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A Deep Survey on Human Activity Recognition Using Mobile and Wearable Sensors

Shaik Jameer[1] and Hussain Syed[2,*]

[1,2]School of Computer Science and Engineering, VIT AP University Amaravati 522237, India

Abstract

Activity-based wellness management is thought to be a powerful application for mobile health. It is possible to provide context-aware wellness services and track human activity thanks to accessing for multiple devices as well as gadgets that we use every day. Generally in smart gadgets like phones, watches, rings etc., the embedded sensors having a wealth data that can be incorporated to person task tracking identification. In a real-world setting, all researchers shown effective boosting algorithms can extract information in person task identification. Identifying basic person tasks such as talk, walk, sit along sleep. Our findings demonstrate that boosting classifiers perform better than conventional machine learning classifiers. Moreover, the feature engineering for differentiating an activity detection capability for smart phones and smart watches. For the purpose of improving the classification of fundamental human activities, upcoming mechanisms give the guidelines for identification for various sensors and wearable devices.

Keywords: Human Activity Recognition (HAR), IoT, Smart Phones, Smart Watches

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*Corresponding author. Email: hussain.syed@vitap.ac.in

1. Introduction

Rise in IoT has led to an explosion of connected devices that can track and monitor a wide range of activities. Among these, wearable devices have emerged as a popular option for tracking human activity [1] and health [2]. But wearable devices are not the only way to track human movement and behavior. In this paper, we will conduct a deep survey of human tracking systems that use various IoT applications and wearable devices. [3] Our survey will cover a wide variety of kinds such as information collection; algorithms used for analyze the data. We will also explore the challenges and limitations of these systems, as well as the potential
systems using IoT applications and wearable devices, and to identify the possibilities in developments as well as new findings in this exciting field [4].
Human Activity Recognition (HAR) has turned into a well-known point [5] somewhat recently to its numerous amounts in demand in areas such as medical services, gaming, sports as well as moreover to the general causes also. Also, these days, the maturing populace was being more essential things to consider [6] which are assessed an populace matured north of 64 that increment by 470 million to some billions by the year of 2060's. The significant increment having enough awareness in medical care results. In screen general, practical, along mental wellbeing in more established grown-ups in their home, HAR is arising as an incredible asset. The objective of HAR is for identifying human activities and diet is in controlled way or not. [7] not withstanding lot of applications [8], this count gets many problems such as applications over multiple sectors like healthcare, sports, along privacy. By end of this survey, we hope to provide the general look for the technique in human tracking.

- Identifying daily routine exercises of a person [9]
- Intra-subject and between subject fluctuation for a similar movement [10]
- The compromise among execution and security [11]

- Computational proficiency in implanted and versatile gadgets and [12]
- Trouble of information explanation [13]

Information for preparing and testing HAR calculations is ordinarily gotten from two fundamental sources.
- Surrounding sensors, and [14]
- Inserted sensors [15]

Surrounding sensors can be ecological sensors, for example, temperature sensors or camcorders situated in unambiguous focuses in the climate. Implanted sensory were coordinated to general items such as mobiles, smart watches, were incorporated to explicit medical gear. Cams were broadly used for HAR mechanisms [16] moreover collecting video data which brings many problems with respect to security as well as technological needs. when camcorders give lot of logical information that limits was brought lot of scientists for working with another encompassing as well as implanted sensoria's, [17] includes profundity pictures like a security saving other option.
As far as algorithmic execution, HAR domain has a blast in Profound Learning (DL) techniques, bringing about an expansion in acknowledgment precision. When DL strategies give lot of exactness to huge movement datasets, [18] in numerous HAR applications Exemplary AI (CML) models may be more qualified because of the little quantity of the information is less than the information along accessibility for master information to forming issue. Rising value over HAR was be related by developing utilization regarding sensoria along gadgets at complete parts of day-to-day existence, particularly concerning wellbeing and prosperity applications. This rising interest in HAR is obvious from the quantity of papers distributed at previous months i.e., 40 to 48 months. [19] Overall sum in total 148 chose distributed documents over HAR, 54 depended over DL methods along 96 depended over CML models. [20]
There are several common smart gadgets that incorporate embedded sensors for human activity recognition. Here are a few examples:
- Smart watches and Fitness Trackers: These devices often have built-in accelerometers, gyroscopes, and heart rate monitors to track activities such as walking, running, cycling, and even sleep patterns.
- Smartphones: Modern smartphones are equipped with various sensors, including accelerometers, gyroscopes, magnetometers, and GPS, which can be utilized for activity recognition. Many fitness and health apps leverage these sensors to track steps, distance, stairs climbed, and other physical activities.
- Smart Home Systems: Some smart home systems utilize motion sensors to detect human presence and activity within a particular area. These sensors can be used for various purposes, including security, lighting automation, and energy management.
- Ambient Sensors: These sensors are embedded in the environment, such as homes or offices, and can monitor activities and behaviors of individuals. Examples include occupancy sensors that detect movement in a room or pressure sensors on furniture to determine if someone is sitting or standing.
- Smart Footwear: There are smart shoes or insoles available that have embedded sensors to track and analyze gait patterns, step count, and foot pressure distribution. These can be used for fitness tracking, sports performance monitoring, and even injury prevention.
- Gesture Control Devices: Gesture recognition devices, such as motion-sensing cameras or wearable bands, enable users to control electronic devices through hand or body movements. These devices can detect and interpret specific gestures, allowing users to interact with their gadgets in a more intuitive manner.
- Smart Clothing: Some clothing items, like smart shirts or sports bras, integrate sensors to monitor heart rate, breathing rate, and other vital signs. These garments can provide real-time feedback during workouts or track biometric data for health and fitness purposes.

