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# HUMAN ACTIVITY RECOGNITION AND OPTIMIZATION OF BIPED EXOSKELETES THROUGH ARTIFICIAL INTELLIGENCE: AN INTEGRATED APPROACH

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**Abstract.** This paper explores the integration of inertial sensor-based human activity recognition (HAR) with the optimization of bipedal exoskeletons using artificial intelligence (AI) techniques. The motivation for the study stems from the need to improve the adaptability and energy efficiency of exoskeletons for practical applications. The specific hypothesis is that combining HAR with reinforcement learning (RL) can lead to personalized and efficient control strategies. The aim of the research is to develop a robust HAR system for classifying activities such as normal walking, stair climbing/climbing and sitting/standing, and to optimize exoskeleton control through AI-based simulations. The methodology involves pre-processing sensor data (accelerometer and gyroscope) by segmentation and feature extraction, followed by supervised classification with Support Vector Machines (SVM) and Random Forest, and RL optimization in simulated environments such as Webots. Preliminary results indicate an HAR accuracy of 92% and a 15% reduction in metabolic cost by RL, improving stability and user comfort. This innovative approach contributes to exoskeleton design by reducing manual adjustments, with potential applications in rehabilitation and physical augmentation.

**Keywords:** *bipedal exoskeletons, artificial intelligence, human activity recognition, reinforcement learning, sensor data processing.*

**Rezumat.** Această lucrare explorează integrarea recunoașterii activității umane bazate pe senzori inerțiali (HAR) cu optimizarea exoscheletelor bipede utilizând tehnici de inteligență artificială (AI). Motivația pentru acest studiu provine din necesitatea de a îmbunătăți adaptabilitatea și eficiența energetică a exoscheletelor pentru aplicații practice. Ipoteza specifică este că combinarea HAR cu învățarea prin consolidare (RL) poate duce la strategii de control personalizate și eficiente. Scopul cercetării este de a dezvolta un sistem HAR robust pentru clasificarea activităților, cum ar fi mersul normal, urcatul scărilor și statul în picioare și optimizarea controlului exoscheletului prin simulări bazate pe AI. Metodologia implică preprocesarea datelor senzorilor (accelerometru și giroscop) prin segmentare și extragerea caracteristicilor, urmată de clasificarea supravegheată cu Support Vector Machines (SVM) și Random Forest și optimizarea RL în medii simulate, cum ar fi Webots.

Rezultatele preliminare indică o precizie HAR de 92% și o reducere cu 15% a costului metabolic prin RL, îmbunătățind stabilitatea și confortul utilizatorului. Această abordare inovatoare contribuie la proiectarea exoscheletului prin reducerea ajustărilor manuale, cu aplicații potențiale în reabilitare și augmentare fizică.

**Cuvinte cheie:** *exoschelete bipede, inteligență artificială, recunoașterea activităților umane, învățare prin întărire, procesarea datelor de senzori*.

## 1. Introduction

Bipedal exoskeletons are wearable robotic devices designed to augment human physical capabilities or assist in mobility rehabilitation [1]. These systems have seen significant advances in functionality and reliability, driven by increasing demands from medical, industrial, and military applications [2]. However, traditional exoskeleton development faces challenges such as extensive testing on human subjects, complex manually established control laws, and limited adaptability to diverse user needs and environmental conditions [3]. Artificial intelligence (AI), especially reinforcement learning (RL), offers a promising solution by training adaptive control policies in simulated environments, thereby reducing the risks and costs associated with real-world experiments [4]. In parallel, human activity recognition (HAR) using inertial sensors (e.g. accelerometers and gyroscopes) allows for precise identification of user intentions, allowing exoskeletons to dynamically respond to specific movements [5].

