A Survey on Wearable Human Activity Recognition: Innovative Pipeline Development for Enhanced Research and Practice

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***Abstract*—Recent trends in Wearable Human Activity Recognition (WHAR) have led to an unprecedented 42.9% increase in scholarly articles in 2022, underscoring the urgency for a comprehensive review to systematically categorize their varied research directions. Moreover, our analysis reveals that the contributions of current articles often deviate from the traditional stages of the human activity recognition pipeline, as established in prior literature. This misalignment suggests the necessity for an updated pipeline that more accurately reflects the intricacies and nuances of WHAR studies. In response, we review WHAR articles from 2021 to 2023 and introduce an innovative WHAR pipeline, emphasizing a research-focused approach. This new pipeline offers distinct advantages: it provides researchers with a clear and systematic categorization of WHAR articles, thereby enhancing understanding of the field. For practitioners, it facilitates the selection of customized methods for each stage, thereby optimizing final assembled model efficacy.**

***Index Terms*—wearable human activity recognition, machine learning, deep learning**

I. Introduction

Progress in scientific endeavor has always been driven by the collection and analysis of data [1]. Recently, the proliferation of wearable devices has been remarkable. Comprehensive surveys have indicated that by the end of 2022, global shipments of wearable devices reaches approximately 500 million units, a dramatic increase from the 82 million units shipped in 2016, an increase of nearly 500%, as shown in Fig. 1. A detailed analysis of the data reveals that smartwatch is the predominant category, comprising 216 million units. Notably, about 20% of adult males in the United States in 2022 own a smartwatch. Other significant categories include smart trackers and smart glasses, with shipments of 105 million and 32 million units, respectively.

Corresponding to the improvement of shipment, in 2022, the academic field of Wearable Human Activity Recognition (WHAR) experienced a notable surge [2], with around 100 new articles marking a significant 42.9% increase from the previous year. Based on their primary contributions, these articles predominantly fall into the following categories:

- **Mitigation Solutions to Persistent Challenges** Innovative methodologies have been introduced to address ongoing issues in WHAR. For instance, Khtun *et al.* [3] explore the use of Fourier coefficients as discriminators for activity detection, effectively addressing the challenge of noisy signals in real-world settings.
- **Extensions to Uncharted Areas** The applicability of wearable sensors in unexplored areas has also been a focus of recent research. Considering the detrimental effects of smoking, especially the correlation with cancer, cardiovascular disease and premature death, Hnoohom *et al.* [4] combine a deep learning framework with a smartwatch for detecting smoking behaviour. This study exemplifies the integration between WHAR and health interventions. Fang *et al.* [5], [6] investigate novel human machine interaction method.
- **Extensions to Unexplored Sensors** The technological limitations of current wearables, particularly the power consumption of inertial activity sensors, have catalysed the search for alternative solutions [7]. On this basis, Solar *et al.* [8] investigate the dual functionality of solar cells, serving concurrently as activity sensors and energy reservoirs.
- **Introduction of Novel Datasets** The advent of sensor technology has, in turn, stimulated the generation of specialized datasets. One example is the surface electromyography (EMG) signal, which is gaining traction in the wearable tech community due to its real-time feedback capabilities. However, existing public EMG datasets predominantly capture hand movements. To this end, Luan *et al.* [9] assemble a comprehensive lower limb

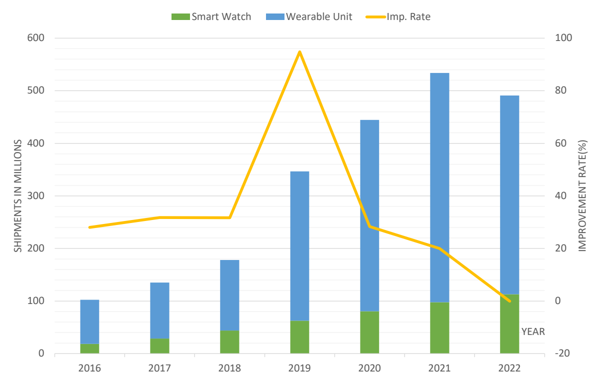

Fig. 1. Global shipment of wearable devices from 2016 to 2022.

EMG dataset using six sensors attached to the left leg.

- **Addressing Emerging Challenges** WHAR continues to face evolving challenges, particularly in model pre-training [10]–[12]. The multimodal nature of WHAR data complicates the application of conventional pre-training techniques, creating a frontier challenge in developing task-independent or sensor-independent models that can be refined with minimal data.

