Institute of Artificial Intelligence

Unlocking Multi-Site Clinical Data: A Federated Learning Approach to Privacy-First Child Autism Behavior Analysis

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Motivation

- Traditional autism diagnosis is subjective and resource-intensive.
- Computer vision can provide objective “digital biomarkers”. Privacy regulations (HIPAA/GDPR) restrict sharing of sensitive pediatric data.
- Data remains in silos, limiting large-scale studies.

Contribution

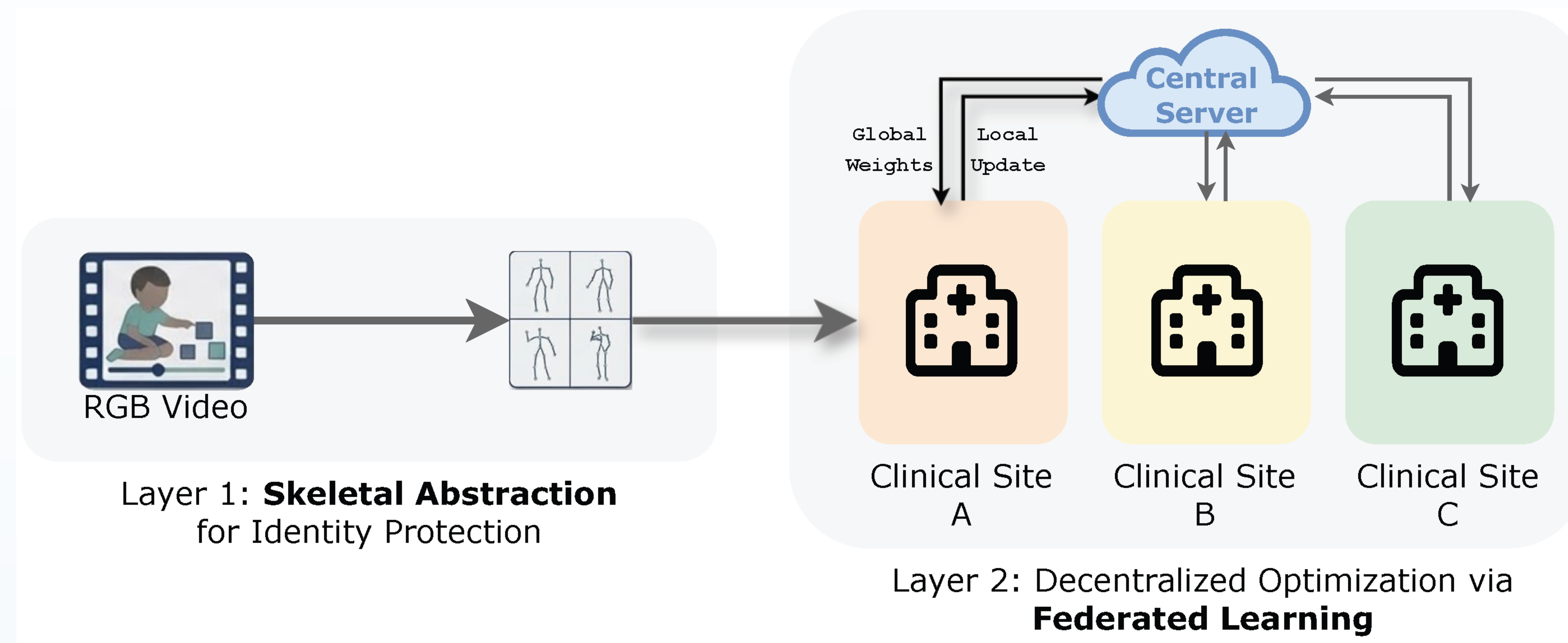
- **Two-Layer Privacy Framework**: Skeletal abstraction combined with federated learning.
- **Efficient FreqMixFormer Backbone**: For robust behavioral analysis on edge nodes.
- **Systematic PFL Investigation**: Evaluation of FedBN, FedPer, and APFL to handle clinical heterogeneity.
- **Federated Benchmark Protocol**: Demonstrating adaptive personalization via APFL as a robust solution.

