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Review Article

A Review on Federated Learning on Sensor-Based Human Activity Recognition

Ting Xian Wu [1], Pang Ying Han [1, 2*], Ooi Shih Yin [1, 2], Lim Zheng You [2], Hiew Fu San [3]

[1] *Faculty of Information Science and Technology, Multimedia University, Bukit Beruang, Melaka 75450, Malaysia.*

[2] *Centre for Advanced Analytics, CoE for Artificial Intelligence, Multimedia University, Bukit Beruang, Melaka 75450, Malaysia.*

[3] *Infineon Technologies, Free Trade Zone, Batu Berendam, 75350 Melaka, Malaysia.*

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Abstract

Deep learning has demonstrated exceptional human activity recognition (HAR) performance by extracting complex features from inertial data. However, this centralized training approach aggregates data from multiple user devices into a central server and raises significant privacy concerns. Federated learning (FL) is proposed as an alternative. It provides a privacy-preserving scheme by training data analytics models on local users' devices rather than transferring raw data to a central server for data processing. Although FL is widely applied to various pattern recognition applications, its use in sensor-based HAR is limited, and reviews of the HAR application are even scarcer. Therefore, this paper provides a comprehensive review of FL in HAR. This paper analyzes FL's architectural design, data model training strategies, and model aggregation techniques. A comparative analysis between FL-based and machine learning methods is presented. The challenges, including data heterogeneity, data privacy, and communication costs, are identified through the findings, while the potential research direction of FL in HAR is underscored. This paper provides insights into the current state of FL for HAR, pinpoints research gaps, and outlines encountered challenges and potential research directions.

Keywords: Artificial Intelligence; Federated Learning; Human Activity Recognition; Sensor-Based; Data Privacy-Preserving.

1. Introduction

The deep learning approach has been extensively explored for data analysis and recognition in various fields in recent years. This approach reveals hidden patterns and intrinsic data structures, which are crucial for data analysis. Previous studies have demonstrated that deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), achieve exceptional recognition performances in various applications [1-5]. However, a huge amount of training samples is required to achieve exceptional performance, and these data samples are centrally processed and analyzed. In other words, each client's data samples must be transmitted/shared and stored in a central server. This raises the risk of cybersecurity attacks, especially during data transmission and storage. A breach in a single system can compromise all the data. Hence, crucial data security and privacy concerns are triggered when implementing a deep-learning approach [6-9]. These concerns are amplified when handling personal and sensitive data [10]. To address these challenges, federated learning (FL) has emerged as a promising alternative [11-13].

* Corresponding author: yhpang@mmu.edu.my

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Unlike deep learning methods, data learning and analysis are conducted in a decentralized practice in the FL framework. In other words, data analytics models are trained directly on users' devices on the client side. This practice eliminates the need to transfer the raw data to a central server and store it at a single location.

Human activity recognition (HAR) manipulates human activity data for activity detection and classification. This technology is increasingly prevalent and applied in diverse applications, including fitness tracking, smart home assistance, healthcare monitoring, and workplace monitoring [12, 14-17]. Privacy and data security concerns arise from the pervasive applications of HAR. HAR systems collect and analyze personal inertial data about individuals' movements, activities, and behaviors. This personal data possibly discloses sensitive information, such as the subject's location, health conditions, daily routine, and social interactions. Hence, the FL framework has been proposed for human activity recognition [13, 18-20]. As aforementioned, FL is a technology that accommodates decentralized data processing and analysis.

Each HAR data analytics model is trained at the local client side by using the respective user's inertial motion data as the training data and the validation data on their device. Then, the updates/model weights from the local client are sent to the global server to update the weights of the global model during the training process. Figure 1 illustrates the overview process flow of a federated learning HAR framework. Firstly, a global model is designed and initialized with initial parameters at a central server. Next, the global model is broadcast to the selected clients using the current global model parameters. On the client side, each local client now possesses a data analytics model trained locally using the respective client's inertial motion data. After completing the local model training, the updates/model weights of the local model are sent back to the global server. The global server aggregates these updates/model weights with a federated aggregation algorithm. The aggregated algorithm helps improve the global model by updating the weights of the global model based on the aggregated values from the local clients. During this process, the data privacy of the raw data from each device is preserved at each local client. The other local clients cannot access the raw data nor the global model because the data sent from the local client to the global server is in the form of model weights. These model weights signify the learned patterns from the inertial data but do not contain any raw data. In this way, FL can protect user privacy while still collaborating with the machine or deep learning for better classification performance.

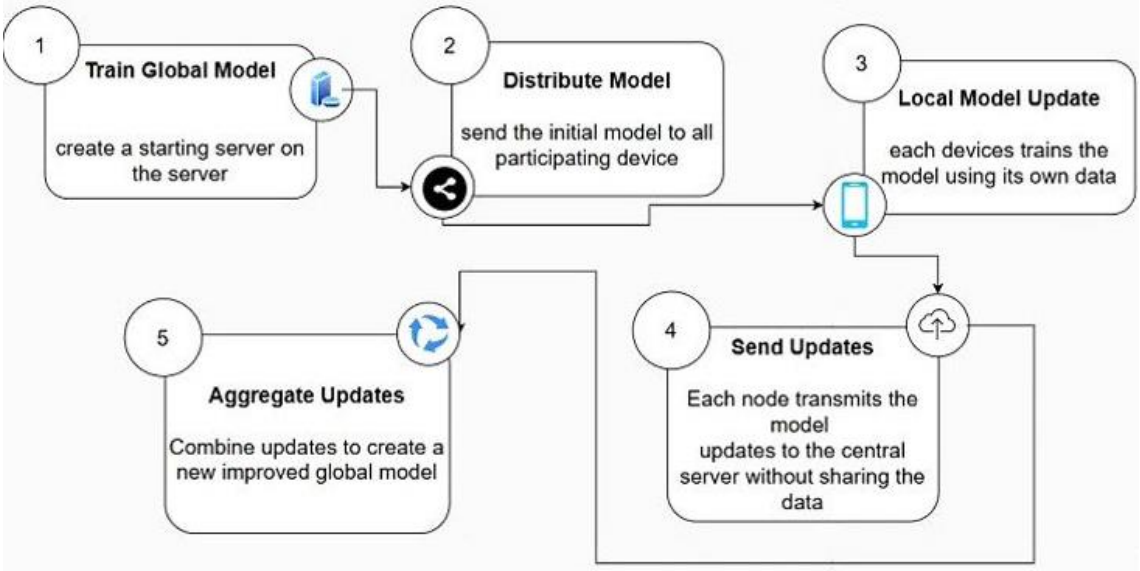

Figure 1. The overview process flow of a federated learning HAR framework

Federated learning has recently shown great potential as a decentralized approach that could offer more privacy and efficiency in diverse applications, especially those involving sensitive personal data. Since it keeps the data on local devices, FL minimizes data transmission and central storage risks. Hence, it is well-suited for sensor-based human activity recognition, where privacy is a top priority. FL offers several advantages:

- Minimizes risks of data breaches: By keeping data on local devices, FL reduces the risks associated with transmitting raw inertial data over networks or storing it in centralized servers. This ensures that sensitive information, such as human activity patterns, remains protected, reducing the possibility of exposure if there is a system compromise.
- Protects user privacy: Unlike centralized approaches, FL ensures that raw sensor data never leaves the user's device. Only model weights, as abstract representations of the learned patterns, are shared with the global server. This privacy-preserving design is significant for HAR applications, where human activity data can reveal sensitive information about the users' daily activities, health conditions, or location.

- Improved generalization: FL enables models to train on diverse, heterogeneous data across users. This helps improve the HAR models' generalization capability to capture the variability in human activity dynamics effectively.

Studies have explored FL in various pattern recognition tasks. However, the adoption of FL in sensor-based human activity recognition remains limited, and reviews of the HAR application are even scarcer [21-27]. In particular, several research gaps exist in this area:

- Limited systematic reviews on FL for sensor-based HAR: Although FL has been studied in healthcare, finance, etc., comprehensive reviews focusing on its application in sensor-based HAR are scarce. Most literature reviews emphasize general FL architecture without addressing HAR-specific challenges and limitations. A review tailored to FL-based sensor-based HAR is needed to bridge this gap.
- Lack of comparative studies between FL and machine learning approaches for HAR: There are limited comparisons against the machine learning approach in HAR-specific tasks. Examining how FL performs compared to machine learning approaches in HAR applications, particularly regarding data processing architectures and privacy implications, remains insufficient.
- Challenges in adapting FL for HAR in real-world deployments: Though FL provides a privacy-preserving solution, its deployment for real-world HAR applications faces several challenges. These include data heterogeneity across users and sensor modalities, communication constraints, and limited computational resources on edge devices.

While prior survey publications concentrated on the conceptual and technical issues of FL, the contributions of our study are summarized as follows:

- Survey of federated learning in sensor-based HAR: This paper thoroughly reviews FL applied to sensor-based HAR. It also includes the architecture of FL frameworks within the context of sensor-based HAR and the comparisons between conventional machine learning and federated learning.
- Exploration of federated learning framework for sensor-based HAR: This includes local training models and model aggregation algorithms used in the FL framework.
- Challenges of federated learning in the sensor-based HAR context: Challenges encountered when implementing FL for HAR are discussed. These include data diversity, privacy and security concerns, and communication costs associated with model updates.

The rest of the paper is organized as follows. Section 2 reviews related work on HAR and federated learning. Section 3 outlines the review methodology employed in our study, and Section 4 presents the fundamentals of federated learning in the context of sensor-based HAR. Section 5 provides a comparative analysis of federated learning and machine learning approaches for HAR-specific tasks. Section 6 discusses the challenges of deploying federated learning in real-world human activity recognition, while Section 7 discusses algorithms for local model training and model aggregation in FL. Section 8 outlines potential research directions of FL in sensor-based HAR, and Section 9 concludes the paper.

2. Related Work

Sensor-based human activity recognition (HAR) is a prevalent technology that utilizes sensors, either wearable sensors or sensors embedded in smartphones, to analyze and understand human movements. The advancements in deep learning significantly boost the performance and robustness of HAR models. However, conventional centralized deep-learning models encounter risks concerning privacy [10]. In these deep learning models, large volumes of sensitive personal data, such as daily activities, locations of the user, health metrics, etc., are transmitted and stored on central servers, thereby raising the risk of data breaches. Furthermore, the continuous data transmission to and from the centralized models may be susceptible to man-in-the-middle attacks. This further heightens the security risks. Federated learning (FL) has recently emerged as an alternative solution [28-32]. This decentralized data processing framework facilitates training HAR models on user devices to address privacy concerns. Various methods are proposed to improve the robustness and efficiency of FL models in human activity recognition applications, yielding better classification performance and model generalization across diverse user data and different devices [10, 18, 33-37].

One of the key contributions of FL frameworks is their design to maintain data privacy. Data analytics models are trained on local devices, while only model updates are transferred to a central server [38, 39]. This decentralized approach minimizes the risk of personal data exposure. In recent years, the Internet of Things (IoT) has gained enormous popularity due to its ability to automate devices and provide conveniences. The application of IoT has created a demand for secure and efficient data processing. By leveraging FL, IoT systems can enhance data privacy-enhancing communication efficiency [40-44]. To preserve user privacy and diminish delay, FL reduces the amount of data transferred between devices and servers, improving system performance and ensuring scalability and efficiency. Implementing FL training directly on devices reduces the requirement for extensive cloud-to-client communication. Thus, those issues associated with communication overhead, privacy issues, and compliance with data protection regulations are mitigated.

