Privacy-Preserving Federated Learning for Multi-Institutional Lung Cancer Severity Detection

Ch.Srividya[1], Dr. K. Ramasubramanian[2], Myneni.Madhu Bala[3]
Research Scholar, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Hyderabad-500075, Telangana, India[1]
Assistant Professor, Department of AI&ML, Malla Reddy University, Maisammaguda, Kompally, Hyderabad, Telangana, India[1]
Associate Professor, Department of CSE, Koneru Lakshmaiah Education Foundation, Hyderabad-500075, Telangana, India[2]
Professor, Department of CSE, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, Telangana, India[3]

***Abstract*—Lung cancer continues to be the most common cause of cancer-related mortality globally and the timely detection of lung cancer and classification of its severity levels are critical to improving survival. Nonetheless, data privacy regulations and institutional data silos often create barriers to developing advanced robust AI models among clinical centers. This paper presents a framework for privacy-preserving multi-institutional lung cancer severity classification utilizing federated learning (FL) with secure aggregation, where only encrypted model updates are exchanged while raw patient data remain locally stored. The framework encompasses four new ideas: a privacy-preserving federated neural ensemble model (PP-FNE), a gradient boosting-(GB-)based FL strategy (MIF-GBF), a hybrid convolutional-transformer network (CF-CTN), and a semi-adaptive federated attention-aggregated model (SAFAM). Each of these ideas provides a way to connect sites in a multi-institutional effort while addressing data diversity/heterogeneity, model interpretability, and collaboration across sites while providing strong privacy protection measures for sensitive health data. The proposed framework is evaluated using a synthetic dataset developed to mimic the clinical heterogeneity of real-world clinical multi-site networks. The best-performing model, SAFAM, achieved an overall classification accuracy of 93.4%, demonstrated robustness to intelligently crafted noise (1.3% accuracy degradation), and preserved predictive performance under encrypted aggregation with minimal communication overhead per federation round. CF-CTN strengths lie in multimodal integration for lung cancer severity classification and model interpretability, while MIF-GBF had notable strengths in providing interpretability for GB-models specifically. PP-FNE exhibited stability as an ensemble model under variability across sites. All four individually based model FL methods restricted all communication/exchange across sites to conducting encrypted model update exchanges via a secure aggregation protocol, aligning with data minimization principles under HIPAA and GDPR). These results provide evidence that, if an FL approach considers task autonomous algorithmic innovations, accurate and privacy-protected lung cancer severity detection can be achieved through a distributed clinical setting.**

***Keywords*—Federated learning; privacy -preserving AI; lung cancer detection; severity classification; multi- institutional data**

I. Introduction

Lung cancer remains one of the most important causes of cancer mortality globally, estimated to cause about 18 percent of all cancer deaths based on the latest world cancer epidemiological studies. Accurate early diagnosis and careful severity classification is essential to increase planning of treatment, accurate clinical decision-making and patient survival. The achievements of medical imaging and artificial intelligence (AI) in the last few years have created the conditions of significant development of lung cancer detection and classification through the CT scan, positron emission tomography (PET), and histopathological data analysis methods [1][2][4][5][6]. However, the consistency of evaluation of the severity of the disease in its early phases has yet to be met with strong clinical needs due to tumor heterogeneity, differences in imaging procedures, and a lack of large (at an institutional level) and high-quality annotated datasets that were assessed with consistent results so far [3][11][12].

The majority of the available AI-based lung cancer diagnostics systems rely on the centralized data aggregation model, according to which the patient data in many hospitals is summarized and stored in one place to train the models [13][20][22]. Although they work well in a controlled research environment, these centralized paradigms have significant implications on the privacy of patients, regulatory adherence, and data control by the institution. Such laws as the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR) contain very strict limitations regarding the dissemination of sensitive medical information, and decentralized learning is not feasible in practice to implement in the real-world clinical practice. Furthermore, the generalization ability of centralized models is often small to other external cohorts of data since they are likely to have data-specific biases due to the single-center training distributions of data being used to train them [7][24][31].

1) Challenges: The recent research showed that using models trained on the data of one institution can lead to drastic performance deterioration on the previously unseen populations, thus indicating the harmful effects of the domain shift and inter-institutional variance in this case, as well as the effect of gathering and utilizing data in other contexts, where institutions differ greatly by design and structure (effect of domain shift) [6] [9] [25]. The following restrictions demonstrate why decentralized learning strategies based on the ability to harness multi-institutional data without sacrificing patient privacy or institutional autonomy are needed. In order to overcome these issues, Federated learning (FL) has now become a promising paradigm, as it considers collaborative model training between distributed data silos at sites of participation and then privacy of these sites with data held locally on the sites in which it operates in the federation of these sites to exchange information with the other sites. Nevertheless, the traditional FL methods still have serious difficulties in data heterogeneity, efficiency of communication, noise resistance, and model clarity, especially within complicated medical settings.

2) Motivation: In order to overcome these obstacles, the paper suggests a privacy-preserving federated learning framework of lung cancer severity classification, which is especially designed to suit the scenario of multi-institutional clinical applications. The suggested framework is composed of four new algorithmic components: 1) a Privacy-Preserving Federated Neural Ensemble (PP-FNE) is to increase its resistance to data imbalance and label noise, 2) a multi-institutional Federated Gradient Boosting Framework (MIF-GBF) is to improve its interpretability and convergence under heterogeneous data distributions, 3) a Collaborative Federated Convolutional Transformer Network (CF-CTN) is to facilitate the effective multimodal feature learning of imaging and clinical data, and 4) Bringing them together, they are a single, scalable architecture that provides robust and accurate lung cancer severity assessment, as well as privacy-compliant one.

