ActivBench: Leveraging Human Activity Inference from Smartphone Sensors for Human Computer Interactions

Basma K. Eldrandaly
Faculty of Computers and Informatics, Zagazig University, Zagazig, 44519 Ash Sharqia Governorate, Egypt
Email: b.eldrandaly@fci.zu.edu.eg

Abstract

Human activity recognition (HAR) from smartphone sensors has gained significant attention due to its potential to enhance user experience (UX) and human computer interaction (HCI) in various domains, HAR can enable personalized, context-aware, and adaptive interfaces that improve accessibility and promote health and wellness in various applications such as healthcare, smart homes, fitness tracking, and context-aware systems. However, evaluating the performance of different machine learning (ML) algorithms on activity recognition tasks remains challenging, primarily due to the lack of standardized benchmark datasets and evaluation protocols. In this paper, we presented ActivBench, an end-to-end computational intelligence benchmark designed to facilitate the evaluation and comparison of ML algorithms for human activity inference from smartphone sensors. We addressed the challenges in benchmarking activity recognition systems by providing a unified evaluation protocol and standardized performance metrics. Through extensive experiments using various state-of-the-art algorithms, we demonstrated the effectiveness of ActivBench in assessing the strengths and limitations of different approaches. The benchmark results provide valuable insights into the strengths and limitations of different algorithms, facilitating the development of robust and accurate activity recognition systems that can enhance human computer interaction in various applications. ActivBench is serving as a valuable resource for researchers and practitioners in human activity recognition and human-computer interaction, enabling fair comparisons and fostering advancements in the field. It also serves as a catalyst for advancements in the field, enabling the exploration of novel algorithms, feature engineering techniques, and sensor modalities.

Keywords: ActivBench; Human Computer Interaction; Computational Intelligence; Benchmark; Human Activity Inference; Smartphone Sensors; Applied Intelligence

1. Introduction

Human activity recognition has gained significant attention in recent years due to its potential applications in improving the user experience in various applications, such as healthcare, fitness tracking, behavior analysis, smart environments, and more. HAR refers to the process of automatically identifying and classifying different activities performed by individuals based on data collected from various sensors. The goal is to develop computational models and algorithms that can accurately infer and classify activities, providing valuable insights into human behavior and enabling personalized, context-aware, and adaptive interfaces that improve accessibility and promote health and wellness. As the field continues to advance, we can expect to see more innovative applications of HAR in various domains, leading to a more seamless and intuitive user experience.

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The widespread use of mobile devices and wearable technology has created new opportunities for HAR in HCI. By recognizing the user's activity, the system can better understand the user's context and adjust its behavior accordingly, providing a more seamless and intuitive user experience. Furthermore, HAR can enable interfaces that adapt to the user's behavior and preferences, improving accessibility and promoting health and wellness. Despite its potential benefits, HAR poses several challenges that need to be addressed for effective implementation. Firstly, the complexity and diversity of human activities make it difficult to develop a comprehensive set of features and models that can capture the intricacies of each activity. Activities can vary in terms of duration, intensity, and execution style, leading to a high-dimensional and heterogeneous data space. Furthermore, there can be variations across different individuals, making it essential to account for inter-subject variability. Secondly, the choice of sensors and their placement can impact the accuracy and robustness of activity recognition systems, which in turn can affect the quality of the interaction. Different activities may require different types of sensors, such as accelerometers, gyroscopes, or wearable cameras, to capture the relevant information accurately. Deciding on the optimal combination of sensors and their placement on the body or in the environment is a crucial factor in achieving reliable activity recognition and improving UX and HCI [1] . Overall, incorporating HAR from mobile sensors in HCI requires addressing these challenges to ensure that the technology is accurate, reliable, and secure while providing meaningful insights to improve the user experience.

Computational intelligence (CI) plays a pivotal role in human activity recognition by providing powerful tools and techniques to analyze and interpret complex sensor data. With the help of computational intelligence approaches such as ML, and pattern recognition, it becomes possible to automatically learn and extract meaningful features from raw sensor data, enabling accurate inference and classification of human activities [2]. These techniques enable the development of robust models that can capture the inherent patterns and temporal dependencies in activity data, enhancing the performance and adaptability of activity recognition systems. This, in turn, enables the creation of more personalized, context-aware, and adaptive interfaces, improving the overall user experience. Furthermore, computational intelligence facilitates the integration of multiple sensors, allowing the fusion of information from different sources and modalities to improve the overall accuracy and reliability of activity recognition. By leveraging computational intelligence, human activity recognition systems can unlock the full potential of sensor data and contribute to various domains, including healthcare, smart environments, and personalized services. This can lead to a more seamless and intuitive user experience, improving the overall quality of HCI.

To this end, it is highly important to have a standardized benchmark to help evaluate the performance of different machine learning algorithms on activity recognition tasks. The focus of this research is to develop ActivBench, a benchmark that will serve as a valuable resource for researchers and practitioners in the fields of human activity recognition and human-computer interaction. ActivBench will enable fair comparisons between different approaches and techniques, facilitating advancements in the field. Additionally, it will act as a catalyst for the exploration of novel algorithms, feature engineering techniques, and sensor modalities, driving further advancements in the field. The remainder of the paper is organized as follows. Background and literature review in Section 2. Section 3 presents the proposed methodology. Section 4 presents the results and discussion. Finally, we conclude this paper in Section 5.

2. Background and Literature Review

In this section, we provide a comprehensive background and review of related studies that form the foundation of our research on human activity recognition. Understanding the context and existing research in this field is crucial for developing innovative and effective approaches. We dive into the fundamental concepts, techniques, and methodologies employed in activity recognition systems, exploring the advancements made in recent years.

