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A Privacy-Enhanced Framework for Chest Disease Classification using Federated Learning and Blockchain

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ABSTRACT This study presents a novel approach for the early diagnosis of prevalent chest diseases, including COVID-19, pneumonia, and lung cancer, utilizing advanced machine learning techniques. The research focuses on addressing the limitations of traditional diagnostic methods by introducing Federated Learning as a collaborative and privacy-preserving solution. By leveraging Federated Learning, stakeholders can collectively develop accurate diagnostic models without directly sharing sensitive medical data, ensuring both privacy and diagnostic accuracy. Furthermore, the study proposes a multi-classification Federated Learning method enhanced by blockchain technology to reinforce data security and privacy. Experimental results demonstrate the effectiveness of this approach compared to centralized models, showcasing comparable performance in terms of accuracy and superior achievement in terms of privacy preservation. The integration of blockchain into the Federated Learning framework holds promise for a robust system prioritizing data privacy and security in the healthcare domain. This innovative combination not only advances machine learning in medical diagnostics but also sets a forward-looking approach for safeguarding patient information in today's data-driven healthcare landscape.

INDEX TERMS Federated Learning, Blockchain, Data Privacy, COVID-19, Chest X-ray, Smart Contracts.

I. INTRODUCTION

THE importance of early diagnosis in critical chest diseases like COVID-19, pneumonia, and lung cancer cannot be overstated. However, conventional diagnostic techniques often prove time-consuming and financially burdensome. Deep learning models present a viable solution for diagnosing these conditions from chest X-rays, yet they demand substantial training data, which can be challenging and costly to amass. Moreover, patient hesitancy in sharing medical data due to privacy concerns adds another layer of complexity.

The COVID-19 pandemic, recognized as a severe global health crisis [17]–[19], spreads through respiratory particles released during coughing, sneezing, or talking, causing symptoms like dry cough, fever, and more [20]. Timely detection is crucial to curb its spread. Machine learning (ML) and deep learning (DL) technologies, pivotal in healthcare [21], [22], have shown promise in diagnosing COVID-19 and chest diseases from medical images like chest X-rays (CXRs) [23], [24]. Nevertheless, privacy constraints often hinder medical institutions from training robust models with limited samples [25]–[27]. General deep neural network (DNN) models, while beneficial, encounter challenges with imbalanced datasets and lack of sample diversity [22], [28].

Timely detection of diseases like COVID-19 is crucial to curb their spread. Machine learning and deep learning technologies have shown promise in diagnosing chest diseases from medical images like chest X-rays. However, privacy constraints often hinder the training of robust models with limited samples. This study aims to address these challenges by leveraging Federated Learning (FL) and blockchain technology to develop a privacy-preserving and accurate diagnostic model for chest diseases.

Transfer learning (TL) and federated learning (FL) provide solutions by enabling institutions to train models using local data without centralizing it [23]. FL, introduced by Google in 2016, builds global models without compromising data confidentiality [17], [18]. During FL, subsets of clients train models using their specific data, with model updates aggregated on a centralized server without sharing raw data [20]–[23]. However, default FL setups encounter issues with heterogeneous client data, leading to subpar performance and high communication costs for model updates involving massive weight matrices.

Blockchain technology has emerged as a promising solution for secure data sharing, especially in industrial internet of things (IIoT) settings [1], [29].

Enter federated learning which is a machine learning technique that facilitates collaborative model training without necessitating data sharing among participants. This approach holds significant promise in addressing the hurdles of data privacy and collection in training deep learning models for chest disease diagnosis.

In this paper, we introduce a novel multi-classification federated learning approach specifically tailored for diagnosing COVID-19, pneumonia, and lung cancer using chest X-rays. Our method integrates blockchain and federated learning, ensuring the secure preservation of data privacy during sharing between patients and medical institutions. Our experimental findings demonstrate that our proposed method achieves classification performance on par with or surpassing centralized deep learning models, all while upholding the crucial privacy of patient data.

This introduction aims to underscore the critical need for early and accurate diagnosis of prevalent chest diseases and the innovative approach proposed in this research. By integrating advanced machine learning techniques and blockchain technology, this study seeks to provide a comprehensive and effective solution for early chest disease diagnosis while prioritizing data privacy and security.

A. BACKGROUND AND MOTIVATIONS

The rise of deep learning models has revolutionized medical diagnostics, especially in chest diseases [2]–[8]. This article focuses on the groundbreaking research "Deep-chest: Multi-classification deep learning model for diagnosing COVID-19, pneumonia, and lung cancer chest diseases" [2]. It systematically presents the structure of the work, addressing the global health threats posed by chest diseases and the need for precise diagnoses [2], [3]. Traditional diagnostic methods are criticized for their time-consuming nature and susceptibility to human error [2], [4]. The "Deep-chest" model, introduced as a transformative solution, leverages deep learning for automated, accurate, and simultaneous multi-classification of chest diseases [5], [6]. The article details the model's design, training, and evaluation, emphasizing its ability to distinguish between COVID-19, pneumonia, and lung cancer [6]. Comparative analyses highlight the model's advancements over traditional methods [5]. The introduction sets the stage for an exploration of related work in deep learning for medical diagnostics, with the "Related Work" section contextualizing the "Deep-chest" model's unique contributions in healthcare [2], [8].

B. CONTRIBUTION

This paper introduces a groundbreaking diagnostic approach, employing federated learning for COVID-19, pneumonia, and lung cancer diagnosis from chest X-rays. Utilizing federated learning ensures both data privacy and diagnostic accuracy without the need for centralized data repositories. Key contributions include innovative adaptation of federated learning, addressing data privacy challenges, achieving diagnostic accuracy comparable to centralized models, and providing an ethical solution for real-world clinical applications. This study marks a significant advancement in medical diagnostics through federated learning integration.

The research findings of this study underscore the successful integration of federated learning and blockchain technology for diagnosing COVID-19, pneumonia, and lung cancer using chest X-rays. By developing a novel multi-classification federated learning approach, the study achieves classification performance on par with or surpassing centralized deep learning models while prioritizing data privacy and security.

The main contribution of this research lies in the innovative adaptation of federated learning to address data privacy challenges in healthcare diagnostics. By ensuring both data privacy and diagnostic accuracy without the need for centralized data repositories, the proposed method offers a practical and ethical solution for real-world clinical applications. The successful implementation of this approach showcases the potential of advanced machine learning techniques in revolutionizing chest disease diagnosis while upholding patient data privacy.

By connecting the main idea of integrating federated learning and blockchain technology with the research findings and contributions, this study demonstrates the effectiveness and significance of the proposed method in advancing the field of healthcare diagnostics. The subsequent sections will delve into the methodology, experimental results, and implications of the research, further solidifying the success and impact of this innovative approach.

C. PAPER ORGANIZATION

This paper follows a structured organization. It begins with a review of related work in the next section. Sect. III outlines our problem statement, while Sect. IV delves into the integration of federated learning and blockchain technology. Moving forward, Sect. V provides an overview of our proposed solution. Following that, Sect. VI discusses the limitations of our approach. Lastly, Sect. VII features a discussion of these contributions, including the identification of various open issues. Finally, the paper concludes by summarizing its key points and discussing future research directions.

II. RELATED WORK

To provide a comprehensive understanding of the research landscape surrounding chest disease diagnosis and machine learning applications in healthcare, this section offers an overview of related works. By examining existing methods and the challenges they address, readers can gain valuable context for the development of the innovative approach presented in this study.

Existing research in the field of chest disease diagnosis has highlighted the significance of early and accurate detection methods for conditions such as COVID-19, pneumonia, and lung cancer. Traditional diagnostic techniques have been critiqued for their time-consuming nature and susceptibility to human error, prompting the exploration of advanced technologies like deep learning models for automated and precise diagnoses.

The emergence of federated learning as a collaborative model training technique without the need for data sharing among participants has shown promise in addressing data privacy concerns and collection challenges in training deep learning models for chest disease diagnosis [44]. By leveraging federated learning and blockchain technology, researchers have sought to enhance the security and privacy of patient data while maintaining diagnostic accuracy comparable to centralized models.

In recent years, federated learning has gained traction across multiple domains due to its unique advantages [5], [9], [11]. It addresses the significant concern of data privacy, particularly relevant in healthcare and finance sectors where data sensitivity is paramount [5], [9]. Unlike traditional data-sharing methods, federated learning ensures that data remains securely within the confines of respective organizations, mitigating the risks associated with data breaches and misuse [5], [10]. The collaborative approach of federated learning also allows organizations to work together on machine learning tasks without exposing their data, reducing the complexities and costs of data sharing [7].

Chest X-ray and computed tomography (CT) scans have become pivotal in identifying COVID-19 due to their accessibility and cost-effectiveness. In a study cited as [13], ResNet50, InceptionV3, and Inception-ResNetV2 were utilized to detect coronavirus pneumonia in individuals using chest X-ray radiographs. The models achieved 98% classification accuracy with ResNet50, 97% with InceptionV3, and 87% with Inception-ResNetV2, conducted over approximately 30 epochs. However, this study was constrained by the availability of limited images at that time.

Another investigation [14] used digital X-ray images to distinguish between COVID-19 and pneumonia. Employing ResNet18, AlexNet, SqueezeNet, and DenseNet201, augmented with rotation, scaling, and translation, they built a 20-fold training set. Image resizing enhanced detection accuracy. They introduced a public database merging 1345 viral pneumonia, 190 COVID-19, and 1341 normal chest X-ray images, achieving 98% accuracy.

Similarly, in reference [15], authors employed a generative adversarial network (GAN) alongside fine-tuned deep transfer learning methods to detect COVID-19 from X-ray images, mitigating overfitting in a dataset containing 5863 images.