Instead of transmitting raw data, FedAvg, which was proposed by McMahan et al., averages model updates to reduce communication overhead since the model updates are smaller than the entire dataset [37]. This requires less bandwidth and improves communication efficiency. Ek et al. further explored the application of FedAvg for smartphone-based HAR [45]. The authors claimed that although federated learning has been applied widely, it still stays at the conceptual stage and needs to be clarified and tested. Their experimental findings demonstrate that FedAvg is more suitable for a heterogeneous and imbalanced database (in their study, the REALWORLD dataset was used) than the in-lab and balanced datasets (UCI was used).

The practicality of FedAvg is constrained by its inability to accommodate heterogeneous model architectures. Hence, Gad and Zubair proposed a novel FL framework for distributed training of heterogeneous models [46]. This approach is called Federated Learning via Augmented Knowledge Distillation, or FedAKD. This proposed approach is more flexible because it can adapt to collaborative heterogeneous deep learning models with diverse learning capacities. From the experimental results on HAR datasets, FedAKD exhibits superior classification performance, attaining up to 20% higher accuracy than other model-agnostic FL models.

Additionally, the communication overhead of FedAKD is much less than that of other FL models that transmit models' gradients. The reduction of communication overhead improves the efficacy of the federated learning procedure. Furthermore, Ek et al. proposed FedDist, a novel federated learning algorithm that revises deep learning models during training to detect neuron dissimilarities among clients [47]. This attempt can ensure the preservation of client specificity without compromising the model's generalization. The authors evaluated their proposed system on three heterogeneous mobile HAR datasets. The empirical results exhibit that the proposed FedDist is superior to the other state-of-the-art FL algorithms for its adaptability to data heterogeneity.

Ouyang et al. devised an FL system specifically for human activity recognition, known as ClusterFL [13]. The proposed ClusterFL is a similarity-aware FL model that facilitates high-performance accuracy while offering low communication overhead for HAR applications. The model offers a strategy that maximizes the training performance of different learned models. It also captures the underlying clustering relationship among data from different nodes. By utilizing the learned cluster relationship, ClusterFL efficiently withdraws the nodes that converge more slowly or have little correlation with other nodes in each cluster. This escalates the model's convergence while retaining the classification performance. Besides that, Shen et al. claimed that HAR is critical in healthcare applications, but collecting personal information for training creates privacy problems [48]. Existing FL approaches have difficulty adapting to new users due to individual variances in activity performance. Shen et al. proposed FedMAT, a new Federated Multi-task Attention framework for human activity recognition, to address this challenge. FedMAT treats each user as a separate learning task. The proposed FL system employs a shared network to learn common features and engages individual attention modules to capture user-specific differences. With these implementations, FedMAT learns generalizable features while adapting to specific users. The reported experimental results demonstrate that the proposed system can perform better for existing and new users.

Yu et al. proposed a personalized federated human activity recognition framework to address the challenges of privacy preservation, real-time, label scarcity, and heterogeneity patterns [20]. The proposed FL framework is known as FedHAR. In FedHAR, distributed learning is conducted to perform model training on local devices for users' privacy preservation. The model adopts semi-supervised learning to aggregate the gradients of all the labeled and unlabeled clients. The reported empirical results demonstrate that the proposed FedHAR is superior to the existing models on two public datasets. Tu et al. highlighted that one of the challenges of the existing HAR-based FL models is the failure to adequately describe the statistical diversity of user data [18]. Besides that, these FL models adopt static aggregation techniques that scarcely adapt to the varying data distributions across subjects. These limitations result in suboptimal recognition performance. Motivated by the challenges, the authors introduce a novel FL system to dynamically capture the intrinsic intraclass similarities for data learning. This feature is vital in exhibiting the inherent environmental and behavioral commonalities. The proposed model also employs a dynamic layer-sharing scheme to capture similarities among users' model weights. The proposed FL model outperforms the existing approaches regarding classification accuracy and model convergence speed because of its lower communication overhead.

While FL provides a privacy-preserving alternative by training data analytics models on user devices, FL suffers from non-independent and identically distributed (i.e., non-IID) data, which significantly varies in user behavior. To overcome this issue, Presotto et al. introduced FedCLAR, a new federated clustering approach for HAR [19]. FedCLAR classifies users with similar activity patterns by examining a subset of the model weights shared with a central server. This selective analysis minimizes communication overhead. The system outperforms conventional FL solutions in HAR tasks. Although FedCLAR can address non-IID data in FL-based HAR via user clustering, labeled data is still required on all devices. Thus, Presotto et al. proposed a semi-supervised FedCLAR, coined SS-FedCLAR, to improve their previously proposed FedCLAR model, which requires labeled data for model training [49]. This model combines FedCLAR's federated clustering with the FedAR algorithm proposed by Presotto et al. to mitigate the labeled data scarcity problem and leverage unlabeled data. SS-FedCLAR assigns pseudo-labels to the unlabeled data using active learning and label propagation. This can extend the training dataset without needing additional labeling. The authors reported that the SS-FedCLAR outperforms the previous algorithms by obtaining higher accuracy with less labeled data.

Arikumar et al. highlighted that Smart Healthcare (SHC) solutions, which use wearable sensors to track human activities, have difficulty managing much unlabeled data on cloud servers [50]. Thus, they proposed the Federated Learning-Based Person Movement Identification (FL-PMI) to address this issue by labeling unlabeled data with deep reinforcement learning. In this system, Bidirectional Long Short-Term Memory is employed to categorize the data for SHC use. FL-PMI can reduce connectivity costs and cloud workloads by shifting computation to edge servers. This approach detects motions with high accuracy (99.67%) while requiring minimal resources and data transfer. Shaik et al. highlighted the challenges of traditional remote patient monitoring systems based on centralized learning [51]. These systems struggle to integrate patient privacy and personalized monitoring with wearable sensors for human activity recognition. The authors devised FedStack, an FL architecture that enables training several AI models on individual devices. Fed-Stack trains models on local devices and sends predictions to a central server. The server combines these predictions to improve a global model. Empirical results show that the proposed FedStack provides high activity detection accuracy (99.6%) while respecting privacy.

Applications such as human activity recognition (HAR) raise privacy concerns and result in high communication costs due to data transfer from edge devices [52]. To address this issue, Al-Saedi et al. introduced Cluster Analysis-based Federated Learning (CA-FL), which enables collaborative model training directly on user devices such as smartphones while keeping data private. CA-FL uses clustering analysis to detect comparable updates from devices. CA-FL uploads only representative updates from each cluster to the central server. This implementation helps lower communication overhead. The authors claimed that the proposed CA-FL provides a communication-efficient FL solution for HAR that ensures accuracy while safeguarding user privacy.

Furthermore, Cheng et al. proposed a novel FL framework to address the challenges of traditional FL in sensor-based human activity recognition, which struggles with non-identical data distributions across devices [10]. The non-identical data distributions can result in slow convergence and inaccurate models. The proposed FL architecture is namely ProtoHAR. This model overcomes the issue by dissociating the representation and classifier in the heterogeneous FL setting. The performance of ProtoHAR was assessed on four datasets: HARBOX, USC-HAD, PAMAP2, and UNIMIB-SHAR for controlled environments and real-world scenarios. The experimental results reveal that this proposed system achieves an encouraging performance and improves model convergence.

In summary, AI models, whether machine learning or deep learning, are crucial for learning data characteristics to achieve accurate outcomes. Model personalization within FL frameworks is vital for optimizing AI models across diverse user populations and device capabilities [53-57]. In diverse environments, users show varying patterns, behaviors, and preferences. By personalizing models, FL frameworks can adapt to the variations. Furthermore, personalization in FL frameworks enriches the user experience by making AI systems more responsive and customized to individuals. Specifically, these personalized models can better analyze and predict individual activities for more accurate monitoring and assistance. Table 1 presents the literature summary of the relevant FL frameworks in HAR applications, recapping various aggregation techniques and AI models employed in applying sensor-based human activity recognition.

Table 1. Summary of related works on FL frameworks for HAR applications

Literature	The proposed system	Database(s)	Methodology	Performance metrics (%)
Gudur & Perepu [58] federated learning with heterogeneous labels and models for mobile activity monitoring	Federated Learning with Model Distillation and Label-Based Averaging for Heterogeneous HAR	HHAR	New federated label-based aggregation, leveraging overlapping information gain across activities using Model Distillation Update. Federated transfer of model scores is proposed from device to server. Data models: CNN and Artificial Neural Network (ANN).	Local update Accuracy 72.293 Global update Accuracy 83.303
Tu et al. [18] FedDL: Federated Learning via Dynamic Layer Sharing for Human Activity Recognition	FedDL	LiDAR, UWB, HARBOX-IMU, IMU and Depth	Uses a dynamic layer-sharing approach to learn the similarity among users' model weights, then merges the models accordingly data model: CNN.	Lidar Mean accuracy 98 Overall mean accuracy for all datasets => 90
Li et al. [59] Meta-HAR: Federated representation learning for human activity recognition	Meta-HAR	HHAR, USC-HAD, and Newly collected dataset	A federated representation learning framework - a signal embedding network is meta-learned in a federated manner, while the learned signal representations are fed into a personalized classification network at each user for activity prediction. The HAR problem at each user is treated as a different task, and the shared embedding network is trained through a Model-Agnostic Meta-learning framework so that the embedding network can generalize.	HHAR Meta-train user Accuracy 98.39 Meta-test user Accuracy 92.50 USC-HAD Meta-train user Accuracy 93.79 Meta-test user Accuracy 91.07 Collected Dataset Meta-train user Accuracy 90.76 Meta-test user Accuracy 93.29
Sarkar et al. [60] GraFeHTy: Graph Neural Network using Federated Learning for Human Activity Recognition	GraFeHTy	MHEALTH and WISDM	Incorporates Graph Convolutional Networks (GCNs) in the federated learning context. A similarity graph from sensor measurements for each user is built, and CGN is applied to perform semi-supervised classification of activities. Weights are averaged using FedAvg.	MHEALTH Centralized Accuracy 98.7 Federated Accuracy 97.9 WISDM Centralized Accuracy 91 Federated Accuracy 81.7