A similar timing span was distributed 47 overviews along 21 documents did not brought up regarding ML-based procedures Quality [21].

(a) CML and [22]
(b) DL mechanisms [23]

The quantity in CML dependent HAR mechanisms with the exception of 2019, more prominent with quantity for DL dependent HAR mechanisms. Here the author audit two DL-dependent along CML-based techniques. We will restrict our audit over no-picture dependent sensoria's, [24] in restrict the degree. Intrigued peruses was urged in peruse referred based on seeing HAR.

This idea gives the fixed work process at planning HAR dependent procedures. While creating HAR dependent utilization [25] initial process was for deciding kind in sensor along gadget which was utilized in gather information (gadget recognizable proof). The subsequent process was to decide subtleties for information assortment procedure which includes comment interaction along conceivably the vital pre-processing (information assortment).

The third step incorporates distinguishing the proper AI model and preparing the model, normally a directed AI model on commented on information (model choice furthermore, preparing). [26] The chose model can likewise impact pre-processing information. At initial procedure the task was assessed as far as the movement acknowledgment measurements like exactness, accuracy, review, and different measurements (model assessment).

Here the exactness like an examination task among different papers because of a way with main normal measurement. All concepts didn't give the outcomes acquired concerning accuracy, review, awareness, [27] F1-Score, [28] Region Under the Bend (AUC) [29] or Beneficiary Working Qualities (ROC) bend, [30] in spite of being more delegate measurements, [31] particularly with unequal information. Utilizing this work was a reference; this article gives an outline of the cutting edge in HAR by looking at each period of the cycle. At last, we are especially keen on sensoria's since which produced great outcomes [32] at HAR techniques as well as over light of the fact that their utilization related to different sensoria's were increasing quickly.

Expansion of various sensors were emphatically connected with the capacity in quantify straight forwardly to development over person activity. [33] What's more, utilizing sensors was reasonable; along a sensors that can incorporate to lot of handheld electronic items individuals own [8].

2. Literature Work

According to A. Akbari et al, [34] In order to lessen the burden on the user, the authors of this paper proposed a profound learning-helped personalization structure for ADL acknowledgment determined to expand personalization execution while limiting info or mark sales. Through a clever dynamic learning model in light of the vulnerability of a given model, the proposed system comprises of solo retraining of programmed highlight extraction layers and regulated calibrating of characterization layers. With stochastic dormant factors in our Bayesian profound convolutional brain organization, we can assess both aleatoric (information reliant) and epistemic (model-subordinate) vulnerabilities in the acknowledgment task. Interestingly, we show in this study that more successful dynamic learning can be accomplished by recognizing the two previously mentioned wellsprings of vulnerability. When contrasted with the circumstance where a model is utilized for another client with no personalization, our proposed technique accomplishes a typical last precision of 88.9 percent, according to the results of the experiments. In addition, our approach outperforms other approaches in terms of personalization accuracy while significantly easing the burden on the user when it comes to collecting inputs and labels.

According to Indranil Bose et al, [35] Portable wellbeing applications are viewed as amazing assets for movement based health the board. By accessibility of various sensors over shrewd gadgets utilized at regular routines, it's feasible for follow person action along convey setting mindful wellbeing administrations. The implanted sensors in normally utilized gadgets, for example, cell phones, smart devices having a lot of data in which coordinated to people action acknowledgment. Examination shows the way that strong supporting calculations can remove information for human action order in a genuine setting. Our outcomes show that helping classifiers outflank customary AI classifiers in the recognition of fundamental human exercises like strolling, stand, sit, performing some action etc., moreover the authors done highlight designing for look at capability for cell phone as well as smart band at movement identification. Component designing methodology gives headings regarding determination for various sensory highlights in development in fundamental person exercises.