2.1 Concepts and Terminologies

Human Activity Recognition

Human activity recognition is the process of automatically identifying and classifying the physical activities and movements of a person through the use of sensors and machine learning algorithms. HAR typically involves the collection of data from various sensors such as accelerometers, gyroscopes, and GPS, which can measure different aspects of the user's physical activities and movements. HAR has numerous applications, including healthcare, sports, security, and gaming. [3]

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Sensor fusion
Sensor fusion is the process of combining information from multiple sensors to improve the accuracy and reliability of activity recognition. Sensor fusion can help to overcome the limitations of individual sensors and enable more robust and accurate activity recognition. [4]

Feature extraction
Feature extraction is the process of identifying relevant features from raw sensor data that can be used for activity recognition. Feature extraction is a critical step in HAR since it enables the transformation of raw sensor data into a format that can be used by machine learning algorithms. [5]

Convolutional neural networks (CNNs)
Convolutional neural networks are a type of deep neural network commonly used for image and video processing, which can also be applied to activity recognition. CNNs are particularly well-suited for HAR since they can automatically learn and extract relevant features from sensor data. [6]

Recurrent neural networks (RNNs)
Recurrent neural networks are a type of deep neural network that can capture temporal dependencies in data, making them well-suited for activity recognition. RNNs can be used to model sequential sensor data, such as accelerometer or gyroscope data, and capture the temporal dependencies between different sensor readings. [7]

Support vector machines (SVMs)
Support vector machines are a type of machine learning algorithm commonly used for classification tasks, including activity recognition. SVMs work by finding the optimal hyperplane that separates different classes of data in a high-dimensional feature space. [8]

Hidden Markov models (HMMs)
Hidden Markov models are a statistical model commonly used for sequential data, including activity recognition. HMMs are particularly well-suited for activity recognition since they can capture the temporal dynamics of different activities and model the transitions between different states. [9], [10]

User interface (UI)
User interface is the visual and interactive components of software or hardware products that enable users to interact with them. UI is particularly important in HCI since it enables the creation of software that is intuitive, easy to use, and meets the needs of users. [11]

Usability testing
Usability testing is a process of evaluating software or hardware products by testing them with representative users. Usability testing is critical in HCI since it enables the identification of usability issues and the refinement of software to better meet the needs of users. [12], [13]

Interaction design
Interaction design is the process of designing the interaction between users and software or hardware products. Interaction design is particularly important in HCI since it enables the creation of software that is intuitive, easy to use, and meets the needs of users. [14]

Human factors
Human factors is the study of how humans interact with technology and how technology can be designed to better meet the needs of users. Human factors is particularly important in HCI since it enables the creation of software that is intuitive, easy to use, and meets the needs of users. [14], [15]

Personalization
Personalization is the process of tailoring software or hardware products to the needs and preferences of individual users. Personalization is particularly important in HCI since it enables the creation of software that is more engaging, effective, and enjoyable for users. [14], [16]

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Accessibility
Accessibility refers to the design of software or hardware products to ensure that they can be used by people with disabilities. Accessibility is particularly important in HCI since it enables the creation of software that is more inclusive and equitable for all users. [17]

Ambient intelligence (AmI)
Ambient intelligence is a concept in which technology is seamlessly integrated into the environment and adapts to the needs and preferences of users. It refers to intelligent interfaces that recognise human presence and preferences, and adjust smart environments to suit their immediate needs and requirements. Ambient intelligence is particularly important in HCI since it enables the creation of software that is context-aware and personalized to the needs of users. [18]

Context-aware interfaces
Context-aware interfaces are user interfaces that can adapt to the context in which they are used, such as the user's location, activities, and preferences. Context-aware interfaces are particularly important in HCI since they enable the creation of software that is more relevant and useful for users in different contexts. [19]

Adaptive interfaces
Adaptive interfaces are user interfaces that can adapt to the needs and preferences of individual users. Adaptive interfaces are particularly important in HCI since they enable the creation of software that is more user-friendly and effective for different types of users. [20]

Augmented reality (AR)
AR is a type of technology that overlays virtual objects onto the real world, creating an enhanced view of reality. AR is particularly important in HCI since it enables the creation of software that is immersive and engaging for users. [21]

Virtual reality (VR)
VR is a type of technology that creates a simulated environment that users can interact with. VR is particularly important in HCI since it enables the creation of software that is immersive and engaging for users. [22], [23]

Mixed reality (MR)
MR is a type of technology that combines elements of both virtual reality and augmented reality to create an immersive experience that blends the real world with virtual objects. MR is particularly important in HCI since it enables the creation of interactive and engaging experiences that can be personalized to the needs and preferences of users. [24], [25]

Metaverse
Metaverse is a concept that refers to a shared virtual space where users can interact with each other and with virtual objects. Metaverse is particularly relevant in HCI since it enables the creation of immersive and interactive experiences that can be personalized to the needs and preferences of users. [26]

2.2 Human Activity Recognition Studies

Thanks to smartphones, information can now be continuously gathered in a non-intrusive manner. Many researchers have conducted extensive studies in the field of sensing technologies and have proposed various techniques for modeling and recognizing human actions. The authors of [27] conducted research on the utilization of acceleration data from smartphones to analyze six different human activities, namely walking, jogging, going up and down stairs, sitting, and standing. They employed logistic regression, J48, and multilayer perceptron learning algorithms in their analysis. [28] and [29] proposed activity recognition techniques using smartphones. These techniques were designed to recognize activities such as walking, running, climbing stairs, descending stairs, driving, cycling, and inactive states. The researchers placed the smartphones in different locations, such as the hand, handbag, pant pocket, and shirt pocket, and evaluated the performance of various supervised machine learning classification algorithms such as Naïve Bayes, Decision Tree, K-Nearest Neighbor and Support Vector Machine classifiers. Also, [29] solved the problem of placing

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the smartphone in different locations through the use of a hidden Markov model (HMM) and a static support vector machine (SVM) classifier. [30] recognized six physical activity patterns using acceleration data generated by a user's cell phone's sensors placed in either the hand or the pant pocket, including slow walking, fast walking, running, going upstairs, going downstairs, and aerobic dancing, using various machine learning algorithms such as multilayer perceptron, support vector machine, random forest, Logistic Model Tree (LMT), simple logistic, and logitboost.

