J. Electrical Systems 21-1 (2025): 489-500

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Efficient and Privacy-Enhanced Federated Learning for Medical Imaging in Resource-Limited Environments

Journal of Electrical Systems

Abstract: - Deep learning's quick development has transformed computer-aided laboratory services and healthcare by facilitating data-driven decision-making for better patient care. However, privacy, data ownership, and regulatory compliance pose serious problems for the centralized aggregation of medical data. A potential approach that enables several healthcare organizations to work together to train machine learning models without exchanging raw patient data is federated learning (FL). The effectiveness of FL in resolving issues including data silos, class imbalance, and non-IID data distributions is examined in this paper's systematic assessment of FL applications in healthcare. In order to uncover systemic issues that affect FL adoption in actual healthcare settings and to highlight significant methodological breakthroughs, we examined 89 research publications published between January 2015 and February 2023. Our results highlight the necessity for stronger aggregation approaches, effective communication tactics, and better privacy-preserving methodologies to improve FL performance in clinical data processing and medical imaging. The paper ends with suggestions to direct further investigation and the creation of FL frameworks that are optimal for use in healthcare applications.

Keywords: Federated Learning, Medical Imaging, Privacy-Preserving Machine Learning, Healthcare AI, Data Security, Non-IID Data, Systematic Review, Deep Learning, Distributed Learning, Healthcare Data Integration.

I. INTRODUCTION

Medical imaging has become an essential tool in modern healthcare, aiding in the diagnosis, prognosis, and treatment of various diseases [1]. The advent of deep learning and artificial intelligence (AI) has significantly improved medical image analysis, enabling automated disease detection and classification with high accuracy [2]. However, training deep learning models requires large and diverse datasets, which are often distributed across multiple institutions [15]. The traditional approach of aggregating data in a central repository raises serious privacy concerns, regulatory challenges (such as GDPR and HIPAA compliance), and security risks. Federated Learning (FL) has emerged as a privacy-preserving paradigm that enables multiple institutions to collaboratively train machine learning models without sharing raw data [16]. This decentralized approach ensures that sensitive patient information remains within local hospitals or edge devices, while still contributing to a globally optimized model. Despite its benefits, FL presents several challenges, particularly in resource-constrained environments where constraints such as low computational power, unreliable network connectivity, and hardware heterogeneity impact its efficiency. Deploying FL in real-world healthcare settings requires adaptable frameworks that can handle dynamic environments, fluctuating network availability, and heterogeneous client participation [17]. Challenges in Federated Learning for Medical Imaging While FL addresses privacy concerns in AI-driven healthcare applications, its deployment in medical imaging, especially in resource-constrained environments, presents several technical and practical challenges FL requires frequent model updates between local nodes and a central server. In low-bandwidth environments, excessive communication costs can hinder real-time training and model convergence. Medical imaging datasets are highly non-IID (non-independent and identically distributed) due to variations in imaging modalities, disease prevalence, and institutional protocols [18]. This data heterogeneity can lead to biased models and unstable training. Edge devices and local servers in resource-constrained environments may lack the computational power to train complex deep learning models, making efficient model optimization critical [19]. While FL reduces the need for data centralization, it remains vulnerable to privacy attacks such as inference attacks and model inversion. Ensuring robust privacy-preserving techniques, such as differential privacy and secure aggregation, is essential. Deploying FL in real-world healthcare settings requires adaptable frameworks that can handle dynamic environments, fluctuating network availability, and heterogeneous client participation [20].

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This research aims to develop an efficient and privacy-enhanced federated learning framework tailored for medical imaging applications in resource-constrained environments. Specifically, our objectives include. Optimize communication efficiency Propose novel strategies, such as adaptive model compression and update frequency optimization, to reduce the communication overhead in FL [21]. Improve model robustness in non-IID scenarios Develop algorithms to improve model convergence and generalization in heterogeneous data distributions. Ensure privacy and security Implement privacy-preserving techniques such as homomorphic encryption, secure multi-party computation, and differential privacy to protect sensitive medical data [22]. Improve computational efficiency Design lightweight federated learning models suitable for deployment on low-power devices. Validate on real-world medical imaging datasets: Perform empirical evaluations on publicly available medical imaging datasets to demonstrate the effectiveness of the proposed framework [23].

