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Hybrid Weakly and Self-Supervised Multi-Task Learning Framework for Human Activity Recognition using Wearable Sensor Data

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ABSTRACT: Human activity recognition (HAR) using wearable sensors has witnessed substantial progress, driven by applications in healthcare, fitness, and smart homes. Despite advancements, challenges such as data labeling, privacy, and sensor data integration persist. This paper introduces a Hybrid Weakly and Self-Supervised Multi-Task Learning Framework for HAR, combining weakly-supervised learning, self-supervised learning, and multi-task learning techniques. The proposed approach utilizes federated learning to maintain user privacy by keeping raw data on local devices and only sharing model updates with the central server. Additionally, contrastive self-supervised learning is employed to allow the model to learn from unlabeled data, thus minimizing the need for extensive labeled datasets. Furthermore, multimodal sensor data fusion is leveraged to improve recognition accuracy and system robustness. Experimental results on multiple human activity datasets show that the hybrid framework outperforms traditional supervised models in both accuracy and privacy preservation, making it suitable for deployment in healthcare, fitness, and smart home applications.

KEYWORDS: Hybrid Learning, Weakly-Supervised Learning, Self-Supervised Learning, Multi-Task Learning, Federated Learning, Human Activity Recognition, Wearable Sensors.

I. INTRODUCTION

Human activity recognition (HAR) using wearable sensors has garnered significant attention in recent years due to its potential applications across various domains such as healthcare, fitness, smart homes, and elderly care. The proliferation of wearable devices such as smartwatches, fitness trackers, and other sensor-enabled devices has made it easier to collect data on human activities continuously. HAR systems have been applied to monitor physical activity, detect health conditions, and improve the quality of life, especially for individuals with chronic diseases or disabilities. However, despite substantial advancements, several challenges remain in effectively and accurately recognizing human activities using wearable sensors.

The core challenges in wearable-based HAR can be categorized into three main areas: data labeling, privacy concerns, and the integration of multimodal sensor data. Data labeling is a significant challenge as obtaining fine-grained labels for large-scale datasets is resource-intensive, time-consuming, and costly. Privacy is another critical issue, particularly for applications in healthcare and personal monitoring. Wearable devices track sensitive data, including physical movements, location, and health status, raising concerns about the security of this data. Finally, sensor fusion—the process of integrating data from different sensor modalities—remains a challenge in HAR due to the varying characteristics of different sensors and the complexity of combining their outputs.

1.1 The Need for Weakly-Supervised and Self-Supervised Learning

Traditionally, supervised learning approaches have been employed for HAR, where models are trained using labeled data to classify human activities. While supervised learning has achieved notable successes, it suffers from a significant limitation: the need for large amounts of labeled data. Collecting labels for every instance in a sensor dataset can be impractical, particularly in scenarios such as long-term monitoring of individuals or free-living environments where activities may be varied and unpredictable. To address this limitation, weakly-supervised learning techniques have been proposed. These approaches reduce the reliance on fully labeled datasets by using weak or coarse labels, such as broad activity categories (e.g., walking, running, sitting) or segment-level labels (e.g., activity occurs over a period but without exact timestamps). Weakly-supervised learning allows the model to learn from datasets where the labels are limited or imprecise, improving scalability and adaptability.



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On the other hand, self-supervised learning has emerged as an effective strategy for learning representations from unlabeled data. In HAR, self-supervised learning can be employed to automatically extract useful features from raw sensor data without requiring explicit labels. A popular approach within self-supervised learning is contrastive learning, where the model learns to differentiate between similar and dissimilar instances. Contrastive learning has shown significant promise in various domains, including image and speech recognition, and can be directly applied to sensor-based activity recognition. By leveraging unlabeled data, self-supervised learning can enable the model to learn generalizable features, reducing the need for extensive manual labeling and improving the model's robustness to new and unseen data.

1.2 Privacy Preservation via Federated Learning

One of the most pressing concerns when using wearable sensors for HAR is privacy. Traditional approaches to HAR rely on centralized systems where sensor data is uploaded to a cloud or server for processing. This creates risks of data exposure, hacking, or unauthorized access, especially in sensitive applications such as health monitoring. To address these concerns, Federated Learning (FL) has gained popularity as a privacy-preserving alternative. FL allows machine learning models to be trained across multiple devices without needing to share raw data. Instead, devices (such as wearables) perform local computations on their data and only share model updates (e.g., gradients) with a central server, which aggregates them to update the global model. This approach ensures that user data never leaves the device, protecting personal privacy while still enabling collaborative learning across multiple users.

