Protecting Older Adults: A Wearable-Based Federated Learning Approach for Pre-Impact Fall Detection

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Abstract

As the aging population grows, the health risks associated with falls, particularly for individuals over 65, have become a major concern. Falls not only place a significant strain on healthcare systems but also cause considerable distress to older adults and their families. This study seeks to develop a non-invasive, privacy-preserving solution for detecting falls before impact, using wearable devices to reduce stress, prevent fall-related injuries, and lessen the burden on public health systems. We present a pre-impact fall detection method based on federated learning, leveraging edge devices to ensure both user privacy and high detection accuracy. To achieve this, we implemented federated learning in our system architecture and employed a quantization technique to optimize model performance on wearable devices. Through an extensive architecture search, evaluating over a thousand configurations, we identified an efficient and effective detection model. This solution offers a reliable and practical approach to pre-impact fall detection, with promising benefits for improving older people's care and quality of life and alleviating pressure on healthcare services.

Motivation

- **Leading Cause of Injury:** Falls are the top cause of injury-related hospitalizations and deaths for people 65+, especially those 70+.
- **Why Prevention is Critical:** High fall rates and an aging population make prevention vital for public health.
- **Older Adults' Perspective:** Fast detection reduces fear and promotes mobility and independence.
- **Caregiver & Family Perspective:** Timely alerts improve care and help identify prevention strategies.
- **Policy Implications:** Preventing falls reduces healthcare costs and supports independent living.

Method

- **Overview:** Designed for privacy-preserving fall detection using federated learning [1] with combined edge devices and TinyML for faster, on-device detection. The method overview is illustrated in Figure 1, and the online detection phase is presented in Figure 2.
- **Pre-Impact Federated Learning Fall Detection Steps:**
  1. Train an initial model using a cloud-based benchmark dataset.
  2. Transfer the model to edge devices.
  3. Fine-tune the model based on individual user data.
  4. Quantize the model and transfer it to the user's microcontroller.
  5. When low-confidence predictions occur, send data samples back to the edge device.
  6. Edge device fine-tunes the model with uncertain samples.
  7. Send updated parameters from the edge to the cloud server.
  8. Cloud server aggregates parameters and updates the global model.
  9. Redistribute the updated model to all edge devices; repeat the process from step 3.
- **Microcontroller Detection Process:** After fine-tuning the model on the edge device to adapt it to a specific user, the optimized model is transferred to the microcontroller via Bluetooth Low Energy (BLE) or by uploading from the edge device. Once the model is deployed, the microcontroller initiates the real-time fall detection phase, enabling rapid and efficient fall prediction directly on the wearable device.

