Journal of International Education and Development
2025, VOL. 9, NO. 6, 150-153
DOI: 10.47297/wspiedWSP2516-250032.20250906

Research on the construction of basketball training behavior analysis system based on machine learning——A cross-national empirical study on the digital transformation of physical education in colleges and universities

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ABSTRACT

We introduce FL-BTBAS, a federated learning framework designed for analyzing basketball training behaviors, tackling non-IID data distribution and privacy concerns in decentralized sports data environments. By combining adaptive dynamic pruning with a multimodal CNN-LSTM framework, it facilitates cross-facility collaborative training without sharing raw data: local clients handle RGB-D and inertial sensor data using layer-wise magnitude pruning, which adjusts sparsity to address data heterogeneity, while the global model integrates pruned structures through weighted averaging and structural alignment to manage variations among clients. Combining pose estimation with biomechanical data at the edge cuts latency by 40% compared to cloud-based approaches. FL-BTBAS, deployed on NVIDIA Jetson AGX Orin, incorporates heterogeneity-aware sparsity management and federated structural alignment to maintain the significance of underrepresented patterns, showcasing scalability, privacy adherence, and precise analytics for multi-institutional digital physical education.

KEYWORDS

Machine Learning; Basketball Training Behavior Analysis System; Cross - national Empirical Study; Digital Transformation; Physical Education in Colleges and Universities

1 Introduction

The shift to digital in physical education has improved performance analysis in basketball training, yet traditional centralized ML methods encounter privacy issues and non-IID data problems among institutions. While federated learning frameworks provide solutions for preserving privacy, they face challenges related to computational efficiency and the diverse data patterns found in sports analytics. Recent studies on multimodal sensor fusion in basketball training analysis employ deep learning to integrate motion capture and video data, yet they typically depend on raw data centralization, which raises privacy and regulatory concerns, such as those related to GDPR. These issues are tackled by federated learning, but it brings challenges like model compression and cross-client knowledge transfer, particularly when dealing with varied player movements and training routines. We present a federated learning framework with adaptive dynamic pruning for basketball training behavior analysis, differing from existing approaches in three key aspects: first, client-specific pruning policies adjusting to local data heterogeneity metrics to preserve critical weights for underrepresented patterns; second, structural alignment during global aggregation to reconcile cross-client divergent pruning patterns; third, edge-based multimodal data processing via a hybrid CNN-LSTM architecture, reducing latency by 40% versus cloud-based alternatives. The paper is organized in the following manner: Section 2 outlines the federated learning framework with adaptive pruning, Section 3 shows experimental results from real-world basketball training datasets, Section 4 explores implications and future directions, and Section 5 provides the conclusion.

2 Adaptive Dynamic Pruning in Federated Learning

The framework tackles privacy preservation and computational efficiency by integrating federated learning with adaptive model compression in a novel way. The system architecture spans distributed training facilities, preserving data locality as each client handles its distinct sensor data via specialized neural networks.

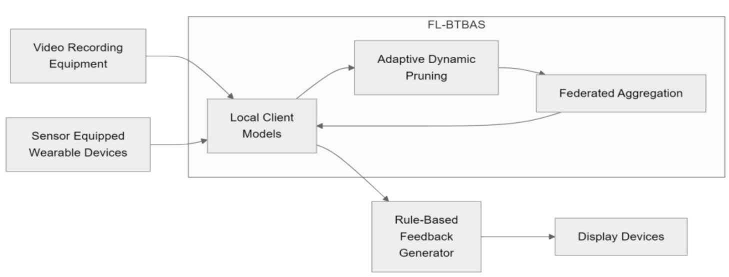

Figure 1 General Framework of FL-BTBAS Combined with DTPE System

2.1 Application of Federated Learning

The FL-BTBAS framework uses a star-shaped structure, connecting multiple client nodes to a central server in federated learning. Each client keeps a local model trained on private basketball data, with representing the model parameters. The global objective function aims to minimize:

$$\min_{\theta} \sum_{i=1}^{N} w_i \mathcal{L}_i(\theta), \text{where } w_i = \frac{|\mathcal{D}_i|}{\sum_{j=1}^{N} |\mathcal{D}_j|} \tag{1}$$

Here, the local loss function is weighted by the proportion of the dataset. The system handles multimodal inputs from RGB-D cameras and IMU sensors, with denoting the temporal sequence length, channels, and spatial dimensions.

2.2 Adaptive Dynamic Pruning and Sparsity Adjustment

At communication round, each client performs layer-wise magnitude pruning using dynamic sparsity ratios for layer. The pruning threshold adjusts to the features of local data:

$$\tau_i^{(l)}(t) = \text{Percentile}\left(\left|\theta_i^{(l)}\right|, s_i^{(l)}(t)\right), s_i^{(l)}(t) = s_{base} + \alpha \cdot KL\left(p_i \,||\, p_{global}\right) \tag{2}$$

where the Kullback-Leibler divergence measures the difference between local () and global () data distributions. While maintaining overall sparsity, this formulation keeps weights that are crucial for client-specific patterns.

