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A Comparative Review of Privacy-Preserving Federated Learning Algorithms for Allergy and Asthma Severity Assessment

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Abstract

The application of artificial intelligence (AI) for allergy and asthma severity assessment involves the processing of highly sensitive patient data, raising significant concerns related to privacy, security, and regulatory compliance [1]. Federated learning (FL) is a decentralized learning approach that allows multiple healthcare entities to jointly train models without exchanging raw patient data. [2]. This paper presents a comparative review of privacy-preserving federated learning algorithms, including Federated Averaging (FedAvg) [2] and Federated Proximal (Fed Prox) [3], in conjunction with classical and advanced machine learning models such as logistic regression, random forest, gradient boosting, and Long Short-Term Memory (LSTM) networks. The reviewed algorithms are evaluated based on key performance metrics, including predictive accuracy, privacy protection, computational complexity, and scalability in multi-institutional healthcare environments. In addition, privacy-enhancing techniques such as secure aggregation [4], differential privacy [5], and homomorphic encryption [6] are examined for their effectiveness in mitigating data leakage while maintaining model performance. The analysis indicates that hybrid frameworks integrating federated learning with ensemble or deep learning models and robust privacy mechanisms provide an optimal balance between model accuracy and data confidentiality. These findings offer valuable insights for the development of secure, scalable, and high-performance AI systems for real-world allergy and asthma severity assessment in distributed healthcare networks.

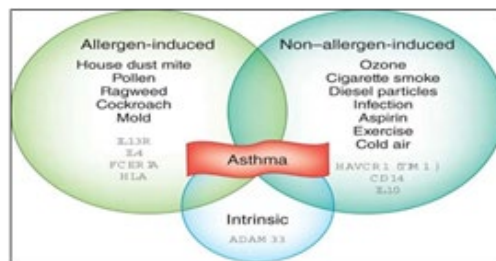


Fig. 1 Allergy-induced Asthma

Introduction to Algorithmic Approaches

Allergy and asthma severity assessment requires the analysis of sensitive patient data such as clinical records, lung function tests, wearable sensor data, and environmental exposure information [7]. Traditional centralized machine learning approaches pose serious privacy risks because patient data must be shared across institutions, often violating healthcare data protection regulations [1]. Federated learning (FL) mitigates this issue by allowing distributed institutions to jointly train models without sharing raw datasets [2]. This section reviews key machine learning and privacy-preserving algorithms used in federated environments for allergy and asthma severity assessment.

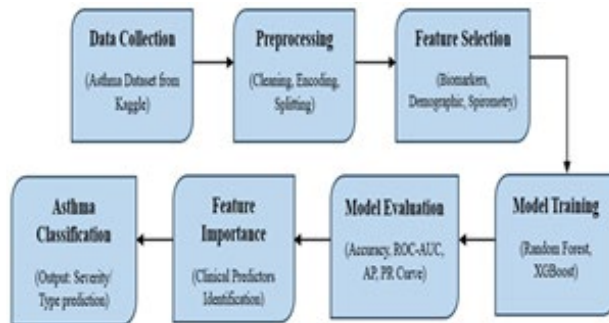


Fig. 2 Algorithmic Approaches

Federated Learning Algorithms

Federated Averaging (FedAvg)

FedAvg is the most widely adopted federated learning algorithm [2]. Each participating institution trains a local model on-site using its patient data, and only the resulting parameter updates are shared with the central server for aggregation. In asthma severity assessment, FedAvg has been applied to classify disease stages (mild, moderate, and severe) using spirometry data, symptom scores, and medication history [8]. Its simplicity and communication efficiency make it suitable for large-scale healthcare systems, although its performance may degrade under heterogeneous data distributions [3].



Fig. 3 Federated Learning challenges

Federated Proximal (FedProx)

FedProx extends FedAvg by introducing a proximal regularization term to mitigate client drift caused by non-identically distributed (non-IID) data [3]. Since allergy and asthma data vary due to environmental, geographic, and lifestyle factors, FedProx improves convergence and robustness in multi-center healthcare studies [9].

Personalized Federated Learning

Personalized federated learning allows each client to maintain a customized local model while benefiting from shared global knowledge [10]. In asthma management, personalized FL supports patient-specific severity prediction by adapting models to individual symptoms, triggers, and treatment responses, thereby improving clinical relevance and prediction accuracy [11].

Machine Learning Algorithms for Severity Assessment

Logistic Regression

Logistic regression is commonly used for asthma and allergy severity classification due to its simplicity and interpretability [12]. Within a federated framework, it enables collaborative learning while allowing clinicians to interpret the influence of clinical risk factors such as allergen exposure and lung function decline.

Support Vector Machines (SVM)

SVMs are effective for distinguishing severity levels in allergy and asthma datasets with limited sample sizes [13]. Federated SVM models allow multiple institutions to train classifiers collaboratively without sharing sensitive patient data [14].

