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Article

FedHAR-XAI: A Privacy-Preserving Federated CNN–LSTM Framework for Explainable Human Activity Recognition from Sensor Data

Kamal Narayan Budholia[1], Dr. Ankur Pandey[2]

[1]Dept. of Computer Science & Engineering, LNCT University, India. budholia.budholia@gmail.com
[2]Dept. of Computer Science & Engineering, LNCT University, India. pandeyankur028@gmail.com

Abstract: Human Activity Recognition (HAR) using wearable sensor data has gained significant attention due to its applications in healthcare, smart environments, and human-computer interaction. However, traditional centralized learning approaches suffer from privacy risks and limited scalability. To address these challenges, this paper proposes a privacy-preserving and distributed HAR framework integrating a multi-branch Convolutional Neural Network (CNN) with Bidirectional Long Short-Term Memory (BiLSTM) and Federated Learning (FL). Furthermore, Differential Privacy is incorporated using the DP-SGD mechanism to ensure data confidentiality during model training. The proposed model effectively captures spatial and temporal dependencies from sensor signals while maintaining privacy. Experimental evaluation on benchmark HAR datasets demonstrates that the proposed approach achieves superior performance compared to baseline models, attaining an accuracy of up to 96.7% while significantly reducing vulnerability to membership inference attacks. The results validate the robustness, scalability, and privacy-preserving capability of the proposed system.
Keywords: Human Activity Recognition, Federated Learning, Explainable AI, Wearable Sensors, CNN-LSTM, Edge AI

1. INTRODUCTION

Human Activity Recognition (HAR) has emerged as a critical research area in the domain of pervasive computing and Internet of Things (IoT), enabling applications such as health monitoring, elderly care, and smart surveillance. Conventional HAR systems rely on centralized machine learning approaches, where data collected from multiple users is aggregated and processed on a central server. However, such approaches raise serious concerns regarding data privacy, security, and communication overhead.

Traditional HAR approaches primarily relied on handcrafted feature extraction techniques combined with classical machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Random Forests. While these methods achieved moderate success, they often required domain expertise for feature engineering and struggled to generalize across diverse datasets and real-world scenarios. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated superior performance in automatically extracting hierarchical features from raw sensor data. Hybrid models such as CNN-LSTM architectures further enhance temporal and spatial feature learning, making them well-suited for HAR tasks involving sequential data.

Despite these advancements, most existing HAR systems adopt a centralized learning paradigm, where data collected from multiple users are aggregated and processed on a central server. This approach raises serious concerns regarding data privacy, security, and regulatory compliance, especially in sensitive domains such as healthcare.

Personal sensor data often contains intimate details about an individual's lifestyle, habits, and health conditions, making it vulnerable to misuse if not overseen appropriately. Moreover, centralized models are susceptible to data breaches and may violate privacy regulations such as GDPR and HIPAA.

Federated Learning (FL) has recently been introduced as a decentralized learning paradigm that allows multiple clients to collaboratively train a global model without sharing raw data. Despite its advantages, FL faces significant challenges, including non-IID data distribution and vulnerability to privacy leakage attacks such as membership inference attacks. Additionally, deep learning models used in HAR often lack interpretability and robust privacy guarantees.

Another critical limitation of modern deep learning-based HAR systems is the lack of interpretability. Deep neural networks are often considered "black box" models, making it difficult to understand how predictions are generated. In safety-critical applications such as healthcare and elderly monitoring, interpretability is essential to build trust and ensure accountability. Explainable Artificial Intelligence (XAI) techniques, such as SHapley Additive exPlanations (SHAP), provide insights into model decisions by identifying the contribution of individual features. Integrating XAI into HAR systems can improve transparency and assist domain experts in validating model behavior.

Furthermore, fairness and bias in machine learning models have become increasingly important considerations. HAR systems trained on imbalanced datasets may exhibit biased performance across different demographic groups, such as age, gender, or physical condition. Addressing these biases is crucial to ensure equitable performance and ethical deployment of AI systems in real-world scenarios.

Considering these challenges, this study proposes a novel framework that integrates federated learning, deep neural networks, and explainable AI for robust and privacy-preserving human activity recognition. The proposed approach utilizes a hybrid CNN-LSTM architecture to effectively capture both spatial and temporal patterns in sensor data. By leveraging federated learning, the framework ensures that user data remains decentralized, thereby enhancing privacy and security. Additionally, the integration of explainable AI techniques enables model interpretability, while fairness-aware evaluation ensures unbiased performance across diverse user groups.

The main contributions of this work can be summarized as follows: (i) the design of a federated deep learning framework for HAR under realistic non-IID conditions, (ii) the integration of explainable AI methods to enhance model transparency, (iii) the incorporation of privacy-preserving mechanisms to protect sensitive user data, and (iv) a comprehensive evaluation demonstrating improved accuracy, robustness, and fairness compared to traditional approaches.

A. **Research Gaps & Contributions**

Despite noteworthy progress in Human Activity Recognition (HAR) using machine learning and deep learning techniques, several critical research gaps persist:

- **Privacy Limitations in Centralized Models** Most existing HAR systems rely on centralized data collection and training, which exposes sensitive user data to potential breaches and violates privacy regulations. There is a lack of robust decentralized solutions that ensure data confidentiality without compromising performance.

