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HUMAN ACTIVITY RECOGNITION WITH SMARTPHONES

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***Abstract**:* These days, smartphones are almost universal, and because of their many built-in sensors, which allow for constant monitoring of everyday activities, they are particularly useful for health research. Different human activity recognition (HAR) systems have been presented by researchers with the goal of converting smartphone readings into different kinds of physical activity. We outlined the current methods for smartphone-based HAR in this review. In order to find peer-reviewed research on the use of cellphones for HAR that was published up to December 2020, we conducted a thorough search of Scopus, PubMed, and Web of Science. We retrieved data on the body location, sensors, and physical activity categories of smartphones as well as the data processing and classification systems used to activity recognition. As a result, we found 108 publications and discussed the different methods for gathering data, preprocessing it, extracting features, and classifying activities. We also identified the most popular techniques and their substitutes. We conclude that HAR research in the health sciences is a good fit for cellphones. Future research should concentrate on enhancing the quality of data collected, addressing missing data, including a wider range of participants and activities, easing phone placement requirements, offering more thorough participant documentation, and disclosing the source code of the methods and algorithms used to achieve population-level impact.

I. Introduction

Scientific advancement has always been propelled by data. In 2020, there were over 5 billion mobile devices in use, and many of them had several sensors (such GPS and accelerometers) that could record precise, continuous, and objective data on a range of life variables, including physical activity. The widespread use of smartphones has created previously unheard-of possibilities for data collecting to research human behavior and health. Smartphones that have enough storage, strong CPUs, and wireless communication capabilities may gather a staggering quantity of data about big groups of people over long periods of time without the need for further gear or apparatus.

Smartphones have great potential as devices for gathering data that can be used to quantify conventional and emergent risk factors for human populations in a repeatable and objective manner. Smartphones in free-living settings may monitor behavioral risk factors, such as physical activity, sleep patterns, and sedentary behavior, among others, by using people's lived experiences. Crucially, unlike some wearable activity trackers, cellphones are no longer a niche product; rather, they are now widely accessible and are being embraced by consumers of all ages in both developed and developing nations3, 4. Positive results from other portable devices, particularly wearable accelerometers, which have shown strong correlations between physical activity and health outcomes like obesity, diabetes, different cardiovascular diseases, mental health, and mortality, have also encouraged their use in health research. Wearables may, however, have several significant drawbacks when it comes to population health research: Wearable device ownership is far lower than that of smartphones (10), most users discontinue usage of their wearables after six months, and wearables often do not provide raw data. Because of the final reason, researchers are often forced to depend on proprietary device metrics, which further reduces the already poor rate of reproducibility of biomedical research in general and almost eliminates the possibility of quantifying measurement uncertainty.

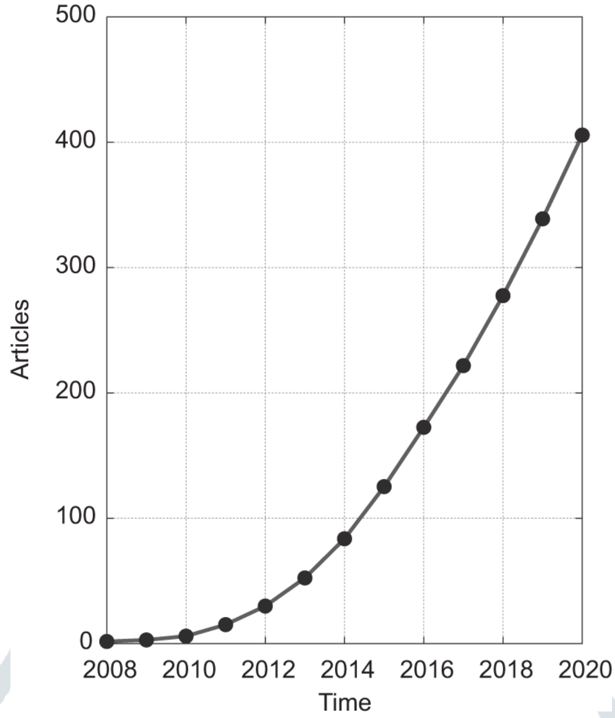

Fig-Cumulative number of peer-reviewed articles on human activity recognition (HAR) using smartphones.

