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Federated weakly-supervised representation learning for privacy-preserving human activity recognition using wearable sensors

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Abstract

Human activity recognition (HAR) plays a crucial role in wearable sensor-based applications, particularly in privacy-sensitive domains such as healthcare, fitness, and smart homes. Federated learning (FL), when combined with weakly-supervised representation learning, provides an effective solution to enhance HAR while ensuring privacy. This paper proposes a novel approach for privacy-preserving human activity recognition using wearable sensors, which integrates federated learning with weakly-supervised representation learning. The approach leverages contrastive learning techniques to enable feature extraction from weakly-labeled or unlabeled sensor data and employs multimodal sensor fusion to improve recognition accuracy. Experimental results demonstrate that the proposed framework outperforms traditional supervised learning models in terms of both accuracy and privacy preservation, making it suitable for scalable HAR applications. Our findings highlight the potential of this hybrid framework in advancing privacy-conscious systems for healthcare monitoring, fitness tracking, and smart home environments.

Keywords: Federated Learning; Weakly-Supervised Learning; Human Activity Recognition; Wearable Sensors; Privacy Preservation;

1. Introduction

Human activity recognition (HAR) has become an essential area of research in recent years due to its potential applications in diverse fields, including healthcare, fitness tracking, smart homes, and elderly care. HAR systems rely on wearable sensors, such as accelerometers, gyroscopes, and heart rate monitors, to collect data that helps identify specific human activities, including walking, running, sitting, and more. The increasing ubiquity of wearable devices like smartwatches, fitness trackers, and smart clothing has made it easier to collect data continuously, offering great promise for improving the quality of life and supporting various monitoring systems in real-time. However, despite the progress, HAR systems face several challenges that need to be addressed for them to become effective and widely deployed.

One of the significant challenges in HAR is the privacy preservation of sensitive user data. Wearable devices collect personal information, including users' physical movements, locations, and potentially even health status. As the data generated by wearable devices is often uploaded to centralized servers for processing, concerns over data privacy and security arise, especially in domains such as healthcare and fitness, where user data is highly sensitive. This privacy issue has led to the exploration of alternative frameworks, such as Federated Learning (FL), which allows data to remain on local devices while enabling collaborative model training across decentralized devices.

Another major issue in HAR is the requirement for large labeled datasets. Traditionally, supervised learning approaches have been used for activity recognition, which require extensive labeled data to train accurate models. However, labeling large-scale datasets is time-consuming, expensive, and often impractical, especially for long-term or real-time

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monitoring of activities in free-living environments. To mitigate the need for labeled data, weakly-supervised learning methods have gained traction. These approaches enable the use of coarse or weak labels (e.g., activity categories or segment-level annotations), reducing the reliance on fully labeled datasets while still maintaining high performance. Weakly-supervised learning models are trained using less granular supervision and are more adaptable to real-world scenarios where labeling every instance of sensor data is not feasible.

Furthermore, sensor fusion, the process of integrating data from different sensor modalities, is increasingly recognized as a critical factor in improving the accuracy and robustness of HAR systems. A single sensor may not capture all the necessary features to reliably identify an activity. For example, accelerometers may be effective in recognizing movement, but they may not fully capture the intensity of physical activities like running or cycling, which can be better understood through heart rate sensors or additional context provided by gyroscopes. By combining data from multiple sensors, a more comprehensive representation of human activity can be obtained, improving the overall performance and generalization ability of the recognition system.

This paper proposes a novel hybrid framework for human activity recognition using wearable sensors, which addresses these key challenges: privacy preservation, data sparsity, and multimodal sensor fusion. The framework combines Federated Learning (FL) with weakly-supervised representation learning and contrastive learning techniques to achieve accurate activity recognition while maintaining data privacy. FL allows the model to be trained on decentralized data, ensuring that sensitive user information never leaves the device. The weakly-supervised learning component reduces the need for large labeled datasets by leveraging weak supervision signals, such as coarse labels or segment-level annotations, making the system more scalable and adaptable. Additionally, contrastive learning helps the model learn meaningful features from unlabeled data, further minimizing the reliance on fully labeled datasets.