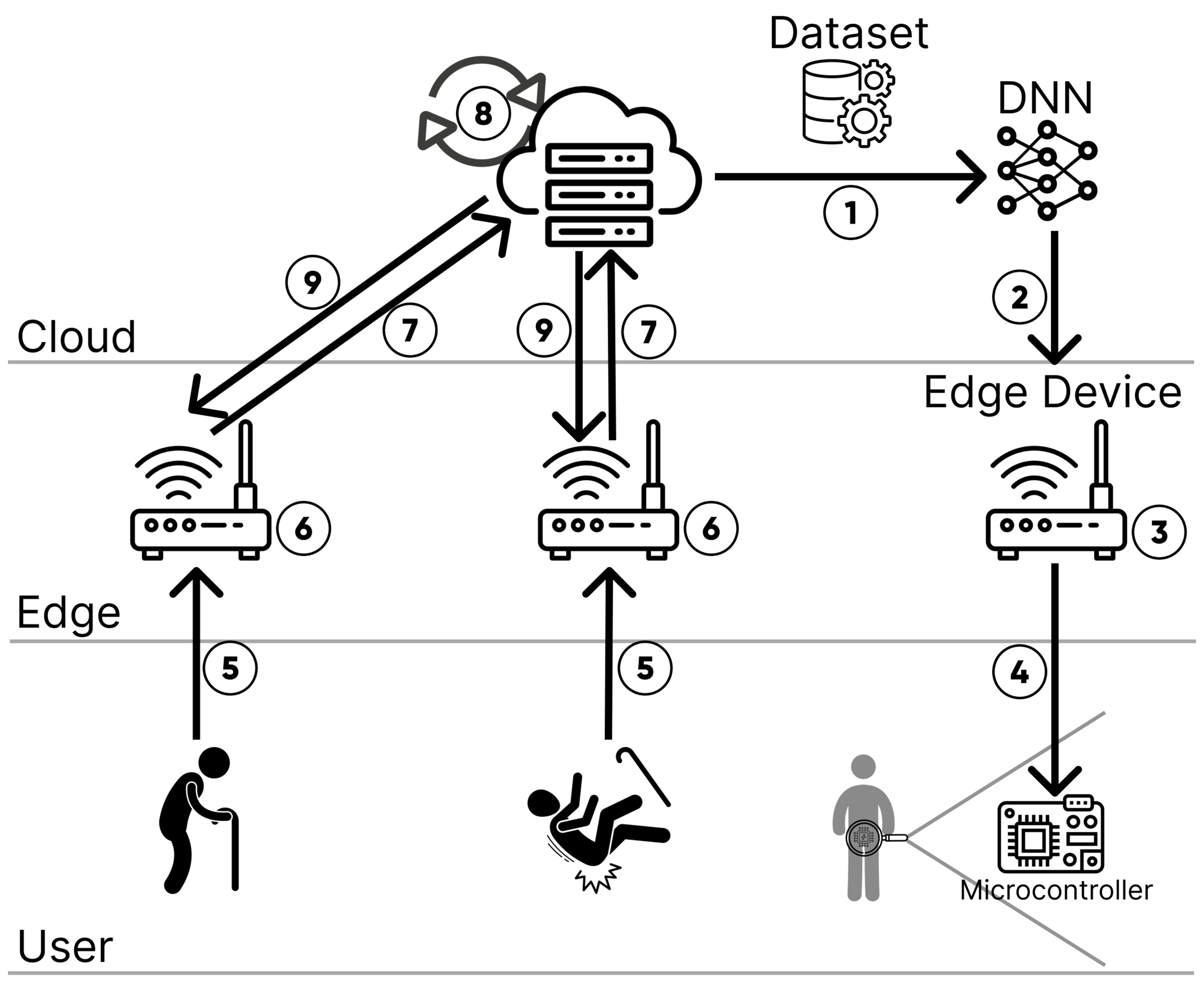

Figure 1. Method diagram illustrating the information flow and training steps

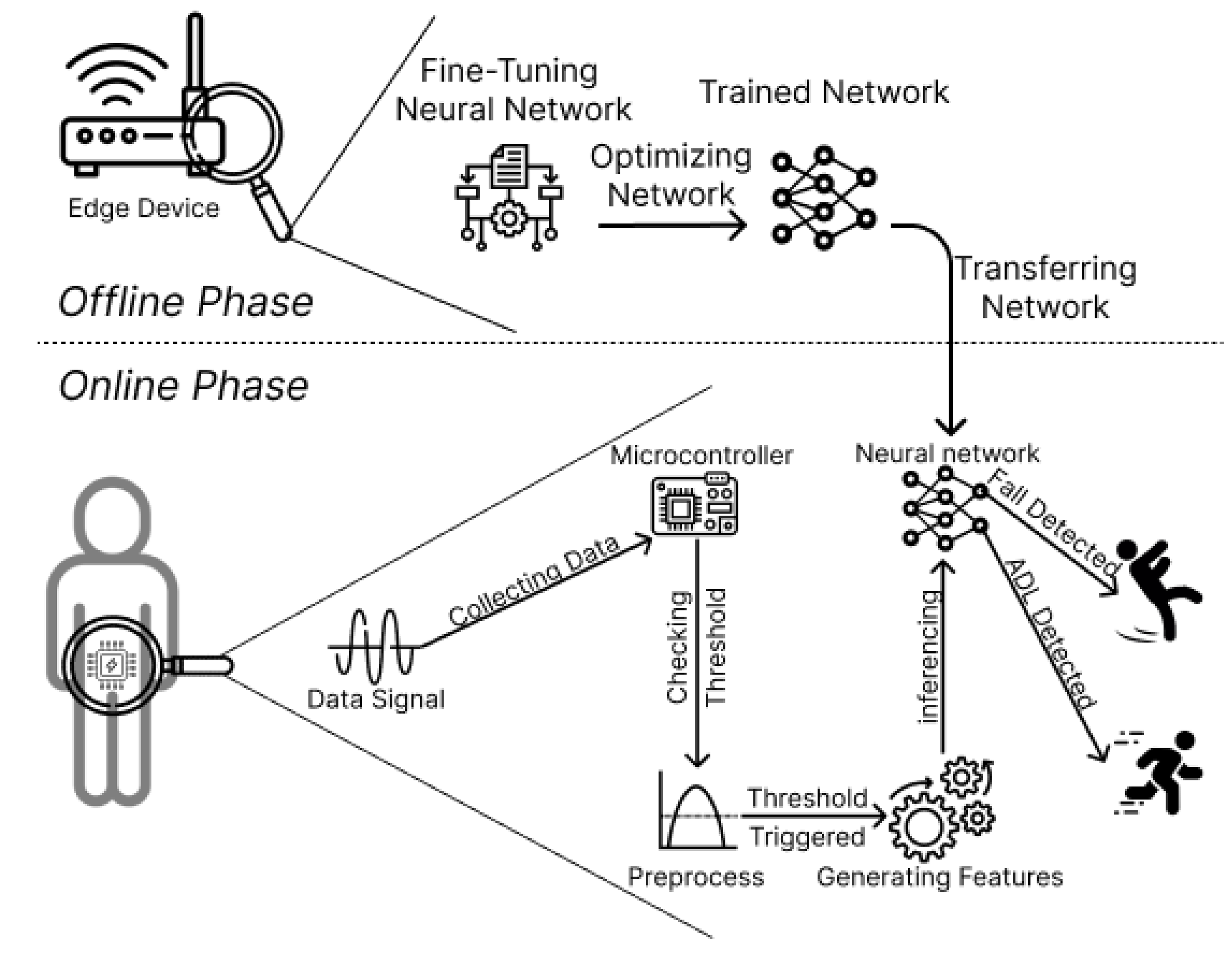

Figure 2. Online Pre-Impact Fall Detection with TinyML in Wearable Devices

- **Online Detection:**
  - Wearable device continuously collects accelerometer data streams.
  - Threshold mechanism detects user movement; triggers further signal processing when the threshold is exceeded.
  - Relevant features or raw data are extracted from the accelerometer data, based on model architecture.
  - The extracted features or raw data are processed by the pre-trained neural network, enabling real-time fall prediction.

Experiments and Results

We used the KFall dataset (sampled at 100Hz) to explore fall detection modelling, including architecture design, model selection, and data preprocessing. We executed an architectural search to find the best models. We illustrated an accumulative percentage of the best features that led us to train the models at different percentiles in Figure 3.