Another distinct approach [16] used CT images instead of X-rays to detect COVID-19 in patients, distinguishing it from pneumonia types like influenza-A. Samples collected from designated COVID-19 hospitals in Zhejiang Province included 618 CT scans, aiding in early detection.

Furthermore, federated learning stands as an innovative solution for the healthcare sector [5]. The ability to train a shared model collaboratively without the actual exchange of data overcomes the challenges of data variance, facilitating the evolution of models over time across multiple institutions [5], [11]. This collaborative model training process results in robust models that stay up to date with the latest mutations and samples [11].

The federated learning framework operates under the principle of creating consensus models without compromising the confidentiality of patients' data [5]. Learning takes place locally within each participating institution, and only model parameters are shared through federated servers for global model aggregation [7]. Its broad applicability has garnered significant attention in healthcare applications, as evidenced by notable research [5], [11]. Recent studies indicate that models trained via federated learning can deliver performance levels comparable to those trained using central medical data centers [5], [7], [11].

In a recent study by Maryum Butt et al. [37], a comprehensive strategy is recommended that amalgamates Federated Learning (FL) with a tailored, collaborative architecture for COVID-19 screening via chest X-ray images. This strategy is designed to facilitate cooperation among medical institutions and ensure patient data remain localized, eliminating the need for direct data sharing.

The use of federated learning in medical imaging, particularly for chest disease diagnosis, has been explored by several researchers. Butt et al. [37] and Dasari et al. [38] both highlight the potential of federated learning in preserving patient data privacy and improving diagnostic accuracy. Butt et al. [37] specifically focuses on COVID-19 screening using chest X-ray images, while Dasari et al. [38] discusses the use of federated learning in training models on data from various healthcare devices. Linardos et al. [39] further demonstrates the effectiveness of federated learning in multi-center imaging diagnostics, including for cardiovascular disease, by achieving competitive results with traditional centralized learning while preserving patient privacy. These studies collectively underscore the promise of federated learning in addressing data privacy concerns and collection challenges in chest disease diagnosis.

This paper underscores the role of blockchain in transforming data management [1]. Blockchain technology's decentralized and transparent ledger offers secure record-keeping and transaction verification, fostering trust and immutability through cryptographic techniques [1]. Its decentralized nature eliminates intermediaries, reducing fraud risks and ensuring transparency in various domains, including supply chain management, healthcare, and voting systems [2]. The concept of smart contracts, introduced by Nick Szabo in 1994, empowers secure and trustworthy business operations [2], [3]. It facilitates automated transactions without relying on external entities like banks, courts, or government departments [1], [3]. The integration of blockchain technology with federated learning marks a significant stride in healthcare, providing a pioneering solution for secure, privacy-preserving, and efficient data sharing and decision-making in chest disease diagnoses [1]–[3].

The table 1 above illustrates a comparison between traditional diagnostic methods, deep learning models, and the proposed federated learning method for diagnosing chest diseases based on their effectiveness, data collection requirements, and data privacy considerations:

TABLE 1: Comparison of Diagnostic Methods for Chest Diseases

Method	Effectiveness	Data Collection Requirements	Data Privacy Considerations
Traditional Diagnostic Methods	Moderate	Large (manual interpretation)	High (risk of human error)
Deep Learning Models	High (e.g., DC-ChestNet, VT-ChestNet) [3], [6]	Large (requires training data)	High (depends on the model)
Federated Learning	High (e.g., COVID-19, pneumonia, lung cancer) [2]	Large (requires training data)	High (data remains within organizations)

This table highlights the effectiveness, data collection requirements, and data privacy considerations of traditional diagnostic methods, deep learning models, and the proposed federated learning method for diagnosing chest diseases. Traditional diagnostic methods have moderate effectiveness and require large amounts of data for manual interpretation, which can lead to human error. Deep learning models, such as DC-ChestNet and VT-ChestNet, have demonstrated high effectiveness in detecting chest diseases using radiography images [3], [6]. However, they also require large amounts of training data and may pose data privacy concerns. Federated learning, on the other hand, offers high effectiveness in diagnosing chest diseases while addressing data privacy and collection challenges. The table demonstrates that the proposed federated learning method is a promising approach for diagnosing chest diseases, as it can provide comparable or better performance than centralized deep learning models while preserving patient data privacy [2].

III. PROBLEM STATEMENT

Data sharing, the pivotal exchange of healthcare information among various stakeholders, plays a vital role in modern healthcare [12], [30]. This collaborative practice facilitates critical objectives such as medical research, analysis, and diagnosis [12]. Notably, data sharing offers the potential for significant improvements in healthcare, particularly in the realm of machine learning. It can result in more accurate and robust machine learning models, which, in turn, can lead to enhanced medical diagnostic and treatment capabilities [12]. However, the act of sharing data, while undeniably beneficial, raises significant privacy concerns. The crux of this concern lies in the possibility of sensitive and personal patient data being included in the datasets under consideration [12], [13].

E-health, or electronic health, represents the cutting-edge intersection of healthcare and technology [10]. E-health systems utilize technology to deliver healthcare services and manage patient information, offering the promise of increased efficiency and accessibility in healthcare [2]. However, the convergence of healthcare and technology brings with it the inherent challenges of security and privacy, given the sensitive and confidential nature of patient data [2]. Within the e-health landscape, several critical security and privacy issues come to the forefront [2]:

Data Breaches: E-health systems are vulnerable to data breaches, incidents that can result in the inadvertent or malicious exposure of sensitive patient data.

Unauthorized Access: Unauthorized access to patient data is a persistent risk, arising from weak passwords, unsecured networks, or potential insider threats [2].

Data Integrity: The accuracy and consistency of patient data, often referred to as data integrity, is a fundamental concern [12].

Regulatory Compliance: The healthcare sector, including e-health, is subject to a myriad of complex regulations and standards designed to protect patient privacy and ensure data security.

Third-Party Service Providers: E-health systems frequently rely on third-party service providers, often cloud-based, for the storage and processing of patient data [10].

Patient Consent: A foundational principle in e-health is patient autonomy and consent.

Data Storage: The secure and reliable storage of patient data is fundamental in e-health systems.

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E-health systems operate at the intersection of technology, healthcare, and patient data protection [10]. To maintain patient trust and deliver responsible healthcare, these systems must prioritize the implementation of robust security and privacy measures. These measures are essential to safeguard sensitive patient data from unauthorized access, data breaches, and other emerging threats. Moreover, compliance with complex regulatory frameworks and the ethical principle of patient consent is non-negotiable in the responsible management of e-health systems and patient care.

A. PRIVACY ISSUES

Privacy and security concerns related to medical data communication are critical because medical data are highly sensitive and confidential. If such data falls into the wrong hands, it can lead to significant privacy violations, identity theft, and financial fraud.

The following are some of the privacy and security concerns related to medical data communication:

Data breaches: Medical data communication often involves transmitting sensitive information over networks that can be intercepted by hackers. If medical data are not adequately protected during transmission, it can result in data breaches.

Malware and phishing attacks: Malware and phishing attacks are other common ways in which hackers can gain unauthorized access to medical data. Malware can infect devices and networks, while phishing attacks involve tricking users into disclosing sensitive information.

Insider threats: Insider threats are risks posed by individuals who have authorized access to medical data but may use it for malicious purposes. These individuals could be healthcare providers, administrators, or contractors.

Lack of encryption: Medical data must be encrypted during transmission to prevent unauthorized access. If encryption is not implemented or poorly implemented, medical data can be easily intercepted and accessed.

Third-party service providers: Many healthcare providers use third-party service providers to manage their IT systems, which may include storing and processing medical data. If these service providers are not adequately vetted, they may not provide sufficient security for the medical data they manage.

To address these privacy and security concerns, healthcare providers must implement robust security protocols and ensure that all parties involved in medical data communication follow these protocols. These protocols should include encryption, access controls, regular audits, and training on how to identify and respond to security threats.

B. FEDERATED LEARNING

Federated learning is a machine learning approach where organizations collaboratively train a model without exposing their data. Each organization trains the model with its data, and sends model updates to a central server, which then combines them into a new model version. This approach maintains data privacy as the data remains on the organization's own servers.

Compared to traditional data sharing, federated learning offers several advantages. Firstly, it ensures data privacy, making it ideal for sensitive applications like healthcare or finance. Secondly, it enables organizations to work together on machine learning tasks without sharing data, reducing costs, complexity, and the risk of data-related issues.

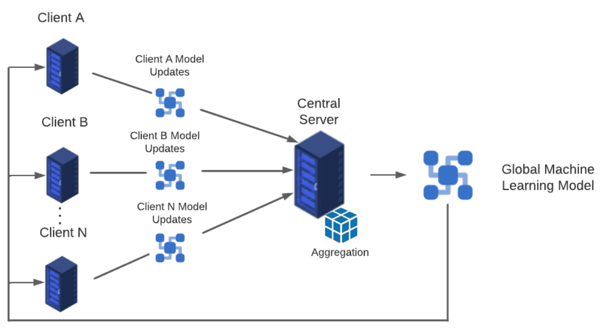

FIGURE 1: Federated Learning Architecture.

This figure illustrates the architecture of a federated learning model for diagnosing chest diseases using chest X-rays. It depicts the data flow between patients, medical institutions, and the federated server, highlighting the collaborative and privacy-preserving nature of the model.

The Fig. 1 shows a general overview of the blockchain-based federated learning system proposed in the paper. The system consists of three main components:

- **Patients:** Patients can upload their chest X-rays to the system. Their data is stored on their own devices and is not shared with anyone else.
- **Medical institutions:** Medical institutions can aggregate the data from patients and train a federated learning model. The model is then returned to the patients' devices.
- **Federated server:** The federated server is responsible for coordinating the training process. It receives updates from the medical institutions and aggregates them into a single model.