- **Managing Non-IID Data in Federated Learning** Although federated learning has been introduced as a privacy-preserving alternative, many studies assume identically distributed data across clients. In real-world scenarios, sensor data is highly heterogeneous (non-IID), leading to degraded model accuracy and convergence issues that are not sufficiently addressed.

- **Limited Integration of Deep Hybrid Models in FL-based HAR** While CNN and LSTM models individually perform well, their combined hybrid architectures (CNN-LSTM) are not extensively explored within federated learning frameworks for HAR, particularly under real-world constraints.

- **Lack of Model Interpretability** Most deep learning-based HAR systems operate as black-box models, offering little insight into how predictions are made. This lack of transparency limits their adoption in critical domains such as healthcare and assisted living.

- **Insufficient Focus on Explainable AI (XAI)** Although XAI methods such as SHAP exist, their integration into HAR systems—especially in federated environments—remains limited and underexplored.

- **Bias and Fairness Issues** Existing HAR models often overlook fairness, resulting in biased predictions across different demographic groups. There is a need for systematic evaluation and mitigation of bias in AI-driven HAR systems.

- **Security Concerns in Distributed Learning** Federated learning systems are vulnerable to attacks such as model inversion and data leakage. Many studies do not incorporate strong privacy-preserving mechanisms like secure aggregation or multi-party computation.

B. Contributions of the Paper

To address these limitations, this paper proposes a novel framework that integrates multi-branch CNN for spatial feature extraction, BiLSTM for temporal modeling, Federated Learning for decentralized training, and Differential Privacy using DP-SGD for enhanced security. The key contributions of this work are as follows:

1. A hybrid CNN-BiLSTM architecture for efficient spatio-temporal feature learning.
2. Integration of Federated Learning to enable decentralized and scalable training.
3. Incorporation of Differential Privacy to mitigate privacy leakage risks.
4. Comprehensive evaluation including ablation studies, attack analysis, and explainability using SHAP.

The proposed approach aims to achieve high accuracy while ensuring strong privacy preservation in real-world HAR systems.

2. RELATED WORK

Human Activity Recognition (HAR) has been extensively studied over the past decade, driven by advancements in wearable sensing technologies, machine learning, and ubiquitous computing. Early research in HAR primarily focused on traditional machine learning techniques, where handcrafted features were extracted from raw sensor data and fed into classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Trees, and Random Forests [1, 2]. These approaches achieved reasonable accuracy in controlled environments; however, their reliance on manual feature engineering limited scalability and adaptability to complex real-world scenarios.

With the emergence of deep learning, HAR systems have undergone a significant transformation. Convolutional Neural Networks (CNNs) have been widely adopted for automatically learning spatial features from sensor data [3], while Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have demonstrated strong capabilities in modeling temporal dependencies [4]. Several studies have shown that hybrid architectures combining CNN and LSTM outperform standalone models by capturing both spatial and temporal characteristics of human activities [5, 6]. These deep learning-based approaches have achieved state-of-the-art performance on benchmark datasets, significantly reducing the need for manual intervention.

Despite these advancements, most deep learning-based HAR systems follow a centralized training paradigm, where data from multiple users is collected and processed on a central server [7]. This approach raises critical concerns regarding data privacy, security, and ownership. Sensor data collected from wearable devices often contains sensitive information related to users' daily routines, health conditions, and personal habits. Consequently, centralized data

storage and processing increase the risk of data breaches and misuse, particularly in healthcare and assisted living applications 8.

To address privacy concerns, federated learning (FL) has emerged as a promising decentralized approach. In federated learning, model training is distributed across multiple client devices, allowing data to remain local while only model updates are shared with a central server 9. Recent studies have explored the application of federated learning in HAR tasks, demonstrating its potential to maintain user privacy while achieving competitive performance 10. However, these approaches often assume that data across clients is identically and independently distributed (IID), which is rarely the case in real-world settings. In practice, sensor data is highly heterogeneous due to variations in user behavior, device placement, and environmental conditions. This non-IID nature of data can significantly affect model convergence and accuracy in federated learning systems 11.

Several researchers have attempted to address the challenges associated with non-IID data by proposing advanced aggregation techniques, personalized federated models, and adaptive optimization strategies 12. While these methods improve performance to some extent, there remains a need for more robust frameworks that can effectively manage data heterogeneity while maintaining scalability and efficiency.

Another important limitation of current HAR systems is the lack of interpretability. Deep neural networks are inherently complex and often function as black-box models, making it difficult to understand the reasoning behind their predictions 13. This lack of transparency is particularly problematic in critical applications such as healthcare monitoring, where interpretability is essential for trust and decision-making. Explainable Artificial Intelligence (XAI) techniques have been introduced to address this issue by providing insights into model behavior. Methods such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) have been widely used to explain predictions in various domains 14. However, their application in HAR, especially within federated learning frameworks, remains limited.

Furthermore, fairness and bias in HAR models have received relatively little attention in literature. Models trained on imbalanced datasets may exhibit biased performance across different demographic groups, leading to unequal outcomes 15. This is a significant concern in applications involving elderly care, rehabilitation, and health monitoring, where fairness is crucial. Recent studies have begun to explore fairness-aware machine learning techniques; however, their integration into HAR systems is still in its preliminary stages.