The rapid advancement in WHAR necessitates a systematic review to summarize the large amount of articles, highlighting current challenges and future directions.

At the same time, our analysis indicates that many contributions of these articles do not easily align with the conventional stages of the human activity recognition pipeline as outlined by Gupta *et al.* [13], which divides the human activity recognition pipeline into four processes namely signal capturing, data pre-processing, model training, and user interface development. For example, the evolving area of model pre-training, while integral to task-specific predictions, does not neatly fit within the standard model training phase. Pre-trained models, invariably require refinement and fine-tuning before practical application. In addition, the definition of data processing process becomes ambiguous when considering data augmentation techniques. Unlike traditional data processing, which focuses on optimizing individual data sample, data augmentation aims to increase sample size and diversity by artificially expanding datasets using machine or deep learning algorithms.

These insights underscore that while the existing pipeline offers a basic outline for constructing WHAR systems, it inadequately captures the complexity and subtlety necessary for research-driven exploration, which necessitates the re-thinking of the WHAR pipeline through a more research-oriented perspective. Adopting this new approach promises dual advantages:

1) For researchers: It provides a clearer delineation of research areas, allowing for a more structured categorization of individual scientific contributions. This clarity not only facilitates effective synthesis of existing research, but also helps emerging researchers to easily identify and explore potential avenues of investigation. Such a framework enhances the comprehensibility and navigability of the WHAR research landscape, facilitating a more focused and efficient research process.
2) For practitioners: The new pipeline allows the selection of the appropriate method from each stage. As a result, it facilitates the rapid identification and combination of the most appropriate techniques tailored to specific situations, thereby optimizing model performance.

Based on these, we reviewed and summarized the recent high quality articles published in the WHAR field.

II. Search Strategy and Literature Review

We collected relevant and important articles for our research target based on the Preferred Reporting Items for Systematic review and Meta-Analysis Protocols (PRISMA-P). We completed this search using two protocols: the search protocol and the exclusion protocol.

Search Protocol: We used Google Scholar for our research because of its comprehensive coverage of academic literature across a range of disciplines. Its constantly updated database provided access to the most recent scientific papers. Our search was guided by three sets of keywords: (”Human Activity Recognition” OR ”HAR”), (”Machine Learning” OR ”Deep Learning” OR ”Neural Network”), and (”Wearable” OR ”Smartphone” OR ”Smartwatch” OR ”Smartglasses” OR ”Smartband”). These were combined with specific search restrictions to match our research objectives. We limited our search to the period from 2021 to June 2023, reflecting our focus on the latest developments in the field. This search yielded 4,960 articles.

Exclusion Protocol: Our selection process emphasized relevance and impact. We first eliminated duplicates, non-English papers, non-conference/journal articles, and those without references. Titles not aligned with our research focus were also excluded. To ensure quality, we sorted the articles by the number of citations and selected accordingly. This initial screening reduced our pool to 274 articles. We then read the abstracts to exclude survey articles and those not specifically focused on WHAR tasks, further narrowing down to 208 papers. After a quick content review of these papers, we removed less rigorous studies and duplicates, culminating in a final selection of 150 papers.

III. Result

Following an exhaustive review of 150 articles, we developed a new pipeline for WHAR, as shown in Fig. 2. This pipeline consists of a number of sequential stages, each of which is critical to the development and implementation of WHAR systems:

- **Data Preparation** This initial stage involves the collection and preparation of sensor data for human activity analysis. The focus in this phase is to generate new datasets, demonstrating the applicability of WHAR across various domains and employing data augmentation to enhance dataset quality and address specific challenges.
- **Model Preparation** Crucial for pattern recognition and predictive accuracy, this phase involves the design of novel deep learning architectures. It also includes the selection of the most effective models through comparative performance analysis across different scenarios.
- **Data Processing** This stage is driven by four main objectives: improving data quality through noise reduction and mitigation of data loss; highlighting specific data features using techniques such as Fourier transformations; extracting detailed features for accurate activity recognition; and transforming data into compatible formats (one, two, or three-dimensional) for various model inputs.
- **Model Pre-training**: Model pre-training involves initially training a model on general datasets, followed by fine-tuning with task-specific datasets to adapt it for specific