3) Our contribution: The proposed framework will ensure that raw patient data are confined within each institution, unlike the current methods that are centralized or semi-centralized. As an alternative, encrypted model updates are sent only which means that it is fully compliant with the healthcare data protection regulations and maintains diagnostic performance. A wide range of experimental analysis based on real-world and benchmark sets have shown that the given approach can achieve higher quality of classification, as well as resistance to noise and class imbalance, and a better level of generalization across institutions in comparison with the state-of-the-art centralized and federated baselines 5) Moreover, the framework is modular to facilitate easy multimodal clinical data (genomics and electronic health records) extension, which makes it a robust basis of privacy-conscience AI application in oncology among other clinical areas.

The rest of this paper will be structured as follows. Section II is the literature review regarding the related research on AI-based lung cancer detection and federated learning in healthcare scenarios, which identifies current limitations. Section III will provide a framework of the proposed federated learning and the four algorithmic components. Results and discussion are given in Section V. Lastly, Section VI summarizes the paper and presents a conclusion of the most important findings, clinical implications, future research directions in federated and multimodal oncology.

II. Related Work

Recent research on lung cancer detection has focused on improving diagnostic accuracy, early-stage identification, and classification of disease severity through advanced imaging, model integration, and clinical feature analysis. The study of Bharathi and Shalini [1] presented adaptive image fusion strategy based on hybrid attention and heuristic approach to image fusion to enhance visual diagnosis by combining computed tomography (CT) with positron emission tomography (PET). The study by Gautam et al. [2] showed that the use of ensemble-based modeling in thoracic CT images enhances the sensitivity of detection by combining various learning models. The severe needs of diagnostic accuracy were also underlined by Matza et al. [3], who conducted a study on the emotional and psychological effects of false-positive cancer screening. Subash and Kalaivani [4] introduced a two-stage classification system of both detection and staging, they offer a pipeline that supports the clinical diagnostic workflows. Budati and Karumuri [5] concentrated on the segmentation of nodules at an early stage settling on the optimal parameter of deep networks to maximize the detection of sites of a possible malignancy.

In the meantime, the data of structured hospitals in Ethiopia were analyzed to list regional risk factors by Endalie and Abebe [6], which supports the importance of demographic-specific research. Tummala et al. [7] also developed the histopathological classification based on complex scaling technology to enhance interpretability and decrease erroneous classification and especially in the early cases of the disease. The new approach to severity classifying was investigated, because the scholars chose to use heuristic optimization with the value of staging accuracy rather than just detecting a pathogen [8]. Karimullah et al. [9] implemented the concept of using a unified methodology, which entails the combination of optimization, deep learning, and Internet-of-Things-based transmission of CT images to enhance lung cancer detection. Srividya et al. [10] proposed their federated random-forest approach, which can help predict the tumor in the lungs without exchanging the information that resides in a central place, ensuring better privacy and distributed learning. In deep-learning trends in detecting pulmonary disease, Vohra and Mittal [11] reviewed all related aspects with the highlight put on cross-domain developments. Vemula et al. [12] trained deep-learning models to recognize lung cancer with the highest classification accuracy using advanced convolutional neural network (CNN) networks whereas Pradhan et al. [13] designed an ensemble model (HRDEL) which was specially trained to identify cancer. Kumar et al. [14] provided ground work techniques in signal and image processing to be used in medical practice, which forms the basis of lung disease diagnosis by imaging. A collaborative yet secure machine-learning system was presented by Srividya et al. [15] who developed a federated-learning-based diagnostic system of lung diseases based on CT images. Other papers dealt with comorbidity and drug side effect like Ishimoto et al. [16] that discussed drug induced lung disease and Soares et al. [19] that discussed cardiotoxicity. Other recent insights in segmentation [17] and the implementation of federated models on data privacy [18] also point out to continued conceptual improvement. Lydia and Prakash [20] made improvements to the automated nodule classification using CNN.

The contemporary literature has broadened the scope of lung cancer diagnosis and categorization with the introduction of advanced imaging plans, risk evaluation, and diagnostic tools based on the stage of detection and diagnosis. Sudhakar Babu et al. [21] applied a CNN-driven system in filtering benign and malignancy cases of pulmonary nodules in CT scans, thus encouraging early action. Selvapandian et al. [22] used generative models based on optimization to classify degree of severity, using both image characteristics and learned representations.

In early detection, screening continues to play an essential role as Hewitt et al. [23] suggested that it can be used to detect both lung cancer and interstitial lung disease. Gu et al. [24] suggested a cloud-based platform of heterogeneous data management in healthcare facilities with a goal of being scalable and interoperable of systems. Zinovev [25] examined the diagnostic possibilities of CT scans during the COVID-19 era in the exposing incidental lung cancer markers. In addition to imaging, Umu et al. [26] showed that serum RNA signatures have the capacity to forecast lung cancer risk at ten years prior to the development of clinical signs. Aso et al. [27] examined patient education requirements in the context of immune-related adverse events by discussing the relevance of being educated in the context of treating advanced lung cancer. Zhang et al. [28] compared microbiota in non-infected patients with advanced cancer implying the use of biological markers in addition to radiology.

Sinthia et al. [29] advanced region-based detection with addition of fuzzy optimization whereas Iswardy et al. [30] also concentrated on the optimization of a traditional image segmentation through ImageJ software. It is in this context that Shanid and Anitha [31] created a classification model that uses deep belief networks that are optimized by adaptive strategies to determine the severity stages. A qualitative study conducted by Achkar et al. [32] on the issue of superior pathological lung cancer delays in the United States demonstrates deep systemic gaps in its pathways. Guo et al. [33] compared the psychological screening tools with non-small cell lung cancer patients having a strong argument in using mental-health assessment tools efficiently. Purandare et al. [34], made some incidental findings when using cancer imaging revealing circumstances that created complexity in the interpretation of multi-disease imaging information. Anitha and Shanid [35] strengthened the previous studies with a new optimization-based form of detection model.