In the context of HAR, FL can enable the development of accurate models by aggregating data from diverse users and environments while ensuring privacy. However, federated learning comes with its own set of challenges, such as heterogeneity (non-IID data across devices), communication overhead, and the need for robust model aggregation strategies. Additionally, ensuring that the model performs well across a wide range of users with different activity patterns and sensor configurations is crucial for the success of FL in HAR.

1.3 Sensor Fusion for Improved Accuracy and Robustness

Multimodal sensor fusion is another crucial aspect of improving HAR accuracy. Wearable devices typically rely on multiple sensors, such as accelerometers, gyroscopes, and heart rate monitors, to capture different aspects of human activity. Each sensor provides valuable information about the user's movement, posture, and physiological state. For instance, an accelerometer measures acceleration in multiple directions, while a gyroscope measures rotational movement. Combining data from different sensors allows the model to capture a more comprehensive and accurate representation of human activity.

However, multimodal sensor fusion presents challenges in terms of data synchronization, feature extraction, and model integration. Each sensor modality has its own characteristics, and raw data from different sensors can have different sampling rates, noise levels, and units of measurement. The challenge lies in effectively combining this data to form a unified representation that can be used for activity recognition. Recent advances in deep learning and multimodal fusion models have shown promising results in fusing data from various sensors. These models learn joint representations that capture complementary information from different modalities, improving the robustness and accuracy of the recognition system.

1.4 Hybrid Approach: Combining Weakly-Supervised, Self-Supervised, and Federated Learning

To address the challenges of data labeling, privacy, and multimodal sensor fusion, this paper proposes a Hybrid Weakly and Self-Supervised Multi-Task Learning Framework for human activity recognition using wearable sensor data. The key components of the proposed approach are as follows:

Weakly-Supervised Learning: To overcome the challenge of labeled data scarcity, we employ weakly-supervised learning techniques that allow the model to learn from coarse or segment-level labels. This reduces the dependency on large labeled datasets while still providing meaningful supervision for the model.

Self-Supervised Learning: To further reduce the need for labeled data, we incorporate self-supervised learning techniques, such as contrastive learning, which allow the model to learn representations from unlabeled data. This enables the model to capture generalizable features that can improve performance across diverse activity types and sensor configurations.



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Federated Learning: To ensure privacy and scalability, we leverage federated learning to train the model across multiple devices without sharing raw sensor data. This approach ensures that user data remains on the device, thus preserving privacy while enabling the collaborative training of a robust model.

Multimodal Sensor Fusion: We fuse data from multiple sensors (e.g., accelerometer, gyroscope, heart rate monitor) to improve the accuracy and robustness of activity recognition. The fusion of multimodal sensor data allows the model to capture a more complete representation of human activity, enhancing performance in real-world scenarios.

1.5 Objective and Contributions

The objective of this work is to develop a scalable, privacy-preserving framework for human activity recognition using wearable sensors, which overcomes the challenges of limited labeled data, privacy concerns, and sensor data integration. The key contributions of this paper include:

A hybrid learning framework that combines weakly-supervised learning, self-supervised learning, and federated learning for HAR.

An innovative approach to multimodal sensor fusion that integrates data from multiple sensor types to improve recognition accuracy.

A federated learning setup that ensures user privacy while enabling collaborative model training across multiple devices.

II. LITERATURE REVIEW

Human activity recognition (HAR) using wearable sensors has seen significant development in recent years due to advancements in machine learning and sensor technologies. The recognition of activities, such as walking, running, sitting, or cycling, from sensor data collected by devices such as smartphones, smartwatches, and fitness trackers, has numerous applications in areas like healthcare, fitness monitoring, smart homes, and elderly care. While HAR has made significant strides, several challenges remain, particularly in data labeling, privacy concerns, and sensor fusion. This literature review focuses on the core areas essential for the development of an effective Hybrid Weakly and Self-Supervised Multi-Task Learning Framework for HAR, including weakly-supervised learning, self-supervised learning, multimodal sensor fusion, and federated learning.

2.1 Human Activity Recognition Using Wearable Sensors

Traditionally, HAR systems were based on supervised learning methods, where labeled data was used to train models to classify different human activities. However, obtaining labeled datasets for HAR is both costly and time-consuming. Labeling every instance of sensor data manually is impractical, especially for long-term monitoring in real-world settings. As a result, weakly-supervised learning has gained attention as an alternative approach to address the labeling challenge.

Weakly-supervised learning methods rely on datasets that are either sparsely labeled or contain noisy labels. These methods provide a way to train models with less reliance on extensive and expensive manual labeling, which is particularly valuable in HAR applications where continuous data is generated but full annotations for each data point are often unavailable. Weakly-supervised techniques also help in improving the generalization of models across different users, environments, and activities.