The method of classifying human behaviors over a predetermined amount of time using discrete measures (such as rotation speed, acceleration, and geographic coordinates) from personal digital devices is known as human activity recognition, or HAR. The field of machine learning research has seen a surge in interest in this area in recent years; as of this writing, over 400 publications have been published on smartphone-based HAR techniques. Comparing just a few stories from a few years ago, there has been a significant growth. The primary constraint in health research is being recognized more and more as smartphone data collecting becomes faster and easier to analyze. Researchers have developed a number of algorithms to address the analytical difficulties presented by HAR, but these vary greatly in terms of the kind of data they use, the ways in which they process the gathered data, and the statistical techniques they apply for classification and/or inference. Publicly available research employs current techniques while also suggesting novel approaches for gathering, analyzing, and categorizing everyday life activities. In addition to comparing the performance of different machine learning classifiers on pre-existing datasets or on datasets they have created from scratch specifically for their research, authors often talk about data filtering and feature selection strategies. Usually, categorization accuracy within several activity groups—such as walking, moving, and exercising—is used to summarize the findings.

In order to effectively integrate advancements in HAR into medical and public health research, it is essential to comprehend the methodologies that have been devised and recognize any possible constraints. The physiological (weight, height, age) and habitual (posture, gait, walking speed) variations of smartphone users must be taken into account, as well as variations in the built environment (buildings and green spaces), which provide the social and physical context for human activities. Furthermore, position (where the user wears the phone on their body) and orientation of the device16 may have an impact on the data collecting and statistical methods often employed in HAR, which makes it more difficult to convert acquired data into outputs that are relevant and easy to understand.

In this work, we provide a thorough analysis of the growing body of research on the use of cellphones for health research in free-living environments. We concentrate our investigation on the methods used for data collecting, data preprocessing, feature extraction, and activity categorization since the primary issue in this subject is moving from data collection to data analysis. We provide light on the many forms of data that are gathered, how digital measurements are converted into human behaviors, and the intricacy and multidimensionality of HAR via the use of cellphones. We talk about the techniques' generalizability and repeatability, or the qualities that are crucial and relevant to large and varied research participant populations. Finally, we list issues that must be resolved in order to hasten the widespread use of smartphone-based HAR in research on public health.

II. Keywords

Human Activity Recognition (HAR), Smartphone sensors, Machine learning, Wearable computing, Accelerometer, Gyroscope, Magnetometer, GPS, Feature extraction, Activity detection, Ambient intelligence

III. Methods

We searched the PubMed, Scopus, and Web of Science databases for publications published up to December 31, 2020, in order to perform our systematic review. Titles, abstracts, and keywords containing the terms "activity" AND ("recognition" OR "estimation" OR "classification") AND ("smartphone" OR "cell phone" OR "mobile phone") were filtered out of the databases. Only English-language, full-length journal articles were included in the search. We examined the titles and abstracts of the remaining papers after eliminating duplicates. Studies that did not look at HAR techniques were not included in the screening process. We then eliminated research that required carrying numerous cellphones and research that used additional equipment, such as wearable or ambient devices. Read in full were only those studies that used consumer-grade cellphones that were available on the market, either personal or loaner devices. Studies that classified activities using a smartphone's microphone or video camera were disqualified because they may have recorded information about a person's surroundings, including information about uninvited persons, raising privacy concerns that would prevent the approach from being widely used. We omitted research that used devices attached or bonded to the body in a fixed position in order to concentrate on trials that imitated free-living conditions.

IV. Results

1901 results met the parameters we had set for our search. There were 108 references in this study after excluding works that did not describe HAR methods (n = 793), used extra hardware (n = 150), or used microphones, cameras, or body-affixed cellphones (n = 149).