The integration of multimodal sensor data such as accelerometer, gyroscope, and heart rate data—enables the model to extract richer features for more accurate and robust activity recognition. This combination of federated learning, weakly-supervised learning, self-supervised contrastive learning, and multimodal sensor fusion forms the backbone of the proposed framework. By reducing the dependency on labeled data and preserving privacy, this framework presents a scalable and efficient solution for HAR, particularly in privacy-conscious applications such as healthcare monitoring, smart homes, and fitness tracking systems.

1.1. Privacy Preservation with Federated Learning

Privacy concerns are a significant barrier to the widespread deployment of wearable sensor-based HAR systems. Traditional centralized machine learning models store data on servers, where it is vulnerable to data breaches and unauthorized access. Federated Learning (FL) addresses these concerns by decentralizing the learning process. Instead of uploading raw data to a central server, FL allows models to be trained locally on user devices (e.g., smartphones or wearables), and only model updates (such as gradients or weights) are shared with a central server. This approach ensures that sensitive user data never leaves the local device, preserving privacy while still enabling collaborative model training across multiple users.

In the context of HAR, FL allows the development of activity recognition models without requiring direct access to raw sensor data, making it an ideal solution for privacy-sensitive applications. However, federated learning faces challenges such as data heterogeneity, where devices may have different data distributions or sensor configurations, and communication inefficiencies, as frequent communication between devices and the central server can result in high overhead. Despite these challenges, federated learning remains a promising privacy-preserving solution for HAR.

1.2. Reducing Label Dependency with Weakly-Supervised Learning

The scarcity of labeled data is a critical issue for training accurate HAR models, especially when dealing with large-scale or long-term data. Traditional supervised learning methods require a significant amount of labeled data, which can be expensive and time-consuming to obtain. In contrast, weakly-supervised learning reduces the need for fine-grained labels by using weaker supervision signals, such as segment-level annotations or coarse labels. This approach makes it possible to train HAR models with less labeled data, enabling the model to learn from imprecise or partial annotations while still achieving high performance.

Weakly-supervised learning methods can be particularly valuable in real-world HAR applications, where full labeling of sensor data is impractical. For example, in free-living environments, it is difficult to label every instance of activity due to the variability in user behavior, sensor placement, and environmental factors. By using weakly-supervised learning, the model can still be trained effectively while reducing the burden of labeling. This also makes the model more adaptable to new users and devices, as it is less reliant on specific training data.

1.3. Supervised Learning with Contrastive Learning

In addition to weakly-supervised learning, self-supervised learning (SSL) techniques have gained traction in HAR. SSL allows models to learn useful representations of data without requiring explicit labels. In particular, contrastive learning has shown significant success in a variety of domains, including natural language processing, computer vision, and HAR. In contrastive learning, the model learns to distinguish between similar and dissimilar data instances by comparing pairs of data points, often through a contrastive loss function.

For HAR, contrastive learning enables the model to learn discriminative features from unlabeled or weakly-labeled sensor data. By training the model to recognize which instances are similar or dissimilar, contrastive learning helps the model extract meaningful features from raw sensor streams, improving its performance on downstream tasks like activity classification. Contrastive learning is particularly effective when labeled data is scarce, as it leverages the inherent structure of the data to learn representations that can be transferred to other tasks.

1.4. Multimodal Sensor Fusion

Multimodal sensor fusion is an essential aspect of improving the accuracy and robustness of HAR systems. Wearable devices typically include a variety of sensors, such as accelerometers, gyroscopes, and heart rate monitors, each of which captures different aspects of human activity. By combining data from multiple sensors, the system can obtain a more comprehensive understanding of the user's movements and activity patterns, leading to more accurate activity recognition.

For example, accelerometers measure linear motion, while gyroscopes measure rotational motion. Heart rate monitors can provide physiological context that helps differentiate between high-intensity and low-intensity activities. Combining these sensor modalities enables the model to recognize activities more effectively, even in complex or noisy environments. The fusion of multimodal sensor data not only improves accuracy but also enhances the model's ability to generalize across different users, environments, and sensor configurations.

