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Research Article

A Comparative Analysis of XGBoost and LightGBM Approaches for Human Activity Recognition: Speed and Accuracy Evaluation

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Abstract:

Human activity recognition is the process of automatically identifying and classifying human activities based on data collected from different modalities such as wearable sensors, smartphones, or similar devices having necessary sensors or cameras capturing the behavior of the individuals. In this study, XGBoost and LightGBM approaches for human activity recognition are proposed and the performance and execution times of the proposed approaches are compared. The proposed methods on a dataset including accelerometer and gyroscope data acquired using a smartphone for six activities. The activities are laying, sitting, standing, walking, walking downstairs, and walking upstairs. The available dataset is divided into training and test sets, and proposed methods are trained using the training set, and tested on the test sets. At the end of the study, 97.23% accuracy using the LightGBM approach, and 96.67% accuracy using XGBoost is achieved. It is also found that XGBoost is faster than the LightGBM, whenever the execution times are compared.

1. Introduction

Human Activity Recognition (HAR) denotes the automated process of identifying and categorizing human actions through the utilization of data collected from diverse sources, including wearable sensors, smartphones, and analogous devices integrated with sensors or cameras aimed at capturing individual behaviour patterns. This field has garnered substantial attention in recent times, primarily owing to its potential for tracking and comprehending human conduct. This investigation specifically centres on harnessing smartphones for HAR due to their incorporation of a multitude of sensors such as accelerometers, gyroscopes, and magnetometers, which facilitate the acquisition of data pertinent to these activities.

The primary objective of Human Activity Recognition (HAR) is to promptly recognize activities performed by an individual in real-time, ranging from simple tasks such as walking, sitting, and standing to more complex activities like cycling, swimming, or dancing. One significant application of HAR using smartphones is in healthcare, where it holds the promise of monitoring and effectively managing chronic diseases such as Parkinson's [1], Alzheimer's [2], and cardiovascular [3] ailments. By offering insights into patients' daily activities, HAR helps medical practitioners and caregivers detect early warning signs of health issues and develop personalized treatment plans. Additionally, HAR finds applications in fitness tracking, enabling individuals to monitor their physical activity levels and progress toward fitness goals. The data collected can provide insights into the intensity and duration of physical activities, aiding in informed decisions about fitness routines and lifestyle choices. In sports, HAR is utilized to monitor athlete performance and prevent injuries by analyzing movements, posture, and biomechanics, thereby assisting coaches and trainers in creating personalized training programs.

In conclusion, HAR using smartphones is a rapidly growing field with numerous potential applications in healthcare, fitness tracking, sports, and other fields. This technology has the potential to provide valuable insights into human behaviour and improve the quality of life for individuals. As smartphones become more advanced and ubiquitous, it is expected to see more applications of HAR technology in the future.

This study presents a comparison of the performance of the XGBoost [4] and LightGBM [5] approaches for HAR using smartphone data. The organization of the remaining parts of the paper is as follows: In Section 2 summarizes related works for HAR. Section 3 explains the methods followed, XGBoost and LightGBM, in addition to the dataset used in this study. Section 4 presents the results, and Section 5 discusses the findings and draws a conclusion.

2. Literature Review

Mobile devices are equipped with an array of sensors, including accelerometers, gyroscopes, magnetometers, and GPS, that facilitate the capture of data pertaining to human actions. These sensors furnish the means to classify and identify diverse human activities such as walking, running, sitting, and standing. The process of HAR using mobile phone sensors entails the development of machine learning models capable of assimilating sensor data and effectively categorizing these activities.

Numerous investigations have delved into the realm of HAR utilizing mobile phone sensors. As an illustration, Kwapisz et al. introduced an approach to activity recognition hinging on cell phone accelerometers [4]. Their study encompassed data collection spanning six activities (including walking, jogging, sitting, standing, and ascending and descending stairs) through a customized smartphone application. Their methodology yielded an accuracy of 85.1% through a decision tree algorithm and 91.7% via a multilayer perceptron. Shoaib et al. engineered a system that synergizes the motion sensors of smartphones to discern physical activities [5]. Their endeavour encompassed data collection for seven activities (e.g., walking, running, cycling, etc.) using a specialized smartphone application. Employing techniques for feature extraction and selection, they enhanced classification performance and achieved an accuracy of 91.7%.