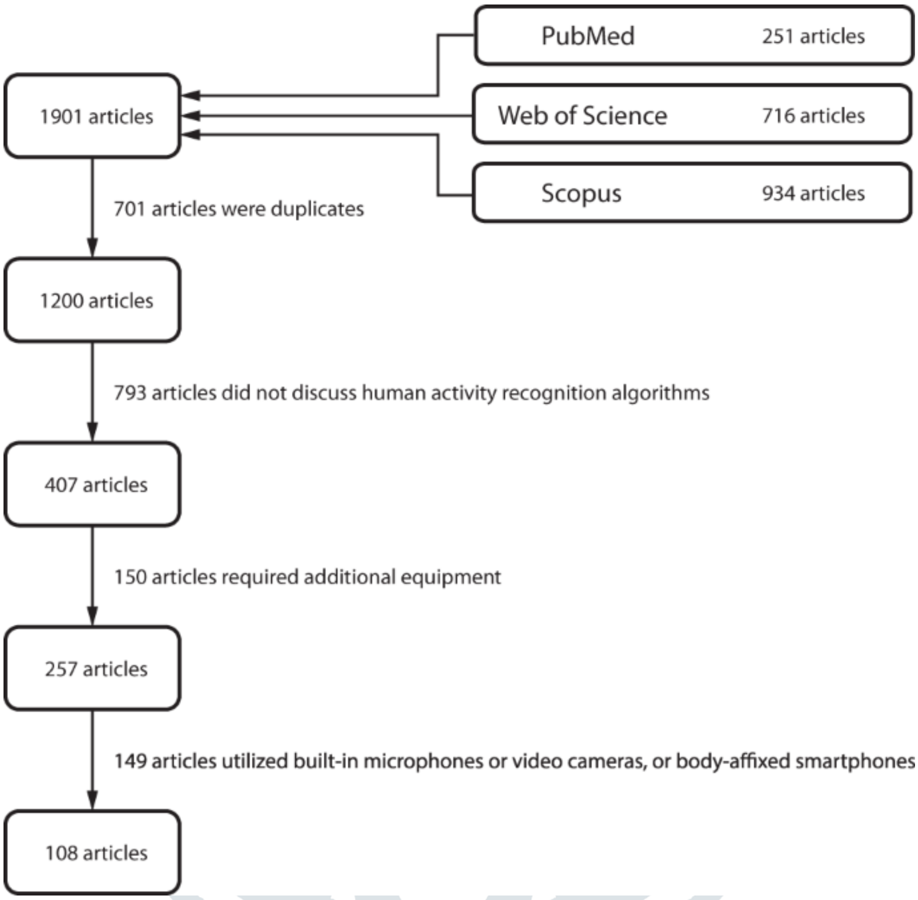

Fig- PRISMA diagram of the literature search process.

The four phases of most HAR techniques are activity categorization, feature extraction, data preparation, and data collecting (Fig. 3). Here, we provide a summary of these procedures and briefly highlight methodologically significant variations among the evaluated papers for each stage. Particulars from each investigation are summed together in Figure 4. Notably, we broke down the data acquisition processes into categories such as sensor type, experimental environment, activities under investigation, and smartphone location. We also identified the studies that preprocessed the measurements using techniques for noise filtering, signal correction, and sensor orientation-invariant transformations. We also categorized the investigations according to the features they extracted from the signals and the feature selection strategies they employed. Lastly, we highlighted the practices for accuracy reporting, adopted activity classification principles, and classifiers that were used. We initially provide a quick overview of the study populations before delving into these technical aspects.