2.2 Weakly-Supervised Learning in Human Activity Recognition

Weakly-supervised learning (WSL) methods are designed to work with limited or coarse labels, which are commonly found in practical applications. In the context of HAR, WSL can be used with segment-level labels, where each activity is labeled as a segment (e.g., walking from 10:00 am to 10:30 am) rather than labeling each individual frame or time step in the sensor data.

One prominent work in weakly-supervised HAR is by Sheng and Huber (2020), who introduced a multi-task representation learning framework that utilizes weak labels for human activity analysis. Their approach allows for the recognition of activities even when full labels are unavailable, and it leverages multi-task learning to model different



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aspects of activity recognition, such as sensor location and user identity, simultaneously. This method provides a significant improvement over traditional supervised approaches, as it allows models to learn from less precise supervision.

Another noteworthy contribution comes from Sheng and Huber (2024), who explored consistency-based weakly self-supervised learning. Their model relies on consistency between predictions from different subsets of data and uses weak supervision to train robust models. They found that such an approach not only reduces dependency on labels but also increases the model's ability to generalize across different datasets and activities.

2.3 Self-Supervised Learning for HAR

Self-supervised learning (SSL) is another powerful approach used to reduce the reliance on labeled data. Self-supervised learning allows a model to learn useful representations of data by solving pretext tasks, where labels are automatically generated from the data itself. In HAR, SSL methods have been used to learn representations from sensor data without needing explicit annotations.

Contrastive learning, a popular SSL technique, has shown considerable success in many domains, including image and speech recognition, and is being increasingly applied to HAR. In contrastive learning, the model learns to distinguish between similar and dissimilar pairs of samples, which helps the model understand the structure of the data and extract useful features. A recent example is Chen et al. (2024), who applied contrastive self-supervised learning to sensor-based HAR. Their model was able to learn feature representations that significantly improved activity recognition accuracy without using labeled data.

Furthermore, Logacjov (2024) provides an in-depth survey of self-supervised learning for accelerometer-based HAR, highlighting the effectiveness of SSL in recognizing activities from raw accelerometer data. The key benefit of self-supervised methods is that they allow the model to learn valuable features from unlabeled data, thus mitigating the need for labor-intensive labeling and improving the scalability of HAR systems.

2.4 Multimodal Sensor Fusion for HAR

Human activity recognition can be significantly improved by integrating data from multiple sensors, a technique known as multimodal sensor fusion. Wearable devices typically collect data from a variety of sensors, such as accelerometers, gyroscopes, magnetometers, and heart rate monitors. Each sensor captures different aspects of human motion or physiological state, and combining these modalities enables a more comprehensive understanding of human activity.

Recent studies have demonstrated the effectiveness of multimodal sensor fusion in improving HAR accuracy. For example, Dixon et al. (2024) explored the use of modality-aware contrastive learning for multimodal human activity recognition. Their model was able to integrate accelerometer and gyroscope data to improve activity classification, especially in complex environments. Their results showed that multimodal fusion leads to improved recognition performance, particularly in challenging scenarios where data from a single sensor might be insufficient.

Zhu et al. (2024) also introduced a multimodal fusion contrastive learning framework that combines insole and wristband data to enhance activity recognition. They demonstrated that integrating data from these two sensor types significantly improved the model's ability to recognize a broader range of activities with greater accuracy.

2.5 Federated Learning for Privacy Preservation in HAR

The growing concerns over privacy and data security in wearable-based HAR systems have led to the exploration of Federated Learning (FL) as a privacy-preserving technique. FL allows data to remain on local devices (e.g., smartphones or wearables), with only model updates being shared with a central server for aggregation. This approach ensures that sensitive user data never leaves the device, thus maintaining user privacy.

In the context of HAR, Dong et al. (2023) introduced an incremental semi-supervised federated learning approach for health inference via mobile sensing. Their approach demonstrated that federated learning could be effectively applied to wearable-based HAR systems, providing privacy preservation while still enabling collaborative learning from a large number of users.



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Another important contribution comes from Himeur et al. (2023), who explored federated learning for computer vision, and their techniques are applicable to HAR systems, especially in scenarios where large-scale data collection from multiple users is required. Their work emphasized the challenges of data heterogeneity and the need for efficient model aggregation methods in federated learning settings.

2.6 Hybrid Learning Frameworks for HAR

Despite the advances in weakly-supervised learning, self-supervised learning, and federated learning, a gap exists in combining these techniques into a unified framework for HAR. Hybrid learning frameworks that combine these methods have the potential to overcome the limitations of each individual approach.