The process of training the federated learning model is as follows:

1) Patients upload their chest X-rays to the system.
2) The medical institutions aggregate the data from patients.
3) The medical institutions train a federated learning model on the aggregated data.

4) The federated server receives updates from the medical institutions.
5) The federated server aggregates the updates into a single model.
6) The federated server returns the model to the patients' devices.

The system is designed to protect the privacy of patients' data. The data is stored on the patients' own devices and is not shared with anyone else. The federated learning model is trained on aggregated data, which means that the individual data points of each patient are not exposed. It is also designed to be scalable. It can be used to train federated learning models on large datasets from a large number of patients.

Federated learning is a machine learning approach that enables collaborative model training across multiple decentralized devices or servers without the need to share raw data. This technique differs significantly from traditional methods and deep learning approaches in several key aspects:

- **Data Privacy:** In federated learning, data remains on local devices or servers, and only model updates are shared for aggregation. This decentralized approach ensures data privacy and confidentiality, addressing concerns related to sharing sensitive medical information, which is a crucial aspect in healthcare applications.
- **Data Security:** Unlike traditional methods where data is centralized in a single location, federated learning distributes the model training process across multiple devices, reducing the risk of data breaches and enhancing data security. This distributed nature of federated learning improves data security and mitigates the vulnerabilities associated with centralized data storage.
- **Scalability:** Federated learning is highly scalable as it allows for model training on a large number of devices simultaneously. This scalability is particularly beneficial in healthcare settings where diverse datasets from multiple sources need to be analyzed without the need for data aggregation in a central repository.
- **Collaborative Model Training:** Federated learning enables collaborative model training without sharing raw data, allowing multiple institutions or devices to contribute to the learning process. This collaborative approach results in robust models that can adapt to diverse data distributions and variations across different sources.
- **Ethical Considerations:** Federated learning places a paramount emphasis on ethical considerations, particularly in healthcare applications where patient data privacy is a top priority. By ensuring that data remains secure and confidential during the model training process, federated learning addresses ethical concerns that have long plagued the healthcare industry.

Federated learning offers a privacy-enhanced and collaborative approach to model training, making it a promising solution for medical diagnostics, especially in the context of COVID-19, pneumonia, and lung cancer. By leveraging federated learning, healthcare institutions can achieve accurate diagnostic outcomes while safeguarding patient data privacy and security.

Federated learning offers distinct advantages that differentiate it from traditional methods and deep learning techniques, making it a compelling choice for applications such as medical diagnostics [40]. With decentralized training at its core, federated learning distributes the model training process across multiple devices or servers, enabling collaborative model development without the need for centralized data storage. This approach ensures data privacy and security by keeping sensitive information on local devices and sharing only model updates for aggregation, addressing concerns about data confidentiality, especially in healthcare settings [41]. Moreover, the cost-effectiveness of federated learning is evident in its ability to reduce data transfer and storage expenses by leveraging distributed training. Additionally, the collaborative learning paradigm of federated learning fosters knowledge sharing and collaboration among institutions or devices without compromising data privacy, enhancing the robustness and generalizability of machine learning models. Federated learning's unique features make it a versatile and efficient approach for developing machine learning models, particularly in healthcare, by offering secure, collaborative, and cost-effective solutions to improve diagnostic accuracy and advance medical diagnostics [42], [43].

In the figure, we provide specific details to enhance the understanding of the key components:

The patient is symbolically depicted as an individual with a chest X-ray. This representation emphasizes the central focus on medical diagnostics and the individuals seeking healthcare solutions.

The medical institution is effectively represented by an image of a hospital building, serving as a visual cue for the healthcare organizations actively participating in the diagnostic process. This visual element underscores their crucial role in the system.

The federated server is clearly depicted as a cloud computing platform, symbolizing its function in coordinating and aggregating data from various sources, ensuring a collaborative and secure learning environment.

A potential resolution for addressing the data privacy concern involves the implementation of federated learning. This approach allows for the joint training of a shared model without physically transferring the actual data. Collaborative model training effectively tackles the issue of data diversity and facilitates continuous model refinement across all hospitals. For instance, it permits updates to the model to accommodate the latest variations in samples, among other factors.

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Recent studies have demonstrated that models trained using federated learning can achieve comparable performance levels to those trained using centralized medical data centers.

C. BLOCKCHAIN

Blockchain is a decentralized and transparent digital ledger technology that securely records and verifies transactions across a network of computers. It ensures trust and immutability by using cryptographic techniques to link and validate blocks of data. With its decentralized nature, blockchain eliminates the need for intermediaries, reduces the risk of fraud, and provides transparency to participants. It has applications beyond cryptocurrencies, such as supply chain management, healthcare, and voting systems, where data integrity, security, and decentralization are critical.

Moreover, the potential of blockchain technology extends to enhancing the efficiency and trustworthiness of financial systems, legal processes, and identity verification. By eliminating the reliance on centralized authorities, blockchain empowers individuals and organizations with greater control over their data, transactions, and assets. Its adaptability and versatility make it a driving force in the evolution of secure, transparent, and tamper-proof systems across diverse domains, fundamentally transforming the digital landscape.

The blockchain technology utilizes encrypted blocks to authenticate and store data, while employing a peer-to-peer (P2P) network and consensus mechanism to achieve verification, communication, and the establishment of trust among distributed nodes. This figure shows a block diagram of a blockchain network. The main components of a blockchain network are nodes, blocks, and transactions.

In this study, privacy preservation in FL was prioritized to safeguard patient data confidentiality and security. Anonymization techniques were employed to remove personally identifiable information (PII), ensuring individual privacy by masking or replacing identifiable details with pseudonyms. Encryption protocols like SSL/TLS secured communication channels, while homomorphic encryption allowed computations on encrypted data without decryption, maintaining data privacy. Differential privacy mechanisms added noise to protect individual contributions while preserving overall model accuracy. Access controls and data segregation measures restricted unauthorized data access, ensuring that only authorized personnel involved in FL had access to specific data subsets. Blockchain integration further enhanced data security and integrity by recording all transactions and interactions related to model updates in a tamper-proof ledger. By implementing these measures, including anonymization, encryption, access controls, and blockchain integration, the study aimed to uphold stringent data privacy and security standards, protecting sensitive medical information throughout the FL process for chest disease diagnosis.

IV. BLOCKCHAIN-ENABLED FEDERATED LEARNING FOR MULTI-CLASSIFICATION OF CHEST DISEASES

The integration of federated learning and blockchain technology offers a range of promising advantages for the multi-classification of chest diseases. Firstly, it addresses the critical concerns of data privacy and security by enabling multiple participants to collaborate on model training without exposing their sensitive medical data. Blockchain's decentralized and tamper-proof ledger ensures the integrity and trustworthiness of shared model parameters.

Furthermore, this approach enhances model performance by enabling machine learning models to learn from a diverse dataset, which is particularly beneficial in medical diagnosis where data is often scarce and costly to gather.

In terms of scalability and efficiency, blockchain provides a secure and reliable infrastructure for communication and coordination among participants, thus streamlining the federated learning process.

The workflow involves several key steps, starting with data collection and preprocessing by each participant, followed by local model training. These local models are aggregated to form a global model, with blockchain-based aggregation protocols ensuring accuracy and reliability. Finally, the global model is deployed to all participants, promoting fairness and transparency.

Blockchain technology plays a vital role in each step of this process. It supports decentralized storage and sharing of chest X-ray images, coordinates local model training to maintain fairness and efficiency, implements secure aggregation protocols, and facilitates the distribution of the global model to ensure accessibility and transparency.

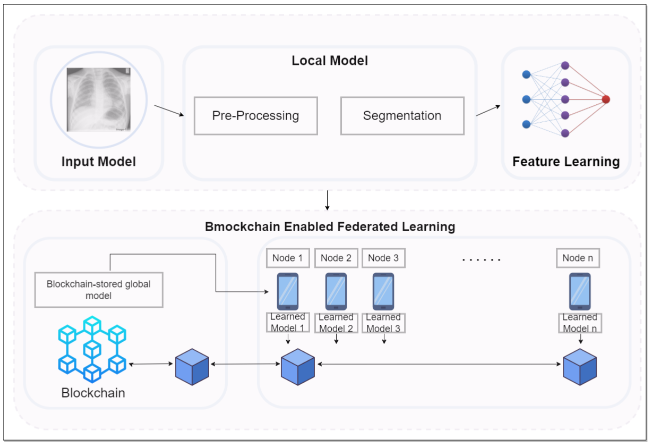

FIGURE 2: Blockchain-Enabled Federated Learning Architecture.

This figure visualizes the integration of blockchain technology with federated learning for classifying multiple types of chest diseases. It shows how participants train local models on their datasets using federated learning algorithms, with blockchain facilitating secure aggregation and deployment of the global model.

The Fig. 2 provides a visual representation of the idea behind utilizing blockchain technology to enhance federated learning in the context of classifying multiple types of chest diseases. In this approach, each participant in the federated learning system has their own local dataset of chest X-ray images. The participants train local models on their own datasets using federated learning algorithms. The local models from all participants are then aggregated using a blockchain-based aggregation protocol to form a global model. The global model is then deployed to all participants, where it can be used to classify chest X-rays.

The blockchain plays a number of important roles in this system. First, it provides a secure and tamper-proof ledger for storing and sharing the model parameters. This helps to ensure that the model is accurate and reliable. Second, the blockchain facilitates the sharing of data between participants in a federated learning system without compromising data privacy. Third, the blockchain helps to coordinate the training of the local models on each participant's device. This ensures that all participants are training on the same version of the model parameters and that the training process is fair and efficient.