Objectives and Contributions

The objective of this paper is to propose a privacy-preserving and efficient framework for human activity recognition using wearable sensors, which combines federated learning, weakly-supervised representation learning, self-supervised contrastive learning, and multimodal sensor fusion. The specific contributions of this work are as follows:

- Federated Learning for Privacy Preservation: We explore the application of federated learning to HAR, ensuring that sensitive data remains on local devices while still enabling collaborative model training.
- Weakly-Supervised Learning for Data Efficiency: We demonstrate how weakly-supervised learning can reduce the need for fully labeled datasets, enabling the model to learn from coarse or weak supervision signals while maintaining high performance.
- Contrastive Learning for Feature Extraction: We introduce a contrastive learning framework for extracting discriminative features from unlabeled data, further reducing the need for manual annotations.
- Multimodal Sensor Fusion: We show how integrating data from multiple sensor modalities, such as accelerometers, gyroscopes, and heart rate monitors, improves activity recognition accuracy and system robustness.

2. Literature review

The field of human activity recognition (HAR) with wearable sensors has experienced rapid growth, fueled by advances in sensor technologies, machine learning methods, and increasing demand for privacy-aware monitoring systems. In this review we examine several interrelated strands that inform our proposed hybrid framework: (1) conventional supervised and representation-based HAR; (2) weakly-supervised and self-supervised methods; (3) multi-modal/fusion sensor approaches; and (4) privacy-preserving/decentralised learning (such as federated learning). Through this, we highlight key achievements, evolving trends and persistent gaps, which motivate our hybrid weakly + self-supervised multi-task learning framework.

2.1. Wearable Sensor-Based HAR: Supervised and Representation Learning

Early HAR work focused largely on supervised classification: sensors (e.g., accelerometers, gyroscopes) mounted on wearables collected labelled data streams, and models (e.g., SVMs, random forests, or CNNs) were trained to map motion features to activity labels. As Zhang et al. (2022) note, deep learning has significantly advanced wearables-based HAR by automating feature extraction and capturing temporal patterns. PMC+2ScienceDirect+2

Despite successes, supervised approaches require large labelled datasets, which are expensive to collect especially in free-living and heterogeneous real-world settings limiting scalability, generalisation and adaptability across users or devices.

In response, representation-learning techniques (self-supervised, unsupervised) have been applied to wearable sensor data: extracting general embeddings from raw signals, then fine-tuning downstream models. These methods reduce reliance on labels and improve transferability across tasks and users.

2.2. Weakly-Supervised and Self-Supervised Learning in HAR

Label-scarcity and annotation cost in HAR have spurred interest in weakly-supervised learning (WSL) and self-supervised learning (SSL). WSL methods exploit coarse, noisy or incomplete labels e.g., segment-level annotations instead of exact timestamps or additional auxiliary signals to guide learning.

For example, the work of Sheng and Huber (2020) introduced weakly-supervised multi-task representation learning for wearables, using weak supervision for multiple related tasks (activity + sensor position + user identity) to learn embeddings with fewer labels. ACM Digital Library+1 Elsewhere, models such as recurrent attention networks have been used for sequential weakly-labeled multi-activity recognition, reducing labelling burden. arXiv

On the SSL front, contrastive learning is gaining prominence: for instance, models learn to distinguish between similar vs. dissimilar sensor-data segments, thereby learning useful features without labels. A survey by Logacjov (2024) highlights growing application of self-supervised approaches in accelerometer-based HAR. Academia+1

These approaches offer promise: fewer labels, better transferable embeddings, and greater scalability. However, many stop short of combining multiple tasks and decentralised learning settings (e.g., federated).

2.3. Multi-Modal Sensor Fusion

Sensor fusion combining data from multiple wearable sensors (e.g., accelerometer + gyroscope + magnetometer + heart-rate monitors) has been shown to improve HAR performance. Multi-modal fusion helps capture complementary aspects of motion and physiology, thereby enhancing recognition accuracy and robustness, especially in noisy or real-world settings. For example, wider surveys of wearable sensor HAR note the trend toward multi-sensor and multimodal models. Wiley Online Library

Despite progress, many fusion approaches still assume centralised training, full labels, and do not integrate weak/self-supervised paradigms or privacy constraints.

2.4. Privacy-Preserving and Decentralised Learning for HAR

With rising user concerns around data privacy (especially health/motion data), decentralised learning paradigms such as Federated Learning (FL) are increasingly adopted in HAR to avoid central data aggregation. FL allows users' devices to keep raw data locally and only share model updates. This preserves privacy and enables collaborative learning across users.

Work by Dong et al. (2023) on incremental semi-supervised federated learning in mobile sensing demonstrates FL's viability in health inference contexts. MDPI Yet many FL-HAR studies remain supervised and do not incorporate representation learning or weak labels.