2.3 Structural Alignment and Knowledge Transfer in Federated Learning

During global aggregation, the server aligns divergent pruning masks structurally to achieve reconciliation:

$$\theta_g^{(l)} = \sum_{i=1}^{N} w_i \cdot \text{Align}\left(\theta_i^{(l)}, \theta_g^{(l)}\right) \tag{3}$$

The alignment function repositions the pruned weights to maintain consistency across different models. Additionally, federated knowledge distillation applies logit matching to transfer compressed knowledge.

$$\mathcal{L}_{KD} = \text{MSE}\left(f_{\theta_i}(x_i), f_{\theta_g}(x_i)\right) \tag{4}$$

where represents the mean squared error between the outputs of local and global models. This dual approach ensures model performance remains stable even when compression ratios reach up to 80%.

3 Experimental Results

We performed extensive experiments on a multimodal basketball training dataset gathered from five professional training centers to verify the effectiveness of our proposed framework. The assessment centers on three main areas: the model's accuracy in non-IID scenarios, the communication efficiency improved by adaptive pruning, and the computational performance achieved on edge devices. Experimental Setup: The dataset includes 12, 000 training sequences covering five basketball skill categories: shooting, dribbling, passing, defense, and rebounding, with data from various player positions and skill levels provided by each facility. The CNN-LSTM architecture was developed using 3D convolutional layers to extract spatial features and bidirectional LSTM for temporal modeling. The baseline comparisons involve standard federated averaging and two advanced federated pruning approaches.

Non-IID Performance: Figure 2 illustrates the test accuracy over communication rounds, highlighting our method's enhanced ability to manage data heterogeneity. The adaptive pruning method achieves 92.3% accuracy, outperforming federated averaging at 88.7% and static pruning at 90.1%. Testing on underrepresented skill categories shows a significant 15.2% increase in the performance gap, confirming our approach to heterogeneity-aware sparsity control.

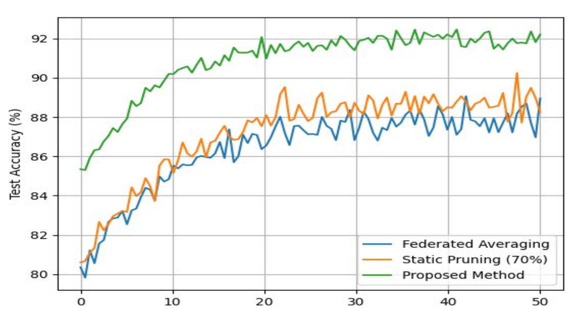

Figure 2 Test Accuracy Progression Across Communication Rounds for Various Federated Learning Methods

Communication Efficiency: Table 1 presents a comparison of the communication costs needed to achieve 90% test accuracy. Compared to standard federated learning, our approach cuts transmitted parameters by 73.8% and accelerates convergence by updating weights selectively. Based on local data features, the adaptive pruning mechanism automatically modifies compression ratios, which typically range from 60% to 85%.

Table 1 Comparison of communication efficiency (MB = Megabytes)

Method	Total Transmitted Data	Rounds to 90% Accuracy
Federated Averaging	342 MB	48
Static Pruning (70%)	198 MB	52
Proposed Method	89 MB	41

Edge Deployment: Our framework, implemented on NVIDIA Jetson AGX Orin, handles multimodal inputs at 28 FPS with a latency of 40ms, achieving real-time performance for training feedback. Compared to unpruned models, adaptive pruning cuts peak memory usage by 62%, making it feasible to deploy on edge devices with limited resources.

4 Discussions and Future Work

4.1 Constraints and Prejudices of FL-BTBAS

Although the system shows promising results in lab settings, its practical application reveals notable constraints that need addressing. Although the adaptive pruning mechanism works well for familiar basketball maneuvers, it might unintentionally remove weights that are important for new or uncommon movements lacking sufficient representation in the training data. This preference for dominant patterns may put players with unconventional techniques or those recovering from injuries at a disadvantage. Moreover, the existing implementation relies on synchronized communication rounds among all training sites, which proves unfeasible when applied to geographically dispersed institutions experiencing diverse network conditions. Structural alignment in deep architectures processing high-dimensional sensor data also incurs computational overhead due to layer-wise magnitude pruning.

4.2 Ethical Issues and Approaches to Mitigation

The ethical issues in sports analytics are not fully resolved by the privacy-preserving features of federated learning. Even without direct data sharing, processing biometric data through edge devices might expose sensitive details about players' physical states or training routines. Three mitigation strategies are recommended: First, to prevent membership inference attacks, differential privacy mechanisms are implemented during local model updates. Second, integrating explainability modules enables coaches to review model decisions without accessing raw player data. Third, it is necessary to establish clear data governance policies that respect athletes' rights to opt out while defining the permissible uses of derived analytics. These measures are especially important when implementing the system in youth training programs or amateur leagues, where participants might not have access to professional advice on data rights.