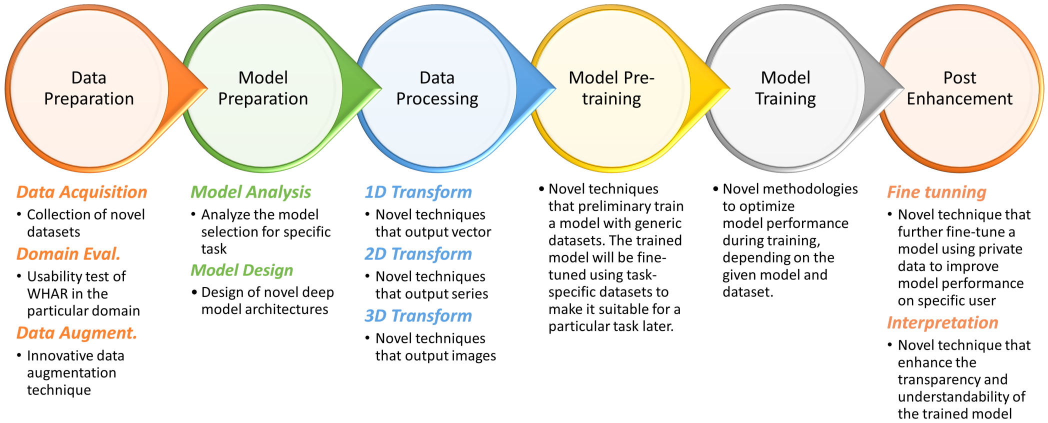

Fig. 2. The proposed Wearable Human Activity Recognition pipeline.

tasks. Mirroring trends seen in vision and natural language processing (NLP) domain, although the number of articles related to WHAR are limited, we are of the opinion that it has a great potential.

- **Task-specific Model Training** This process focuses on refining a pre-trained or initial model to suit a specific target task. Researches in this stage concentrate on optimizing model performance based on the specificities of the model and dataset, culminating in a model ready for application in the intended task.
- **Model Post Enhancement** The final stage includes two critical aspects: model privatization and model explanation. Model privatization involves fine-tuning the model with private data to enhance user-specific performance. In contrast, model explanation aims to make the model's decision-making processes transparent and understandable, fostering trust and facilitating effective human-machine collaboration.

A. *Observation*

Before specifically describing the study of each stage in the pipeline, we present several key observations focusing on two main areas in the field:

Focus on Model Architecture and Data: Our review reveals that a significant portion of the articles (50%) are dedicated to model preparation, with another 30% focusing on data preparation. This distribution underscores the critical roles these elements play in WHAR. However, it also highlights potential research gaps in the areas of model pre-training and post-training techniques, which constitute only 4% and 5% of the articles, respectively. The relatively lower emphasis on these techniques suggests untapped potential for future research, particularly in enhancing the generalizability and efficiency of models.

Evaluation Metrics: The prevalent use of accuracy and f1-score as evaluation metrics demonstrates their widespread acceptance as standard measures of model performance in WHAR. Nonetheless, the limited attention to factors like time, energy, and computational complexity (FLOPs) reveals a gap in current research. These aspects are particularly crucial for applications involving real-time and edge computing. Future studies are therefore suggested to broaden their scope to include metrics such as latency, energy efficiency, and computational complexity, in addition to traditional accuracy and f1-scores.

B. *Data Preparation*

WHAR systems function by meticulously analyzing data from sensors in smart devices. With advancements in equipment technology and research, the art and quality of collected data are continually evolving, necessitating ongoing exploration of new data. This exploration is multi-dimensional, and from the articles reviewed, discussions on data preparation can be categorized into three primary areas:

Articles that present novel data sets These scholarly articles provide detailed explanations of the processes involved in data collection. Key aspects covered include the rationale behind data collection, settings chosen for data accrual, demographic distribution of participants, preferences for equipment, methods of equipment application [14], selection of activities, and techniques for data collection. Additionally, these articles offer access to the data they generate within their articles. Table I summarizes newly available public datasets in WHAR since 2021.

Articles that demonstrate the viability of WHAR within a particular domain These studies typically involve extensive experimentation using a range of machine learning and deep learning algorithms. The effectiveness of WHAR in these domains is often validated by the accuracy or f1-score of the most efficient models identified through the research. Recent key studies in this area include: Sandhu *et al.* [8] investigate the innovative use of solar cells mounted on a wrist device as both activity sensors and power sources. They encoded activity-related information by monitoring the variable power levels in response to the user's movements. This approach proved more accurate in detecting activity (an 8.3% improvement) than methods relying on converting kinetic energy to electrical energy. Additionally, the energy yield from the solar method greatly surpassed that of the kinetic approach. Human walking is a complex orchestration that requires precise coordination

TABLE I
SUMMARIZE OF THE NEW WHAR DATASETS FROM 2021 TO 2023, WHERE IMU STANDS FOR INERTIAL MEASUREMENT UNIT AND EMG FOR ELECTROMYOGRAPHY.