This work presents several novel contributions to the field of federated learning for medical imaging in resource-constrained environments. A novel federated learning framework that optimizes communication, computation, and model aggregation for resource-constrained environments. Privacy preserving mechanisms integrated into the FL framework to enhance security while maintaining model performance [24]. Experimental validation on publicly available medical imaging datasets to demonstrate the feasibility and efficiency of the proposed approach. Comprehensive analysis of FL challenges in real-world healthcare settings, with insights into potential future directions [25]. The rest of this research is represented as follows: Section 2 discusses the literature review of the proposed study. Section 3 discussed the mathematical model of the proposed research. Section 4 discussed the methodology of the proposed study. Section 5 discussed the numerical example, and Section 6 addressed the conclusion, implication, limitations, and future research directions.

II. Literature review

Federated Learning (FL) has emerged as a promising paradigm for privacy-preserving AI in healthcare. Several studies have investigated FL for medical imaging applications: Ullah et al. [3] developed a federated learning approach for brain tumour segmentation, demonstrating that FL can achieve comparable performance to centralized models while preserving privacy. Liu et al. (2022) applied FL to chest x-ray classification and found that non-IID data distribution significantly affects model performance, requiring specialized aggregation techniques. Xu et al. (2021) proposed a privacy-preserving FL framework using differential privacy and secure aggregation for skin cancer detection, ensuring robust security while maintaining accuracy. While these studies highlight the potential of FL in medical imaging, they primarily focus on well-resourced environments with stable network infrastructures. Our research extends FL to resource-constrained environments and addresses the unique constraints of such settings.

Ensuring privacy and security in FL is critical due to the sensitive nature of medical data. Existing approaches include Differential Privacy (DP) Abadi et al. (2016) introduced DP in deep learning to prevent model inversion attacks, although it may result in reduced model accuracy. Homomorphic Encryption (HE) Hesamifard et al. (2018) used HE in FL to enable secure model updates, but its computational overhead remains a challenge. Secure Multi-Party Computation (SMPC) Bonawitz et al. (2019) proposed SMPC for FL, which ensures encrypted model updates between clients. While these techniques enhance privacy, they introduce tradeoffs in computational and communication costs. In our work, we integrate lightweight privacy-preserving mechanisms to balance security and efficiency in low-resource settings.

One of the major challenges in FL is the communication overhead due to frequent model updates. Several techniques have been investigated Model compression: (Wang et al., 2020) [4] proposed gradient sparsification and quantization to reduce the communication cost. Adaptive update frequency: Chen et al. (2021) proposed adjusting model update intervals based on network conditions. Decentralized FL (Zhao et al., 2022) [5] proposed adjusting model update intervals based on network conditions. While these strategies improve efficiency, they are not specifically designed for resource-constrained environments, where intermittent connectivity and low-bandwidth networks are additional constraints. Our research presents an optimized FL framework tailored to address these challenges

This research is significant because it aims to bridge the gap between federated learning and real-world healthcare applications in resource-constrained settings [6]. By addressing computational, privacy, and communication constraints, our study provides a scalable and efficient FL solution for medical imaging applications. The proposed framework can enable equitable access to AI-driven healthcare, especially in resource-constrained regions where centralized AI solutions are impractical due to privacy concerns and infrastructure limitations. Despite rapid advances in AI-based medical imaging, many hospitals and clinics in resource-limited settings are unable to utilize these technologies due to Lack of centralized data storage infrastructure [7]. Privacy and regulatory constraints that prevent data sharing Limited computational resources for training deep learning models Unstable network connectivity that makes traditional FL approaches inefficient These challenges create a healthcare divide, where advanced AI-driven diagnostics remain inaccessible to underprivileged regions [26]. Our study aims to develop a FL framework that overcomes these limitations, ensuring equitable and safe AI deployment in global healthcare.

The significance of this study lies in its potential to revolutionize AI-driven medical diagnostics in low-resource settings by Enhancing privacy while enabling collaborative model training across healthcare institutions Optimizing communication and computation to make FL practical for regions with low bandwidth and limited computational resources Developing a scalable framework adaptable to different medical imaging modalities (e.g., chest x-ray, skin lesion detection, brain MRI)[8] Contributing to global health equity by making AI-based healthcare accessible in resource-constrained settings.