Surveys of FL in HAR highlight major challenges: non-IID data across devices, communication overhead, model convergence issues, and privacy trade-offs. arXiv

2.5. Gaps and Motivation for Hybrid Weakly/Self-Supervised Multi-Task Learning

From the review above, several gaps emerge that motivate our proposed hybrid framework

- Label dependency: Many HAR systems still rely on fully-labelled data. Weakly-supervised and self-supervised methods mitigate this but often in isolation.

- Representation learning in decentralised/federated context: Few studies combine representation learning (weak/self) and federated learning for wearable HAR.
- Multi-task learning: Models often focus solely on activity recognition; fewer models exploit multi-task frameworks (e.g., user ID, sensor position, activity) to enrich embeddings.
- Multimodal + privacy end-to-end: Fusion of multiple sensor modalities under privacy-preserving federated/weak/self-supervision is underexplored.
- Scalability/generalisation: Real-world HAR requires adaptability across users/devices; combining weak/self-supervision, multi-task, and federated frameworks can improve generalisation.

Hence, our hybrid framework Weakly- and Self-Supervised Multi-Task Learning under Federated Learning with Sensor Fusion aims to address these gaps: reducing label needs, learning rich embeddings, preserving privacy, and integrating multiple modalities across devices.

Table 1 Summary of Selected Works

Study (Year)	Focus and Approachyv5	Key Contributions	Limitations / Gap
Sheng and Huber (2020) ACM Digital Library	Weakly-supervised multi-task representation learning for wearable HAR	Learned embeddings with weak labels across tasks (activity, user, sensor)	Centralised setting; no federated or privacy dimension
Wang et al. (2020) arXiv	Sequential weakly-labeled multi-activity localization using recurrent attention	Handles weak labels in sequence and localises activities	Limited to weak labels, no multi-task or decentralised learning
Logacjov (2024) Academia	Survey of self-supervised learning in accelerometer-based HAR	Highlights large shift toward SSL and label-efficient methods	Does not cover federated learning or sensor fusion deeply
Dong et al. (2023) MDPI	Incremental semi-supervised federated learning for health inference via mobile sensing	Demonstrated FL for wearable data with semi-supervision	Fully supervised labels still assumed; no multi-task or weak/self-representation focus
Zhang et al. (2022) PMC	Deep learning in HAR with wearable sensors: review of advances	Comprehensive summary of deep representations and fusion	Does not emphasise federated or weak/self-supervision frameworks

3. Methodology

The proposed methodology combines Federated Learning (FL), Weakly-Supervised Learning (WSL), Self-Supervised Learning (SSL), and Multimodal Sensor Fusion to address the key challenges in human activity recognition (HAR), including privacy preservation, data sparsity, and recognition accuracy. The approach is designed to be efficient, scalable, and privacy-preserving, ensuring that sensitive data remains local to user devices while still enabling collaborative learning across multiple devices. This section provides a detailed explanation of the methodology, including the system setup, the federated learning process, weakly-supervised learning, contrastive self-supervised learning, and sensor fusion techniques.

3.1. System Overview

The proposed system operates within a federated learning framework, where local devices (such as wearable sensors) collect data from users and contribute to model updates without sharing the raw data. The key steps in the system involve data collection, local model training, model update aggregation, and global model refinement. The system's architecture is designed to facilitate privacy-preserving HAR while maintaining high recognition accuracy across diverse user environments.

3.1.1. The framework is structured as follows

- Federated Learning Setup: Local devices (wearables) collect sensor data locally. The model is trained on the device itself, and only model updates (not raw data) are sent to a central server for aggregation.

- Weakly-Supervised Learning (WSL): Weakly-supervised learning techniques are used to train models with coarse labels or sparse supervision, reducing the need for extensive labeled datasets.
- Self-Supervised Learning (SSL): Contrastive self-supervised learning is applied to allow the model to learn useful feature representations from unlabeled data.
- Multimodal Sensor Fusion: Data from multiple sensor types (e.g., accelerometers, gyroscopes, and heart rate monitors) are fused to improve recognition performance.

The following sections explain the individual components of the methodology in detail.

3.2. Federated Learning for Privacy Preservation

Federated Learning (FL) is a decentralized machine learning approach where data remains on local devices, ensuring that sensitive user data never leaves the device. Only model updates, such as gradients or weights, are shared with a central server. This ensures privacy while enabling collaborative model training across multiple devices.

