Human Activity Recognition Using Federated Learning

20BCE0638 | J.Solomon Abhilash Martin | Prof Raja S.P | SCOPE

Introduction

Unlocking the potential of smartphones, this project focuses on human activity recognition—a vital technology for health monitoring and elder care support. By leveraging smartphone sensors, the system automates tasks like rehabilitation assistance. Innovative methods like active learning streamline training, enhancing accuracy with minimal user input.

Motivation

Human Action Recognition (HAR) using sensor data is an emerging field that enhances functionalities across health monitoring, smart home automation, and human-computer interaction. This approach leverages everyday device sensors to improve user interactions and system efficiencies while addressing privacy concerns of video-based systems.

Scope of the Project

The project aims to develop a Framework that enables edge devices, equipped with sensors like accelerometers and gyroscopes, to train models locally. It also seeks to implement a Federated Learning system that aggregates updates from multiple devices to enhance a global model while maintaining data privacy. Additionally, the project will assess scalability across various devices and environments. Finally, it will demonstrate the system's practical applications in fields such as health monitoring, fitness tracking, and smart home systems.

Methodology

Key Components :

1. **Client Devices**: Client devices, such as distributed sensors or smartphones, are worn by users to locally collect activity data. These devices independently process and analyze sensor data to identify human activities, keeping data on-device to ensure privacy and reduce the risk of exposure.
2. **Central Server**: Serving as the orchestrator for federated learning, the central server coordinates interactions between client devices. It manages the training and aggregation of models, updating the global model with inputs from all participating devices.
3. **Communication Protocol**: Secure, efficient, secure protocol to facilitate encrypted communication between client devices and the central server, optimizing federated learning efficiency.

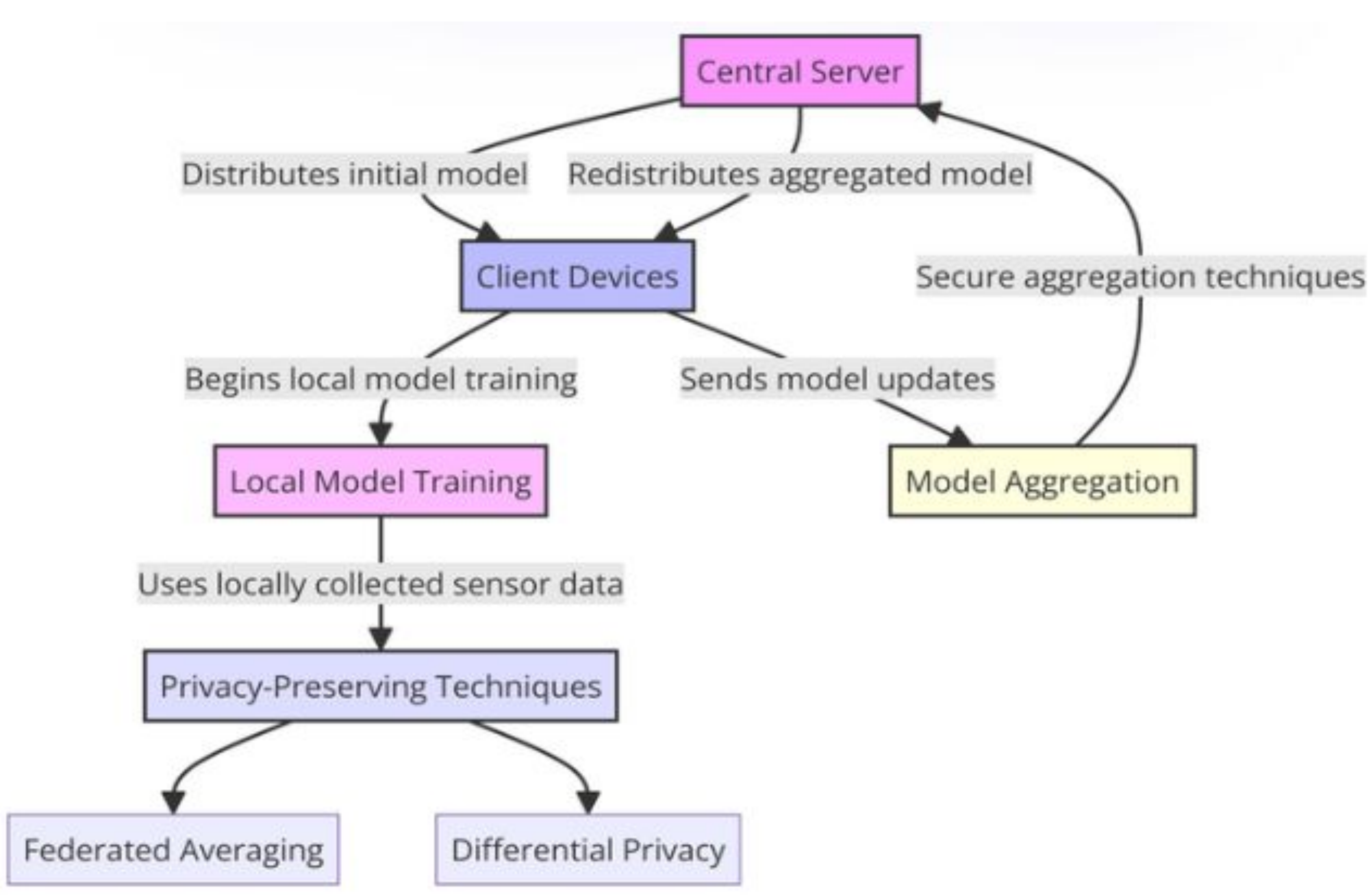


FIGURE 1: SYSTEM ARCHITECTURE

Workflow:

1. **Initialization**: The federated learning process begins with the central server distributing an initial model to client devices. These devices then start local training with their unique datasets.
2. **Local Model Training**: Each client device trains the model independently using data collected from onboard sensors. Techniques such as federated averaging and differential privacy are implemented to keep user data confidential during this phase.
3. **Model Aggregation**: Client devices submit their model updates to the central server, which uses secure aggregation methods to enhance the global model. These updates are then redistributed to clients for further training cycles.
4. **Model Deployment and Real-Time Prediction**: The global model is converted to a TensorFlow Lite format optimized for mobile devices. As users engage in various activities, the app collects sensor data, processes it through the model, and updates the interface with the current activity probabilities.

Results

The following set of graphs represents the training and validation loss and accuracy over 25 epochs for a client model within a federated learning system. The left graph shows a sharp decrease in both training and validation loss, indicating effective learning and generalization capabilities of the model. The right graph displays a significant initial increase in accuracy for both training and validation, followed by stabilization, reflecting the model's ability to accurately predict human activities.

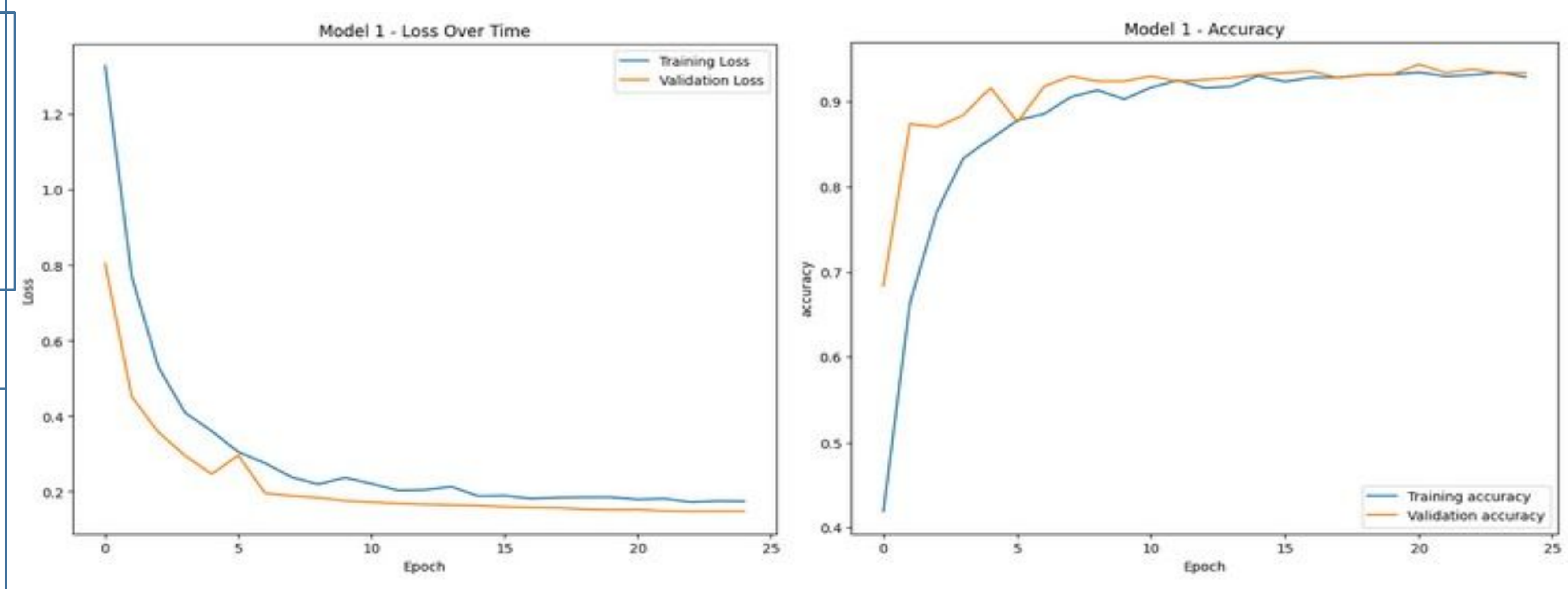
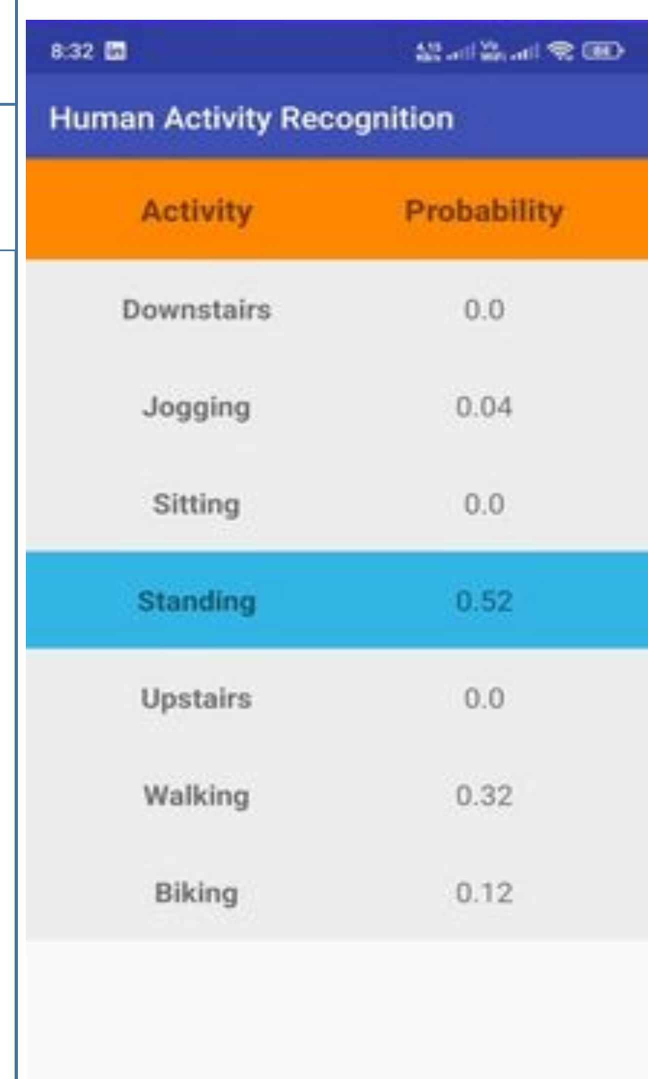