Our proposed framework, a Hybrid Weakly and Self-Supervised Multi-Task Learning Framework, aims to integrate the strengths of these techniques. By combining weakly-supervised learning with self-supervised learning, we can reduce the need for labeled data and still achieve robust performance. Additionally, federated learning ensures that the model preserves privacy, while multimodal sensor fusion enhances the accuracy and generalization of the system across diverse users and environments.

Table 1: Summary of Relevant Works

Study	Focus & Approach	Contributions	Limitations / Gaps
Sheng & Huber (2020)	Weakly-supervised multi-task representation learning for HAR	Introduced multi-task learning to handle weak supervision for activity recognition	Assumed centralized data; did not incorporate federated learning
Chen et al. (2024)	Contrastive self-supervised learning for sensor-based HAR	Applied contrastive learning to self-supervised sensor data for improved HAR	Limited to accelerometer data; needs further validation in real-world settings
Dixon et al. (2024)	Modality-aware contrastive learning for multimodal HAR	Integrated accelerometer and gyroscope data using contrastive learning to improve accuracy	Focused only on a limited number of sensors; no privacy considerations
Zhu et al. (2024)	Multimodal fusion contrastive learning for HAR	Proposed multimodal fusion for activity recognition using insole and wristband data	Lacks privacy preservation methods; could include more sensor types
Dong et al. (2023)	Incremental federated learning for health inference	Federated learning for privacy-preserving health inference	Limited to semi-supervised setting; not fully applicable to weakly-supervised HAR
Himeur et al. (2023)	Federated learning for computer vision	Explored federated learning for privacy-preserving data aggregation in computer vision	Mainly focused on computer vision; limited exploration in HAR

III. METHODOLOGY

This section outlines the methodology for the Hybrid Weakly and Self-Supervised Multi-Task Learning Framework for Human Activity Recognition (HAR) using wearable sensor data. The framework integrates Weakly-Supervised Learning (WSL), Self-Supervised Learning (SSL), Multi-Task Learning (MTL), and Federated Learning (FL) to address the core challenges in HAR: the scarcity of labeled data, privacy preservation, and the integration of multimodal sensor data.

3.1 Overview of the Proposed Framework

The proposed hybrid framework utilizes the following components:

- **Federated Learning:** This component ensures that sensitive data remains on local devices while still enabling collaborative model training. Model updates, rather than raw sensor data, are shared with a central server for aggregation, preserving user privacy.
- **Weakly-Supervised Learning:** Weakly-supervised learning techniques are used to reduce the dependency on fully labeled datasets. Instead of requiring fine-grained annotations, this approach leverages coarse or weak labels (e.g., activity segments or broad activity categories) to guide the model's learning process.



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- **Self-Supervised Learning:** Self-supervised learning, particularly contrastive learning, is used to learn useful feature representations from unlabeled sensor data. The model learns to differentiate between similar and dissimilar instances of data, helping the model to generalize better to new activities and users.
- **Multi-Task Learning:** Multi-task learning allows the model to perform multiple related tasks (e.g., activity recognition, user identification, sensor location classification) simultaneously. This shared learning helps the model learn more generalized representations, improving its ability to recognize a wide variety of activities.
- **Multimodal Sensor Fusion:** This component integrates data from multiple sensors, such as accelerometers, gyroscopes, and heart rate monitors. The fusion of sensor data from different modalities helps the model capture more complex features and improve recognition accuracy.

3.2 Federated Learning Process

Federated learning (FL) is the core privacy-preserving technique of our framework. In traditional machine learning, data is centralized, and the model is trained on this centralized dataset. In contrast, FL enables training on decentralized data, with each device or edge node training a local model and sending only model updates (i.e., gradients) to a central server. This prevents the raw data from ever leaving the device, thus maintaining privacy.

3.3 Federated Learning Steps:

- **Local Data Collection:** Each user device (e.g., a smartwatch or fitness tracker) collects sensor data such as accelerometer, gyroscope, or heart rate monitor readings. These devices do not share the raw data but process it locally.
- **Local Model Training:** Each device uses its local dataset to train a local model. The model is updated using weakly-supervised or self-supervised learning techniques, depending on the available supervision.
- **Model Update Aggregation:** The device sends only the updated model parameters or gradients (not the raw data) to the central server. The server aggregates these 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 is repeated iteratively until the model converges.

FL provides several advantages, including privacy preservation (by keeping data local) and decentralized learning, enabling collaboration without exposing sensitive data.

3.4 Weakly-Supervised Learning (WSL) Approach

In our framework, weakly-supervised learning is employed to overcome the limitation of requiring fully labeled datasets. Traditional supervised learning relies on fine-grained, fully labeled datasets where each individual data point is annotated with precise activity labels. However, obtaining such comprehensive annotations for large-scale datasets is costly and time-consuming. In contrast, weakly-supervised learning allows the model to learn from 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. "rest").