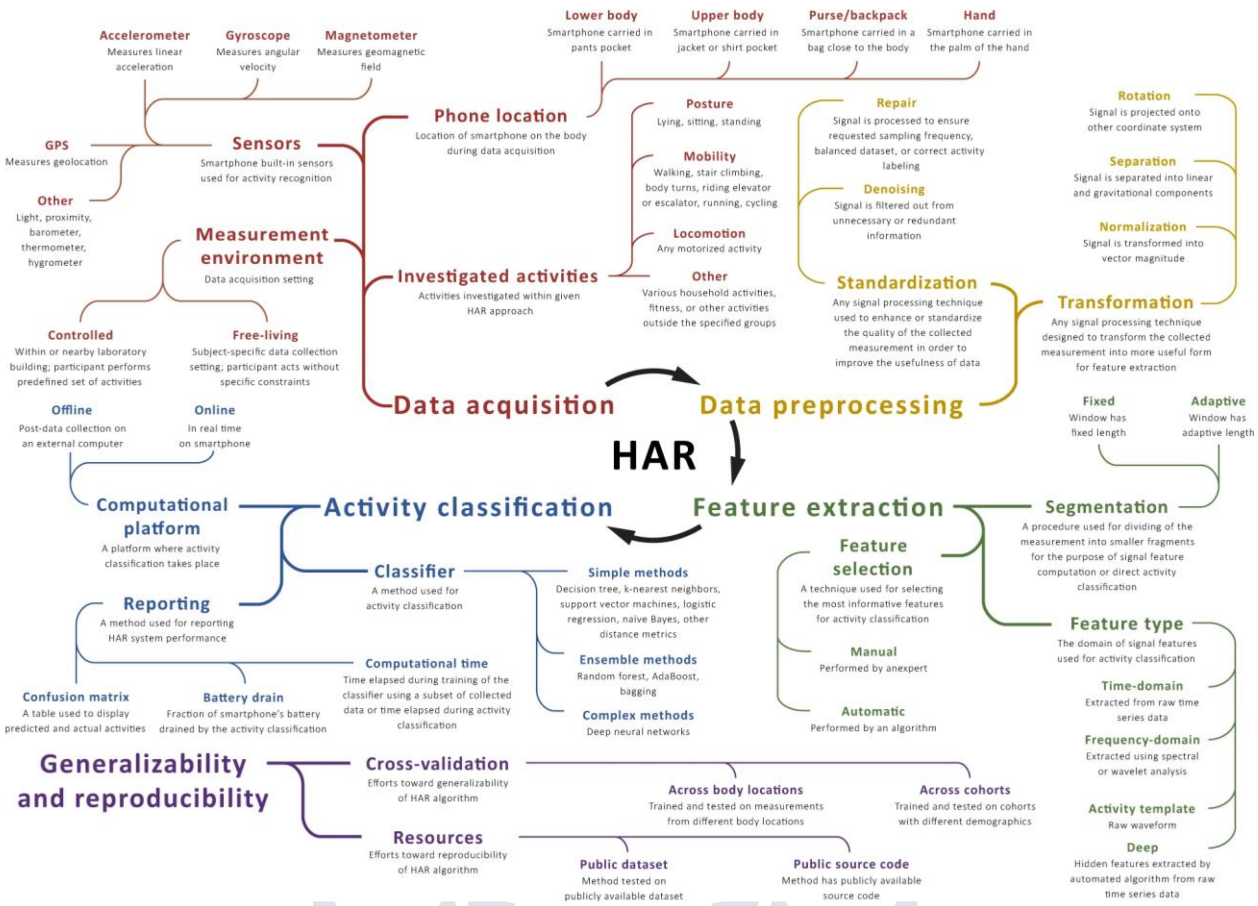

Fig- Human activity recognition (HAR) concepts at a glance.

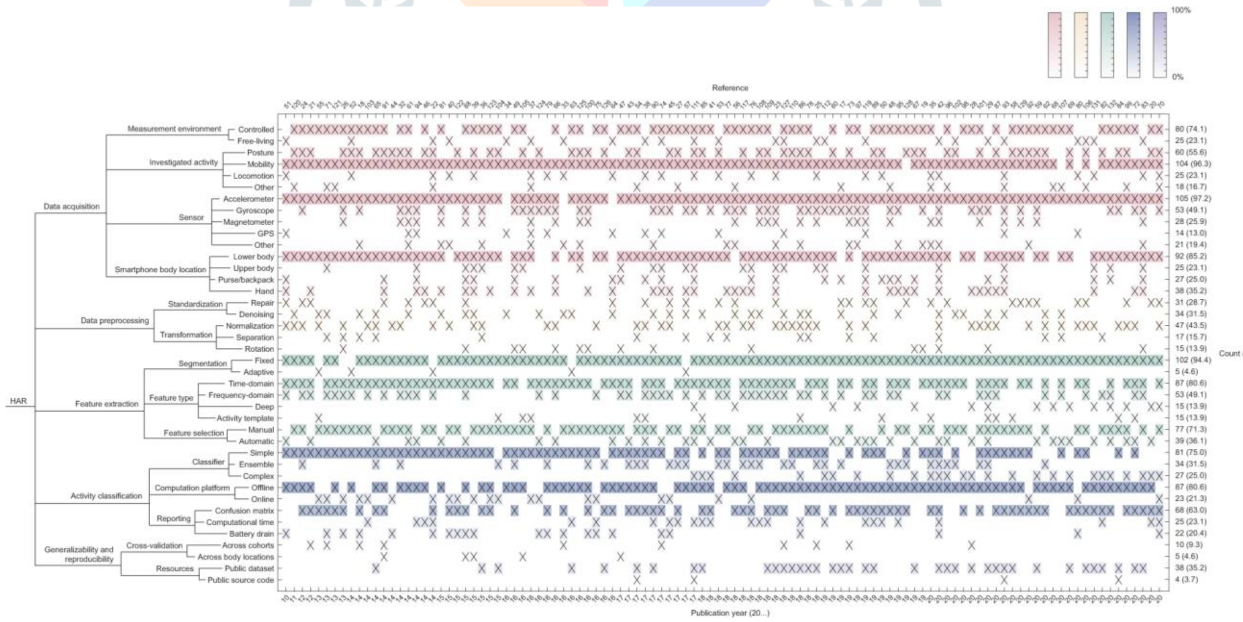

Fig- Summary of HAR systems using smartphones.

The 108 examined studies are represented by the columns, and the various technical features of each research are represented by the rows. Cells bearing a cross (x) indicate that the specified technique, methodology, or strategy was used in the specified research. A given aspect's frequency of occurrence throughout the studies is shown by the color coloring of the rows, which have been categorized to correlate to distinct phases of HAR, such as data processing (darker shade implies greater frequency).