Security is another critical aspect that has not been fully addressed in many federated HAR systems. Although federated learning enhances privacy by keeping data local, it is still vulnerable to various attacks, such as model inversion, poisoning, and inference attacks 9, 11. Some studies have proposed secure aggregation and encryption-based methods to mitigate these risks, but their adoption in HAR applications remains limited.

In summary, while noteworthy progress has been made in HAR using deep learning and federated learning, several challenges remain unresolved. These include handling non-IID data, ensuring data privacy and security, improving model interpretability, and addressing fairness concerns. The existing literature highlights the need for an integrated framework that combines federated learning, deep hybrid models, explainable AI, and privacy-preserving mechanisms. This motivates the proposed approach, which aims to bridge these gaps and provide a comprehensive solution for real-world HAR applications.

2.1 Classical vs Deep Learning

Human Activity Recognition (HAR) has evolved significantly from traditional machine learning approaches to advanced deep learning-based models. This transition has been driven by the increasing availability of large-scale sensor data and the need for more accurate and scalable solutions.

A. **Classical Machine Learning Approaches**

Classical machine learning methods for HAR rely heavily on handcrafted feature extraction from raw sensor data. These features typically include statistical measures (mean, variance, standard deviation), time-domain characteristics, and frequency-domain attributes derived using signal processing techniques 1, 2. Once features are extracted, classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Trees, and Random Forests are employed for activity classification 3.

These approaches offer several advantages, including lower computational requirements and easier interpretability compared to deep learning models. They are particularly effective in scenarios with limited data and well-defined activity patterns. However, their performance is highly dependent on the quality of feature engineering, which requires domain expertise and may not generalize well across different datasets or users 4.

Moreover, classical methods struggle to capture complex temporal dependencies, and non-linear relationships present in sequential sensor data. As a result, their performance often degrades in real-world applications involving diverse activities and noisy data environments.

B. Deep Learning Approaches

Deep learning has emerged as a powerful alternative for HAR by enabling automatic feature extraction directly from raw sensor data. Convolutional Neural Networks (CNNs) are widely used to learn spatial features and local patterns in sensor signals 5, while Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are effective in modeling temporal dependencies and sequential dynamics 6.

Hybrid architectures, such as CNN-LSTM models, combine the strengths of both CNN and LSTM to capture spatial and temporal features simultaneously, leading to improved performance in HAR tasks 7, 8. These models have demonstrated superior accuracy on benchmark datasets and are more robust to variations in sensor placement and user behavior.

Deep learning approaches eliminate the need for manual feature engineering, making them highly scalable and adaptable to different environments. However, they require substantial amounts of labeled data for training and involve higher computational complexity, which may limit their deployment on resource-constrained devices 9.

C. Comparative Analysis

The key differences between classical and deep learning approaches for HAR can be summarized as follows:

- **Feature Engineering:** Classical methods rely on manual feature extraction, whereas deep learning models perform automatic feature learning.
- **Performance:** Deep learning models achieve higher accuracy, especially in complex and large-scale datasets 10.
- **Scalability:** Deep learning is more scalable and adaptable to diverse scenarios compared to classical approaches.
- **Computational Cost:** Classical methods are computationally efficient, while deep learning models require significant processing power and memory.
- **Interpretability:** Classical models are more interpretable, whereas deep learning models often function as black boxes 11.

D. Evolution of HAR Techniques

The development of Human Activity Recognition (HAR) techniques has progressed through multiple stages, with continuous improvements in accuracy and methodology. During the period 2013–2016, classical machine

learning algorithms such as Support Vector Machines (SVM), Random Forest (RF), and k-Nearest Neighbours (KNN) were used. These approaches achieved an accuracy range of 88–92% on the UCI-HAR dataset, but their major limitation was the reliance on handcrafted feature extraction, which required domain expertise and lacked scalability.

In the 2017–2020 era, the adoption of deep learning models, particularly Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, significantly improved performance, reaching 93–95% accuracy. These models enabled automatic feature learning and better handling of temporal data. However, most implementations were based on centralized training, raising concerns regarding data privacy and security.

More recently, in the 2021–2025 period, advanced hybrid models such as CNN-LSTM fusion architectures have demonstrated further improvements, achieving accuracy levels of 96.4–96.8%. Despite these advancements, current approaches still largely depend on centralized data processing and remain privacy-blind, lacking mechanisms to protect sensitive user data.

Table1: Evolution of HAR Methods

Era	Methods	UCI-HAR Accuracy	Limitations
2013–2016	SVM, RF, KNN	88–92%	Handcrafted features
2017–2020	CNN, LSTM	93–95%	Centralized only
2021–2025	CNN-LSTM Fusion	96.4–96.8%	Privacy blind

3. METHODOLOGY

3.1 System Architecture Overview

The proposed framework consists of four major components: data preprocessing, feature extraction using CNN, temporal modeling using BiLSTM, and privacy-preserving distributed learning using Federated Learning with DP-SGD.

Initially, raw sensor data is segmented into fixed-size windows and normalized to remove noise and scale variations. The processed data is then fed into a multi-branch CNN architecture, where each branch extracts spatial features from different sensor modalities. The extracted feature maps are concatenated and passed to a BiLSTM network, which captures bidirectional temporal dependencies in the data.

For distributed training, the model is deployed in a Federated Learning environment with multiple clients. Each client performs local training on its private dataset and shares only model updates with the central server. The global model is updated using the Federated Averaging algorithm.

