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Signal Feature Extraction and Machine Learning Techniques for Human Activity Recognition

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Abstract

Human Activity Recognition (HAR) has emerged as a critical field of study with diverse applications in healthcare, fitness tracking, smart homes, and human-computer interaction. The aim of this research is to create an efficient HAR system through advanced techniques characterized by signal feature extraction and machine learning algorithms. The MEMS sensors are used appropriately during data mining to extract time-domain, frequency-domain, and statistical features, which are subsequently passed to the models for classification. Majority of the implementations of the experiments conducted in this study will be based on formulations of support vector machines (SVM), random forest, and neural networks to classify activities like walking, running, sitting, and lying down. Feature selection applications, such as PCA, were integrated into their methods to optimize the feature set, which further advanced the goal of efficiency and accuracy of the machine learning models. The experimental results prove the proposed approach as mostly accurate across the dataset in multiple activities conducted. Key performance indicators for the model include precision, recall, and F1-score, which help evaluate its effectiveness. These highlight the importance of combining optimized signal feature extraction with machine learning techniques to design real-time, reliable HAR systems. This study results in a contribution to scalable and adaptive HAR frameworks that lead to smart applications and intelligent systems monitoring them. Works will further delve into deep learning techniques and multimodal sensor data to enhance the performance of these systems.

Keywords: Human Activity Recognition, signal feature extraction, machine learning algorithms, support vector machines, random forest, neural networks

INTRODUCTION

Human Activity Recognition (HAR) is an important tool that enables modern technology-enabled applications across the domains of healthcare, smart homes, fitness, and security. In the healthcare domain, HAR allows patient monitoring, early fiscal health problems, and rehabilitation support through tracking physical activities and mobility patterns [1]. In smart homes, HAR helps automate functions and enhances user convenience with adaptive environments responding to a resident's behavior, such as adjusting lighting or temperature based on detected activities. In fitness, HAR powers Wearables and apps that offer tailored fitness plans, monitor exercise routines, and assess progress against health goals. Within the realm of security, HAR feeds into surveillances to pick up on unusual or possibly hazardous behaviors, thus inculcating public safety and preventing crime. By exploiting the cutting edge of sensor technologies and machine learning methods, HAR makes real-time and accurate recognition of human behavior possible,

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hence constituting the basis on which intelligent user-centered systems that heighten the quality of life and safety are built [2]. The field of Human Activity Recognition (HAR) has seen significant progress, transitioning from conventional methods to advanced data-driven techniques (Figure 1).

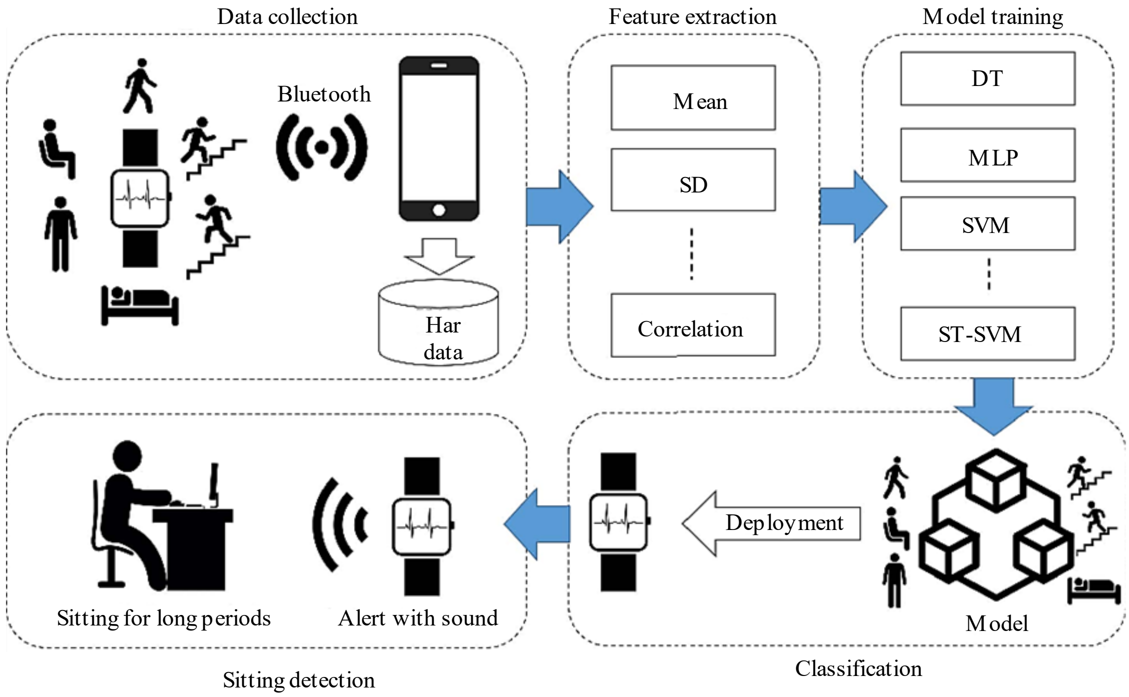

Figure 1. Human activity recognition workflow.

Traditional HAR methods relied mainly on rule-based systems and statistical models. Mostly, handcrafted features coming from sensor data, which took time and frequency domains, were combined together with simple classifiers, such as decision trees or k-nearest neighbors (k-NN) [3]. While these methods were computationally efficient and interpretable, they struggled with scalability, robustness to noise, and adapting to complex activities or large datasets. Modern HAR approaches leverage machine learning and deep learning techniques for more accurate and robust activity recognition. Machine learning algorithms, including Support Vector Machines (SVM), Random Forest, and Gradient Boosting, are employed to classify activities based on features derived from sensor data. Deep learning models, that is, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have revolutionized HAR by automating feature extraction and capturing complex temporal and spatial dependencies found in sensor data [4]. These models perform excellently well with large datasets and multimodal sensor inputs, such as accelerometer, gyroscope, and camera data. Further, modern HAR systems involve transfer learning, ensemble methods, and hybrid architecture bolstering performance. With progress made in edge computing and lightweight deployment of models, RT-HAR has also been made possible. Traditional methods remain useful in fairly simple applications and resource-constrained environments, while modern approaches act as enablers of innovation in HAR, resulting in more accurate, scalable, and versatile systems across varied domains. The integration of signal feature extraction and machine learning provides a highly efficient and powerful approach to Human Activity Recognition (HAR). Signal feature extraction enables raw sensor data to be represented meaningfully in a compact manner that contains its essential information about human activities [5]. This significantly cuts down the computational complexity, enhances the interpretability, and provides better discrimination of activity patterns; all this sure positively heightens the landscape for accurate classification. Machine learning algorithms further utilize these extracted features to model complex and nonlinear relationships in the data; this empowers robust and adaptable activity recognition [6]. Through the combination of feature extraction, machine learning systems demonstrate robust performance even in contexts involving limited training data with variances because of diverse user populations with different environmental conditions. Such a configuration also allows the system to generalize and recognize a huge variety of activities while remaining less dependent on the characteristics of the observations in the case study. Moreover, feature extraction integrated with machine learning is in line with the rising demand in real-time HAR applications for the various fields of healthcare, fitness, and smart environments. It provides a rather balanced computational efficiency and classification accuracy that is suitable for implementation in edge devices and Wearables. This marriage fosters supporting work in HAR research and drives development in intelligent systems and personalized technology solutions.