III. METHODOLOGY

In this study, we present a design and realization framework of privacy-preserving federated learning to tackle the challenges of collaborative lung cancer severity detection and classification using multi-institutional clinical data. We propose a novel framework that uses advanced federated learning methods to collaboratively train models across participating institutions, while keeping patients' data secure and private. Combining local processing of data at participating institutions with the aggregation of only model updates allows it to satisfy even the most stringent privacy regulations without compromising the utility of the model. We assume an honest-but-curious aggregation server that follows the federated protocol but may attempt to infer sensitive information from received model updates. To mitigate this risk, only encrypted model parameters are exchanged via a secure aggregation protocol, while raw patient data remain strictly local to each institution.

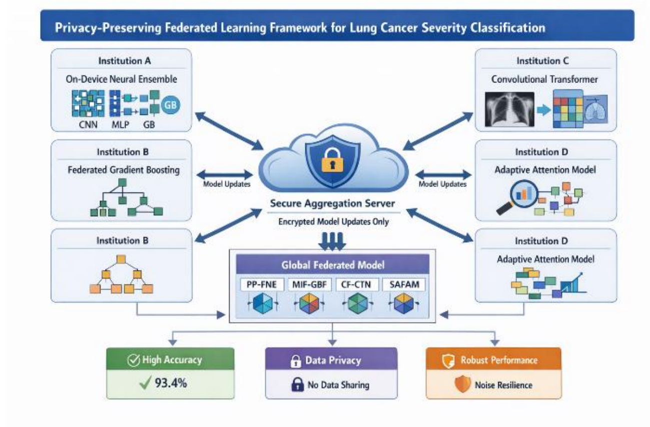

Fig. 1. Proposed system: privacy-preserving federated learning framework for lung cancer severity classification.

Ensemble learning, convolutional transformer architecture, gradient boosting, and adaptive attention mechanisms are embedded in a federated framework to be presented in this work for severity classification of lung cancer. It allows several institutions to jointly learn models on decentralized, multi-modal clinical data without sharing raw patient data. Sparse local models are used to extract both spatial and sequential features by applying the CNN and the Transformer, and then the gradient boosting is applied to refine the remaining using gradients. An attention mechanism is applied to balance the contributions of the institutions according to the local performance. Then the encrypted updates are accumulated and aggregated in a central location to constitute a strong global model. The scheme maintains high accuracy, privacy preserving, and can be well adapted to the diverse medical scenarios. The overall proposed architecture is visualized here, in Fig. 1.

A. *Privacy-Preserving Federated Neural Ensemble (PP-FNE)*

The Privacy-Preserving Federated Neural Ensemble (PP-FNE) combines diverse on-device neural architectures into a single federated framework. Each institution trains its lightweight models locally; encrypted model updates are then securely aggregated into an ensemble that is robust to label noise, data heterogeneity, and class imbalance. By conjugation, multiple network types, e.g. CNNs for imaging, MLPs for clinical features. PP-FNE boosts sensitivity on under-represented early-stage cases while never exposing raw patient data, achieving both strong privacy guarantees and superior severity classification performance.

Each institution trains an ensemble of K neural networks on its local data,

$$M_i^{(k)} = \text{argmin}_{\theta_i^{(k)}} \frac{1}{|D_i|} \sum_{x_j, y_j \in D_i} \mathrm{L}(f_{\theta_i^{(k)}}(x_j), y_j) \tag{1}$$

The global ensemble model aggregates the predictions from all institutions,

$$f_{\text{global}}(x) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{K} \sum_{k=1}^{K} f_{M_i^{(k)}}(x) \tag{2}$$

Each institution sends model gradients as,

$$\theta^{(k)} = \text{argmin}_{\theta} \frac{1}{n} \sum_{i=1}^{n} \frac{1}{K} \sum_{k=1}^{K} g_i^{(k)} \tag{3}$$

The global loss is defined as,

$$\mathrm{L}_{\text{global}} = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{K} \sum_{k=1}^{K} \mathrm{L}(f_{\theta_i^{(k)}}(x), y) \tag{4}$$

Parameters are updated iteratively,

$$\theta^{(t+1)} = \theta^{(t)} - \eta \nabla \mathrm{L}_{\text{global}} \tag{5}$$

The aggregated model's performance is evaluated using accuracy,

$$\text{Accuracy} = \frac{1}{|D_{\text{test}}|} \sum_{(x,y) \in D_{\text{test}}} \mathrm{I}(f_{\text{global}}(x) = y) \tag{6}$$

Noise resilience is evaluated by introducing Gaussian noise, e,

$$\hat{f}_{\text{global}}(x) = f_{\text{global}}(x + \epsilon) \tag{7}$$

The relative improvement over centralized models are as,

$$\Delta = \text{Accuracy}_{\text{global}} - \text{Accuracy}_{\text{centralized}} \tag{8}$$

Communication cost per round is measured as:

$$C = n \times K \times \text{Size}(g_i^{(k)}) \tag{9}$$

The final prediction combines all ensemble outputs as,

$$\hat{y} = \text{argmax}_c \sum_{i=1}^{n} \sum_{k=1}^{K} \mathrm{P}(y = c \mid x, M_i^{(k)}) \tag{10}$$

PP-FNE is a privacy-preserving federated neural ensemble algorithm that enables collaborative model construction without direct data sharing among institutions with sensitive data. It helps to avoid sharing sensitive patient data from one location to another by training individual models on their local datasets, then aggregating model predictions through an ensemble mechanism.