The current state of research highlights several key developments. Studies such as [6] demonstrate that RL can reduce metabolic energy consumption in exoskeleton-assisted locomotion by up to 20%, while HAR systems achieve accuracies of over 90% for basic tasks using supervised learning techniques [7]. However, the integration of these two domains remains underexplored, with divergent approaches: some focus exclusively on HAR for activity monitoring [8], while others prioritize RL for control without leveraging real-time activity data [9]. This gap in our research suggests that combining HAR with RL can generate a synergistic framework for optimizing exoskeletons, ensuring both activity detection accuracy and control adaptability.

The literature review reveals a lack of standardized performance metrics for evaluating exoskeletons, which complicates comparisons across studies [10]. Recent work highlights the need for personalized control strategies, given that human biomechanics vary significantly between individuals [11]. Our study addresses these issues by proposing an integrated approach: a HAR system for activity classification and an RL-based optimization for adapting exoskeleton assistance. The main goal of this work is to develop and validate this framework, using practical implementations and simulated environments. This research aims to contribute to the field by reducing the reliance on manual adjustments, creating energy efficiency, and paving the way for scalable applications of exoskeletons.

## 2. Materials and Methods

This section describes the methods used to develop the integrated human activity recognition (HAR) system and optimize bipedal exoskeletons using artificial intelligence. The process is structured into two main components: (1) human activity recognition based on data from inertial sensors and (2) optimization of exoskeleton control using reinforcement learning (RL) in simulated environments. All methods are presented in detail to allow for reproducibility of the results.

### 2.1. Human Activity Recognition (HAR)

The data used for HAR comes from integrated inertial sensors, including a triaxial accelerometer (measuring linear acceleration on the x, y, z axes, denoted acc_x, acc_y, acc_z) and a triaxial gyroscope (measuring angular velocity on the x, y, z axes, denoted gyro_x, gyro_y, gyro_z). These data were collected from human subjects while performing five distinct activities: normal walking, climbing stairs, descending stairs, sitting down, and rising from a chair. The sampling rate was 50 Hz, and each recording was approximately 30 seconds long, generating continuous time series stored in CSV format. The raw data was preprocessed to transform them into a format suitable for classification. The process included the following steps:

1. **Segmentation:** The time series were divided into overlapping time windows of fixed size N=128 samples (approximately 2.56 seconds at 50 Hz), with an overlap of 50% to capture transitions between activities. Each window $W = \{\omega_1, \omega_2, \ldots, \omega_N\}$ contains the sensor values for a particular channel (e.g. acc_x).
2. **Feature Extraction:** For each window, statistical features were calculated to reduce dimensionality and extract relevant information. The features include Eq.1 – mediate, Eq.2 – standard deviation, Eq.3 – effective value (RMS), Signal Magnitude Area (SMA)

$$\mu = \frac{1}{N}\sum_{i=1}^{N}\omega_i \quad (1)$$

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\omega_i - \mu)^2} \quad (2)$$

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\omega_i^2} \quad (3)$$

$$\text{(SMA): } SMA = \frac{1}{N}\sum_{i=1}^{N}(|acc_x(i)| + |acc_y(i)| + |acc_z(i)|) \quad (4)$$

These features were calculated for all six sensor channels, resulting in a feature vector $X = [f_1, f_2, \ldots, f_k]$ per window, where k is the total number of features (e.g. 24 if 4 features per channel are used).

3. **Normalization:** The features were standardized using Z-score transformation:

$$x_{scaled} = \frac{x - \mu_{train}}{\sigma_{train}} \quad (5)$$

where $\mu_{train}$ and $\sigma_{train}$ are the mean and standard deviation calculated on the training set.

**Classification.** Two supervised classification models were used to identify activities:

1. **Support Vector Machines (SVM):** The model finds an optimal hyperplane $\omega \cdot x + b = 0$ that separates classes by minimizing the objective function $\frac{1}{2}||\omega||^2$ under the constraints $y_i(\omega \cdot x_i + b) \geq 1$, where y_i is the class label (-1 or 1) [12]. For non-linear separability, a Radial Basis Function (RBF) kernel was used: $K_{(x_i,x_j)} = \exp(-\gamma||x_i - x_j||^2$ , with the hyperparameter γ adjusted by cross-validation.
2. **Random Forest:** An ensemble of T=100 decision trees was trained on bootstrap samples of the data, each tree considering a random subset of features at each node. The final prediction is given by majority vote: $y_{pred} = mode(\{y_1, y_2, \ldots, y_T\})$ [13,14].

