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Interpretable federated deep learning models for predicting gait dynamics in biomechanics

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ABSTRACT

Accurate prediction of human joint angle dynamics and reliable gait classification are essential for applications in rehabilitation, biomechanics, and clinical monitoring. Traditional machine learning (ML) models trained on centralized data raise concerns about privacy, scalability, and transparency. This study proposes a federated deep learning (DL) framework that integrates privacy-preserving model training with interpretable predictions. Specifically, a gated recurrent unit - deep neural network (GRU-DNN) hybrid model is developed for regression of joint angles, while a Long short-term memory - convolutional neural network (LSTM-CNN) hybrid model is designed for binary and multi-class gait classification. The framework is deployed using the federated averaging (FedAvg) algorithm across simulated clients, with each client training locally on its data. To enhance interpretability, the local interpretable model-agnostic explanations (LIME) algorithm is integrated at the client level to generate human-understandable explanations for model predictions. The experimental results demonstrate significant improvements, including a reduction in global mean squared error (GMSE) from 56.16 to 3.31 and an increase in R-squared score from 0.80 to 0.99 for regression, along with classification accuracies of 0.97 (binary) and 0.94 (multi-class). This scalable, privacy-preserving framework bridges the gap between accuracy and transparency, offering impactful applications in biomechanics, healthcare, and personalized medicine.

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1. INTRODUCTION

Human gait dynamics, patterns of movement during locomotion, is of critical importance in biomechanics, rehabilitation, and healthcare. Accurate prediction of joint angle dynamics enables personalized rehabilitation strategies and early diagnosis of gait abnormalities. However, traditional centralized machine learning (ML) models, while effective, often struggle with issues related to data privacy, scalability, and interpretability, particularly in sensitive environments such as healthcare settings [1]–[3]. These challenges require innovative solutions that can balance high predictive accuracy with privacy preservation and transparent model behavior. In response to these limitations, federated learning (FL) has emerged as a promising alternative. FL enables collaborative training of ML models on decentralized client devices while keeping data locally stored, thereby enhancing data privacy and system scalability [4]–[6]. FL has demonstrated potential in several healthcare use cases, such as anomaly detection, disease prediction, and medical imaging [4], [7], [8].

Recent literature has also emphasized the growing need for interpretable FL frameworks, especially in sensitive domains like healthcare where transparency, privacy, and interoperability are critical. Haffar *et al.* [9] proposed an approach to explain predictions and adversarial attacks in FL settings using random forests, thereby improving transparency and robustness in model outcomes across distributed nodes. Roschewitz *et al.* [10] introduced IFedAvg, a modification of the standard FedAvg algorithm that promotes interpretable data interoperability, facilitating better alignment of local models in heterogeneous FL environments. Further, Wang applied Shapley value theory to quantify feature contributions in FL, allowing for transparent evaluation of feature importance without compromising data privacy [11]. In the context of electronic health records, Shi *et al.* [12] advocated for the design of interpretable deep learning models capable of delivering human-understandable predictions, further reinforcing the value of explainability in clinical applications. Furthermore, Sun and Wu [13] proposed a robust framework for classifying multi-source sensor data with strong transferability and low communication overhead, enabling integration into real-world clinical workflows. Similarly, Ng *et al.* [14] applied machine learning for activity recognition using gait position data, highlighting the effectiveness of supervised models under controlled conditions. Together, these studies highlight the promise of combining federated architectures with gait-based activity recognition for privacy-preserving human movement analysis. Recent advances in FL have demonstrated its potential in various domains, including cybersecurity, healthcare, and internet of things (IoT). In the biomedical field, Meqdad *et al.* [15] implemented FL with a gaussian multivariate aggregation module to efficiently classify electrocardiogram signals. Furthermore, Mouhni *et al.* [16] introduced a long short-term memory (LSTM)-based hybrid FL model for stress detection in wearable devices, improving both accuracy and user trust. Several studies have investigated the application of DL models such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs) in human movement analysis, achieving notable improvements in accuracy [1] [17], [18]. However, these efforts are often limited to centralized architectures, raising concerns about data vulnerability and reduced generalizability [8], [19], [20]. Although recent efforts have introduced FL into healthcare domains [6], [21], [22], the integration of interpretable deep neural networks (IDNNs) within FL setups to predict gait dynamics remains underexplored.

