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Enhanced Human Activity Recognition (HAR) with IMU Sensors in Smartphones: Insights from Machine Learning Models

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ABSTRACT

Human Activity Recognition (HAR) is the main software component in healthcare, sports, and interactive mobile applications. The accuracy of HAR component is strongly tied with the sensor used for the motion detection and it dictates the overall performance of the application. This paper investigates the use of Inertial Measurement Unit (IMU) sensors embedded in smartphones to investigate the HAR accuracy through machine learning approach. The accelerometer and gyroscope outputs are utilized to classify six human activities: going downstairs, going upstairs, sitting, standing, walking, and running, using Recurrent Neural Network (RNN), Random Forest (RF), and Deep Learning (DL) algorithms. A time series dataset comprising XYZ-axis measurements from accelerometer and gyroscope sensors across four types of smartphones, involving 30 participants is used to train the machine learning (ML) models. To enrich the dataset, sensor filtering, and fusion techniques are employed to evaluate different scenarios. The findings of the study provide significant insights into the capabilities of smartphone-embedded IMUs for HAR in mobile applications.

1.Introduction

In the Artificial intelligence (AI) era, human activity detection and recognition is the main software component of mobile applications. It adds capabilities, functionalities, usability, excitement and satisfaction, especially in the domain of game, healthcare, sports, virtual reality and interactive systems (Haoran Duan 2024). Recent advancements in wearable technology and Machine Learning (ML) have opened new approaches for highly accurate activity recognition. ML model's accuracy is directly related with the quality of its training data. In the context of HAR, data is produced and collected from different wearable sensors (Gupta, 2021;Vincenzo Dentamaro, 2024).

Inertial Measurement Unit (IMU) is a small device that uses a combination of accelerometers, gyroscopes, and in some cases magnetometers to determine the rigid body's orientation and motion in a three-dimensional space (Hasan et al., 2019). IMU is a wearable sensor that can be attached to the body so that it can determine different movement patterns, helps in differentiating between the different types of physical activities, and provides real-time data of the user's movement (Nasrabadi et al., 2022). The IMU can be used in robotics, motion tracking, and navigation for calculating the position, velocity and the orientation of an object or body. Nowadays, most smartphones are equipped with IMUs to facilitate building context-aware mobile applications (Aziz et al., 2021).

IMU can sense the most subtle changes in the movement of the body that the device is attached to, it is portable and cost-effective in comparison to other motion analysis systems, these characteristics made IMU a crucial component in smartphones and other mobile devices. An IMU consists of three types of sensors: the accelerometer, which measures linear acceleration; the gyroscope, which measures angular velocity; and the magnetometer, which measures the magnetic field strength (Shkel and Wang, 2021). While the accelerometer and gyroscope are essential components of the IMU, the magnetometer may not be available in all IMU devices. In this study, only the readings from the accelerometer and gyroscope were used, for a detailed overview of the structure and functionality of IMUs.

The combination of ML and IMU provides an efficient technique for HAR, when the IMU is used for data collection and an appropriate ML algorithm can accurately use these data to classify physical activities. This integration of ML and IMU provides real-time processing and analysis; this property is essential in many industrial, social, and healthcare environments as it provides immediate and direct feedback on the person's activity. It can also process and analyze data from multiple sources simultaneously which makes it efficient to be used in larger populations.

As smartphones are widely available, they present a feasible option for HAR since smartphones are equipped with IMUs (Friedl De Groote, 2021;Gu et al., 2023). However, it is important to determine whether smartphone-embedded IMUs are sufficient for classifying and recognizing human activities to meet healthcare standards. This paper utilizes a feature-rich dataset to evaluate various scenarios involving smartphone-embedded IMU measurements for HAR. Following this introduction, the paper is organized as follows: the second section reviews some related work on HAR and IMUs; the third section describes the methodology used to prepare the dataset and the ML algorithms applied; the fourth section discusses the results of the training models and prediction accuracy; and the final section provides the conclusion.