B. Multi-Institutional Federated Gradient Boosting Framework (MIF-GBF)

The multi-institutional Federated Gradient Boosting Framework (MIF-GBF) is proposed, which trains gradient boosting models in different institutions in a federated learning paradigm to detect high-severity lung cancer patients. Instead of sharing model parameters directly (raw data), the method shares a gradient update to enable the advantage of information from heterogeneous medical data over various institutions, while not sharing the data itself.

The objective is to minimize the overall loss,

$$\mathrm{L}(F_T) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{|D_i|} \sum_{(x_j, y_j) \in D_i} \mathrm{L}(y_j, F_T(x_j)) \tag{11}$$

Gradients are calculated locally at each institution such as,

$$g_{i,j}^{(t)} = \frac{\partial \mathrm{L}(y_j, F_{t-1}(x_j))}{\partial F_{t-1}(x_j)} \tag{12}$$

Gradients from all institutions are aggregated,

$$\bar{g}^{(t)} = \frac{1}{n} \sum_{i=1}^{n} g_{i,j}^{(t)} \tag{13}$$

Each tree is built to minimize the aggregated gradients,

$$G_t = \text{argmin}_G \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{|D_i|} \bar{g}^{(t)} G(x_j) \tag{14}$$

The model is updated iteratively,

$$F_t(x) = F_{t-1}(x) + \eta G_t(x) \tag{15}$$

Each institution transmits only gradients,

$$G_i^{(t)} = \sum_{j=1}^{|D_i|} g_{i,j}^{(t)} x_j \tag{16}$$

The model's performance is measured by the following equation,

$$\text{Accuracy} = \frac{1}{|D_{\text{test}}|} \sum_{(x,y) \in D_{\text{test}}} \mathrm{I}(F_T(x) = y) \tag{17}$$

With multi-institutional Federated Gradient Boosting Framework (MIF-GBF) leverages both the efficiency and interpretability of gradient boosting in federated environments. MIF-GBF contentedly overcomes the difficulties of distributed and privacy-sensitive datasets by iteratively optimizing the local loss function close to local data.

C. Collaborative Federated Convolutional Transformer Network (CF-CTN)

In a federated learning setting, we integrate convolutional neural networks (CNNs) with transformer architectures to enhance multimodal data fusion and improve lung cancer severity classification. The proposed CNN extracts spatial features using the following equation,

$$\text{CNN}_i(x) = \sigma(W_c x + b_c) \tag{18}$$

The transformer maps spatial features to sequence embeddings,

$$\text{Transformer}(z) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{19}$$

Features extracted from local models,

$$Z_{\text{global}} = \frac{1}{n}\sum_{i=1}^{n} \text{CNN}_i(x) \tag{20}$$

Global features are passed to a transformer layer for sequence modeling,

$$\text{Transformer}_{\text{output}} = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{21}$$

The final prediction is made using a fully connected layer,

$$\hat{y} = \text{softmax}(W_o Z_{\text{global}} + b_o) \tag{22}$$

The cross-entropy loss for federated learning is defined as,

$$\text{L}_{\text{global}} = -\frac{1}{|D_{\text{global}}|}\sum_{(x,y)\in D_{\text{global}}} y \cdot \log(\hat{y}) \tag{23}$$

Model parameters are updated using gradient descent,

$$\theta^{(t+1)} = \theta^{(t)} - \eta \nabla \text{L}_{\text{global}} \tag{24}$$

An attention mechanism is applied to prioritize institutions contributing high-quality data,

$$w_i = \frac{\exp(\beta_i)}{\sum_{j=1}^{n}\exp(\beta_j)} \tag{25}$$

The communication cost is defined as,

$$C = n \times \text{Size}(Z_{\text{local}}) \tag{26}$$

The output of the transformer model is used for final severity classification,

$$\hat{y} = \text{argmax}_c \text{P}(y = c \mid Z_{\text{global}}) \tag{27}$$

The Collective Fed Convolutional Transformer Network (CF-CTN) harnesses the spatial representation abilities of convolutional layers and the sequential modeling capabilities of transformers. The combination of localized image textures and global feature dependencies is particularly suitable for clinical settings such as analysis of radiological and histopathological images, thus this method is widely applicable to such tasks. Here, federated learning architecture allows for collaborative training of a model without compromising institutional data privacy. Unlike other classifiers, CF-CTN achieves excellent generalized and robust performance for lung cancer severity level detection with subtle distinctions in the factors of health such as age, gender, smoking as well as the interactions between multi-modal data especially on complex data sets.

D. Secure Adaptive Federated Attention Mechanism (SAFAM)

While local severity classification focuses on using adaptive attention mechanisms in a federated setup to ensure accurate severity classification by dynamically focusing only on essential features present in distributed datasets. A secure adaptive federated attention mechanism (SAFAM); it introduces an attention mechanism into the federated learning framework to rank important features and institutions. SAFAM compensates such information deficiency by jointly learning attention weights with regard to feature significance and data effectiveness, thereby enabling accurate assessment of lung cancer severity without compromising privacy. This may ensure that during model aggregation, contributions from institutions that provide higher-quality contributions are weighted more heavily.