According to William Robson Schwartz et al, [36] here we brought up with multiple and scalable outfit dependent technique in profound convolution brain organizations for accessing sensors depending person movement acknowledgment. Before performing the fusion, characteristics of every sensory can be uniquely learned using our method, and we can design in a modern manner and can be used in multiple ways. By thoroughly analysing seven significant datasets, we were going to identify its capability for HAR on wearable sensor data. Adaptation of the interception module networking is uses a basic technique for proposed mechanism as well as for estimation process and this method outperforms previous cutting-edge results. The authors defined that there method function over sensor information without any preprocessing, making it general and reducing engineering bias.

According to Ying Wah The et al, [37] The application of automated training mechanism based on features to people task identification was a gaining traction which was a consequence of the consistent ascent at calculation offices and huge datasets accessible through portable and wearable detecting, the Web of Things (IoT), and publicly supporting. Here the author looked at a number of deep-learning techniques that automatically extracting features in person task identification like CNN, RNN, Restricted Boltzmann machines along other deep learning techniques were discussed, along with their characteristics, benefits, and disadvantages. There are three types of deep learning methods such as generative, discriminative as well as hybrid. The review and describe applications of DL for people task identification with help of making use of the classifications. banned Boltzmann product, auto encoder, extra code along depth mixed mechanism are generative methods, CNN, RNN, deep neural model as well as hydrocarbon are discriminative mechanisms. The research DL techniques for person identification were recently dominated by hybrid mechanisms which combined generated along discrimination mechanisms for developing upcoming tasks. Auto encoder, Restricted Boltzmann Machine, and convolutional neural network are examples of hybrid techniques. They also jointly perform certain mechanisms like CNN as well as less memory. In addition, we offer a few of the benchmark datasets that are freely accessible for the purpose of modelling and evaluating deep learning algorithms to recognizing human activity. OPPORTUNITY, Skoda along PAMAP2 were famous by traditional ML techniques, are some of these datasets that are frequently used for evaluation. These ML methods were expected for developing research on person task identification as a result of increased online along live information over wearable devices and moreover defining lot of CPU resources.

According to Chaolei Han et al [38] for activity recognition tasks, we propose an original convolution activity that can heterogeneously use the convolutional channels inside a particular convolutional layer. We acquaint a down-testing activity with change the open field inside one channel gathering and use it to recalibrate the other typical channel gathering to make the channels more different. Our preliminaries show clear advantages of heterogeneous convolution in general HAR circumstances, which can provoke basic execution gain across a broad assortment of HAR application spaces without changing the association's designing. For the most part, through the top tier models, the heterogeneous two-stream convolution structure shows an unprecedented potential to see human activities from substantial data. This allows CNN to encode logical data at various transient scales, making the removed action includes more discriminative. We ostensibly show the component depictions delivered by the heterogeneous convolution with different down-testing rates, which exhibits its power over standard CNN. Through various removal studies, we additionally talk about the productivity and viability of heterogeneous convolution.

According to Saurabh Gupta [39] this technique is known as CNN-GRU was brought up in this study to classifying intricate human activities. Here study, raw information is taken from WISDM information set was used. By general pure information set separate information sets of smartphones as well as smart bands were carved. During preprocessing, moving window is a technique which is used in transforms the information. In the study, no manual feature engineering was done. Auto ML, which is based on the open-source McFly package, was also used to create the baseline models Deep Conv LSTM and Inception Time, significantly reducing the amount of work required to create these complex deep neural network models. In addition the training as well as comparison datasets was used to verify the findings. Based on these findings, smart watches outperform smart bands whenever it is brought into recognizing difficult human tasks. Our subsequent research will take into account more complex deep neural network models in addition to CNN and GRU. Deep Transformer models can also be used in future projects to classify human activities from the WISDM dataset over time series. Transformers are self-attention-based neural networks that can be used to explore and learn dependencies in the raw sensor data i/p step. When it is available, an extended WISDM dataset with additional activities and participants can be used to further classify additional activities.

According to Nandy [40] we have proposed in this work the technique to the cleared and very well explained information at both fixed and dynamic actions, such as standing or standing with weight. Due to the different positions of sensors and movements of our limbs, it is difficult to differentiate between activities of varying intensities. This framework makes use of a heart rate sensor and accelerometer that are both based on smartphones. The data has been gathered from four users of various heights and weights. Through feature selection and extraction, the proposed framework does an excellent job. Subparts of features are grouped together. In order to boost the framework's overall performance, latest heart beat technique was brought into existence. With proposed feature subpart, exactness of 94 percent was succeeding. It has been discovered that compared to an individual classifier, the developed stack dependent technique classifiers performs clear information about the tasks with recognition significantly higher exactness (95.9%).