In their study, [31] gathered data from six distinct locations on the body, including two front and two back trouser pockets, as well as two front pockets of a coat, while considering four different orientations of the smartphone. The goal was to recognize five different human activities, namely static, walking, running, walking upstairs, and walking downstairs. The authors utilized supervised classification algorithms such as Decision Tree (DT), Naive Bayes (NV), and Sequential Minimal Optimization (SMO) to accurately identify the aforementioned activities. This study [32] involved using an ensemble of classifiers approach for accelerometer-based activity recognition. The researchers developed an activity prediction model using machine learning classifiers, such as J48 decision tree, MLP, and Logistic Regression techniques, and combined them using the average of probabilities combination rule. The results indicated that the proposed model outperformed the MLP-based recognition approach, highlighting the effectiveness of an ensemble of classifiers approach for activity recognition. The study emphasizes the importance of using multiple classifiers to improve the accuracy of activity recognition.

[33] proposed a MEMS-based Human Activity Recognition (HAMR) system that utilizes smartphone sensors to improve the accuracy of classifying human activities. The system was designed to recognize activities such as walking, running, going upstairs, going downstairs, standing, sitting, and cycling. The authors used a combination of time-series features and wavelength coefficients to extract features from the data and improve the accuracy of classification. The authors of [34] conducted a comparative study on different kernel functions of the one-versus-all multiclass SVM classification method for recognizing six different human activities from smartphone sensors, including walking, sitting, standing, lying, walking upstairs, and walking downstairs. In [35], a 1-D CNN is introduced that utilizes smartphone accelerometer data from different body positions, such as the bag, hand, and pocket, for activity recognition. By incorporating data from different body positions, the system ensures the position-independent property, making it effective for activity recognition regardless of the smartphone's position.

[36] presented a real-time activity monitoring algorithm that uses smartphone and wristband sensors for recognizing human activities and estimating energy expenditure. The algorithm detects the presence of devices, normalizes orientation data, and selects a location-specific classification model for activity recognition. The recognized activity is then used for selecting one or multiple regression models for estimating the user's energy expenditure. The study optimized the features using automatic feature selection and evaluated the algorithm and device configurations. In [37] a smartphone-based position-independent activity recognition system that uses a Convolutional Neural Network (CNN) was introduced. The system uses time-domain statistical features, and mean-centering is employed to convert the raw input to a suitable form for training the optimum threshold without bias.

[38] classified ten different human activities using four different classifiers, including K-nearest neighbor, random forest, support vector machine, and conventional deep neural network. The activities were sitting, walking, jogging, lying, walking upstairs, walking downstairs, cycling, standing, squatting in a toilet, and fallen down. The authors of [39] addressed the challenge of capturing the temporal dependencies and sequential patterns present in human activities by leveraging the capabilities of LSTM networks. By stacking multiple LSTM layers, their proposed model effectively captured the complex temporal relationships in the sensor data, enabling more accurate and robust activity recognition. They preprocessed the sensor data and segment it into fixed-width sliding windows to extract activity-specific features. These features are then fed into the stacked LSTM network for activity classification. In [40], the authors addressed the challenge of effectively representing time series data by introducing the concept of GAF, which transforms the time series data into an image-like representation that preserves the temporal information while capturing the underlying patterns. This representation was then used as input to a DCNN, which is capable of automatically learning and extracting discriminative features from the GAF images.

This paper [41] discusses various considerations for Human Activity Recognition (HAMR) systems, including the importance of energy efficiency, using a combination of sensors for data collection, considering age, gender, and

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human behavior, device-independent HAMR, and position and orientation-independent HAMR. The authors suggest that researchers should consider complex activities, address the problem of missing signal or unknown activity, and explore deep learning and ensemble methods for improved performance. They also recommend studying the application of classified activity data to create smart environments. This paper [42] discusses the various applications of HAR in computer vision, HCI, robotics, security, and home monitoring, highlighting the importance of understanding and interpreting human activities in these domains. The classification system proposed in the paper takes into account the nature of the acquisition device and the stage of recognition in which the methods can be applied, which are relevant to HCI applications. The paper also emphasizes the potential for integration of HAR systems in smartphones, which are widely accepted by society and can overcome privacy barriers in standard HAR systems. Overall, the paper provides insights into the use of HAR in HCI and its potential for improving the interaction between humans and computers.

The authors of [43] studied human activity recognition by proposing a novel framework that utilizes Graph Neural Networks (GNNs) for accurate activity classification based on smartphone sensor data. They addressed the limitations of traditional approaches by leveraging the power of GNNs, which excel at capturing complex relationships and dependencies among data points represented in a graph structure. In their framework, they constructed a graph representation of the sensor data, where each sensor reading is treated as a node, and the relationships between the nodes are defined based on the temporal and spatial proximity of the sensor readings. The authors of [2] propose a standardized evaluation benchmark to assess state-of-the-art techniques for Human Activity Recognition using six publicly available datasets. The authors introduce a hybrid experimental approach that combines enhanced handcrafted features and a neural network architecture, which outperformed top-performing techniques on MHealth, USCHAD, and UTD-MHAD datasets. The study emphasizes the importance of standardized evaluation benchmarks for comparing and improving HAR techniques and showcases the potential of a hybrid feature and neural network architecture for HAR.