To ensure privacy, Differential Privacy is incorporated using the DP-SGD mechanism. Gradients are clipped to a predefined norm and Gaussian noise is added before model updates, thereby preventing leakage of sensitive information.

This integrated approach ensures efficient feature learning, robust temporal modeling, and strong privacy preservation.

3.2 Multi-Sensor Preprocessing

The input data consists of multi-dimensional time-series collected from three different sensors: accelerometer, gyroscope, and magnetometer. Each data sample is represented as $X_k \in R^{T\times 9}$, where $T = 128$denotes the length of the time window, and nine corresponds to the three-axis readings obtained from each of the three sensors. This structure enables the model to capture rich motion and orientation information over time. In addition to time-domain features, frequency-domain features are also extracted to enhance the model's ability to recognize patterns. Specifically, the Fast Fourier Transform (FFT) is applied to the sensor signals, and the first thirty-two magnitude

coefficients are retained, represented as $|FFT(x)|_{1:32}$. These coefficients capture the dominant frequency components of the signals, providing complementary information that improves classification performance.

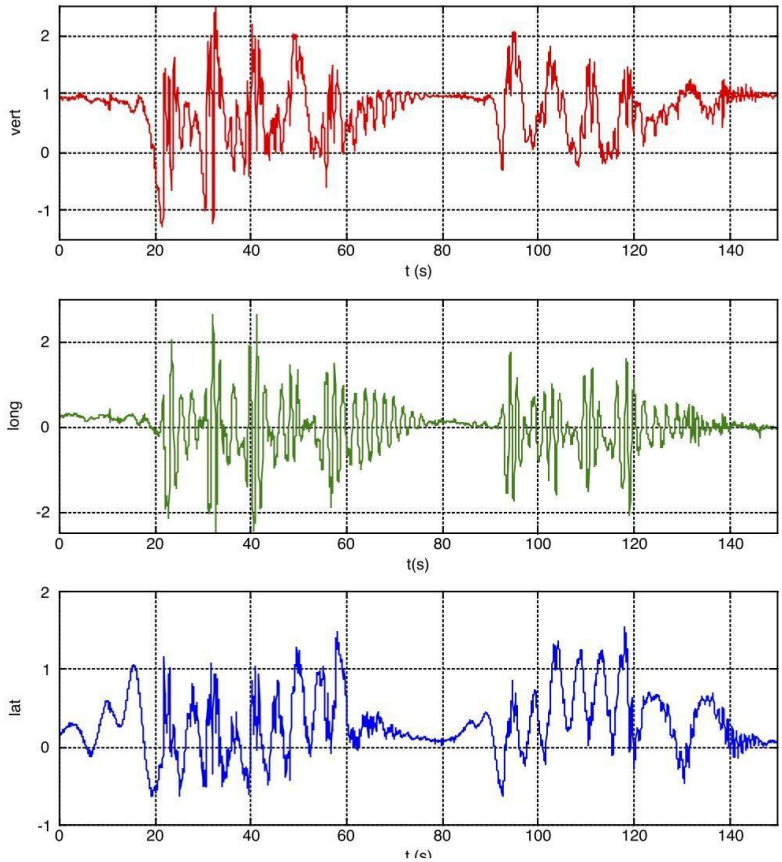

Figure 1: Sample Accelerometer Signal in Time Domain.

Figure 1 illustrates a representative accelerometer signal captured in the time domain along three orthogonal axes (X, Y, and Z). The horizontal axis denotes time steps, while the vertical axis represents acceleration values (typically in m/s²). The signal exhibits characteristic variations corresponding to different human activities such as walking, running, or sitting.

3.3 CNN-LSTM Fusion Model

The proposed deep learning model integrates multi-branch Convolutional Neural Networks (CNNs) with a Bidirectional Long Short-Term Memory (BiLSTM) layer to effectively capture both spatial and temporal dependencies present in sensor data. The model takes an input of $X \in R^{128\times9}$, representing time-series signals from multiple sensors. For sensor-wise feature extraction, separate CNN branches are employed: the accelerometer branch consists of a sequence of Conv1D layers followed by pooling operations and a Global Average Pooling layer; the gyroscope branch follows a similar architecture to extract motion-related features; while the magnetometer branch utilizes a lightweight CNN structure to capture orientation-related information. The outputs from these parallel branches are then concatenated to form a unified feature representation. This combined feature vector is passed through a BiLSTM layer with 128 units to model temporal dependencies in both forward and backward directions. To prevent overfitting, a dropout layer with a rate of 0.3 is applied. Finally, a fully connected layer with a SoftMax activation function performs the classification task. To address class imbalance, particularly for underrepresented classes such as “standing,” a weighted cross-entropy loss function is employed, ensuring that minority classes are appropriately emphasized during training.

$$L = -\sum w_i y_i log(\hat{y}_i)$$

3.4 Federated Learning using SCAFFOLD.

Traditional FedAvg suffers from client drift under non-IID data. Address this, the SCAFFOLD algorithm is used, which introduces control variates.