FIGURE 2:Training and Validation Loss & Accuracy for Client Model



The displayed screenshot represents an implementation of a Human Activity Recognition (HAR) system, showcasing our mobile application interface that predicts various activities based on sensor data. The app displays a list of activities such as Standing, Walking, Jogging, and Biking, along with their respective probabilities. For instance, the app currently highlights 'Standing' as the most probable activity with a 52% likelihood, followed by 'Walking' at 32%, indicating real-time analysis and user interaction facilitation within the HAR framework. This application is a practical example of utilizing machine learning to interpret sensor data for enhancing user engagement and activity tracking.

Conclusion

In conclusion, our proposed federated machine learning architecture for Human Activity Recognition (HAR) presents a comprehensive solution to the challenges inherent in traditional HAR systems. By decentralizing data processing to client devices while maintaining robust privacy and security measures, our system not only preserves user privacy but also enhances scalability and efficiency. Through the orchestration of model training and aggregation by a central server, our architecture ensures seamless collaboration between client devices while minimizing communication overhead. With the successful implementation of our system workflow, we demonstrate the viability and effectiveness of federated learning in HAR, paving the way for innovative solutions in activity recognition while safeguarding user data privacy.

References

Journal:

1. Chen, H.; Gouin-Vallerand, C.; Bouchard, K.; Gaboury, S.; Couture, M.; Bier, N.;Giroux, S. Enhancing Human Activity Recognition in Smart Homes with Self-Supervised Learning and Self-Attention. Sensors 2024, 24, 884. https://doi.org/10.3390/s24030884
2. Müller, P.N.; Müller, A.J.; Achenbach, P.; Göbel, S. IMU-Based Fitness Activity Recognition Using CNNs for Time Series Classification. Sensors 2024, 24, 742. https://doi.org/10.3390/s24030742
3. Subburam, R.; Chandralekha, E.; Kandasamy, V. An Elderly Fall Detection System Using Enhanced Random Forest in Machine Learning. Eng. Proc. 2023, 59, 172. https://doi.org/10.3390/engproc2023059172
4. Hassan, N.; Miah, A.S.M.; Shin, J. A Deep Bidirectional LSTM Model Enhanced By Transfer-Learning-Based Feature Extraction for Dynamic Human Activity Recognition. Appl. Sci. 2024, 14, 603. https://doi.org/10.3390/app14020603
5. Bouazizi, M.; Mora, A.L.; Feghoul, K.; Ohtsuki, T. Activity Detection in Indoor Environments Using Multiple 2D Lidars. Sensors 2024, 24, 626. https://doi.org/10.3390/s24020626
6. Ordóñez, F.J.; Roggen, D. Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition. Sensors 2016, 16, 115.https://doi.org/10.3390/s16010115