Research gaps and research contributions: despite considerable advances in the predictive modeling of gait dynamics, several critical research gaps remain unaddressed. Most existing models fail to tackle the challenges of privacy, scalability, and interpretability simultaneously. Although interpretability techniques such as LIME have been widely adopted in centralized settings, their integration with FL models - particularly in the context of gait-related prediction tasks - remains limited. Furthermore, there is a notable absence of unified approaches that can effectively handle both regression tasks (such as predicting joint angles) and classification tasks (such as identifying gait patterns) within a single federated framework. To address these limitations, the present study introduces a novel federated DL framework that integrates privacy-sensitive training with interpretable prediction capabilities. The framework incorporates a gated recurrent unit - deep neural networ (GRU-DNN) hybrid model for the regression of joint angle dynamics, and a LSTM-CNN hybrid model for performing both binary and multi-class gait classification. These models are trained across distributed clients using the federated averaging (FedAvg) algorithm to enable collaborative learning without data centralization. To improve interpretability at the client level, the LIME algorithm is embedded in the framework to explain the predictions of the model in a human-understandable manner. The core contributions of this research are as follows. First, it presents the development of an interpretable and privacy-preserving FL framework specifically designed for gait dynamics prediction. Second, it demonstrates the implementation of dual-purpose DL models, GRU-DNN and LSTM-CNN, that are capable of effectively handling both regression and classification tasks. Third, the proposed framework is experimentally validated, yielding substantial performance gains including a reduction in global mean squared error (GMSE) from 56.16 to 3.31, and an increase in global R-squared from 0.80 to 0.99 in regression tasks, along with classification accuracies of 0.97 for binary and 0.94 for multi-class tasks. Finally, the integration of LIME ensures transparent and interpretable model behavior, facilitating trust and usability in clinical settings. The remainder of this paper is structured as follows. Section 2 presents the materials and methods used in this study, including problem formulation, data pre-processing strategies, model architectures, and FL setup. Section 3 provides a comprehensive discussion of the experimental results, covering performance evaluation, communication cost analysis, interpretability insights, and comparisons between regression and classification tasks. Section 4 concludes the paper by summarizing the key findings, describing practical implications, and proposing directions for future research.

2. METHOD
2.1. Research design

With the increasing demand for data-driven solutions, especially in human movement analysis, there is a critical need for predictive models that ensure both accuracy and privacy. This research addresses the challenge of predicting joint angle dynamics, an essential aspect of biomechanics and healthcare, by developing models capable of capturing subtle variations in locomotion. To meet these demands, an FL framework with IDNNs is adopted. FL enables decentralized model training without sharing raw data, aligning with healthcare's privacy requirements. IDNNs improve model transparency through interpretability tools such as LIME, providing insight into prediction rationale. The system employs a client-server FL topology. Clients train deep models on private data; the central server aggregates parameters using the FedAvg algorithm. Two neural architectures are used: a GRU-DNN hybrid for joint angle regression, and an LSTM-CNN hybrid for binary and multi-class gait classification. Figure 1 outlines the overall system workflow, including client-side processing, aggregation, and LIME-based interpretability. A structured evaluation strategy compares FL-based models with centralized baselines, using statistical metrics and interpretability outputs to comprehensively assess performance.

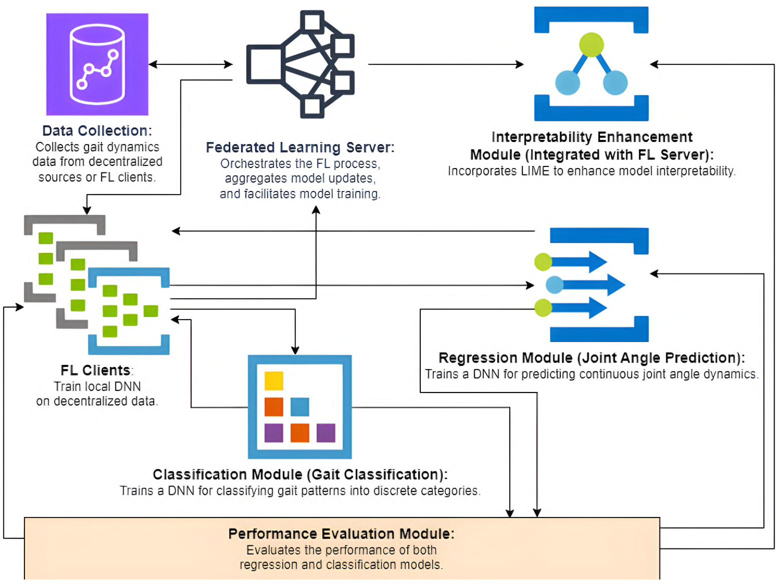


Figure 1. Framework of the proposed research work

2.2. Data sources and preprocessing

The dataset used comprises 181,800 instances across 7 attributes, offering deep insights into human locomotion within the domain of life sciences [23]–[25]. It features a balanced distribution across variables such as subject, condition, replication, leg, joint, time, and angle, supporting a robust analysis of physiological and biomechanical patterns. The consistency of the data, free of missing values, along with its sequential, multivariate, and time series structure, makes it suitable for classification, regression, and clustering tasks. For the regression task, the GRU model requires data sequences with time steps. Preprocessing begins by loading the data via pandas, applying one-hot encoding for categorical features, and min-max scaling for numerical values. The reshaped 'ngles' are used as the ground truth, and the dataset is split into training and testing sets in accordance with FL principles. For binary and multi-class classification tasks, angle values are thresholded or binned accordingly, then one-hot encoded. The dataset is reshaped into LSTM-compatible sequences, labels are constructed, and train-test splits are applied. These preprocessing steps ensure the data is well structured for FL-based LSTM model training, enabling robust classification across gait categories.