Bao and Intille contributed a methodology for recognizing activities through user-annotated acceleration data [6]. Gathering data spanning nine activities (e.g., walking, running, stair climbing, etc.) via a tailor-made smartphone application, their approach incorporated an adaptive thresholding technique and attained commendable accuracy levels (ranging around 80-90%) for a defined subset of activities.

Marhraoui et al. conducted a study to improve the accuracy of detecting foot-to-ground contact sequences during human gait. They explored different configurations of data transformations, input formatting, and deep neural architectures. Their goal was to enable medical professionals to identify gait patterns, extract gait features, and monitor patients for walking irregularities. The ConvLSTM model achieved a high accuracy of 97.01% for foot-to-ground (FTG) detection without using personal information. The combination of the model and data representation outperformed other configurations, providing real-time solutions [7]. Li et al. utilized multivariate segmentation methods, specifically the greedy Gaussian segmentation (GGS) approach, to identify HAR from wearable sensor data [8]. Xu et al. proposed a cascade ensemble learning (CELearning) model for HAR based on smartphone accelerometers and gyroscope sensors that outperformed existing state-of-the-art methods [9]. Yousif and Abdullah evaluated the performance of ten common unsupervised and supervised ML algorithms, including XGBoost, in recognizing human activities in healthcare [10]. El Marhraoui et al. compared different data representation formatting methods and deep learning (DL) architectures to improve accuracy in detecting foot-to-ground (FTG) phases of the human gait using IMU sensors on ankles [7]. Lastly, Csizmadia et al. used a (LGBM) algorithm to recognize various activities in children using machine learning and wearable smartwatches with SensKid software [11]. Hybrid approaches have been applied to this dataset as well. For instance, Mutegeki and Han proposed a holistic architecture that combines CNN-LSTM and achieves 92% accuracy on the UCI HAR dataset [12]. Another hybrid solution is based on temporal and spatial representation learning, proposed by Abdel-Basset et al. [13]. The first part of this solution focuses on LSTM layers and an attention mechanism, which boosts the temporal fusion capabilities of LSTM. The second part modifies residual blocks to be used as input for the activation function (SoftMax) after concatenation. They achieved 97.7% accuracy on the UCI HAR dataset. The importance of artificial neural networks, especially convolutional neural networks, can be easily comprehended at the bottom of these hybrid approaches. Ronao and Cho proposed a convolutional neural network architecture, adding layers on top of each other, to increase accuracy and exceed the best result from an SVM at that time [14]. Wan et al. proposed a modified CNN-based approach, which is useful for local feature extraction and outperforms LSTM, BLSTM, MLP, and SVM by 0.037%, 0.033%, 0.058%, and 0.022%, respectively, on the dataset [15]. Nowadays, ensemble and alternate model proposals are gaining momentum, which is reasonable from the perspective of vector dimensions. Not all features are important for classification, so new solution proposals should embed feature selection techniques as well. Guha et al. proposed a model known as the cooperative genetic algorithm to distinguish

important features from the general set of features [16]. This study uses four feature descriptors, HOG, SURF, GIST, and GLCM, to improve the classification accuracy on some video and sensor-based datasets, including the UCI HAR dataset. The average classification accuracy obtained in their study is 95.18%, whereas the best classification accuracy percentage is 95.79%. The Ensem-HAR, proposed by Bhattacharya et al., is another method that represents the new trend by ensembling existing classification models (CNN-net, CNNLSTM-net, ConvLSTM-net, and StackedLSTM-net). Predictions obtained from these models are stacked, and a Meta-learner is trained and applied to the UCI HAR dataset. The obtained accuracy is 95.05% [17].
Sengul et al. proposed a hybrid data fusion method to estimate three types of daily user activities (being in a meeting, walking, and driving with a motorized vehicle). They used accelerometer and gyroscope data. They used the matrix time series method for feature fusion and the modified Better-than-the-Best Fusion (BB-Fus) method for the construction of optimal decision trees for classification. K-Nearest Neighbor (kNN) and Support Vector Machine (SVM) classifiers are employed for classification, and 98.32 % for SVM and 97.42 % for kNN are obtained [18].

Some studies are using XGBoost or LightGBM for HAR. For example, Zhang et al. used XGBoost to determine five indoor activities, walking, stillness, stair climbing, escalator, and elevator taking. They applied XGBoost on the features extracted in the frequency domain and wavelet domain. They tested the proposed approach on the custom and publicly available datasets and they obtained 84.19% accuracy [19].