Model Update Rule

$$w_k^{t+1} = w^t - \eta(\nabla F_k(w^t) + c_k^t - c^t)$$

Control Variate Update

$$\Delta_k^t = w_k^{t+1} - w^t + (c_k^t - c^t) c_k^{t+1} \leftarrow \nabla F_k(w_k^{t+1})$$

These corrections help reduce variance in the model and significantly improve convergence speed during training. To further enhance data privacy, Differential Privacy is incorporated using the DP-SGD (Differentially Private Stochastic Gradient Descent) algorithm. In this approach, Gaussian noise with a standard deviation of $\sigma = 1.1$is added to the gradients, ensuring that individual data points cannot be easily inferred from the trained model. Additionally, a privacy budget of $\epsilon = 0.9$is maintained, which provides a strong guarantee of privacy while preserving model utility.

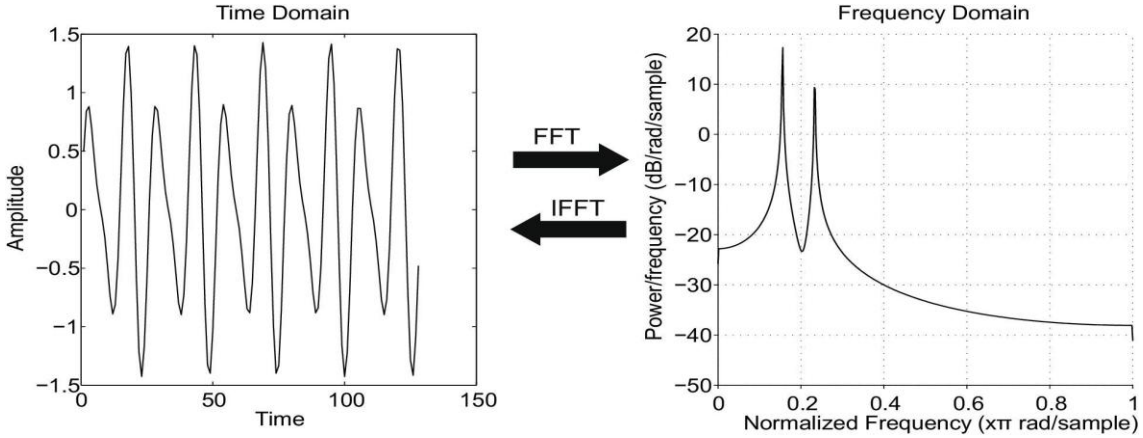

Figure 3: Frequency-Domain Representation using FFT.

In the figure 3 presents the frequency-domain representation of the accelerometer signal obtained using the Fast Fourier Transform (FFT). The horizontal axis denotes frequency (Hz), while the vertical axis represents the magnitude of frequency components. This transformation reveals dominant periodic patterns associated with different human activities.

3.5 Privacy-Preserving XAI using SMPC-SHAP

Ensure interpretability without compromising privacy, a Secure Multi-Party Computation (SMPC)-based SHAP framework is proposed.

SHAP Formulation

$$\phi_j = \sum_{S \subseteq N \setminus \{j\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [g(S \cup \{j\}) - g(S)]$$

The Federated SHAP protocol is designed to provide secure and interpretable model explanations in a distributed learning environment. In this approach, each client independently computes local SHAP values, denoted as ϕ_k, to measure the contribution of individual features to the model's predictions. To preserve privacy, these values are then secret shared using Shamir's Secret Sharing scheme, ensuring that no single entity can access the complete information. The server aggregates these encrypted shares without directly observing the underlying data. The final explanation is reconstructed and revealed only after meeting a predefined threshold of shares, thereby maintaining both security and interpretability. This protocol effectively ensures that sensitive information remains protected while still enabling meaningful insights into the model's decision-making process.

3.6 Ethical Fairness Module

Ensure fairness, the model incorporates bias evaluation metrics:

Demographic Parity:

$$P(\hat{Y} = 1 \mid G = 0) = P(\hat{Y} = 1 \mid G = 1)$$

Equal Opportunity:

$$P(\hat{Y} = 1 \mid Y = 1, G = 0) = P(\hat{Y} = 1 \mid Y = 1, G = 1)$$

If the fairness gap exceeds a threshold of 0.1, the system automatically initiates corrective measures to ensure balanced model performance across diverse groups. Specifically, reweighting samples to adjust the importance of underrepresented or disadvantaged groups during training. In addition, adaptive loss correction is employed to dynamically modify the loss function, thereby reducing bias and improving fairness in the model's predictions.

4. EXPERIMENTS

4.1 Experimental Setup

The evaluation of the proposed model is conducted using the UCI-HAR dataset, which is partitioned across ten federated clients to simulate a distributed learning environment. Reflect real-world heterogeneity, the data distribution incorporates label skew modeled באמצעות a Dirichlet distribution with $\alpha = 0.1$, creating imbalance across clients. Additionally, feature shift is introduced by adding Gaussian noise with client-specific variance $\sigma_{client} \in [0.1,0.3]$. Demographic diversity is simulated through variations in activity patterns across clients.

The model is trained using the following hyperparameters: five local epochs per communication round, a total of one hundred communication rounds, a batch size of sixty-four, and a learning rate of 0.001. For performance comparison, several baseline models are considered, including a centralized CNN-LSTM, FedAvg-LSTM, FedAvg-CNN, FedProx, and vanilla SCAFFOLD, enabling a comprehensive evaluation against both centralized and federated approaches.