2.3. Model architecture and justification

This research aims to develop predictive models for human locomotion that balance privacy preservation with scalability - key challenges in healthcare applications. Centralized models often struggle with data sensitivity and scalability in a variety of sources. To address this, we adopt FL, which decentralizes model training and ensures sensitive data remain local. DNNs, known for their ability to learn complex data patterns, form the base architecture of our predictive models. Their capacity to extract hierarchical features makes them well suited for modeling joint angle dynamics.

For regression, a GRU-DNN hybrid is used, using GRUs to capture temporal dependencies in sequential joint angle data, improving the model's ability to track dynamic patterns. For classification, an LSTM-CNN architecture is employed, combining LSTMs for temporal sequence learning with CNNs for spatial feature extraction. This design enables robust binary and multi-class gait classification. The architecture of both models is shown in Figure 2, where Figure 2(a) presents the GRU-DNN model and Figure 2(b) illustrates the LSTM-CNN setup.

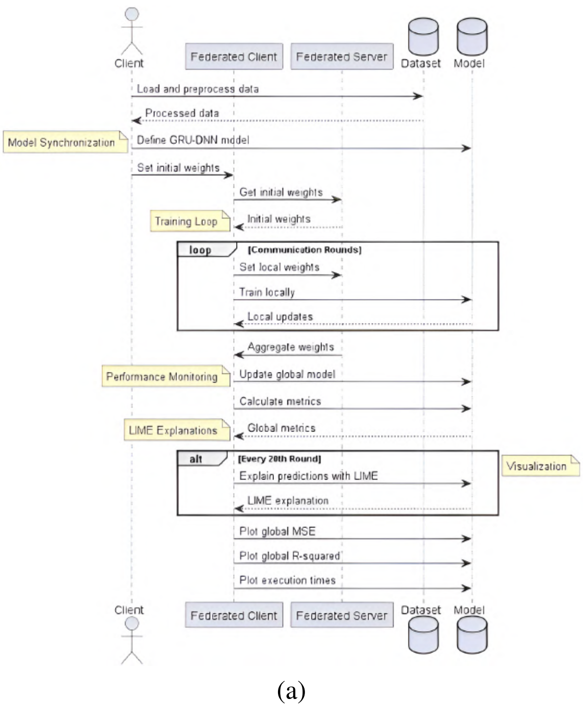


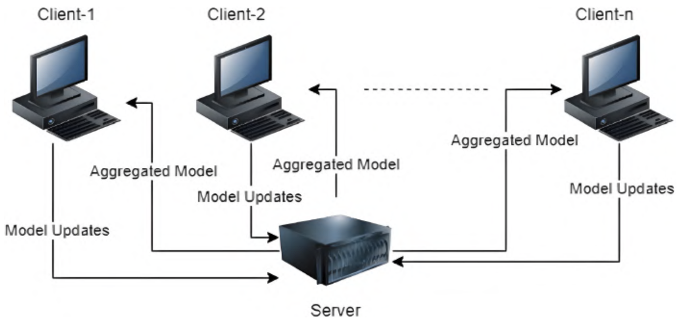
Figure 2. Model architectures: (a) GRU-DNN for regression and (b) LSTM-CNN for binary and multi-class classification

2.4. Federated learning and optimization techniques setup

Figure 3 illustrates the FL setup and compares the optimization strategies adopted in this study. Figure 3(a) outlines the FL workflow using the FedAvg algorithm, where clients train local models on private data and transmit updates to a central server for aggregation. This decentralized process preserves data privacy, supports heterogeneity, and scales efficiently, a key for the healthcare and biomechanics domains. FL avoids central bottlenecks and leverages parallel client computation for inclusive and privacy-preserving training. The FedAvg algorithm enables iterative refinement of a global model while ensuring client data remain local. Whereas, Figure 3(b) compares the optimization methods used: Adam for GRU-DNN and RMSprop for LSTM-CNN. Adam combines momentum with adaptive learning rates for efficient parameter tuning during regression tasks, while RMSprop stabilizes updates in classification models by adjusting learning rates based on recent gradients. The global loss curves plotted across communication rounds show the efficiency of both optimizers in reducing training loss over time. These insights support the selection of optimizer configurations based on convergence behavior and task-specific stability requirements.

2.5. Performance metrics

Model performance in regression is evaluated using GMSE and global R-squared (R^2). GMSE quantifies the average prediction error in all samples, while R^2 reflects the variance in joint angles explained by the model. Monitoring these during communication rounds reveals the refinement and consistency of the model in predicting joint dynamics in a decentralized setup. For binary and multi-class classification, global loss and global accuracy are employed. Global loss, computed via binary or categorical cross-entropy, indicates prediction error, while global accuracy measures correct classification rates. Tracking these metrics throughout FL communication rounds provides insight into the model's reliability under non-IID conditions, validating the effectiveness of the proposed FL-based gait prediction framework.