The authors of theis systemetic review [44] discusses the limitations of current HAR classifiers, which are often trained on a limited set of activities and may overestimate the activities they were trained on while missing other activities. The authors propose an improved scheme that assumes observed activities are a sample from a broader spectrum of possible behaviors and suggests an adaptive approach for health-related interventions. The study also highlights the importance of addressing missing sensor data, which is a common problem in studying human behavior using personal digital devices, and the need to propagate uncertainty in a statistically principled way. The authors emphasize that dealing with missing data and accounting for resulting uncertainty is vital to avoid excluding participants from a study arbitrarily. The paper provides valuable insights for researchers interested in studying human behavior using personal digital devices and highlights the importance of considering a broad spectrum of possible behaviors and addressing missing data and uncertainty in statistical analyses.

The authors of [45] suggest several directions for future research in Human Activity Recognition systems, including the use of generative models for handling class imbalance, expansion of HAR to future activity prediction, incorporation of contextual information in open datasets, development of a standardized data representation system, and creation of robust HAR systems that can account for environmental effects.

3. Proposed Methodology

The proposed methodology aims to infer human activity from mobile sensors and use that information to create more intelligent and adaptive user interfaces that in turn provides better user experience. This will be achieved by collecting sensor data from mobile devices such as mobile phones and smart watches, and using machine learning algorithms to recognize and classify human activities. And finally customizing the UI design and layout based on the identified activity. The overall process can be broken down into three main steps: data collection , activity recognition, and user interface adaptation as depicted in figure 1.

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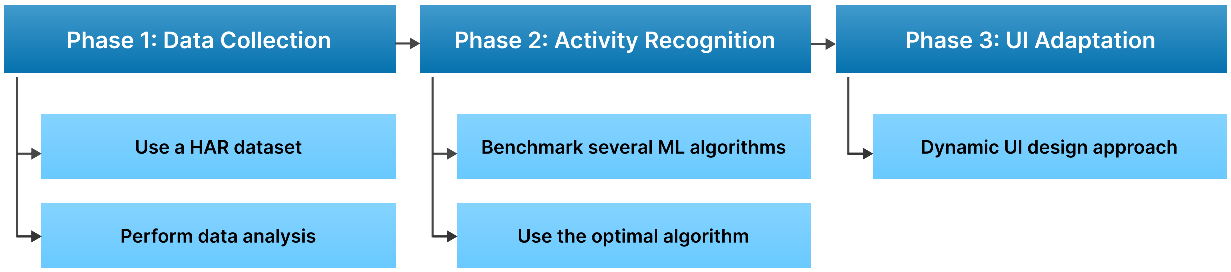

Figure 1:The proposed methodology.

3.1 Data & Exploration

As a case study, we use Human Activity Recognition database from [46] to do experimental validations of our work. The data was composed of recordings of 30 individuals doing daily living activities while doing a waist-mounted Samsung Galaxy S II mobile phone with implanted inertial sensors. The age of the individuals in our case study was between 19 and 48 years, and each of them is doing six activities WALKING_UPSTAIRS, WALKING, SITTING, WALKING_DOWNSTAIRS, LAYING, STANDING. The attached mobile phones contain an implanted gyroscope and accelerometer, dedicated to recording 3-axial angular velocity, and 3-axial linear acceleration at a continuous frequency of 50Hz. To label the data, the experiments were recorded on video. The resulting dataset was then randomly divided into two sets: one for training data, which included 70% of the volunteers, and the other for test data, which included the remaining 30%. Prior to analysis, the sensor signals underwent pre-processing steps to ensure their quality. This involved applying noise filters and sampling the signals in fixed-width sliding windows with a duration of 2.56 seconds and a 50% overlap. To isolate the relevant components, the sensor acceleration signal was separated into two distinct parts, namely body acceleration, and gravity, using a Butterworth low-pass filter. The low-pass filter, with a cutoff frequency of 0.3 Hz, effectively captured the low-frequency components associated with gravitational force. From each sliding window, a feature vector was extracted by calculating various variables from both the time and frequency domains [40], [46]–[49].

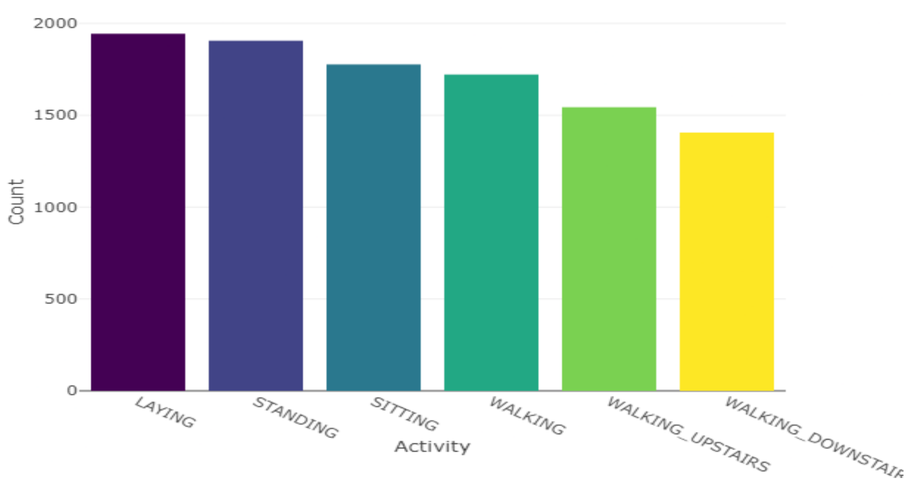

Figure 2: class distribution analysis for activities in our case study.

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In order to gain insights into the class distribution of the human ac tivity recognition dataset, we performed a comprehensive analysis of the data. The dataset consists of samples collected from multiple individuals engaging in various activities. By examining the distribution of activity classes, we can better understand the prevalence of different activities within the dataset. Figure 2 presents a bar chart depicting the class distribution of the dataset. The x-axis represents the different activity classes, while the y-axis shows the corresponding frequency or count of each class. The bar heights reflect the relative occurrence of each activity class within the dataset. To assess the separability of activities or participation in the human activity recognition dataset, we performed a T-SNE visualization analysis. T-SNE (t-Distributed Stochastic Neighbor Embedding) is a dimensionality reduction technique commonly used for visualizing high-dimensional data in a lower-dimensional space.