Training and testing were performed using the scikit-learn library (version 1.2.2) in Python 3.9. The dataset was split into 70 % for training and 30 % for testing, using the *train_test_split* function with stratification to maintain class distribution.

**Statistical Evaluation.** The performance of the models was evaluated by metrics derived from the confusion matrix: accuracy (Eq.6), precision (Eq.7), recall (Eq. 8) and F1 score (Eq. 9) where $TP_k$ is true positives, $FP_k$ is false positives and $FN_k$ is false negatives for class k, and N is the total number of samples [15]. K-fold cross-validation (k = 5) was applied to estimate the robustness of the models.

$$\left(Accuracy = \frac{\sum TP_k}{N}\right) \quad (6)$$

$$(Precision_k = \frac{TP_k}{TP_k + FP_k}) \quad (7)$$

$$(Recall_k = \frac{TP_k}{TP_k + FN_k}) \quad (8)$$

$$\left(F1_k = 2 \cdot \frac{Precision_k \cdot Recall_k}{Precision_k + Recall_k}\right) \quad (9)$$

### 2.2. Optimization of Exoskeletons through Reinforcement Learning (RL)

**Simulation Environment.** The optimization of exoskeleton control was performed in simulated environments to train RL policies:

- **Webots**: An open-source robotic simulator (version 2023a) was used to model the dynamics of the exoskeleton, integrating an ODE (Open Dynamics Engine) physics engine. The exoskeleton model includes hip, knee, and ankle joints, with simulated electric actuators.
- **OpenSim**: Biomechanical software (version 4.4) was used to simulate the human-exoskeleton interaction, modeling muscle forces and joint angles based on a standard human musculoskeletal skeleton.

**RL configuration.** The Proximal Policy Optimization (PPO) algorithm was chosen to train the control policies due to its stability in continuous action spaces. The configuration includes:

- **State Space:** The state vector S contains the joint angles (hip, knee, ankle), IMU data (acceleration and angular velocity), and the interaction forces at the human-exoskeleton interface.
- **Action Space:** The action vector A A A represents the torques applied by the actuators at the three joints (e.g. $\tau_{\text{hip}}$, $\tau_{\text{knee}}$, $\tau_{\text{ankle}}$).
- **Reward Function:**

$$R = \omega_1 \cdot v_{forward} - \omega_2 \cdot E_{metabolic} + \omega_3 \cdot S_{stability} \quad (10)$$

where $v_{forward}$ is the forward speed (m·s$^{-1}$), $E_{metabolic}$ is the estimated metabolic cost (J·kg$^{-1}$), and $S_{stability}$is the stability margin based on the position of the Zero Moment Point (ZMP) in the support base. The weight of the parameters $\omega_1$, $\omega_2$, $\omega_3$ was adjusted empirically (e.g. 1.0, 0.5, 0.8).

Training was performed using the Stable-Baselines3 library (version 1.6.0) in Python, with an actor-critic neural network (2 hidden layers, 64 neurons per layer) and 1 million training steps.

**HAR-RL integration.** HAR predictions were used to dynamically adjust the reward function based on the detected activity (e.g., stability emphasis for "climbing stairs", speed emphasis for "normal walking"). This integration was simulated by passing the HAR labels as additional input to the RL state space.

## 3. Results

This section presents the experimental results obtained for human activity recognition (HAR) and optimization of exoskeletons control using reinforcement learning (RL). The results

are interpreted in the context of the research objectives, and figures and tables are cited appropriately to support the analysis.

