Toward robust and frugal AI Models for capture and analysis of Physiological Signals using Federated Learning

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As technology advances, machine learning is being utilized more and more in smart healthcare and Internet of Things systems [1]. These advancements result in more significant issues with the processing and categorization of physiological data, especially real-time signals such as PPG, ECG, and EEG.

In order to create accurate and potent statistical models, ML currently requires a significant amount of data gathered from numerous sources. Federated Learning (FL) is used to guarantee privacy, security, and efficiency of the system [2],[3]. However, FL will also increase model complexity when compared to conventional machine learning. Creating lightweight AI architectures that maximize computational efficiency while preserving high predictive accuracy is the main goal. The key objective is to downsize AI models, architecture and parameters to tend towards frugal but powerful inference engines for time series classification.

This research implements a neural network to collect data from patients (ECG signals, blood oxygen levels, EEG signals, …) then classify them [4]. Additionally, a Federated Learning framework is employed to enable robust model training across decentralized and heterogeneous datasets while preserving data privacy [5] [6]. Next, we use the model pruning methods to find the balance between maintaining or improving model accuracy but also reducing overall model size [7].

In the future, we will integrate model quantization methods into the model to increase its efficiency, compression and accuracy [8].

Références :

[1] Thippun, P., Sasiwat, Y., Buranapanichkit, D. et al. (2023) Implementation and experimental evaluation of dynamic capabilities in wireless body area networks: different setting parameters and environments. J. Eng. Appl. Sci. 70

[2] Zhu, H., & Jin, Y. (2019) Multi-objective evolutionary federated learning. IEEE transactions on neural networks and learning systems, 31(4), 1310-1322

[3] Li, C., Li, G., & Varshney, P. K. (2021) Communication-efficient federated learning based on compressed sensing. IEEE Internet of Things Journal, 8(20), 15531-15541

[4] Nkengue Marc Junior, Xianyi Zeng, Ludovic Koehl, Xuyuan Tao. (2023) X-RCRNet: An explainable deep-learning network for COVID-19 detection using ECG beat signals. Biomedical Signal Processing and Control. 87

[5] Raza, A., Tran, K. P., Koehl, L., & Li, . (2023) Designing ECG monitor ing healthcare system with federated transfer learning and explainable AI. Knowledge-Based Systems, 236,107763

[6] Raza, A., Li, S., Tran, K. P., & Koehl, (2022) L. Using Anomaly Detection to Detect Poisoning Attacks in Federated Learning Applications. arXiv preprint arXiv:2207.08486. (submitted to IEEE Transactions on Dependable and Secure Computing)

[7] H. Cheng, M. Zhang and J. Q. Shi. (2024) A Survey on Deep Neural Network Pruning: Taxonomy, Comparison, Analysis, and Recommendations, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 46, no. 12, pp. 10558-10578

[8] S. Lee and H. Jang, (2025) BiPruneFL: Computation and Communication Efficient Federated Learning With Binary Quantization and Pruning, in IEEE Access, vol. 13, pp. 42441-42456