4.1 Study Populations

Research population is the word used to describe the set of people who are the subject of a certain research. Although one bigger research assessed data from 440 healthy adults, most of the reviewed studies obtained data from less than 30 participants. Very few studies recruited older participants; most examined healthy people in their 20s and 30s. The majority of research merely reported the participants' mean age or age range, not the whole age dispersion. Assuming that the participants in each research are equally distributed in age between the lowest and maximum ages—which may not be the case—we sought to rebuild an overall estimated age distribution in order to get an understanding of the distribution of participant ages. The age range of study participants has to be widened for future HAR research in health settings, as shown by a comparison of the reconstructed age distribution with national age distributions. Studies examining groups with distinct medical and demographic features, such as the elderly and those with Parkinson's disease, received less attention.

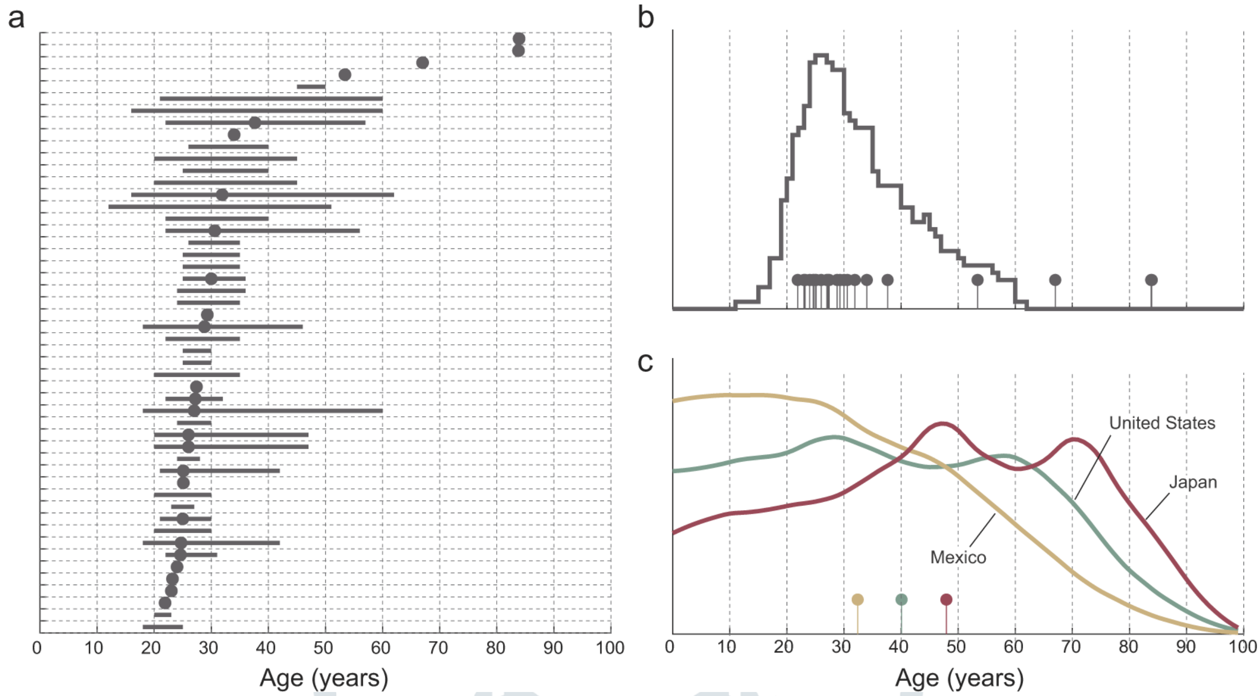

Fig. 5: Age of populations examined in the reviewed studies in contrast with the nationwide age distribution of selected countries.

Panel A shows the population's age corresponding to specific studies, which is usually represented by its mean (dots) or range (lines). The reconstructed age distribution from the examined research is shown in **Panel B (see the text).** The age distributions of the three nations' national populations shown in **Panel C** provide a striking contrast to the reconstructed age distribution of research participants.

4.1 Data acquisition

For the sake of HAR, we designate to the process of gathering and storing raw sub-second-level smartphone readings as "data acquisition." Usually, an application that operates on the device and periodically samples data from the smartphone's built-in sensors gathers the data from the users. For information on the population under investigation, the measuring environment, the activities carried out, and the settings of the smartphone, we carefully reviewed the chosen literature.

The majority of the examined studies' data collection activities happened in adjacent open spaces or at a research facility. Study participants were required to engage with specified items and complete a series of tasks along predefined pathways in these settings. The participant was under the supervision of a member of the research team, and the study protocol normally dictated the time and sequence of the performed tasks. A strategy that is less popular is observation in free-living settings, when people carry out tasks without explicit guidance. These kinds of investigations were probably going to shed more light on the many patterns of activity that result from personal habits and unpredictability in everyday life. Studies carried out in free-living conditions also enabled researchers to watch behavioral trends over many weeks or month, in contrast to a single laboratory visit.