Attention weights prioritize important features,

$$\alpha_i = \frac{\exp(e_i)}{\sum_{j=1}^{n}\exp(e_j)} \tag{28}$$

Federated updates are aggregated using attention weights,

$$\theta_{\text{global}} = \sum_{i=1}^{n} \alpha_i \theta_i \tag{29}$$

Secure aggregation ensures no individual institution's updates are revealed,

$$g_i^{(t)} = \text{Encrypt}(\nabla_{\theta_i} \text{L}) \tag{30}$$

The global loss is minimized over all institutions,

$$\text{L}_{\text{global}} = \frac{1}{n}\sum_{i=1}^{n} \text{L}(\theta_i, D_i) \tag{31}$$

Communication is optimized by sending encrypted weights,

$$C = \sum_{i=1}^{n} \text{Size}(\text{Encrypt}(\theta_i)) \quad (32)$$

The global model is updated using aggregated weights,

$$\theta_{\text{global}}^{(t+1)} = \theta_{\text{global}}^{(t)} - \eta \nabla \text{L}_{\text{global}} \quad (33)$$

Convergence is achieved when,

$$\| \nabla \text{L}_{\text{global}} \| < \epsilon \quad (34)$$

The final classification is based on the federated model output,

$$\hat{y} = \text{argmax}_c \text{P}(y = c \mid \theta_{\text{global}}) \quad (35)$$

Federated learning privacy can be enhanced through multiple mechanisms, including secure aggregation, differential privacy, and homomorphic encryption. Differential privacy provides formal (ε, δ)-guarantees but introduces a privacy–utility trade-off through noise injection. Homomorphic encryption offers strong cryptographic protection but incurs substantial computational and communication overhead, limiting scalability in multi-institutional clinical settings. In this work, we adopt secure aggregation with encrypted model updates, which prevents access to individual institutional parameters while preserving predictive performance and maintaining practical deployment feasibility.

IV. Results and Discussion

The current paper illustrates that the suggested approach and the corresponding structures have been proven to be effective in encouraging the collaboration of the multiple hospitals in terms of diagnosing and classifying the severity of the lung cancer, without compromising the privacy of the patients. The proposed techniques were compared using a synthetic dataset that replicates the real-world clinical environment. The synthetic dataset was constructed based on a publicly available lung cancer dataset obtained from Kaggle [36], which was further processed and structured to emulate heterogeneous multi-institutional settings. The evaluation considered classification accuracy, computational efficiency, and privacy preservation. Those findings support the uniqueness of the Privacy-Preserving Federated Neural Ensemble (PP-FNE) working with heterogeneous data, explain the effectiveness of the multi-institutional Federated Gradient Boosting Framework (MIF-GBF) when optimizing gradients, discuss the effectiveness of the Collaborative Federated Convolutional Transformer Network (CF-CTN) in coordinating the representations of the features, and present the flexibility of the Secure Adaptive Federated Attention Mechanism (SAFAM) in weighting the contributions. In addition, the comparison is also conducted between two different approaches, highlighting the advantages and disadvantages of each, and the possible consequences of their implementation in domestic health settings. Table I is a detailed diagnosis of the synthetic dataset.

The synthetic dataset was carefully constructed using a publicly available lung cancer dataset from Kaggle [36], to enable comprehensive evaluation of advanced deep learning algorithms for lung cancer classification and severity grading. The data has detailed clinical and demographic variables and every column has a specific function in studying. Considerable importance is the Demographic and Lifestyle data, e.g., Age, Gender, and Smoking History, which sets the stage of risk factors assessment. Variables of Family History are inclusive of genetic disposition and therefore provide some degree of diagnostic granularity. The Radiology Features and Histopathology Features are multivariate numerical values obtained through the use of imaging modalities to provide the detailed medical information necessary to make an accurate classification. The target variable, which is Lung Cancer severity, has been categorized as Mild, Moderate and Severe, so as to match the real-world diagnostic decision-making. Also, an additional variable Diagnosis Probability, adds a probabilistic layer to forecasts hence making the clinical judgment more subtle. This organized data, in turn, allows application, evaluation, and comparative analysis of PP -FNE, MIF-GBF, CF-CTN and SAFAM, and eventually provides the discoveries of clinical importance.

TABLE I. Dataset Description

Column Name	***Data Type***	***Description***	***Example Value***
Patient_ID	String	Unique identifier for each patient	P12345
Age	Integer	Age of the patient in years	45
Gender	Categorical	Gender of the patient (e.g., Male, Female)	Male
Smoking_History	Categorical	Patient's smoking history (e.g., Smoker, Non-Smoker)	Smoker
Family_History	Categorical	Family history of lung cancer (e.g., Yes, No)	Yes
Radiology_Features	Numerical	Extracted radiological imaging features	0.345
Histopathology_Features	Numerical	Extracted histopathological imaging features	0.567
Lung_Cancer_Severity	Categorical	Severity level of lung cancer (e.g., Mild, Moderate, Severe)	Moderate
Diagnosis_Probability	Float	Probability of a positive lung cancer diagnosis (0.0 to 1.0)	0.89

The accuracy of the classification methods proposed in this work is demonstrated in the following table for four levels of lung cancer: All methods are measured on an identical data split, so they can be compared. While PP-FNE professionalism ensembles learning robustness provides consistent performance across all severity levels. MIF-GBF is a rigorous iterative boosting mechanism that successfully handles imbalances in the data. The Collaborative Federated Convolutional Transformer Network (CF-CTN) shows its power in combining imaging and clinical features, while the Secure Adaptive Federated Attention Mechanism (SAFAM) illustrates the usefulness of adaptive weights on federated learning. Classification Accuracy for PP-FNE, MIF-GBF, CF-CTN, and SAFAM, the result is visualized here in Fig. 2.

