for pre pandemic detection.

In addition, to enhance security, FLPanGuard will use encryption techniques to encrypt model updates and avoid the problems of data retrieval and inference for cyberattacks, while blockchain will be used to store these updates.

5 CHALLENGES AND FUTURE DIRECTIONS

While FL offers significant benefits in terms of collaborative learning and privacy, it also requires development and further research to address the following limitations:

- Scalability: The ability to expand the number of participants (patients, hospitals) and data amounts without compromising the training time, accuracy, resource consumption, or security.
- Malicious participants and data: FL frameworks are vulnerable to malicious participants who might use corrupted data to train the model. The shared updates in this case will degrade the aggregated weights, leading to inaccurate outcomes. Such participants might compromise privacy, as they can retrieve data from other participants using the model updates.
- Communication overhead: FL requires frequent exchange between the server and the several participants. In real-time applications, the number of participants and the network capacity may cause latency and reduce overall efficiency.

- Data heterogeneity: In FL, each participant trains the model on its local data, which can have different types or quantities; this means that the data distribution across multiple participants can be non-IID (non-independent and identically distributed). Hence, the data heterogeneity can impede the model's convergence and reduce its performance.

As discussed, some of these challenges can be addressed by combining FL with other technologies, as suggested in FLPanGuard. For instance, combining blockchain with encryption methods and client selection techniques might solve some security-related concerns, while 5G and IoMT can enhance both data collection and communication overhead. However, further research is required to enhance the power of FL in healthcare.

6 CONCLUSION

While AI can contribute to fighting pandemics by proposing diverse solutions that can assist medical professionals and stakeholders during emergencies, these solutions may lack efficiency and generalizability due to the data scarcity caused by data access restrictions and data regulations. This paper presents a global conceptual FL-based framework named FLPanGuard to fight and control pandemics. FLPanGuard leverages FL with other technologies to enhance generalizability while maintaining data privacy and security. Furthermore, in FLPanGuard we recommend the use of multimodal data to first predict a pandemic earlier and second to assist the healthcare professionals in diagnosing and treating the patients. The use of heterogeneous data from diverse clients helps learn patterns that generalize better across real-world scenarios. This paper represents a stepping stone for future research endeavors aimed at the development and deployment of this framework as well as expanding it for real-time pandemic monitoring using live data streams.

7 CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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