Kirsten et al. [61] Sensor-Based Obsessive- Compulsive Disorder Detection with Personalized Federated Learning	Combined personalized federated learning for OCD detection	OPPORTUNITY	Detects Obsessive-Compulsive Disorder (OCD) through federated learning, augmented by the OPPORTUNITY dataset-comprises repetitive activities that can indicate OCD. Data model: a two-layer bidirectional Long Short-Term Memory (LSTM) with a fully connected output layer and dropout between every layer. Evaluates three personalized federated learning strategies for OCD detection utilizing augmented sensor data from the OPPORTUNITY dataset.	OPPORTUNITY AUPRC ~95
Al-Saedi et al. [52] Reducing Communication Overhead of Federated Learning through Clustering Analysis	Cluster Analysis- based Federated Learning (CA-FL)	mHealth and Pamap2	Lessens communication overhead without compromising accuracy by diminishing the number of worker updates transferred. Initializes by clustering local updates from available workers, then selects representative workers for training, using only their data to build the global model. The process is iterative, adapting worker partitioning and selecting new representatives each round - aggregating global model updates by representing groups of similar local parameters.	MHealth F1 score (IID) (round 100) 56.7 F1 score (non IID) (round 20) 57.4 Pampa2 F1 score (IID) (round 20) 96.2 F1 score (non IID) (round 80) 96.6
Presotto et al. [19] FedCLAR: Federated Clustering for Personalized Sensor-Based Human Activity Recognition	FedCLAR	WISDM and MobiAct	Federated learning for personalized HAR using hierarchical clustering and transfer learning. User clustering technique that utilizes server-side similarity computation. Only a portion of the model weights is shared by each participating user. Solves the non-IID issue through the integration of federated clustering with transfer learning.	WISDM Accuracy 89 MobiAct Accuracy 94
Zhou et al. [14] 2D Federated Learning for Personalized Human Activity Recognition in Cyber-Physical-Social Systems	2-Dimensional Federated Learning (2DFL)	Combined datasets of UniMiB-SHAR and Personal Gadget Dataset	Two federated learning schemes: the vertical and horizontal FL schemes Integrates shareable features across heterogeneous data from different devices using vertical federated learning and collects encrypted local models built from multiple individual users' data through horizontal federated learning data model: CNN	Combined dataset Accuracy 93 Recall 89 F1 score 90
Shen et al. [34] Federated Multi-Task Attention for Cross-Individual Human Activity Recognition	FedMAT	HHAR, PAMAP2, ExtraSensory and SmartJLU	Applies federated multi-task learning for HAR, where each user's HAR is considered a task. Uses a central model combined with individual-specific models. CNN-RNN is used to analyze sensor data and attention-based masks to extract individual characteristics. FedAvg enables the aggregation of updates of local models on IoT devices.	HHAR Accuracy 96.88 Macro F1 96.81 PAMAP2 Accuracy 92.61 Macro F1 91.84 ExtraSensory Accuracy 75.72 Macro F1 75.03 SmartJLU Accuracy 89.78 Macro F1 83.02
Arikumar et al. [50] FL-PMI: Federated Learning-Based Person Movement Identification through Wearable Devices in Smart Healthcare Systems	FL-PMI	UniMiB-SHAR and Realworld	Leverages deep reinforcement learning for auto-labeling the data. Bidirectional Long Short-Term Memory (BiLSTM) is employed to analyze and classify the data. Uses FedAvg to aggregate local model parameters from edge devices.	Accuracy 99.67 Precision 99.37 F1-Score 98.92 Recall 99.11
Shaik et al. [51] FedStack: Personalized activity monitoring using stacked federated learning	FedStack	MHEALTH	Overcomes the limitations of traditional federated learning (aggregating the heterogeneous model). Build a heterogeneous global model across devices with different AI models, using heterogeneous stacking to aggregate non-identical architectural models Supports ensembling heterogeneous architectural client models. Three AI models (ANN, CNN, and BiLSTM) are trained on individual data. The federated learning architecture is applied to these models to build a local and global model.	MHEALTH ANN Accuracy 99.6 CNN Accuracy 99.6 Bi-LSTM Accuracy 98.6
Cho et al. [62] FLAME: Federated Learning across Multi-device Environments	FLAME	RealWorld, PAMAP2, and Opportunity	Focusing on the user-centered synchronization of data from different devices to overcome the statistical and systematic heterogeneity, providing maximized inference performance with minimized required resources. Integrates model personalization to adjust the global model for each device and thus improve the inference performance and multi-device consistency.	RealWorld Device Macro F1 83.8 Global Macro F1 52.6 F1 score 58.0 Opportunity Device Macro F1 57.5 Global Macro F1 48.5 F1 score 50.5 PAMAP2 Device Macro F1 53.0 Global Macro F1 39.7 F1 score 39.0

Raza et al. [28] Lightweight Transformer in Federated Setting for Human Activity Recognition in Home Healthcare Applications	TransFed	WISDM, Self-collected dataset	Develops a novel lightweight transformer, complemented by the proposed TransFed framework for privacy-preserving collaborative model training across distributed devices. The proposed TransFed is the first framework for activity classification based on federated learning and transformers. A central server distributes a transformer model to edge devices for local training. Trained parameters are returned to the server for aggregation, creating a global model. Edge devices then download and update their local models accordingly.	WISDM Accuracy 98.89 Self-collected Dataset Federated Setting Accuracy 98.74 Centralized Setting Accuracy 99.14
Presotto et al. [49] Federated Clustering, and Semi-Supervised learning: A new partnership for personalized Human Activity Recognition	SS-FedCLAR	WISDM and MobiAct	Combines federated learning with the semi-supervised learning scheme to solve the non-IID and data scarcity issues. Each client employs a mix of active learning and label propagation to create pseudo labels for unlabeled data, which is subsequently utilized to train a Federated Clustering model collaboratively.	WISDM Hierarchical F1 score 88 MobiAct Hierarchical F1 score 96
Albaseer et al. [63] Semi-Supervised Federated Learning Over Heterogeneous Wireless IoT Edge Networks: Framework and Algorithms	Federated semi-supervised learning (FedSemL)	HAR, CIFAR-10, and MNIST	Works with unlabeled data and considers issues such as computation limitations, communication costs, and deadlines. Involves an initialization phase in which the model and IoT devices' parameters are determined, then multiple training rounds in which the server gathers the devices' information, sets the time deadlines, and selects devices that will be involved in the training process. Devices complete local updates by pseudo-labelling, labeling the unlabeled data, and applying strong augmentation during training. The server aggregates these updates to create a new global model, optimizing resource constraints usage, like energy and communication costs.	Testing accuracy >95 (with >100 global training rounds)
Ouyang et al. [13] ClusterFL: A Similarity- Aware Federated Learning System for Human Activity Recognition	ClusterFL	UWB, IMU, and Depth	By grouping users into activity similarity for learning within clusters, reducing excessive communication overhead through straggler removal and significant nodes' selection. Perform aggregate using the Alternating Direction Method of Multipliers (ADMM). Data modeling: SVM (UWB), DNN (IMU), CNN (Depth)	UWB Balanced mean accuracy 89.06 Unbalanced mean accuracy 92.71 IMU Balanced mean accuracy 90.47 Unbalanced mean accuracy 89.05 Depth Balanced mean accuracy 71.82 Unbalanced mean accuracy 70.68
Yu et al. [20] FedHAR: Semi-Supervised Online Learning for Personalized Federated Human Activity Recognition	FedHAR	RealWorld and HAR-UCI	Federated learning with semi-supervised online learning to handle label scarcity, the need for real-time processing, and the heterogeneity of human activity recognition. Combines both supervised and unsupervised gradients while permitting the intermediate model fine-tuning for local performance enhancement. The aggregation method combines supervised gradients from labeled data with unsupervised gradients (calculated based on similar sensor sequences) using a semi-supervised loss function. Data model: hierarchical attention-based neural network.	Real-world Accuracy 65.31 F1 score 62.77 HAR-UCI Accuracy 82.61 F1 score 81.62
Cheng et al. [10] ProtoHAR: Prototype Guided Personalized Federated Learning for Human Activity Recognition.	ProtoHAR	PAMAP2, UNIMIB-SHAR, USC-HAD, and HARBOX	The prototype aggregation-based algorithm for activity recognition in the heterogeneous FL scenario. Uses prototypes to refine the global representation, decoupling feature representation, and the classifier. Exchanges information via sharing prototypes and representations. Each abstract prototype is viewed as an activity class by the mean representations of the observed samples from the same activity category. Data model: CNN (three convolutional layers, two max-pooling layers, two fully connected layers, and one SoftMax layer).	PAMAP2 Accuracy 87.727 F1 score 87.336 AUC 97.839 USC-HAD Accuracy 76.416 F1 score 71.714 AUC 96.518 UNIMIB-SHAR Accuracy 94.470 F1 score 92.088 AUC 99.678 HARBOX Accuracy 95.110 F1 score 95.034 AUC 99.086
İsgüder et al. [35] FedOpenHAR: Federated multi-task transfer learning for sensor-based human activity recognition	FedOpenHAR	OpenHAR	A federated multi-task transfer learning incorporated with the Deep Convolutional and Long Short-Term Memory (DeepConvLSTM) for human activity classification and device position identification with motion sensor data. Server's aggregation algorithm: FedAvg. Data model: DeepConvLSTM.	OpenHAR Accuracy 72.4

Wang et al. [64] Hydra: Hybrid-model federated learning for human activity recognition on heterogeneous devices	Hydra	HHAR, HARBox, and MobiAct	A hybrid-model FL framework that enables heterogeneous devices to co-train high-performance models with large and small sizes tailored to their diverse computing capabilities. Introduces loss-based sample selection for effective co-training among high-performance computing devices (HCDs)and low-performance computing devices (LCDs). Formulates a large-to-small knowledge distillation to enhance the efficiency of transferring knowledge from HCD to LCD. Data model: CNN for HAR task.	HHAR Accuracy 94.1 MobiAct Accuracy 98.6 HARBox Accuracy 94.4
Pham et al. [65] Extension of physical activity recognition with 3D CNN using encrypted multiple sensory data to federated learning based on multi-key homomorphic encryption	3D CNN model	Daily and Sports Activities (Sport) and Daily Life Activities (DaLiAc)	Recognizes human activities using data from wearable sensors by employing 3D convolutional neural networks (3D-CNNs). Uses bitwise XOR operator for data encryption. Further enhances the models for FL by incorporating federated averaging and multi-key homomorphic encryption to improve privacy.	Sport Accuracy 94.6 DaLiAc Accuracy 94.9
Shen et al. [48] Federated Meta-Learning with Attention for Diversity-Aware Human Activity Recognition	DivAR	Two multi-individual heterogeneous	Considers user differences by making various user groups for social-related factors and then personalizing the model for those various groups. Classifies individuals into clusters based on their behavior and social relations, fine-tuning a federated meta- learning model with local models endowed with a CNN-based attention mechanism to learn cluster-specific features, and updating a global model that learns across the population while maintaining privacy. The aggregation method consists of averaging the updated parameters from the decentralized local models to improve the central model's parameters.	Dataset1 Accuracy 93.48 F1 Score 90.37 Dataset2 Accuracy 89.55 F1 Score 83.19 DatasetMix Accuracy 83.95 F1 Score 78.36
Khan et al. [66] A Privacy and Energy-Aware Federated Framework for Human Activity Recognition	Integrating spiking neural networks (SNNs) with long short-term memory (LSTM)	UCI and Realworld	Combines spiking neural networks (SNNs) and LSTM for data modeling the model is trained using surrogate gradient learning, backpropagation. FL on devices without sharing data.	UCI Accuracy 97.36 RealWorld Accuracy 89.69
Chai et al. [36] A profile similarity-based personalized federated learning method for wearable sensor-based human activity recognition	PS-PFL	RealWorld Sisfall	A new personalized federated learning approach by leveraging profile-based similarity, enhancing model personalization and generalizability by considering individual profile features. Computes similarities between individuals based on their profiles and uses these similarities to aggregate personalized global models. Data models: CNN and Long Short-Term Memory (LSTM). *Note:* Avg_A is average accuracy; Avg_P is average precision Avg_R is average recall, Avg_F1 is average f1.	RealWorld CNN Avg_A 94.88 Avg_P 95.42 Avg_R 94.69 Avg_F1 94.95 RNN Avg_A 93.65 Avg_P 94.22 Avg_R 93.85 Avg_F1 93.88 SisFall CNN Avg_A 94.50 Avg_P 92.91 Avg_R 92.41 Avg_F1 91.29 RNN Avg_A 78.57 Avg_P 65.81 Avg_R 65.02 Avg_F1 70.53
Orzikulova et al. [29] Federated Learning with Incomplete Sensing Modalities	FLISM	PAMAP2, RealWorld, and WESAD	Federated Learning with Incomplete Sensing Modalities (FLISM) to enable multimodal FL with incomplete modalities. Employ simulation techniques to learn robust representations - handling missing modalities and transferring model knowledge across clients with diverse modality sets.	PAMAP2 F1 score 77 WESAD F1 score 58.9 RealWorld F1 score 77.8
Jiang et al. [67] FLSys: Toward an Open Ecosystem for Federated Learning Mobile Apps	FLSys	Self-collected dataset	A mobile-cloud FL system smartphone with mobile sensing data. A complete prototype of FLSys is developed in Android and AWS. Balances model utility with resource consumption on the phones, tolerates client failures, supports multiple deep learning models, provides support for advanced privacy protection mechanisms, and acts as a "central hub" on the phone for managing training, updating, and access control of FL models for different apps. Data model: CNN Aggregators: FedAvg, FedYogi, FedAdam, and FedAdagrad are available	HAR-W-128-centralized Accuracy 82.62 Precision 85.29 Recall 84.49 F1-score 84.84 FLSys Using Android Emulation Accuracy 69.07 Precision 59.22 ~86.06 Recall 64.50~86.55 F1-score 66.68 ~76.80