Dataset	Year	#Subjects	#Activities	Domain	Device
WEAR [15]	2023	18	18	Daily Living, Sport	Camera, Smartwatch
XUHAR [16]	2023	10	32	Daily Living; Sport	Smartglass, IMU
Hang-Time [17]	2023	24	15	Sport (basketball)	Accelerometer
EmoPain [18]	2023	18	101	Daily Living (chronic pain)	IMU
HUHAR [19]	2023	14	16	Daily Living	Smartband, Smartphone
Ego4d [20]	2022	931	110	Daily Living	Camera, IMU
UCA-EHAR [21]	2022	20	8	Daily Living	Smartglass
FLAAP [22]	2022	8	10	Daily Living	Smartphone
MPJA-HAD [23]	2022	10	6	Daily Living	IMU
BON [24]	2022	25	18	Office Activities	Camera
ClimHAR [25]	2022	52	24	Daily Living	Smartband
CareHAR [26]	2022	7	9	Care Activities	IMU
BijalHAR [27]	2022	30	7	Daily Living	IMU
DamenHAR [28]	2022	37	149	Kitchen Activities	Camera
ActionSense [29]	2022	10	20	Kitchen Activities	IMU
Har-semg [9]	2021	9	5	Daily Living	Trigno Wireless Biofeedback System
Oppo++ [30]	2021	4	18	Daily Living	Kitchen Activities
harAGE [31]	2021	19	11	Daily Living	Smartwatch
HARTH [32]	2021	22	12	Daily Living	Camera, Accelerometer
CSL-SHARE [33]	2021	20	22	Locomotion, Sport	IMU, EMG, Electrogonimometer, Michrophone

between cerebral functions and the lower limbs. Chakraborty *et al.* [34] evaluate the practicality of using low-cost leg mounted sensors (termed 'm-module') in tandem with fingertip pulse sensors (termed 'p-module'). The aim was to distinguish regular walking activity from the repetitive, regressive swinging motions typically observed in a seated position. The aforementioned studies explore innovative data acquisition devices and their synergistic applications. In contrast, another significant study by Yeh *et al.* [35] explores the feasibility of real-time action recognition using a Raspberry Pi platform connected to Inertial Measurement Units (IMUs) positioned on the user's right wrist, waist, and right ankle. Their findings show a latency of 2.6 seconds for the first action recognition, reducing to 1.33 seconds for subsequent recognition, while maintaining an accuracy rate of over 98%.

Articles emphasising innovative data augmentation techniques Data augmentation has been proved to be an advance method to address common challenges associated with existing datasets, particularly data skewness and paucity of labelled data. Recently several strategies have been proposed: Ni *et al.* [36] employ the SMOKE technique to address the issue of uneven sample sizes across different activity classes. This method aims to create a more balanced distribution of samples, enhancing the robustness of the training process. Khaertdinov *et al.* [37] augment data sets through a range of operations such as jittering, scaling, channel shuffling, rotation and permutation. Shi *et al.* [38] utilize Generative Adversarial Network (GAN) to generate new samples. GANs are particularly effective in creating realistic synthetic data, thereby enriching the dataset with diverse examples that may not be present in the original data.

C. Model Preparation

The model in WHAR system is tasked with extracting distinct activity patterns from the provided input data to facilitate subsequent predictions. Its architecture is fundamentally connected to its feature extraction capabilities. A rigorous model selection, design and optimization process is essential to ensure the effectiveness of WHAR systems. In the surveyed academic articles, this phase of model preparation is distinguished by two predominant research directions:

Articles that elucidate the design of novel deep model architectures The focus of these academic articles is to enhance WHAR models' capability to extract features from raw data by introducing innovative model architectures.

WHAR model architecture is continually evolving, with deep learning currently being the most prominent. However, the influence of traditional machine learning, though reduced, remains significant, contributing valuable insights and methodologies. For example, Liu *et al.* [39] decompose human activity into common, discriminative states called 'motor units', analogous to phonemes in speech recognition, and use Hidden Markov Models (HMM) to predict activity. Vu *et al.* [40] propose the use of Uniform Manifold Approximation and Projection (UMAP) to map high-level data to 30-dimensional features, and then refine these features for activity prediction using data from the target domain.