2.Related Works

During the Fourth Industrial Revolution (IR4), automation and technological solutions based on Information Technology (IT) have become priorities across various industries, including healthcare systems that require HAR. Many healthcare systems and devices with HAR component currently uses Machine Learning (ML) for motion and activity classification and data analysis. In this section, the application of IMU in HAR in both academic research and industrial sector is reviewed.

Traditional methods such as individual self-reporting, video monitoring, wearing pedometers and heart rate monitors for HAR are often unreliable and inaccurate. These HAR systems sometimes struggle to fully differentiate between Activities, and using multiple sensors has proven uncomfortable for aged adults (Biagetti et al., 2018;Mannini et al., 2013;Pantelopoulos and Bourbakis, 2008).

The HARMamba architecture was proposed. It is a lightweight and resource-efficient architecture that is designed for the purpose of recognizing human activities using the data collected from wearable sensors. In this architecture, selective bidirectional state space models (SSM) are combined with hardware design principles to optimize accuracy and resource utilization. The SSM allows for efficient processing for long sequences while simultaneously maintaining performance. The purpose of this architecture is to minimize computational load and minimize the number of parameters (Li et al., 2025).

A novel fall detection device was designed to help elderly individuals and those with mobility issues. The methodology utilizes a single sensor to capture acceleration and angular velocity data along with a multi-feature approach, allowing for more accurate identification of falls during daily activities and reducing false alarms. The SVM was employed, it was capable of differentiating between falls and other daily activities, maintaining two important factors: precision and sensitivity (Zhang et al., 2025).

Patients suffering from stroke and Parkinson's disease often face challenges with gait and balance. An approach was proposed for estimating ground reaction force (GRF) using two IMUs placed on the shank of patients. This method, which combines a four-link walking model simplified with Newton's Euler equations, estimates GRF while minimizing motion interference. Additionally, a virtual elastic force unit on the shanks and thighs adapts to different gait performances (Liu et al., 2024).

Another study validated the use of three IMU sensors by comparing their measurements to those from the Camera-Based Motion Capture (CBMC) system, which is the golden standard for motion analysis. The findings demonstrated a strong correlation between IMU and CBMC data, indicating that IMUs are a reliable source for long-term measurement of knee and hip angles. Calibrating (Zeroing) the sensors before taking measurements was shown to increase the accuracy of IMU data (Oliveira et al., 2023).

Researchers have also proposed systems for monitoring and improving rehabilitation both at home and in clinical settings. These systems use IMUs worn on the wrist, which provide six data channels: three for orthogonal acceleration and three for rotational rates for capturing gestures (Gomez-Arrunategui et al., 2022). Additionally, another approach involves wearing the IMU as a necklace for fall detection (Dastan, 2023).

For stroke patients, predicting post-stroke walking abilities has traditionally required clinic visits and demographic information, a time-consuming process. Researchers used ML and IMUs to collect detailed motion data, classifying patients as either household or community ambulatory in a time-efficient manner, without extensive resources (O'Brien et al., 2022).

Children with Idiopathic Toe Walking (ITW) face abnormalities such as poor balance, increased risk of falling, and delays in motor development. Researchers used ML to classify gait patterns, A wearable IMU sensor was used for continuous monitoring. These techniques identified whether the initial foot contact during walking was a heel or toe strike and quantified the number of toe walking steps (Soangra et al., 2022).

Recently, energy-efficient, low-cost microsensors have been integrated into glasses, shoes, smartwatches, and smartphones, or directly affixed to the body. These sensors collect huge amount of data on body position, orientation, and movement, which can be used to analyze human activities by extracting relevant and effective movement features. In this study, the ML-based HAR using accelerometer and gyroscope data from IMUs embedded in smartphones was explored, evaluating different scenarios including data filtering and sensor fusion.