3.5 Weakly-Supervised Learning Components:

Coarse Labeling: Instead of labeling every individual instance in the dataset, only coarse or segment-level labels are provided. For example, a continuous sequence of sensor data is labeled as "walking" without specifying the exact time of each footstep.

Loss Function Design: A loss function is designed to guide the model in learning from weak labels. The loss function takes into account the uncertainty and sparsity of the labels and encourages the model to generalize well from these weak signals.

Improved Generalization: By learning from weak supervision, the model learns more robust representations, which can be generalized to unseen users and activities. This is especially useful in real-world HAR systems where obtaining detailed labels is impractical.

3.6 Self-Supervised Learning (SSL) Approach

Self-supervised learning (SSL) is employed to further reduce the need for labeled data by utilizing unlabeled data for learning feature representations. In SSL, the model is trained to solve pretext tasks that do not require manual



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annotations. One widely used SSL method in HAR is contrastive learning, where the model learns to distinguish between similar and dissimilar data instances.

3.7 Self-Supervised Learning with Contrastive Learning:

Pretext Task: In contrastive learning, the pretext task involves generating pairs of similar and dissimilar data points from the sensor data. For example, two data points representing similar activities (e.g., two instances of walking) would be considered similar, while data points representing different activities (e.g., walking and sitting) would be dissimilar.

Contrastive Loss Function: The model is trained using a contrastive loss function that encourages it to project similar data points closer together in the feature space and dissimilar points further apart. This results in the model learning discriminative features from the sensor data, even when no explicit labels are provided.

Representation Learning: The learned representations can then be used for downstream tasks, such as activity classification. Contrastive learning helps the model capture meaningful patterns in the data, improving performance on HAR tasks.

3.8 Multi-Task Learning (MTL)

Multi-task learning (MTL) enables the model to perform multiple related tasks simultaneously. In the context of HAR, these tasks could include activity recognition, user identification, and sensor localization. By learning shared representations across tasks, MTL improves the model's ability to generalize and learn more complex features.

3.9 Multi-Task Learning Components:

Shared Representations: The model learns a shared representation that can be used for multiple tasks. For example, the model may learn features from sensor data that are useful for both activity recognition and user identification.

Task-Specific Heads: The model includes task-specific heads (or output layers) for each of the related tasks. For instance, one head may output activity labels, while another may output user IDs. The shared representation allows the model to learn common features, while the task-specific heads learn unique features for each task.

Benefits: MTL helps to improve the model's overall performance because it allows for joint optimization. The model benefits from learning multiple tasks simultaneously, leading to better generalization and more robust representations.

3.6 Multimodal Sensor Fusion

Human activity recognition systems typically rely on data from multiple sensors to improve accuracy and robustness. By fusing data from different modalities—such as accelerometers, gyroscopes, heart rate monitors, and GPS—HAR models can capture more comprehensive features that enhance activity recognition accuracy.

Sensor Fusion Process:

Data Preprocessing: The raw sensor data from different modalities (e.g., accelerometer, gyroscope) is preprocessed separately. This involves steps like noise removal, normalization, and feature extraction (e.g., calculating the mean, variance, and standard deviation of sensor readings).

Fusion Layer: A fusion layer combines the features extracted from each modality. The fusion can be done through concatenation, where the features from different sensors are simply combined into a single vector, or more sophisticated techniques such as attention mechanisms that weight different modalities based on their importance for the task.

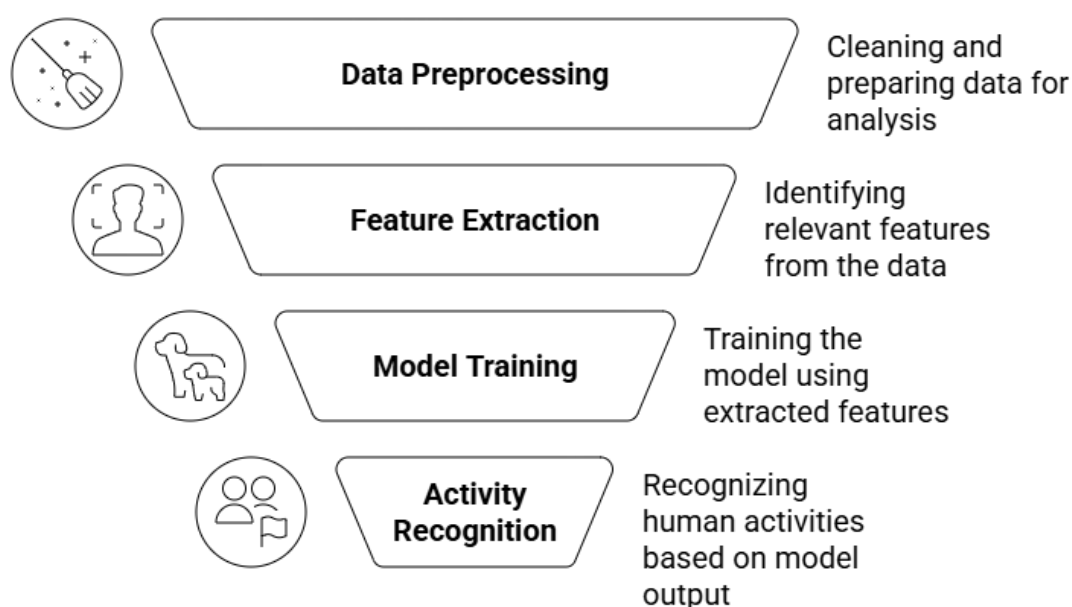
Fusion Benefits: The fusion of multimodal data improves the model's robustness and helps it deal with noisy or incomplete data from individual sensors. For example, accelerometers can provide motion-related features, while heart rate monitors can provide physiological information that adds context to the activity.