To provide a structured comparison, we consolidate previous studies from the above table into Table 2 under four key aspects to understand the methods. The comparison aspects are: (1) Types of FL – Distinguishing different FL paradigms, i.e., horizontal, vertical, or hybrid, based on data partitioning mechanisms; (2) Data Model Implementation – specifying the models or algorithms used to process the captured inertial data, (3) Privacy and Security – about security measures such as differential privacy or cryptographic techniques, and (4) Communication Architecture – differentiating between centralized and decentralized FL structures. From Table 2, we can observe that most FL approaches implement a horizontal FL paradigm. This may be because horizontal FL is more suitable for scenarios with different clients, but recording the same types of activity data. Specifically, the studies collected similar types of sensor data, i.e., accelerometer and gyroscope, from multiple clients. It is worth noting that the work of Zhou et al. [14] incorporates a hybrid FL paradigm. This method is unique because it integrates horizontal and vertical FL paradigms, facilitating the incorporation of heterogeneous data from different sources.

Table 2. Comparison of Federated Learning approaches for HARs

Method	Types of FL	Data Model Implementation	Privacy Security	Communication Architecture
Gudur & Perepu [58] federated learning with heterogeneous labels and models for mobile activity monitoring	Horizontal	Convolution Neural Network and Artificial Neural Network	Not specified	Centralized
Zhou et al. [14] 2D federated learning for personalized human activity recognition in cyber-physical-social systems	2-dimensional FL framework, including the vertical and horizontal FL phases	Convolutional Neural Networks	Somewhat Homomorphic Encryption (SWHE)	Centralized
Shen et al. [34] federated multi-task attention for cross- individual human activity recognition	Horizontal	Convolution Neural Network-Recurrent Neural Network	Not specified	A shared feature representation network (central server) with individual-specific attention modules (decentralized nodes)
Arikumar et al. [50] FL-PMI: federated learning-based person movement identification through wearable devices in smart healthcare systems	Horizontal	Bidirectional Long Short-term Memory	Not specified	Centralized
Jiang et al. [67] Flsys: toward an open ecosystem for federated learning mobile apps	Horizontal (with an option for extension to Vertical FL and Federated Transfer Learning)	Convolution Neural Network	Differential privacy	Centralized
Presotto et al. [19] Fedclar: federated clustering for personalized sensor-based human activity recognition	Horizontal	Feed-forward deep neural network	Not specified	Centralized

Additionally, it is noticed that most HAR-specific FL implementations work on a centralized communication architecture. Clients transmit the generated model updates to a central server to perform aggregation and redistribute the updated model to the clients. The wide use of the centralized approach may be due to the fact that this kind of central server simplifies model updates, diminishing coordination complexity. Nevertheless, the study of Shen et al. [34] employs a decentralized FL approach. In this framework, a federated multi-task model constituted of a shared feature representation network is managed by a central server. In contrast, multiple individual-specific networks with attention modules are stored in decentralized nodes.

3. Review Methodology

This section outlines the methodology used to review FL for sensor-based HAR. The review process involved systematically searching and screening for relevant literature from diverse electronic academic databases. These include but are not limited to IEEE Xplore, arXiv, Google Scholar, ResearchGate, ACM Digital Library, and ScienceDirect. The cited research articles in this study were downloaded from these electronic databases. Furthermore, the queried keywords used in the search engine were “Federated Learning”, “Human Activity Recognition”, “sensor”, and “smartphone”, and combinations of the terms. After performing all the queries, we initially downloaded 150 articles. Next, the collected articles were selected by examining their titles, publication years, abstracts, and conclusions. We selected papers published between 2019 and 2024 to ensure up-to-date and comprehensive information. Since our core focus was to gather articles on sensor-based human activity recognition in which FL is employed for data privacy and model training in the sensor-based HAR context, 80 articles were excluded because they were unsuitable for this review study. 70 selected articles were further studied, and 31 research articles out of these 70 articles were determined to be the most appropriate to be referred to in this review paper. The reviews and discussions of some of these articles are outlined in the Related Work section and Table 1. The review methodology process is depicted in Figure 2.

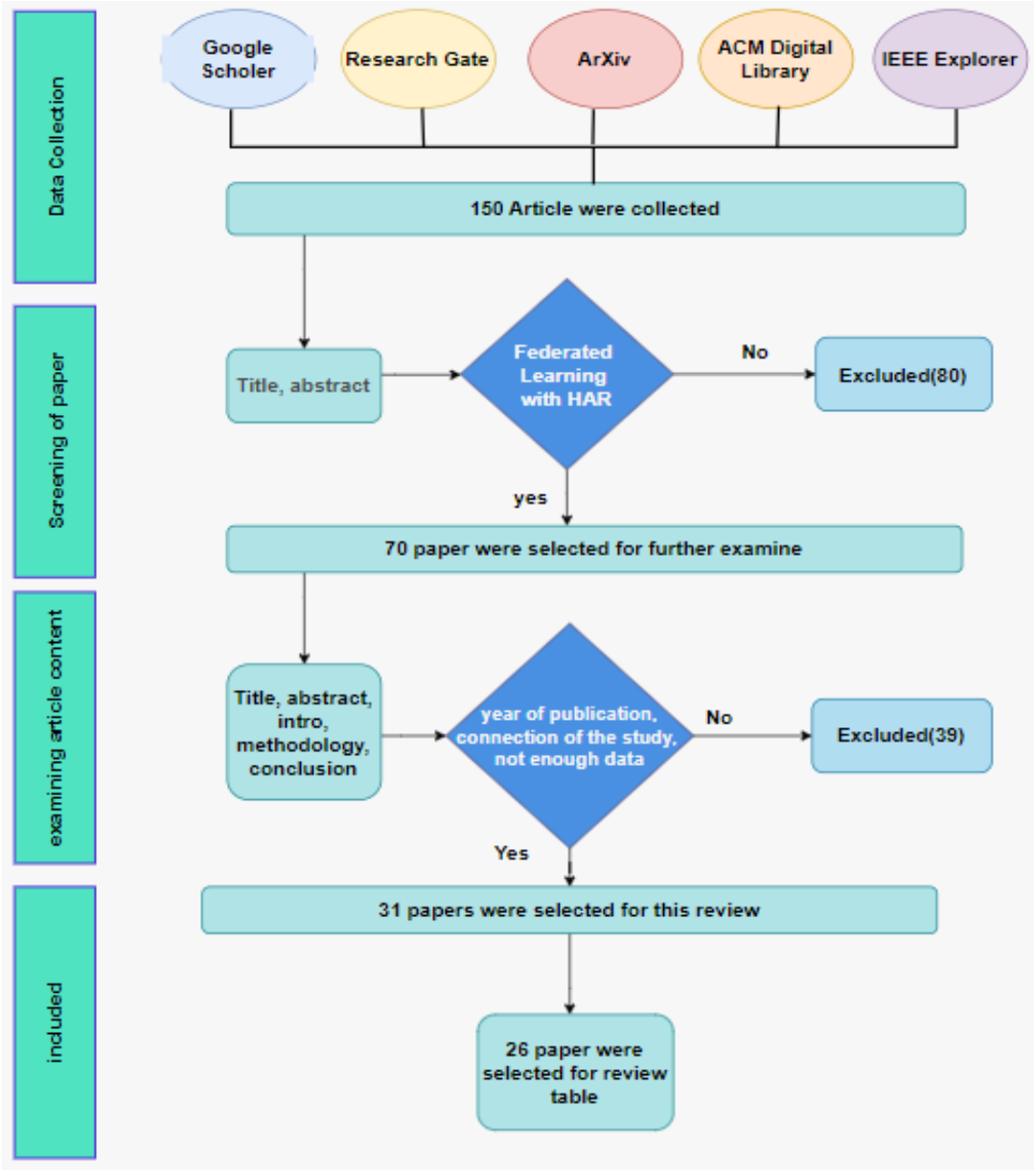

Figure 2. Review methodology

4. Federated Learning

Federated Learning (FL) was introduced by Google and used for the first time in 2016 to improve text input predictions of the Google Keyboard on many Android devices [68]. The primary idea is to enhance the predictive text function while keeping users' data local instead of transmitting it to the central server for processing [69]. In other words, FL is a machine learning approach that facilitates decentralized model training without centralizing the data. Unlike traditional machine learning models that aggregate raw data from various sources, FL allows every edge device to build its local data model using its own data. Only the generated model updates are then shared with a central server. This server will then aggregate these model updates to construct and optimize a universal model, which is disseminated to the local devices for further localized learning.

There are apparent advantages to using Federated Learning in HAR applications. HAR systems rely on information feeds from clients' devices, such as wearable fitness trackers or smartphones, that collect the users' physical movement data [70]. FL enables these devices to train a central activity recognition model collaboratively while keeping the activity data local and private. Every edge device first trains its model using its data, then only transmits the generated model updates to a central server. The global server aggregates these updates to fine-tune the global HAR model, which will then be redistributed to the edge devices for further training. This iterative process guarantees that personal activity data remains secure on local devices while diverse data sources from different devices are utilized to improve the recognition of the activities model.