3.Methodology

It is well known that not all ML algorithms perform equally well across different feature combinations, as they are sensitive to factors such as data types, the number of features, target labels, and the nonlinear correlation between features and the target variable.

This study aims to evaluate HAR by presenting a comprehensive analysis of data from various combinations of accelerometer and gyroscope sensors in different types of smartphones, considering a diverse range of individuals in terms of age, sex, and body index, and applying different ML algorithms and scenarios with hyperparameters tuning.

3.1. The Dataset

In this study, A Wild-SHARD dataset was used, which provides data gathered in uncontrolled, real-world environments at the National Institute of Technology Silchar (AminChoudhury and BadalSoni, 2024). The dataset includes time series data on human activities gathered using different smartphone brands and models, such as the Samsung Galaxy F62 and A30s, Poco X2, OnePlus 9 Pro, etc. These smartphones, equipped with accelerometers and gyroscopes, were mounted vertically in the front pockets of the participants during the tests. The 40 individuals represent a range of ages, genders, and body indices. Participants performed activities naturally to provide data on daily activities including going downstairs, going upstairs, sitting, standing, walking, and running, both indoors and outdoors. The dataset has the activity type as the only target variable.

The accelerometers and gyroscopes measure acceleration and rotational rate along the XYZ axes in a spatial space, respectively. The dataset includes the features; linear acceleration (Acc), gravity (gravity), acceleration due to gravity (AG), rotational rate (RR), rotational vector (RV), and cosine of the rotational rate(cos). The dataset contains 483,896 observations with a 100 Hz recording rate. A sample of the Wild-SHARD dataset is shown in Table 1.

Table 1. Sample data from the Wild-SHARD dataset

AG-X	AG-Y	AG-Z	Acc-X	Acc-Y	Acc-Z	Gravity-X	Gravity-Y	Gravity-Z	RR-X	RR-Y	RR-Z	RV-X	RV-Y	RV-Z	cos	activity
2.103	-10.0781	0.48195	0.012928	-0.50116	0.773655	2.090072	-9.5769	-0.29171	-0.54436	-0.69011	0.011275	-0.68855	0.204547	-0.33555	0.609485	Downstairs
1.947	-10.311	-0.70905	-0.14386	-0.73667	-0.34722	2.0905	-9.57295	-0.39858	-0.5742	-0.88591	-0.05156	-0.69179	0.202928	-0.33215	0.608217	Downstairs
2.25195	-10.3541	-0.76695	0.162793	-0.78236	-0.33258	2.089157	-9.57169	-0.43437	-0.52415	-0.87326	-0.0143	-0.69513	0.200782	-0.32818	0.607269	Downstairs
2.12895	-10.3151	-0.582	0.045556	-0.74476	-0.09273	2.083394	-9.57029	-0.48927	-0.31983	-0.74044	0.008113	-0.69758	0.199202	-0.32504	0.606673	Downstairs
2.082	-10.421	-0.82695	0.00248	-0.85077	-0.31936	2.07952	-9.57018	-0.50759	0.09735	-0.62315	-0.03561	-0.69848	0.197974	-0.32344	0.606897	Downstairs
1.98105	-10.416	-0.98205	-0.10143	-0.84491	-0.50469	2.082477	-9.57109	-0.47736	0.808225	-0.27555	-0.1441	-0.6984	0.194842	-0.3214	0.609082	Downstairs
1.53495	-10.361	-0.654	-0.55412	-0.7878	-0.25282	2.091959	-9.57448	-0.35135	0.9955	-0.27665	-0.17394	-0.69632	0.192151	-0.32119	0.612417	Downstairs
1.36995	-10.311	-0.261	-0.71581	-0.73518	0.090732	2.100139	-9.57614	-0.23973	1.21055	-0.26936	-0.20694	-0.69325	0.189144	-0.3216	0.616605	Downstairs
1.43295	-10.3901	0.195	-0.67252	-0.81382	0.37718	2.109564	-9.57623	-0.1265	1.20725	-0.18975	-0.21436	-0.68981	0.185906	-0.32228	0.62108	Downstairs
1.26	-10.3061	0.45795	-0.85123	-0.72965	0.533534	2.110117	-9.57689	-0.03044	0.91465	-0.15208	-0.12925	-0.68652	0.183438	-0.32296	0.625097	Downstairs