Deep learning's dominance in WHAR stems from its autonomous feature extraction capacity. This is exemplified in the diverse architecture of deep models.

Ismail *et al.* [41] use a genetic algorithm to optimize Convolutional Neural Network (CNN) architecture, segmenting a CNN block into conv1d, batch normalization, and LeakyReLU, and encoding it with a 5-bit system, where the first three bits indicate the parameters of conv1d, such as the number of filters, padding and activation function. The fourth bit indicates batch normalization, while the fifth bit indicates the parameter value of the LeakyReLU activation function. Hurtado *et al.* [42] present an autoencoder architecture that is trained simultaneously using both the reconstruction loss of unlabeled data and the prediction loss of labeled data. Hnoohom *et al.* [4] merge the residual model with the Squeeze-and-Excitation block to form a ResNetSE block. A deep CNN model is then constructed based on this new block.

The research by Haresamudram *et al.* [10] is based on contrastive predictive coding. The study investigates the effectiveness of integrating stridden convolutions, causal convolutional aggregators, and replacing masks with future predictions in improving the performance of human activity recognition models. Sarkar *et al.* [43] use the Continuous Wavelet Transform (CWT) to transform time series data into image formats. Following this transformation, a CNN architecture is used for feature extraction. These extracted features are then selected using an unsupervised genetic algorithm based on metrics such as mutual information, Relief-F and m-RMR. The final stage of the process uses the K-Nearest Neighbours (KNN) algorithm for activity prediction. Normalization procedures often lead to the phenomenon of "channel collapse": many channels converge to minima, resulting in a significant fraction of channels contributing minimally to the overall output. Huang *et al.* [44] present a novel method, termed "channel equalization", which aims to revitalize these dormant channels through whitening or decorrelation operations. Given the limited computational resources of edge devices, to improve CNN performance without increasing memory or computational load, Tang *et al.* [45] propose the concept of hierarchical segmentation convolution to promote superior multi-scale feature representation. Sensor signals are first segmented into fixed length windows using a sliding window approach. These windows are then passed through a convolutional layer to produce a basic feature map. Subsequent processing involves partitioning these feature maps, performing selective convolution operations, and applying identity mapping or cascading operations. This complex process of splitting and merging continues iteratively, culminating in a concatenation of refined sub-feature maps. These are then passed through standard convolutional layers for further feature reconstruction.

The architectures illustrated above focus solely on the CNN module for deep models. There is research that uses Long Short-Term Memory (LSTM) component as the primary building block. For example, Ramos *et al.* [46] use the residual bidirectional LSTM block for feature extraction, suggesting the potential of LSTMs in WHAR applications. The Transformer module has been proven as a powerful tool in the NLP domain, its practicability in the WHAR domain is validated by Dirgova *et al.* [47].

There is a trend towards hybrid models that combine different architectures. Such hybrid models seek to exploit the strengths of individual architectures to achieve improved performance in specific applications.

For example, combining convolutional layers with recurrent layers allows for effective spatial and temporal feature extraction [48], [49]. [50] extend this setup by integrating residual module and bidirectional LSTMs. Transformers provide powerful attention mechanisms. Shavit *et al.* [51] combine CNN with a Transformer to integrate the capability of extracting long term dependency. Multi-branch techniques, like those employed by Lu *et al.* [52] and Park *et al.* [53] process data from different channels separately before aggregation. These varied approaches underscore the ongoing evolution of HAR architectures, emphasizing adaptability based on data type, computational resources, and task-specific needs.

Ensemble methods, recognized for improving predictive performance, are increasingly applied in deep learning for WHAR tasks. Bhattacharya *et al.* [54] present a variant of the ensemble approach. It involves splitting the training set into two parts. Different deep learning architectures are trained on the first subset, and the second subset is used to gather predictions from these trained models. The collected predictions are then used as features for a final prediction head. This approach capitalizes on the different representations captured by different architectures and uses another model to find the optimal combination of these representations.