4.1. The Architecture of Federated Learning

Federated Learning (FL) is an innovative approach that enhances user data privacy by enabling decentralized machine learning. The FL framework has several key components to ensure privacy-preserving and efficient model training [65, 66]: the devices, the central server (also called the global server), and the communication framework. The devices are local edge devices with different specifications that generate and own the data. They contribute to local model training using local data and share the generated model updates with the central server rather than the raw data. The central server aggregates the model updates and fine-tunes the global HAR model. This process is iterative and facilitated by the communication framework for continuous improvement of the data model while preserving user data privacy. While the data computation aspect focuses on training the local and global models, the communication aspect handles the transfer of model updates between the devices and the central server. This iterative training strategy, which involves local training, model aggregation, and model update communication, relies on the three aforementioned key components of the FL architecture (see Figure 3).

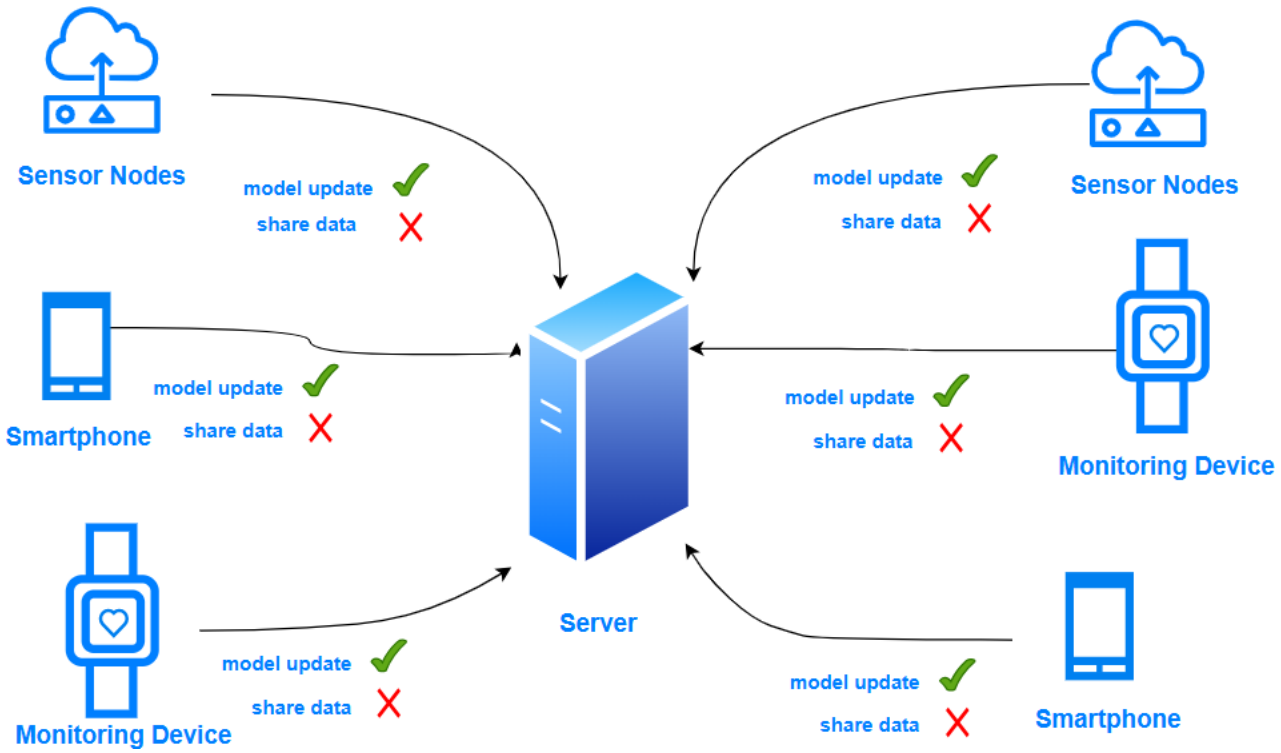

Figure 3. The conceptual idea of FL, where model updates are shared instead of raw data

Federated Learning (FL) provides a robust approach to safeguarding user privacy by enabling decentralized machine learning directly on user devices. This design choice addresses privacy concerns inherent in centralized data handling. Unlike traditional approaches that rely on collecting and processing raw data centrally, FL ensures that data remains on users' devices, reducing the risk of unauthorized access and data breaches. This is particularly crucial for sensitive HAR data, where privacy is paramount. In FL, model training occurs locally on each device, and only model updates, such as gradients or weights, are sent to a central server. This aggregated information allows for global model improvement without exposing any individual's raw data.

Additionally, secure aggregation protocols ensure that the server can only access the combined contributions from all devices, preventing it from viewing any single user's update, while differential privacy techniques further enhance security by adding controlled noise to model updates, protecting against potential inference attacks. This layered approach allows FL to mitigate privacy risks at each step, and the framework's iterative communication process focuses on transmitting only essential information, reducing exposure and communication costs. Together, these mechanisms, like data locality, secure aggregation, and differential privacy, establish FL as a powerful method for HAR applications, balancing high model performance with strong privacy protections.

Figure 4 shows the architecture of Basic Federated Learning. A central server connects to multiple devices, and there is a two-way data flow between the server and the devices. The devices locally train a model using their local data and return the model updates to the server. Then, the central server aggregates these updates, thus refining the global model. This process is decentralized, facilitating collaborative model training without sharing raw data, thereby illustrating a privacy-preserving system [67].

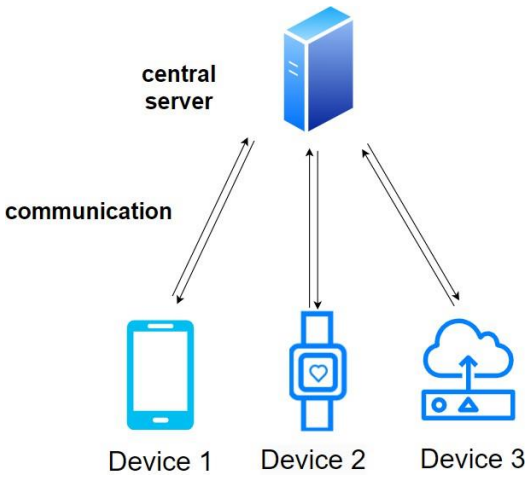

Figure 4. Basic Federated Learning

4.2. Types of Federated Learning

Federated Learning (FL) incorporates different approaches for data distribution scenarios and applications [71-73]. In the literature, we can categorize the types of FL into three: horizontal federated learning, vertical federated learning, and federated transfer learning. Each of these will be discussed in the following section.

4.2.1. Horizontal Federated Learning

In horizontal federated learning, devices are similar but have different user data [32]. In other words, the devices have identical feature types (i.e., the same feature space), but the individual users' data may differ. For instance, in the application of fitness tracker human activity recognition, horizontal federated learning allows multiple trackers, each with similar sensor data types (i.e., the number of steps, heart rates, etc.) but from different individuals, to train a model collaboratively, as depicted in Figure 5.

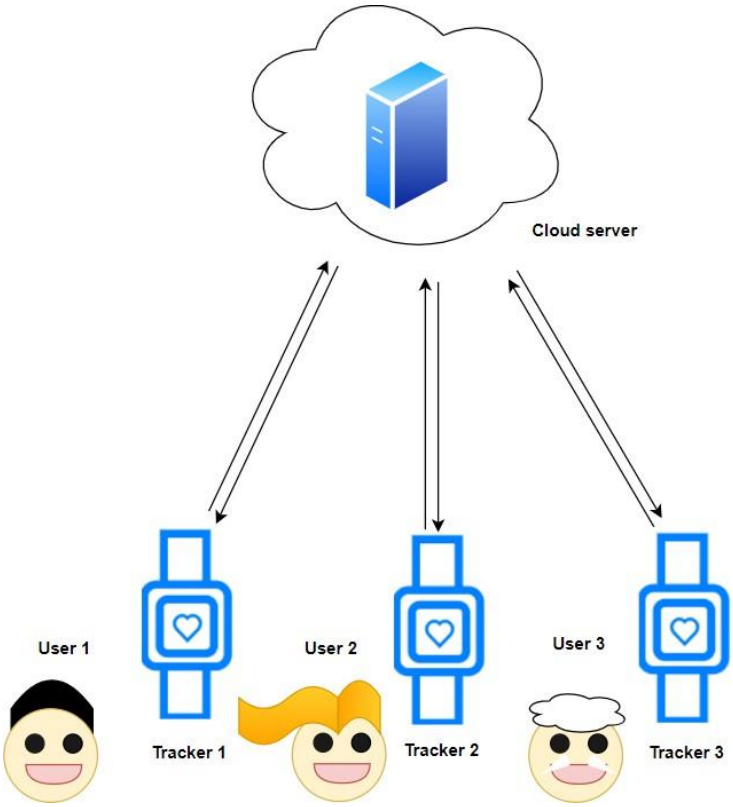

Figure 5. Horizontal Federated Learning

4.2.2. Vertical Federated Learning

Vertical federated learning is devised to handle scenarios where different datasets have overlapping users but distinct feature spaces. Specifically, the clients share the same users but have different features [74, 75]. This approach is useful

in applications where multiple health monitoring systems are engaged. For instance, consider a fitness tracker company (Client I) that collects users' physical activities, such as steps and heart rate, and a sleep tracking app (Client II) that tracks users' sleep behaviors. By incorporating these datasets with different features but shared users through vertical federated learning, the global model can utilize these combined data profiles to interpret better and comprehend complex user behaviors. It is worth noting that a sample alignment procedure is required to ensure that data from multiple sources are accurately associated with the same users before joint training. This avoids mismatches between user data from different sources, affecting model learning and degrading performance, as shown in Figure 6.

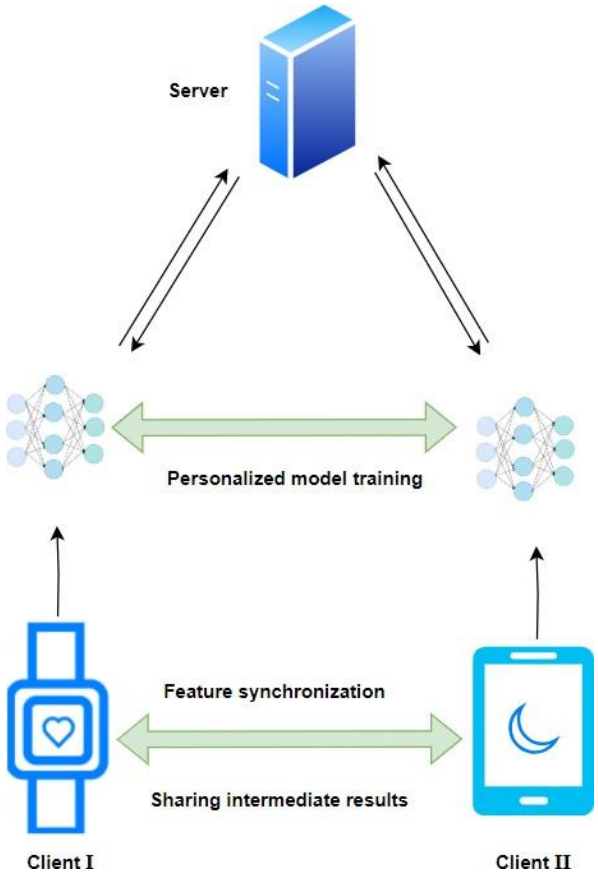

Figure 6. Vertical Federated Learning

4.2.3. Federated Transfer Learning

Federated transfer learning addresses scenarios where datasets are either non-overlapping or minimally overlapping regarding features and users [76]. For instance, a fitness tracker company, Client (III), collects data on users' physical activities (i.e., steps and heart rates), and a smart home service company (Client IV) collects data on users' home movement patterns. In such cases, federated transfer learning can transfer knowledge from the fitness tracking data to improve the HAR model for home activity monitoring. This approach is valuable when the adopted datasets are highly differing. Although the datasets may involve different attributes and populations, federated transfer learning can assist in constructing a global HAR model by leveraging knowledge from source and target domains [77].