Selecting activities is one of the most important parts of HAR. A limited number of activities, such as sitting, standing, walking, running, and stair climbing, were often the focus of the research in our evaluation. Different forms of mobility, locomotion, fitness, and household routines were less common. Examples included sharp body turns, multiple modes of transportation (car, bus, tram, train, metro, and ferry), and household tasks (sweeping a floor, carrying a shopping bag, etc.). Only walking identification was the focus of more recent studies. The different measured activities in the reviewed studies can be classified into classes, as illustrated in Fig. "Posture" includes lying, sitting, standing, and any combination of these; "mobility" includes walking, climbing stairs, body turns, using an elevator or escalator, running, cycling, and any combination of these; "locomotion" includes motorized activities; and "other" includes other household and fitness activities or single actions outside of the previously mentioned groups.

The range of activities under investigation dictates which sensors are employed to collect data. As of this writing, a typical smartphone has several hardware sensors and protocols built in, such as an accelerometer, gyroscope, magnetometer, GPS, proximity sensor, and light sensor, that can be used to track activity and also gather data on temperature, humidity, and ambient pressure. It is difficult to estimate widely accessible sensors accurately over time due to the multitude of smartphone models and manufacturers, as well as the variance in their uptake across national boundaries. Global data on smartphone market shares and flagship model characteristics suggest that by 2010, accelerometer, gyroscope, magnetometer, GPS, proximity, and light sensors were quite widely accessible. A few years later, other smartphone sensors were produced. For instance, the Samsung Galaxy S III, which was released in 2012, came with a barometer, and the Samsung Galaxy S4, which was released in 2013, came with a thermometer and hygrometer.

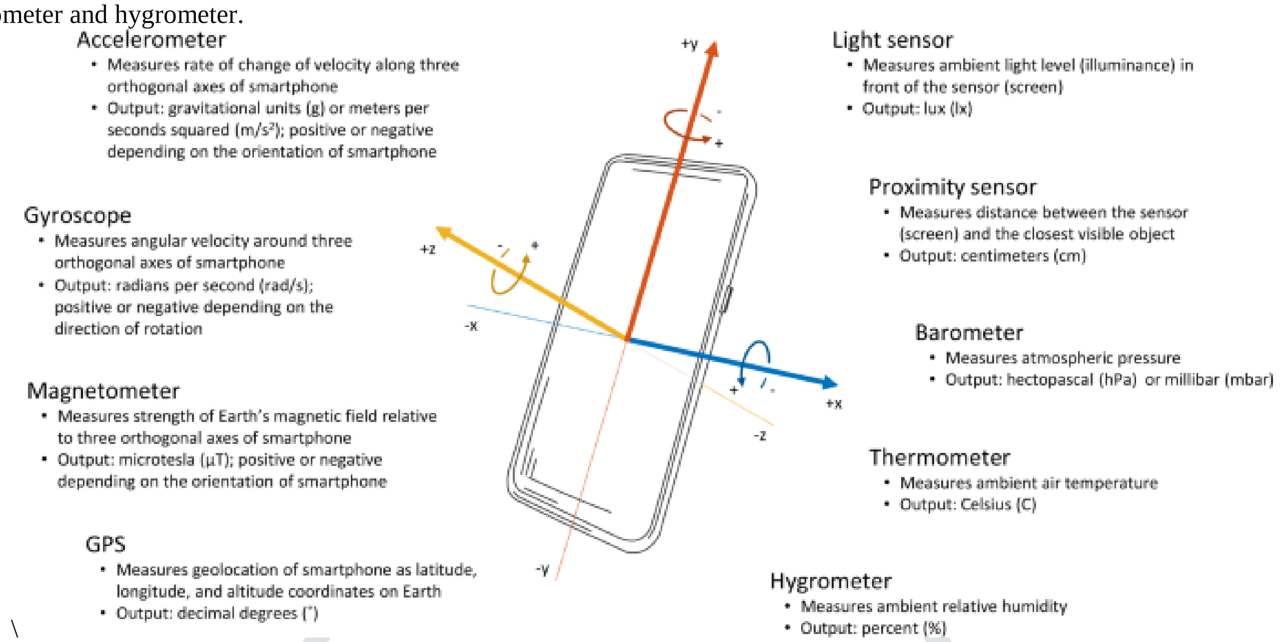

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Fig- Overview of standard smartphone sensors.

