SF2D: Semi-supervised Federated Learning for Fall Detection using (Un)labelled Data in Edge-Cloud

Analytics Everywhere Lab AT THE UNIVERSITY OF NEW BRUNSWICK

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Seyed Alireza Rahimi Azghadi[1], Hung Nguyen[1], Irina Kondratova[4], Hélène Fournier[4], Monica Wachowicz[3], Francis Palma[2], René Richard[4], Hung Cao[1]

[1]Analytics Everywhere Lab, University of New Brunswick
[2]SE+AI Research Lab, University of New Brunswick, Canada
[3]RMIT University, Australia
[4]National Research Council, Fredericton, New Brunswick, Canada

Abstract

The aging population faces increased health risks, with falls being a major concern for individuals over 65, leading to healthcare strain and distress. We propose a semi-supervised federated learning-based fall detection (SF2D) method that leverages edge devices to maintain user privacy while ensuring accurate detection. Our approach first trains an unsupervised autoencoder with federated learning, then uses its encoder to train a cloud-based classifier with benchmark datasets. Our proposed SF2D improves accuracy by 1% and recall by 4% over state-of-the-art systems, offering a practical, accurate solution for fall detection and elderly care.

Introduction

- Falling is a leading cause of mortality, mobility loss, and cognitive decline in aging populations.
- Fall Detection Systems (FDS) categorized into:
  - Vision-based systems
  - Environmental signal detection
  - Wearable sensors (smartwatches, fitness trackers)
- Wearable sensors offer portability but face challenges with privacy, accuracy, and diversity.
- Federated Learning (FL) enhances privacy by processing data locally.
- FL-based fall detection methods include Fed-ELM, FL-FD, and FEEL.
- **Challenges**: Reliance on labeled data, which raises privacy concerns.
- **Proposed Solution**: Semi-supervised Federated Learning Fall Detection (SF2D) using both labeled and unlabeled data for privacy-preserving, accurate detection.

Related Works

- **FL in Fall Detection**: Local data processing for privacy and accuracy. Studies (Yu et al. [1], Ghosh et al. [2]) demonstrate FL's potential for personalized fall detection.
- **Semi-Supervised FL for Privacy-Preservation**: Combines labeled and unlabeled data for improved accuracy and privacy. Zhao et al. and Tashakori et al. [3, 4] show its effectiveness.

Method

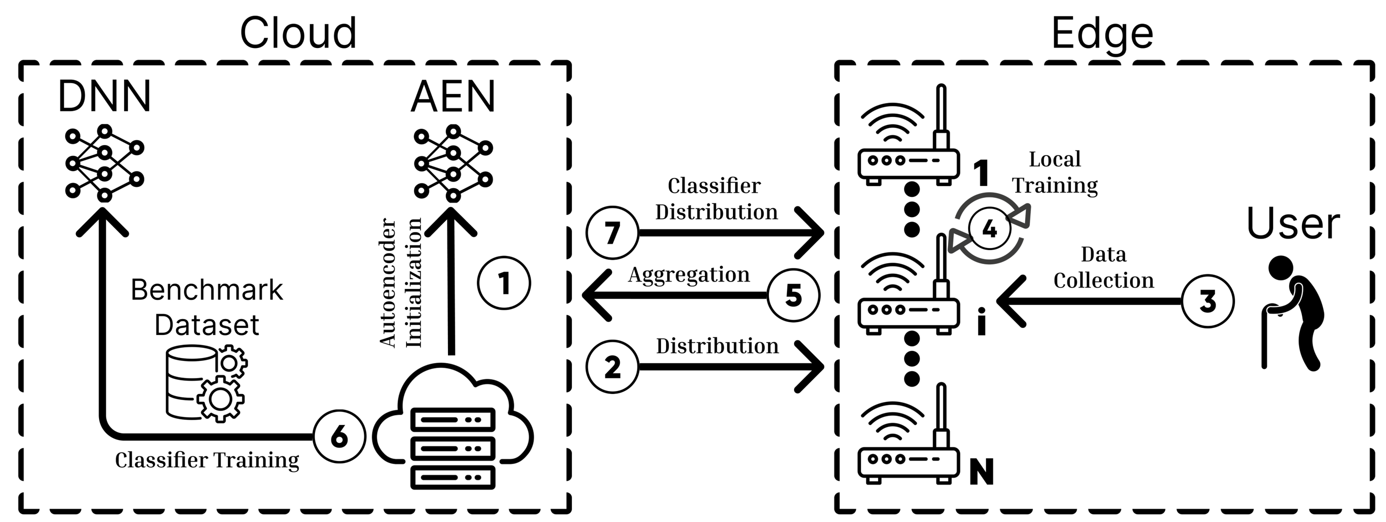

Figure 1. Our SF2D Fall Detection System Overview, showcasing the system's steps for fall detection and communication between cloud and edge