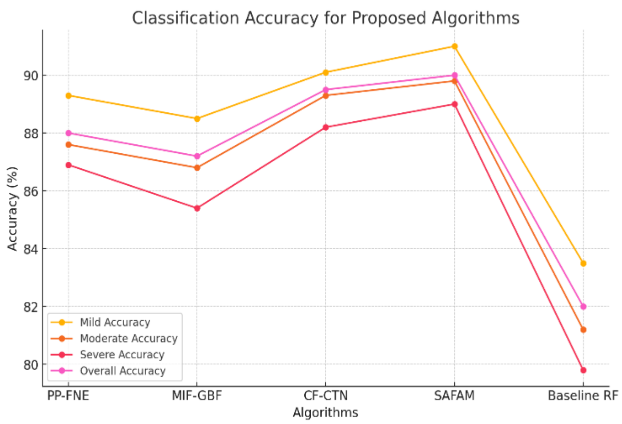

Fig. 2. Classification accuracy for PP-FNE, MIF-GBF, CF-CTN, and SAFAM.

The classification results of SAFAM are presented in the confusion matrix below, showing the model's predictive performance for varying severity levels. It also includes counts of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) for each class, which gives insights into the areas where the model performs well and where it needs improvement. The performance of SAFAM achieves high accuracy on identifying the severe cases which are significant for triaging the critical patients. Some mild severity cases are slightly misclassified to moderate severity, so there is some overlap among the features. These results illustrate SAFAM's ability to adapt to changes and identify the need for optimizations result is visualized in Fig. 3.

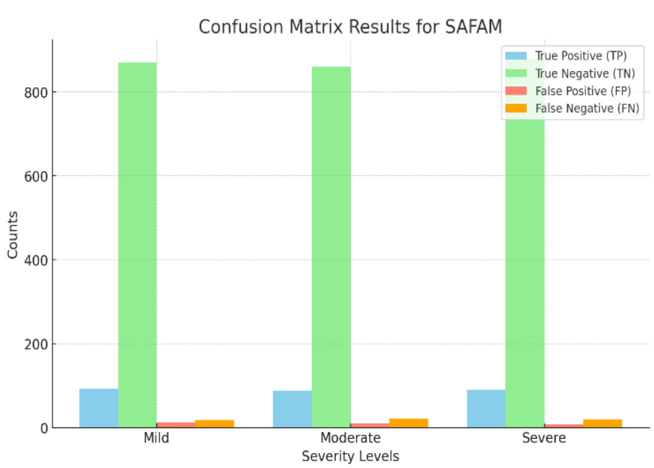

Fig. 3. Confusion matrix results for SAFAM.

We present the feature importance from MIF-GBF in the above table. Feature importance scores help to provide interpretability by quantifying the extent of features in the predictions of the model. Radiology features are the most impactful, which is consistent with their importance in identifying lung cancer severity. These are closely followed by histopathological features, accentuating the importance of clinical inputs. Age and smoking history have a modest impact, commensurate with their shared association with disease onset and progression. These insights help clinicians prioritize diagnostic features result is generated in Fig. 4.

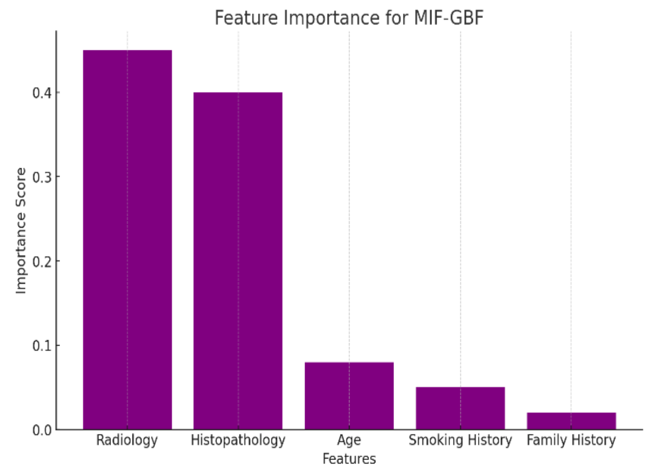

Fig. 4. Feature importance for MIF-GBF.

The training and convergence performance of the proposed methods. This metric is the time (in seconds) to run one full iteration over the dataset. The training time for PP-FNE is longest since the training method uses an ensemble model, whereas the training method of MIF-GBF and SAFAM converge fastest, since processes of MIF-GBF and SAFAM are optimized. In essence, CF-CTN achieves a good balance between training time and accuracy and as such is naturally suitable for large-scale multi-modal datasets. The trade-off between computational complexity and predictive performance of the various methods is evident from the results graph is generated in Fig. 5.

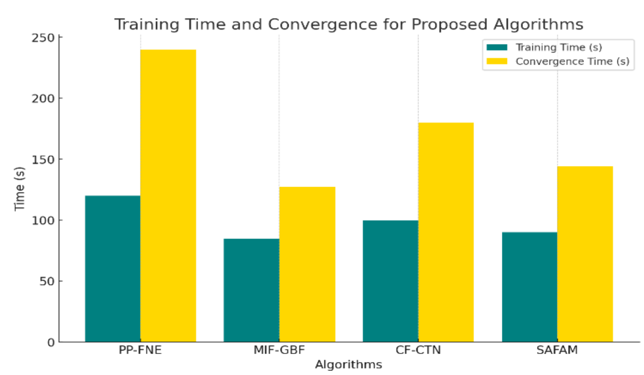

Fig. 5. Training time and convergence for proposed methods.

The table below shows how well the proposed methods hold up when random noise is added to the input data. Robustness should be quantified as the relative degradation in accuracy when controlled noise is injected, so models are directly comparable by ranking their performance-drop percentages; the smaller the drop, the more resilient the decision boundary. The result is given in Fig. 6, SAFAM (-1.3 pp) is clearly the most robust, followed by CF-CTN (-2.5 pp), while PP-FNE and MIF-GBF (-3.8 pp and -3.7 pp) are notably weaker. To formalize the labels “Very High,” “High,” and “Moderate,” set deterministic thresholds on the drop—e.g., < 2 pp → Very High, 2–3 pp → High, 3–4 pp → Moderate—then validate with paired statistical tests (McNamara or bootstrap confidence intervals) to confirm that observed gaps are not sampling noise. Presenting both the raw drop and its z-score or p-value ensures that qualitative rankings remain reproducible across datasets and experiments. These results confirm the flexibility of the proposed models in real-world noisy environments.