Conclusion

- We proposed a privacy-first framework for pose-based autism behavior recognition.
- Two-layer privacy (skeletal abstraction + FL) enables secure multi-site collaboration.
- Adaptive personalization (APFL) is crucial for handling clinical data heterogeneity.

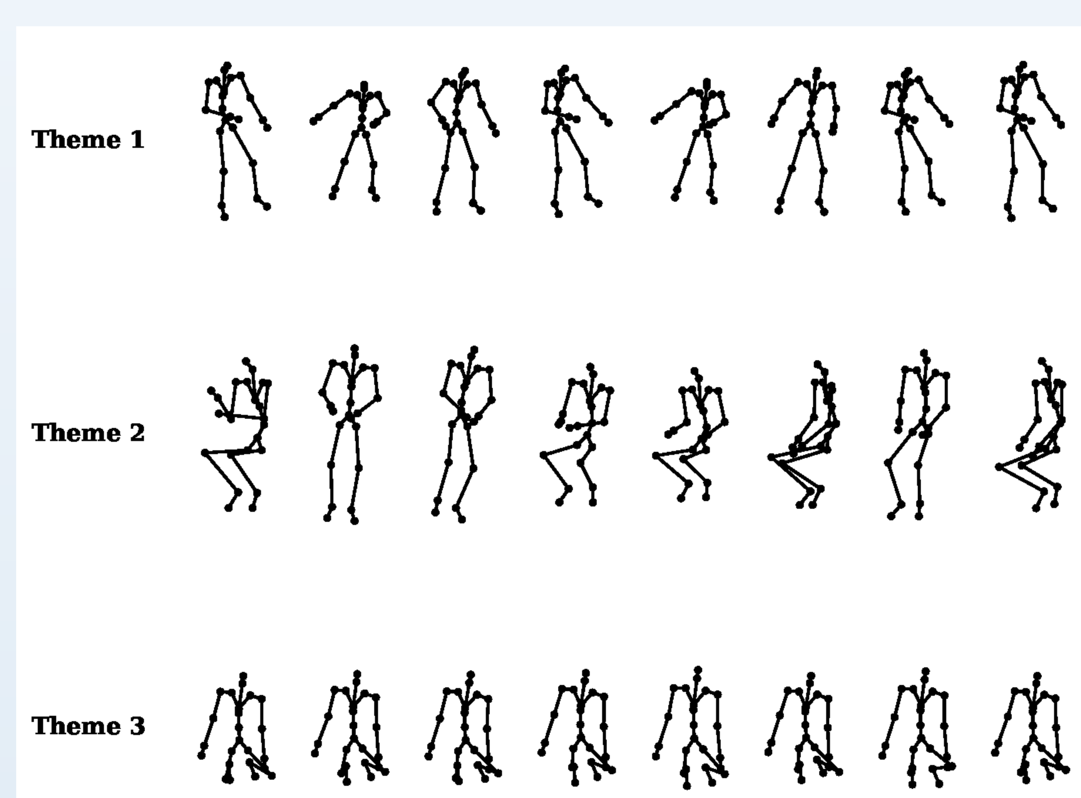
Overview

- **Layer 1: Skeletal Abstraction:** 3D skeletons preserve motion while discarding identifiable features (face, clothes).
- **Layer 2: Federated Learning:** Models are trained locally; only anonymized parameter updates are shared.



- **FreqMixFormer Backbone:** Frequency-aware mixed transformer for efficient and robust skeletal action recognition.
- **Personalized FL:** APFL adaptively mixes global and local models.