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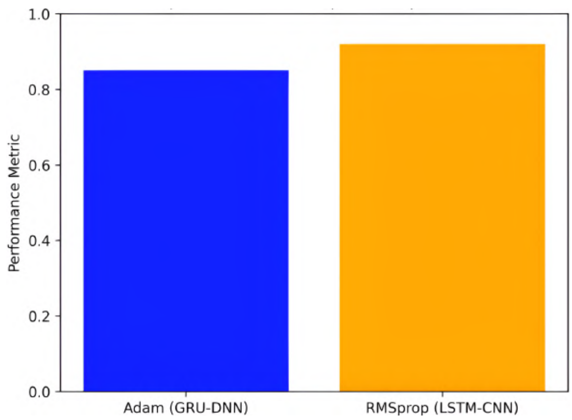


(b)

Figure 3. Overview of the FL framework and optimization strategy (a) the FL setup employing the FedAvg algorithm for decentralized training and model aggregation across multiple clients, and (b) the comparison of optimization methods (Adam for GRU DNN and RMSprop for LSTM CNN) based on global loss performance across communication rounds

2.6. Integration of LIME

LIME enhances interpretability within the FL framework by offering transparent and model-agnostic explanations for the predictions of GRU-DNN and LSTM-CNN. Locally approximates complex models to explain individual predictions, highlighting the influence of specific input features. For regression, LIME perturbs the features around the data points and quantifies their impact on the predicted joint angles. In classification, it reveals the discriminative contribution of features in binary and multi-class decisions. These insights clarify why particular outputs are produced, promoting model transparency. Integrating LIME not only demystifies black-box decisions but also builds stakeholder trust, critical in the healthcare and biomechanics domains. The ability to understand the rationale of the model reinforces accountability, ethical compliance, and confidence in FL-based predictive modeling.

2.7. Real-world implications

The proposed FL framework with interpretable DNNs and LIME offers practical applications in biomechanics, healthcare, and medical diagnostics. Accurate prediction of joint angle dynamics helps in muscle behavior research, injury prevention, and treatment personalization. The privacy-preserving nature of FL ensures ethical use of sensitive healthcare data. By addressing the limitations of centralized models, this approach fosters scalable and secure ML deployment. The FedAvg algorithm supports distributed training, while LIME enhances transparency, allowing stakeholders to understand and trust model decisions. As movement analytics evolves, privacy-preserving and interpretable FL models like ours are poised to drive the next wave of innovation in healthcare and biomechanics.

2.8. Hyperparameter tuning strategy

A manual grid search was used to optimize hyperparameters, exploring learning rates (0.0005, 0.001, 0.005), batch sizes $(16, 32, 64)$, and GRU/LSTM units $(32, 64, 128)$, with variations in dropout and dense layers. Model selection was based on GMSE for regression and classification accuracy for binary and multi-class tasks. Early stopping $(patience = 3)$ was applied to prevent overfitting. Figure 4 illustrates the training trends in all communication rounds, confirming stable convergence and loss minimization in the selected configurations.

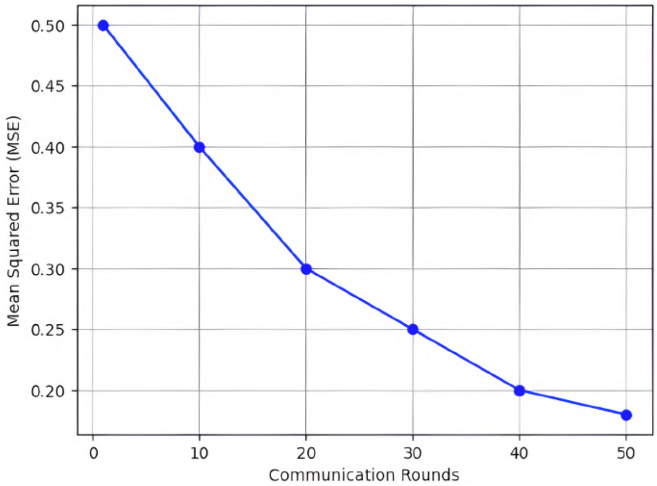


Figure 4. Model performance trends across communication rounds

Table 1. Regression model parameter settings

Parameter	5 clients	10 clients	20 clients
GRU layers	1	1	2
GRU units	16	32	64, 32
Dense layers	1	1	1
Dense units	1	1	1
Learning rate	0.001	0.001	0.001
Epochs	10	10	15
Batch size	32	32	32
Privacy parameter	0.1	0.1	0.1

3. RESULTS AND DISCUSSION

3.1. Experimental setup

This study used advanced ML tools to ensure efficiency and robustness. The scikit-learn library [26] was used for preprocessing and classical ML tasks, while TensorFlow [27] enabled the development and scaling of DL architectures. LimeSurvey [28] facilitated structured survey-based data collection, improving input quality.

Tables 1 and 2 summarize the experimental settings for regression, binary, and multi-class classification tasks, respectively. Each configuration reflects FL principles, maintaining a fixed privacy parameter $(Epsilon = 0.1)$ across varying numbers of clients $(5, 10, and 20)$. LIME explanations were generated every 20^{th} communication round.