According to F JhonDian [41] in a great deal of certifiable applications, wearable IoT can give an abundance of new open doors. In the wake of distinguishing more than 100 papers as the huge writing in this field, the papers were dissected and isolated into four significant bunches in light of their applications, giving a study of the main endeavors of the examination local area in the field of wearable’s and the Web of Things. Each bunch's techniques were likewise placed into gatherings. At the point when coordinated Web of Things frameworks are made accessible, wearable’s have a great deal of potential. Along these lines, the genuine capability of consolidating IoT and wearable innovation has not been perceived. Furthermore, the handheld IoT that do not gotten a lot in consideration from the exploration local area as yet, could be changed by cell IoT.

According to G. Pravadelli et al, [42] Over the beyond a decade, HAR frameworks have advanced essentially and turned into a developing area of exploration. Sensor-based HAR, specifically, enjoys numerous upper hands over vision-based HAR techniques, which are restricted by computational necessities and raise security concerns. HAR is progressively depending on ML and DL-based action acknowledgment calculations. We broke down the explored writing in light of the most generally concentrated on human exercises, the most normally involved electronic sensors to information where the lot of notable gadgets which coordinate by the sensors with not considering video-based procedures, beginning with a meta-survey of the current HAR studies. Especially of interest was sensor-based information that was seen by ecological, inertial, and physiological sensors. The accompanying gadget types were likewise broadly contemplated:

a) Smart phones
b) Standalone devices as well as
c) Smart watches

The output was presented at typical values of datasets used to test the procedures, the typical number of perceived exercises, and the normal accuracy for each category. Methodologies based on accelerometers, gyroscopes, and magnetometers were also discussed in this survey. We additionally talked about the preprocessing approaches and their outcomes in view of element extraction, commotion expulsion, and standardization strategies. In addition, we focused primarily on publicly accessible datasets when discussing datasets in the literature. Finally, we described the most often utilized acknowledgment models in HAR. Hence, they have brought up lot by and large using DL along ML mechanisms as well as outputs which as indicated by viewpoint for significant worth along sum. Author construed the HAR experts actually slant toward praiseworthy ML models, in a general sense considering the way that they require a more unobtrusive proportion in information as well as low computer speed when compared to DL models. These models, then again been demonstrated to be more adroit at perceiving various complex exercises. The improvement of systems with further developed speculation abilities and the acknowledgment of additional complicated exercises should be the primary focus of future work.

According to k xia et al, [43] The article proposes neural network to person task identification that combines LSTM and convolutional layers. CNN's weight parameters primarily target the completely established connection. Light of the trademark, Hole mechanism was used to displace the totally related part below the convolutional part that fundamentally decreases the method limits by keeping lot of affirmation cost. The crude information gathered by portable sensors is taken care of into a two-layer LSTM followed by convolutional layers in the proposed engineering. This makes it fit for learning the transient elements on different time scales in view of the boundaries advanced by the LSTMs, which improves accuracy. The trial utilized the three public datasets UC-HAR, WISDM, and Chance to exhibit the proposed model's generalizability and viability. The F1 score was utilized to assess the model's exhibition since exactness is certainly not a reasonable or complete execution measure. On various datasets, separately, the F1 score at last came to 95.78%, 95.85%, and 92.63%. In addition, we similarly examined the power of few limits over architecture execution, for instance, amount for channels, and sort those enhancers along bundle width. To prepare model, the best hyper-boundaries for the last plan were at last picked. To sum up, differentiated and the procedures proposed in various composed works, the LSTM-CNN model shows unsurprising unmatched execution and has extraordinary hypothesis. Under the supposition of a couple of model boundaries, it can stay away from complex component extraction as well as have high acknowledgment precision.

Concurring to Dua et al, [44] in the fields of recovery, shrewd reconnaissance, mechanical technology, and medical care, HAR assumes a vital part. The different wearable sensors used to gather movement information, famous public datasets for HAR, and application areas of HAR utilizing wearable innovation have all been examined in this paper. Also, we have surveyed the headways that have been made in DL approaches for wearable HAR and examined different profound learning strategies that are used in the writing for HAR. We have moreover perceived challenges and expected open entryways around here ultimately made a couple of thoughts to possibility upcoming course for impel an investigation over HAR.

According to Liu et al, [45] the application of various handheld devious were using in sector is gaining popularity. We use HAR systems, for instance, to identify patients' early mobility activities in the intensive care unit and to examine DMD patients' symptoms. The development of HAR devices over healthcare is the focus of this overview paper, which focuses on healthcare applications. Sensor factors, data segmentation, feature selection and extraction, AI mechanism and other essential HAR system components are emphasized. We additionally feature the difficulties and chances of HAR frameworks for medical services.

