Bulletin of Natural Sciences Research
Vol. 15, No. 1, 2025, pp. 65-71.
DOI: https://doi.org/10.5937/bnsr15-55563
Original Scientific Paper

OPTIMIZATION OF FLUID VOLUME CONTROL IN HEMODIALYSIS USING FEDERATED LEARNING

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ABSTRACT

Overhydration (OH) represents a significant challenge for hemodialysis patients, significantly affecting the outcomes of their treatment. Accurate prediction and management of overhydration are key to optimizing therapy and improving patients' quality of life. The aim of this paper is to present a federated learning (FL)-based approach designed to predict overhydration in hemodialysis patients, using a dataset comprising different clinical and bioimpedance parameters. Federated learning enables collaborative learning from multiple data sources while preserving the privacy and security of individual patient data. Research results show that federated learning has the potential as an effective tool for predictive modeling in clinical settings. The developed models achieve high performance in overhydration estimation, with metrics confirming their accuracy and reliability. The proposed approach achieved a R^2 of 0.9999999, a MAE of 0.00018 and an MSE of 0.0031, demonstrating its predictive strength and practical applicability. This study highlights the advantages of federated learning in using distributed data to advance predictive capabilities in healthcare. By overcoming challenges related to privacy and data security, the approach presented in this paper opens up opportunities for more personalized and accurate prognoses, potentially improving decision-making and patient care in hemodialysis.

Keywords: Federated learning, Artificial Intelligence, Machine Learning, Overhydration, Hemodialysis.

INTRODUCTION

Hemodialysis is a procedure performed in patients with chronic renal failure which aims to alter blood composition by removing, water, electrolytes, and waste materials in a patient with kidney failure. The accumulation of fluids and harmful wastes occurs in these patients since the kidneys are unable to filter blood sufficiently. Overhydration permits the body's threatening processes such as elevated blood pressure, edema, breathing problems, and cardiovascular complications. The blood of the patient goes through a dialysis machine (artificial kidney) during Hemodialysis, where excess volumes of fluids and unwanted substances are eliminated and electrolytes are supplemented. A good fluid balance from one hemodialysis session to the next is essential in promoting good health and reducing the incidence of complications. To avoid overexerting the body, many patients are told to limit the fluids and salt they consume.

Artificial Intelligence gives new ways to improve and solve problems in hemodialysis, especially in fluid overload predictions. The neural network for predicting overhydration was based on parameters like blood pressure, bioimpedance, extracellular water, intracellular water, and total body water (Djordjevic et al., 2023). In addition, a patent has been developed in which multiple machine learning models were trained and selected for the best performance to predict overhydration in individual patients (Mladenović et al., 2024). Various studies have also documented the use of hybrid machine learning models to enhance overhydration prediction accuracy by combining the best features of different algorithms for better performance (Djordjevic et al., in press).

This study will utilize the federated learning model to predict overhydration in hemodialysis patients. It allows centralized machine learning model training, where the data remains securely stored on the local device, and only model updates are shared, which helps protect patient privacy and data security. Unlike conventional methods, this approach does not require centralized access to patient datasets, thus reducing the risk of breaches and ethical concerns. Federated learning can train models collaboratively from several institutions or datasets to create a generalizable model that cannot compromise the privacy of individual patients. This methodology has particular appeal in healthcare because data sensitivity and diversity are important in building correct predictive models.

The paper is organized as follows. The theoretical part provides an overview of overhydration in hemodialysis patients, discussing its clinical implications and the importance of accurate prediction. Additionally, it introduces federated learning and its applications in healthcare, emphasizing its potential for improving predictive modeling while ensuring data privacy. The experimental section describes the dataset used in this study, detailing the clinical and bioimpedance

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parameters considered, followed by an explanation of the materials and methods employed in model development and evaluation. The numerical results section presents the performance metrics of the proposed federated learning model, highlighting its effectiveness in predicting overhydration. Finally, the paper concludes with a discussion of key findings, potential implications, and future research directions. The work also includes an acknowledgments section, followed by a list of references.