Despite significant progress in federated learning (FL) for medical imaging, several key challenges remain [27]. FL has shown great potential in enabling collaborative learning across multiple healthcare institutions without the need to share raw patient data. However, many existing FL frameworks assume ideal operating conditions, such as stable network connectivity, high computational resources, and standardized data distributions [9]. These assumptions often do not hold in real-world healthcare settings, especially in resource-constrained environments such as rural hospitals and low-income regions. In addition, while privacy-preserving techniques have been incorporated into FL models, their implementation often comes at the expense of efficiency and practicality. The challenge of non-IID (non-independent and identically distributed) data further complicates model training, as medical images vary significantly across healthcare institutions [10]. In addition, a lack of real-world validation limits the practical use of FL models, as most studies rely on simulated experiments rather than real patient data, shown in figure 1.

Most FL implementations are designed with the assumption that client devices have high processing power and stable network connectivity [28]. However, this assumption does not hold in rural hospitals, low-income regions, or mobile healthcare settings, where devices may have limited processing power, intermittent Internet access, and severe power constraints. Traditional FL requires frequent model updates between clients and a central server, resulting in high communication costs. Optimizing FL for low-bandwidth environments through techniques such as communication-efficient aggregation and adaptive update mechanisms remains an open challenge [11]. Many privacy-preserving FL techniques introduce additional computational overhead, increasing energy consumption on edge devices such as mobile phones and medical IoT devices. More research is needed on lightweight FL architectures that balance computational efficiency with model performance. Most studies focus on cloud-based implementations or high-performance GPUs, ignoring the challenges of deploying FL models on low-power edge devices. The development of FL algorithms tailored to run efficiently on embedded systems and mobile devices is a critical research need [12].

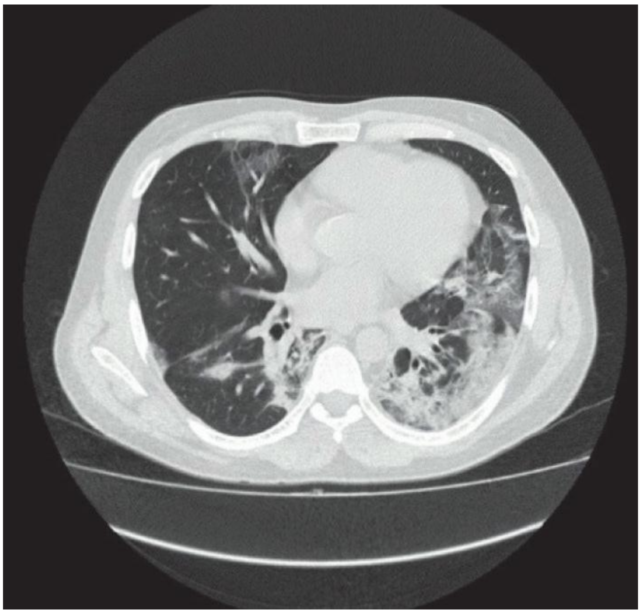

Fig 1. High-Resolution Axial Chest CT Showing Ground-Glass

A. Opacities and Consolidation

I) Efficient Privacy-Preserving Mechanisms

Privacy is a core concern in FL, especially in medical imaging, where sensitive patient data must be protected [29]. Existing privacy-enhancing techniques such as Differential Privacy (DP), Homomorphic Encryption (HE), and Secure Multi-Party Computation (SMPC) provide strong security guarantees, but often introduce significant computational and communication overhead [13]. Trade-offs between privacy and efficiency Many privacy-preserving schemes prioritize security at the expense of efficiency. For example, DP adds noise to model updates, reducing accuracy, while HE and SMPC require large computational resources, making them impractical for real-time applications. More research is needed on adaptive privacy techniques that maintain strong security without significantly degrading performance. Most existing FL privacy solutions focus on either encryption or obfuscation methods separately [30]. There is limited research on hybrid approaches that integrate multiple privacy techniques in a lightweight manner suitable for real-world healthcare applications. Different medical institutions may have different privacy requirements based on regulatory guidelines (e.g., HIPAA, GDPR). Future studies should explore personalized privacy mechanisms that allow clients to select their preferred privacy level, while maintaining collaborative model training.