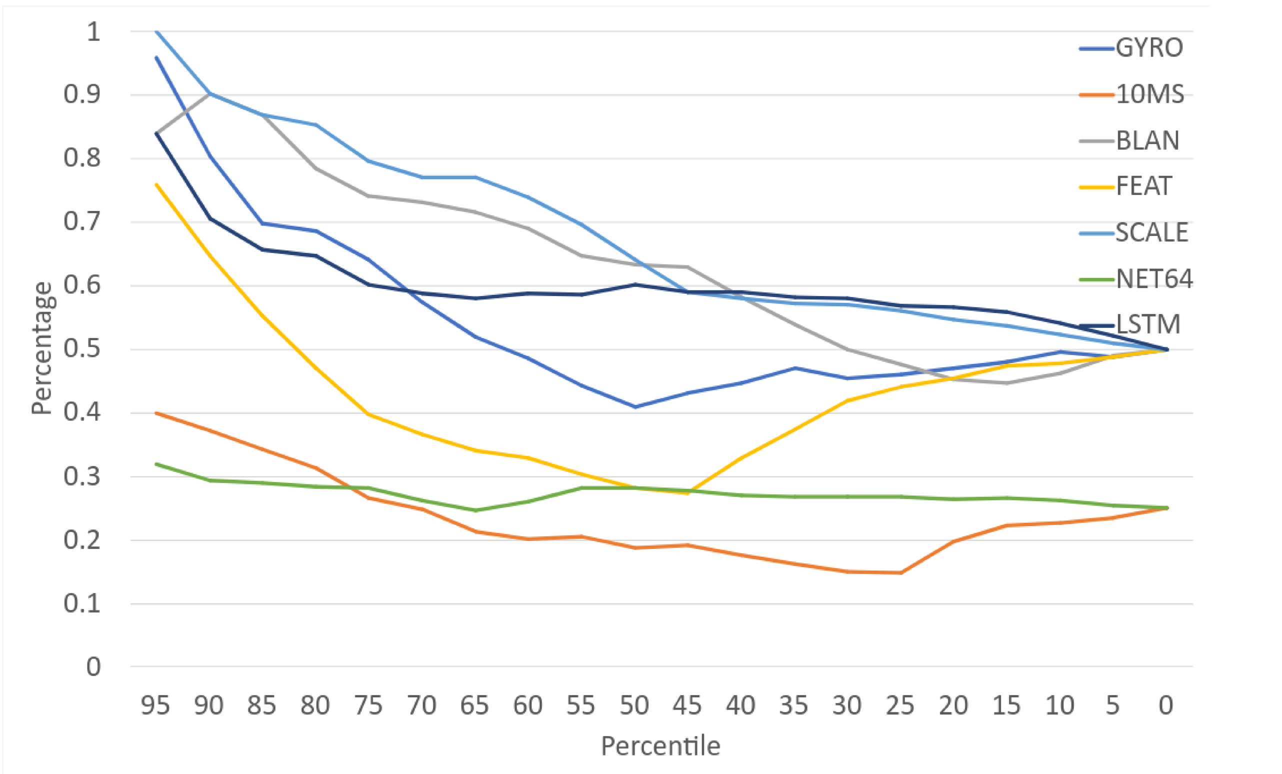

Figure 3. Top features percentage in models with best performance

In Figure 3, we showed most of the models in the 95 percentile (top 5%) have **SCALE** and **GYRO**, which demonstrates the importance of scaling and using gyroscope data.
In our architectural search, we used two data types with or without **gyroscope** data merged with accelerometer data, **resampled the data** at different temporal resolutions, **balanced** the classes, and normalized the data using **min-max scaling**. We **generated 54 features** with TSFEL [2] and tested **LSTM** and **CNN**-based autoencoder models with varying **neuron counts** and extra prediction layers.
Our analysis shows that smaller LSTM models trained with generated features from balanced, scaled 10Hz gyroscope and accelerometer data achieved the best performance in both accuracy and F1 metrics. Our best model accuracy is **94.1%** and has an **87.6%** F1 score.
We used quantization to convert our models to TensorFlow Lite (TFLite) [3], reducing their size and improving inference efficiency on edge devices. This process transformed model weights from 32-bit floating-point to lower precision, achieving an average size reduction of about 88.0%. The smallest network, with 64 neurons in the first layer, was reduced to approximately 100 KB, showcasing the effectiveness of quantization for resource-constrained environments.

Conclusion and Future works

This poster presents a novel fall detection system that ensures user privacy, detects pre-impact falls, and delivers reliable performance. Our design utilizes federated learning and TinyML, supported by a neural architecture search and hyperparameter analysis. The results demonstrate that federated learning is effective for pre-impact fall detection while maintaining privacy through edge device training. Future work will focus on optimizing model quantization and updates, as well as exploring real-world scenarios to create a more personalized network for improving fall detection accuracy, particularly for older adults.

References

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