4.2 Data Preprocessing

We refer to a set of operations intended to correct, clean, and modify measurements obtained for HAR as data preparation. Such a step is required for three reasons: (1) measurement systems embedded in smartphones are often less stable than research-grade data acquisition units, and the data might therefore be sampled unevenly or there might be missingness or sudden spikes that are unrelated to an individual's actual behavior; (2) the spatial orientation (how the phone is situated in a person's pocket, say) of the device influences tri-axial measurements of inertial sensors, thus potentially degrading the performance of the HAR system; and (3) despite careful planning and execution of the data acquisition stage, data quality may be compromised due to other unpredictable factors, e.g., lack of compliance by the study participants, unequal duration of activities in the measurement (i.e., dataset imbalance), or technological issues.

In our assessment of the literature, signal processing methods were usually used to overcome the first set of challenges. For example, researchers suggested using spline interpolation or linear interpolation to reduce the discrepancy between the required and effective sampling frequency. A variety of impacted sensors were subject to such protocols; they usually included the accelerometer, gyroscope, magnetometer, and barometer. Additional time-domain preprocessing examined data trimming, which is done to eliminate unnecessary data elements. For this reason, the start and finish of each activity bout—a brief burst of a particular form of activity—were excised as nonrepresentative points for the activity in question. The researchers also addressed dataset imbalance at this point, which happens when the training dataset has varying amounts of observations for various activity classes. In these circumstances, the classifier is prone to overfitting in favor of the bigger class; up-sampling or down-sampling of the data was used in the evaluated research to address this problem1. Furthermore, the data underwent high-frequency noise reduction processing, sometimes known as "denoising." The literature review identified a number of techniques appropriate for this task, such as the use of weighted moving average; moving median; singular-value decomposition; and low-pass finite impulse response filters (with a cutoff frequency typically equal to 10 Hz for inertial sensors and 0.1 Hz for barometers)60,61, which remove the portion of the signal that is unlikely to result from the activities of interest. GPS data were occasionally de-noised based on the maximum allowed positional accuracy.

4.3 Activity Classification

The process of linking extracted characteristics to specific activity classes according to the chosen classification principle is referred to as "activity classification" here. Usually, a supervised learning algorithm that has been taught to identify patterns between characteristics and classified physical activities in the training dataset does the classification. After that, the fitted model is tested using other observations and a validation dataset, which is often made up of information from the same research participants. One may evaluate the accuracy of the method by comparing the model's predictions with the known true labels. In addition to summarizing the techniques for validation and categorization, this section offers some guidance on how to report on HAR performance.

The goal of selecting a classifier is to find the best technique for the datasets that have been gathered and for the particular data processing environment (online vs. offline, for example). A wide variety of classifiers were included in the reviewed literature, ranging from ensemble classifiers like random forest, XGBoost, AdaBoost, bagging, and deep neural networks simple decision trees, k-nearest neighbors, support vector machines, logistic regression, naïve Bayes, and fuzzy logic. In many cases, the optimal answer in the particular measurement circumstance was found by comparing simple classifiers. For ensemble classifiers, a similar kind of study was used. To adjust the categorization model to fresh data streams and unobserved actions, incremental learning approaches were developed Alternative semi-supervised methods have been suggested to enhance the customization of HAR systems and data annotation by using unlabeled data. Some research used a hierarchical method, in which the classification was carried out in discrete phases with the potential to utilize a different classifier at each level, in an effort to enhance the efficacy of HAR. The multi-stage method was utilized to address the problem of changing sensor location (body location first, then activity) and for the progressive breakdown of activities (coarse-grained initially, then fine-grained), and . The categorization of complex activities—that is, activities made up of several basic activities—and the identification of basic activities associated with various sensor locations—both benefit from the use of multi-instance multi-label approaches.

V. Discussion

Numerous research have used cellphones to study HAR within the last ten years. The literature review offers comprehensive explanations of crucial elements related to feature extraction, activity categorization, data preprocessing, and data collecting. Studies were carried out with one or more goals in mind, such as minimizing computing needs (e.g., for online data processing directly on the device), maximizing classification accuracy, and limiting technical defects (e.g., no GPS signal reception inside). We provide an overview of the most popular techniques and suggest some alternatives.

As anticipated, no single activity recognition method was found to be effective in all contexts. This highlights the significance of developing techniques and algorithms that specifically address health-related research questions while taking the unique characteristics of the study cohort (e.g., age distribution, degree of device use, and type of disability) into consideration. Although most datasets were gathered in laboratory environments, there was no proof that algorithms developed with these carefully regulated datasets could be applied to real-world situations. The length, frequency, and particular methods of carrying out any task in a free-living environment depend on the situation and the person, and these degrees of freedom must be taken into account while developing HAR systems. Since the main benefit of HAR systems for public health will come from transportable and scalable applications in large-scale, long-term observational studies or real-world treatments, validation of this data in free-living environments is crucial.