Experiments

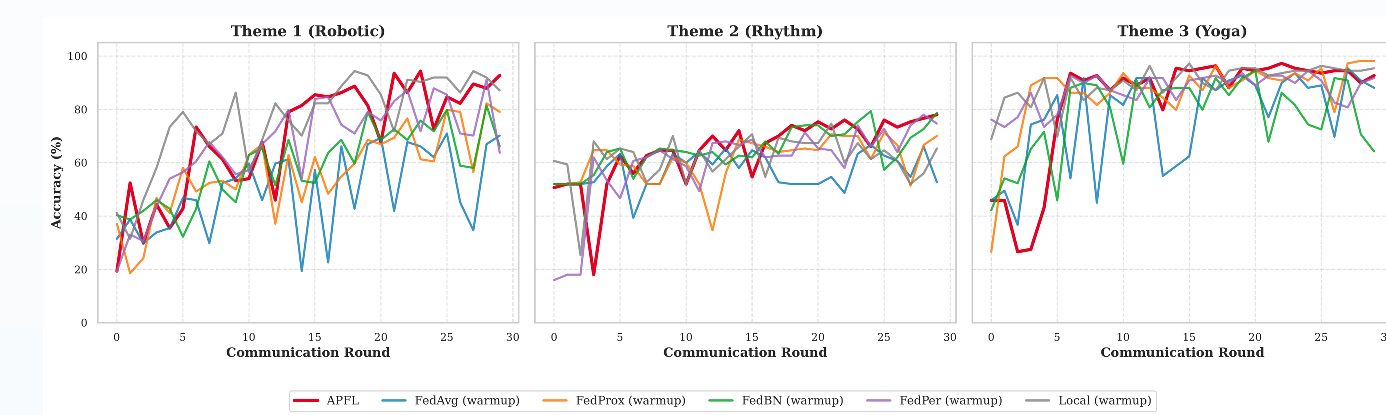


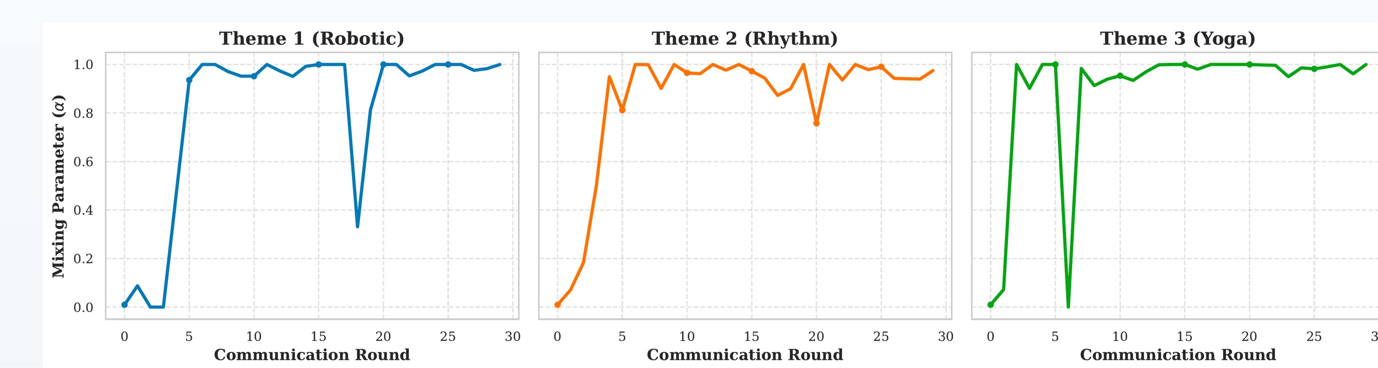
- **Dataset:** MultiModal ASD (MMASD+) benchmark, designed for privacy-preserving autism analysis.
- **Clinical Themes:**
  - Robotic-assisted therapy
  - Rhythm-based activities
  - Yoga-based poses

Results

Performance evolution across 30 communication rounds.

	Method	Theme 1	Theme 2	Theme 3	Avg (%)
Baseline	Local	87.10	65.33	95.41	82.61
FL	FedAvg	70.16	52.67	88.07	70.30
	FedProx	79.03	70.00	**98.17**	82.40
Personalized FL	FedBN	66.13	78.67	64.22	69.67
	FedPer	63.71	74.67	91.74	76.71
	APFL	**92.74**	**78.00**	92.66	**87.80**





Insights & Takeaway

- **Privacy-First AI Works**: Combining skeletal data with Federated Learning is a practical and effective way to protect patient privacy.
- **Standard FL is Not Enough**: Basic Federated Learning fails on heterogeneous clinical data, performing worse than models trained in isolation.
- **Personalization is Crucial**: Adaptive personalization (APFL) is the key to success, enabling models to learn from the network while specializing to local data.
- **Smart Collaboration Wins**: With APFL, our federated model achieved 87.8% accuracy, significantly outperforming isolated models (82.6%).
- **Efficiency Matters**: Lightweight models like FreqMixFormer are essential for real-world clinical deployment.