- **1. Autoencoder Initialization:** Initialize an autoencoder network $\mathbf{A}$ with random parameters $\theta^0_{\mathbf{A}}$ stored in the cloud. This ensures uniform training and model convergence across all users.
- **2. Distribution:** Distribute the initialized autoencoder parameters $\theta^0_{\mathbf{A}}$ to all edge devices. Each user i's edge device $\mathcal{E}_i$ is responsible for training the model locally.
- **3. Data Collection:** Each edge device $\mathcal{E}_i$ collects data $\mathcal{U}_i$ from the user's wearable device. This data is used exclusively for local training and discarded afterward to ensure privacy. No labels are involved in this phase.
- **4. Local Training:** Preprocess the collected data (e.g., resample, noise reduction with EWM filter, and sequence resizing). The edge device then trains the autoencoder on the local data to update the parameters $\theta^{(i)}_{\mathbf{A}}$.
- **5. Federated Averaging:** After local training, the updated parameters are sent to the cloud server. The server aggregates these parameters using Federated Averaging (FedAvg), weighted by the data size M_i from each edge device.
- **6. Classifier Training:** The autoencoder's encoder $\mathbf{E}$ is used as a feature extractor. A fully connected neural network (FCNN) is trained on labeled data to predict activity labels, including fall detection.
- **7. Classifier Distribution:** The trained classifier is distributed back to the edge devices for real-time fall detection. Raw data never leaves the edge device, ensuring privacy and decentralized operation.

Experiment and Evaluation

- **Dataset:** SiSFall dataset [5] with 38 participants (23 young, 15 older), including 15 falls and 19 activities of daily living (ADL).
- Data divided into benchmark subset ($\mathcal{D}$) with labels and real-world data ($\mathcal{U}$) without labels (40% benchmark, 60% real-world).
- Network Architecture:
  - **Autoencoder:** 3 LSTM layers, L2 regularizer, Adam optimizer, MSE loss.
  - **Classifier:** 3-layer dense network with two output classes: "Fall" and "ADL".
- Training Modalities:
  - **Centralized learning (CL):** Autoencoder trained on $\mathcal{U}$ for 50 epochs; classifier trained on labeled $\mathcal{D}$.
  - **Federated learning (FL):** Autoencoder trained on $\mathcal{U}$ using Flower framework for 50 rounds; classifier trained on labeled $\mathcal{D}$.

Result and Evaluation

Table 1. Performance metrics comparison of different methods (ACC = Accuracy, PR = Precision, RE = Recall, and F1 = F1 score).

Method	ACC	PR	RE	F1
Fed-ELM† [1]	98.01	-	95.25	-
CL (Ours)‡	**99.33**	99.67	**99.63**	**99.65**
FL (Ours)‡	99.19	**99.69**	99.47	99.58

† Supervised ‡ Semi-supervised

- **Top Performance:** CL achieved the highest performance (99.33% accuracy, 99.65% F1 score), with FL close behind (99.69% precision).
- **Fed-ELM Comparison:** CL and FL outperformed Fed-ELM across all metrics.
- **Minimal Gaps:** FL and CL showed minimal differences, demonstrating robustness.
- **Practical FL:** FL works in real-world scenarios without labels, preserving privacy while achieving near-baseline performance.

Conclusion and Future Works

- **Introduction of SF2D:** SF2D is a semi-supervised, privacy-preserving fall detection method using wearable devices and Federated Learning (FL).
- **Edge Device and Autoencoder Integration:** The approach uses edge devices and an unsupervised autoencoder to ensure privacy and accuracy in fall detection.
- **Future Work:** Future work will focus on data quality monitoring, drift detection, and model updates within the FL framework.
- **Further Evaluation:** Additional evaluation will include testing on benchmark datasets, real-world scenarios, and exploring alternative preprocessing techniques to improve predictive performance.

References

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alireza.rahimi@unb.ca