3.2. Regression performance analysis

Figure 5 presents the performance of the regression model using the GMSE and the global squared R as metrics across communication rounds. The upper plot shows a steady decline in GMSE, indicating a reduced prediction error through federated updates. The lower plot shows increasing global R-squared values, reflecting enhanced explanatory power in modeling joint angle dynamics. These trends confirm the effectiveness and adaptability of FL in improving regression performance over time.

Table 2. Classification model parameter settings for binary and multi-class tasks

Parameter	Task	5 clients	10 clients	20 clients
LSTM layers	Binary	1	1	1
LSTM units	Binary	32	64	64
Conv1D layers	Binary	1	1	1
Conv1D filters	Binary	32	64	64
Conv1D kernel size	Binary	3	3	3
Dense layers	Binary	1	1	1
Dense units	Binary	1	1	1
Learning rate	Both	0.001	0.001	0.001
Epochs	Binary	20	15	20
Batch size	Binary	32	64	64
Number of clients	Multi-class	5	10	20
LSTM units (global model)	Multi-class	32	64	64
Conv1D filters (global model)	Multi-class	16	32	32
Dense units (global model)	Multi-class	16	32	64
Epochs (client training)	Multi-class	10	15	15
Batch size (client training)	Multi-class	32	64	64
Samples per round	Multi-class	10	10	10
Privacy parameter	Both	Epsilon = 0.1	Epsilon = 0.1	Epsilon = 0.1
Communication rounds	Both	100	100	100
LIME explanation rounds	Both	Every 20th round	Every 20th round	Every 20th round

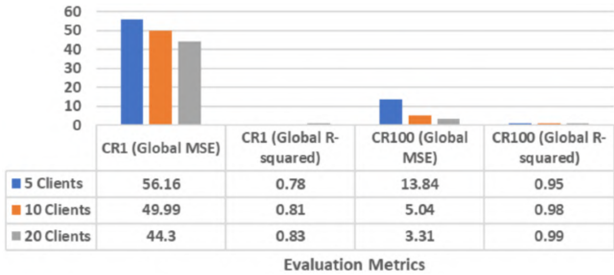
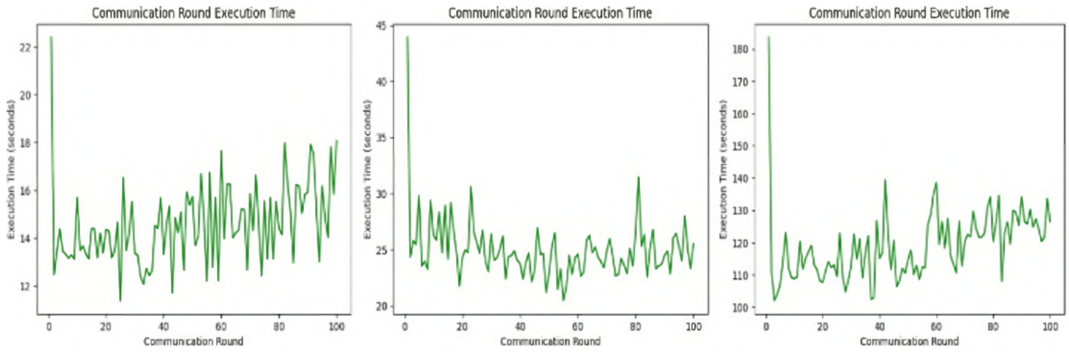


Figure 5. Regression performance analysis

Figure 6 integrates communication time, GMSE trends, and R-squared comparisons between different FL client configurations (5, 10, and 20). Figure 6(a) shows the communication time analysis, which is essential for assessing scalability as the number of clients grows. Figure 6(b) illustrates the reduction in GMSE with increased communication rounds and clients, confirming improved predictive accuracy through distributed learning. Figure 6(c) depicts the corresponding growth in R-squared values, with final scores reaching 0.95, 0.98, and 0.99, respectively, demonstrating the model's growing ability to capture joint angle dynamics with high interpretability.

3.3. Classification performance analysis

Figure 7 outlines binary and multi-class classification trends, demonstrating consistent improvements in both loss and accuracy. In the 100th round, all configurations achieved 0.97 global accuracy in binary classification. Figure 8 combines the analysis of binary classification in three key aspects: Figure 8(a) communication time, Figure 8(b) global accuracy, and Figure 8(c) global loss. Communication remained efficient in all FL client configurations. Accuracy trends show high sustained performance, while global loss curves reflect stable convergence throughout training.