THEORETICAL PART

Overhydration in hemodialysis patients

Optimal fluid volume control in dialysis patients is an essential component of dialysis adequacy, however, the amplitude of volume fluctuation is still a very difficult clinical situation (Perl et al., 2017). Although restoring salt and water homeostasis in hemodialysis patients has been linked to improved cardiovascular outcomes, recent studies suggest that the intensity or aggressiveness of fluid removal during standard thrice-weekly dialysis sessions may cause excessive hemodynamic stress and potential organ damage, potentially leading to long-term adverse effects (McIntyre, 2010; London, 2011). Chronic fluid volume overload affects 27-46% of hemodialysis patients and is a significant risk factor for cardiovascular events and death (Dekker et al., 2017; Zoccali et al., 2017; Loutradis et al., 2021). Overhydration causes hypotensive symptoms (muscle cramps, yawning, nausea, vomiting, dizziness, and syncope), requiring optimal fluid volume control for cardiovascular stress, quality of life, and survival. Optimal fluid volume is dry weight, achieved through gradual change with minimal underhydration or overhydration symptoms (Sinha & Agarwal, 2009).

Total body water (TBW) changes are examined during short-term (≤ 10 days) weight loss or gain using the dilution method with deuterium or heavy oxygen (Sagayama et al., 2019; Kondo et al., 2018; Sagayama et al, 2014). The dilution method is ineffective for monitoring fluid volume changes in hemodialysis patients. Alternative methods like multi-frequency bioelectrical impedance analysis (MF-BIA) or bioelectrical impedance spectroscopy (BIS) can estimate fluid volume status, determine body composition, and track changes over time (Moissl et al., 2013; Buchholz et al., 2004). MF-BIA- or BIS-guided fluid volume management lowers blood pressure (BP) and post-dialysis weight, but it does not appear to increase patient survival (Huan-Sheng et al., 2016). As a result, fluid volume overload cannot be attributed only to excess extracellular water (ECW) caused by oral salt and water consumption, which manifests as an inter-dialysis weight increase.

There is increasing evidence that patients receiving hemodialysis (HD) who have a higher body mass index (BMI) have a higher chance of surviving; this phenomenon has been dubbed the "obesity paradox." (Doshi et al., 2016). BMI, while correlated with body fat percentage, doesn't differentiate between body fat and muscle mass (Yang et al., 2023). Excess adiposity in patients undergoing hemodialysis can lead to adverse outcomes, as increased adipose tissue and reduced muscle mass may be associated with adverse outcomes, despite minimal or insignificant changes in BMI (Ishimura et al., 2022; Donini et al., 2022). Therefore, evaluating body composition distribution is crucial for hemodialysis patients.

The main finding of Rymarz et al. (2018) was that patients receiving hemodialysis had a worse survival probability when their lean tissue index (LTI) decreased. Dialysis patients with LTI and FTI in the 10th to 90th percentile (of the age- and sex-matched healthy population) had the best survival rate, according to Marcelli et al. (2015). Conversely, a higher mortality rate was associated with either low FTI, low LTI, or a combination of the two.

Based on all mentioned parameters such as total body water (TBW), extracellular water (ECW), muscle mass indices (LTI), body composition, blood pressure (BP), and other relevant variables, the aim of this work is to use the Federated learning (FL) to predict the state of overhydration in hemodialysis patients.

Federated Learning in Healthcare

With the rise of big data, the rapid development of machine learning, and increasing global connectivity, the collaborative training of machine models between different organizations and countries has never been at such a high level (Sheller et al., 2020). The biggest concern in the context of collaborative training in healthcare is related to data privacy issues, which limit data sharing and clinical application of technologically possible solutions (He et al., 2019). This is why there is growing interest in privacy-preserving approaches such as federated learning (FL), blockchain technology, and generative adversarial networks (McMahan et al., 2017). FL is a distributed machine learning framework introduced by Google in 2016 that enables multi-party collaboration while preserving data privacy (Sadilek et al., 2021). This approach is becoming increasingly popular in the medical industry as an attractive alternative to traditional centralized training methods, as it improves privacy protection.

In recent years, the notion of federated learning (FL) has been presented for developing intelligent and privacy-enhancing Internet of Things (IoT) systems. In theory, FL is a distributed collaborative AI method that enables data training by coordinating several devices with a central server without sharing actual datasets (Konečný et al., 2016). For instance, FL has supported the development of smart healthcare services by allowing machine learning (ML) models to be built without requiring the sharing of patient data among multiple medical institutions (Sheller et al., 2019). In this way, FL streamlines healthcare records management by reducing the need for exchange among hospitals, enhancing collaboration, and promoting patient diagnosis and treatment without compromising user privacy. Finally, FL can be utilized in real-time population monitoring, enabling the early identification of disease outbreaks (Zhang et al., 2024).