According to Uddin et al, [46] here multiple mechanisms vigorous person movement acknowledgment framework was researched utilizing devices along sensors were strong profound strategy, NSL in light of time-successive information model LSTM inside it. On the basis of non-linear generalization discriminate analysing, efficient tasks were extracted from the body sensor data. A deep activity NSL has been trained with the features to model twelve distinct human activities. Finally, behind the task of examining the information has been identified by trained model. On the MHEALTH activity dataset, the proposed method produced a more recalling value of 0.999. On the other hand conventional methods produced a maximum value of 0.94. On the PUC-Rio dataset uses a proposed method also demonstrated 99 percent accuracy, whereas; the conventional methods were unable to reach 93%. As a result, the experimental results demonstrated the proposed strategy's durability. In addition, the machine learning model's decision has been defended using the fast XAI algorithm LIME. Despite the fact that the overall system for monitoring people's mentality as well as technically challenging, Additionally, people value an increased data security along data confidentiality over smart systems which offer in terms of privacy.

2.1 Comparison with existing articles

Table 1 shows the literature on deep learning-based human activity detection and existing issues. There are many researchers were doing more active research in human activity identity mechanism.

Table 1. Literature Survey

Reference	Sensors/Tools Used	Algorithm/ Techniques Used	Advantages	Disadvantages	Performance
T. L. M. van Kasteren et al., [47], 2018	WSN and Sensors	Naive Bayes, Hidden Markov, Hidden semi-Markov and Conditional random field.	1. Non-invasive 2.Continuous monitoring 3. Objective assessment 4.Automation	1. Data Quality 2. Privacy Concerns 3. Limited Range 4. Complexity.	Studied research on 16 participants showed accuracy of 93.77% & 95.64% respectively
Kun Xia, [48], 2016	Object and Telephone Sensor	CNN, GAP, BN	1. High accuracy 2. Robustness 3. Fast Training	1. High Computational Cost 2. Complexity 3. Over fitting	Used 2 datasets. For WISDM shows 95.85% accuracy and for OPPURTUNITY dataset 92.63%accu
G. Singla,[49], 2016	Motion, item, water, burner, cabinet, phone and temperature sensor.	Complimentary Filter Algorithm, Multi sensor fusion algorithm, Complimentary Filter Algorithm,	1. Natural Interaction 2. Versatility 3. increased accessibility 4. Real time Feedback	1. Calibration. 2. sensitivity to environmental factors 3. Cost 4. Limited Accuracy.	The experimental proofs showing that the authors claimed better results with excellent accuracy.
D. Anguita et al., [50], 2015	Accelerometer and gyroscope	Shadow detection algorithm,	1. convenient and non-invasive 2. accurate 3. Real time monitoring 4. Behavioral insights	1. Inaccuracies in liquids. 2. Limited food recognition 3. Potential Discomfort 4. Limited Battery Life	The exactness of 3 various kinds of food items such as chips, chocolates and water is 85.3%, 81.4%, and 84.5%, respectively.
R. Chavarriaga et al., [51], 2020.	Inertial Sensors and Accelerometers	Peak finding algorithm, Longest/periodic sub sequence algorithm, Prominence algorithm, DBSCAN algorithm, Gradient Boosting Algorithm,	1. Non-Intrusive 2. Accurate 3. Objective 4. Versatile	1. Cost 2. Privacy Concerns 3. Accuracy 4. User Acceptance	got nearly 82.21% accuracy results
O. Banos et al., [52], 2021	Accelerometers, ECG, Gyroscope and Magnetometer	DTW Algorithm, Classification Algorithms, Connectionist Temporal Classification algo rithm,	1. Enhanced User Experience 2. Hands Free 3. Comfortable 4. Accessibility 5. Privacy	1. Limited Time 2. Data Processing 3. Battery Life 4. Social Acceptability 5. Cost	97.1% of accuracy was achieved

Background Study of the Algorithm
Human activity tracking systems use various algorithms to detect and interpret human movements and behaviors. Some common algorithms used in these systems include:

Machine learning algorithms [53]. These algorithms are used to train the system to recognize specific patterns of movements and behaviors. They use data from sensors to create a model of human movements and behaviors, which is then used to classify and predict future movements.

This is the first study of its sort to create a wearable sensor-based physical activity classification system employing boosting algorithms, a type of supervised machine learning approach. The study compares the performance of several boosting algorithms (extreme gradient boosting—XGB, light gradient boosting machine—LGBM, gradient boosting—GB, cat boosting—CB, and AdaBoost) using a uniform dataset, feature set, feature selection method, performance metric, and cross-validation techniques.

Sensor fusion algorithms. These algorithms combine data from multiple gadgets like accelerometer, gyroscope along magnetometer for providing a lot of nearby as well as full-fledged picture of human movements and behaviors.