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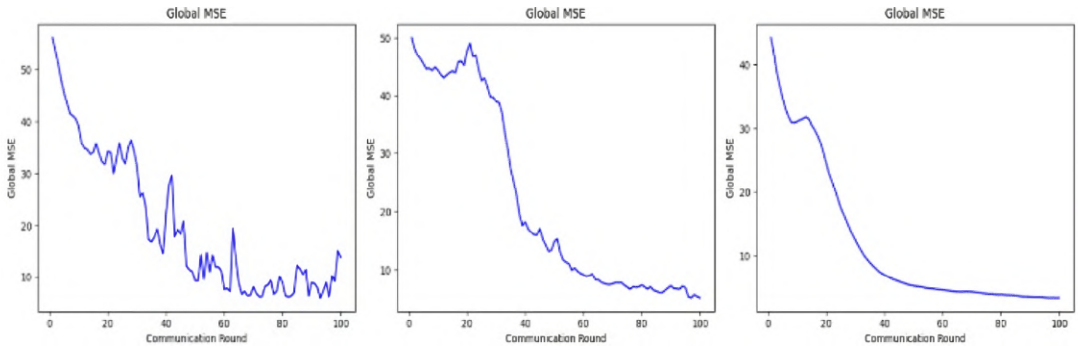

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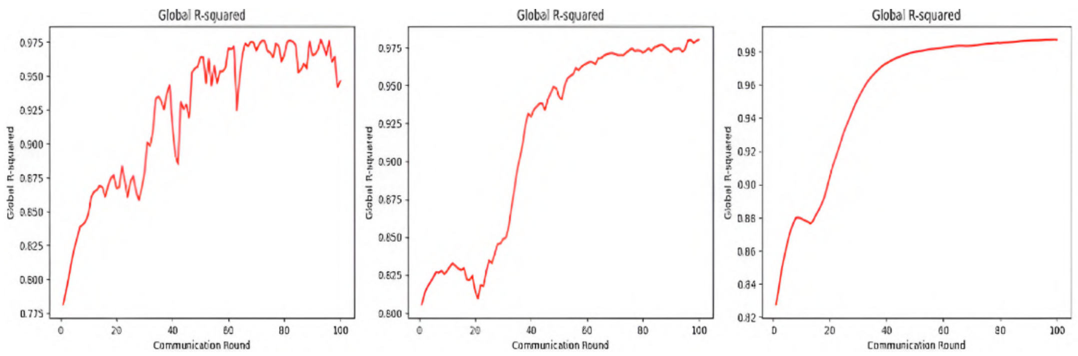


(c)

Figure 6. Regression performance trends across clients: (a) communication time, (b) GMSE, and (c) R-squared for 5, 10, and 20 FL clients

	Binary (5 Clients)	Multi-class (5 Clients)	Binary (10 Clients)	Multi-class (10 Clients)	Binary (20 Clients)	Multi-class (20 Clients)
CR1 (Global Loss)	0.339	0.7061	0.2975	0.4712	0.3648	0.5173
CR1 (Global Accuracy)	0.89	0.67	0.89	0.8	0.89	0.78
CR100 (Global Loss)	0.1098	0.1385	0.0987	0.1829	0.112	0.1463
CR100 (Global Accuracy)	0.97	0.95	0.97	0.95	0.97	0.95