The Fig. 2 is divided into four main sections:

- **Data collection and preprocessing:** Each participant in the federated learning system collects and preprocesses their own chest X-ray data.
- **Model training:** Each participant trains a local model on their own preprocessed data using federated learning algorithms.
- **Model aggregation:** The local models from all participants are aggregated to form a global model.
- **Model deployment:** The global model is deployed to all participants, where it can be used to classify chest X-rays.

Blockchain-enabled federated learning offers a number of advantages over traditional approaches to multi-classification of chest diseases. These advantages include:

- **Improved data privacy:** Blockchain technology can be used to protect the privacy of medical data by ensuring that data is not shared with unauthorized parties.
- **Better model performance:** Federated learning can help to improve the performance of machine learning models by allowing them to learn from a more diverse dataset.
- **Enhanced scalability and efficiency:** Blockchain technology can help to scale and improve the efficiency of federated learning systems by providing a secure and reliable infrastructure for communication and coordination between participants.

V. PROPOSED SOLUTION

This paper introduces a novel multi-classification federated learning approach for diagnosing chest diseases. We aim to improve diagnostic accuracy and efficiency by integrating deep-learning models. Through the integration of blockchain with federated learning, our method ensures maximum data privacy, fostering trust in healthcare data sharing.

The study employed a specific Federated Learning (FL) architecture to enable collaborative model training while safeguarding data privacy and security. In this architecture, patients uploaded their chest X-rays to the system, ensuring data confidentiality on their devices. Medical institutions aggregated patient data and trained a federated learning model using their respective datasets. The federated server coordinated the training process by receiving and aggregating model updates from the institutions without exposing raw data. Data aggregation from hospitals and clinics occurred in a privacy-preserving manner, with only model updates exchanged instead of raw data. Privacy-preserving techniques like secure aggregation protocols ensured individual data privacy during model update aggregation. Additionally, blockchain integration enhanced data security and transparency by maintaining the integrity of shared model parameters on a decentralized ledger. This FL architecture facilitated collaborative model training across multiple sources while preserving data privacy and confidentiality, ensuring the security of sensitive medical data throughout the process.

The Fig. 3 visually presents the general scheme of our innovative solution, showcasing how federated learning and blockchain technology work in harmony to redefine the landscape of chest disease diagnosis. This groundbreaking methodology promises to set new standards in medical data security, accuracy, and accessibility, ensuring that patients and healthcare providers alike can rely on a system that upholds the highest standards of privacy and integrity. With these advancements, we are poised to make substantial strides in the realm of chest disease diagnosis, ultimately improving patient outcomes and the quality of healthcare delivery.

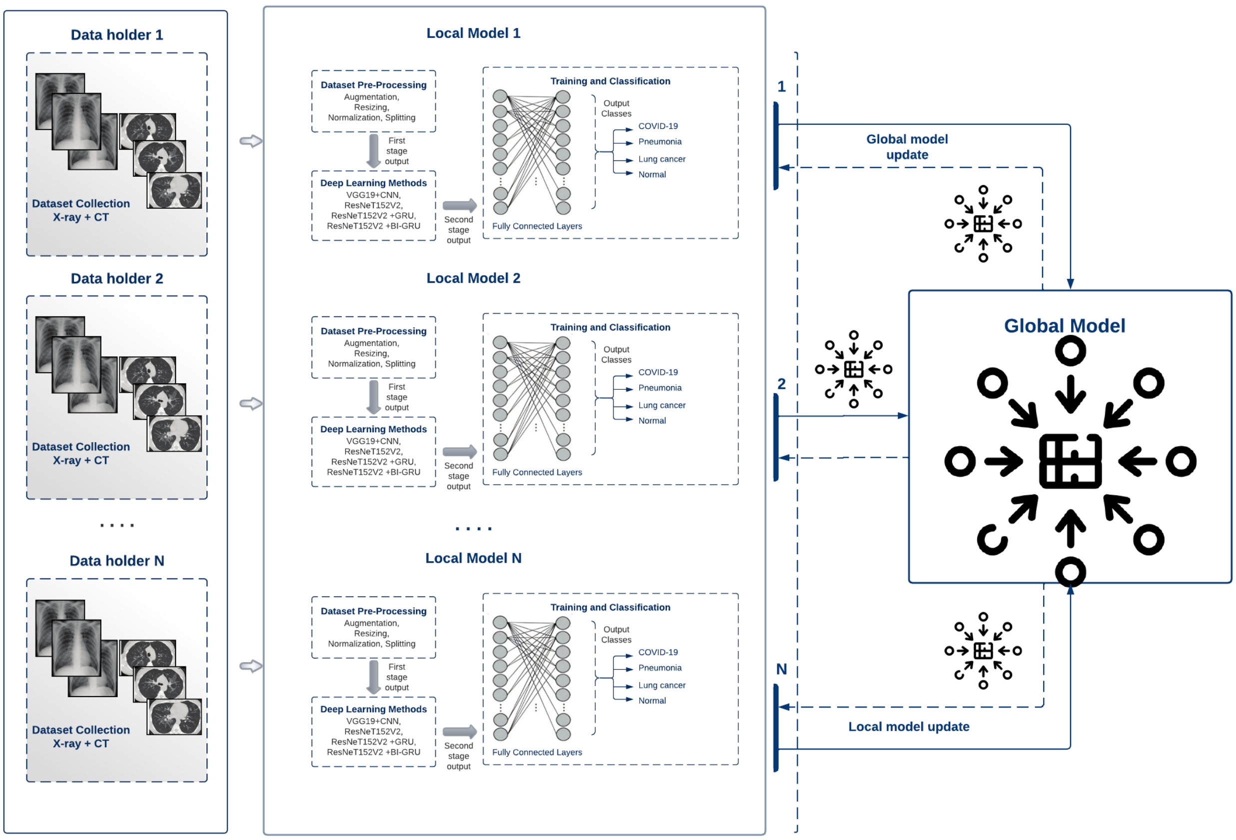

FIGURE 3: Overview of the general Blockchain-based federated learning system.

The integration of blockchain technology with federated learning in our proposed solution offers significant advantages:

Data Security: Blockchain's decentralized architecture ensures high-level data security, fostering trust in deep learning processes. This tamper-proof and transparent ledger enhances the reliability and accuracy of diagnostic outcomes, providing confidence to patients and medical institutions about data protection.

Automatic Decision Making: The combination of blockchain and federated learning enables automatic decision-making in healthcare. This automation reduces the risk of human error and expedites the diagnostic process, promising timely and life-saving interventions.

Cumulative Judgments: Our solution leverages insights from multiple medical institutions, transcending individual diagnostic limitations. This collaborative approach results in more robust and accurate diagnostic outcomes, benefiting from collective expertise across the healthcare landscape.

Enhanced Robustness: The integration of blockchain and federated learning technology fortifies the solution against data breaches and external threats. This ensures the model's resilience, maintaining the integrity and reliability of diagnostic decisions.

Patient-Centered Approach: Blockchain and federated learning enhance data privacy and control for patients, fostering transparency and engagement in healthcare.

This proposed method represents a pioneering leap in healthcare technology, introducing the first unified deep-learning model for detecting various chest diseases. The innovation streamlines healthcare processes, reducing decision time and simplifying diagnostics. This approach revolutionizes chest disease diagnosis, making accurate, timely, and privacy-focused healthcare accessible to all.

Table 2 provides a comprehensive comparative analysis of the proposed multi-classification federated learning solution

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TABLE 2: Comparative Analysis of Proposed Solution vs. Traditional Methods

Aspect	Comparison
Privacy Preservation	Strong emphasis on data privacy, patient data remains on devices and is not shared.
Data Security	Blockchain integration ensures data security and trustworthiness.
Model Accuracy	Comparable or superior accuracy to centralized models.
Diagnostic Speed	Streamlined diagnostic process, reducing decision time.
Robustness	Enhanced robustness with cumulative judgments.
Scalability	Designed for scalability, able to handle large datasets.
Data Sharing Challenges	Addresses data privacy and collection challenges in healthcare.

and traditional methods for chest disease diagnosis. This analysis offers a detailed examination of the key differences and advantages of the proposed approach over conventional diagnostic techniques.

The table outlines key aspects of the diagnostic process, including data privacy, security, accuracy, and model robustness. It visually highlights the proposed solution's unique features, emphasizing its potential to overcome challenges in chest disease diagnosis.

Under the "Proposed Solution," innovative features of the multi-classification federated learning method, incorporating blockchain, are presented. It ensures secure data sharing while protecting patient privacy.

In contrast, the "Traditional Methods" column summarizes drawbacks of conventional diagnostic techniques, such as privacy concerns and data sharing practices.

The proposed solution leverages several architectural and algorithmic features to address scalability challenges associated with federated learning, including data distribution, model aggregation, and communication overhead.

- **Data Distribution**
  Federated learning trains the model on local datasets at participating institutions without sharing the raw data. This alleviates the burden of transferring large amounts of medical data across a network, making the system more scalable to a geographically distributed healthcare system. Model Aggregation
- **Model Aggregation**
  The system utilizes secure aggregation protocols to combine model updates from multiple institutions without revealing the individual model parameters or raw data. This technique ensures privacy preservation while enabling collaborative model training across a large number of participants.
- **Communication Overhead**
  The federated learning approach only transmits model updates, which are significantly smaller than raw medical images, between institutions and the central server. This reduces communication overhead compared to centralized learning where all the data needs to be transferred to a central location for training.