3.2 Data Preprocessing

The Wild-SHARD is a raw dataset with no missing values, and all record observations are complete. The features are numerical, while the target is categorical and has been converted to numerical values in this study. There are six types of targets, downstairs, upstairs, sitting, standing, jogging and walking which has been mapped into numerical values 1, 2,3 ,4 ,5 and 6 respectively. The features related to gravity, directly or indirectly, have magnitudes greater than 1, including both positive and negative values, while the acceleration features are less than unity. To avoid underfitting, the gravity features have been normalized. The normalization process has been done through Max-Min Normalization approach. This approach ensures that the features are on the same scale, preventing the features with larger values from dominating the learning process, each new value is obtained through the equation of Max-Min Normalization, the value is subtracted by the minimum value of the feature, then its result is divided by the difference between the maximum value of the feature and the minimum value of the feature. Additionally, due to the relatively slow appearance of activities compared to the high original sampling frequency, which is 100 Hz, the data was segmented using a step size of 50. This adjustment is based on the understanding that a lower sampling rate can still adequately capture the dynamics of the activities while reducing data volume and computational load. Consequently, the dataset sampling at a reduced 50 Hz frequency, which indicates that the data is being collected at a rate of 50 samples per second. The dataset went from having 483,896 observations to 9,677 observations. this improves efficiency without affecting the quality of the data as it reduces the volume of the data and reduces power consumption.

3.3 Human Activity Recognition (HAR)

Currently, there are two approaches to HAR: vision-based and wearable-based sensors. Vision-based HAR utilizes video cameras to capture activity features, while wearable-based HAR employs sensors worn on the body or embedded in clothing to detect motion and movement features (ChenKaixuan et al., 2021). The sensor data are processed for HAR in two primary methods: threshold-based analysis measurements and training on historical data using ML. In this study, the wearable approach is used, while ML data processing is applied for the motion detection and recognition. Our technique includes data collection from accelerometer and gyroscope embedded in smartphones, preprocessing the dataset, using ML algorithms to train the dataset, which is then used practically to predict unseen new data for classification. The study phases is shown in Figure 1 (Gupta, 2021).

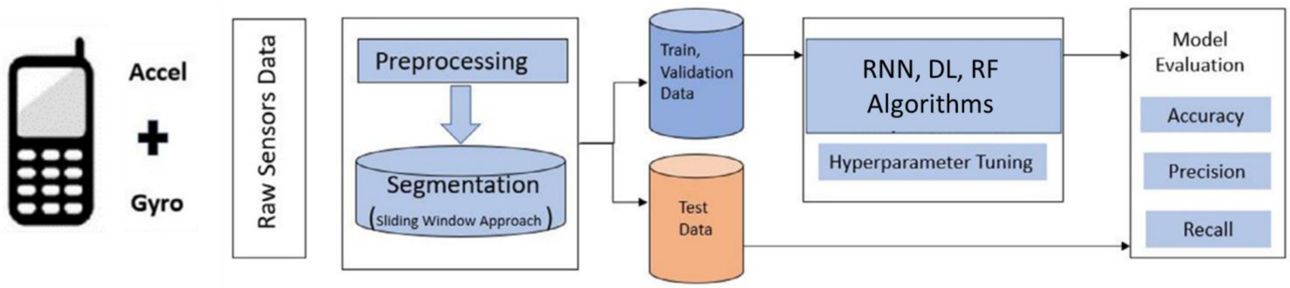

Fig. 1 Human Activity Recognition Approaches modified from (Gupta, 2021)

While many ML algorithms are available in the Artificial Intelligence (AI) and ML literature, but their effectiveness can vary significantly depending on the specific problem. For the HAR problem, three algorithms were examined, evaluating their suitability for HAR specific challenges.