PROBLEM STATEMENT

Constructing real-time accurate Human Activity Recognition (HAR) systems encounters various challenges owing to the complexity of human behavior and limited technology to be accommodated. Human activity variability is one of its major challenges, as an individual will perform the same activity differently based on physical attributes, habits, and context [7]. This variability complicates proper generalization of a HAR system across users and activity settings. Environmental noise poses a further challenge to HAR due to the introduction of irrelevant signals when data is collected by sensors. Background vibrations, ambient sound, or other extraneous noise can sufficiently diminish the perceptibility of activity patterns, thereby lessening the accuracy of activity recognition. Such unpredictable noises characterizing real-world usage pose great challenges to developers of robust HAR systems. Sensors in themselves play a significant role in HAR performance. Some sensors have a limited range, resolution, or sensitivity, leading to poor or missing coverage in data capture. Moreover, in wearable sensors, issues like misalignment, displacement, and battery limitations will impact data quality and consistency [8]. Real-time processing requirements make this task even more difficult, as HAR systems need to balance between computational efficiency and accuracy. It can be particularly difficult to process large amounts of data in real time, low latency, and with minimal resource consumption, especially for edge devices and embedded systems. Solutions to these problems involve advanced signal processing, robust feature extractions, and machine learning algorithms that can adapt to various conditions. Hybrid and ensemble approaches combined with multimodal sensor integration are the promising avenues to provide solutions to the hurdles in achieving real-time HAR systems with accuracy and robustness [9].

OBJECTIVE OF THE STUDY

The primary focus of this study lies on the enhancement of accuracy and robustness of human activity recognition system supported with a host of signal feature extraction techniques and advanced machine learning algorithms. This includes finding and extracting meaningful features from sensor data, like accelerometer and gyroscope signals, meant to reduce noise and better class activity. There would be designing and testing of feature optimization techniques maximizing discrimination power while minimizing complexity, where complexity tends to refer to the hardware capacity and capability. Also, the research seeks to explore and implement several machine learning algorithms to effectively model complex and nonlinear patterns within the human activity data [10]. The study proposes to identify the most fitting algorithms for real-time HAR applications and scale its applications by making comparisons of support vector machines, Random Forest, and deep Learning Models, ensuring systematic comparisons across each of the algorithms. The overarching goal is to create a HAR framework that is accurate across heterogeneous user populations and contexts and to be robust against such challenges as movement variability, environmental noise, and sensor inconsistencies. This framework would create a positive contribution toward adopting HAR in critical application sectors such as healthcare, fitness monitoring, smart homes, and security systems.

LITERATURE REVIEW

Methods and algorithms for Human Activity Recognition are divided into two basic categories: Traditional and Modern [11]. While the former relied majorly on rule-based systems, statistical models, and template matching, the recent methods relied mostly on the machine learning paradigm. Rule-based systems employed some preset thresholds and conditions to classify activities based on sensor data, but could hardly adapt to changes in activity or identify new activity patterns. Other statistical models, such as Hidden Markov Models and Gaussian Mixture Models, provided an effective means to represent temporal dependencies from activity sequences; however, their majority relied on handcrafted features, limiting their scalability and robustness [12]. Template matching approaches directly compared the incoming sensor data with predefined templates of an activity pattern; however, they imputed different behaviors of users across different iterations along with noisy inputs. On the contrary, the contemporary HAR methods employ learning algorithms that make it possible to learn automatically patterns from the data offered, hence making it a lot more flexible and accurate compared to the earlier methods [13]. Among such methods, supervised learning methods of classification that include Support Vector Machines, Random Forest, and k-Nearest Neighbors are among the most commonly used based on the features pulled out from the sensor data. CNNs and RNNs are increasingly popular for the hierarchical and temporal feature-learning capabilities that allow raw data to be fed directly into them. The combination of different models is also sometimes referred to as ensemble approaches (e.g. boosting and bagging) to achieve better performances and robustness [14].

In addition, transfer learning is another effective technique used to deploy pre-trained models to new datasets with limited labeled data in a new environment. Hybrid and multimodal techniques integrate data from various sensors, including accelerometers, gyroscopes, and cameras, to improve the precision and dependability of Human Activity Recognition (HAR), particularly in challenging or noisy environments [15]. Together, these methods have bolstered the state-of-the-art in HAR, allowing additional precise, real-time, and context-aware action recognition systems. Techniques of signal processing are critical for HAR since they transform the raw data from the sensors into meaningful features that downcast noises and high-dimensional data and can hence be used in machine learning algorithms to help classify the activities accurately. Other studies directly set up signal processing methods optimized for various domains of HAR endeavors, contributing to activity-recognition performance [16]. Time-domain analysis is one of the most commonly adopted signal processing techniques in HAR, where various basic statistical features are extracted from raw sensor signals for activity recognition. Such measured basic features include the mean, standard deviation, variance, skewness, and kurtosis for characterization of activities such as walking, running, or sitting. But while studies have shown that time-domain features may indeed capture natural patterns of motion, these features were often not adequate for more complex patterns, since the more differentiation in activity dynamics warranted the use of further signal processing techniques. Frequency-domain analysis is again a popular approach here, which incorporates transforming the sensor data into the frequency domain using methods such as the Fast Fourier Transform (FFT) [17].