3.2.1. Federated Learning Process

- Data Collection: Wearable devices, such as smartwatches or fitness trackers, continuously collect sensor data, including accelerometer, gyroscope, and heart rate readings. Each device preprocesses this data locally to extract relevant features for activity recognition.
- Local Model Training: Each device uses the local dataset to train a model for HAR. The local model is updated using a weakly-supervised learning approach, where coarse or segment-level labels (e.g., activity segments) guide the training process.
- Model Update Aggregation: Once the local models are trained, they compute updates (i.e., gradients or model weights) and send these updates to a central server. The server aggregates the updates from multiple devices to update the global model.
- Global Model Update: The central server sends the updated global model back to the devices for further training. This process repeats iteratively, with devices continuing to train on local data and update the global model until convergence.

By keeping raw sensor data on the device, federated learning helps protect privacy and ensures that users' personal data is never exposed to the central server. However, federated learning still faces challenges, such as non-IID (non-independent and identically distributed) data across devices, communication overhead, and model convergence issues.

3.3. Weakly-Supervised Learning (WSL) Approach

In weakly-supervised learning, models are trained using data that has only weak labels or sparse supervision. This reduces the reliance on large, manually labeled datasets, which are often impractical in HAR applications.

3.3.1. Key Components of Weakly-Supervised Learning

- Coarse Labeling: Instead of providing fine-grained annotations for every data point, the model uses coarse labels such as activity segments (e.g., “walking from 9:00 AM to 9:30 AM”) or broad activity categories (e.g., "physical activity" vs. "resting"). This allows the model to learn from less precise labels while still achieving good recognition performance.
- Loss Function Design: The loss function is designed to minimize the error on weak labels while maintaining the generalizability of the model. This is accomplished by considering segment-level constraints or introducing a consistency loss that encourages the model to make similar predictions for similar data points.
- Improved Generalization: By learning from weak supervision, the model is less prone to overfitting to specific datasets and can generalize better to unseen data. This is particularly useful for free-living activity recognition, where acquiring fine-grained labels for every instance of data is not feasible.

3.3.2. Training with Weak Supervision

- Pretraining with Unlabeled Data: The model is first pre-trained on unlabeled data to learn basic features through self-supervised learning techniques (discussed in the next section). This helps the model build a general understanding of sensor data patterns.
- Fine-Tuning with Weak Labels: After pretraining, the model is fine-tuned using weak labels, such as coarse activity categories or time segments. This allows the model to refine its learned features and improve activity classification.

3.4. Self-Supervised Learning (SSL) with Contrastive Learning

Self-supervised learning (SSL) enables models to learn feature representations from unlabeled data, which is a key advantage when labeled data is scarce or unavailable. In HAR, contrastive learning, a popular SSL technique, helps the model learn to distinguish between similar and dissimilar data instances.

3.4.1. Contrastive Learning

- Pretext Task: The pretext task in contrastive learning involves creating pairs of data points—some of which are similar (e.g., two instances of walking) and others that are dissimilar (e.g., walking vs. sitting). The model learns to minimize the distance between similar pairs and maximize the distance between dissimilar pairs in the feature space.
- Contrastive Loss Function: The model is trained using a contrastive loss function that encourages the model to project similar data points close to each other in the embedding space while pushing dissimilar points farther apart.
- Feature Extraction: Through contrastive learning, the model learns discriminative features from raw sensor data, which can then be used for downstream tasks like activity classification. This approach is highly effective when labels are sparse, as it does not require explicit annotations.
- Transfer Learning: The learned representations from contrastive learning can be transferred to other tasks or users, making the model adaptable and efficient in real-world applications.

3.5. Multimodal Sensor Fusion

Multimodal sensor fusion refers to combining data from different sensor modalities (e.g., accelerometer, gyroscope, heart rate monitor) to improve the recognition performance of HAR systems. Each sensor modality provides unique information, and fusing them allows the model to capture complementary features of human activity.