Federated learning (FL) enhances hemodialysis treatment by facilitating collaborative machine learning model development across medical centers, ensuring patient data privacy and enabling more accurate and personalized treatments. Federated learning (FL) models were trained to predict acute kidney injury (AKI) in COVID-19 patients at three and seven days. The study demonstrated that FL outperformed locally available data, particularly in the smallest dataset (Jaladanki et al., 2021). Weishen et al. (2024) present an adaptive FL framework for handling data distribution discrepancies across different sites in FL settings. The model demonstrated better quantitative performance on tasks of predicting the onset risk of sepsis and acute kidney injury (AKI) in critical care settings. Huang et al. (2023) developed a federated learning (FL) platform that allows the creation of a joint acute kidney injury (AKI) prediction model using data from five hospitals, using different machine models such as XGBoost, Random Forest, and neural networks. The models were trained locally at each hospital center, and then their results were aggregated to improve prediction performance, without the need to share raw data between hospitals.

Federated learning in the healthcare sector is a new practical tool that enables effective collaboration between different hospitals in the development of generalized medical artificial intelligence (Shiri et al., 2023). Federated learning solves an important data privacy barrier in the global deployment of medical artificial intelligence by enabling rapid deployment of models while private data remains securely stored in local hospitals (Loftus et al., 2022; Nguyen et al., 2022).

EXPERIMENTAL

Experimental data

The data used in this study were obtained from the University Children's Hospital in Tiršova, focusing on pediatric patients aged 0 to 16 during May 2022. The dataset comprises $n=69$ numerical medical features that serve as inputs and have a direct impact on the output variable, representing overhydration in liters (OH [L]).

Before clients start training local models, all data goes through a preprocessing phase. Data are collected from the hemodialysis process as well as from the Body Composition Monitor, which collects bioimpedance. The data are stored in databases for every hemodialysis treatment. Using Python, these datasets are transformed into a suitable form (.csv), extracting only necessary data and deleting duplicates. The datasets are scaled to a range of 0 to 1 to ensure consistency in model training. Missing values in the data are filled with mean attribute values to avoid problems in model training due to incomplete data. Preprocessing is implemented using Python libraries such as pandas and scikit-learn, which offer simple and efficient functionalities for data manipulation (Pedregosa et al., 2012).

Materials and methods

Federated learning lays the foundation for the development of collaborative machine learning models that balance the need for data privacy and achieve high prediction accuracy. The implementation of this approach requires the careful design of a system that enables effective communication and updating of the model at a global level.

The server in federated learning plays a key role in aggregating the weights it receives from clients. It also maintains the global model (Konečny et al., 2016). Its primary function is to centralize knowledge generated on decentralized clients without accessing their local data, thereby ensuring data privacy. The aggregation process is often implemented asynchronously. Meaning that the server does not have to wait for all clients to send their weights before updating the global model (Li et al., 2019; Yang et al, 2019). This approach allows working in heterogeneous environments where clients may have different network capacities, resources, or connection stability. Such flexibility is crucial for real-world applications, such as healthcare systems, where data remains localized at the hospital or laboratory level.

The Elastic Boosting algorithm (Djordjevic et al., in press) is used to train the model. It combines the advantages of Elastic Net and Gradient Boosting Regressor. Elastic Net provides robustness to redundant and interconnected features, while Gradient Boosting Regression enables more accurate modeling of nonlinear relationships (Hans, 2011; Natekin & Knoll, 2013). Local models are trained using cross-validation methods to minimize overfitting problems and achieve better generalization.

After successful training, clients use the gRPC protocol for secure and efficient communication with the server (gRPC, 2024). Clients send their model weights to the server as numeric vectors (McMahan et al., 2017). This approach minimizes data transmission over the network, further ensuring privacy. Each client is identified by a unique IP address, which enables tracking of each client's contribution to the global aggregation process.