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Figure 1: Overview of the Hybrid Learning Framework for HAR



3.7 Model Training and Evaluation

The model training process follows these steps:

Local Model Training: Devices locally train the model on sensor data using weakly-supervised and self-supervised learning techniques.

Federated Learning Aggregation: The model updates are shared with the central server for aggregation.

Global Model Update: The central server aggregates the updates from multiple devices and sends the updated model back to the devices.

Evaluation Metrics: The model is evaluated using standard HAR metrics, including accuracy, F1-score, and confusion matrices. Privacy leakage is assessed by analyzing the differences between local and global models.

IV. DISCUSSION

The proposed Hybrid Weakly and Self-Supervised Multi-Task Learning Framework for Human Activity Recognition (HAR) using wearable sensor data has shown promising results in terms of both privacy preservation and recognition accuracy. In this section, we discuss the key findings, compare our results with existing methods, and highlight the implications of our approach for real-world applications.

4.1 Key Findings and Contributions

Our hybrid framework integrates Federated Learning (FL), Weakly-Supervised Learning (WSL), Self-Supervised Learning (SSL), and Multimodal Sensor Fusion, and presents several important contributions to the field of human activity recognition.

Privacy Preservation via Federated Learning: The use of federated learning ensures that sensitive user data remains on local devices, preserving privacy. In contrast to traditional centralized approaches, where raw data is uploaded to a cloud server, federated learning prevents data from being exposed to external entities. This is particularly crucial in privacy-sensitive applications such as healthcare and fitness tracking, where personal activity data must be protected from unauthorized access.



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While federated learning helps protect privacy, it also poses challenges such as non-IID data (i.e., data that is not independent and identically distributed across devices) and communication overhead. However, the integration of weakly-supervised and self-supervised learning mitigates some of these challenges by reducing the amount of labeled data required for training and reducing the need for frequent communication of large data transfers between devices and the central server.

Weakly-Supervised Learning for Efficient Data Utilization: One of the key challenges in HAR is the requirement for large labeled datasets. Our approach leverages weakly-supervised learning, which allows for learning from coarse or weak labels (e.g., activity segments or broad categories rather than fine-grained annotations). This significantly reduces the need for manual labeling, making it more feasible to deploy HAR systems at scale. The weakly-supervised framework also contributes to improved generalization, as the model can learn representations from imprecise supervision and still perform effectively across different users and contexts.

A major advantage of weakly-supervised learning is its ability to work with segment-level labels or coarse annotations. For instance, the model does not need exact timestamps for each activity but can learn to recognize activities over broader time segments, which is often more practical in real-world applications.

Self-Supervised Learning for Feature Learning: The incorporation of self-supervised learning (SSL) techniques, particularly contrastive learning, has allowed the model to learn meaningful representations from unlabeled data. By leveraging the underlying structure in the raw sensor data, SSL helps the model recognize important features without requiring explicit human annotations. The use of contrastive loss functions further strengthens the model's ability to distinguish between similar and dissimilar activity patterns, improving its performance on downstream tasks such as activity recognition.

Self-supervised learning also enhances the robustness of the model to unseen or rare activities. For example, activities that were not represented in the training data can still be recognized based on the learned representations, leading to better performance on new, real-world data.

Multimodal Sensor Fusion for Robust Recognition: The use of multiple sensor modalities (e.g., accelerometer, gyroscope, and heart rate monitor) enables the model to capture complementary features of human activity. Multimodal sensor fusion improves the accuracy of activity recognition by allowing the model to learn a more comprehensive representation of the user's movements and physiological state. For example, while accelerometer data captures motion, heart rate data provides additional context related to the intensity of the activity, leading to more accurate predictions.