3.3.1 Recurrent Neural Networks (RNN)

The RNN algorithm is well known for good performance with sequential data (Safwan Mahmood Al-Selwi 2024). For HAR problem, it is considered a good choice because of its ability to effectively model time-series data, capturing the dynamic patterns and correlations appears in human activity sequences.

The RNN algorithm processes the input sequences one step at a time, maintaining a hidden state that grasp information about previous steps (Anwar, 2021). This hidden state is updated at each time step based on the current input and the previous hidden state, allowing the network to remember important features from the past. The output at each time step is affected by both the current input and the accumulated knowledge from previous inputs, making RNNs particularly suited for tasks where context and order matter, such as HAR. For the detailed description of the RNN algorithm, refer to (Salem, 2022).

3.3.2 Deep Learning (DL)

Deep learning is a neural network algorithm with more than three layers. It can model complex patterns and relationships in datasets (Haider & Ali, 2022). We have selected DL for the HAR problem because of its ability to automatically learn and extract high-level patterns from sensor data, leading to better accuracy in recognizing and classifying human activities (Saputra et al., 2024). The details of this algorithm are well documented in the literature, see (Goodfellow et al., 2016).

3.3.3 Random Forest (RF)

Random Forest algorithm starts by constructing a multitude of decision trees during training and outputting the mode of the classes of the individual trees. RF is good to be used in the HAR problem because of its good performance with high-dimensional data and its robustness to overfitting. RF is also well-suited for processing the diverse and noisy sensor data typically involved in HAR datasets. The RF algorithm is very mature and well documented in the ML literature, for the detailed steps refer to (Moshood A. Hambali, 2022).

4.Results and Discussion

The Wild-SHARD dataset is a rich and comprehensive, containing nine directly recorded features from smartphone's accelerometer and gyroscope and seven indirectly additional calculated features, and a multi target variable with six objectives. In the context of HAR, it is necessary to examine and evaluate these features both individually and in combination to identify the optimal feature set that yields the highest accuracy and performance.

The three algorithms, RNN, DL, and RF were tested on different combinations of features, including linear acceleration (Acc), acceleration with gravity effect (AG), a combination of acceleration and gravity (Acc-Gravity), AG and gravity (AG-Gravity), AG with a cosine transformation (AG-cos), RR and Acc-RR. All tests were conducted using Python 3.12 with the scikit-learn, Keras and TensorFlow libraries. The dataset was randomly split into 80% for training and 20% for testing, with different hyperparameter tunings and various k-fold cross-validation techniques applied to prevent overfitting or underfitting and to minimize bias.

The performance of the tests was evaluated using precision, recall, F1-score and Accuracy. For the definition and equations of these metrics refer to (Varoquaux and Colliot, 2023).

Precision is the ratio of correctly predicted positive observations to the total number of positively predicted observations. Table 2 presents the results of the precision for the three algorithms across all designed feature combinations. The results show that RNN is the most precise algorithm across the board, especially with the Acc alone, and Acc-Gravity and Acc-RR feature combinations, indicating its strong suitability for tasks involving time-series data. The precision ranges from 81.93% for AG alone and 99.37% for Acc-Gravity combination. DL, while having some potential with specific feature combinations, underperforms compared to RNN and RF, suggesting that further model tuning, or different network architectures might be required. RF offers a balance between stability and precision, performing well across most feature combinations but with the best case, 80%, is not reaching the peak precision of RNN.