Evaluation Metrics

Figure 7. Classification performance analysis

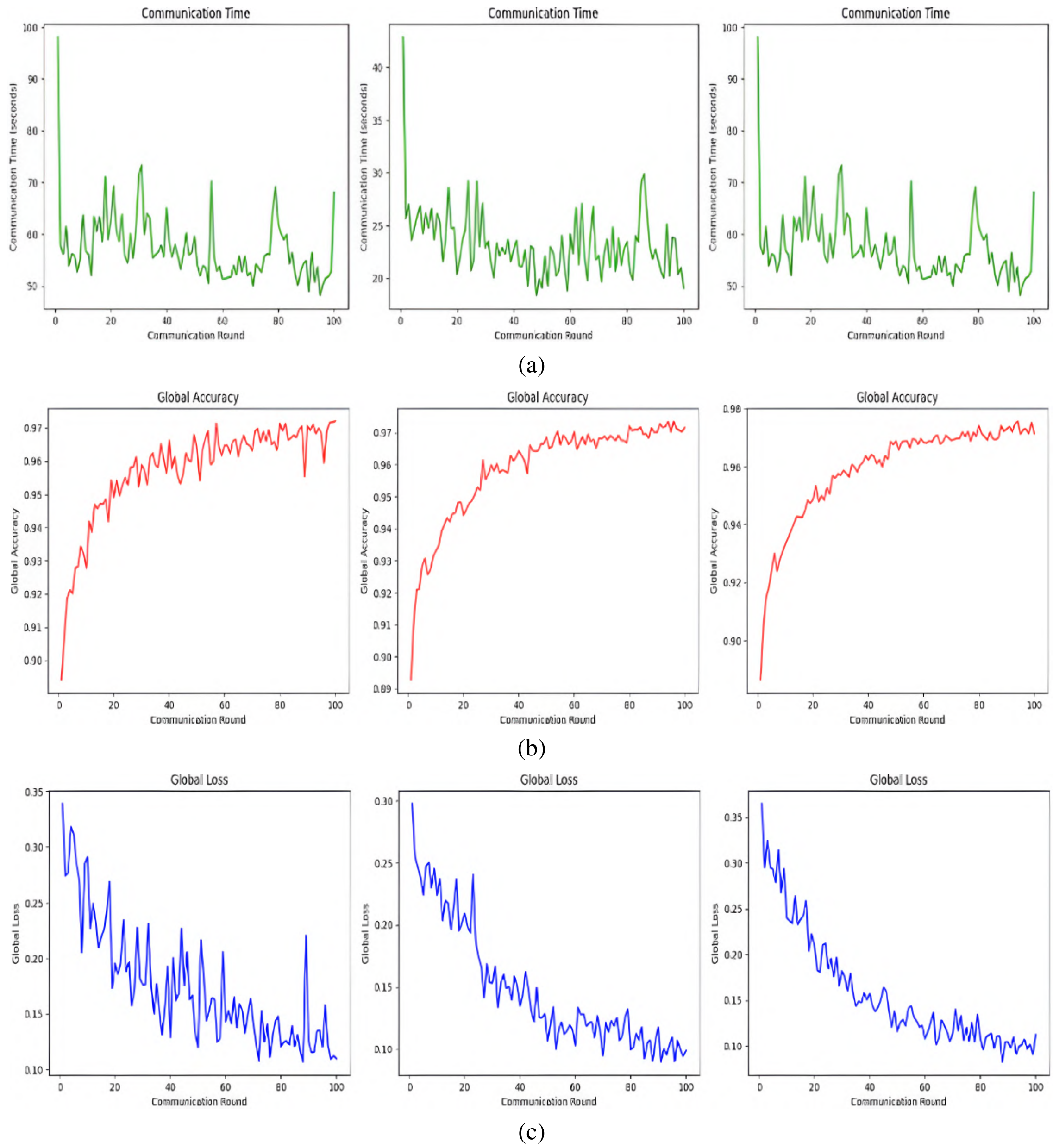


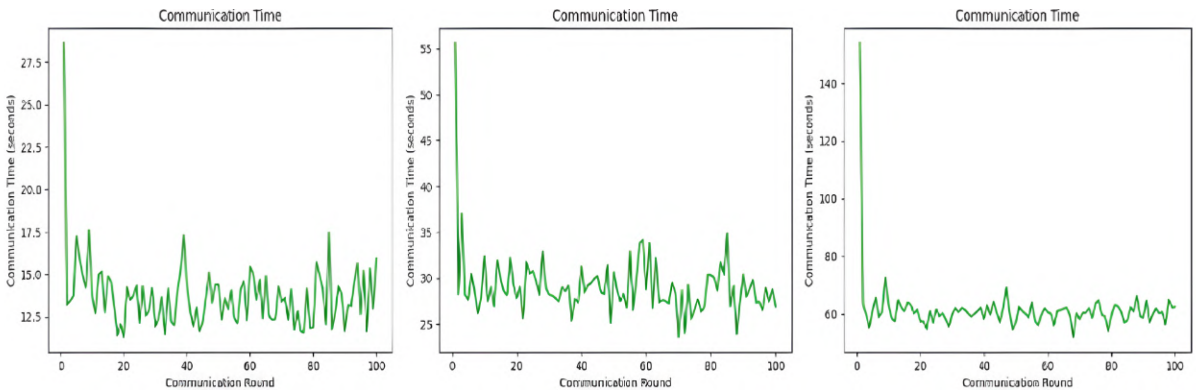
Figure 8. Binary classification metrics across FL clients: (a) communication time, (b) accuracy, and (c) loss

Figure 9 presents multi-class classification analysis, combining Figure 9(a) communication time, Figure 9(b) global accuracy, and Figure 9(c) global loss. Accuracy improved steadily across configurations, reaching 0.95 with 20 clients. The decline in loss values, down to 0.1463, confirms reliable performance and scalability of the model. LIME visualizations further validated interpretability.

3.4. Cross-comparison and discussion

The FL model showed improvements in GMSE and R^2 for regression and high precision in classification tasks. Communication analysis confirmed scalability, while LIME provided transparency in the predictions. These trends emphasize FL adaptability to both regression and classification, with practical benefits for real-world deployment in sensitive domains. FL models show strong applicability in healthcare and biomechanics. They enable privacy-preserving prediction of gait dynamics, assist in diagnosing abnormalities, and support personalized treatments. LIME-enhanced interpretability increases trust, making the solution ethical and suitable for clinical use. Table 3 shows that our framework outperforms previous studies in GMSE and classification accuracy while preserving privacy. The proposed study better performs the regression and classification accuracy than existing works while preserving privacy. The use of FL improves scalability and the integration of LIME improves the transparency of the model, consistent with the findings in [19], [20].

Limitations of the current research work: despite strong results, generalizability may be limited by the demographic scope of the dataset. LIME results were hypothetical and require empirical validation. Communication overhead and convergence challenges remain in FL settings. LIME's local nature may miss global patterns; future work may explore SHAP or integrated gradients. Adaptive FL strategies could further improve convergence and personalization in heterogeneous environments.