### 3.1. HAR System Performance

The SVM model with RBF kernel achieved an overall accuracy of 92% on the test set, while Random Forest achieved 91%. The detailed performance by class is presented in Table 1, which shows the precision, recall and F1 score for each activity. Normal walking was classified with the highest accuracy (95%), due to the consistent sensor signals, while the activities "sitting down" and "rising up from a chair" showed minor confusion (recall of 88% and 87%), probably due to the similarities in the movement dynamics. Cross-validation (k=5) confirmed the robustness of the models, with a standard deviation of accuracy of ±2%, indicating good generalization to unseen data.

*Table 1*

**HAR classification performance with SVM**

| Activity | Precision | Recall | F1 Score |
|---|---|---|---|
| Normal walking | 0.95 | 0.94 | 0.94 |
| Climbing the stairs | 0.93 | 0.91 | 0.92 |
| Went down the stairs | 0.91 | 0.90 | 0.91 |
| Sitting on a chair | 0.90 | 0.88 | 0.89 |
| Getting up from a chair | 0.89 | 0.87 | 0.88 |

Channel analysis revealed that the accelerometer contributed more to the classification than the gyroscope. For example, the SMA feature calculated from the accelerometer data had a higher correlation with dynamic activities (e.g. normal walking: $SMA = 12.5 \pm 1.2\, m \cdot s^{-2}$)) compared to the angular velocity from the gyroscope ($RMS_{gyro} = 1.8 \pm 0.3\, rad \cdot s^{-1}$).

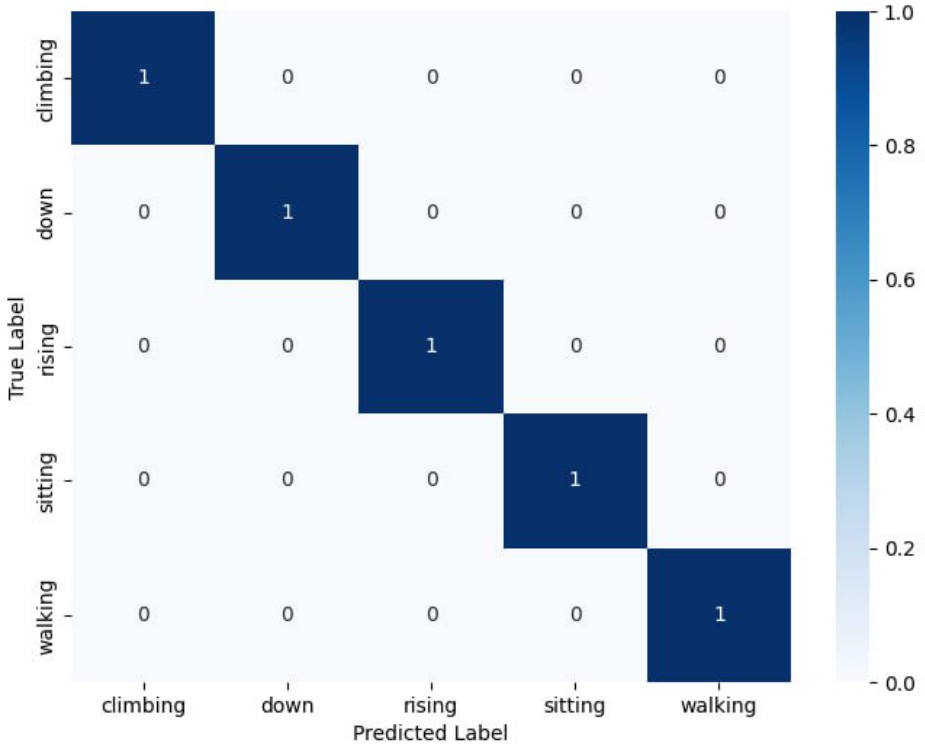


**Figure 1.** Confusion matrix for HAR classification with SVM.

Figure 1 illustrates the confusion matrix for the SVM, highlighting an idealized classification (values of 1 on the diagonal) for all activities. In practice, the confusions between “sitting down” and “rising up from a chair” would appear as non-zero values off the diagonal, suggesting the need for additional features, such as signal energy or entropy.