5. Differences Between Federated Learning and Machine Learning

Federated Learning (FL) and machine learning have a common objective: achieving effective data learning outcomes. In this paper, machine learning encompasses conventional machine learning models such as Random Forest, Decision Tree, Support Vector Machine, etc., and deep learning models like Convolutional Neural Networks, Long Short-Term Memory Networks, Recurrent Neural Networks, etc. However, FL and machine learning differ fundamentally in their architecture and data handling methodologies. Machine learning can be categorized into centralized and distributed approaches. In centralized machine learning, data from users' inertial sensors embedded in smartphones or wearable devices is collected and transmitted to a centralized server. The entire model training process takes place on this single server. Since all computations are implemented on a single machine, training models, especially deep learning models, requires substantial computational resources. Furthermore, this centralized approach increases the risk of privacy breaches and security vulnerabilities because users' data is stored and processed in a single location. In other words, this centralized processing approach poses data privacy and security concerns.

In contrast, FL decentralizes the model training process on users' local devices, keeping raw sensor data locally. Instead of sharing raw data, only model updates, such as model weight adjustments or gradient updates, are transmitted to a central aggregation server. Therefore, FL enhances data privacy security by ensuring that personal activity data remains on the user's device while facilitating collaborative learning across multiple users. While distributed ML and FL possess similar data processing architectures where the computational load is distributed across multiple devices, their data handling manners differ. Distributed ML analyzes and processes data on central servers. In other words, raw data from different sources can be stored in the central servers, raising the risk of privacy breaches. Although some distributed systems may use techniques to minimize data sharing, it is less common than FL. Conversely, FL provides a privacy-heightening solution where data model training is performed directly on the users' local devices. Only model updates are shared with a central server instead of raw sensor data. Specifically, private and sensitive activity data is kept in the users' devices, reducing the need for sensitive data transfers. The architectural differences between FL, centralized, and distributed MLs are depicted in Figure 7. A summary of the differences in data privacy, access, and communication is presented in Table 3.

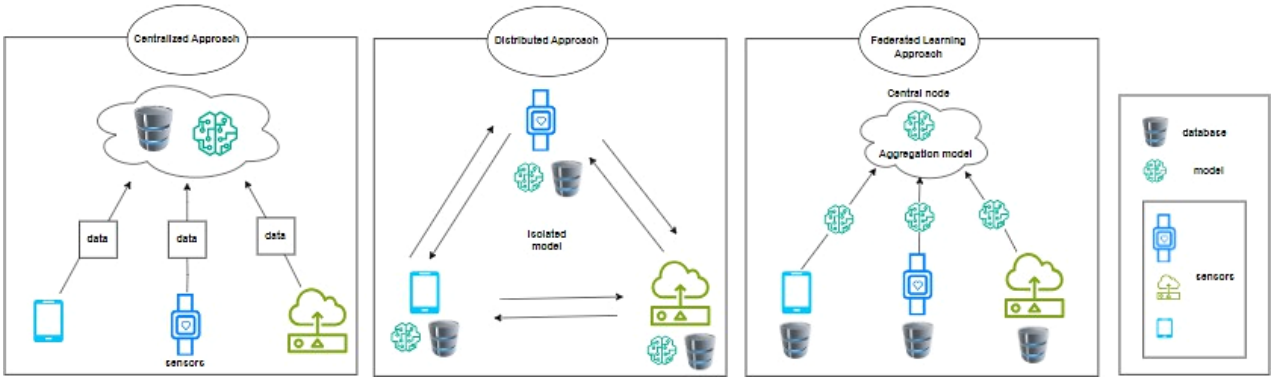

Figure 7. Comparison between centralized, distributed, and federated learning

Table 3. Federated Learning VS Machine Learning

	Classical Machine Learning	Decentralized Machine Learning	Federated Learning
Privacy	High risk	Moderate risk	Enhanced privacy
Access to data	The central server has full access	The central server has full access	The central server has access to model updates only

6. Challenges in Federated Learning

6.1. Privacy Security

Federated Learning (FL) is a new, innovative approach to machine learning. It reduces privacy risks associated with data centralization and provides model training across multiple users while keeping their data local and decentralized [78]. However, the decentralized approach introduces other security vulnerabilities. Thus, privacy-preserving techniques such as Secure Multi-Party Computation (SMC) and Homomorphic Encryption (HE) are required to harden the privacy and security of FL.

SMC secures the input data of each involved party by using encryption. This is to ensure that parties gain no information about others' data. On the other hand, HE is an encryption method that enables the central server to perform algebraic operations directly on encrypted model parameters, such as model updates, without requiring decryption. Nevertheless, user privacy security can barely be guaranteed in the FL scheme with HE technology, particularly if participants with the same secret key collude. Furthermore, SMC and HE technologies encounter limitations due to their high communication costs and computational complexity associated with preserving privacy [74]. In HAR systems, inertial data is gathered from multiple users and different devices, producing huge amounts of information. The encryption and decryption processes to secure this personal data can be computationally intensive. The situation becomes worse for low-resource devices with limited processing power. The study in Khan et al. [66] highlights that the increased communication costs and latency negatively impact system performance, leading to inefficiencies in real-time applications.

6.2. Communication

Generally, FL diminishes the risk of privacy violation by decentralizing data and sharing only model updates, which is beneficial in sensor-based HAR applications since personal sensitive data is involved [52, 79]. Even though FL complements the benefits of privacy, it suffers from significant communication challenges. These challenges can impact its practicability and efficiency, especially when numerous devices are involved. The cost of transmitting model updates from devices to the central server exceeds the computation cost, resulting in increased communication overhead in FL.

In HAR, real-time activity recognition requires frequent model updates since human movements and behavior patterns are dynamically changing. The timely data transmission of model updates from edge devices is crucial for achieving instantaneous and accurate activity recognition and monitoring. However, frequent data transmission increases network latency and congestion, especially for resource-constrained, low-power devices with limited bandwidth.

Furthermore, data from diverse devices, such as fitness trackers and smartphones, must be continuously analyzed and processed for pattern recognition [80]. Consequently, each edge device must frequently transmit its local model updates to the central server. This frequent data transmission raises the communication overhead in FL and further impacts the model processing and updating, resulting in substantial delays. The high communication cost results in low application efficiency, hindering the feasibility of FL in real-world applications, particularly in real-time HAR recognition and monitoring, which require continuous model updates with minimal delay.

6.3. Data Heterogeneity

Data heterogeneity presents significant challenges in Federated Learning (FL) for human activity recognition applications [10]. Data heterogeneity arises due to inconsistencies and variability in the data collected by diverse clients. This includes the variations in environmental conditions, human activities, types of edge devices and/or sensors, and their specifications. Consequently, the collected data can vary significantly in distribution, quality, and quantity. These inconsistencies lead to non-independent and identically distributed data, resulting in difficulties training a global model that performs well for all users.

One major factor contributing to data heterogeneity is HAR's diversity in sensing devices. A smartwatch that tracks activities of daily living continuously gathers accelerometer and gyroscope data throughout the day and generates a complete dataset of the user's daily activities. This dataset contains detailed motion patterns of activities such as standing, sitting, walking, cycling, etc. Conversely, a smartphone, typically carried in a pocket or bag, may only collect less activity data from less frequent interactions, yielding incomplete daily activity representations. This variability results in heterogeneous data, challenging this information's effective aggregation and modeling. Furthermore, imbalanced data distributions across clients can skew the global model's learning process, as some devices collect sparse, low-frequency samples while others provide rich, high-frequency data.

7. Algorithms in Federated Learning

In this section, we will further discuss different Federated Learning (FL) algorithms, focusing on aggregation techniques and data model approaches.

7.1. Aggregation Techniques

Data heterogeneity presents significant challenges in Federated Learning (FL), particularly in the context of human activity recognition applications [10]. Data heterogeneity occurs due to inconsistencies and variability in the data collected by diverse clients. This includes the differences in environmental conditions, human activities, types of edge devices and/or sensors, and their specifications. Consequently, the collected data can vary significantly in distribution, quality, and quantity. For instance, a smartwatch that tracks activities of daily living continuously throughout the day will generate a complete dataset of the user's daily activities. Conversely, smartphones may only gather less activity data from less frequent interactions. This variability results in heterogeneous data, challenging this information's effective aggregation and modeling.

7.1.1. Federated Averaging (FedAvg)

The central server aggregates local model updates in FL to form a global model. The aggregation is performed using a weighted average, where the weights are proportional to the number of data samples on each client [37]. Specifically, the global model at the next iteration is computed as follows:

$$w_{t+1} = \frac{1}{K}\sum_{k=1}^{K} w_{t+1}^{k} \quad (1)$$

where w_{t+1} is the updated global model, K is the total number of clients and w_t^k is the model update from device k at iteration t. In summary, FedAvg updates the global model by aggregating model updates from each client with a weightage corresponding to the data contribution. In other words, clients with more data will have a greater weightage/influence on updating the global model. In other words, FedAvg reduces communication costs by enabling multiple local updates per communication round. It leverages local stochastic gradient descent to calculate updated averages among the clients to facilitate the training of deep networks.

7.1.2. Federated Proximal (FedProx)

By keeping local models in reasonable proximity to the global model, FedProx enhances performance, particularly when dealing with datasets that exhibit significant differences. It can address the problem of data heterogeneity and improve the reliability of the federated learning process [81].

$$h_k(w, w_t) = F_k(w) + \frac{\mu}{2}\|w - w_t\|^2 \quad (2)$$

where $h_k(w,w_t)$ represents the modified local objective function incorporating a proximal term. The goal is to minimize a function that includes two parts: the local loss function $F_k(w)$ measuring the model's performance on the client's data, and a proximal term $\frac{\mu}{2}\|w - w_t\|^2$ penalizing deviations from the global model w_t. μ is a regularization parameter that controls the strength of this proximal constraint such that local models do not drift too far from the global model. The proximal term helps keep the local model close to the global model, improving overall stability and convergence in federated learning. FedProx addresses system heterogeneity by adding a proximal term to local loss functions such that even partially trained models can contribute meaningfully to the global model.

7.1.3. Federated Normalized Averaging (FedNova)

Wang et al. [82] highlighted that FedAvg faces challenges when dealing with non-IID data across clients. Specifically, the substantial variations in client data distributions may make local models distinct from global ones, thereby degrading the overall model performance and stability. FedNova is proposed to address these limitations. This aggregation technique normalizes and scales local model updates before averaging and aggregating them into the global model. This implementation could guarantee a more stable and balanced aggregation process. The update rule for Fed-Nova is defined as follows:

$$w_{(t+1,0)} - w_{(t,0)} = -\tau_{eff}^{(t)} \sum_{i=1}^{m} p_i \,.\, \eta d_i^{(t)} \quad (3)$$

where $d_i^{(t)} = \frac{G_i^{(t)} a_i^{(t)}}{||a_i^{(t)}||1}$. The normalized stochastic gradients d_i are aggregated. When the local solver is vanilla SGD, $a_i = [1, \ldots, 1] \epsilon \mathbb{R}^{\tau i}$ and $d_i^{(t)}$ is a simple average over the current round's gradients.