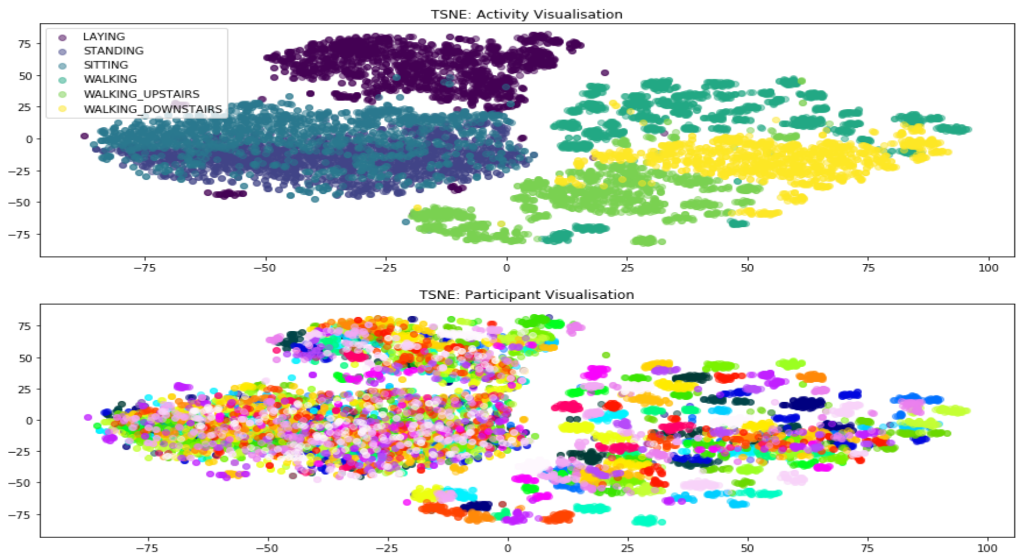

Figure 3: T-SNE visualization of activities and participants in our case study.

Figure 3 displays the T-SNE plot, where each data point represents a sample from the dataset. The plot visualizes the relationships and similarities between the samples based on their feature representations. Upon examining the T-SNE plot, we observe that the activities are mostly separable, which indicates that they exhibit discernible patterns. It is also notable that everybody has for example a unique/sparable walking style (on the upper right). The presence of well-defined clusters suggests that the features used for activity recognition effectively capture the variations and characteristics specific to each activity or participation.

More, Figure 4 shows the participation of each user in the human activity data in our case study. it could be noted that users 19-21 are the most contributing to the data collection process. The other users contribute to the data at almost equal rates. In Figure 5, we show the distribution analysis of different classes of activities in our data according to the gravity and accelerometer magnitude. It can be noted that laying activity gains the top gravity while walking downstairs is gaining the highest accelerometer magnitude.

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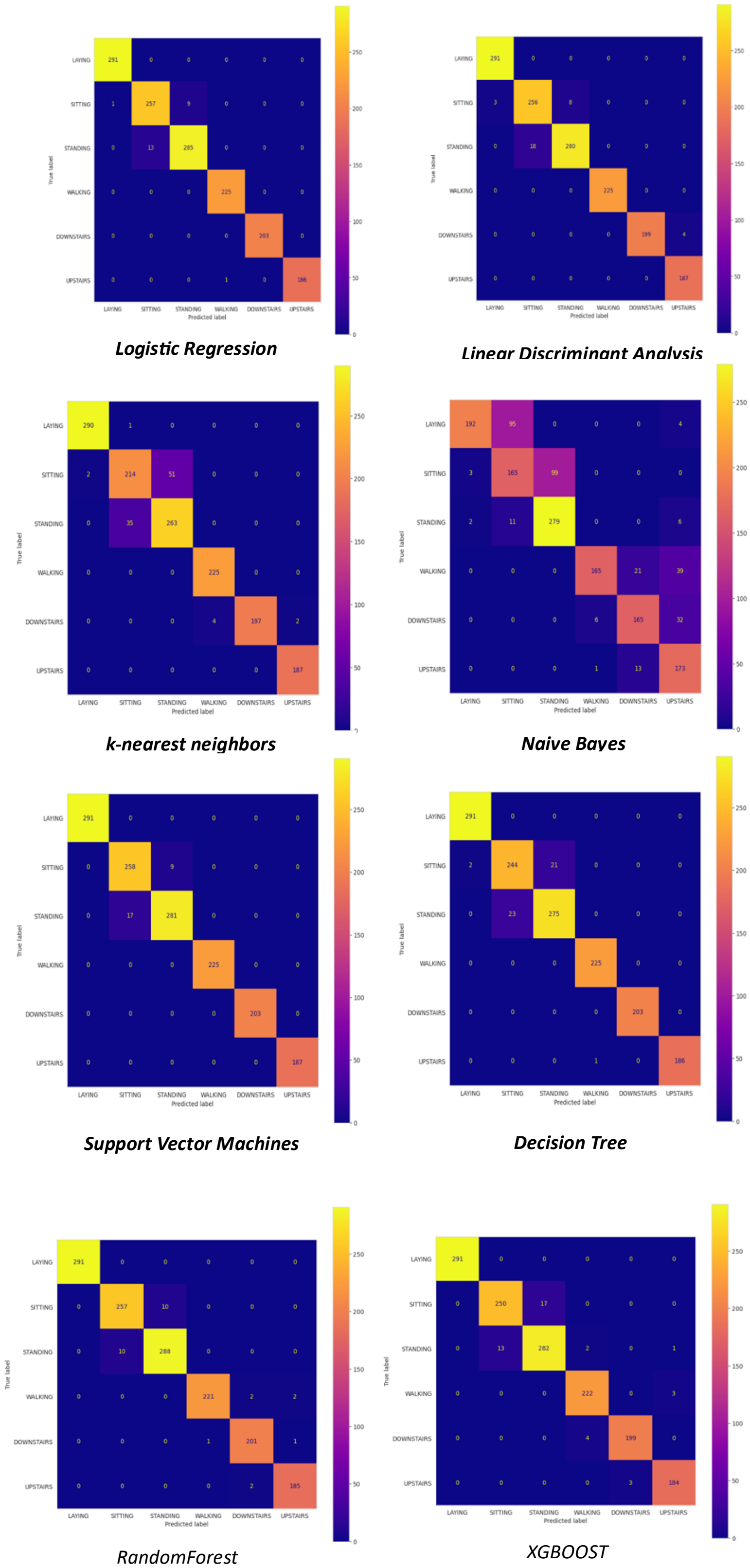