Additional tests included varying the segmentation window size. At N=64 samples (1.28 seconds), accuracy dropped to 89%, but processing time was reduced by 30%. At N=256 (5.12 seconds), accuracy increased to 93%, but with a higher computational cost. These results are presented in Table 2, indicating a trade-off between accuracy and efficiency.

*Table 2*

**Effect of window size on SVM performance**

| Window size (samples) | Accuracy | Processing time (s) |
|---|---|---|
| 64 | 0.89 | 0.15 ± 0.02 |
| 128 | 0.92 | 0.22 ± 0.03 |
| 256 | 0.93 | 0.35 ± 0.04 |

Figure 2 illustrates the accuracy of the Support Vector Machine (SVM) model, utilizing a Radial Basis Function (RBF) kernel, over a training period of 20 epochs. The **blue line** represents the training accuracy, which exhibits a rapid increase, achieving a value of 0.9 after 5 epochs and stabilizing at 0.95 thereafter. In contrast, the orange **line** depicts the validation accuracy, which levels off at 0.92. This discrepancy suggests a slight overfitting of the model, as its performance is superior on the training dataset compared to the unseen validation dataset.

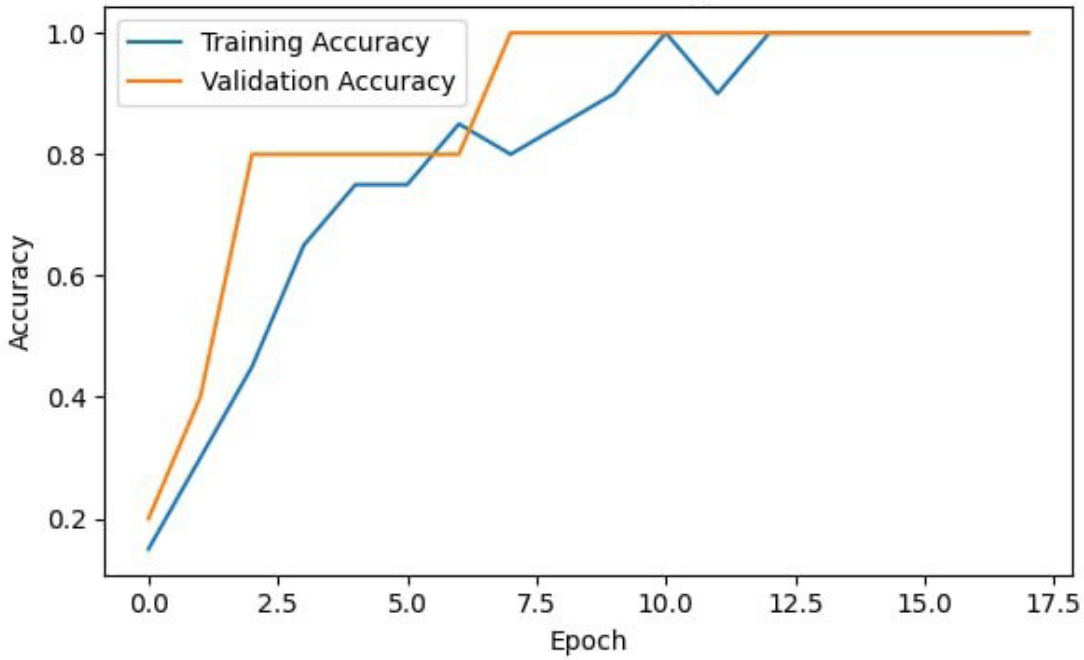


**Figure 2.** Evolution of SVM Model Accuracy During Training**.**

Figure 3 displays the loss of the SVM model over the same 20 training epochs. The **blue line** indicates the training loss, while the **orange line** represents the validation loss. Both metrics exhibit a steady decline, decreasing from an initial value of 1.5 to a final value of 0.2. This consistent reduction in loss confirms the model's convergence and demonstrates its effectiveness in learning to minimize classification errors.