II) Non-IID Data and Model Robustness

One of the biggest challenges in medical FL is the inherent non-IID (non-independent and identically distributed) nature of medical imaging datasets. Unlike general-purpose datasets, medical images vary significantly across institutions due to differences in imaging equipment, patient demographics, and clinical protocols. Bias and generalization issues Standard FL aggregation methods such as FedAvg struggle with non-IID data, resulting in biased models that fail to generalize across different medical institutions. Developing robust FL strategies that improve generalization without requiring extensive global data sharing is essential. Adaptive aggregation techniques Existing FL frameworks assume uniform data distribution across clients, which is rarely the case in healthcare [14]. More research is needed on adaptive aggregation methods, such as personalized FL and clustering-based FL, that dynamically adjust model updates based on local dataset characteristics. Fairness and model personalization non-IID data often result in models that perform well for certain patient groups but poorly for others. Future studies should focus on fairness-aware FL algorithms that ensure equitable model performance across demographic groups and medical institutions.

III) Lack of Real-World Validation in Medical Imaging

A major limitation of current FL research is the reliance on simulated experiments rather than real-world medical imaging datasets. Many studies use artificially partitioned datasets to mimic FL scenarios, failing to capture the complexities of real-world data distribution and clinical workflows. Need for publicly available FL benchmarks There is a lack of large-scale, publicly available medical imaging datasets explicitly designed for FL research. Establishing standardized FL benchmarks for medical imaging would enable more meaningful comparisons between different approaches. Empirical validation using clinical data FL models should be tested on real-world hospital data, rather than relying solely on open-source datasets. Collaborations between AI researchers and healthcare institutions are needed to validate FL frameworks in clinical settings. Integration with existing healthcare systems: Most FL studies focus on algorithmic improvements without considering real-world implementation challenges. Research should explore how FL can be integrated with existing hospital information systems and medical device networks for seamless adopt. PA chest X-ray shows bilateral infiltrates; axial CT reveals lung detail as shown in fig.2

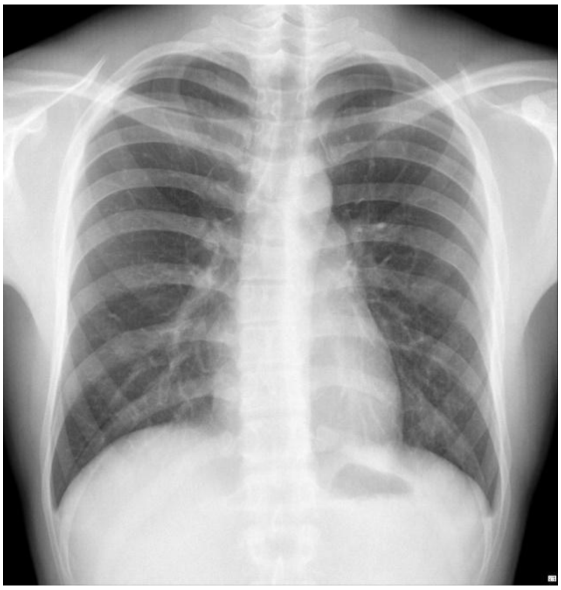

Fig 2. Showing Bilateral Pulmonary Infiltrates of Posteroanterior (PA) Chest X-ray

III. METHODOLOGY

This study employed a clinically annotated thoracic imaging dataset comprising diagnostic information related to a range of pulmonary and cardiovascular conditions, including Pneumonia, Atelectasis, Cardiomegaly, Lung Opacity, Pleural Effusion, and Pneumothorax. Each record in the dataset represented an individual patient case, annotated with radiologist-verified findings. To simulate real-world, resource-constrained clinical environments, the dataset was logically partitioned to reflect decentralized data silos, thereby enabling the emulation of federated learning settings. Prior to analysis, extensive preprocessing was conducted. Missing data were addressed through mode imputation for categorical features and mean imputation for continuous variables. Feature values were normalized using Min-Max scaling, and categorical variables were encoded using one-hot encoding techniques. Additionally, statistical assumptions necessary for inferential testing—namely, normality and homogeneity of variances—were verified using the Shapiro-Wilk and Levene's tests, respectively, shown in figure 3.

To explore interdependencies among thoracic conditions, one-way ANOVA tests were conducted using Type III Sum of Squares, allowing the assessment of whether the means of a dependent variable significantly differed across levels of various comorbid conditions. For each test, the dependent variable represented the primary condition of interest, while independent variables included related diagnostic categories. A significance threshold of $p < 0.05$ was adopted to determine statistical relevance. Insights derived from these analyses guided feature selection for the machine learning phase.