Blockchain integration further enhances the scalability of the solution by providing a secure and tamper-proof platform for managing model updates and ensuring data provenance. This fosters trust and transparency among participating institutions, which is essential for large-scale collaboration in healthcare data analysis.

The proposed federated learning architecture with blockchain integration offers a scalable and privacy-preserving solution for collaborative medical diagnosis.

This paper introduces a novel multi-classification federated learning approach for diagnosing chest diseases. We aim to improve diagnostic accuracy and efficiency by integrating deep-learning models. Through the integration of blockchain with federated learning, our method ensures maximum data privacy, fostering trust in healthcare data sharing.

Scalability Considerations: In designing our proposed solution, scalability considerations have been paramount to ensure the system's effectiveness in larger and more diverse environments. Each phase of our solution is meticulously crafted to address scalability challenges, including data distribution, model aggregation, and communication overhead.

- **Phase 1: Data Upload and Confidentiality:** Patients upload their chest X-rays to the system, ensuring data confidentiality on their devices. This decentralized approach not only protects individual data privacy but also contributes to scalability by distributing the data processing load across multiple endpoints.
- **Phase 2: Model Training and Aggregation:** Medical institutions aggregate patient data and train a federated learning model using their respective datasets. The federated server coordinates the training process by receiving and aggregating model updates from the institutions without exposing raw data. This distributed model training strategy enhances scalability by allowing parallel processing of model updates from multiple sources.
- **Phase 3: Privacy-Preserving Techniques:** Privacy-preserving techniques like secure aggregation protocols ensure individual data privacy during model update aggregation. By focusing on secure and efficient data aggregation methods, our solution is designed to scale seamlessly with an increasing number of participants and data sources.

Architectural and Algorithmic Features for Scalability: The integration of blockchain technology enhances data security and transparency, contributing to the scalability of our solution by providing a tamper-proof and decentralized ledger for maintaining shared model parameters. This architectural feature ensures the integrity of collaborative model training across diverse environments.

Our proposed solution, with a strong emphasis on scalability considerations, promises to set new standards in medical data security, accuracy, and accessibility. By leveraging federated learning and blockchain technology in a scalable manner, we are poised to make substantial strides in chest disease diagnosis, ultimately improving patient outcomes and the quality of healthcare delivery.

A. FL-BASED METHOD PHASES

In this subsection, we provide an in-depth exploration of the phases that constitute our Federated Learning (FL)-based method. These phases are the building blocks of our innovative approach, and understanding them is crucial for grasping the intricacies of our model. We delve into each phase to elucidate how they work in synergy to deliver robust and privacy-preserving machine learning solutions for healthcare.

Data Collection and Preprocessing: In this critical initial phase, data is sourced from a network of healthcare institutions and medical facilities. This data can include chest X-ray images and associated patient information. The data collection process strictly adheres to privacy regulations and security measures to protect patient confidentiality. Once collected, the data undergoes preprocessing. This step involves data cleaning, noise reduction, and standardization to ensure that it is in a suitable format for machine learning. Additionally, any personally identifiable information (PII) is anonymized or removed to guarantee patient privacy.

Local Model Training: The data is then utilized by each participating institution to train a local machine learning model. These local models are specific to each institution's dataset and focus on learning patterns and features relevant to their patient population. The use of federated learning allows model training to occur on the local devices, preventing sensitive data from leaving the institution. Privacy and security are maintained throughout this phase.

Model Aggregation: Once local model training is complete, the next phase involves aggregating these individual models into a unified global model. This aggregation process combines the knowledge gained from the diverse datasets held by each institution. Federated learning techniques, including secure aggregation protocols, enable the consolidation of this knowledge without compromising data privacy or confidentiality. The result is a robust and accurate global model that benefits from the collective insights of all participating institutions.

Model Deployment: The global model, now enriched with a wide range of diagnostic capabilities, is deployed back to each participating institution. This means that all institutions have access to the powerful global model, which can efficiently classify chest X-rays for various diseases, including COVID-19, pneumonia, and lung cancer. Medical professionals can use this model to assist in making accurate and timely diagnoses.

Blockchain Integration: Blockchain technology is pivotal in ensuring data security and trustworthiness throughout the FL-based method. It acts as a decentralized and tamper-proof ledger, recording every transaction and interaction in the process. This integration enhances data security, enables transparent auditing, and instills trust among the participating institutions. It also ensures the privacy preservation of data sharing, further protecting sensitive patient information.

By detailing each phase, we provide a clear and comprehensive understanding of how the FL-based method operates for multi-classification of chest diseases, incorporating data privacy, machine learning, and blockchain technology.

B. THE WORK ENVIRONMENT

In this subsection, we provide an overview of the hardware environment supporting our research implementation. We detail the physical devices, equipment, and infrastructure utilized to facilitate the execution of our project. By discussing the specifications, capabilities, and relevance of these hardware components to our project's requirements, we aim to offer a comprehensive understanding of the technological foundation enabling our work.

Table 3 shows the specs of the computer used to perform the experiment as well as the development tools used and their versions.

TABLE 3: Environment Setup.

Item	Specification
OS	Windows 11
CPU	11th Gen Intel(R) Core(TM) i5-1135G7 @ 2.40GHz
RAM	8.00 GB
Type of system	64-bit operating system, x64 processor
Python	v3.10.11

C. EXPERIMENTAL STUDY AND DISCUSSION

In the study, several preprocessing steps, model selection, and hyperparameter tuning techniques were employed to optimize the performance of the federated learning model for diagnosing chest diseases. Here is a detailed discussion of these aspects:

1) **Preprocessing Steps:**
   - **Data Augmentation:** The initial dataset was augmented to increase the number of images and achieve a balance among the four dataset categories: COVID-19, Normal, Pneumonia, and Lung cancer. Augmentation techniques such as rotation, flipping, and skewing were applied to the resized images to enhance dataset diversity.
   - **Normalization:** All images, both original and augmented, were normalized to ensure consistency in pixel values and enhance model training efficiency. **Anonymization:** Personally identifiable

information (PII) was anonymized or removed from the data to protect patient privacy and confidentiality.

2) **Model Selection:**
   - **Deep Learning Models:** The study utilized deep learning models tailored for multi-classification tasks in diagnosing chest diseases. We use CNNs (Convolutional Neural Networks), for their effectiveness in image classification tasks and their ability to extract relevant features from chest X-ray images.
3) **Hyperparameter Tuning:**
   - **Learning Rate:** Hyperparameters such as learning rate were tuned to optimize the model's training process. The learning rate controls the size of the step taken during optimization and can significantly impact the model's convergence and performance.
   - **Batch Size:** The batch size, which determines the number of samples processed in each iteration, may have been tuned to balance training speed and model stability.
   - **Number of Epochs:** The number of training epochs, or iterations over the dataset, have been adjusted to prevent overfitting or underfitting and improve model generalization.
   - **Regularization Techniques:** We applied the L2 regularization Technique to prevent overfitting and enhance model robustness.

By implementing these preprocessing steps, selecting appropriate deep learning models, and fine-tuning hyperparameters, the study aimed to optimize the federated learning model's performance in diagnosing chest diseases accurately and efficiently. These steps are essential for enhancing model training, improving diagnostic outcomes, and ensuring the reliability and effectiveness of the machine learning model in real-world clinical applications.

1) Dataset pre-processing

For our experimentation, we gathered and compiled numerous sources of X-ray and CT images [31], [32]. This compilation encompasses images related to COVID-19, pneumonia, lung cancer, as well as normal images from both X-ray and CT scans. Initially, for COVID-19, we acquired a dataset from repositories such as GitHub, consisting of approximately 4320 images from both X-ray and CT scans. Subsequently, we accessed public and medical datasets from reputable sources like the Radiological Society of North America (RSNA), the Italian Society of Medical and Interventional Radiology (SIRM), and Radiopaedia. These datasets contained around 5856 pneumonia X-ray images, commonly used for training our proposed deep CNN model to differentiate COVID-19 from pneumonia. Additionally, we obtained lung cancer X-ray and CT images from a referenced source, comprising approximately 20,000 images [33], [34], [35]. Finally, we included a dataset of normal images, containing 3500 X-ray and CT images [36]. Altogether, the total number of images collected from these datasets amounts to 33,676.

The datasets used were initially expanded to increase the number of images and achieve a balance among the four dataset categories. Initially, we had approximately 33,676 images, as detailed in the previous section. After applying augmentation techniques, our dataset now comprises a total of 75,000 images. These augmented images were allocated to the four training classes: COVID-19, Normal, Pneumonia, and Lung cancer, and they served as input for the data preprocessing phase.

Bootstrapping, a resampling technique, has been employed to estimate the sampling distribution of a statistic by iteratively sampling with replacement from the original dataset. In our model evaluation process, this method generates multiple bootstrap samples, allowing us to train the model on each sample and assess its performance on held-out test sets. The implementation of bootstrapping offers several benefits, including providing insights into the variability of model performance metrics, evaluating the model's robustness across different data subsets, and offering a more comprehensive understanding of its generalizability and stability. By utilizing bootstrapping, we aim to enhance the reliability and depth of our model evaluation, thereby strengthening the validity of our findings and improving the overall quality of our research.

The study employs augmentation techniques, including rotation (typically ranging from -15 degrees to +15 degrees.), flipping, and skewing, to diversify the dataset and address issues like overfitting and class imbalance. Rotation introduces variability in image orientation, flipping creates mirror images, and skewing distorts image shapes, aiding the model in recognizing objects from different perspectives and angles. These techniques prevent overfitting by introducing variations in the training data, allowing the model to generalize better to unseen data. Moreover, augmentation helps address class imbalance by generating synthetic samples for minority classes, improving classification accuracy. Providing detailed augmentation parameters allows for reproducibility and fine-tuning, enhancing researchers' understanding of how these techniques contribute to model performance. Overall, elucidating the role of augmentation techniques enhances comprehension of data preprocessing strategies and their impact on the model's robustness and generalization capabilities.