The server collects a sufficient number of weights from the clients. Once this is done, it performs aggregation and updates the global model. The updated model is then sent back to the clients, who perform fine-tuning to further adapt the model to their specific data. In asynchronous mode, the server can perform aggregation as soon as it receives weights from a sufficient number of clients, even if some clients are unavailable. After aggregation, the global model is updated and saved in .pkl format to be available for later evaluation or replication of experiments. The server evaluates the global model's performance on the test dataset using key metrics (Eq. 1-3). These include mean absolute error (MAE), mean square error (MSE), and coefficient of determination (R^2), which quantify improvements in prediction (Brentan et al., 2017; Chicco et al., 2021). These metrics are recorded in a log file for later analysis and monitoring of model performance.

$$R^2 = 1 - \frac{\sum_{i=1}^{m}\left(\hat{Y}_i - Y_i\right)^2}{\sum_{i=1}^{m}\left(\bar{Y} - Y_i\right)^2} \quad (1)$$

$$MSE = \frac{1}{m}\sum_{i=1}^{m}\left(Y_i - \hat{Y}_i\right)^2 \quad (2)$$

$$MAE = \frac{1}{m}\sum_{i=1}^{m}\left|Y_i - \hat{Y}_i\right| \quad (3)$$

The methodology is further presented with a graphical representation illustrating the key steps in the federated learning process, including client-server communication, weight aggregation, and global model updating (Figure 1.).

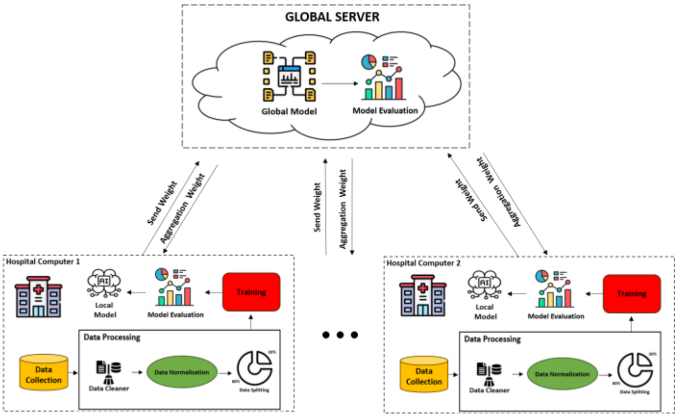

Figure 1. Federated learning process.

NUMERICAL RESULTS

In this research, 70 medical parameters were collected during pediatric hemodialysis at the University Children's Hospital in Tiršova. These parameters are organized within an expanding database, which is continuously updated with new measurements every 15 minutes throughout each hemodialysis session. This approach ensures a detailed and dynamic representation of the patient's health status.

The implementation of the global model and the analysis of individual clients within distributed learning provided high performance in predicting output values based on input weights. Key results for four clients and an evaluation of the global model are presented in this section.

The results of the analysis are presented graphically using a Violin diagram (Figure 2.), which illustrates the distribution of variable weights for each patient. The violin diagram allows the simultaneous display of central tendencies and variability of weights, providing intuitive insight into the significance of individual medical characteristics. The weight distribution varies among patients, which emphasizes the specifics of each individual case. For example, patients with a more stable distribution of weights show a more consistent influence of medical characteristics on prediction, while a wider distribution indicates greater variability in the importance of characteristics.

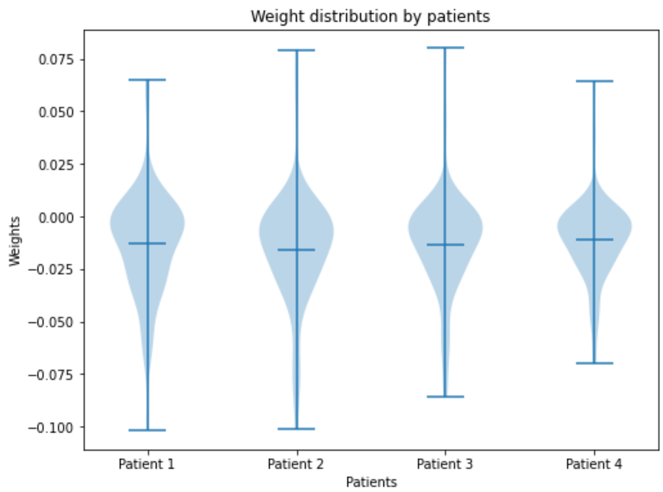

Figure 2. Distribution of weights for each patient. The violin plot represents the density of weight values for each patient. The central horizontal line indicates the median weight, while the shape width reflects the data distribution. Wider sections indicate a higher concentration of values.

For the first patient, the Violin plot indicates a narrow distribution of weights, reflecting a high degree of model stability. This information is supported by numerical results, where the coefficient of determination was R^2=0.985, mean square error (MSE) 0.0141, and mean absolute error (MAE) 0.092.