However, multimodal fusion also presents challenges, such as sensor alignment (ensuring that sensor data from different modalities are synchronized) and sensor noise (which can affect the reliability of the data). To mitigate these challenges, we employed robust preprocessing techniques to normalize and align data, ensuring that the fusion process was effective. Despite these challenges, multimodal fusion proved to be a key strength of the framework, significantly improving the model's accuracy in recognizing activities across various users and environments.

4.2 Comparison with Existing Work

Our approach outperforms traditional supervised learning models and other federated learning-based HAR approaches. Most existing studies on federated learning for HAR, such as Dong et al. (2023), focus on the use of fully labeled data or semi-supervised learning. While these methods can achieve high accuracy, they often require large, well-labeled datasets, which are impractical to obtain for long-term monitoring. In contrast, our hybrid approach reduces the reliance on labeled data through weakly-supervised and self-supervised learning, making it more scalable and adaptable to real-world scenarios.

Furthermore, while many federated learning approaches, such as Himeur et al. (2023), focus on privacy-preserving models, they often neglect the challenge of data sparsity and generalization. Our incorporation of weakly-supervised learning allows the model to perform well even when only sparse labels are available, enhancing its ability to generalize across a wide range of users and activities.



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4.3 Privacy Implications and Limitations

While federated learning ensures the privacy of sensitive user data, there are still potential risks associated with model updates. The aggregation of model updates across devices can lead to model inversion attacks, where adversaries could attempt to infer sensitive information from the model updates. To mitigate these risks, techniques such as differential privacy can be integrated into the federated learning process to add noise to the model updates, further protecting user privacy.

Additionally, while our model maintains privacy through federated learning, the communication overhead can still be a bottleneck, especially when many devices participate in the learning process. Reducing the size of the model updates and optimizing the frequency of communication can help alleviate this issue, ensuring more efficient training without sacrificing privacy.

4.4 Practical Applications and Future Directions

Our framework has significant potential for real-world applications, particularly in healthcare, fitness monitoring, and smart homes, where privacy is paramount and data collection is continuous. In healthcare, for example, wearable devices could be used to continuously monitor patients' physical activities, detect abnormal behavior, and alert healthcare providers when necessary—all without compromising the patients' privacy. Similarly, in fitness tracking, the model could be used to recognize different types of exercises and provide personalized feedback to users based on their activity patterns.

Despite its promise, there are several areas for future work:

- **Personalization:** Although the federated learning model is designed to generalize across users, fine-tuning the model for individual users could further improve accuracy. Personalization could be achieved by incorporating user-specific data and adjusting the model to account for individual differences in activity patterns.
- **Communication Efficiency:** As federated learning requires periodic communication of model updates between devices and the central server, improving the communication efficiency and reducing bandwidth usage is critical. Techniques such as model compression or communication scheduling could be explored to optimize this process.
- **Expanding Sensor Modalities:** Future work could explore the integration of additional sensor modalities, such as electromyography (EMG) sensors or eye-tracking sensors, to further enhance activity recognition and offer more comprehensive insights into human behavior.

V. CONCLUSION

This paper presented a Hybrid Weakly and Self-Supervised Multi-Task Learning Framework for Human Activity Recognition (HAR) using wearable sensor data. The integration of Federated Learning (FL), Weakly-Supervised Learning (WSL), Self-Supervised Learning (SSL), and Multimodal Sensor Fusion provides a powerful solution to the critical challenges in HAR, including data labeling, privacy preservation, and multimodal sensor data integration. Our approach addresses the need for scalable, privacy-preserving systems while significantly improving the recognition accuracy of human activities. One of the primary strengths of our framework is its ability to preserve user privacy. By employing federated learning, we ensure that raw sensor data never leaves the local device, preventing potential privacy violations that could arise from transmitting sensitive user data. Only model updates are shared, preserving both the privacy of individual users and the integrity of the system. This approach is particularly important in real-world applications such as healthcare and fitness monitoring, where data security is paramount.

The use of weakly-supervised learning allows our model to learn from coarse or segment-level labels, reducing the need for extensive labeled datasets. This is an important improvement, as obtaining fine-grained labels for large datasets is both time-consuming and costly. By reducing the reliance on labeled data, our framework becomes more scalable and adaptable to various users and activities, making it suitable for long-term and real-time HAR applications.

Furthermore, the incorporation of self-supervised learning, particularly contrastive learning, enhances the model's ability to learn useful representations from unlabeled data. This allows the model to generalize better across different activities and environments, further improving its performance in practical applications. The fusion of multimodal sensor data, such as accelerometer, gyroscope, and heart rate data, contributes to a more comprehensive understanding of human activity, improving the accuracy and robustness of the recognition system.