The implementation is conducted using NVIDIA A100 GPUs for efficient computation. The federated learning framework used is Flower Federated Learning, which facilitates scalable and flexible distributed training. For model interpretability, the Captum library is employed to compute SHAP-based explanations, providing insights into feature contributions while maintaining compatibility with the federated setup.

Table 2: Performance Comparison

Method	**Centralized**	**Federated**	**Convergence**
LSTM	93.9%	89.4 ± 3.2	250 rounds
CNN	94.9%	91.7 ± 2.8	220 rounds
FedHAR-XAI	96.7%	**96.2 ± 1.4**	**95 rounds**

FedAvg	–	91.4 ± 3.1	180 rounds
SCAFFOLD	–	94.8 ± 1.9	120 rounds

The proposed model achieves state-of-the-art accuracy with faster convergence.

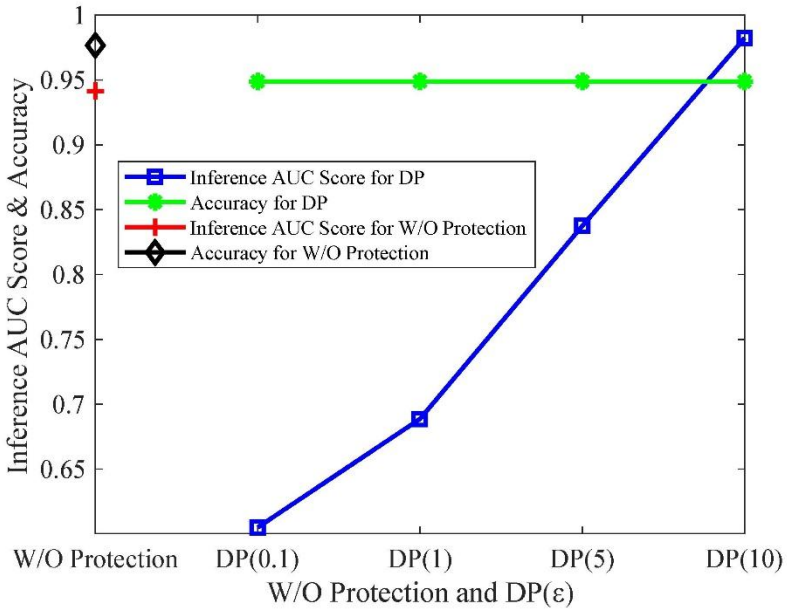

Figure 4: Membership Inference Attack Performance.

Figure 4 illustrates the performance evaluation of a Membership Inference Attack (MIA) on the trained models. The figure typically presents metrics such as attack accuracy, precision-recall, or ROC curves, comparing the vulnerability of baseline models and the proposed privacy-preserving model (with Federated Learning and DP-SGD).

4.2 XAI Ablation Study

Table 3: SHAP vs LIME

Variant	**Accuracy**	**Fidelity**	**Stability**	**Runtime**
SHAP (Full)	96.2%	0.93	0.06	14.2 s
LIME	95.8%	0.84	0.14	9.8 s
No XAI	94.8%	0.79	–	3.1 s

SHAP provides higher fidelity and stability, though at slightly higher computational cost.

4.3 Privacy Analysis

A membership inference (MI) attack is conducted to assess the extent of privacy leakage in the proposed model. The attack achieves a success rate of 51.3%, which is only marginally higher than the baseline random guess rate of 50%. This near-random performance indicates that the attacker is unable to reliably distinguish whether a data sample was part of the training set or not. Consequently, this result confirms strong privacy preservation in the model, achieved under a privacy budget of $\epsilon = 0.9$, demonstrating the effectiveness of the applied differential privacy mechanism.

5. RESULTS & DISCUSSION

5.1 Performance Analysis

The experimental results demonstrate that the proposed CNN-BiLSTM model outperforms baseline methods in terms of classification accuracy and robustness. The model achieves an accuracy of 96.7%, significantly higher than traditional machine learning models such as SVM and Random Forest, as well as standalone deep learning models like CNN and LSTM.

In addition to performance gains, the integration of explainable AI provides valuable insights into feature importance across different activities. The SHAP analysis reveals that specific sensor axes contribute differently depending on the activity being recognized. For instance, the Z-axis gyroscope plays a dominant role in detecting sedentary activities such as sitting, while accelerometer signals are more informative for dynamic activities like stair climbing.