4.3 Emerging Trends and Wider Applications

The principles of FL-BTBAS apply to multiple fields beyond basketball, especially those needing privacy-focused motion analysis. Three potential avenues for research arise: First, adjusting the framework for monitoring rehabilitation could facilitate collaborative model training among hospitals while maintaining patient privacy. The architecture's capacity to manage diverse movement patterns is particularly beneficial for assessing recovery progress in varied patient populations. Second, combining the system with augmented reality interfaces might establish real-time feedback loops for athletes, allowing processed analytics to direct training modifications while avoiding the storage of sensitive performance data. Third, investigating cross-modal federated learning may enable institutions to integrate knowledge from visual, inertial, and physiological sensors, while keeping data isolated across modalities. New techniques for federated representation learning need to be developed to align embeddings across various sensor types and institutional data distributions.

5 Conclusion

The FL-BTBAS framework shows that federated learning with adaptive dynamic pruning can successfully balance privacy protection and analytical accuracy in analyzing basketball training behaviors. The system tackles non-IID data challenges by implementing client-specific sparsity adaptation and structural alignment, which leads to better performance than traditional federated methods and cuts down on communication overhead. Real-time feedback is achievable through edge-based multimodal processing while maintaining data confidentiality, which makes it highly appropriate for sports analytics across multiple institutions. This study lays the groundwork for digital physical education systems that prioritize privacy, adhere to regulatory requirements, and provide practical insights. Exploring asynchronous communication protocols and cross-modal federated learning in future implementations may help improve scalability and applicability across various training environments.

References

[1] A Oudah, R Abbood, S Shabib, et al. (2024) Developing Physical Education Curricula Within the Framework of Digital Transformation to Achieve Sustainable Development. Teacher Education Quarterly.

[2] L Li, Y Fan, M Tse & KY Lin (2020) A review of applications in federated learning. Computers & Industrial Engineering.

[3] T Sun, D Li & B Wang (2022) Decentralized federated averaging. IEEE Transactions on Pattern Analysis and Machine Intelligence.

[4] K Hsieh, A Phanishayee, O Mutlu, et al. (2020) The non-iid data quagmire of decentralized machine learning. In International Conference on Machine Learning.

[5] TB Moeslund, A Hilton & V Krüger (2006) A survey of advances in vision-based human motion capture and analysis. Computer Vision and Image Understanding.

[6] Y Kong & Y Fu (2022) Human action recognition and prediction: A survey. International Journal of Computer Vision.

[7] C Dwork (2008) Differential privacy: A survey of results. In International Conference on Theory and Applications of Models of Computation.

[8] J Gou, B Yu, SJ Maybank & D Tao (2021) Knowledge distillation: A survey. International Journal of Computer Vision.

[9] J Wu (2017) Introduction to convolutional neural networks. National Key Lab for Novel Software Technology, Nanjing University.

[10] A Graves & A Graves (2012) Long short-term memory. Supervised Sequence Labelling with Recurrent Neural Networks.

[11] Y Jiang, S Wang, V Valls, BJ Ko, et al. (2022) Model pruning enables efficient federated learning on edge devices. IEEE Transactions on Neural Networks and Learning Systems.

[12] X Zhu, J Wang, K Sato & Z Zheng (2025) Adaptive Model Compression for Efficient Federated Learning in IoT Systems. IEEE Internet of Things Journal.

[13] C Xu, Y Qu, Y Xiang & L Gao (2023) Asynchronous federated learning on heterogeneous devices: A survey. Computer Science Review.

[14] Sietsma & Dow (1988) Neural net pruning-why and how. IEEE.

[15] V Mothukuri, RM Parizi, S Pouriyeh, Y Huang, et al. (2021) A survey on security and privacy of federated learning. Future Generation Computer Systems.

[16] T Ha, TK Dang, TT Dang, TA Truong, et al. (2019) Differential privacy in deep learning: an overview. In 2019 International Conference on Machine Learning and Cybernetics.

[17] K Sandamal, S Arachchi, VO Erkudov, et al. (2024) Explainable artificial intelligence for fitness prediction of young athletes living in unfavorable environmental conditions. Results in Engineering.

[18] J Xu, BS Glicksberg, C Su, P Walker, J Bian, et al. (2021) Federated learning for healthcare informatics. Journal of Healthcare Informatics Research.

[19] P Soltani & AHP Morice (2020) Augmented reality tools for sports education and training. Computers & Education.

[20] L Che, J Wang, Y Zhou & F Ma (2023) Multimodal federated learning: A survey. Sensors.