However, since periodic patterns in activities can be seen using this method, repetitive activities such as running or cycling may be recognized. According to studies, frequency-domain features such as spectral entropy and dominant frequency provide a better classification of activities with cyclical movements. They might not be ideal for tasks that involve irregular or unpredictable patterns. Wavelet Transform is finding more popularity in HAR owing to the capacity of the technique to analyze non-stationary signals with features characterized simultaneously in time and frequency [18]. Continuous wavelet transform and discrete wavelet transform allow for multi-resolution analysis, hence suitable for recognizing activity patterns at multiple scales. In numerous studies, features based on wavelets have been shown to increase the classification's accuracy, especially for the detection of activities with sudden changes or varying durations. Statistical and higher-order moments, such as skewness and kurtosis, extracted from raw signals or from pre-processed signals can provide additional information about the nature of the activity. These moments give information about the distribution and shape of the data, which can be used to distinguish between activities that have similar motion patterns but different statistical properties. A new single technique is multivariate signal processing, where features are extracted from data captured by multiple sensors (accelerometers, gyroscopes, and magnetometers). This multivariate way enables richer contextual information for better activity recognition since the system can analyze movements through multiple axes and planes. Many researchers have found out that the combination of diverse sensors enhanced the robustness of HAR systems, especially in dynamic and real-world environments. Techniques such as PCA and ICA, commonly used for feature selection and dimensionality reduction, are extensively researched for simplifying data while retaining critical information. By removing redundant features, these methods enhance the classification process's speed and efficiency. Adaptive filtering and noise reduction techniques have also been recently used to address sensor imperfections and environmental noise. Methods such as Kalman filters, median filtering, and moving averages are commonly used to smooth noisy sensor data before feature extraction to improve the quality of the input for machine learning models [19]. Overall, the signal processing technique in HAR will play a key role in feature extraction, improving data quality, and enhancing machine learning model accuracy in classification. As sensor technology advances and the complexity of targeted activities increases, research in signal processing will remain crucial for building accurate, real-time, and scalable HAR systems. It is computationally efficient and more straightforward to derive but has limits in the information it can grasp about complex behaviors. Frequency domain features are used suitably for repeated activities but seem less appropriate in the case of non-repeating behaviors. The flexibility to capture non-stationary signals and multivariate data is richer for the information retrieved from multiple sources, but certainly, it brings in more complication. Feature selection methods are useful for dimension reduction but might filter out subtle interaction relations in the underlying data. Machine Learning Models are Simpler models such as SVM and k-NN, are better suited for small data sets or when computation speed is essential but are challenged with high dimensional data or complicated patterns.

The random forest provides a good trade-off between the two factors: accuracy and interpretability, with large data sets [20]. Deep learning models, including CNNs and RNNs, can handle huge and complex data but need tremendous computational resources and large training data. It mainly depends on the complexity of data, the desired interpretability, and computational constraints. In a nutshell, it can be concluded that optimized feature extraction techniques in combination with appropriate machine learning models significantly affect the performance of HAR systems. This again depends upon the specific application, the nature of activities to be recognized, available computational resources, and the quantity of labeled data. Although there have been considerable advancements in Human Activity Recognition (HAR), there are still several research gaps and limitations present in the current methods. The generalization of HAR models across different environments and users is one of the major challenges. Most HAR systems are trained and evaluated using specific datasets, often collected in controlled settings with a limited number of subjects. This leads to models that fail to generalize to real-world scenarios where activities vary widely across individuals, environments, and contexts. The variability in human movements and the influence of personal characteristics, such as age, fitness level, and health conditions, further complicate the task of building universally accurate HAR systems. Additionally, sensor limitations pose a significant challenge. Most existing systems focus on a specific type of sensors, such as accelerometers or gyroscopes. These sensors have the disadvantage that they are quite sensitive to noise and placement variability, which introduces errors in recognizing activities. Adding multiple sensor modalities can improve this limitation.

However, previous methods fail to effectively fuse different sources of information to enhance their accuracy [21]. One of the greatest limitations of most HAR systems is their real-time performance and scalability. While machine learning models, particularly deep learning techniques, have achieved promising results for improving classification accuracy, they typically require large amounts of data and computational resources and are therefore not very practical for real-time applications or resource-constrained devices like Wearables or smartphones. Many of the feature extraction techniques also do not adapt well to dynamic or evolving activities. Consequently, HAR systems fail to recognize complex or transitional activities that do not fit predefined patterns. Activity labeling and the lack of large annotated datasets are still major barriers for training more robust models. The lack of large, diverse, and accurately labeled datasets is a barrier to the development of HAR systems that can work effectively in diverse environments. Finally, whereas some studies have focused on the optimization of algorithms for activity classification, there is a lack of comprehensive studies that address user privacy, security concerns, and ethical considerations in the collection and use of sensor data. Further research into more adaptable, efficient, and scalable HAR methods that can account for real-world complexities and promote wider adoption in everyday applications will fill these gaps [22].

SIGNAL DATA COLLECTION AND FEATURE EXTRACTION

In Human Activity Recognition (HAR), a variety of sensors are used to capture the motion and behavior of individuals in order to classify different activities accurately. The most commonly used sensors are accelerometers and gyroscopes, which measure specific physical properties such as acceleration and angular velocity [23]. Accelerometers measure linear acceleration along one or more axes (commonly 3D: x, y, and z) and report critical information regarding the speed and direction of a person's movement. The sensors are popular because they are inexpensive, small, and can easily be embedded in wearable devices such as smartphones, smart watches, and fitness trackers. Accelerometers are more effective for activity recognition such as walking, running, or sitting because they can capture movement intensity and patterns. Gyroscopes measure angular velocity, detecting rotational movements, such as changes in orientation or posture. They are useful for recognizing activities involving turning, bending, or complex rotational motions, such as cycling, swimming, or jumping [24]. Accelerometers and gyroscopes, when used together, provide a more complete view of the activity of a person and improve the robustness of the HAR systems (Figure 2).

Other wearable devices feature magnetometers, which are capable of measuring the Earth's magnetic field and detecting shifts in orientation. Wearable devices combining multiple sensors, including accelerometers, gyroscopes, and magnetometers, are known as inertial measurement units (IMUs). These provide valuable, complex data that can enhance the precision of activity recognition models. Moreover, smart watches and fitness trackers assemble these sensors into compact wearable formats that provide real-time data collection, which further facilitates personal health monitoring and activity tracking. Increasing availability of low-cost portable devices has increased the range of HAR applications from healthcare and fitness to security and smart home systems. Despite their advantages, challenges remain, such as sensor placement sensitivity, data noise, and energy consumption, which researchers continue to address in the development of more efficient and accurate HAR systems [25]. HAR, therefore, obtains data of multiple types to ascertain the accurate classification of human activity. The primary data type, time-series, is usually sensed through accelerometers and gyroscopes. Time-series data captures all sensor readings over a time period to generate a continued flow of measurements as there are always changes in how one moves or maintains posture over time.