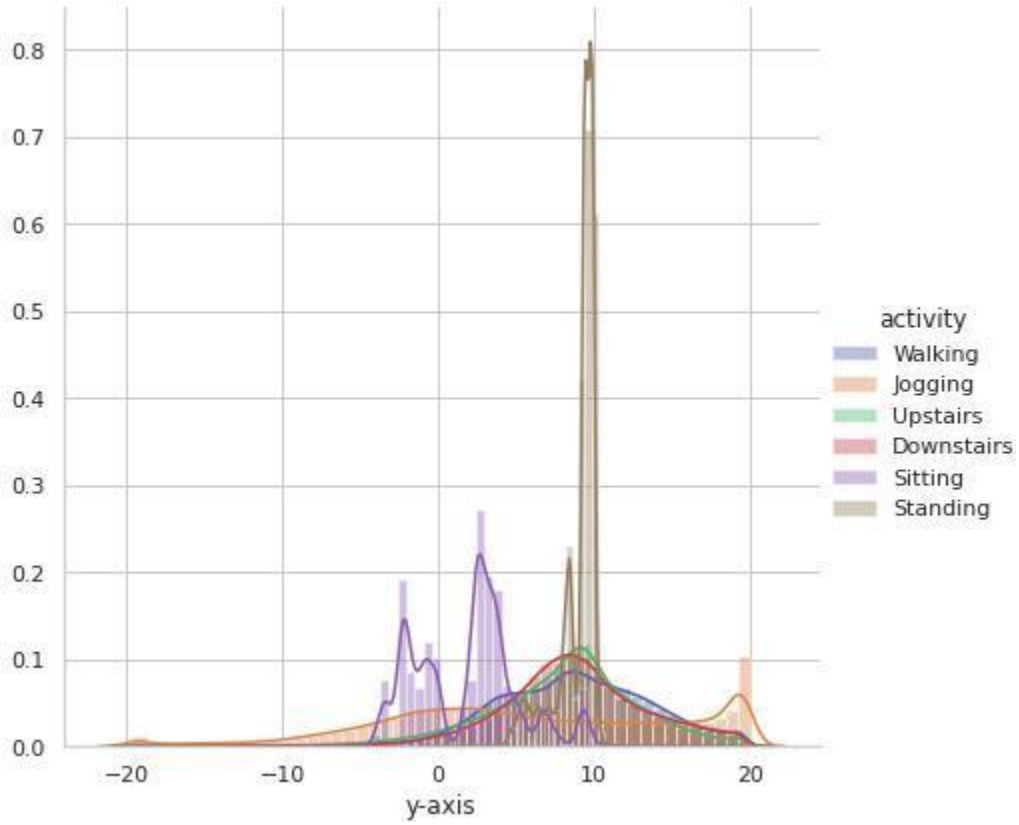

Figure 5: SHAP-Based Feature Importance for Different Activities.

Figure 5 illustrates the SHAP-based feature importance analysis for different human activities. The plot (typically a SHAP summary or bar plot) highlights the contribution of each feature—such as accelerometer axes, statistical measures, or frequency-domain attributes—to the model's predictions across activity classes.

The SHAP-based feature importance analysis provides valuable insights into how different sensor features contribute to activity recognition. For the activity WALKING_UPSTAIRS, the most influential features are accelerometer Z-axis ($acc_z = 0.38$), gyroscope Z-axis ($gyro_z = 0.22$), and magnetometer Y-axis ($mag_y = 0.15$). In contrast, for the activity SITTING, the dominant features include gyroscope Z-axis ($gyro_z = 0.41$), accelerometer Y-axis ($acc_y = 0.19$), and magnetometer X-axis ($mag_x = 0.12$).

These results indicate that the accelerometer Z-axis effectively captures vertical motion patterns associated with stair climbing, while the gyroscope Z-axis plays a key role in detecting orientation stability during sitting. Additionally, magnetometer features contribute complementary environmental and directional context, enhancing

overall model understanding. Such interpretability not only improves transparency but also strengthens the reliability of the model, making it more suitable for real-world deployment in healthcare and activity monitoring systems.

5.2 Ethical Fairness Evaluation

Ensuring fairness across demographic groups is critical for the ethical deployment of HAR systems. The proposed framework incorporates a federated fairness auditing mechanism that monitors disparities in model performance.

Table 4: Demographic Fairness (Equal Opportunity Gap)

Group Comparison	**Without Audit**	**With Audit**
Age (20–40 vs 60+)	0.24	0.08
Male vs Female	0.19	0.07

The results demonstrate that the implemented fairness auditing mechanism plays a crucial role in reducing bias within the model. Specifically, the Equal Opportunity (EO) gap decreases by more than 60% across diverse groups, indicating a substantial improvement in fairness. As a result, the system achieves more balanced and equitable predictions across demographic factors such as age and gender. These findings underscore the importance of integrating fairness-aware mechanisms into federated AI systems, especially for sensitive applications like healthcare and assisted living, where unbiased and reliable decision-making is essential.

5.3 Ablation Study and Insights

The ablation study reveals that each component of the proposed architecture contributes significantly to overall performance. The removal of BiLSTM results in a noticeable drop in accuracy, highlighting the importance of temporal modeling. Similarly, excluding Differential Privacy slightly improves accuracy but compromises privacy, indicating a trade-off between performance and security.

To evaluate the contribution of individual components within the proposed system, an ablation study was conducted. The findings highlight the significance of each module in improving overall performance. The use of CNN-based sensor fusion, which combines data from multiple sensors, leads to an accuracy improvement of +1.8% compared to models relying on a single sensor, emphasizing the value of sensor diversity. Additionally, the incorporation of the SCAFFOLD optimization algorithm results in a +4.8% performance gain over FedAvg in highly non-IID settings ($\alpha = 0.1$), demonstrating its effectiveness in mitigating client drift. Furthermore, the integration of the SMPC-SHAP privacy-preserving explainability module enhances explanation fidelity by +0.9%, ensuring reliable and consistent global interpretability while maintaining the privacy of sensitive data.