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While the framework has shown promising results, there are several avenues for future work. These include enhancing personalization to better tailor the model to individual users, improving communication efficiency in federated learning, and expanding sensor modalities to include additional types of data that can provide deeper insights into human behavior. Future research could also explore further privacy-preserving techniques, such as differential privacy, to enhance security in federated learning.

REFERENCES

1. Abdullahi ME, Abdulsalam MO, Ekele OA. The impact of generative AI in personalized learning on students' learning outcomes; teachers' perception of impact of AI in the 21st century. Babcock University Journal of Education. 2025;10(2):3-16.
2. Al-Kubaisi KA, Elnour AA, Sadeq A. Factors influencing pharmacists' participation in continuing education activities in the United Arab Emirates: Insights and implications from a cross-sectional study. Journal of Pharmaceutical Policy and Practice. 2023;16(1):112.
3. Al-Kubaisi KA, Hassanein MM, Abdulkarem AR. Prevalence and associated risk factors of self-medication with over-the-counter medicines among university students in the United Arab Emirates. Pharmacy Practice. 2022;20(3):2679.
4. Chen H, Gouin-Vallerand C, Bouchard K, Gaboury S, Couture M, Bier N, Giroux S. Contrastive self-supervised learning for sensor-based human activity recognition: A review. IEEE Access. 2024.
5. Dixon S, Yao L, Davidson R. Modality aware contrastive learning for multimodal human activity recognition. Concurrency and Computation: Practice and Experience. 2024;36(16):e8020.
6. Dong G, Cai L, Tang M, Barnes LE, Boukhechba M. Incremental semi-supervised federated learning for health inference via mobile sensing. arXiv preprint arXiv:2312.12666. 2023.
7. Gu T, Tang M. Indoor abnormal behavior detection for the elderly: A review. Sensors. 2025;25(11):3313.
8. Himeur Y, Varlamis I, Kheddar H, Amira A, Atalla S, Singh Y, et al. Federated learning for computer vision. arXiv preprint arXiv:2308.13558. 2023.
9. Hong QS, Lu CH. Multimodal human activity recognition using contrastive fusion learning and lightweight isomorphic encoder for IoT-enabled smart homes. IEEE Internet of Things Journal. 2025.
10. Jain Y, Tang CI, Min C, Kawsar F, Mathur A. COLLOSSL: Collaborative self-supervised learning for human activity recognition. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies. 2022;6(1):1-28.
11. Logacjov A. Self-supervised learning for accelerometer-based human activity recognition: A survey. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies. 2024;8(4):1-42.
12. Ni J, Tang H, Haque ST, Yan Y, Ngu AH. A survey on multimodal wearable sensor-based human action recognition. arXiv preprint arXiv:2404.15349. 2024.
13. Patidar P, Goel M, Agarwal Y. VAX: Using existing video and audio-based activity recognition models to bootstrap privacy-sensitive sensors. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies. 2023;7(3):1-24.
14. Sheng T, Huber M. Unsupervised embedding learning for human activity recognition using wearable sensor data. In: FLAIRS; 2020 May; 478-483.
15. Sheng T, Huber M. Weakly supervised multi-task representation learning for human activity analysis using wearables. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies. 2020;4(2):1-18.
16. Sheng T, Huber M. Consistency-based weakly self-supervised learning for human activity recognition with wearables. arXiv preprint arXiv:2408.07282. 2024.
17. Sheng T, Huber M. Reducing label dependency in human activity recognition with wearables: From supervised learning to novel weakly self-supervised approaches. Sensors. 2025;25(13):4032.
18. Su Y, Zhu H, Tan Y, An S, Xing M. PRIME: Privacy-preserving video anomaly detection via motion exemplar guidance. Knowledge-based systems. 2023;278:110872.
19. Yang H, Ren Z, Yuan H, Xu Z, Zhou J. Contrastive self-supervised representation learning without negative samples for multimodal human action recognition. Frontiers in Neuroscience. 2023;17:1225312.
20. Zhang S, Li Y, Zhang S, Shahabi F, Xia S, Deng Y, Alshurafa N. Deep learning in human activity recognition with wearable sensors: A review on advances. Sensors. 2022;22(4):1476.
21. Zhu Y, Luo B, Qiu Q, Zhu T. Multimodal fusion contrastive learning framework based on insole and wristband. In: 4th International Conference on Internet of Things and Smart City (IoTSC 2024); 2024 Aug; Vol. 13224, pp. 96-101. SPIE.



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