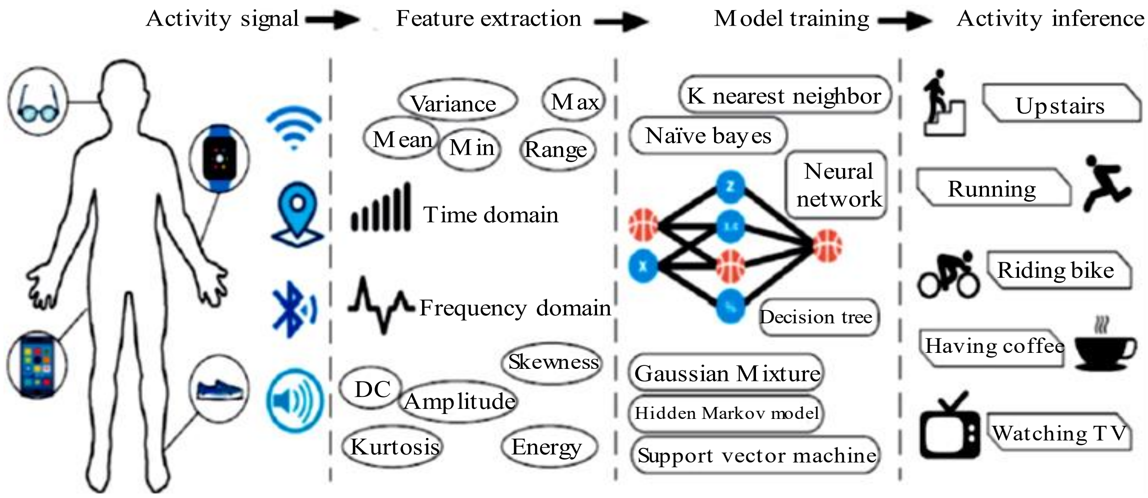

Figure 2. Process of human activity recognition using hand-crafted features modeled with Machine learning algorithms [3].

This data is highly important in discovering temporal patterns and trends; it is essential, therefore, in activities where successive movements take place, like walking, running, or even going up stairs. Motion data forms a specific set of time-series data, mainly the physical movement of the body, thus including measurements on acceleration, velocity, angular velocity, and displacement, captured through sensors like accelerometers and gyroscopes. Motion data is very important for activity recognition, especially when the activities are of different types, such as cycling, jumping, or bending. Besides motion data, physiological data is increasingly being used in HAR, especially in healthcare or fitness tracking contexts. Physiological data includes heart rate, body temperature, skin conductivity, and respiratory rate, which are usually measured through wearable devices, such as smart watches, fitness bands, or chest straps. Physiological data shows the response of the body towards physical activities and adds an additional layer of information that may increase the accuracy in activity recognition. For example, heart rate information can differentiate between running and walking or help indicate the intensity of activity. In addition, environmental data, such as ambient temperature, light, or pressure, can be collected, though it is less commonly used compared to motion and physiological data. Combining time-series data, motion data, and physiological data, HAR systems can gain a more comprehensive understanding of an individual's activities, improving the accuracy and robustness of activity classification across different contexts and environments [26]. Feature extraction is one of the most important parts of a Human Activity Recognition system, which converts raw sensor data into meaningful information that can be used for classification. One of the main challenges in HAR is the high dimensionality of the data, especially when collecting time-series data from multiple sensors. Sensor data can be vast and noisy, which makes it challenging to discern meaningful patterns or connections. This feature extraction actually reduces the data's dimension but still captures its main characteristics which are vital for precise activity recognition. For example, if mean, variance, skewness, and entropy features of accelerometer data are extracted, it will condense the raw data into a set of values which represents the significant aspects of activity. These extracted features make it easier for the machine learning algorithm to go through the motion patterns underlying the activities being measured, thereby ensuring proper classification. Moreover, extraction of features increases the efficiency of learning algorithms by eliminating unwanted or superfluous information. Therefore, in a high-dimensional set of data, many features may be interrelated or less helpful, which increases the chances of overfitting and poor generalization. Application of techniques such as PCA or ICA reduces dimensionality without much loss of important information, which also makes the models more robust and computationally efficient. Feature extraction also enables incorporating domain-specific knowledge, such as human motion patterns or activity-specific thresholds, into the recognition process. This process of reducing data complexity while preserving meaningful patterns is important to improve the accuracy and scalability of HAR systems, especially in real-time applications where computational resources may be limited. In summary, feature extraction allows critical activity-specific characteristics to be extracted from raw sensor data, thus leading to better performance in HAR systems. Following are details of types of features extracted, shown in Figure 3.

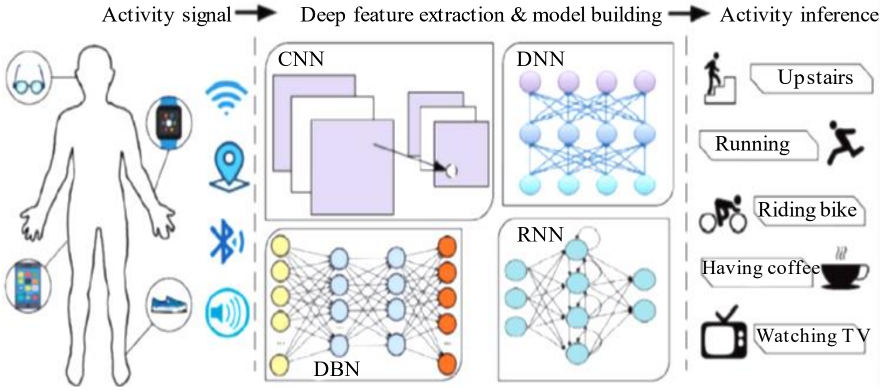

Figure 3. Process of human activity recognition using raw inertial signals modeled with deep learning algorithms [3].