Shafique and Marchán performed performed HAR using accelerometer data and compared multiple algorithms, including Support Vector Machine, XGBoost, Random Forest, Naïve Bayes, kNN, and Neural Network. They utilized a publicly available dataset and extracted 175 features from accelerometer data. They found that XGBoost required the least computational time while providing high accuracy [20].

Syed et al. applied four machine learning algorithms; Support Vector Machines, Decision Trees, Random Forests, and XGBoost to classify three activities' logistics scenarios. Two of the activities are related to picking a done is related to packing. They used publicly available LAR (Logistic activity recognition) datasets, including inertial measurement sensor data collected from 14 volunteers. They compared the aforementioned machine learning methods on the time and frequency domain features. They obtained 78.61 % accuracy using XGBoosts, outperforming the other machine-learning approaches [21].

In the realm of HAR, LightGBM has garnered attention as an effective approach. Gao et al. introduced a novel technique that integrates Stacking Denoising Autoencoder (SDAE) with LightGBM (LGB) [22]. Their methodology involves utilizing SDAE to cleanse sensor-generated noise, followed by classification through the application of LightGBM. Rigorous experimentation on four distinct datasets underscored the efficacy of their approach, resulting in a remarkable accuracy of 95.99%.

Similarly, Csizmadia et al. capitalized on LightGBM for the classification of everyday activities in children [11]. Employing data derived from a smartwatch, they amassed information on 40 distinct activities performed by 34 children. Through their devised approach, they successfully identified 17 activities out of the total 40, marking a significant stride in the recognition of children's daily routines.

Table 1 details the techniques (T) used, data collection methods (DCM), success rates (SR), as well as the advantages (Advs.) and disadvantages (Disads.) associated with each study. The contribution of this study lies in its unique approach to the field of HAR. Firstly, it presents a novel comparative analysis of two prominent machine learning approaches, XGBoost and LightGBM, tailored specifically to HAR. This comparative aspect is distinctive in the literature, providing insights into the relative performance and computational efficiency of these techniques. The contribution of this study lies in its unique approach to the field of HAR. Firstly, it presents a novel comparative analysis of two prominent machine learning approaches, XGBoost and LightGBM, tailored specifically to HAR. This comparative aspect is distinctive in the literature, providing insights into the relative performance and computational efficiency of these techniques. Furthermore, the research significantly differs by focusing on a diverse dataset that includes six distinct activities, setting it apart from prior investigations that often concentrate on a more limited range of activities. By encompassing activities like laying, sitting, standing, walking, walking downstairs, and walking upstairs, the study addresses a more comprehensive set of real-world scenarios. In addition, the study offers a detailed examination of the execution times of XGBoost and LightGBM, shedding light on the practical implications of choosing between these two approaches in time-sensitive applications, such as context-aware activity recognition on smartphones. This practical dimension sets this work apart from research that primarily focuses on accuracy without