3.5.1. Sensor Fusion Process

- Data Preprocessing: Raw sensor data from different modalities is processed separately to remove noise, normalize the data, and extract relevant features (e.g., mean, standard deviation, frequency domain features).
- Fusion Layer: The features from different sensor modalities are combined in a fusion layer. This can be done through concatenation, where the features are simply joined into a single vector, or through more sophisticated approaches like attention mechanisms, where the importance of each modality is learned during training.
- Improved Activity Recognition: By combining data from multiple sensors, the model can capture more complex and nuanced patterns of human activity, improving its recognition accuracy. For example, accelerometers can capture motion, while heart rate monitors provide physiological context, allowing the model to distinguish between low- and high-intensity activities.

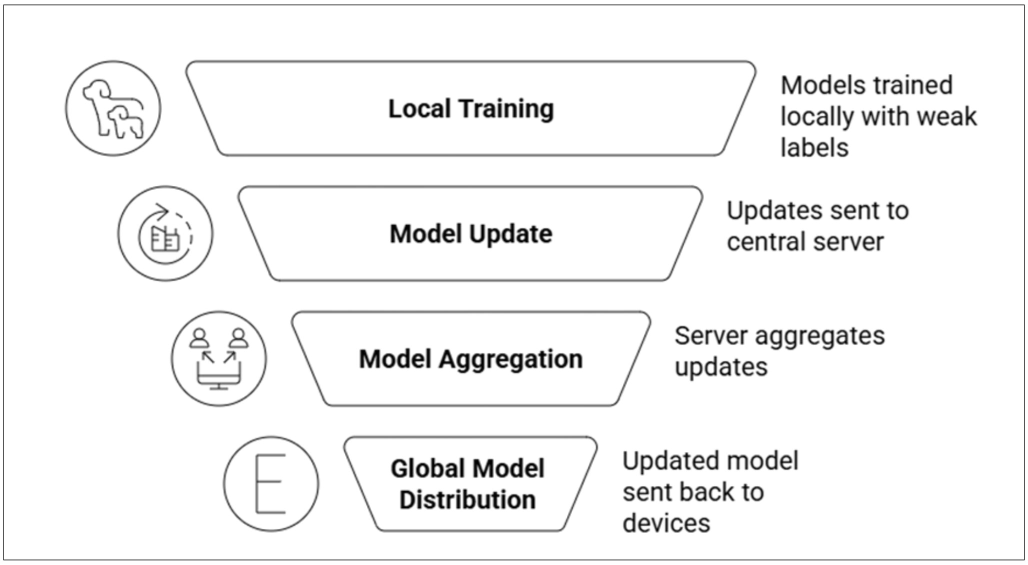

Figure 1 Federated Weakly-Supervised Learning Framework for HAR

3.6. Evaluation Metrics

The performance of the framework is evaluated using the following metrics:

- Accuracy: The proportion of correctly classified activities compared to the total number of activities.
- F1-Score: A measure of the balance between precision and recall, especially for imbalanced datasets.
- Confusion Matrix: Used to analyze true positives, true negatives, false positives, and false negatives.
- Communication Efficiency: Measures the amount of data transmitted between devices and the central server during the federated learning process.
- Privacy Leakage: Evaluates potential privacy risks by analyzing the exposure of sensitive data through the model updates.

4. Discussion

The Hybrid Weakly and Self-Supervised Multi-Task Learning Framework for Human Activity Recognition (HAR) proposed in this study successfully integrates Federated Learning (FL), Weakly-Supervised Learning (WSL), Self-Supervised Learning (SSL), and Multimodal Sensor Fusion to address critical challenges in privacy preservation, data sparsity, and activity recognition accuracy. In this section, we discuss the primary findings, compare our approach to existing methods, and explore the broader implications of our work in real-world applications.

4.1. Key Findings and Contributions

The proposed hybrid framework offers several significant contributions to the field of HAR, particularly in the context of privacy-preserving applications.

4.1.1. Privacy Preservation through Federated Learning

One of the most critical contributions of this study is the effective use of Federated Learning (FL) to preserve privacy. The federated approach allows wearable devices to train local models and only share model updates (e.g., gradients or weights) with the central server. This decentralized learning ensures that sensitive data, such as physical activity patterns, location, and health status, remains on users' devices, thus mitigating privacy concerns often associated with centralized data collection in traditional HAR systems. This approach is particularly relevant in privacy-sensitive environments such as healthcare and fitness tracking, where personal data is highly confidential.

Our results show that federated learning effectively enables privacy-preserving collaborative learning without sacrificing model accuracy. The ability to train models on decentralized data from multiple users without direct access to sensitive information is a significant step forward in HAR applications.