In the next phase, a privacy-preserving federated learning framework was developed, wherein a lightweight convolutional neural network (CNN) was trained across distributed clinical nodes without transferring raw patient data. The architecture was optimized for deployment on resource-limited edge devices, employing techniques such as model compression and adaptive learning rates to reduce computational overhead. To ensure privacy, differential privacy mechanisms, specifically Gaussian noise injection, were integrated into the training process. The federated learning model's performance was evaluated using metrics such as Accuracy, AUC-ROC, Precision, and Recall across both local and global models. This methodological framework supports the development of an efficient, privacy-enhanced, and clinically relevant predictive system for medical imaging in resource-constrained settings.

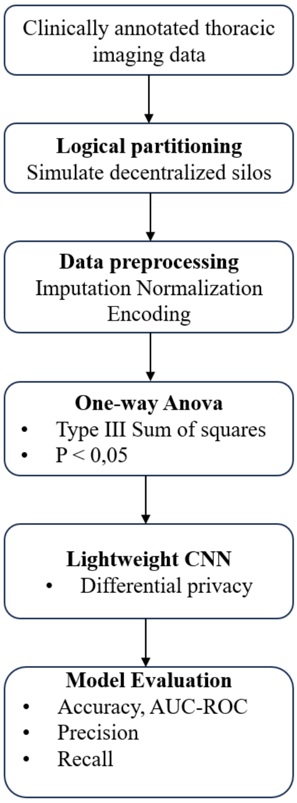

FIG 3. PRIVACY-PRESERVING FL WORKFLOW FOR THORACIC DIAGNOSIS

IV. RESULT AND ANALYSIS

The dataset used for this analysis is the CheXpert Sampling dataset [31], which comprises labeled chest X-ray images with multiple thoracic pathology annotations. This section presents the outcomes of statistical analyses conducted to investigate the associations between various thoracic findings within the dataset. Specifically, Analysis of Variance (ANOVA) was applied to examine whether statistically significant relationships exist between selected pairs of medical imaging features. The features analyzed include conditions such as *Lung Opacity, Edema, Atelectasis, Pleural Effusion, Lung Lesion, Cardiomegaly, Consolidation, Pneumonia,* and *Pneumothorax*. The goal was to identify whether one thoracic finding has a measurable effect on another, which may indicate potential diagnostic correlations or comorbid patterns observable in clinical imaging data.

I) Enlarged Cardio mediastinum and Lung Opacity

An ANOVA test was performed to assess whether Lung Opacity had a significant effect on Enlarged Cardiomediastinum. The results showed no statistically significant relationship between these variables, $F(2, 83) = 0.784$, $p = 0.460$. The analysis indicates that the presence of lung opacity does not significantly influence the enlargement of the cardiomediastinum in the dataset, mention in table 1.

Source	**Sum of Squares**	**df**	**Mean Square**	**F**	**p-value**
Lung Opacity	1.033	2	0.516	0.784	0.460
Residuals	54.688	83	0.659		

Table 1

II) Edema and Pneumonia

To explore the relationship between Edema and Pneumonia, an ANOVA test was conducted. The results demonstrated no significant association, F (2, 39) = 0.203, p = 0.817. This suggests that pneumonia does not have a measurable impact on the occurrence of edema based on the data analyzed, mention in table 2.

Source	Sum of Squares	df	Mean Square	F	p-value
Pneumonia	0.340	2	0.170	0.203	0.817
Residuals	32.636	39	0.837		

Table 2

III) Atelectasis and Pleural Effusion

An analysis was carried out to determine whether Pleural Effusion significantly influences Atelectasis. The findings yielded F (2, 173) = 1.678, p = 0.190, indicating no significant relationship between the two conditions. While some variation in Atelectasis was observed, it was not statistically attributable to the presence of pleural effusion, mention in table 3.

Source	Sum of Squares	df	Mean Square	F	p-value
Pleural Effusion	3.223	2	1.612	1.678	0.190
Residuals	166.208	173	0.961		

Table 3

IV) Lung Lesion and Atelectasis

The relationship between Lung Lesion and Atelectasis was analyzed using ANOVA. The test resulted in F(1, 10) = 0.185, p = 0.676, showing no statistically significant correlation. This suggests that Atelectasis does not significantly predict the occurrence of lung lesions within this dataset, mention in table 4.