Time-Domain Features

Time-domain features are directly extracted from the raw sensor data, focusing on the statistical properties of the signal over time. These features capture the general characteristics of the motion and can be easily computed. Some common time-domain features include:

- *Mean:* The average value of the sensor signal over a specific time window, representing the overall level of the signal.
- *Variance:* A measure of the signal's variability or spread around the mean, which indicates the intensity of movement or change.
- *Skewness:* The degree of asymmetrical distribution. Positive skewness refers to a distribution where the tail on the right side is extended, while negative skewness indicates a distribution with a longer tail on the left side.
- *Kurtosis:* Measures the "tailedness" of the distribution of the signal. Higher kurtosis points to spiky peaks and heavier tails; a lower value for kurtosis indicates that the distribution is flat. These are features to differentiate regular movements from irregular movements.

Time-Domain Features are useful to recognize simple activities, such as sitting, standing, or walking but cannot pick out more subtle complex movements.

Frequency-Domain Features

Frequency-domain features can be extracted by transforming the time-domain signal into its frequency components, which expose periodic patterns in the data [27]. This is typically done by applying a Fourier transform, which breaks a signal down into its individual frequency components. There are a few key frequency-domain features:

- *Fourier Transform:* This technique converts a time-domain signal into its frequency-domain representation, indicating the dominant frequencies in the activity. High-frequency components may represent rapid movements, whereas low-frequency components may represent slower, sustained activities.
- Power Spectral Density (PSD) represents the distribution of power across various frequency ranges. The information it carries can be utilized in distinguishing activities by their respective frequency characteristics since the energy contained within the signal is represented at different frequencies. For instance, walking may carry more low-frequency energy, whereas fast running may be more high frequency.

Frequency-domain features are more suitable for activities that involve periodic movements or vibrations, such as running, cycling, or jumping, etc.

Statistical and Geometric Features

In addition to the basic time and frequency-domain features, statistical and geometric features capture higher-order characteristics of the data. Such features include:

- *Median:* Similar to the mean but not very susceptible to outliers, median represents the middle value of the signal.
- *IQR:* This measure calculates the range between the 25th percentile and the 75th percentile, thus telling how much variation there is within the signal.
- *Autocorrelation:* A way to check on how well a signal auto-correlates with a shifted version of itself to detect periodicities in repeated actions.
- *Geometric Features:* Euclidean distance or angles between sensors are geometric features, which could be used in characterizing relative movements and posture of the body in multi-sensor setups such as in body-worn devices.

These features allow both capturing the shape of the signal and relationships among different sensors.

Wavelet-Based Features

Wavelet-based features are extracted based on wavelet transforms that split a signal into components at several scales or resolutions [28]. While Fourier transform provides global frequency representation, the wavelets give the time-frequency analysis that might describe non-stationary signals well, like the human movements. Some common wavelet-based features are:

- *Wavelet Transform:* It breaks up the signal to be analyzed as a collection of basic functions with locality in the time and frequency domains. It can grasp transient or locally localized features, and therefore is favorable for capturing time-varying, complex behaviors.
- *Wavelet Energy:* Calculated from wavelet transform is the total amount of energy existing in a predefined band of frequencies. It presents an insight into human activity at every scale about their frequency characteristics.

Wavelet-based features are particularly useful in complex activities like gestures or transitions between different movements, where features based on the time domain or frequency domain could miss important information.

Feature Selection Techniques

Feature selection is an essential part of optimizing HAR systems, reducing the dimensionality of the data and eliminating the irrelevant or redundant features. Among the common techniques for feature selection are:

- *Principal Component Analysis (PCA):* PCA is an orthogonal technique for data reduction based on linear transformation, whereby the original features are transformed into a smaller set of uncorrelated components, namely principal components, which represent the maximum variance in the data. So, by retaining the most significant components, PCA reduces the dimensionality and saves computation.
- Linear Discriminant Analysis (LDA) is a supervised method that identifies linear combinations of features to effectively distinguish between different activity classes. It maximizes the between-class variance while minimizing the within-class variance and is thus useful for improving the accuracy of classification.
- *Mutual Information:* This technique measures the dependency between features and the target class, and it selects the features that give the most information about the activity class.
- Recursive Feature Elimination (RFE) is a process that repeatedly ranks features based on their significance and removes the least important ones until the most relevant subset of features is identified.

These feature selection techniques help optimize the performance of HAR systems in terms of better performance, reduced computational load, and generalization improvement for more accurate and real-time activity recognition.

SIMULATION AND EXPERIMENTAL SET UP

In HAR, various algorithms are used based on machine learning to classify the activity using features extracted from the sensor data [29]. They can be categorized mainly into supervised, unsupervised, and deep learning algorithms, depending upon the nature of the given problem and data. The following are some of the common algorithms used in HAR,

1. Support Vector Machine (SVM) is a type of supervised learning algorithm that works by identifying the best hyperplane in a multi-dimensional feature space to distinguish between various activity classes. It is particularly effective and resilient, especially when dealing with non-linear data, thanks to the use of kernel functions. It is especially effective in HAR tasks with relatively small datasets and high-dimensional feature spaces.
2. Random Forest is an ensemble learning technique that merges several decision trees to enhance classification accuracy while reducing the risk of overfitting. It works by generating lots of trees on random subsets of the training data and making decisions in accordance with the majority vote

from all the trees. As a result of this property, it gets widely applied in HAR, especially to handle large-sized datasets and to deal with noisy data for reliable activity recognition.

3. K-Nearest Neighbors (k-NN) is a straightforward, instance-based algorithm where the classification of a new data point is determined by the majority class of its k closest neighbors in the feature space. Since it does not require a training phase, it is computationally efficient. However, it can struggle with the curse of dimensionality and may not perform optimally in high-dimensional settings.
4. Neural networks, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are widely used in Human Activity Recognition (HAR). CNNs can be used to extract spatial features, while RNNs can be used with sequential data so are more likely to be good in time-series data for HAR. Neural networks, particularly deep learning models, can independently identify and learn complex features directly from raw data, removing the necessity for manually designed features.

Steps in ML Model Development

1. Data preprocessing is a crucial step in preparing raw sensor data, ensuring it is clean, consistent, and suitable for use in machine learning models.
2. Normalization/Standardization: It puts the data on the same scale. Normalizing sensor data to the range {0, 1} or standardizing data by removing the mean and scaling to unit variance can help avoid features from overwhelming the model as they would naturally because of differing scales.
3. Noise Removal: Sensor data often contains noise due to external factors or inaccuracies in sensor readings. Techniques like low-pass filtering, median filtering, or moving average smoothing are used to remove high-frequency noise and improve signal quality.
4. During the training phase, the machine learning model identifies the connections between features and activity labels using the training data. The model is then tested on unseen data (test set) to evaluate its performance, which can be in terms of accuracy, precision, recall, or F1-score.
5. Cross-validation is a technique used to assess how effectively a model generalizes new data. One of the most common methods is k-fold cross-validation, where the data is split into k sections. In this method, the model is trained in k-1 sections and tested on the remaining one, with the process repeating for each section. This reduces the possibility of overfitting and improves the model's performance on other portions of the data. Leave-one-out cross-validation is a unique form of k-fold cross-validation. It is applied when the size of the dataset is small.