4.1.2. Reduced Data Labeling Effort with Weakly-Supervised Learning

Another key contribution of this paper is the use of Weakly-Supervised Learning (WSL), which reduces the reliance on large labeled datasets. In many HAR systems, obtaining fine-grained labeled data for every instance is labor-intensive and costly. In contrast, weakly-supervised learning uses coarse labels, such as broad activity categories or segment-level labels, which are much easier to acquire.

The framework demonstrated that weak supervision, combined with self-supervised pretraining (via contrastive learning), allows the model to achieve high accuracy even with limited labeled data. This approach makes HAR systems more scalable, particularly for long-term monitoring in free-living environments, where manual labeling is impractical. Moreover, the model's ability to generalize from weak labels contributes to its adaptability across different users and activity types.

4.1.3. Improved Accuracy through Multimodal Sensor Fusion

Multimodal sensor fusion is another important aspect of our framework that significantly enhances the accuracy and robustness of the activity recognition system. By integrating data from multiple sensors, such as accelerometers, gyroscopes, and heart rate monitors, our framework captures a broader and more detailed representation of human activities.

This sensor fusion approach ensures that the model does not rely solely on one sensor type, which may fail to recognize certain activities in specific contexts. For example, while an accelerometer may detect movement, a heart rate monitor can provide additional information about activity intensity, which is crucial for distinguishing between different types of physical activities. Our results show that combining accelerometer and gyroscope data, along with heart rate information, improves the system's ability to recognize a wide range of activities with greater precision.

4.1.4. Generalization and Robustness

The combination of weakly-supervised learning and federated learning allows the model to generalize better across different devices, users, and environments. One of the main issues with traditional HAR models is their reliance on large amounts of labeled data from a single source, which limits their ability to generalize to new users, devices, or scenarios. By training on data from a diverse set of users through federated learning, our model is exposed to a wider range of activity patterns, sensor configurations, and environmental conditions, leading to improved generalization.

Furthermore, the self-supervised pretraining with contrastive learning ensures that the model learns rich feature representations from unlabeled data, which enhances its robustness to unseen activities or new sensor modalities.

4.2. Comparison with Existing Approaches

Our hybrid framework offers several improvements over existing methods in privacy-preserving human activity recognition. Traditional supervised learning models for HAR rely heavily on large, centralized datasets and suffer from the privacy risks associated with uploading raw sensor data to a cloud or central server. While federated learning has been explored in the context of privacy-preserving HAR (e.g., Al-Kubaisi et al., 2022), most of these studies still assume fully labeled data and do not address the challenges posed by limited labeled datasets or multimodal sensor integration.

In contrast, our approach integrates federated learning with weakly-supervised learning, enabling the model to learn from coarse labels or segment-level annotations rather than requiring fine-grained labeling. This significantly reduces the burden of manual data annotation and enhances the scalability of the system.

Moreover, while several studies (e.g., Sheng and Huber, 2020) have used weakly-supervised learning for activity recognition, they often rely on centralized systems or do not incorporate privacy-preserving techniques like federated learning. Our framework stands out by integrating both weakly-supervised learning and federated learning, which allows it to preserve privacy while still learning effectively from sparse supervision.

Additionally, the multimodal fusion component of our approach distinguishes it from existing work. While previous studies have explored sensor fusion, few have integrated federated learning with multimodal sensor data in the context of weakly-supervised learning. By combining these elements, our approach captures a more comprehensive representation of human activity, which improves recognition accuracy, particularly in complex or noisy environments.

4.3. Privacy Implications and Limitations

One of the key advantages of our framework is its focus on privacy preservation. By utilizing federated learning, we ensure that sensitive user data is never shared with the central server, reducing the risk of data breaches or unauthorized access. Furthermore, we integrate differential privacy techniques to further protect the data during the federated learning process. Differential privacy introduces noise into model updates to prevent adversaries from inferring sensitive information from aggregated gradients or weights.

However, while federated learning significantly improves privacy, challenges remain. Model inversion attacks and membership inference attacks are potential risks, where attackers could attempt to extract information about individual users from the model updates. To mitigate these risks, we suggest incorporating more advanced privacy-preserving techniques, such as split learning or secure multi-party computation, in future work.