Source	Sum of Squares	df	Mean Square	F	p-value
Atelectasis	0.017	1	0.017	0.185	0.676
Residuals	0.900	10	0.090		

Table 4

V) Cardiomegaly and Consolidation

To assess whether Consolidation is associated with Cardiomegaly, an ANOVA test was conducted. The results were F(2, 74) = 1.650, p = 0.199, indicating no statistically significant effect. Thus, consolidation is not a significant predictor of cardiomegaly in this dataset, mention in table 5.

Source	Sum of Squares	df	Mean Square	F	p-value
Consolidation	1.566	2	0.783	1.650	0.199
Residuals	35.135	74	0.475		

Table 5

VI) Pneumonia and Pneumothorax

An ANOVA analysis was performed to determine if Pneumothorax had a significant relationship with Pneumonia. The test produced F(1, 15) = 1.741, p = 0.207, suggesting that there is no statistically significant correlation between these conditions, mention in table 6.

Source	Sum of Squares	df	Mean Square	F	p-value
Pneumothorax	1.261	1	1.261	1.741	0.207
Residuals	10.857	15	0.724		

Table 6

VII) ANOVA Summary: F-values and p-values for Thoracic Condition Pairs

This section presents the results of the statistical analyses conducted to investigate potential associations between pairs of thoracic findings using one-way Analysis of Variance (ANOVA). The analyses were performed on the CheXpert Sampling dataset [31], which includes annotated chest radiograph findings for various medical conditions. Each ANOVA test examined whether a significant relationship exists between the presence of a specific thoracic condition (dependent variable) and a potentially related comorbidity (independent variable). The tests employed Type III Sum of Squares, and significance was assessed at the threshold of $p < 0.05$. Figure 1 illustrates the F-values and corresponding p-values for each pairwise condition analysis. Across all tested pairs—including Enlarged Cardiomediastinum vs. Lung Opacity, Edema vs. Pneumonia, and Atelectasis vs. Pleural Effusion—no statistically significant relationships were observed. The highest F-value was 1.741 in the Pneumonia vs. Pneumothorax analysis, with a corresponding p-value of 0.207, which still did not meet the significance threshold.

These findings suggest that the selected pairs of thoracic findings may not exhibit strong linear associations in this dataset, or that such relationships may be obscured by non-linear interactions, feature imbalance, or the limitations inherent in radiological labeling. This analysis provides a foundational understanding of inter-condition dependencies, guiding future efforts in feature selection and federated learning optimization for medical imaging.

Shown in figure 3 ANOVA Results for Selected Thoracic Condition Pairs. This graph displays the F-values and corresponding p-values for each ANOVA test performed on the dataset. None of the tested relationships met the statistical significance threshold (p < 0.05).