Articles that focus primarily on the facet of model selection. These articles meticulously assess various models across diverse scenario configurations for specific WHAR tasks, offering valuable insights into model selection through a comparative analysis. Jimale *et al.* [55] explore the impact of subject variability on machine learning classifiers and convolutional neural networks. Palimkar *et al.* [56] provide an extensive comparative study of traditional machine learning models in WHAR. Their review encompasses a broad range of models, including support vector machines, multilayer perceptron, decision tables, C4.5, k-nearest neighbors, naive Bayes, adaptive boosting, hidden Markov models, logistic regression, rule-based classifiers, Bayes nets, best-first trees, K-stars, conditional inference trees, random forests, extra tree classifiers, ensemble extra trees, label propagation, and label spreading. This comprehensive analysis offers a detailed perspective on the efficacy and applicability of each model in the context of WHAR, thereby guiding researchers and practitioners in their model selection process.

D. Data Processing

Raw sensor data in WHAR often contains various forms of noise, such as electronic disturbances and external environmental interference. Effective data processing, which includes cleaning and filtering, is crucial for mitigating these issues.

Additionally, data processing plays a pivotal role in enhancing the quality of data for subsequent modeling. It can accentuate certain desirable features, like energy or frequency variations, and suppress unwanted characteristics. This selective highlighting and suppression facilitates better model performance. Furthermore, given the multi-modal nature of WHAR data, processing is essential to adjust and align the collected data to meet specific model requirements.

Data processing in WHAR differs from data preparation in that it focuses more on the qualitative aspects of data rather than merely quantitative elements. Based on the manner in which the processed data is presented, data processing methods in WHAR can be categorized into three distinct types.

1D Transformation These transformations produce feature vectors as outputs, where each vector represents a unique sample. Each component within the vector corresponds to a distinct feature, with features maintaining independence from each other. Thakur *et al.* [57] exemplify this by extracting signal features in both time and frequency domains, followed by feature selection using a guided regularized random forest. In the [58], an initial denoising step is applied to the input data, followed by windowing and segmentation. After pre-processing, the data is subjected to a feature extraction module, which retrieves features such as Parseval energy, skewness, kurtosis, Shannon entropy, along with time and frequency domain statistical characteristics. It further refines the feature selection process by employing the Luca metric-based fuzzy entropy (LFE) and the Lukasiewicz similarity measure (LS), resulting in a 25% reduction in the feature set. The research then applies a feature optimization algorithm based on the Yeo-Johnson power transformation. The research carried out by [59] employs a multi-dimensional approach for feature extraction, utilizing a Butterworth low-pass filter, time differentiation, and the Fast Fourier Transform. The importance of these features is assessed using the Gini coefficient, and varying levels of Laplace noise are added to ensure data confidentiality and prevent unintentional data leakage.

2D Transformation This transformation results in 2D arrays as outputs, with the first dimension representing different features and the second dimension indicating the value for each feature. Although different features retain their independence, there is a sequential relationship between the values within an individual feature. [60] integrates a Kalman filter to reduce noise in the original data. Similarly, [61] delves into the analysis of the energy distribution across different signal frequencies using Welch's method for power spectral density plotting. [62] introduces wavelet-based learnable filters for sensor channel selection.

3D Transformation This transformation yields a three-dimensional array as its output. The first dimension often referred to as the 'channel', denotes various features. The subsequent second and third dimensions provide the value of these features, typically in the form of an image. Gholamrezaii *et al.* [63] generate spectrograms via FFT as distinguishing features and Gholamiangonabadi *et al.* [64] explore the effectiveness of the stationary wavelet transform coupled with empirical mode decomposition in action recognition.

E. Model pretraining

The effectiveness of pre-training has been strongly demonstrated in multiple domains such as text and vision. It facilitates the transfer of knowledge gained from large datasets to more specialized tasks. This knowledge transfer not only speeds up the training process, but also improves model performance when the available labeled dataset is modest in size, as is the case in WHAR. Training a large model from its inception on a limited dataset can inadvertently lead to overfitting. In recent research, [65] employs a cyclical training scheme for a multitask model, thereby fostering a task-agnostic backbone. [37] performs feature extraction from augmented data via a transformer and then employs nt-xent loss for unlabeled data in the model's pre-training phase.

F. Model training

In model training, a critical aspect is the exploration of methods to adjust and optimize model parameters to effectively meet pre-defined objectives. This process involves using data in innovative ways to refine the decision-making mechanism of the model and applying automatic machine learning strategy [66] for training parameter optimization.

Tang *et al.* [67] leverage both the labeled dataset and an unlabeled dataset. First, a "teacher" model is trained using the labeled dataset. The teacher model then annotates the unlabeled data. A "student" model is then trained with the prediction and unlabeled data and fine-tuned with labeled data. Hu *et al.* [68] introduce a dynamic sample weighting mechanism designed to tailor the model to specific user profiles. This innovative strategy incorporates a domain classifier to determine the source of samples and a weight allocator that adjusts sample weights based on loss metrics. Such a personalized approach is critical in addressing the variability inherent in user data and enhancing model performance for individual users.