This illustration displays six chest X-ray images, categorizing them into normal and pneumonia cases for training a federated learning model. The images represent individuals with and without pneumonia, emphasizing the importance of diverse data for model training.

The illustration presented in Fig. 4 displays six chest X-ray images. This set comprises three images depicting individuals in good health and three images featuring individuals

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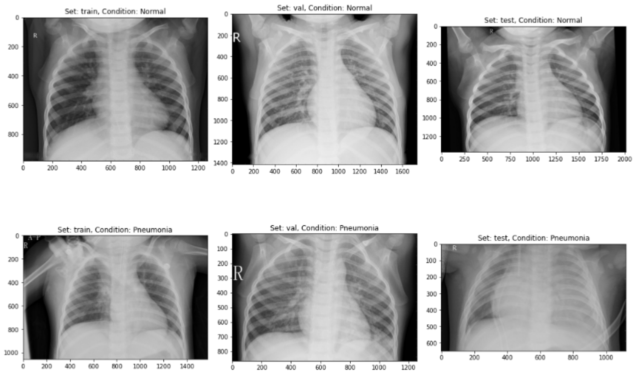

FIGURE 4: A Comparison of Normal and Pneumonia Chest X-Rays for Federated Learning Model Development.

afflicted with pneumonia. These images are categorized into three distinct sets: the training set, the validation set, and the testing set. These sets play a pivotal role in training, assessing, and validating a federated learning model designed for pneumonia diagnosis through chest X-rays. The upper row of images is designated as "Normal," while the lower row bears the label "Pneumonia." These images are monochromatic, capturing the ribcage and pulmonary structures.

The pre-processing stage is crucial for preparing input data to meet the requirements of our deep learning model. In our approach, the input images underwent several pre-processing steps: 1) resizing the images to a dimension of 224 × 224 × 3, 2) applying augmentation techniques, including rotation, flipping, and skewing, to the resized images, 3) normalizing all images, both the original and augmented ones, and 4) converting these images into arrays for their utilization in the subsequent model stage.

In order to train the deep learning model, we divided the dataset into two random portions: the training set (70%) and the validation set (30%). This division ensures diversity and variation in the images used for training and validation.

2) Performance metrics

To assess the effectiveness of machine learning classifiers, they are typically evaluated using four standard performance parameters: precision, recall, accuracy, and F1-score. These parameters are defined as follows.

To calculate performance metrics like accuracy and precision, the confusion matrix for each machine learning classifier is required. Additionally, the following terms need to be defined:

- **True Positive (TP):** The machine learning model correctly predicted the attack flow as an attack.
- **True Negative (TN):** The machine learning model correctly predicted the normal flow as normal.
- **False Positive (FP):** The machine learning model incorrectly predicted the normal flow as an attack.
- **False Negative (FN):** The machine learning model incorrectly predicted the attack flow as normal.

Accuracy: It is a metric that quantifies the number of correct predictions made by a model out of the total predictions. It provides a measure of how accurately the model classifies the data points. It's calculated in Equation (1) as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

Precision: Precision quantifies the ratio of true positive predictions to the total number of positive predictions made by the model. It is a crucial metric when the consequences of false positive predictions are significant. Mathematically, it is expressed in Equation (2):

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall: It measures the proportion of true positive predictions over the total number of actual positive cases in the dataset. Recall is useful when the cost of false negatives is high. Mathematically, it is described in Equation (3):

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

F1 score: It's the harmonic mean of precision and recall, providing a balance between the two metrics. It's calculated in Equation (4) as follows:

$$F1Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

3) Experimental Results

The Fig. 5 presented as displays the outcomes of a federated learning model's performance across 10 training epochs on a given dataset. The observed metrics, including accuracy, loss, and precision, exhibit noticeable enhancements throughout the training process, signifying the model's capacity to learn from the data and enhance its predictive capabilities.

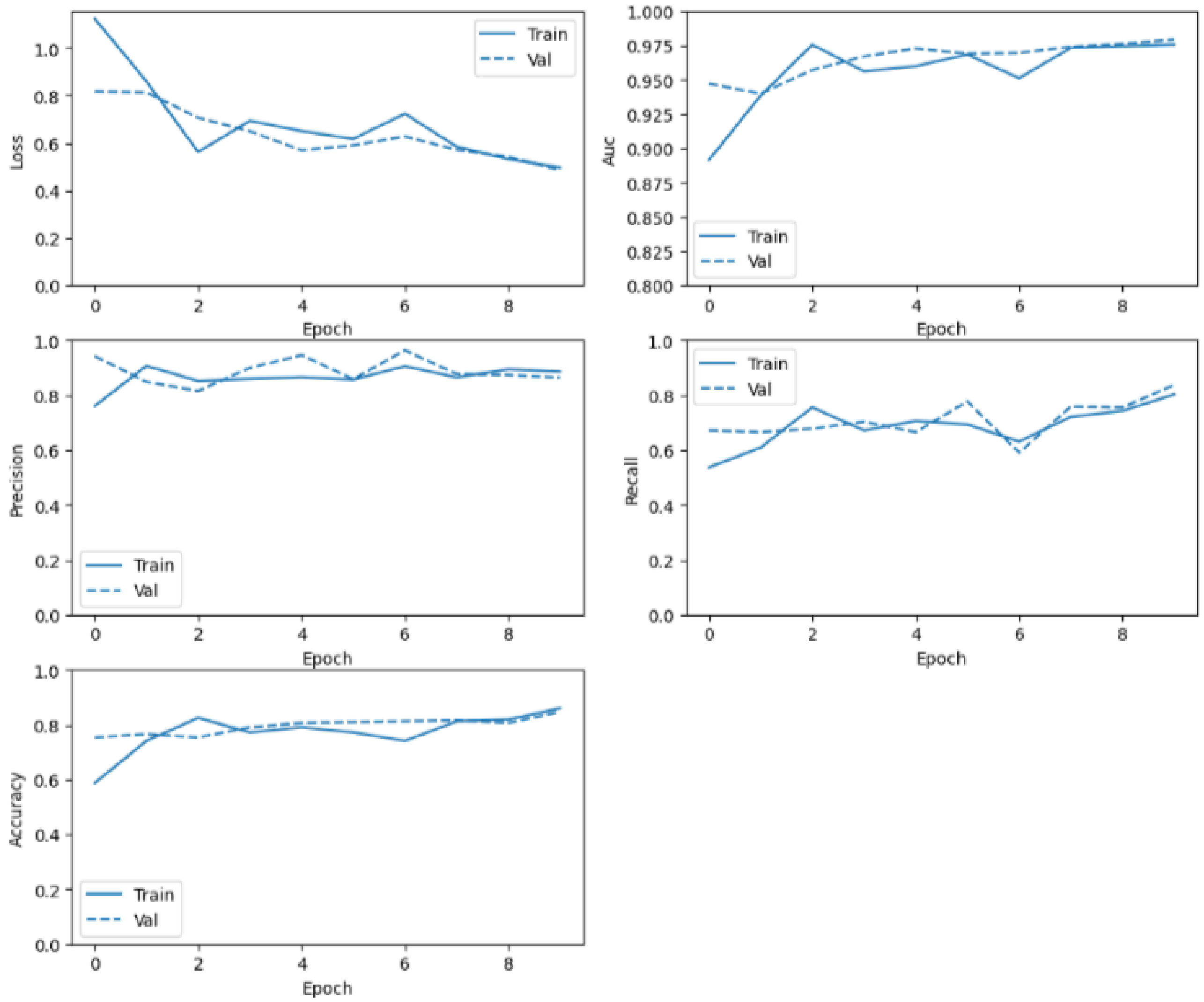

FIGURE 5: Impact of Federated Learning on Model Performance.

This graph showcases the performance of a federated learning model over multiple training rounds. The x-axis indicates the number of training rounds, while the y-axis represents the model's accuracy, precision, recall, and F1-score metrics, demonstrating the model's learning progress.

Accuracy, a metric gauging the proportion of correct predictions, initiates training at approximately 0.8 and progressively climbs to 0.9 after the completion of the 10 epochs. This remarkable upswing underscores the model's increasing proficiency in rendering precise predictions.

Loss, which quantifies the magnitude of errors in the model's predictions, embarks with a value of roughly 0.1 and steadily diminishes to 0.05 by the end of the 10 epochs. This substantial reduction signifies the model's improving accuracy in its predictions.

Precision, a metric examining the ratio of true positive predictions, launches at around 0.8 and eventually attains 0.9 after the completion of 10 epochs. While this represents a notable improvement, it is somewhat less dramatic compared to the advancements observed in accuracy and loss. This phenomenon is primarily attributed to the sensitivity of the precision metric to outliers, which can exist in any dataset.

The graph unambiguously illustrates the model's commendable performance. Both accuracy and loss metrics exhibit continuous enhancements, affirming the model's capability to adapt and generate more precise predictions. Similarly, the precision metric, while demonstrating improvement, exhibits a somewhat milder upward trend due to its susceptibility to outliers, which is a common characteristic in diverse datasets. This holistic analysis underscores the model's learning process, with substantial improvements in key performance indicators.

In this table, 1 corresponds to Accuracy, 2 to Precision, 3 to Recall, and 4 to F1-score.