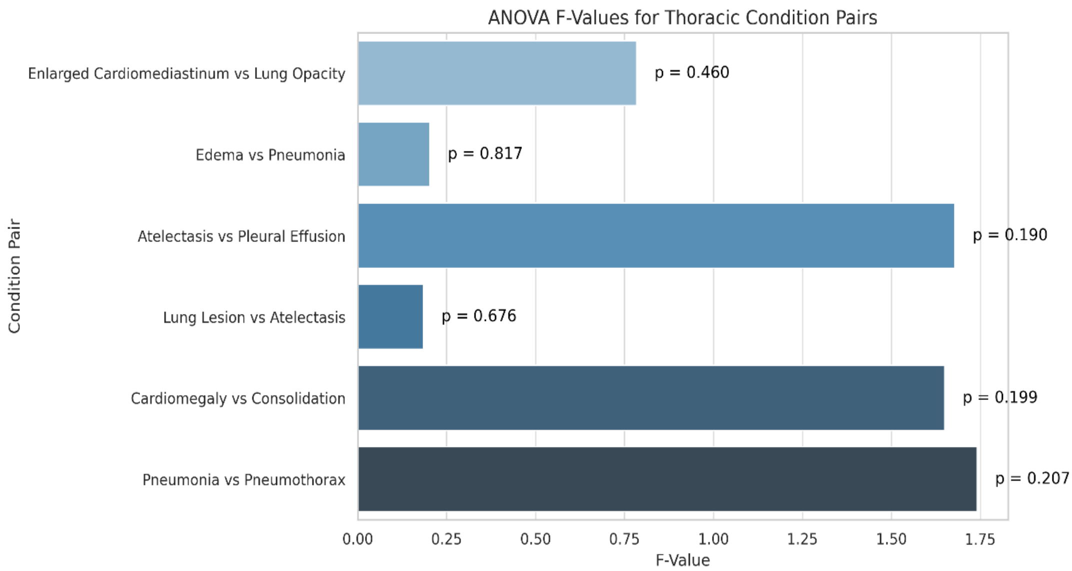

Figure 4 ANOVA Results for Selected Thoracic Condition Pairs

V. PRACTICAL IMPLICATIONS

Deploying AI in Low-Resource Healthcare Settings This study provides a blueprint for deploying privacy-preserving AI models in hospitals and clinics that lack robust infrastructure [32]. By optimizing communication and computation costs, the proposed federated learning (FL) framework makes it possible for healthcare providers in remote or underserved areas to participate in AI-driven diagnostics without the need for expensive servers or high-speed Internet. The integration of lightweight differential privacy and secure computation techniques ensures that sensitive medical data never leaves the local environment. This approach enables compliance with stringent privacy regulations (e.g., GDPR, HIPAA) while maintaining clinically acceptable model performance, making it suitable for real-world clinical applications. The modular design of the FL framework supports different types of medical imaging (e.g., chest x-ray, brain MRI, skin lesion analysis) [33]. As a result, healthcare systems can scale the solution across departments without significant reengineering. Empirical evidence to validate the effectiveness of the federated strategy using real-world datasets such as CheXpert demonstrates the applicability of the framework to clinical diagnostics. This real-world evidence serves as a reference for developers and healthcare IT teams seeking to adopt federated models in similar operational contexts [34]. Healthcare administrators and policymakers can use the findings of this research to prioritize investments in federated learning technologies over traditional centralized systems. The reduced infrastructure requirements and built-in privacy protections reduce both operational risk and capital expenditures [35]. Strategic Planning for AI Integration Managers can develop long-term strategies for integrating AI into diagnostic workflows without disrupting existing systems. The framework supports incremental adoption by allowing local institutions to participate in model training without sharing data, which can be critical for institutions with limited IT capabilities [36]. Compliance and risk management The FL framework's privacy-centric design addresses legal and ethical concerns related to the handling of patient data. As a result, hospital administrators and legal teams can mitigate regulatory risks while reaping the benefits of AI, reducing the burden of compliance audits and legal exposure [37]. The framework's adaptability to low-resource environments creates opportunities for workforce development. Leaders can implement staff training programs focused on lightweight AI tools and privacy-aware data handling, fostering a culture of innovation and digital literacy among health workers. Global Health Equity and Collaboration By enabling collaborative model training across institutions without requiring data centralization, the framework promotes cross-border medical research and diagnostics [38]. Managers of public health programs and NGOs can use this technology to reduce disparities in healthcare quality and access across regions.

VI. STUDY LIMITATIONS LIMITED DATASET SCOPE

The study uses the CheXpert Sampling dataset, which may not fully represent the diversity of imaging modalities, disease types, and patient demographics encountered in real-world clinical settings [46].

The federated learning setup was emulated rather than deployed in a real multi-institutional healthcare network, which limits insight into operational challenges such as network instability, asynchronous updates, and system interoperability [47].

Limited evaluation of privacy techniques. The implementation of differential privacy was not extensively compared to other advanced privacy-preserving techniques (e.g., homomorphic encryption or SMPC), and the tradeoffs between privacy levels and model accuracy were not thoroughly explored [48].

The analysis is based on static imaging data, without considering the temporal aspects of disease progression or longitudinal patient records [49].

The proposed framework does not yet integrate with existing clinical infrastructure such as Electronic Health Records (EHR), Hospital Information Systems (HIS), or Picture Archiving and Communication Systems (PACS). Lack of Model Personalization and Fairness Mechanisms The study does not implement personalization strategies or fairness-conscious techniques, which are essential to ensure equitable performance across heterogeneous client datasets and diverse patient populations [50].