Figure 4: confusion matrices for the ml-based human activity

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3.2 Human Activity Recognition

To anvistigate applying ML for human activity recognition and assess the performance of the various machine learning algorithms, we will implement a benchmarking process. Our approach combines the power of ML techniques with feature engineering to accurately classify and recognize different activities.

3.2.1 Dimentionality Reduction

In the first step of our applied benchmark, we apply Principal Component Analysis (PCA) for dimensionality reduction and feature extraction in activity recognition data. The first step involved in performing PCA for activity recognition is preparing the sensor measurements to ensure that the data is properly preprocessed and normalized to remove any biases or inconsistencies.

$$\mathrm{X} = (x_{ij})_{n*p} = \begin{bmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \vdots & \vdots \\ x_{n1} & \cdots & x_{np} \end{bmatrix}, \tag{1}$$

$$x_{ij}{}^{*} = \frac{x_{ij} - \overline{x_j}}{s_j}, \tag{2}$$

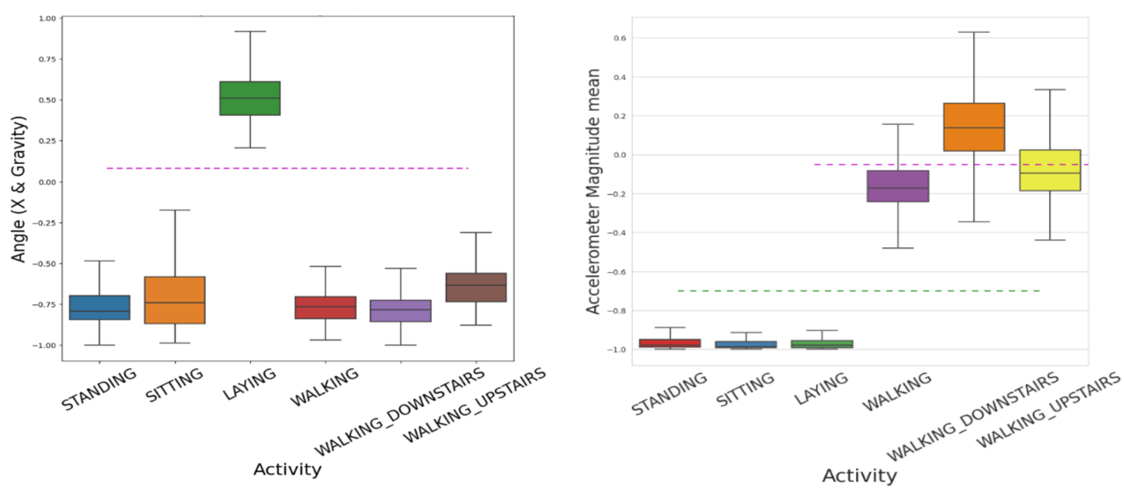

Figure 5: visual illustration of the sensor importance with respect to each class of activity.

Then, we calculate the covariance matrix of the input data. The covariance matrix measures the relationships between different features and indicates how they vary together. It provides valuable information about the interdependencies and correlations among the features.

$$\mathrm{R} = (r_{ij})_{p*p} = \frac{1}{n-1}\sum_{t=1}^{n} x_{ti}{}^{*} * x_{tj}{}^{*} \; (i, j = 1,2, \cdots, p\&\&) \tag{3}$$

Eigenvalue-Eigenvector Computation: Compute the eigenvalues and eigenvectors of the covariance matrix. Eigenvalues represent the variance explained by each eigenvector, while eigenvectors represent the directions or principal components of maximum variance in the data. Sort the eigenvalues in descending order to identify the most significant principal components.

$$F_i = u_{i1}x_1^* + u_{i2}x_2^* + \cdots + u_{in}x_n^* \; (i = 1, 2, \cdots, n) \tag{4}$$

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Followingly, we select a subset of the principal components based on their corresponding eigenvalues. This selection is done based on the desired level of dimensionality reduction or the amount of variance explained that is acceptable for the specific application. Retaining the principal components with high eigenvalues ensures that most of the variability in the data is preserved.

$$F = \frac{\lambda_1}{\lambda_1+\lambda_2+\cdots+\lambda_n} F_1 + \frac{\lambda_2}{\lambda_1+\lambda_2+\cdots+\lambda_n} F_2 + \cdots \frac{\lambda_n}{\lambda_1+\lambda_2+\cdots+\lambda_n} F_n \tag{5}$$

After that, we project the original activity recognition data onto the selected principal components to obtain a lower-dimensional representation. This projection captures the most important patterns and variations in the data, effectively reducing the dimensionality while retaining the key information.

3.2.2 Benchmarking the ML Algorithms

In our benchmark study for activity recognition, we employed and taxonomized various ML algorithms to explore their effectiveness in accurately classifying human activities based on smartphone sensor data. We categorized these algorithms into different groups based on their underlying principles and approaches.