Supervised Learning for HAR uses labeled data to train models, Unsupervised Learning identifies patterns in unlabeled data, while Deep Learning leverages layered neural networks for automatic feature extraction and robust predictions as shown in Table 1 [30].

EXPERIMENTAL SETUP AND EVALUATION METRICS

Experimental Setup and Environment for Data Collection

The experimental setup of Human Activity Recognition typically involves a controlled environment in which a set of sensors is used to capture data while the subject performs different predefined activities. In most cases, the setup contains wearable devices such as smartphones, smartwatches, or fitness trackers equipped with accelerometers, gyroscopes, and sometimes with additional sensors such as magnetometers or heart rate monitors. These devices are mounted on particular body parts, such as the wrist, waist, or chest, to capture relevant motion data [31]. The environment for data collection can range from a laboratory or clinical setting, where activities are performed in a controlled manner, to real-world scenarios, where participants perform everyday tasks in natural settings, such as homes, offices, or outdoor spaces. Most of the studies have subjects performing various activities such as walking, running, sitting, climbing stairs, or doing household chores, while sensors collect data continuously with time. The environmental setup also considers sensor calibration and proper synchronization of data among multiple sensors to increase the accuracy of the study. Some configurations may include additional equipment, such as video cameras or motion capture systems, for ground truth labeling to help verify and enhance the accuracy of activity recognition models.

Table 1. Key differences between Supervised**,** Unsupervised**,** and Deep Learning approaches for Human Activity Recognition (HAR).

Aspect	Supervised Learning	Unsupervised Learning	Deep Learning
Definition	Learns from labeled data, where both input features and activity labels are available.	Learns from unlabeled data, finding patterns or clusters in the data without predefined labels.	Uses multi-layered neural networks to automatically learn features from raw data.
Data Requirements	Requires large amounts of labeled data.	Requires no labeled data; only raw input data is needed.	Requires large amounts of labeled or unlabeled data for training.
Algorithms	SVM, Random Forest, k-NN, Decision Trees, etc.	k-means, DBSCAN, Hierarchical Clustering, etc.	CNNs, RNNs, LSTMs, Autoencoders, etc.
Performance	High accuracy if labeled data is abundant.	May have lower accuracy compared to supervised learning.	Can achieve state-of-the-art accuracy with sufficient data and resources.
Application	Suitable for problems with well-defined classes and labeled datasets.	Suitable for discovering patterns or clusters in data without prior knowledge of classes.	Suitable for complex data representations, temporal sequence modeling, and large-scale problems.
Complexity	Moderate to high, depends on the algorithm (e.g., SVM may be complex, k-NN is simpler).	Generally simpler to implement but harder to interpret.	High computational complexity, requires specialized hardware and large datasets.
Interpretability	Generally easier to interpret results (e.g., decision trees, feature importance in Random Forest).	Results are harder to interpret, as patterns or clusters must be manually analyzed.	Low interpretability due to the “black-box” nature of neural networks.
Scalability	Can be less scalable, particularly with large datasets and high-dimensional features.	Scales well with large datasets but may struggle with very high-dimensional data.	Highly scalable, especially when using GPUs or specialized hardware.
Handling of Temporal Data	May struggle with sequential or temporal dependencies unless specifically designed (e.g., SVM with time-series kernels).	Not well-suited for temporal data without additional modifications.	Well-suited for temporal data, especially with RNNs or LSTMs.
Use Cases	Activity classification when data is labeled and there are clear class boundaries.	Clustering or anomaly detection in activity data when labels are not available.	Complex activity recognition tasks, such as gesture recognition or multi-modal HAR.
Training Time	Moderate, depends on the size of the dataset and complexity of the model.	Typically shorter, but the quality of results may vary.	High, especially for deep learning models with large datasets.

Simulation

- Here we have considered examples of how to extract features from smartphone accelerometer signals to classify human activity with a machine learning algorithm. The feature extraction for the data involves the use of signal Time Feature Extractor and signal Frequency Feature Extractor objects. These are then used to train a support vector machine (SVM) model.
- The Sensor HAR (human activity recognition) App was used to collect raw accelerometer signals. The smartphone was worn by a subject during five different types of physical activities. The data set was then buffered to obtain 44 sample-long signals corresponding to a particular activity. The Dancing activity from the data set and the accelerometer signals in the y and z directions were removed in order to develop the Buffered Human Activity data set, which was stored in the Buffered Human Activity. Mat file that was utilized during this exercise.

- The accelerometer signals could be thought to consist of two major components. One is of "fast" variations over time due to the body dynamics, the physical movements of the subject. The other consists of "slow" variations over time due to the position of the body with respect to the vertical gravitational field.
- To decouple the signal variations that rapidly change from the slower ones, we will apply a high pass filter on original signals. Various features are taken off the filtered as well as non-filtered signal using the two objects: signal Time Feature Extractor and signal Frequency Feature Extractor. Such objects enable a performant calculation of multiple time and frequency features in one single function call.
- For time features, two signal Time Feature Extractor objects are configured. One is used to extract the mean of the unfiltered signals (meanFE) and the second is used to extract the root mean square, shape factor, peak value, crest factor, clearance factor, and impulse factor of the filtered signals (timeFE).
- For frequency features, signal Frequency Feature Extractor is used to extract the mean frequency, band power, half-power bandwidth, peak amplitude and peak location of the filtered signals.
- The computation of spectral peaks can be refined by setting more parameters. For instance, the maximum number of peaks is set to 6, and the minimum distance between each spectral peak is set to 0.25 Hz. Additionally, we choose an FFT length of 256 and a rectangular window of 44 samples (i.e., the signal length) to compute the spectral estimates.
- The computation of features for all the signals can be parallelized using transformed array datastores. The datastores read each matrix column and compute features using the extract function of the feature extractor objects.
- Call the readall method of transformed datastore with the "UseParallel" option set to true to distribute the computations across a pool of workers if Parallel Computing Toolbox is installed. The resulting computed features are combined to end up with 22 features for each one of the 7776 signal observations.