With the proliferation of personal sensor data from wearable devices, traditional centralized model training presents significant risks regarding user data privacy. Federated Learning (FL) has emerged as a viable solution, offering distributed training while ensuring data privacy and reducing communication overheads. Gonul *et al.* [69] and Arikumar *et al.* [70] conduct empirical evaluations comparing FL with centralized training methods, finding similar performance metrics between the two approaches. This highlights FL's effectiveness in maintaining model performance while offering enhanced privacy protections. Lu *et al.* [52] propose a bifurcated FL framework that tackles challenges such as data isolation and secure data sharing. This framework is designed to integrate heterogeneous data into a unified feature space. It also incorporates encryption schemes for the secure aggregation of parameters, addressing privacy and security concerns in a distributed training environment.

G. Post Enhancement

Post-training optimization techniques in machine learning models, particularly in the context of WHAR, play a crucial role in refining performance, adaptability, efficiency, and explainability [71]–[73]. Various studies have proposed innovative methods in this regard.

Suh *et al.* [74] utilize self-knowledge distillation, where the student model's predictions serve as "soft targets" to enhance the final performance of the target model. This technique leverages the model's own outputs for further improvement. An *et al.* [12] investigate the user independence of intermediate layer outputs in a CNN architecture. They divide the architecture into user-independent and user-dependent segments, where the user-independent part remains fixed during new user encounters. This approach not only boosts accuracy for target users but also reduces the time needed for model retraining. Contoli *et al.* [75] analyze the impact of three model compression methods on model performance and energy consumption, namely lite conversion, dynamic quantization and full integer quantization. Cui *et al.* [76] employ reinforcement learning to train an agent capable of deciding whether new data samples require labeling, based on the confidence level of the classifier's posterior probability. This method enhances the model's adaptability to novel data. Amrani *et al.* [77] present a scenario where data in the target domain is split to train two models, which then operate in conjunction with the original model for final prediction in an ensemble manner. This approach increases the robustness and personalization of the predictions. Das *et al.* [78] introduce a methodology based on traditional explainability techniques like LIME and SHAP. Huang *et al.* [71] explain human activity with state sequence.

These post-training techniques are essential in refining the capabilities of machine learning models, particularly in the dynamic and diverse domain of WHAR, ensuring they are not only high-performing but also user-friendly, and energy-efficient.

IV. Challenge and Research Direction

The challenges in WHAR stem from the complexity and diversity of the data involved as well as the need to be user-centred, driving the need for continuous methodological advancements to enhance accuracy and reliability in real-world scenarios. These challenges include:

The WHAR data is complex. The WHAR data encapsulates a multifaceted relationship between users and their activities, making activity recognition challenging due to complex data associations. Chen *et al.* [79] note that identical activities can vary significantly. From the user perspective, identical activities can vary significantly not only among different individuals but also within the same person under different circumstances [55]. This variability is influenced by numerous factors, including, but not limited to, differences in the exercise habits [64], how the device is worn [80], variations in health conditions [81], age [82], and the specific environment where the activity occurs [79]. These factors necessitate a nuanced and meticulous approach in data collection and analysis to accurately interpret activity data. In addition, the range of activities that need to be recognized varies across different application domains. Each type of activity recognition requires specific data acquisition devices and tailored methodologies for processing the data. This diversity demands extensive datasets that cover a wide range of activities and scenarios, underscoring the importance of continuous data collection and analysis. Moreover, the evolving nature of wearable technology further accentuates the need for ongoing data collection. As devices develop, they introduce new capabilities and data types, making it imperative to continually update the data used for training and validating WHAR systems. This evolution necessitates a sustained effort in data collection and analysis to keep pace with technological advancements and ensure the continued relevance and effectiveness of WHAR systems.