Table 2 The precision of the ML algorithms against different feature combination

ML Algorithms	Feature combinations						
	Acc	AG	Acc-Gravity	AG-Gravity	AG-cos	RR	Acc-RR
RNN	0.9787	0.8193	0.9937	0.9056	0.8382	0.9125	0.9620
DL	0.5618	0.6583	0.7505	0.7573	0.6600	0.5615	0.6266
RF	0.64	0.71	0.80	0.80	0.74	0.63	0.76

Recall measures the ability of a ML model to correctly identify all relevant instances in the dataset. Mathematically, it is the ratio of correctly predicted positive observations to all observations in the actual positive class. Table 3 shows the recall for the three algorithms for all feature combinations. The results show that RNN consistently high recall across all feature combinations, with values ranging from 82.12% for AG alone and 99.36 % for Acc-Gravity combination. The highest recall is achieved with the Acc-Gravity feature combination, similar to the precision results, indicating that RNN is very effective at correctly identifying positive instances when these features are used together.

Table 3 The Recall of the ML algorithms against different feature combination

ML Algorithms	Feature combinations						
	Acc	AG	Acc-Gravity	AG-Gravity	AG-cos	RR	Acc-RR
RNN	0.9785	0.8212	0.9936	0.9041	0.8331	0.9037	0.9611
DL	0.5537	0.6720	0.7536	0.7603	0.6715	0.5615	0.6126
RF	0.64	0.71	0.80	0.80	0.75	0.63	0.76

The F1-score is another metric which have been used in this evaluation. It is the weighted average of recall and precision. This index provides a balanced measure of a model's performance, especially where there is an uneven class distribution.

Table 4 presents the results of F1-score. It shows that the highest F1 score is achieved with the

Acc-Gravity feature combination 99.36%, indicating that RNN excels when these specific features are used. The DL model exhibits moderate F1-scores across the board, ranging from 54.92% for Acc to 0.7574 for AG-Gravity. The RF values show stable F1 scores across all feature combinations, ranging from 64% Acc to 80% Acc-Gravity and AG-Gravity. These values of the F1-score for RNN, DL and RF suggests that RNN is very effective in capturing the relevant patterns in the data, leading to an excellent balance between precision and recall.

Table 4 The F1-score of the ML algorithms against different feature combination

ML Algorithms	Feature combinations						
	Acc	AG	Acc-Gravity	AG-Gravity	AG-cos	RR	Acc-RR
RNN	0.9786	0.8190	0.9936	0.9041	0.8330	0.9012	0.9610
DL	0.5492	0.6599	0.7502	0.7574	0.6560	0.5408	0.6114
RF	0.64	0.71	0.80	0.80	0.74	0.63	0.76

Accuracy is the percentage of correct (i.e. true) predictions metrics which is a major index for ML model evaluation. The accuracy results for all cases are shown in Table 5. The peak accuracy of 99.36% with the Acc-Gravity combination indicates that RNN is highly effective at utilizing both acceleration and gravity in combination to make accurate predictions. The highest accuracy for DL is observed with the AG-Gravity feature combination, which is 75.15%, indicating that this combination provides better information for the DL model to make accurate predictions. While RF does not reach the high accuracy levels of RNN, its consistency makes it a strong candidate when stability across different feature sets is important.

Algorithm 1: PCA Algorithm

Input: The features X, $X \in R^{n*d}$

Output: The new subspace (the feature set) Y, $Y \in R^{n*k}$

1.Organise the covariance matrix $X.X^T$

2.Apply Eigenvalue decomposition to the covariance matrix $X.X^T$ to calculate Eigenvalues and Eigenvectors

3.Sort Eigenvalues in descending order, select the k top correspondent Eigenvectors.

4.Construct the transformation matrix W, $W \in R^{d*k}$

5.Obtain the new subspace Y=X.W

6.End

Table 5 The accuracy of the ML algorithms against different feature combination

ML Algorithms	Feature combinations						
	Acc	AG	Acc-Gravity	AG-Gravity	AG-cos	RR	Acc-RR
RNN	97.50%	82.12%	99.36%	90.41%	83.31%	90.37%	96.11%
DL	55.37%	67.05%	74.95%	75.15%	67.72%	56.15%	61.26%
RF	64.05%	71.44%	80.17%	80.22%	74.64%	63.22%	75.77%

The RNN outperformed both DL and RF due to its ability to handle sequential data and the capability of capturing temporal dependencies, while RF relies on fixed-size features resulting in not considering temporal dynamics. The dataset is time-dependent as each data point is reliant on the previous data point. RNN can process data with varying lengths, while DL can process fixed-length data.