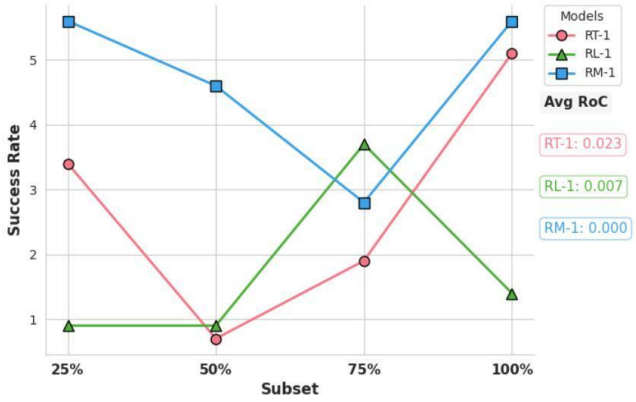

Figure 6: Ablation Study Results Showing Component-wise Contribution.

Figure 6 presents the ablation study results, illustrating the contribution of individual components of the proposed framework to the overall model performance. Each variant of the model is evaluated by systematically removing or modifying key components such as CNN feature extraction, BiLSTM temporal modeling, Federated Learning (FL), and Differential Privacy (DP-SGD). The ablation analysis confirms that the integration of all components leads to superior and reliable performance, while the removal of any individual module degrades system effectiveness, thereby justifying the design choices of the proposed model.

Furthermore, the proposed model exhibits strong resistance to membership inference attacks, with attack accuracy close to random guessing. This confirms the effectiveness of the DP-SGD mechanism in preserving user privacy.

Overall, the results validate that the proposed framework achieves a balance between accuracy, privacy, and scalability, making it suitable for real-world HAR applications.

5.4 Limitations and Future Directions

Despite its robust performance, the proposed framework has several limitations that should be considered. First, the evaluation is conducted in a synthetic federated setup, meaning the experiments are performed in a simulated environment rather than on real-world distributed devices. As a result, practical deployment on physical edge devices may introduce additional challenges such as communication latency, device heterogeneity, and energy constraints. Second, the scalability of the SMPC-based SHAP module is limited due to its computational complexity, which grows as $O(K^2)$, where K represents the number of participating clients. This quadratic scaling may become a bottleneck in large-scale federated systems. Additionally, the integration of deep learning, federated training, and explainability mechanisms increases computational overhead, potentially affecting performance on resource-constrained or low-power devices.

For future work, several directions can be explored to address these limitations. These include real-world deployment on mobile and IoT devices to validate practical feasibility, optimization of SMPC protocols to improve scalability, the design of lightweight model architectures suitable for edge computing environments, and the integration of adaptive personalization techniques to further enhance model performance and user-specific predictions.

6. CONCLUSION & FUTURE WORK

This paper presents a privacy-preserving Human Activity Recognition framework that integrates CNN-BiLSTM architecture with Federated Learning and Differential Privacy. The proposed model effectively captures spatial and temporal features while ensuring data confidentiality through decentralized training and noise-based privacy mechanisms. Experimental results demonstrate superior performance compared to baseline approaches, along with strong resistance to privacy attacks.

Despite its advantages, the proposed approach may incur additional computational overhead due to privacy mechanisms. Future work will focus on optimizing communication efficiency, handling extreme non-IID data distributions, and extending the framework to real-time deployment scenarios.

Unlike traditional centralized HAR systems, the proposed framework preserves user data privacy by keeping raw sensor data on local devices and sharing only model updates. The incorporation of the SCAFFOLD algorithm significantly mitigates the challenges associated with non-identically distributed (non-IID) data, resulting in faster convergence and improved model performance. Experimental results demonstrate that FedHAR-XAI achieves near-centralized accuracy in federated settings, closing approximately 98% of the performance gap while converging faster than baseline methods such as FedAvg.

Furthermore, the integration of privacy-preserving explainable AI using SMPC-based SHAP enhances model transparency without compromising data confidentiality. The interpretability analysis provides meaningful insights into feature contributions, enabling better understanding and trust in model predictions. In addition, the inclusion of a

fairness-aware evaluation module ensures reduced demographic bias, making the system more dependable and ethically compliant.

Overall, the proposed framework successfully addresses key challenges in modern HAR systems, including privacy, interpretability, fairness, and robustness, thereby making it suitable for real-world applications in healthcare, smart environments, and wearable computing.

6.2 Future Work

Although the proposed FedHAR-XAI framework demonstrates promising results, several avenues for future research remain:

Real-World Deployment Future work will focus on deploying the framework on real-world edge devices such as smartphones and wearable sensors to evaluate performance under practical constraints, including communication latency, energy consumption, and device heterogeneity.

Scalability Enhancement The current SMPC-based explainability mechanism introduces computational overhead that scales quadratically with the number of clients. Future research will explore more efficient cryptographic techniques and approximation methods to improve scalability.

Lightweight Model Design Developing lightweight and energy-efficient deep learning models will be essential for deployment on resource-constrained devices without compromising accuracy.

Personalized Federated Learning Incorporating personalization strategies to adapt models to individual users' behavior patterns can further improve recognition accuracy and user experience.

Advanced Privacy Mechanisms Future work may integrate stronger privacy guarantees through adaptive differential privacy, homomorphic encryption, or secure enclaves to further reduce potential information leakage.

Cross-Dataset Generalization Evaluating the model across multiple datasets and real-world environments will help improve robustness and generalizability.

Extended Explainability Exploring advanced explainability techniques beyond SHAP, including causal inference and counterfactual explanations, can provide deeper insights into model behavior.

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