Combining these strategies helps FedNova better manage the impact of client heterogeneity on the global model for more stable and effective federated training. FedNova normalizes the local updates against the local epoch, which aids in achieving fair aggregation and reducing bias for non-IID environments.

7.1.4. Federated Stochastic Gradient Descent (FedSGD)

Unlike the aforementioned aggregation techniques, which aggregate local model updates from clients, FedSGD aggregates the gradients computed from each client [37]. In this technique, each client computes the gradient of its local objective function. Then, the gradients are passed to the central server. The global model is then updated based on the aggregated gradients. This update process ensures that while each client owns their data, they can contribute to the global model through their gradients. The local objective function $F_k(w)$ of client k is calculated as:

$$F_k(w) = \frac{1}{n_k} \sum_{i \in p_k} f_i(w) \quad (4)$$

where n_k is the number of data samples on the client k, p_k is the set of data samples on the client k, and $f_i(w)$ is the loss function for the ith sample with model parameter w. The gradient gk of this local objective function for the current model parameters w_t is then computed:

$$g_k = \nabla F_k(w_t) \quad (5)$$

where ∇ denotes the gradient operator concerning the current model parameters w_t. The server aggregates these gradients g_k to update the global model using a weighted average. The weights are proportional to the number of data samples on each client, ensuring that clients with more data have a greater influence on the model update. The global model is updated based on the following rule:

$$\omega_{t+1} = w_t - \eta \sum_{k=1}^{K} \frac{n_k}{n} g_k \quad (6)$$

where η is the learning rate, K is the total number of clients, and $\frac{n_k}{n}$ is the proportion of data samples on client k, and g_k is the gradient from client k. The updated global model ω_{t+1} is obtained by subtracting the weighted sum of the gradients from the current model parameters w_t. FedSGD synchronizes all clients' gradients at every round, maximizing model utility and minimizing drift in the event of heterogeneous data. Even though this synchronization renders it less communication-efficient than techniques like FedAvg, FedSGD enhances the overall model convergence consistency.

7.2. Data Model

Deep learning is a prevalent data modeling tool in sensor-based HAR applications. Deep learning has exhibited exceptional performance in the literature due to its exclusive capability to capture intricate features from raw inertial signals. This ability enables deep learning models to discriminate complex inertial patterns in human activities, yielding substantial improvements in accuracy over traditional machine learning approaches. This section briefly describes the

popular deep learning algorithms widely used in sensor-based HAR applications, exploring their architecture and characteristics.

7.2.1. Artificial Neural Network (ANN)

ANN is a computational model inspired by the human brain to perform complex pattern analysis and recognition [80]. An ANN comprises an input layer, one or more hidden layers, and an output layer. Each layer is made of neurons, which are linked by weights. These weights adjust the strength of the interconnections between neurons. The input layer receives raw data and passes it to the hidden layer(s) for data computation. In the hidden layer(s), nonlinear transformations are performed via activation functions. This process is crucial for introducing nonlinearity into the model because real-world data is complex and nonlinear. Nonlinearity enables the model to learn and capture intricate data patterns. A simple feed-forward neural network with one hidden layer is illustrated in Figure 8, and the formulation is below.

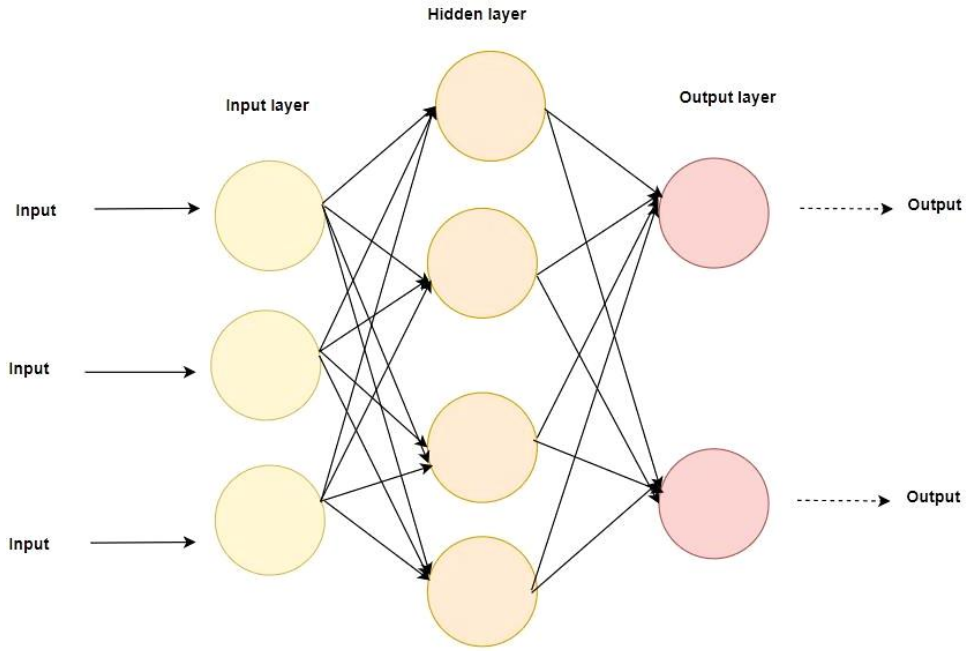

Figure 8. Architecture for ANN

The output of the hidden layer, denoted as H_{out}, is computed as follows:

$$H_{out} = ACT(W_1 X + b_1) \quad (7)$$

where W_1 represents the weight matrix that links the input layer to the hidden layer, X denotes the input vector, b_1 is the bias vector for the hidden layer, and ACT represents an activation function (e.g. sigmoid function, hyperbolic tangent, Rectified Linear Unit (ReLU)).

The output of the ANN is computed as below:

$$Y_{out} = ACT(W_2 H_{out} + b_2) \quad (8)$$

where W_2 represents the weight matrix that links the hidden layer to the output layer, and b_2 is the bias vector for the output layer.

7.2.2. One-Dimensional Convolutional Neural Networks (1D CNNs)

Convolutional Neural Networks are widely used for processing data that is sampled on a grid, such as image data [83]. On the other hand, 1D-CNN is particularly designed to process one-dimensional input data, such as biomedical signals and inertial signals. For a one-dimensional input signal S and a kernel W, the convolution is defined as below:

$$(S^* W)_n = \sum_{i=1}^{|w|} W_i S(i + n - 1) \quad (9)$$

$$O'_n = (S_{|W(i.j)|} * W(i,j)) \quad (10)$$

* denotes the discrete convolution process, S is the input data, W is the convolutional filter, $S_{|W(i,j)|}$ represents the elements in S from n to the dimension of $W(i, j)$.

Figure 9 depicts a 1D Convolutional Neural Network sample for Human Activity Recognition. Six data inputs corresponding to the 3-axis data from an accelerometer and a gyroscope are inputted to the model. Each input is processed by convolutional and pooling layers. The outputs are then concatenated and fed into fully connected layers, respectively. Lastly, activities are classified using a SoftMax layer.

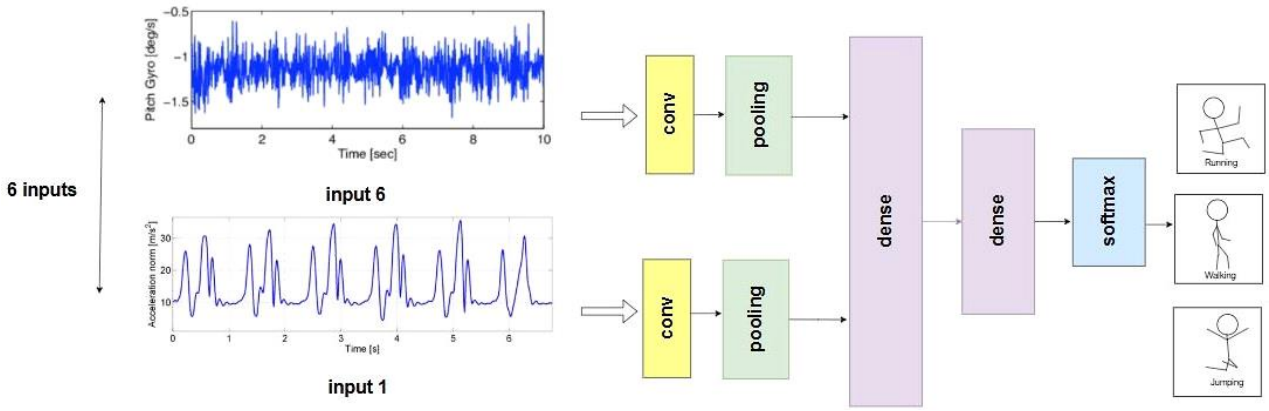

Figure 9. Architecture of a 1D CNN structure

7.2.3. Long Short-Term Memory (LSTM) Networks

LSTM networks are recurrent neural networks capable of extracting and modeling temporal dependencies in time-series data [83]. Unlike traditional recurrent neural networks, LSTM addresses the problem of vanishing gradients associated with long-term dependencies in time-series data. LSTMs consist of multiple memory cells that store and process information over time, as depicted in Figure 10. LSTM networks use input gates, output gates, and forget gates. The inputs are divided into two components: input state at $t(x_t)$ and output state at $t-1(h_{t-1})$. The input gate can be represented as:

$$i_t = \sigma(W[x_t, h_{t-1}, C_{t-1}] + b_i) \quad (11)$$

$$C_t = f_t . C_{t-1} + i . tanh(W[x_t, h_{t-1}, C_{t-1}] + b_c) \quad (12)$$

The forget gate determines what data will be forgotten from the cell memory.

$$f_t = \sigma(W_f[h_{t-1}x_t] + b_f) \quad (13)$$

The forget gate and the input gate both update the cell unit state.

$$C_t = C_{t-1}f_t + \tilde{C}_t i_t \quad (14)$$

Finally, the output is produced via the output gate.

$$o_t = \sigma(W[x_t, h_t-1, C_t] + b_o) \quad (15)$$

$$h_t = tanh(C_t) . o_t \quad (16)$$

where i_t is the state of the current input gate, f_t is the state of the current forget gate, x_t is the input sequence, and h_{t-1} is the output. C_t and C_{t-1} are the current cell state and the previous cell state, respectively. b is the bias vector, and W is the weight vector for each input. σ is the logistic sigmoid function.