Logistic Regression is a widely used supervised learning algorithm that models the relationship between input features and the probability of an event occurring. Although primarily used for binary classification, it can be extended to handle multi-class classification tasks as well. Logistic Regression utilizes the logistic function (sigmoid function) to map the input features to a probability value between 0 and 1. This probability represents the likelihood of an activity belonging to a specific class. By fitting the model to the training data using maximum likelihood estimation or gradient descent, Logistic Regression learns the optimal coefficients for the input features.

$$h_\theta(x) = g(\theta^T x) = \frac{1}{1+e^{-\theta^T x}}, \quad g(z) = \frac{1}{1+e^{-z}} \tag{6}$$

In our benchmark study, we applied Logistic Regression to the activity recognition task, training the model on smartphone sensor data and evaluating its performance in accurately classifying activities.

In addition, we also included Linear Discriminant Analysis (LDA) as a supervised dimensionality reduction technique that aims to find a linear combination of features that maximizes the separation between different activity classes. LDA works by projecting the input data onto a lower-dimensional space while maximizing the ratio of between-class scatter to within-class scatter. In other words, it seeks to minimize the within-class variance and maximize the between-class variance[46], [50], [51]. By doing so, LDA finds a subspace where the different activity classes are well-separated. In the context of human activity recognition, LDA can effectively capture the discriminative information present in the sensor data and enhance the separability of different activities. It helps in reducing the dimensionality of the input features while preserving the class-specific information that is crucial for accurate classification.

Besides, we incorporated the k-nearest neighbors (k-NN) algorithm is a simple yet powerful supervised learning algorithm that can be applied to classify activities by measuring the distance between an input sample and the training samples in the feature space.

$$\| A - B \| = \sqrt{\sum_{i=1}^{d} (a_i - b_i)^2} \tag{7}$$

$$|A - B| = \sum_{i=1}^{d} |a_i - b_i| \tag{8}$$

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In the context of human activity recognition, k-NN leverages the similarities between feature vectors extracted from smartphone sensor data [51]. By measuring the distance between the input sample and the training samples, the algorithm identifies the k nearest neighbors and assigns the input sample to the activity class that is most prevalent among its neighbors.

Moreover, the Naive Bayes algorithm is a probabilistic classifier that applies Bayes' theorem with the assumption of independence among features. Naive Bayes works by estimating the probabilities of different activity classes given the observed features. It calculates the conditional probability of each class given the feature values and selects the class with the highest probability as the predicted activity. In the context of human activity recognition, Naive Bayes leverages the probabilities of feature values to classify activities based on smartphone sensor data.

$$P(A \mid B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$
(9)

It assumes that the features are conditionally independent, meaning that the presence or absence of one feature does not affect the likelihood of another feature being present. One advantage of k-NN is its simplicity and ease of implementation. It does not require complex model training or assumptions about the underlying distribution of the data.

Support Vector Machines (SVM) is a powerful supervised learning algorithm that aims to find an optimal hyperplane to separate different activity classes in a high-dimensional feature space [52]. SVM works by mapping the input data into a higher-dimensional space using kernel functions and then finding the hyperplane that maximizes the margin between the classes. It classifies new instances based on their position relative to the hyperplane.

$$\omega \cdot \phi(x) + b = 0,$$
(10)

SVM can handle both linearly separable and non-linearly separable data by employing different types of kernels, such as linear, polynomial, and radial basis functions (RBF).

$$F(\alpha) = \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{j,k=1}^{m} \alpha_j \alpha_k y_j y_k K(x_j, x_k), \quad (11)$$

$$\sum_{i=1}^{m} y_i \alpha_i = 0, C \geq \alpha_i \geq 0, i = 1, \dots, m. \quad (12)$$

In the context of human activity recognition, SVM leverages the ability to handle high-dimensional feature spaces and capture complex decision boundaries. By finding the optimal hyperplane, SVM aims to accurately classify activities based on the patterns present in the smartphone sensor data. During our benchmark study, we applied SVM to the activity recognition task by training the model on the smartphone sensor data. By tuning the hyperparameters, such as the kernel type and regularization parameter, we optimized the SVM model's performance and evaluated its accuracy in classifying activities.

In our benchmark study for human activity recognition, we incorporated Decision Trees and Random Forests as machine-learning algorithms. Decision Trees are a non-parametric supervised learning method that builds a tree-like model to make decisions based on input features. Random Forests, on the other hand, is an ensemble learning method that combines multiple Decision Trees to improve predictive accuracy and reduce overfitting. Decision Trees work by recursively splitting the input data based on the values of the features. Each internal node represents a feature and a splitting criterion, while each leaf node represents a class label. The tree structure allows for easy interpretation of the decision-making process. Random Forests build an ensemble of Decision Trees by training each tree on a random subset of the training data and using random feature subsets. During prediction, the class label is determined by aggregating the predictions of individual trees through voting or averaging. In the context of human activity recognition, Decision Trees and Random Forests can capture non-linear relationships between sensor data and activity

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labels. They can handle both numerical and categorical features, making them suitable for analyzing smartphone sensor data [53].

In our benchmark study for human activity recognition, we also explored boosting method to combine multiple weak classifiers to create a strong classifier with improved predictive accuracy. Boosting algorithms work iteratively by sequentially training a series of weak classifiers, with each subsequent classifier focusing more on the misclassified instances from the previous classifiers. The final prediction is made by combining the predictions of all weak classifiers, typically through weighted voting. The objective of XGBoost is formulated as follows:

$$O = \sum_{i=1}^{n} L(y_i, F(x_i)) + \sum_{k=1}^{t} R(f_k) + C \tag{13}$$

with regularization term $R(f_k)$ defined as follows:

$$R(f_k) = \alpha H + \frac{1}{2}\eta \sum_{j=1}^{H} w_j^2 \tag{14}$$

3.3 User Interface Adaptation

Once the activity is recognized, the UI can be customized to display a design that is relevant to that activity. This can involve selecting a color scheme, font, and layout that is suitable for the activity. For example, if the user is jogging, the UI can display a sleek and minimalistic design that is easy to read while on the move. Alternatively, if the user is sitting, the UI can display a more detailed and interactive design that is optimized for longer periods of screen time. In addition to designing the UI, the layout of the user interface can also be customized based on the identified activity. This can involve deciding on the size and positioning of UI elements, as well as the type of interaction (touch, voice, etc.) that is most appropriate for the activity. For example, if the user is driving, the UI can be optimized for voice commands and audio feedback, while if the user is setting, the UI can be optimized for touch interactions and gestures.