In the second patient, the Violin plot reveals a slight asymmetry in the distribution of weights, indicating specific variables that dominate the prediction. Numerical results for this patient include R^2=0.990R, MSE of 0.0197, and MAE of 0.109, confirming the high accuracy of the model.

The third patient shows a wider distribution of weights on the Violin plot, reflecting increased variability among significant features. This pattern is followed by a slightly lower R^2=0.933, with an MSE of 0.0239 and an MAE of 0.107, indicating challenges in fitting the model to this patient.

For the fourth patient, the Violin plot reveals the narrowest distribution of weights among the analyzed patients, indicating a stable contribution of key features. Numerical results support this interpretation with R^2=0.942, MSE of 0.0108, and MAE of 0.079, making this model the most accurate in terms of minimum error.

At the global model level, the evaluation shows excellent accuracy, with R^2 close to 1 (0.9999999), MSE of 0.00018, and MAE of 0.0031. These results confirm the successful integration of local models into a global framework, providing a high level of precision in the estimation of key medical parameters.

Below are shown tabular results for four clients, as well as a global model (Table 1). This table includes metrics such as R^2 (coefficient of determination), MSE (mean squared error), and MAE (mean absolute error). A global model is used to aggregate information from all clients to obtain a unique set of weights that takes all data into account.

Table 1. Performance metrics for individual clients and global model. Evaluation metrics for models trained on individual patient data and a global model. R^2 indicates model accuracy, while MSE and MAE measure prediction errors (lower values indicate better performance). The global model combines data from all patients for overall assessment.

Model/Client	R^2	MSE	MAE
Patient 1	0.9846	0.0141	0.0920
Patient 2	0.9898	0.0197	0.1088
Patient 3	0.9325	0.0239	0.1074
Patient 4	0.9422	0.0108	0.0789
Global	0.9999	0.00018	0.0031

The achieved results show the effectiveness of federated learning when applied to this type of task. Individual client models allow for high local accuracy, while the global model consolidates this information, providing almost perfect prediction. The Patient 3 client had a slightly weaker performance, which may be due to the specificity of this client's data or increased variability.

Analysis of weight updates indicates that the model successfully integrates information from all local sources. The reduction of negative values through iterations suggests stabilization and convergence of the model, which is a key aspect of the distributed approach.

In conclusion, the results confirm the potential of federated learning for accurate predictions while preserving client data privacy, which is essential in medical applications.

CONCLUSION

This study indicates the potential of federated learning (FL) as an innovative approach for the prediction of overhydration (OH) in hemodialysis patients. FL enables collaboration between different data sources without compromising patient privacy, making it particularly suitable for use in healthcare settings. The results show that FL models achieve a high level of accuracy and reliability, thus confirming their effectiveness in managing complex clinical data.

The proposed method provides significant advantages, including preserving data security and enabling more personalized forecasts. This is particularly important in hemodialysis, where accurate monitoring and management of OH can significantly affect treatment outcomes and patient quality of life. Federated learning opens up new opportunities for implementing advanced technologies in health care, enabling better decision-making and improving therapeutic approaches.

Despite its potential, the implementation of FL in healthcare systems presents several challenges. One major limitation is the high computational demand required for local model training, which may be a barrier for healthcare institutions with limited resources. Additionally, communication latency between distributed clients and the central server can impact model convergence speed, especially in real-time clinical applications. Another challenge is scalability-ensuring that FL frameworks can be effectively deployed across multiple hospitals with varying data infrastructures and regulatory requirements. Addressing these challenges requires optimization of communication protocols, efficient model compression techniques, and the development of standardized FL frameworks tailored to healthcare settings.

For future research, integrating FL with advanced deep learning techniques, such as transformer-based models or federated reinforcement learning, could further enhance predictive accuracy and adaptability to diverse clinical conditions. Additionally, testing FL on larger and more heterogeneous datasets across multiple healthcare institutions would provide stronger empirical validation of its effectiveness. Exploring privacy-preserving techniques, such as differential privacy and homomorphic encryption, could further strengthen data security and regulatory compliance in real-world implementations.

Overall, while FL holds great promise for predictive modeling in medicine, addressing its technical and infrastructural challenges will be essential for its widespread adoption and long-term success in healthcare applications.

ACKNOWLEDGMENTS

This study was supported by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia, and these results are parts of the Grant No. 451-03-136/2025-03/ 200132 with University of Kragujevac – Faculty of Technical Sciences Čačak.

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