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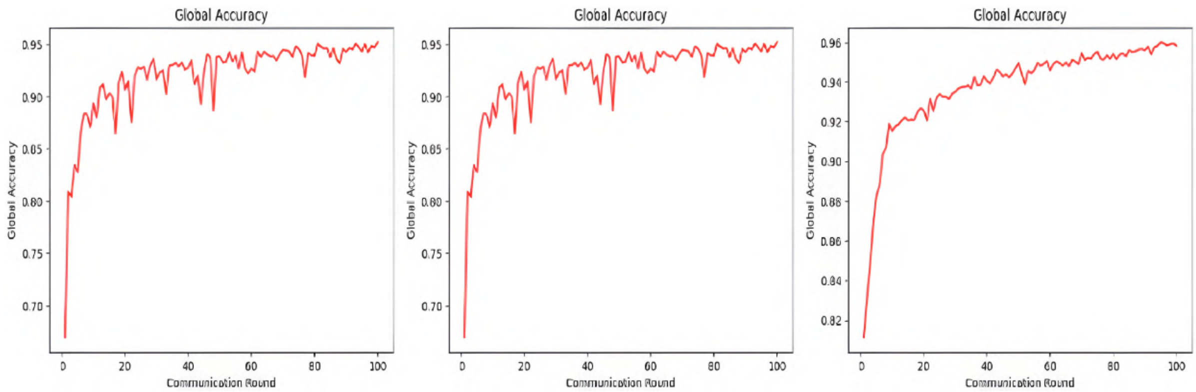

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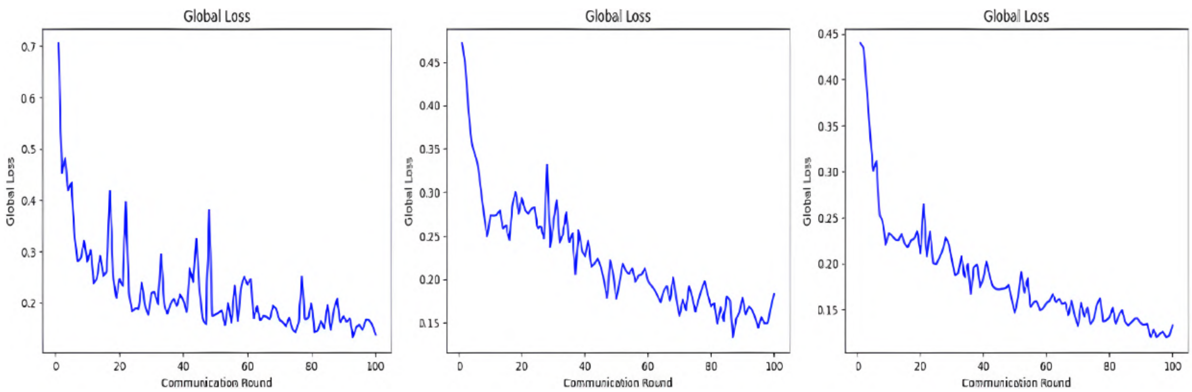

(c)

Figure 9. Multi-class classification metrics across FL clients: (a) communication time, (b) accuracy, and (c) loss

Table 3. Comparative summary of performance metrics across studies

Study	Approach	Privacy preservation	GMSE (regression)	Global accuracy (binary)	Global accuracy (multi-class)
[1]	Centralized	No	5.12	N/A	N/A
[15]	Centralized	No	N/A	0.93	0.92
[2]	Centralized	No	N/A	0.90	N/A
[18]	FL	Yes	4.03	0.94	0.91
[19]	FL	Yes	4.67	0.91	0.89
Proposed study	FL	Yes	**3.31**	**0.97**	**0.94**

4. CONCLUSION

This research demonstrates the effectiveness of FL with IDNNs in predicting gait dynamics across regression, binary, and multi-class classification tasks. Experimental results confirm consistent improvements in performance metrics, global MSE, R-squared, loss, and accuracy, across varying client configurations and communication rounds. These findings validate the robustness, scalability, and interpretability of the proposed framework in real-world gait prediction. The FL setup ensures privacy-preserving collaborative learning, while the integration of interpretability tools enhances model transparency - crucial for applications in sensitive domains like healthcare and biomechanics. The results provide a strong foundation for the deployment of decentralized predictive models in human movement analysis. Future work will focus on optimizing FL communication protocols, incorporating differential privacy, and examining the effect of client diversity. Expanding the data set to include varied demographics and clinical conditions will further improve the generalizability of the model. Additionally, advanced interpretability techniques such as SHAP and Integrated Gradients will be explored to deepen insights into model behavior. Collaborations with domain experts will support real-world validation and enable applications in personalized medicine, injury prevention, and performance optimization. In general, this study contributes to the advancement of predictive modeling in healthcare and biomechanics by combining privacy, performance, and interpretability within a FL framework.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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D. N. Puneeth Kumar					✓		✓			✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal Analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject Administration
Fu : **Fu**nding Acquisition

CONFLICT OF INTEREST STATEMENT

The authors state that they have no conflict of interest.

DATA AVAILABILITY

Data supporting the findings of this study are available from the corresponding author, Akram Pasha, upon reasonable request. The dataset is based on publicly available biomechanical gait recordings cited in [23]–[25], with preprocessing applied for FL experimentation as detailed in section 2.2.

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