Activity recognition algorithms. These algorithms use data from sensors to classify and recognize different types of activities, such as walking, running, and cycling.
Context-aware algorithms. These algorithms use contextual information, such as time of day, location, and weather, to better understand and interpret human behaviors.
Clustering algorithms. These algorithms group similar movements and behaviors together, which can be useful for identifying trends and patterns in large datasets.
Deep learning algorithms. These algorithms use neural networks to learn and recognize patterns in large datasets. They are particularly useful for complex and multi-dimensional datasets, such as those generated by human activity tracking systems.

Overall, the algorithms used in human activity tracking systems are designed to be flexible and adaptable, so they can be customized to suit different types of activities and user preferences.
Work going on in this domain

There are many research works going on human activity tracking systems. Human activity tracking devices were developed for monitor as well as analyze movements as well as behaviors of individuals for gain insights into their health, well-being, and overall activity levels. These systems are typically used in healthcare, sports, and fitness industries, and can also be used in the workplace to monitor employee productivity and safety.

Some of the research areas that are currently being explored in the field of human activity tracking systems include:

Sensor Technology. Researchers are exploring the use of various sensor technologies, including accelerometers, gyroscopes, and GPS, to accurately track and monitor human activity.
Machine Learning. Machine learning algorithms are being developed to analyze the data collected by activity tracking systems and provide insights into patterns and trends in human behavior.
Wearable Technology. Wearable devices such as smart watches, fitness trackers, and activity monitors are becoming increasingly popular for tracking human activity. Researchers are exploring ways for improving an exactness and reliability for these devices.

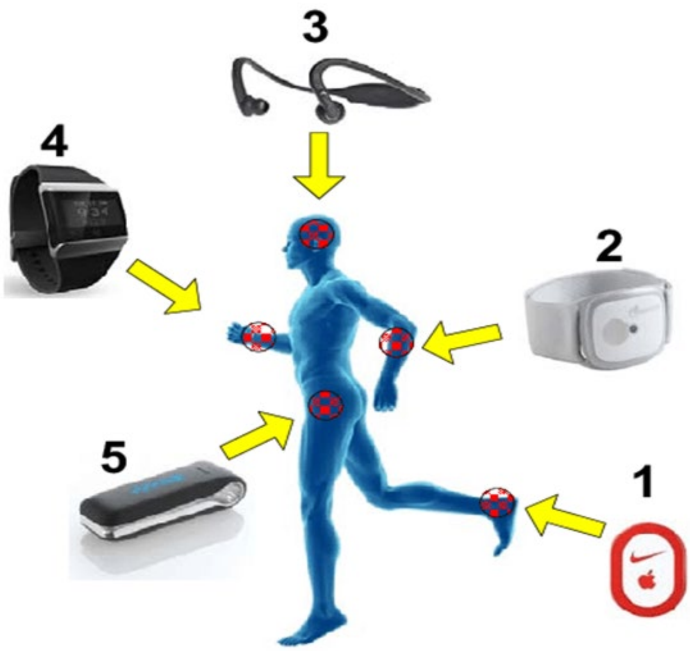

Figure 1. Scenario of Human Activity System

Data Privacy and Security. With growing usage in activity tracking systems, researchers are also exploring ways for making sure regarding confidential to the information collected by these systems.

Overall, human activity tracking systems are a rapidly evolving field with many exciting research opportunities.

Research challenges. Human activity tracking systems are becoming increasingly popular with the rise of wearable devices and mobile applications. These architectures were developed for track as well as monitor user physical tasks, such as steps taken, distance travelled, and calories burned. However, there is several research challenges associated with human activity tracking systems, including:

Accuracy. One of the main challenges of human activity tracking systems is ensuring accurate data collection. Various kinds of sensors used to bring information may introduce errors or inaccuracies, leading to incorrect activity readings.

Developing accurate algorithms for data collection and processing is crucial to address this challenge.

Data integration. Human activity tracking systems may collect data from multiple sources, such as wearable devices, mobile applications, and environmental sensors. Integrating data from these sources can be challenging, especially when information was brought in various formats as well as at different frequencies.

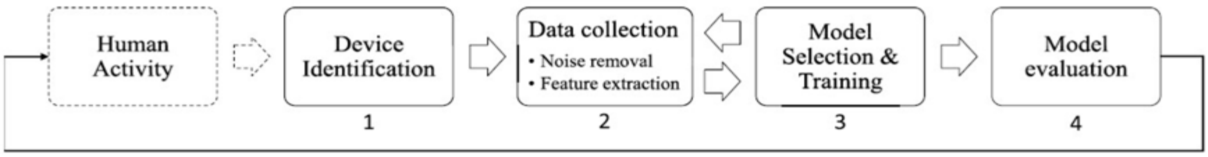

Figure 2. Architecture of Human Activity Recognition

Privacy and security. Human activity tracking systems may take confidential information such as health data. Making sure regarding the data security as well as privacy of data is essential to protect users from potential harm. Developing secure and privacy-preserving data collection and storage methods is crucial to address this challenge.
User engagement. Another challenge of human activity tracking systems is user engagement. Users may lose interest in using the system over time, leading to incomplete data collection. Developing engaging and motivating user interfaces and feedback mechanisms is crucial to address this challenge.