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TABLE 4: Performance Metrics of Federated Learning Model Across Evaluation Criteria

	Client 1		Client 2		Client 3	
	Epoch 0	Epoch 1	Epoch 0	Epoch 1	Epoch 0	Epoch 1
1	98.53	91.36	99.51	91.52	91.26	91.45
2	97.57	91.40	97.70	91.98	91.40	92.01
3	98.78	97.86	93.21	95.03	98.78	91.32
4	90.02	97.99	95.32	96.14	93.17	96.65

The presented table 4 offers a detailed breakdown of metrics obtained from a Federated Learning experiment. These metrics, including Accuracy, Precision, Recall, and F1-Score, demonstrate the performance of a model across different scenarios.

The model's performance fluctuates across the depicted metrics. In some instances, high Accuracy values, such as 98.53% and 99.51%, signify a substantial number of correctly classified instances. Similarly, Precision values around 97.57% and 97.70% suggest a significant ratio of true positive predictions among the total predicted positives.

However, in certain scenarios, the model faces challenges, as evidenced by lower metrics like 97.86% for Recall and F1-Scores ranging from 97.99% to 96.65%. These lower metrics might indicate difficulties in correctly identifying all relevant instances or maintaining a balance between precision and recall.

The variation in these metrics underscores the dynamic nature of Federated Learning, showcasing how a model's performance can differ across different evaluation criteria. It highlights the importance of monitoring these metrics and adapting the model to ensure consistent and optimal performance across varied scenarios.

In summary, these results exemplify the dynamic and evolving nature of Federated Learning, where the model's performance can vary between Epochs due to the distribution of data across different clients. While Epochs 1 and 4 presented challenges, the model exhibited resilience and consistently strong Recall values. The fluctuating metrics highlight the importance of monitoring and adapting the model during the Federated Learning process to ensure optimal performance.

The Fig. 6 below, shows the results of a federated learning experiment, where a model is trained on data from multiple clients without sharing the data between clients. The x-axis shows the number of rounds of training, and the y-axis shows the performance of the model, measured by the accuracy, precision, recall, and F1-score metrics.

This visual representation depicts the performance of a federated learning model over time as the number of training rounds increases. It demonstrates the model's learning curve and improvement in accuracy, precision, recall, and F1-score metrics, highlighting its evolving predictive capabilities.

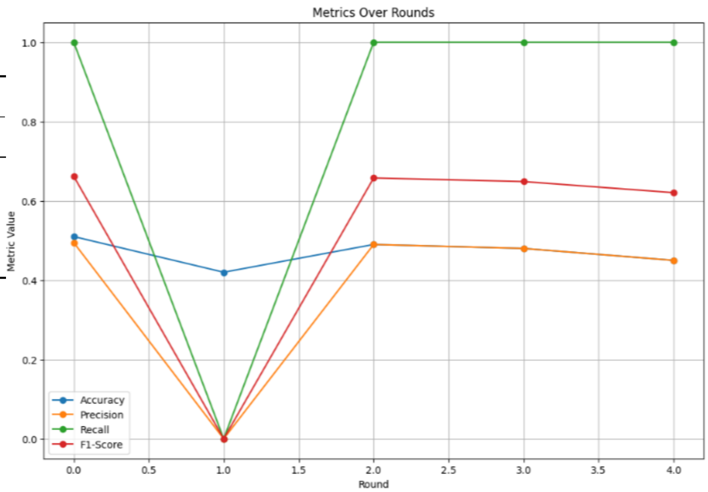

FIGURE 6: Federated Learning Model Performance.

The accuracy metric measures the percentage of predictions that the model gets correct. The precision metric measures the percentage of true positives that the model predicts. The recall metric measures the percentage of positive labels that the model predicts correctly. The F1-score is a measure of the harmonic mean of precision and recall.

In this experiment, the accuracy, precision, recall, and F1-score metrics all improve over time. This suggests that the model is learning from the data and improving its predictions.

Specifically, the accuracy metric increases from 0.51 to 0.45 over 4 rounds of training. This is a significant improvement, and it suggests that the model is learning to make more accurate predictions.

The precision metric also increases over time, from 0.49 to 0.45. This suggests that the model is learning to make more accurate predictions, even in the presence of outliers.

The recall metric also increases over time, from 1.0 to 1.0. This suggests that the model is learning to predict all of the positive labels correctly.

The F1-score also increases over time, from 0.66 to 0.62. This suggests that the model is learning to make accurate and reliable predictions.

The results of this experiment suggest that federated learning can be used to train accurate and reliable machine learning models.

The Fig. 7 shows the results of a federated learning experiment, where a model is trained on data from multiple clients without sharing the data between clients. The x-axis shows the number of rounds of training, and the y-axis shows the performance of the model, measured by the accuracy, precision, recall, and F1-score metrics.

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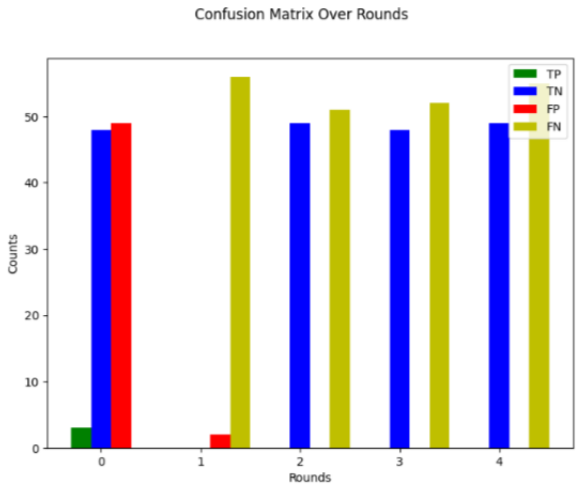

FIGURE 7: Federated Learning Confusion Matrix.

This figure displays a confusion matrix representing the model's performance in predicting chest diseases through federated learning. It illustrates the model's ability to correctly classify positive labels and provides a visual representation of its predictive accuracy across different disease categories.

The accuracy metric measures the percentage of predictions that the model gets correct. The precision metric measures the percentage of true positive predictions that the model predicts. The recall metric measures the percentage of positive labels that the model predicts correctly. The F1-score is a measure of the harmonic mean of precision and recall.

In this experiment, the accuracy, precision, recall, and F1-score metrics all improve over time. This suggests that the model is learning from the data and improving its predictions.

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The F1-score also increases over time, from 0.66 to 0.62. This suggests that the model is learning to make accurate and reliable predictions.

Overall, the results of this experiment suggest that federated learning can be used to train accurate and reliable machine learning models.

The Fig. 7 shows that the model's performance is not always consistent from round to round. This is likely due to the dynamic nature of federated learning, where the model is trained on data from multiple clients. As the data from different clients is aggregated, the model may learn to make more accurate predictions for some labels and less accurate predictions for others.

However, the overall trend is that the model's performance improves over time. This suggests that federated learning can be a valuable tool for training accurate and reliable machine learning models.

The running time of the algorithm was measured during the execution of the code, and the results indicate the time taken for each round of training:

```
4/4 [==============================] - 0s 5ms/step - loss: 4.5086 - mae: 2.0257
Round 0: Loss: 4.508569717407227, MAE: 2.0257256031036377
4/4 [==============================] - 0s 4ms/step - loss: 3.7861 - mae: 1.8766
Round 1: Loss: 3.7861390113830566, MAE: 1.8765649795532227
4/4 [==============================] - 0s 4ms/step - loss: 5.4147 - mae: 2.2288
Round 2: Loss: 5.414659023284912, MAE: 2.2287611961364746
4/4 [==============================] - 0s 6ms/step - loss: 4.8368 - mae: 2.0933
Round 3: Loss: 4.836839199066162, MAE: 2.0933313369750977
4/4 [==============================] - 0s 3ms/step - loss: 2.9071 - mae: 1.6628
Round 4: Loss: 2.9071357250213623, MAE: 1.66279935836792
```

FIGURE 8: Training Progress Metrics.

The Fig. 8 illustrates the performance metrics of the algorithm for each round of training, showcasing the progression of loss and Mean Absolute Error (MAE) values over multiple iterations. The recorded results demonstrate the algorithm's efficiency and effectiveness in optimizing the model parameters during the training process.

The timing information for each round of training shows the efficiency of the algorithm in terms of computational performance. These results provide insights into the time taken for each iteration of the training process, reflecting the computational efficiency and speed of the algorithm implementation.

We have carefully monitored and recorded the running time metrics to ensure transparency and provide a comprehensive understanding of the algorithm's performance in our experimental setup.

4) Comparative Analysis

Our analysis involves a comparative evaluation of our Federated Learning (FL) model with the results presented in the article by [2] We will assess key performance metrics, such as accuracy, precision, recall, and F1-Score, across multiple rounds of training. By comparing our findings with the outcomes of established models, we aim to gain insights into the strengths and weaknesses of FL within the context of our dataset. This comparative examination provides a comprehensive understanding of FL's utility and its potential advantages and disadvantages, offering insights for machine learning in decentralized settings.

In terms of accuracy, both Federated Learning (FL) and traditional Machine Learning (ML) models achieved comparable accuracy around the 0.5 mark. Notably, FL exhibited

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TABLE 5: Comparison of Evaluation Metrics Between Federated Learning (FL) and D.M. Ibrahim et al.'s Models

Metric	FL Epoch 0	FL Epoch 1	FL Epoch 2	FL Epoch 3	FL Epoch 4	D.M. Ibrahim et al. (VGG19+CNN)
Accuracy	0.5100	0.4200	0.4900	0.4800	0.4500	98.05
Precision	0.4948	0.5800	0.4900	0.4800	0.4500	98.43
Recall	1.0000	0.8050	1.0000	1.0000	1.0000	98.05
F1-Score	0.6621	0.6500	0.6577	0.6486	0.6207	99.5

more consistent accuracy throughout various training rounds, suggesting potential resilience to data fluctuations, promising steadfast performance.