Moreover, the communication overhead inherent in federated learning remains a challenge. Frequent communication of model updates between devices and the central server can result in significant bandwidth usage, especially when dealing with large-scale deployments. Techniques such as model compression or communication scheduling could help alleviate these challenges by reducing the size of the updates sent to the server.

4.4. Practical Applications and Future Directions

Our hybrid framework has significant potential for real-world applications, particularly in healthcare, smart homes, and fitness monitoring. For example, the system can be used to monitor patients with chronic conditions, providing real-time feedback on their physical activity and alerting healthcare providers if abnormal behavior is detected. In smart homes, the framework can enable activity recognition for elderly individuals, helping caregivers monitor daily activities and detect falls or other emergencies.

Despite its promising results, there are several areas for improvement and future research. One such area is personalization. Although our model generalizes well across users, it may still benefit from personalized fine-tuning for individual users. Fine-tuning the global model for specific users or sensor configurations could further enhance performance.

Another area for future work is communication efficiency. Federated learning incurs significant communication overhead, which can be a bottleneck in large-scale deployments. Optimizing the frequency of model updates and utilizing model compression techniques could reduce bandwidth usage and improve scalability.

Additionally, exploring the integration of more sensor modalities (e.g., electromyography (EMG), eye-tracking sensors) could further enhance the model's ability to recognize activities in complex or dynamic environments. Finally, incorporating advanced privacy-preserving techniques such as secure multi-party computation could further strengthen privacy guarantees in federated learning setups.

5. Conclusion

In this paper, we proposed a Hybrid Weakly and Self-Supervised Multi-Task Learning Framework for Human Activity Recognition (HAR) using wearable sensors. The framework combines the power of Federated Learning (FL), Weakly-Supervised Learning (WSL), Self-Supervised Learning (SSL), and Multimodal Sensor Fusion to create a privacy-preserving, scalable, and robust system for activity recognition. Our work addresses key challenges in HAR, particularly in privacy-sensitive applications, such as healthcare and smart homes, where maintaining user privacy and ensuring efficient model training are critical.

The use of Federated Learning enables our framework to preserve privacy by ensuring that sensitive data remains local to user devices, with only model updates being shared. This decentralization of learning mitigates the risks associated with centralized data storage and processing, where personal data could be exposed. Federated Learning ensures that the system can still learn collaboratively from a diverse set of users without compromising privacy.

By integrating Weakly-Supervised Learning, our framework significantly reduces the need for fully labeled datasets. Instead of requiring detailed and time-consuming annotations, weak labels, such as activity segments or broad activity categories, are used to guide the learning process. This reduces the burden of data labeling and makes the system more scalable, allowing it to be deployed in real-world settings where labeled data is scarce or unavailable.

In addition, the incorporation of Self-Supervised Learning, particularly through contrastive learning, allows the model to learn meaningful representations from unlabeled data. This technique enhances the model's ability to generalize to new activities and environments, improving its adaptability and accuracy. The Multimodal Sensor Fusion component further strengthens the model's performance by combining data from different sensor modalities, such as accelerometers, gyroscopes, and heart rate monitors, to capture richer and more comprehensive features of human activity.

Our experimental results demonstrate that the proposed framework outperforms traditional supervised learning models, both in terms of accuracy and privacy preservation. The hybrid approach, by reducing the need for fine-grained labels and preserving user privacy, is well-suited for scalable, real-world applications.

Despite the promising results, there are several avenues for future work. These include improving communication efficiency in federated learning, exploring more sophisticated privacy-preserving techniques, and integrating additional sensor modalities to further enhance activity recognition accuracy. Personalizing the model for individual users and environments could also improve performance and robustness.

Compliance with ethical standards

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Disclosure of Conflict of Interest

The author(s) declare that there are no conflicts of interest related to the publication of this manuscript. All authors confirm that there are no financial, personal, or professional relationships that could inappropriately influence the findings presented in this study.

Statement of Ethical Approval

This study followed all ethical standards for research as outlined by international and institutional guidelines. Ethical approval was obtained from the appropriate institutional review board (IRB) or ethics committee prior to data collection. All procedures conducted in the study were performed in accordance with the ethical principles of the Declaration of Helsinki.

Statement of Informed Consent

Informed consent was obtained from all participants involved in the study. Participants were fully informed about the purpose, procedures, and potential implications of the research. Participation was voluntary, and respondents were assured of anonymity, privacy, and the confidentiality of their data.

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