Generalizability. Human activity tracking systems may be designed for specific populations or activities, leading to limited generalizability. Developing systems that can be used across different populations and activities is crucial to address this challenge.
Overall, human activity tracking systems have the potential for improving health condition. Addressing the above research challenges can help to develop more accurate, reliable, and engaging systems that can be used to promote physical activity and improve health outcomes.

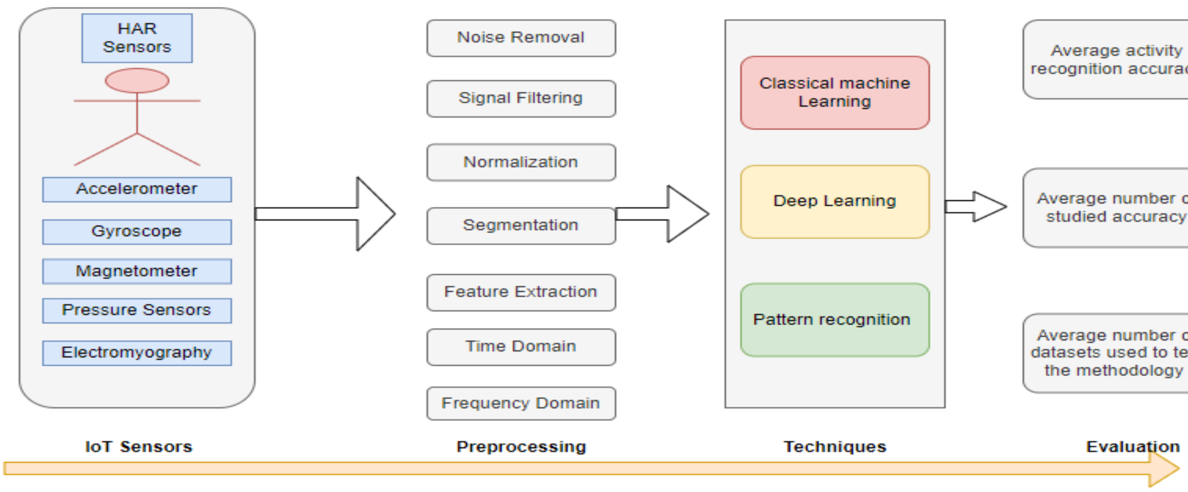

Figure. 3. A Systematic view of Human Activity Recognition (HAR) approaches.

Healthcare. Human activity tracking systems could play an important role in preventive healthcare, by monitoring vital signs, activity levels, and sleep patterns. This could help individuals identify potential health issues before they become serious, and allow healthcare providers to offer more personalized treatment and guidance.
Workplace productivity. Human activity tracking systems could also be used to monitor employee productivity, by tracking work patterns, time management, and stress levels. This could help employers optimize work schedules, reduce burnout, and improve overall productivity.
Sports and fitness. Human activity tracking systems are already widely used in sports and fitness applications, but there is still room for growth in this area. As sensors and wearable's increased a lot advanced as well as available in user friendly price which may become easy for monitor large range for metrics, including hydration, nutrition, and recovery.
Smart homes and cities. Human activity tracking systems could also play a role in creating smarter homes and cities, by providing data on how people use spaces and move around. This could help city planners and architects design more efficient and sustainable buildings and public spaces.
Overall, the future of human activity tracking systems is likely to be very exciting, with potential applications in many different areas of life. However, it's important to remember that these systems also raise important questions around privacy, security, and the responsible use of personal data.

3. Discussion

Human task identifying is a technique of knowing and classifying actions performed by a person based on sensor data. This concept has become increasingly popular because of on developing for wearable technology and IoT which can provide rich data on human activities.
There are many applications of human activity recognition, such as health checking, body tracking, automation, along security. For example, activity recognition which is used for monitor an daily tasks of old people as well as provide assistance if needed. It can also be used to track exercise routines and provide personalized coaching depends on people activity level.

This process for human activity identification typically involves collecting sensor data from various sources, such as accelerometers, gyroscopes, and GPS sensors. ML techniques were then using for analyze data as well as identify activities being performed. The accuracy of these algorithms which change based on quality in data as well as strictness for activities being recognized.