Decision Trees

Decision trees provide rule-based severity assessment and are widely used in clinical decision support systems [15]. In federated settings, they enable transparent modeling of asthma symptoms and allergy triggers while preserving data privacy.

Random Forest

Random Forest operates as an ensemble model by combining multiple decision trees, thereby increasing classification accuracy and robustness in complex datasets [16][4]. Federated Random Forest models are particularly useful for asthma exacerbation risk prediction, as they handle missing values and complex feature interactions effectively [17].

Gradient Boosting Algorithms

Advanced gradient boosting techniques like XGBoost and LightGBM are widely recognized for their robust predictive capabilities and ability to analyze feature relevance [18][5]. When integrated with federated learning and privacy-preserving mechanisms, these models support accurate allergy severity scoring while maintaining data confidentiality [19].

Deep Learning Algorithms in Federated Settings

Artificial Neural Networks (ANN)

ANNs capture complex nonlinear relationships among clinical, environmental, and behavioral factors [20]. Federated ANNs enable collaborative training across healthcare institutions without exposing sensitive patient data.

Convolutional Neural Networks (CNN)

CNNs are widely used for medical image analysis and lung sound classification [21]. In federated setups, CNNs enable privacy-preserving training for wheeze detection and airway inflammation analysis [22].

Long Short-Term Memory (LSTM)

LSTM architectures efficiently capture temporal dependencies in time-series data, such as peak flow measurements and wearable sensor data streams [23][7]. Federated LSTM models support early detection of asthma exacerbations by analyzing longitudinal patient data securely [24].

Privacy-Preserving Algorithms

Secure Aggregation

Secure aggregation ensures that the central server cannot access individual model updates during federated training [4]. This technique is critical for maintaining confidentiality in federated allergy and asthma applications.

Differential Privacy

Differential privacy introduces controlled noise into model updates to prevent re-identification of individuals [5]. It provides formal privacy guarantees but may slightly reduce predictive accuracy in federated asthma severity assessment systems [25].

Homomorphic Encryption

Homomorphic encryption enables computation on encrypted model parameters [6]. Although computationally expensive, it offers strong privacy protection for highly sensitive medical datasets [26].

Table I. Performance Comparison of Algorithms in Federated Allergy and Asthma Severity Assessment

S.No	Algorithm	Model Accuracy	Privacy Protection	Computational Complexity	Suitability for Healthcare
1	Federated Averaging (FedAvg)	Medium-High	High	Low	Highly suitable
2	Federated Proximal (FedProx)	High	High	Medium	Highly suitable
3	Personalized Federated Learning	Very High	Very High	High	Excellent
4	Logistic Regression (FL-based)	Medium	Medium	Very Low	Suitable
5	Support Vector Machine (FL-based)	Medium-High	Medium	Medium	Suitable
6	Decision Tree (FL-based)	Medium	Medium	Low	Suitable
7	Random Forest (FL-based)	High	Medium-High	High	Very suitable
8	Gradient Boosting (FL-based)	Very High	Medium-High	High	Very suitable
9	Artificial Neural Network (FL-based)	High	High	High	Very suitable
10	Convolutional Neural Network (FL-based)	Very High	High	Very High	Suitable (imaging data)
11	LSTM (FL-based)	High	High	Very High	Suitable (time-series data)
12	Secure Aggregation	No impact	Very High	Medium	Essential

13	Differential Privacy	Slightly reduced	Very High	Medium	Essential
14	Homomorphic Encryption	No impact	Very High	Very High	High-security use

Discussion and Research Challenges

Federated learning (FL) has gained increasing attention in healthcare due to its ability to preserve data privacy while enabling collaborative model training across distributed institutions [2], [9]. In the context of allergy and asthma severity assessment, FL allows hospitals and clinics to build predictive models without sharing sensitive patient data, thereby addressing major privacy and regulatory concerns [1], [7].

Despite these advantages, several challenges persist. One of the primary issues is communication overhead, as frequent model updates exchanged between participating clients and the central server can lead to increased latency and bandwidth consumption [2], [9]. Additionally, statistical heterogeneity among healthcare datasets—caused by variations in patient populations, data acquisition methods, and disease prevalence—can negatively affect model convergence and stability [3]. Federated Proximal (FedProx) has been proposed to mitigate this issue by introducing regularization to handle heterogeneous data distributions [3].

Another significant challenge is the trade-off between privacy preservation and model performance. Privacy-enhancing techniques such as secure aggregation [4] and differential privacy [5] provide strong confidentiality guarantees but may slightly degrade model accuracy due to encryption overhead or noise injection. Advanced cryptographic methods such as homomorphic encryption offer very high security but introduce substantial computational complexity, limiting their practicality for large-scale or real-time clinical applications [6].