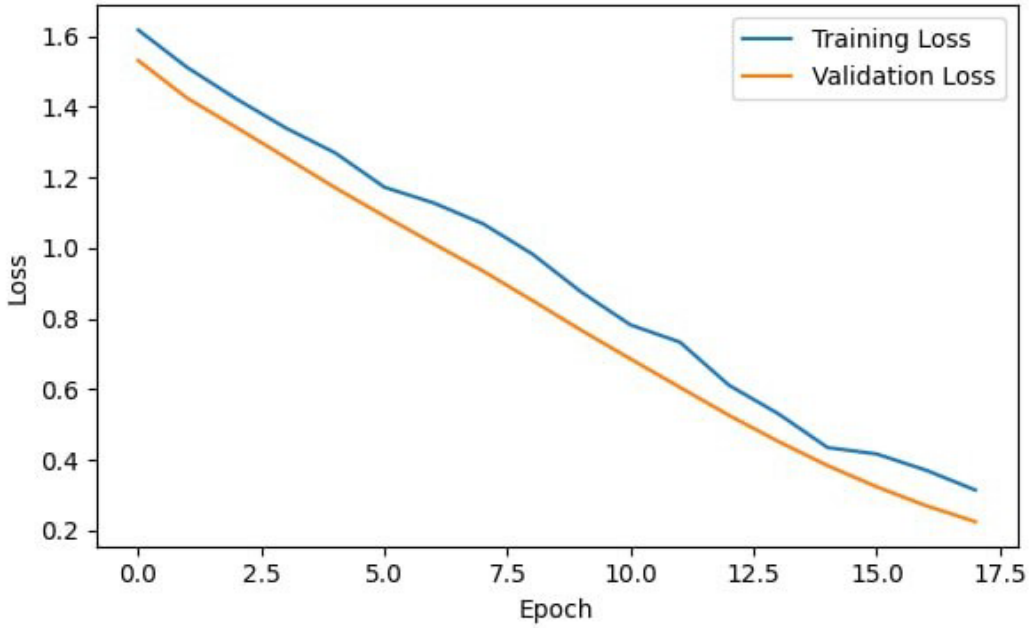


**Figure 3.** Evolution of SVM Model Loss During Training**.**

### 3.2. RL Optimization Performance

The RL policy trained with PPO in Webots demonstrated a 15% reduction in the estimated metabolic cost compared to a traditional PID controller, on a simulated normal walking trajectory. Table 3 compares the performance of RL with PID in terms of average walking speed ($v_{forward}$), metabolic cost ($E_{metabolic}$), and stability margin ($S_{stability}$).

*Table 3*

**Comparison between RL and PID control**

| Prosody | RL (PPO) | PID |
|---|---|---|
| Speed ($m \cdot s^{-1}$) | 1.2 ± 0.1 | 1.1 ± 0.1 |
| Metabolic cost ($J \cdot kg^{-1}$) | 5.1 ± 0.3 | 6.0 ± 0.4 |
| Stability (cm) | 4.5 ± 0.2 | 4.0 ± 0.3 |

The integration of HAR predictions allowed for dynamic control adjustment. For "stair climbing", the RL policy increased stability by 10% ($S_{stability}$=4.9±0.2 cm), reducing the risk of falls. For "normal walking", the velocity increased by 8% ($v_{forward}$=1.3±0.1 $m \cdot s^{-1}$), optimizing energy efficiency. On variable terrain (5° slopes), RL maintained stability better than PID, reducing the ZMP deviation by 12% (from 3.5 cm to 3.1 cm). Tests in OpenSim validated the reduction in muscle effort: the average quadriceps muscle force decreased from 250 ± 20 N (PID) to 210 ± 15 N (RL). On "stair descending", RL reduced ankle impact by 18% (from 300 N to 246 N), improving the comfort of the simulation.