The problems in human activity identification were dealing with variability and diversity of human activities. Activities can vary greatly in terms of duration, intensity, and sequence. Moreover, activities can be performed in different contexts and environments, which can affect the sensor data and make it harder to recognize activities accurately.
Despite these challenges, human activity recognition has great potential to improve our lives by providing personalized assistance and monitoring. With further advances in technology and machine learning algorithms, we can expect to see even more applications of human tasks identification in the upcoming days.

3.1 Applications

Numerous applications for Human activity identification. Few applications include:
Health monitoring. Human activity recognition which is used to identify people in physical manner condition like diabetes, heart problems along obesity. This can help healthcare providers to develop personalized treatment plans and improve outcomes.
Fitness tracking. Human activity recognition can be used to track exercise routines and provide feedback to users on their progress. This can motivate users to stay active and make healthier choices.
Home automation. Human activity recognition can be used to automate home appliances and systems based on the user's activities. For example, lights and air conditioning can be automatically turned off when the user leaves the room.
Security. Human activity recognition can be used to monitor homes and businesses for suspicious activity. This can improve security and help prevent theft and other crimes.
Gaming. Human activity recognition can be used to create immersive gaming experiences that respond to the user's movements and actions. This can provide a more engaging and interactive gaming experience.

Overall, human activity recognition has many potential applications in healthcare, fitness, home automation, security, and gaming. With further advancements in technology, we can expect to see even more applications of this concept in the future.

3.2 Context-aware wellness services for HAR

- Personalized Fitness and Exercise: Activity recognition can be used to develop personalized fitness programs and exercise routines. By monitoring and analyzing a person's activities and movements, context-aware wellness services can provide tailored recommendations for workouts, track progress, and offer real-time feedback to optimize physical fitness.
- Health Monitoring and Chronic Disease Management: Human activity recognition can assist in monitoring the health status of individuals with chronic diseases or conditions. By tracking activities, sleep patterns, and vital signs, context-aware wellness services can provide insights into overall health, detect abnormalities, and alert users and healthcare providers about potential health risks or deviations from normal behavior.

- Elderly Care and Aging in Place: Context-aware wellness services can support elderly individuals in living independently and safely at home. By monitoring activities and behavior patterns, these services can detect falls, changes in mobility, deviations from regular routines, and other potential signs of distress or health issues. They can alert caregivers or emergency services to ensure timely assistance.
- Stress Management and Mental Health Support: Human activity recognition can contribute to stress management and mental health support. By analysing activity patterns, sleep quality, and physiological data, context-aware wellness services can identify potential stressors, provide relaxation techniques, suggest mindfulness exercises, and offer personalized strategies to improve mental well-being.
- Workplace Wellness and Productivity: Activity recognition can be employed to enhance workplace wellness and productivity. Context-aware wellness services can monitor employees' activity levels, posture, and work patterns to promote healthy behaviors, encourage regular breaks, and provide ergonomic recommendations. This can improve employee well-being, reduce fatigue, and potentially increase productivity.
- Rehabilitation and Physical Therapy: Human activity recognition can support rehabilitation and physical therapy programs. By tracking movement patterns and providing real-time feedback, context-aware wellness services can assist individuals in performing exercises correctly, monitor progress, and adjust therapy plans accordingly. This can aid in injury recovery, improve motor skills, and enhance overall rehabilitation outcomes.
- Smart Home Automation and Energy Management: Activity recognition can be utilized in smart home systems to automate tasks and optimize energy management. By detecting human presence and activities within the home, context-aware wellness services can adjust lighting, heating, and cooling systems, control appliances, and optimize energy consumption based on occupancy patterns.

4. Conclusion

To conclude the topic of human activity identification system, it is important to summarize the key points and findings related to this subject.

First, human activity identification systems use various sensors and algorithms to recognize and classify different activities performed by individuals, such as walking, running, sitting, or standing.

Second, these systems have lot of domains like health, sports, entertainment along security. For example, they are used physical diseases such as heart diseases, track the performance of athletes, enhance virtual reality experiences, or detect suspicious behavior in public places.

Third, the accuracy and reliability of human activity identification systems depends on various conditions like quality used in sensors, complexity of algorithms, diversity in the activities and individuals involved. Therefore, ongoing research and development are need for improve performance as well as usability for systems.

Overall, it’s emergency to make a key note regarding the security and privacy problems in human activity identification systems, especially in relation regarding collect as well as usage in personal information. Proper safeguards and regulations should be in place to makeover of these devices were used in a good manner for transparent purpose.

Finally, human activity identification systems have the potential to benefit society in many ways, but their development and deployment should be guided by a balanced and thoughtful approach that considers both the opportunities and challenges associated with this technology.

Human activity tracking systems have already gained significant popularity at present days the concept is spread rapidly adoption in wearable devices along fitness tracking apps. Future scope of these systems is likely to be even broader and more diverse, as new technologies and applications emerge.

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