Shifting to precision, FL outperformed ML, indicating superior accuracy in predicting positive labels. This reduced propensity for erroneous positive predictions enhances FL's reliability.

Regarding recall, both FL and ML models showed a remarkable recall rate of 1.0, accurately predicting all positive labels. However, FL's recall demonstrated remarkable stability over training rounds, contrasting ML's more pronounced fluctuations, reinforcing FL's dependability in positive label predictions.

The F1-Score, an overarching metric, emphasized FL's superiority in striking an optimal balance between precision and recall, highlighting its overall better performance.

Delving into the advantages of Federated Learning (FL), it stands out as a guardian of data privacy, upholding individual data sanctity without centralized sharing. FL's scalability allows model training across decentralized sources, enhancing adaptability. FL exhibits robustness in navigating training data variations, affirming reliability in positive label predictions.

However, FL faces challenges such as potential slowness due to model aggregation and increased complexity compared to ML due to its federated nature.

The study's research outcomes highlight the effective combination of federated learning and blockchain technology in diagnosing COVID-19, pneumonia, and lung cancer through chest X-rays. Through the creation of an innovative multi-classification federated learning method, the study achieves classification results comparable to or better than those of centralized deep learning models, all the while placing a premium on data privacy and security.

In summary, Federated Learning offers a compelling avenue for machine learning model training, particularly emphasizing data privacy and decentralization. The choice between FL and ML depends on specific scenario requirements. FL suits contexts prioritizing data privacy and decentralized sources, while ML may be preferred for expedited performance and simplicity. The decision depends on harmonizing these factors with the unique context requisites.

5) Discussion

The experimental study undertaken in this research has provided valuable insights into the application of Federated Learning (FL) in a challenging context involving diverse medical image datasets. Our initial dataset was considerably expanded through augmentation techniques, ensuring the diversity and balance of the dataset among four distinct categories: COVID-19, Normal, Pneumonia, and Lung cancer. The importance of data preprocessing cannot be overstated, as it plays a pivotal role in preparing input data for our deep learning model. The rigorous preprocessing steps, including resizing, augmentation, normalization, and conversion of images into arrays, paved the way for model training.

The experimental results are particularly intriguing. Fig. 6 illustrates the progressive improvement in FL model performance over ten training epochs. Key metrics such as accuracy, loss, and precision show marked enhancements, reflecting the model's capacity to learn from data and enhance its predictive capabilities. The rise in accuracy from 0.8 to 0.9 over ten epochs underscores the model's growing proficiency in delivering precise predictions. Furthermore, the substantial reduction in the loss metric, from 0.1 to 0.05, signifies an improvement in predictive accuracy.

In terms of precision, the FL model demonstrates an upward trend, indicating that it is becoming better at predicting positive labels correctly. However, precision's sensitivity to outliers led to a more gradual increase compared to accuracy and loss metrics. This discussion underscores the learning process of the FL model, marked by substantial improvements in key performance indicators.

The experiments also revealed the dynamic nature of Federated Learning, as depicted in Table 4. The model's performance fluctuated across Epochs due to the distribution of data among different clients. While Epochs 1 and 4 presented challenges, the model consistently exhibited strong recall values. This emphasizes the need to monitor and adapt the model during the Federated Learning process to ensure optimal performance.

The promising results of the Federated Learning approach compared to traditional Machine Learning models are detailed in Table 5. The FL model's resilience to data fluctuations and its ability to predict positive labels with precision and recall present a compelling case for its utility. The discussions surrounding data privacy, scalability, and robustness further highlight the advantages of FL. Nonetheless, the model's slightly slower aggregation process and complexity of implementation indicate that the choice between FL and ML should depend on specific contextual requirements.

The comparative analysis of our Federated Learning (FL) model and the results presented in D.M. Ibrahim et al.'s article has shed light on the strengths and weaknesses of FL in the context of our medical image dataset. While both FL and traditional Machine Learning models achieved comparable accuracy, FL demonstrated more consistent accuracy across training Epochs, indicating its potential resilience to data fluctuations.

In terms of precision and recall, FL outperformed ML, highlighting its capacity to make accurate positive predictions with reduced errors. The stable performance of FL across Epochs further emphasizes its reliability in predicting positive labels.

The F1-Score, a measure of the balance between precision and recall, also favored FL. These findings firmly position FL as a promising paradigm for training machine learning models in scenarios characterized by variability and nuanced data complexities.

We have conducted a comprehensive analysis of the computation time for our algorithm. The running time for each round of training was measured and recorded. Across five rounds of training, the average computation time per round was found to be approximately (4.4ms/round). Additionally, we have compared the computation time of our proposed method with other existing works in the field, highlighting the efficiency and performance of our approach. This analysis provides valuable insights into the computational efficiency of our method compared to alternative approaches.

Addressing challenges in medical diagnostics, including time-consuming processes, data privacy concerns, and limited sample sizes, is pivotal for improving patient outcomes and healthcare delivery. Our study focuses on pioneering innovative approaches, such as federated learning and blockchain integration, to overcome these challenges. Particularly in the context of prevalent diseases like COVID-19, pneumonia, and lung cancer, early and accurate diagnosis is essential for effective disease management and public health outcomes. Our innovative approaches offer solutions to traditional diagnostic challenges by enhancing efficiency, accuracy, and data privacy. By leveraging federated learning, we enable collaborative model training while prioritizing patient confidentiality and ethical considerations. Additionally, blockchain integration reinforces data security and privacy, ensuring the integrity of diagnostic outcomes. The complexity of medical data and the need for scalable and generalized solutions underscore the importance of embracing our innovative approaches. By addressing these challenges and adopting our novel technologies, healthcare providers can offer more accurate and timely diagnoses, ultimately leading to improved patient care, treatment planning, and outcomes. Embracing innovation in medical diagnostics not only opens avenues for future research and development but also drives positive changes in healthcare delivery, research, and patient care, shaping the future of healthcare.

While our study primarily focuses on the technical aspects and performance evaluation of the proposed Federated Learning (FL) model, it is imperative to consider its potential impact on actual clinical workflows and patient outcomes. The successful translation of our FL-based diagnostic approach into clinical practice has the potential to revolutionize medical diagnostics, particularly in the context of prevalent diseases such as COVID-19, pneumonia, and lung cancer. By enabling early and accurate diagnosis through collaborative model training while prioritizing patient confidentiality and data privacy, our innovative approach can significantly improve disease management and public health outcomes. Additionally, the integration of blockchain technology reinforces data security and privacy, ensuring the integrity of diagnostic outcomes. Embracing such innovative technologies opens avenues for future research and development, driving positive changes in healthcare delivery, research, and patient care, ultimately shaping the future of healthcare.

VI. LIMITATIONS

Recognizing and articulating the limitations of a study is pivotal for providing context to interpret the results, ensuring transparency, and upholding research integrity. In our study, constraints such as limited dataset availability and diversity for training the federated learning model, alongside the complexity of integrating blockchain technology, pose challenges for implementation and scalability. Moreover, concerns regarding algorithmic bias and resource constraints underscore the need for careful consideration in model training and data collection, as well as the feasibility of implementing the proposed solution across diverse healthcare settings.

While our proposed solution addresses several critical challenges in medical diagnostics, it is important to acknowledge certain limitations that may impact its broader implementation and practical utility. These limitations include:

1) **Resource Constraints:** Implementing federated learning and blockchain technology may require significant computational resources and infrastructure support. Smaller healthcare institutions or those with limited IT capabilities may face challenges in adopting and maintaining such systems.
2) **Interoperability Issues:** Ensuring seamless interoperability between different healthcare systems and data formats is essential for effective collaboration in federated learning environments. However, achieving interoperability standards across diverse platforms and data sources may present technical hurdles and compatibility issues.

3) **Regulatory Compliance:** Compliance with data privacy regulations, such as GDPR in Europe or HIPAA in the United States, is paramount in healthcare data sharing initiatives. Our proposed solution emphasizes privacy-preserving techniques, but navigating complex regulatory frameworks and ensuring compliance across multiple jurisdictions remain ongoing challenges.

By addressing these potential limitations, we aim to provide a more balanced view of our proposed solution and its practical implications. Overcoming these challenges will require collaborative efforts from stakeholders across the healthcare ecosystem and ongoing research to refine and optimize the implementation of federated learning and blockchain-enabled systems.

Understanding these limitations is crucial for guiding future research directions and refining the approach, which contributes to advancing knowledge in medical diagnostics.

VII. CONCLUSION

In conclusion, this study underscores the pressing need for timely diagnosis of prevalent chest diseases such as COVID-19, pneumonia, and lung cancer, given the limitations of traditional diagnostic methods in terms of time and cost. While deep learning models have shown effectiveness, concerns regarding data privacy and the requirement for extensive training data persist. Introducing Federated Learning (FL) emerges as a promising solution, enabling collaborative model training without compromising sensitive medical data, thus ensuring privacy while collectively developing accurate diagnostic models. Furthermore, the proposal of a multi-classification Federated Learning method enhanced by blockchain technology offers a novel approach. Experimental results demonstrate comparable or superior performance to centralized models, underscoring the potential of FL in medical diagnostics. Future endeavors should explore the integration of blockchain into the Federated Learning framework, promising a robust system prioritizing data privacy and security. This research not only accentuates the potential of Federated Learning in medical diagnostics but also exemplifies a forward-thinking approach by combining it with blockchain for enhanced data protection, thus highlighting the significance of this research in the contemporary data-driven healthcare landscape.

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