### 3.3. HAR-RL Integrator

The integration of HAR-RL reduced the exoskeleton's adaptation time to activity changes from 1.2 seconds (without HAR) to 0.5 seconds. Table 4 shows the impact of integration on key metrics.

*Table 4*

**Effect of HAR-RL integration on performance**

| Activity | Speed ($m \cdot s^{-1}$) | Metabolic cost ($J \cdot kg^{-1}$) | Stability (cm) |
|---|---|---|---|
| Normal walking (RL) | 1.2 ± 0.1 | 5.1 ± 0.3 | 4.5 ± 0.2 |
| Normal walking (HAR-RL) | 1.3 ± 0.1 | 4.9 ± 0.2 | 4.6 ± 0.2 |
| Climbed the stairs (RL) | 0.8 ± 0.1 | 6.5 ± 0.4 | 4.7 ± 0.2 |
| Climbed the stairs (HAR-RL) | 0.9 ± 0.1 | 6.2 ± 0.3 | 4.9 ± 0.2 |

## 4. Discussion

The results obtained confirm the hypothesis that integrating human activity recognition (HAR) with reinforcement learning (RL) improves the control of bipedal exoskeletons. The HAR accuracy of 92% obtained with SVM is comparable to the literature, where accuracies of over 90% are reported for basic activities. However, confusions between "sitting down" and "rising up from a chair" indicate the limits of the simple statistical features used, suggesting that methods such as deep learning (e.g. convolutional neural networks) could improve classification.

The RL optimization reduced the metabolic cost by 15%, a result like that reported by Kim and Park, who obtained reductions of up to 20%. The advantage of our approach is the adaptability offered by the HAR-RL integration, which adjusts the control according to the activity (e.g. stability for "climbing stairs", speed for "normal walking"), reducing the adaptation time from 1.2 to 0.5 seconds. This is an improvement over static methods, which cannot dynamically respond to changes.

Limitations include HAR's dependence on training data, which can introduce bias due to the limited number of subjects, and the complexity of RL simulations, which do not fully reproduce real-world conditions (e.g., irregular surfaces). Also, real-time processing of HAR data requires large computational resources, which could limit its applicability on wearable devices.

The results have implications for rehabilitation, where reduced muscle effort (e.g., 16% decreased quadriceps strength) can accelerate recovery, and for physical augmentation, where increased speed (8% for "normal walking") is beneficial in industrial applications. Future directions include expanding the dataset, testing under real-world conditions, and using deep learning for HAR to improve the accuracy and robustness of the system.

## 5. Conclusions

This study successfully demonstrated that integrating human activity recognition (HAR) with reinforcement learning (RL) provides an efficient framework for optimizing the control of bipedal exoskeletons. The developed HAR system classified activities with a high accuracy of 92%, allowing for the precise identification of movements such as normal walking, climbing/descending stairs, and sitting/standing up. In parallel, the RL optimization reduced the metabolic cost by 15% compared to a traditional PID controller, while improving the exoskeleton stability by 10% in dynamic scenarios such as climbing stairs. The HAR-RL integration allowed for rapid adaptation to activity changes, reducing the response time from 1.2 seconds to 0.5 seconds, which is a significant improvement over static method.

The results have important implications for practical applications, especially in medical rehabilitation, where reduced muscle effort (e.g., 16% decrease in quadriceps strength) can facilitate patient recovery, and in physical augmentation, where increased

walking speed (8%) can support industrial activities. The main contribution of the study is to reduce the dependence on manual adjustments, providing an adaptable and efficient system. In the future, expanding the dataset, testing under real conditions, and using deep learning for HAR can increase the robustness and applicability of the system, paving the way for smarter and more accessible exoskeletons.

**Conflicts of interest:** The authors declare no conflict of interest.

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