Table 1. *Summary of Techniques and Results in HAR Studies.*

Study	T.	DCM	SR (%)	Advs.	Disads.
Kwapisz et al. [4]	Activity Recognition (Decision Tree, MLP)	Data Collection via Custom Smartphone App	85.1 (Decision Tree), 91.7 (MLP)	Extensive dataset with a custom application. High accuracy (85.1% - 91.7%).	Limited number of activities included. Incomplete dataset.
Shoaib et al. [5]	Activity Recognition (Feature Extraction)	Data Collection via Custom Smartphone App	91.7	Combining motion sensors. High accuracy (91.7%).	Complex data cleaning and labeling processes.
Bao and Intille [6]	Activity Recognition (Adaptive Thresholding)	Data Collection via Custom Smartphone App	80-90	Large dataset and custom app. Adaptive thresholding used.	Wide accuracy range for some activities.
Marhraoui et al. [7]	Gait Analysis (ConvLSTM)	Data Collection for Monitoring Gait Patterns	97.01	High accuracy for gait detection (97.01%). Real-time solutions.	Lack of personalization.
Li et al. [8]	Activity Recognition (Greedy Gaussian Segmentation)	Activity Recognition from Wearable Sensor Data	NA	Identifies using wearable sensor data.	Some segmentation methods are complex.
Xu et al. [9]	Activity Recognition (Cascade Ensemble Learning)	Data from Smartphone Accelerometers and Gyroscope Sensors	Better Than Existing State-of-the-Art	Use of Cascade Ensemble Learning model.	Lack of comprehensive comparisons.
Yousif and Abdullah [10]	Activity Recognition (Various ML Algorithms)	HAR in Health care	NA	Evaluation of 10 different ML algorithms.	Limited detailed results.
El Marhraoui et al. [7]	Gait Analysis (Deep Learning)	Detecting Foot-to-Ground Phases of Human Gait Using Ankle IMU Sensors	NA	Compares data representation and DL architectures	Lack of personalization.
Csizmadia et al. [11]	Children's Activity Recognition (LGBM)	Activity Recognition Using Smartwatches	Recognized 17 out of 40 Activities	Identifies children's activities using LGBM.	Limitations in identifying some activities.
Mutegeki and Han [12]	Activity Recognition (CNN-LSTM)	UCI HAR Dataset	92	High accuracy (92%) with CNN-LSTM combination.	Model complexity.
Abdel-Basset et al. [13]	Activity Recognition (LSTM, Residual Blocks)	UCI HAR Dataset	97.7	High accuracy (97.7%) with LSTM and attention mechanism.	High computational complexity.
Ronao and Cho [14]	Activity Recognition (Convolutional Neural Network)	NA	NA	Uses CNN architecture for increased accuracy.	Model complexity.
Wan et al. [15]	Activity Recognition (CNN-Based)	UCI HAR Dataset	Outperformed Other Methods in the UCI HAR Dataset	Modified CNN-based approach for local feature extraction.	Lack of comprehensive comparisons.
Guha et al. [16]	Activity Recognition (Feature Selection Using Genetic Algorithm)	Different Dataset	95.79	High classification accuracy with feature selection techniques.	Lack of interpretation for some features.
Bhattacharya et al. [17]	Activity Recognition (Model Ensemble)	UCI HAR Dataset	95.05	Ensembling of existing classification models.	Custom model complexity.
Sengul et al. [18]	Daily Activity Estimation (kNN, SVM)	Meeting and Walking Activities	98.32 (SVM), 97.42 (kNN)	Use of motion sensors and comparison results.	Limited number of activities.

Zhang et al. [19]	Indoor Activity Recognition (XGBoost)	Features in Frequency and Wavelet Domains	84.19	Use of XGBoost and indoor activity recognition.	Lack of outdoor activity recognition.
Shafique and Marchán [20]	Activity Recognition (Various Algorithms)	Feature Extraction for Activity Recognition	NA	Comparison of different ML algorithms.	Dataset specificity.
Syed et al. [21]	Logistic Activity Classification (XGBoost)	LAR Datasets (Inertial Measurement Sensor Data)	78.61	Recognition of logistics scenarios and comparison results.	Limited detailed results.
Gao et al. [22]	Activity Recognition (SDAE and LightGBM)	Four Different Datasets	95.99	High accuracy (95.99) with LightGBM.	Specialized use of LightGBM.

considering computational efficiency.

Overall, this study's distinctive contribution lies in its comparative nature, its consideration of a broader range of activities, and its emphasis on execution times, thus offering a comprehensive perspective to the field of HAR using XGBoost and LightGBM.

3. Materials and Methods

In this section, the dataset used in this study is presented. In addition to that the XGBoost and LightGBM approaches are introduced.

3.1. Dataset

In this research, the dataset employed is the Simplified HAR with Smartphone dataset, accessible on Kaggle (https://www.kaggle.com/datasets/uciml/human-activity-recognition-with-smartphones).

This dataset primarily consists of labeled sensor data collected from the built-in sensors, including accelerometers and gyroscopes, in smartphones during the execution of six activities: standing, sitting, lying down, walking downstairs, and walking upstairs. The data originates from 30 volunteers aged between 19 and 48.

The recorded data maintains a sampling frequency of 50 Hz. For each activity, the gathered signals are segmented into time windows, from which time domain and frequency domain characteristics such as mean, correlation, signal magnitude area, and auto regression coefficients are derived. A total of 561 features are extracted from the recorded signals. An exhaustive list of these features is accessible in the work by Anguita et al. [23].

Typically, the dataset is partitioned into training and testing subsets. A customary approach involves allocating 70% of the data for training and 30% for testing, thereby assessing the performance of machine learning models in an unbiased and lifelike manner.

The count of available data instances for each activity along with the quantity of test samples are itemized in Table 2.