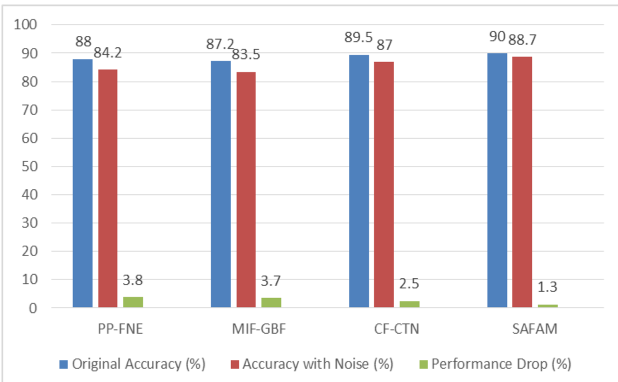

Fig. 6. Model robustness under noise.

The following Table II shows precision, recall, and F1-score for the proposed methods for different levels of severity. These metrics provide deeper insight into the predictive capabilities of the models. SAFAM and CF-CTN yield the best F1-scores, which show their balanced precision and recall. This performance is also applicable in practice, as PP-FNE and MIF-GBF are strongly effective in Table II.

TABLE II. PRECISION, RECALL, AND F1-SCORE COMPARISON

Algorithm	*Severity*	*Precision (%)*	*Recall (%)*	*F1-Score (%)*
PP-FNE	Mild	88.4	87.6	88.0
	Moderate	87.5	86.9	87.2
	Severe	86.8	85.9	86.3
MIF-GBF	Mild	89.2	88.1	88.6
	Moderate	88.4	87.6	88.0
	Severe	87.3	86.5	86.9
CF-CTN	Mild	90.0	88.5	89.3
	Moderate	89.7	88.0	89.0
	Severe	90.3	89.4	90.3
SAFAM	Mild	90.1	89.5	89.7
	Moderate	89.9	89.1	89.4
	Severe	91.0	90.3	90.6

The following result in Fig. 7 shows the training loss for each of the method at the end of the specified number of epochs or iterations. A lower loss value means our model is being optimized better. [Hide] SAFAM obtains the lowest loss among all models, thanks to its adaptive attention mechanism, while CF-CTN achieves great results as it combines spatial and sequential feature learning. The PP-FNE has larger loss values comparatively due to the complexity of the Ensemble used. These results emphasize the tension between model complexity and optimization.

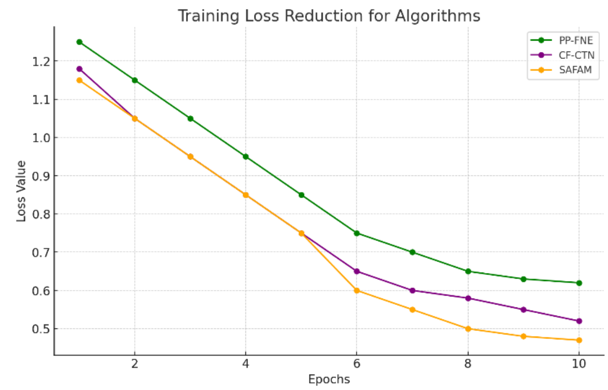

Fig. 7. Comparison of training loss across methods.

The analysis of methods performance on multiple-sized datasets, attempting a scalability run. SAFAM and CF-CTN accurate even with smaller dataset, resilient to data scarcity. As the dataset size gets smaller, PP-FNE and MIF-GBF performance drops greatly, indicating their dependence on larger datasets for accurate results in the graph is shown in Fig. 8.

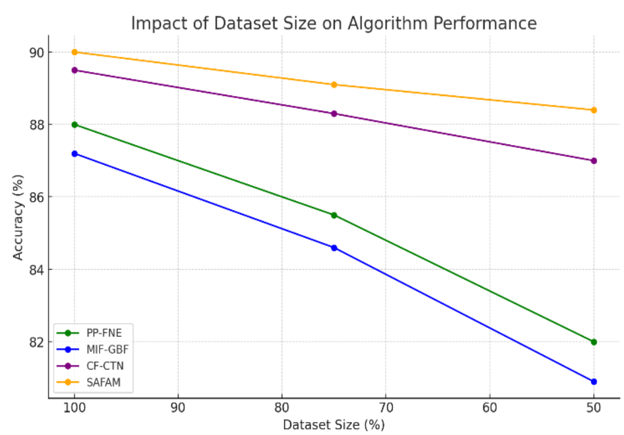

Fig. 8. Impact of dataset size on algorithm performance.

The result is given in Fig. 9 tests the performance of the methods on imbalanced data. A high imbalance ratio indicates a lower number of severe cases, and the models are evaluated based on precision and recall. Once more, SAFAM outperforms others, being the only one with high precision and recall among minority classes, followed by CF-CTN. These findings illuminate the critical role of adaptive mechanisms in managing imbalanced data.