Several research were carried out using a limited number of healthy participants. This restricts the approach's capacity to be applied to more varied populations while simultaneously simplifying the data management and classification procedure. In two of the research that were looked at, the latter point was clearly shown. The first study's authors found that when a classifier is validated on an older cohort after being trained on a younger cohort, its performance declines noticeably. Comparable findings may be made from the second research, which found that the findings made on healthy subjects did not hold true for those with Parkinson's disease21. These data emphasize the need of algorithmic fairness, also known as machine learning fairness, which holds that an algorithm's performance shouldn't be influenced by factors deemed sensitive, such as racial or ethnic background, sexual orientation, age, or handicap. The decision by certain major corporations, such as IBM, to cease supplying police agencies with facial recognition technology for widespread surveillance and the European Commission's consideration of a ban on the use of face recognition in public spaces are two prominent examples of this. These choices were made in response to research showing that face recognition algorithms performed poorly on people with darker skin tones.

Most of the research that we looked at used cellphones that were locked to one body position—that is, a certain pocket on pants—and sometimes even had a set orientation. However, these kinds of research should be seen more as proofs of concept since real-world events involving such circumstances are uncommon. As multiple studies have shown, inertial sensor data may not, in fact, share similar features across body locations, and the orientation of smartphones introduces extra artifacts to each axis of measurement, making it challenging to use distribution-based features (e.g., mean, range, skewness) without the necessary data preprocessing. Numerous studies gave little information on demographics, the surrounding environment, and the specifics of the activities carried out, and they only partially described the experimental setup and research methodology. It is important to submit this information as completely and precisely as you can.

It seems sense that privacy issues would arise from the gathering of behavioral data via cellphones; nevertheless, as health data are often seen as private and personal, researchers in the field of health research are well-positioned to comprehend and resolve these concerns. As a result, there are established procedures and standard guidelines for research involving human subjects, and one of the main pillars of any study carried out ethically is the individual's informed permission to participate. Federated learning is a machine learning approach that uses just local data (data from the individual device) and eliminates the need to communicate data with other devices to train an algorithm across decentralized devices, in this case cellphones. At first glance, this method seems to provide a strong answer to the privacy issue since personal information never leaves the user's phone and only learning process outputs—typically, parameter estimates—are shared with third parties. But here is where the conflict between the need for repeatable research and privacy emerges. Although the goal of data collecting is to provide information that can be used broadly, just 6% of medical research were fully replicable, and 65% of studies showed conflicting results when retested. Of the 108 papers that we have analyzed, just 4 have made the techniques or source code for the research publicly accessible. investigations that are not repeatable need gathering more private and personal data for a specific scientific topic; this emphasizes the significance of reproducibility in investigations, particularly in the health field where research involves ethical and economical concerns. Federated learning cannot be the only answer to the privacy issue if it does not provide for the opportunity of verifying data analyses, re-analyzing data using other techniques, or pooling data across projects. However, the strategy might serve as a model for creating privacy-preserving techniques that also allow for study replication in the future. Using publicly accessible datasets is one option. Source code may be shared more widely so that HAR approaches could be evaluated on publicly accessible datasets, perhaps along the lines of how machine learning research uses datasets with handwritten numbers to evaluate classification techniques. While there have been some attempts in this area, the suggested approach is predicated on gathering and evaluating data from a broad range of sensors on a variety of understudied populations and certifying classifiers against generally acknowledged gold standards.

VI. Conclusion

Smartphone-based human activity recognition (HAR) has become a potent tool for comprehending human behavior. Through the use of an array of integrated sensors, such as magnetometers, gyroscopes, and accelerometers, HAR systems convert the language of human movement into useful information. As the maestro, machine learning algorithms identify actions with ever-increasing precision by identifying attributes from the sensor data. This technology has enormous promise in a variety of fields, including the creation of intelligent surroundings that can adjust to human requirements and the promotion of fitness and health via individualized monitoring. Further investigation into sensor fusion methods and the incorporation of more sensors, such as GPS, holds potential for improving the resilience of HAR systems. But resolving privacy issues and guaranteeing energy efficiency continue to be critical factors for the moral and sustainable development of this game-changing technology. With smartphones, HAR has a bright future ahead of it. It has the ability to completely change our perception of human behavior and its uses in an increasingly intelligent society.

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