Title:

Federated Learning-Based Secure and Scalable AI-Driven Fall Detection System for Real-Time Optimization in Elderly Care

Aim of the Project

The aim of this research is to develop a secure, scalable, and privacy-preserving AI-driven fall detection system utilizing federated learning (FL) to enable real-time optimization in elderly care. The project seeks to address the limitations of conventional centralized AI models in terms of data privacy, computational scalability, and real-time inference for detecting falls among the elderly.

Statement of the Problem

Falls among elderly individuals are a leading cause of injury, disability, and even mortality. Traditional AI-based fall detection systems rely on centralized data processing, raising concerns regarding data privacy, security, and scalability. Additionally, existing methods face challenges related to real-time detection latency, edge-device compatibility, and model generalization across diverse healthcare environments.

The major challenges include:

1. Privacy Risks: Centralized AI models require data aggregation, leading to potential data breaches and privacy concerns.

2. Scalability Issues: Large-scale deployment in multiple healthcare facilities is challenging due to computational and communication constraints.

3. Real-Time Optimization: Existing models lack adaptive learning capabilities for continuous improvement and real-time inference.

4. Edge Device Compatibility: Conventional models struggle with efficient execution on IoT and edge devices.

This research proposes an FL-based AI system to mitigate privacy risks, enhance real-time detection, and enable scalable deployment in elderly care.

Overview of Literature

A review of existing literature highlights various approaches to fall detection, including:

- Computer Vision-Based Systems: These rely on CCTV cameras and deep learning, but they pose privacy concerns and require constant video surveillance.

- Wearable Sensor-Based Systems: Devices such as accelerometers and gyroscopes detect falls but suffer from user discomfort and battery constraints.

- IoT-Based Fall Detection: These solutions integrate motion sensors, pressure sensors, and AI but often rely on centralized cloud processing, raising latency and security issues.

- Federated Learning in Healthcare: Recent research demonstrates the potential of FL to enable decentralized learning without sharing raw data, improving both privacy and scalability.

Gaps identified in the literature include lack of privacy-aware, real-time optimization frameworks for AI-driven fall detection and the absence of federated learning integration in real-world elderly care systems.

Conceptual Framework

The conceptual framework is based on the integration of federated learning, edge AI, and real-time optimization techniques in fall detection. The key components include:

1. Federated Learning: Distributed training of AI models across multiple elderly care centers without sharing sensitive data.

2. Edge AI: Deploying lightweight deep learning models on IoT-based edge devices for real-time fall detection.

3. Secure Communication: Implementing homomorphic encryption and differential privacy techniques for secure data exchanges.

4. Adaptive Model Optimization: Leveraging reinforcement learning for continuous model improvement based on real-time data streams.

Research Hypothesis

H1: A federated learning-based AI-driven fall detection system can achieve comparable or superior accuracy compared to centralized AI models.

H2: Implementing federated learning can enhance privacy and security without compromising real-time performance.

H3: A decentralized AI framework can provide scalable and efficient fall detection across multiple elderly care facilities.

Research Methodology

The research methodology consists of the following steps:

1. Data Collection & Preprocessing

- Collect fall detection data from public datasets (e.g., MobiFall, UR Fall Detection) and real-world IoT sensors.

- Data preprocessing includes noise reduction, feature extraction (e.g., accelerometer signals, skeletal key points), and normalization.

2. Federated Learning Model Development

- Implement deep learning-based fall detection models (e.g., CNN, LSTM, Transformer models).

- Train models using federated learning across multiple edge devices.

- Apply differential privacy and secure aggregation techniques for privacy preservation.

3. Real-Time Deployment & Optimization

- Deploy FL-trained models on edge devices, such as Raspberry Pi, NVIDIA Jetson Nano.

- Implement edge AI inference engines for real-time fall detection.

- Optimize models using quantization, pruning, and model distillation.

4. Performance Evaluation

- Evaluate the model using accuracy, F1-score, latency, and energy consumption.

- Compare FL-based models with centralized deep learning approaches.

- Conduct user trials in elderly care environments for validation.

5. Security & Privacy Validation

- Assess data leakage risks, model inversion attacks, and adversarial robustness.

- Implement homomorphic encryption and secure multi-party computation techniques.

Implications

The proposed FL-based fall detection system has several key implications:

1. Enhanced Privacy & Security: Eliminates the need for sharing sensitive health data while ensuring high accuracy.

2. Scalability: Enables large-scale deployment across multiple elderly care centers and smart home environments.

3. Real-Time Optimization: Allows continuous model updates without central server dependency.

4. Healthcare Innovation: Supports AI-driven remote monitoring and personalized healthcare interventions.

5. Cost-Effectiveness: Reduces reliance on cloud computing, lowering operational costs for healthcare providers.

References