Future research should prioritize the development of adaptive and personalized federated learning algorithms, which tailor models to individual patient characteristics while maintaining global knowledge sharing [10], [11]. Moreover, explainable federated AI is essential to enhance clinical trust and interpretability, particularly for decision-making in chronic disease management such as asthma and allergy severity prediction [8], [17].

Conclusion

This review demonstrates that federated learning, when integrated with machine learning, deep learning, and privacy-preserving mechanisms, provides a secure and effective framework for allergy and asthma severity assessment. By eliminating centralized data collection, federated approaches significantly reduce privacy risks while enabling collaborative intelligence across multiple healthcare institutions [2], [9].

The comparative analysis indicates that hybrid federated frameworks combining ensemble methods, deep learning models, and secure aggregation techniques achieve high predictive accuracy with strong privacy guarantees, making them suitable for real-world clinical deployment [4], [11]. While challenges related to communication efficiency, computational cost, and data heterogeneity remain, continued advancements in personalized federated learning and lightweight encryption methods are expected to further enhance system scalability and clinical applicability [3], [5], [6].

Overall, federated learning represents a promising direction for next-generation, privacy-aware healthcare intelligence systems, particularly for chronic respiratory disease monitoring and personalized patient care.

References

1. R. Shokri and V. Shmatikov, "Privacy-preserving deep learning," Proc. ACM CCS, 2015.
2. H. B. McMahan et al., "Communication-efficient learning of deep networks from decentralized data," AISTATS, 2017.
3. T. Li et al., "Federated optimization in heterogeneous networks," MLSys, 2020.
4. K. Bonawitz et al., "Practical secure aggregation for privacy-preserving machine learning," ACM CCS, 2017.
5. C. Dwork et al., "The algorithmic foundations of differential privacy," Found. Trends Theor. Comput. Sci., 2014.
6. C. Gentry, "Fully homomorphic encryption using ideal lattices," STOC, 2009.
7. GINA Report, "Global strategy for asthma management and prevention," 2023.
8. J. Finkelstein et al., "Asthma severity prediction using machine learning," IEEE JBHI, 2020.
9. P. Kairouz et al., "Advances and open problems in federated learning," Found. Trends ML, 2021.
10. A. Smith et al., "Federated multi-task learning," NeurIPS, 2017.
11. X. Chen et al., "Personalized federated learning in healthcare," IEEE TMI, 2022.
12. D. Hosmer et al., Applied Logistic Regression, Wiley, 2013.
13. C. Cortes and V. Vapnik, "Support-vector networks," Machine Learning, 1995.
14. J. Kim et al., "Privacy-preserving SVM in federated settings," IEEE Access, 2021.
15. L. Breiman et al., Classification and Regression Trees, CRC Press, 1984.
16. L. Breiman, "Random forests," Machine Learning, 2001.
17. S. Badnjevic et al., "Machine learning approaches to asthma prediction," Med. Biol. Eng. Comput., 2018.
18. T. Chen and C. Guestrin, "XGBoost," KDD, 2016.
19. Y. Liu et al., "Federated gradient boosting for healthcare," IEEE JBHI, 2021.
20. I. Goodfellow et al., Deep Learning, MIT Press, 2016.
21. G. Litjens et al., "Deep learning in medical image analysis," Med. Image Anal., 2017.
22. A. Sheller et al., "Federated learning in medical imaging," Phys. Med. Biol., 2020.
23. S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural Computation, 1997.
24. M. Min et al., "Time-series modeling for asthma prediction," IEEE Access, 2020.
25. Q. Yang et al., "Federated learning with differential privacy," IEEE TPDS, 2020.
26. A. Acar et al., "A survey on homomorphic encryption for machine learning," ACM CSUR, 2018.
27. Kumudham, R., V. Rajendran, D. Ravikumar, R. Jaganathan, and P. Deepakjain. Pipeline recognition in side scan sonar image using adaptive network based fuzzy inference system (ANFIS) classifier." In AIP Conference Proceedings, vol. 2463, no. 1, p. 020013. AIP Publishing LLC, 2022.
28. Namath, Sini, D. Ravikumar, and S. Ramesh. Wideband microwave head imaging system to detect subdural hematoma brain injury." In AIP Conference Proceedings, vol. 2463, no. 1, p. 020020. AIP Publishing LLC, 2022.
29. Revathy, G., K. Selvakumar, P. Murugapriya, and D. Ravikumar. Smart manufacturing in Industry 4.0 using computational intelligence." In Artificial intelligence for Internet of things, pp. 31-48. CRC Press, 2022.
30. Ganesh, E. N., V. Rajendran, D. Ravikumar, P. Sai Kumar, G. Revathy, and P. Harivardhan. Remote sensing analysis framework for maritime surveillance application International Journal of Oceans and Oceanography 15, no. 1 (2021): 11-17.