The constraint of data quality substantially limits practical applications of WHAR. The practicality of WHAR systems is significantly impacted by data quality constraints, primarily stemming from the inherent characteristics of the sensors used and the efficiency of data transmission mechanisms. Two key factors illustrate these challenges:

i The accuracy of models in WHAR systems varies widely based on their sensor type and cost. Lower accuracy sensors tend to introduce greater data noise and signal distortion. These inaccuracies compromise the reliability and validity of the collected data, hindering precise interpretation and application in WHAR systems [83]; *ii* Various technical and systemic issues contribute to data loss in WHAR systems. This includes power constraints that limit continuous sensor operation, limitations in sensor data transmission, hardware malfunctions, and network-related issues such as packet collisions, unreliable communication links, and accidental data corruption [84]. These challenges underscore the need for careful attention to sensor selection and deployment, as well as robust data handling and transmission strategies, to mitigate the adverse effects of data quality limitations in WHAR applications.

We need to train recognition models in a privacy-preserving manner. The training of WHAR models necessitates a strong emphasis on preserving user privacy, given the inherently sensitive nature of the data involved. WHAR data offers detailed insights into a user's daily activities, health, movement patterns, biometric indicators, and routines. Such personal data is highly sensitive and requires stringent security measures to prevent unauthorized access or misuse, thereby safeguarding user privacy. It is therefore imperative that appropriate measures and controls are built when training the WHAR systems. Ensuring the protection of personal privacy while enabling the accuracy of the trained recognition models is a complex but essential aspect of ethical practice in the use of WHAR technologies.

Federated learning represents a distributed learning paradigm with significant implications for privacy and data security. In federated learning, models are trained locally on individual devices, and only the updated models are shared centrally. This method effectively maintains the confidentiality of user data. Articles like [69], [70], [85] have explored this approach within the WHAR context, demonstrating its potential to safeguard user privacy while enabling effective model training.

Besides, [59] employs methods such as the Butterworth low-pass filter to extract the features of the input data in the time and frequency domains, and after confirming the importance of these features through the Gini coefficient, different levels of Laplace noise are added according to the importance, as a way to ensure that these features do not reveal the user's information.

These research efforts highlight the critical importance of user privacy in WHAR. By prioritizing privacy-preserving methods like federated learning and strategic noise addition, the field is aligning with responsible and ethical data usage practices. Such initiatives are not only pivotal for the current state of human activity recognition but also signify a major research direction for future developments in the field. The balance between privacy preservation and model accuracy remains a complex but essential aspect of WHAR technology, emphasizing the need for continuous innovation and refinement in privacy-centric methodologies.

Real-Time Processing Requirements: Some applications of WHAR necessitate immediate or near real-time activity detection. This demand places substantial stress on the computational resources of wearable devices and requires sophisticated optimization of algorithms to achieve real-time processing without compromising accuracy or efficiency.

Model deployment is under constraints. The deployment of WHAR models faces significant constraints due to the inherent limitations of wearable devices. These constraints influence the design and functionality of WHAR models in several key ways: *(i)* Limited computational resources: Wearable devices typically possess reduced computational power and limited storage capacity. This makes it challenging to host complex machine learning models on these devices, necessitating the development of models that are computationally efficient yet effective; *(ii)* The operation of complex models on wearable devices can lead to increased power consumption, which in turn reduces battery life. This factor is crucial in the design of WHAR models, as they need to be energy-efficient to ensure prolonged device usability; *(iii)* Some applications of WHAR necessitate immediate or near real-time activity detection. This demand places substantial stress on the computational resources of wearable devices and requires sophisticated optimization of algorithms to achieve real-time processing without compromising accuracy or efficiency.

Given these limitations, the use of WHAR models requires innovative solutions that balance model sophistication with the practical limitations of wearable technology. Research in this area is currently progressing in three main directions:

The first direction is research on small volume models. Develop small but powerful models through network architecture design or automated methods [86], [87]. The second is the model quantization. This approach involves investigating the effects of model compression techniques on performance and energy consumption. Techniques such as streamlined transformation, dynamic quantization, and full integer quantization are explored to reduce the computational load and memory requirements of models without significantly impacting their effectiveness. This research direction is pivotal in developing WHAR models that are both efficient and practical for deployment on wearable devices with limited capabilities. The third option could be employing next-generation computing devices that beyond von-Neumann architecture, e.g., neuromorphic computers [88] that have integrated memory and processing units and allow high computing efficiency. In this area, several initial works have been progressed [89]–[91] and may be favorable platforms for WHAR deployment in the near future.

Model Personalizing is needed The challenge of model Personalizing stems from the inherent heterogeneity of datasets, which often leads to overfitting in machine learning models. This overfitting results in models that perform well on training data but exhibit suboptimal performance when generalized to previously unseen individuals. The key question is how these models can be fine-tuned using either unlabeled data or a small amount of labelled data from the target user to improve performance specifically for that user.

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