Dimensionality reduction (DR) in sensor-based datasets is an important preprocessing step for developing hardware-based ML systems because it simplifies the circuitry and computation, reducing both cost and complexity while enhancing reliability. There are many dimensionality reduction algorithms in the literature (Schneider and Xhafa, 2022).The Principal Component Analysis (PCA) algorithm was selected and applied it DR to the Wild-Shard to create a new dataset that retains only two and three features in two separate cases. The new dataset preserves the influence of all original features.

PCA is a transformation algorithm, when applied to a dataset, it projects an existence dataset to a new one with less features called Principal Components. The PCA is summarized in Algorithm 1 (Anowar et al., 2021), where $w \in R^{x*y}$ is the transformation matrix, d is the dimension of the original X space and k is the dimension of the new mapped space Y.

The three ML algorithms were then tested on these new transformed datasets with k-features. The results are presented in Table 6, where it shows that RNN performs very well when features are integrated into two (accuracy=94.55%) or three (accuracy=96.59%) new features that combines the effects of all original features.

Table 6 The performance of the ML algorithms against modified datasets

ML Algorithms	Modified feature structure	
	Two PCA	Three PCA
RNN	94.55%	96.59%
DL	51.50%	61.16%
RF	65.08%	70.40%

The RNN performs better with three PCA rather than two PCA given that the additional component offers a more detailed and in-depth understanding of the data, capturing a larger portion of its variation. The two PCA puts a risk in losing crucial information, especially in scenarios in which the data is complex and high-dimensional but the three PCA protects the variability that might be lost, leading to an improvement in the performance.

5.Conclusion

The performance of accelerometer and gyroscope sensors in smartphones in the HAR were evaluated. A dataset called Wild-Shard has been used in the evaluation process. The dataset included the readings of an embedded accelerometer and gyroscope sensors in different smartphone models by recording six main human activities of 30 volunteers. Many combinations of features have been tested with a variety of variable justifications and k-folding cross sections and hyperparameter tunings to check the applicability of these sensors in HAR. Also, dimensionality reduction analysis (PCA) algorithm has been used to transform the input feature to just two or three features while retaining the essence of the original data. This reduction not only optimizes the computational load but also significantly reduces the complexity and cost of potential hardware implementations.

The findings indicate outstanding performance of RNN algorithm in the Acc-Gravity, Acc-Gravity-RR feature combinations (99.36% and 96% respectively). This demonstrates that RNN is able to capture temporal dependencies and complex patterns effectively when the data integrates motion, gravitational and angular velocity influences. In this problem, DL models displayed moderate success, with the best results in the feature combination AG-Gravity and Acc-Gravity combinations (75.15% and 74.95%, respectively). This moderate performance indicates that while DL can process complex features from sensor data, achieving high accuracy depends on DL architecture. RF in the other side, offers consistent, though not superior, results across different feature combinations, with the highest accuracy in the combinations AG-Gravity and Acc-Gravity (80.22% and 80.17%, respectively). RF is capable to process mixed sensor data but lacks good performance seen in temporal pattern-focused models like RNNs. The tests underscore the robustness of RNNs in processing datasets with temporal sequences typical in HAR tasks. The comparative underperformance of DL models suggests a need for further tuning and possibly exploring more customized network structures tailored for HAR problem. RF, while it is reliable and easier to implement, falls short in handling sequences like HAR datasets.

6.Conflict of Interest

There is no conflict of interest relevant to this article.

7.Acknowledgment

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