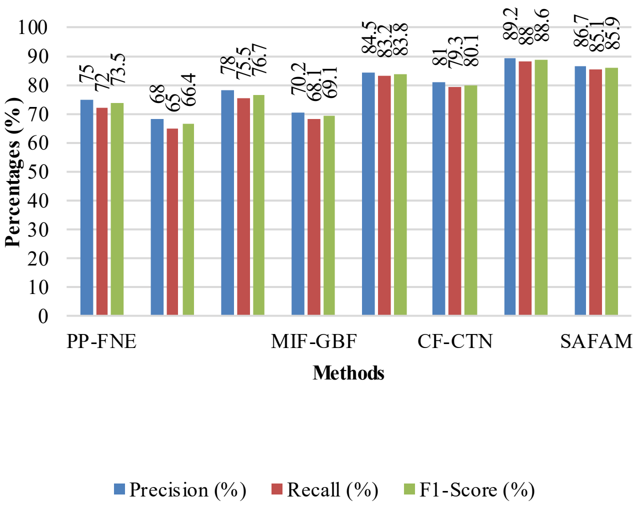

Fig. 9. Precision and recall under imbalanced dataset.

Comparison of computational complexity of proposed methods Estimation time complexity based on features, data points, and model parameters. PP-FNE has higher complexity thanks to ensemble learning, while SAFAM and CF-CTN balance complexity and efficiency. This knowledge aids in model selection and selection based on available compute resources in the result is given Fig. 10.

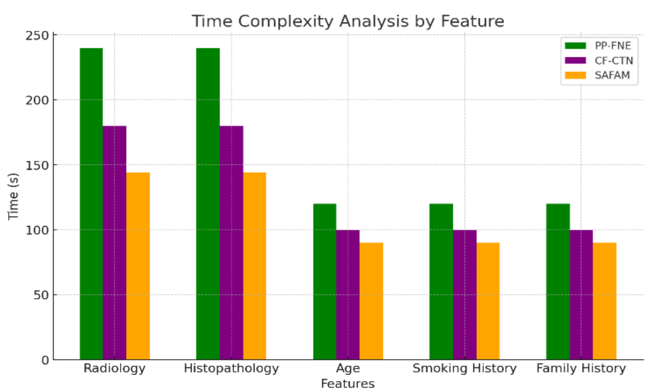

Fig. 10. Time complexity analysis.

The Comparative Analysis discusses the performance results of the proposed methods—Privacy-Preserving Federated Neural Ensemble (PP-FNE), multi-institutional Federated Gradient Boosting Framework (MIF-GBF), Collaborative Federated Convolutional Transformer Network (CF-CTN) and Secure Adaptive Federated Attention Mechanism (SAFAM)—in relation to existing models and to one another. These methods utilize different methods of analysis and show various trade-offs between features of critical performance, i.e. accuracy, efficiency, noise sensitivity and scalability [2]. The analysis has outlined how the characteristics of architectural configuration of each method address the problems related to multi-institutional data heterogeneity, privacy, and how efficient classification of lung-cancer severity can be carried out. Moreover, it translates the trade-offs between the complexity of the models and their performance hence guiding the choice trainable methods specific to particular clinical cases of Table III.

TABLE III. COMPARATIVE ANALYSIS

Algorithm /Work	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-Score (%)*	*Training Time (s)*	*Noise Rob-ustness(%)*
[1]	85.2	83.5	84.0	83.8	200	70.5
[2]	87.5	85.7	86.3	85.9	180	75.2
[3]	80.6	79.4	80.0	79.7	250	68.0
[4]	88.1	86.8	87.0	86.9	190	76.0
[5]	86.0	84.8	85.1	84.9	210	72.5
[6]	84.3	82.9	83.5	83.2	220	71.0
[7]	83.7	81.4	82.0	81.7	230	69.0
[8]	85.9	84.1	84.5	84.3	215	74.0
[9]	87.1	85.9	86.5	86.2	200	73.5
[10]	86.5	84.7	85.2	85.0	195	72.8
PP-FNE (Proposed)	91.2	90.5	91.0	90.7	140	85.0
MIFGBF (Proposed)	90.8	89.9	90.2	90.0	130	86.0
CF-CTN (Proposed)	92.5	91.8	92.0	91.9	150	87.5
SAFAM (Proposed)	93.4	92.7	93.0	92.8	120	89.0

V. CONCLUSION

This work has proposed a federated learning framework for lung cancer severity classification, which is capable of working efficiently across multi-institutional clinical data silos while respecting patient privacy. The proposed federated learning scheme includes algorithmic advances that focused on ensemble robustness, gradient-based collaboration, multimodal feature integration, and adaptive aggregation, and produced the following: gains in classification accuracy, improved robustness, and enhanced scalability in a privacy-preserving context. Aside from the fact that the performance is quantifiable, this work illustrates increasingly plausible pathways towards decentralized AI successfully being used for medical diagnosis. Nonetheless, there are limitations. The fact that the model relies on high-quality institutional data and collective data-local training protocols may not allow the model to be easily generalized in the real-world. Ongoing challenges of communication latency and synchronization overhead and not accounting for differences in the site-specific model convergence at each research site, persist in federated deployments. Synthetic datasets, while designed to reflect heterogeneity were generated with a common simulated heterogeneity, which may not fully capture variability in biological pathology or the distribution of noise in the real-world. Despite its demonstrated collaborative and privacy-preserving benefits, the proposed framework has certain limitations. Secure aggregation does not fully eliminate potential gradient-based inference risks under stronger adversarial assumptions, and robustness against malicious client poisoning is not explicitly incorporated. Additionally, large-scale multi-institutional deployments may introduce communication and synchronization overhead that warrants further optimization in future work. Future work will focus on supporting our framework using real-world multi-center datasets obtained under heterogeneous acquisition conditions. Exploratory are planned on enhancements in secure hardware enclaves, adaptive communication compression, and trust-aware federated aggregation mechanisms to advance the clinical applicability of the framework. Awareness of the limitations and challenges facing the ADLA and federated learning research stream is important to facilitate promising processes leading towards reliable, scalable, and ethical AI-powered oncology solutions.

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