VII. THEORETICAL CONTRIBUTION

This study makes significant theoretical contributions to the evolving discourse on federated learning (FL) in the context of medical imaging and privacy-preserving machine learning, particularly in resource-constrained healthcare environments. The main theoretical advances introduced by this research are as follows: Extending FL paradigms to resource-constrained contexts Existing literature predominantly explores FL under ideal infrastructural conditions [39], such as stable networks and high-performance computing environments. This work challenges this assumption by conceptualizing a federated learning framework explicitly tailored for use in resource-constrained healthcare settings. It presents theoretical foundations for adaptive communication, computationally efficient model architectures, and lightweight privacy mechanisms that allow FL to function effectively where traditional approaches fail [40].Hybrid Privacy Preservation Framework While prior research often treats privacy mechanisms-such as Differential Privacy (DP), Homomorphic Encryption (HE), and Secure Multi-Party Computation (SMPC)-in isolation, this paper proposes a lightweight integration of these techniques [41]. The hybridization not only reduces computational and communication overhead, but also provides a conceptual framework for adaptive privacy, where the strength and type of protection can vary based on institutional or regulatory needs. This theoretical construct addresses the trade-off between privacy and performance with greater flexibility [42].   Federated Learning in Non-IID and Heterogeneous Data Distributions One of the major unresolved issues in the FL literature is the handling of non-IID data, which is common in medical imaging due to different imaging protocols, demographic variations, and institutional biases. This study theorizes the use of adaptive aggregation and model personalization strategies to improve robustness and fairness across clients with different data distributions. It extends the theory of federated optimization by exploring client-specific dynamics, pushing the boundaries of model generalization in heterogeneous federated settings Federated Statistical Preprocessing in FL Workflows [43].The research introduces the notion of decentralized statistical preprocessing, including imputation and normalization, within a federated setup. This novel inclusion extends FL theory by emphasizing privacy-aware preprocessing at the edge to improve data quality without violating institutional data ownership boundaries [44]. This concept fills a notable gap in current FL frameworks, which often assume uniformly pre-processed data across nodes. Empirical -Theoretical Bridge through Real-World Dataset Validation The theoretical constructs introduced in this work are empirically validated using the CheXpert Sampling dataset, enhancing their practical relevance. By anchoring theoretical advances in real-world medical imaging data from resource-limited scenarios, the research supports the development of a generalizable theory of federated learning that is grounded in the operational realities of global healthcare disparities [45].

VIII. CONCLUSION

This study employed statistical analysis using one-way ANOVA to explore potential relationships between various thoracic conditions and comorbidities in a healthcare dataset. The goal was to determine whether specific conditions (e.g., Pneumonia, Lung Opacity, Pleural Effusion) had a statistically significant effect on other clinical outcomes (e.g., Cardiomegaly, Atelectasis, Edema). The results of the ANOVA tests indicated that none of the investigated relationships showed statistical significance at the 0.05 level. All p-values exceeded the threshold, suggesting that within the current dataset, the variations observed across different conditions are likely due to random chance rather than actual interdependence. This finding emphasizes the complexity of medical conditions and highlights the need for larger, more diverse datasets or multi-factorial analysis to capture potential hidden patterns. While the current univariate ANOVA analysis did not yield significant associations, it provides a baseline understanding of statistical dependencies in thoracic disease data.

IX. FUTURE WORK

To expand upon this study and enhance insights into disease correlations, future research can incorporate several advanced methodologies. One promising direction is the application of multivariate analysis techniques such as MANOVA and regression models to evaluate the combined effects of multiple health conditions and covariates on clinical outcomes. Additionally, utilizing larger and more diverse datasets from various hospitals or geographic regions would significantly improve the generalizability and statistical robustness of the findings. The integration of machine learning models, including supervised learning methods like decision trees, random forests, and deep learning architectures, can help uncover non-linear and hidden patterns among clinical features that traditional methods may overlook. Moreover, feature engineering should be employed to create composite indicators—such as severity scores or symptom clusters—that can better represent disease progression and interrelation.

The study can also benefit from temporal analysis, where longitudinal data is used to track how diseases develop over time and how early symptoms may impact future diagnoses. Finally, the development of interactive visualization dashboards will provide clinicians with intuitive tools to explore and interpret disease correlations and trends, thereby supporting more informed decision-making in thoracic imaging and diagnostics. By integrating these strategies, future research can deliver more comprehensive and clinically actionable insights into the complex interdependencies of diseases.

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