Train an SVM Classifier Using Extracted Features

One can import the features and activity labels into the Classification Learner app to train an SVM classifier. Alternatively, you can create an SVM template and classifier using a feature table containing the features (predictors) and the activity labels (response) as shown in Figure 4.

The SVM has an overall accuracy of about 95%. Most of the errors occur when misclassifying running as walking and standing as sitting [32, 33].

Data Partitioning and Evaluation Metrics for HAR

Data Partitioning

Data partitioning is a critical step in machine learning model development to ensure the generalization ability of the model. It helps avoid overfitting and provides insights into how the model will perform on unseen data. The common data partitioning techniques in Human Activity Recognition (HAR) are:

1. *Train-Test Split:*
   - The dataset is divided into two subsets: one for training the model and the other for testing.
   - Typically, a 70–30 or 80–20 split is used, where 70–80% of the data is used for training, and the remaining 20–30% is reserved for testing.
   - This approach is quick but may lead to variability in performance based on how the data is split.
2. *K-Fold Cross-Validation*
   - The dataset is split into k subsets (or folds). The model is trained on k-1 folds and tested on the remaining fold. This process is repeated k times, with each fold used as the test set once.
   - This method provides a more robust performance estimate by averaging the results over multiple splits, helping reduce bias due to random data partitioning.
   - k is often set to 5 or 10, though it may vary depending on the dataset size.

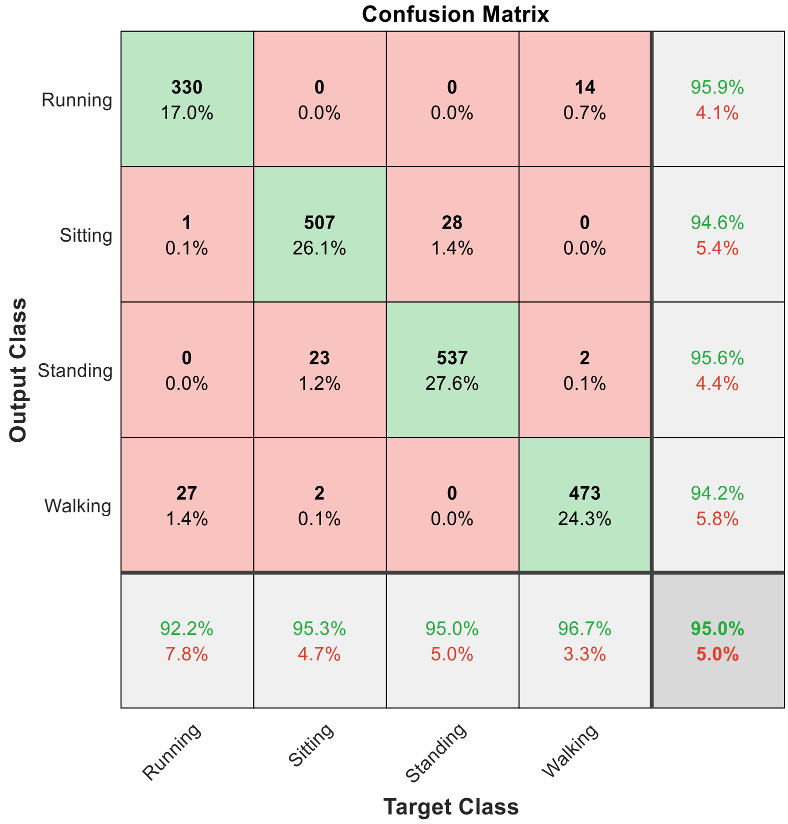

Figure 4. Confusion Matrix.

Metrics for Evaluating Model Performance

1. *Accuracy:*
   - Accuracy is the proportion of correct predictions made by the model, expressed as the ratio of correct predictions to the total number of predictions.
   - $\text{Accuracy} = \dfrac{\text{True Prositve} + \text{True Negative}}{\text{Total predictions}}$
   - Accuracy is often used for classification tasks, but it may not be sufficient when the data is imbalanced (i.e., one class appears more frequently than others).
2. *Precision:*
   - Precision measures the proportion of correctly predicted positive instances out of all instances predicted as positive. It indicates how many of the predicted positive activities were actually correct.
   - $\text{Precision} = \dfrac{\text{True Prositve}}{\text{True Prositve} + \text{False positive}}$
   - Precision is especially important when false positives (predicting an activity incorrectly as active) are costly.
3. *Recall (Sensitivity):*
   - Recall measures the proportion of correctly predicted positive instances out of all actual positive instances. It shows how well the model detects positive instances.
   - $\text{Recall} = \dfrac{\text{True Prositve}}{\text{True Prositve} + \text{False positive}}$
   - Recall is crucial when the cost of false negatives (failing to recognize an activity) is high.
4. *F1-Score:*
   - The F1-score is the harmonic mean of precision and recall. It is used when a balance between precision and recall is needed, especially in imbalanced datasets.

- $\mathrm{F-Score} = 2 \times \dfrac{\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recal}}$
- The F1-score is useful when neither false positives nor false negatives can be ignored.

5. *Confusion Matrix:*
   - The confusion matrix provides a detailed breakdown of the model's performance, showing the number of true positives, true negatives, false positives, and false negatives (Table 2).
   - By analyzing the confusion matrix, one can understand specific types of errors (e.g., false positives or false negatives) and optimize the model accordingly.

6. *Computational Efficiency and Real-Time Feasibility*
   - *Computational Efficiency:* This refers to the model's ability to provide predictions quickly, especially when working with large datasets or complex algorithms. It involves measuring the model's time complexity, memory usage, and the resources required for training and inference.
   - *Real-Time Feasibility:* In many HAR applications, such as wearable devices, real-time performance is crucial. Models need to make predictions quickly to provide immediate feedback. The feasibility of real-time deployment depends on factors like:
     - Model inference time (i.e., the time taken to classify a new observation).
     - Latency requirements (i.e., how quickly predictions need to be made).
     - Model size (i.e., the storage required for the model).

Table 2. A confusion matrix for a binary classification problem.

	Predicted Positive	**Predicted Negative**
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

RESULTS AND DISCUSSION

The performance of machine learning models in Human Activity Recognition (HAR) significantly depends on the quality and types of features extracted from sensor data. Different feature sets, such as time-domain features, frequency-domain features, statistical features, and wavelet-based features, contribute differently to the model's predictive capability. The analysis typically involves comparing the model’s performance using distinct sets of features to identify which subset provides the most accurate and reliable results.