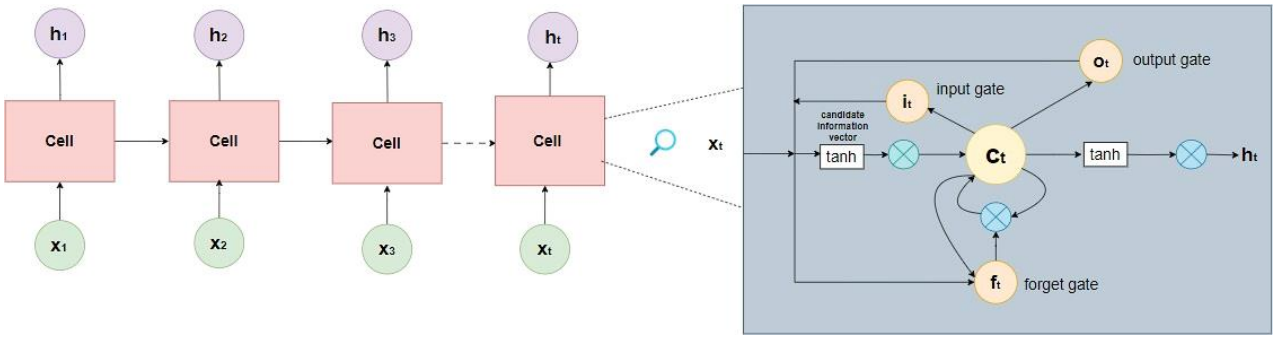

Figure 10. The Architecture for LSTM

7.2.4. Bidirectional LSTM (BiLSTM)

LSTM models process data in a single direction, which can limit their capability to comprehend the data. Thus, BiLSTM is proposed to enhance ordinary LSTMs by processing data in both forward and backward directions, as depicted in Figure 11. This implementation facilitates BiLSTM to capture information from past and coming data, yielding better model performance.

In a BiLSTM model, the output of the backward layer (h_t^b) and forward layer (h_t^f) are used to produce the final hidden state at time t, i.e. h_t, using weighting factors α and β (or trainable parameters) that control how the forward and backward states are combined in the BiLSTM model is generated as:

$$h_t = \alpha h_t^f + \beta h_t^b \quad (17)$$

$$x_0^1 = y_t = \sigma(h_t) \quad (18)$$

where x_0^1 is the final output from the BiLSTM at time t, y_t denotes the output at time t, and σ is the sigmoid activation function**.** BiLSTM is useful in HAR because it can further improve the temporal dependencies learned from the sensor data of wearable devices by considering both previous and future readings. This results in higher accuracy of classifying activities and increased ability to handle noise. HAR activities include data gathering and preprocessing, feature extraction with BiLSTMs, activity classification, and performance assessment, leading to better activity recognition and lower error levels. The BiLSTM networks make HAR models more effective in dealing with temporal patterns because bidirectional processing yields better classification accuracy and makes the activity recognition systems more efficient. The structure of BiLSTM is shown in Figure 11.

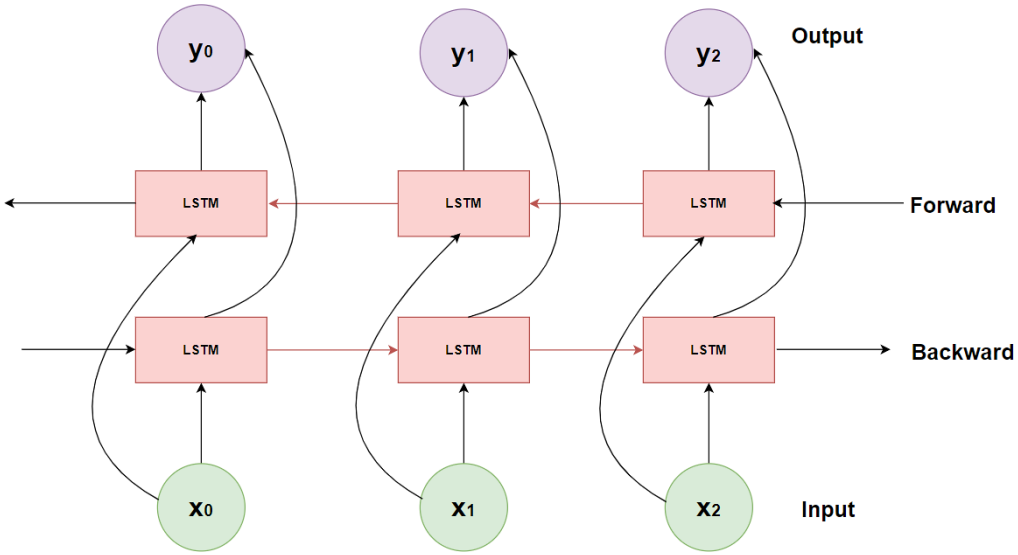

Figure 11. The architecture for BiLSTM

8. Analysis of Federated Learning Methods for Human Activity Recognition

Federated learning (FL) is a decentralized data processing approach that allows multiple devices to collaboratively train a model while keeping the data at the local devices. In the FL framework of human activity recognition, each device, such as smartphones or wearable sensors, trains a local model using its sensor data for basic data learning. After that, the local model updates of each device are transmitted to a central server to integrate these updates using aggregation algorithms. This collaborative process facilitates the development of accurate models while preserving data privacy. This is beneficial for HAR applications since the data involved is usually personal.

Table 4 summarizes several popular model aggregation techniques and local training models used in HAR. FedAvg is a simple and widely used aggregation technique that averages local model updates. However, it struggles with non-IID data. On the other hand, FedProx enhances stability in diverse data settings with an added regularization term. FedNova scales model updates to ensure fair aggregation, but its performance heavily depends on hyperparameter tuning. FedSGD synchronizes the model gradients closely. However, frequent communication is required, making it less efficient for real-time applications. For local training models, various architectures are proposed to learn inertial patterns of sensor data. ANN is a brain-inspired model composed of input, hidden, and output layers. The model can recognize diverse data by learning complex patterns through weight updates.

Table 4. Summary of the model aggregation techniques and local training models

Aggregation Technique	Description	Remarks
FedAvg	Averages local model updates, weighted by each device's data amount.	• Simple and easy to implement, reduced communication cost with fewer update rounds • Sensitive to differences in data (non-IID data) • Unreliable clients may lead to slower model convergence
FedProx	Adds a penalty term during local training to keep each device's model close to the global model.	• Improves stability and convergence in diverse data settings • Better handles data heterogeneity • Increase the computation burden on resource-limited sensors
FedNova	Normalizes and scales local updates before combining them to balance contributions from all devices.	• Ensures fairer aggregation in non-uniform settings • Reduces bias in model updates • Extra computational overhead • Sensitive to hyperparameter selection
FedSGD	Aggregates gradients computed on each device rather than full model updates.	• Reduces model drift by synchronizing gradients closely • Requires frequent communication • May not be efficient for real-time applications due to high communication overhead

On the other hand, 1D CNN is efficient for sequential data such as inertial signals. Its low computational cost makes it suitable for real-time and low-cost applications. LSTM models temporal dependencies in time-series data using memory cells. Unlike RNNs, LSTM effectively resolves vanishing gradient problems. BiLSTM is an enhanced LSTM variant that captures both past and future data context. This feature improves richer temporal relations, yielding promising classification performance for sequential tasks.

9. Future Directions

Human activity recognition (HAR) using sensor data has gained significant attention due to its applications in health monitoring, fitness tracking, and smart environments. Sensor-based HAR typically relies on data from accelerometers, gyroscopes, and other wearable devices to detect and classify activities. However, the sensitive nature of this data poses substantial privacy challenges. Recent studies leveraging FL in sensor-based HAR have demonstrated its potential to preserve privacy while achieving competitive performance. Building on this foundation, future advancements in FL could focus on resolving challenges such as integrating heterogeneous multi-source data, improving personalization, and ensuring resource-efficient deployment in real-world HAR applications.

Federated Learning for Heterogeneous Multi-source Data: FL can improve the quality of human activity recognition by integrating data from multiple sources, including accelerometers, gyroscopes, heart rate monitors, and other wearable devices. Multi-modal sensor fusion allows models to capture more complementary information, which is particularly important for correctly identifying complex activities [84]. Besides that, systems such as the Passive Multi-Modal Sensor Fusion for Human Identification and Activity Recognition (PRF-PIR) framework, incorporating passive and non-intrusive sensing devices, constitute a sound example of how sensor fusion may enhance accuracy because of external interference or limited fields of view challenges [85]. Nonetheless, the heterogeneity of multi-source data poses significant challenges in FL frameworks. Diverse data formats, sampling rates, sensor modalities, and noise across devices can negatively impact the model's performance.

Furthermore, sensor placements and user gait/motion variations also contribute to the diversity. Advanced aggregation techniques, reliable data harmonization strategies, and innovative architectures are essential to deal with the complexities. Future research may focus on developing scalable methods for effectively integrating these heterogeneous data.

Federated Learning for Personalized HAR Models: FL facilitates personalizing HAR models to individual users without compromising privacy. For instance, FedHAR represents a semi-supervised federated learning framework, combining active learning and label propagation to overcome the problem of scarcity of data through semi-automatic annotation of sensor data for activity recognition on mobile devices [20]. Personalization is crucial in healthcare and fitness tracking, where users exhibit different behaviors, characteristics, and needs. To advance this field, future research should prioritize scalable and flexible personalization approaches to improve user-focused HAR in federated settings. Designing adaptive learning procedures may be investigated further.

Federated Learning for Resource-efficient HAR on Wearable Devices: Wearables, including smartwatches and trackers, are an increasingly common device type for HAR. However, these devices face resource constraints in terms of battery life, computation power, and storage [86]. These device constraints could limit the efficacy of HAR models in real-world applications. Future research should be directed to the design of lightweight FL architectures, energy-aware algorithms, and communication-efficient protocols to optimize resource usage in these devices. Developing strategies for adaptive computation, where the model can dynamically adjust its complexity based on available resources, could be a good alternative for real-time HAR in diverse settings.

10. Conclusion

Deep learning methods have demonstrated superior performance in identifying human activities from inertial data by learning high-level, intricate features. However, these centralized architectures that transmit raw sensor data to a central server present critical privacy and security concerns. Federated Learning (FL) offers an alternative solution by decentralizing the training process. Specifically, only model updates are shared, while personal data remains on local devices in FL environments. This is particularly valuable for human activity recognition applications since human activity data can reveal sensitive and confidential information. This paper provides a comprehensive overview of FL in sensor-based HAR, highlighting how it surpasses traditional machine learning in distributed environments. This paper also discusses key FL components, such as local training models and model aggregation strategies. The limitations of HAR-specific FL models, including data heterogeneity, communication, and privacy challenges, are also deliberated.

In summary, FL demonstrates its potential to transform sensor-based HAR by achieving an optimal balance between system reliability, scalability, and privacy. Future research should optimize communication efficiency, address heterogeneous data distributions, and enhance privacy-preserving approaches to meet the demands of even more advanced applications. Furthermore, exploring adaptive aggregation techniques and developing reliable local models is vital to overcoming limitations in HAR-specific federated learning environments. With these advancements, FL-based HAR solutions will be capable of achieving robust, secure, and efficient activity recognition in real-world environments to enhance healthcare, fitness, and smart homes. We anticipate further advancements in this area to lead to more integrated, user-centric systems that ensure improved overall quality of life.

11. Declarations

11.1. Author Contributions

Conceptualization, X.W., Y.H., S.Y., and Z.Y.; methodology, X.W., Y.H., and F.S.; writing—original draft preparation, X.W.; writing—review and editing, X.W. and Y.H.; visualization, X.W. and F.S.; supervision, Y.H., S.Y., and Z.Y.; project administration, Y.H. and S.Y. All authors have read and agreed to the published version of the manuscript.

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Not applicable.

11.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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