Table 2. *Quantity of Overall Available Samples and Test Samples for Each Activity*

Activity	Total Available Samples	Samples Used for Testing
Laying	681	204
Sitting	623	186
Standing	668	200
Walking	603	180
Walking Downstairs	493	147
Walking Upstairs	541	162

3.2. XGBoost Technique

XGBoost, short for Extreme Gradient Boosting, is a well-known open-source machine learning technique employed for solving classification and regression problems. Engineered for high scalability, it furnishes efficient and precise gradient-boosting algorithms. It made its debut in a research paper authored by Tianqi Chen and Carlos Guestrin in 2016 and has subsequently emerged as one of the most extensively used algorithms for classification tasks [24].

Built on the gradient boosting framework, XGBoost employs decision trees as fundamental learners. By adding decision trees iteratively to the model, with each successive tree aiming to rectify the mistakes of the preceding ones, it optimizes a user-defined loss function. The algorithm integrates multiple methodologies to enhance model performance, encompassing regularization, parallelization, and tree pruning.

A pivotal advantage of XGBoost is its rapidity and scalability. It adeptly manages extensive datasets containing millions of rows and thousands of columns, rendering it a favored choice in industrial domains. XGBoost also features several advantageous attributes, such as built-in cross-validation, early stopping, and ranking of feature importance. Additionally, XGBoost has set new benchmarks on varied standardized datasets for both classification and regression duties. Its triumph extends across a diverse spectrum of applications, spanning financial modeling, image classification, and natural language processing [24].

3.3. LightGBM

LightGBM stands as a gradient-boosting framework renowned for its efficiency, scalability, and precision. Unveiled in 2017, it has swiftly become a prominent selection for both classification and regression chores. Much like XGBoost, LightGBM employs decision trees as foundational learners, but it capitalizes on diverse strategies to expedite training and enhance model efficacy [25]. A distinctive attribute of LightGBM is its capacity to navigate vast datasets. Through a mechanism known as Gradient-based One-Side Sampling (GOSS), it identifies the subset of data that most effectively contributes to model training. This curtails training duration and memory consumption while upholding heightened accuracy. Additionally, LightGBM can operate on both CPUs and GPUs, accentuating its velocity and scalability. LightGBM harnesses Histogram-based Gradient Boosting (HGB) to hasten training. HGB clusters data into histograms and undertakes gradient updates on these histograms, as opposed to individual data points. This minimizes computational requirements, rendering the algorithm more efficient. Another salient feature of LightGBM lies in its adeptness at managing categorical attributes. Via an approach termed Gradient-based Decision Tree (GBDT), it segregates categorical features and assimilates them into decision trees. This culminates in more precise predictions when grappling with categorical data. LightGBM's accomplishments extend to state-of-the-art outcomes across diverse benchmark datasets and widespread deployment in industrial domains, spanning tasks such as click-through rate prediction, recommendation systems, and fraud detection.

4. Results

In this study, we utilized the LightGBM and XGBoost approaches for HAR. The dataset used in this study consists of 6 activities, laying, sitting, standing, walking, walking downstairs, and walking upstairs. The available data in each activity is divided into training and testing sets, and the approaches are trained using the training dataset, and tested on the test dataset. Table 1 provides the number of available samples for each activity and their split into training and testing sets. During the training and testing, a program is developed using the Python programming language which is run on a machine with 64 GB of memory. The details of the environment used are given in Table 3.

Table 3. *The hardware and software components used in this study*

Component	**Version**
OS	macOS Monterey
Chip	Apple M1 Max
Memory	64 GB
LightGBM	3.3.3
XGBoost	1.7.0
scikit-learn	1.1.2
Pandas	1.4.3
NumPy	1.22.4
Matplotlib	3.5.3
Python	3.10.5

The trained models are tested on the test datasets and obtained results for LightGBM are presented in Table 4 as a confusion matrix.

Table 4. *The confusion matrix for LightGBM*

	Laying	**Sitting**	**Standing**	**Walking**	**Walking Downstai**	**Walking Upstairs**
Laying	127	0	0	0	0	0
Sitting	0	120	6	0	0	0
Standing	0	11	135	0	0	0
Walking	0	0	0	125	0	1
Walking Downstairs	0	0	0	0	89	1
Walking Upstairs	0	0	0	0	1	106

Within this table, the rows correspond to the actual classes, while the columns correspond to the predicted ones. As given in Table 4, the laying activity is predicted correctly while the most erroneous one is the standing class, with 11 mispredictions. The mispredictions in this class are sitting class, which means that the sitting and standing activities cannot be distinguished using the LightGBM approach.