- *Time-domain features* (e.g., mean, variance, skewness, and kurtosis) are often used for basic activity recognition, especially when simple activities are involved.
- *Frequency-domain features* (e.g., Fourier Transform, power spectral density) can capture periodic patterns in the signal, making them suitable for identifying more dynamic activities.
- *Wavelet-based features* offer advantages for capturing non-stationary and multi-scale behavior in the signal, which is essential for complex activity patterns.

By evaluating models on different feature sets, one can determine the importance of each feature type in improving accuracy and robustness. This analysis helps refine the feature extraction process, ensuring the model learns from the most relevant information.

Impact of Signal Preprocessing and Feature Extraction on Accuracy

Signal preprocessing and feature extraction play a crucial role in improving the accuracy of HAR models. Raw sensor data can often be noisy or inconsistent, making preprocessing a necessary step to ensure the features fed into the machine learning models are relevant and clean.

- *Signal Preprocessing* includes techniques like *denoising*, *normalization*, and *resampling* to reduce noise and handle sensor imperfections. Proper preprocessing ensures that the features reflect the actual human activity rather than noise or sensor anomalies.

- *Feature Extraction* helps transform raw data into meaningful representations. For example, computing statistical features from time-domain data or extracting frequency-domain components via Fourier Transform can reveal patterns critical for distinguishing between activities. By removing irrelevant or redundant information, feature extraction reduces dimensionality, making the model more efficient and improving accuracy.

The accuracy of the model is often directly correlated with how well the data is preprocessed and how effective the feature extraction techniques are in representing the underlying human activities (Tables 3 and 4).

Table 3. Comparison of machine learning models based on common performance metrics used in Human Activity Recognition (HAR).

Machine Learning Model	Accuracy	Precision	Recall	F1-Score	Computational Efficiency	Real-Time Feasibility
Support Vector Machine (SVM)	High (for well-separated data)	High for binary classification	Moderate (depends on hyperparameters)	High (balanced precision and recall)	Moderate (depends on kernel complexity)	Low (requires more computational power for large datasets)
Random Forest	High (for larger datasets)	High (handles imbalance well)	Moderate	High (good trade-off)	Moderate (slower than some models)	Moderate (suitable for real-time with tuning)
k-Nearest Neighbors (k-NN)	Moderate (depends on distance metric)	Moderate	Moderate	Moderate	High (simple algorithm with low complexity)	High (fast inference but may struggle with large datasets)
Neural Networks (ANN, CNN, RNN)	Very High (with sufficient data)	High	High	Very High (especially deep learning)	Low (computationally expensive)	Low (requires powerful hardware, but deep learning models can adapt to real-time needs with optimization)
Decision Tree	Moderate	Moderate	Moderate	Moderate	High (simple and fast)	High (quick inference but may overfit)
Logistic Regression	Moderate	Moderate	Moderate	Moderate	High (simple and fast)	High (fast for real-time applications with small feature sets)

Table 4. Challenges encountered in Human Activity Recognition (HAR) and the solutions.

Challenge	Description	Solution Implemented
Data Imbalance	Some activities may be underrepresented, leading to biased models that favor more common activities.	• *Oversampling* minority classes (e.g., SMOTE).
		• Undersampling majority classes.
		• Use of class-weighted loss functions in models.
Noisy Sensor Data	Sensors may capture environmental noise or inaccurate readings, affecting model accuracy.	• Signal filtering (e.g., low-pass filters).
		• Denoising algorithms like wavelet transforms.
		• Normalization techniques to standardize sensor data.
Time and Space Variability	Human activities can vary widely across individuals or environments, causing generalization issues.	• Domain adaptation techniques.
		• Use of temporal models (e.g., RNNs, LSTMs) to capture activity dynamics.
		• Feature selection techniques like PCA and LDA.

High Dimensionality	A large number of features may lead to overfitting and computational inefficiency.	• Use of *dimensionality reduction* methods to retain relevant features.
Real-Time Processing Requirements	Many HAR applications need low-latency and efficient model inference for real-time action.	• Optimization of *feature extraction* methods.
		• Use *of lightweight models* (e.g., decision trees, random forests).
		• *Model quantization* and compression to reduce inference time.
Sensor Limitations	Variability in sensor quality, placement, and calibration can lead to inconsistent data.	• *Calibration* of sensors before data collection.
		• Use of *multiple sensor modalities* to increase robustness (e.g., accelerometer + gyroscope).
Overfitting	Models may perform well on training data but fail to generalize unseen data.	• *Cross-validation* techniques to assess generalization.
		• Use of regularization methods (e.g., L2 regularization).
Scalability	Scaling models to handle larger datasets or complex activity patterns.	• Use of *ensemble methods* (e.g., Random Forest, XGBoost).
		• *Data augmentation* to artificially increase dataset size.

CONCLUSION AND FUTURE WORK

This study offers an in-depth examination of human activity recognition (HAR) by leveraging signal feature extraction and machine learning methods. Key findings include the importance of selecting appropriate features, such as time-domain, frequency-domain, and wavelet-based features, to enhance model accuracy. The research emphasizes the crucial role of preprocessing and feature extraction in enhancing the effectiveness of machine learning models. The research contributes to a deeper understanding of how different algorithms such as SVM, Random Forest, and neural networks perform in HAR tasks, providing valuable insights for selecting the most suitable model for specific applications.

The results of this study hold great importance for advancing the creation of more precise and reliable human activity recognition (HAR) systems. The study suggests that optimizing signal feature extraction methods and utilizing more advanced machine learning algorithms can lead to enhanced performance in real-time applications, such as healthcare, fitness tracking, and security systems. Furthermore, the research highlights the potential for integrating multimodal sensor data to improve activity recognition across varied environments and conditions, paving the way for more adaptive and reliable systems.

Simulation shows how to extract features for human activity based on smartphone sensor signals using signal Time Feature Extractor and signal Frequency Feature Extractor. It shows how to use the extracted features to train an SVM model which resulted in about 95% accuracy. As an alternative approach, one can also explore using a feature Input layer to train a deep learning classifier.

Future research on HAR systems could explore the integration of deep learning techniques, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to efficiently analyze complex temporal and spatial patterns in activities. Additionally, incorporating multimodal sensor data, combining accelerometers, gyroscopes, and physiological data (e.g., heart rate), could further improve accuracy and robustness. Further studies should also focus on optimizing models for real-time processing and scalability, making HAR systems more applicable for large-scale, real-world deployments.

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