One approach to customizing the UI based on the identified activity is to create a set of pre-made UI designs that are optimized for different activities. For example, we can create a minimalist design for activities like running or cycling, and a more detailed and interactive design for activities like sitting or standing. However, a more efficient approach would be to use a dynamic UI design that adapts in real-time based on the identified activity. This can be achieved through the use of flexible UI components and a modular design that allows for easy customization. For example, we could use a layout engine that dynamically adjusts the positioning and size of UI elements based on the current activity. we could also use a component library that includes pre-built UI components optimized for different activities. By using a dynamic UI design that adapts in real-time, we can create a more personalized and engaging user experience that is optimized for the user's current activity. This approach can also reduce the amount of design work required upfront, as the UI can be designed to be flexible and modular from the outset. And with the help of generative AI capabilities, designing different UI components styles and layouts will be an easy task.

4 Results and Discussion

4.2 Results

In our benchmark study, we conducted a visual comparison between different ML classifiers to assess their performance in human activity recognition. The goal was to evaluate and identify the most effective classifier for accurately categorizing activities based on smartphone sensor data. To perform the visual comparison, we employed the confusion matrix visualization technique to gain insights into the classification results by illustrating the distribution of true positive, true negative, false positive, and false negative predictions for each activity class (see Figure 4). These matrices allowed us to analyze the classifier's ability to correctly classify different activities and identify any potential misclassifications or confusion between classes.

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4.3 Discussion and Use Cases

Mobile devices are already part of our daily lives, and users are used to carrying them around and interacting with them. HAR from mobile sensors can be seamlessly integrated into the user's daily routine without requiring any additional equipment or setup, making it highly accessible, convenient, and non intrusive. Hence, human activity recognition from mobile sensors has the potential to bring significant benefits to various fields, including:

Ambient computing and context-aware interfaces: HAR from mobile sensors can be used in ambient computing to create more personalized and context-aware experiences for users. Mobile devices are often used in various contexts, making them ideal for HAR-based ambient computing applications. By recognizing the user's activities, location, and context, ambient computing systems can adjust their settings and interfaces to provide relevant information and services based on the user's context, the collected insights can be sent from the mobile phone to the ambient computing systems such as in smart homes to provide more seamless and natural interactions.

Adaptive interfaces and personalization: HAR enables the tailoring of user interfaces based on the user's specific needs and preferences. By recognizing the user's activities, machine learning algorithms can predict the user's behavior and adjust the interface accordingly. This can improve the overall usability and effectiveness of user interfaces, providing a more personalized and engaging user experience. For example, a running app can adjust its interface to provide larger buttons and simpler interactions while the user is running, making it easier to use and reducing distractions.

Mixed reality and metaverse applications: HAR can bring several benefits to mixed reality applications. By recognizing the user's activities and movements, HAR can enable more natural and intuitive interactions with virtual objects, enhancing the overall user experience and increasing immersion in the virtual environment. HAR can also enable the development of adaptive interfaces in MR applications that adjust to the user's behavior and movements, making it easier for the user to interact with virtual objects. Additionally, HAR can improve the accuracy and reliability of gesture recognition in MR applications, providing more accurate and reliable interactions. Finally, HAR can enable MR applications to be more contextually aware by recognizing the user's activities and movements in the real world and adjusting the environment accordingly, hence providing a more seamless and integrated user experience.

Sustainability, health, and wellness: HAR can be used to track and monitor the user's physical activity levels, providing insights into their health and wellness, this can be extremely helpful in fitness apps, mental health apps, and health monitoring apps. HAR can also be used to create sustainable computing systems that adapt to the user's behavior and energy usage patterns, reducing the environmental impact of computing.

Usability testing: HAR provides more objective and accurate measures of user behavior and interactions. By recognizing the user's activities, machine learning algorithms can provide more detailed insights into the user's behavior, preferences, and interactions with the interface. This can enable designers and researchers to better understand users interactions with the system, identify usability issues and optimize the user interface for better user experiences.

5 Conclusions

In this paper, we have presented ActivBench, an end-to-end computational intelligence benchmark designed to address the challenges in human activity inference from smartphone sensors. ActivBench provides a comprehensive collection of diverse activity recognition datasets, a unified evaluation protocol, and a wide range of state-of-the-art ML algorithms. Through extensive experiments and evaluations, we have demonstrated the effectiveness of ActivBench in assessing and comparing the performance of different algorithms on activity recognition tasks. The results obtained from ActivBench highlight the strengths and limitations of various ML algorithms, including decision trees, and ensemble methods.

Furthermore, as discussed earlier, the use of machine learning and activity recognition has the potential to enable personalized and adaptive user experiences. By leveraging this technology, HCI professionals can create interfaces that adapt to the user's activities, providing a more engaging, effective, and seamless user experience. For example, by using a dynamic UI design approach that adapts in real-time based on the identified activity, we can customize the

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UI design, layout, and feedback to optimize the user experience. Researchers and practitioners can utilize ActivBench as a valuable resource to develop and evaluate robust activity recognition systems that also incorporate UI adaptation. The standardized evaluation protocol ensures fair comparisons and facilitates advancements in the field. Overall, ActivBench is a significant step towards advancing the field of human activity inference from smartphone sensors and creating more personalized and adaptive user experiences.

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