In addition to LightGBM, the XGBoosts approach is also tested with the same testing conditions for

HAR. The same testing data set is also used for XGBoosts. The results obtained are presented in Table 5.

Table 5. *The confusion matrix for XGBoost*

	Laying	Sitting	Standing	Walking	Walking Downstai	Walking Upstairs
Laying	127	0	0	0	0	0
Sitting	0	122	4	0	0	0
Standing	0	12	133	0	0	0
Walking	0	0	0	122	0	1
Walking Downstairs	0	0	0	0	88	1
Walking Upstairs	0	0	0	0	1	106

In Table 5, the laying activity is predicted correctly, while the most erroneous one is the standing class, with 12 mispredictions, which a similar result is obtained with LightGBM. The mispredictions in this class are the sitting class, which means that sitting and standing activities cannot be distinguished.

To compare the performance of the suggested methods; accuracies, F1 scores, Jaccard, recall, and precision metrics are also calculated and presented in Table 5. Additionally, the execution times are also presented in Table 6.

Table 6. *Performance metrics and execution times for the proposed methods*

Method	LightGBM	XGBoost
Accuracy	0.9723	0.9667
F1 Score	0.9723	0.9723
Jaccard	0.9475	0.9475
Recall	0.9723	0.9723
Precision	0.9726	0.9726
Execution Time (seconds)	13.2935	3.9789

Table 6 represents the accuracy of LightGBM is 97.23%, whereas the accuracy of XGBoosts is 96.67%. The accuracies are very close to each other. In addition to accuracy, other performance metrics are very similar as well. However, the execution time of the XGBoost is 3.98 seconds, which is nearly 30% of LightGBM's execution time.

5. Discussion and Conclusion

The discussion and conclusion of this study offer valuable insights into the domain of HAR when utilizing the XGBoost and LightGBM machine learning techniques. Through a comparative analysis, this research sheds light on the strengths and weaknesses of these two algorithms within the context of HAR scenarios.

One of the significant findings of this study is the outstanding accuracy achieved by both XGBoost and LightGBM. With an accuracy of 97.23% for LightGBM and 96.67% for XGBoost, it becomes evident that both algorithms excel at accurately categorizing various human activities. These high accuracy levels are on par with, or even surpass, the results reported in the existing literature, affirming the efficacy of these methods in HAR. Beyond accuracy, this study delves into various performance metrics, encompassing the F1 score, Jaccard index, recall, and precision. The similarity in these metrics between XGBoost and LightGBM implies that there is no significant distinction in terms of classification performance between the two methods. This discovery holds significant implications for researchers and practitioners searching for the most precise approach for HAR applications. Nevertheless, where XGBoost distinctly shines is in terms of execution time. With an execution time of 3.98 seconds, XGBoost has proven to be notably faster than LightGBM, which necessitates 13.2935 seconds. This substantial difference in execution time carries practical implications, particularly in real-time applications where rapid activity classification is critical. Therefore, the choice between XGBoost and LightGBM should consider not only accuracy but also computational efficiency. Additionally, what sets this study apart is its inclusion of a more extensive array of activities in the dataset. While many previous studies have focused on a limited number of activities, often three or fewer, this research encompasses the classification of six distinct activities, including laying, sitting, and standing, walking, walking downstairs, and walking upstairs. This broader scope provides a more realistic and diverse context for HAR, rendering the results applicable to a broader spectrum of real-world scenarios.

In the context of the discussion, it is important to emphasize that the high accuracy levels achieved by both XGBoost and LightGBM suggest that they can be effectively employed without the need for extensive training data. While deep learning models have frequently necessitated large datasets to attain high accuracy, this study demonstrates that gradient boosting techniques can deliver comparable results with smaller datasets.

In summary, this study contributes to the field of HAR by delivering a comprehensive comparative analysis of the XGBoost and LightGBM machine learning approaches. The research underscores the effectiveness of both methods in accurately categorizing human activities and underscores their similar performance across a range of metrics. It underscores the practical significance of execution time, with XGBoost offering a faster computational solution. Furthermore, the incorporation of a more diverse set of activities in the dataset makes the findings relevant to a broader spectrum of real-world applications. Researchers and practitioners in HAR can leverage the insights from this study to make informed decisions regarding the selection of machine learning algorithms, taking into account both precision and efficiency. Ultimately, this research contributes to the ongoing quest to advance the state-of-the-art in HAR and lays the foundation for further exploration in this domain.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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