EMG-Based Lower Limb Activity Recognition for Exoskeleton-Assisted and Unassisted Locomotion Using Deep Learning

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Abstract. With advancements in exoskeleton technology, the integration of advanced machine learning techniques with sensor data can essentially improve the accuracy and effectiveness of activity detection. This paper explores the potential of machine learning algorithms to detect activities with the help of features extracted from Electromyogram (EMG) signals at a window length of as small as 100 ms, with and without an exoskeleton. Accurate activity recognition is also important for social and assistive robots, enabling more adaptive human–robot interaction and context-aware assistance in rehabilitation, healthcare, and occupational assistance environments. Electromyogram signals were collected from trunk, abdominal and thigh muscles of healthy participants. A one-dimensional convolutional neural network (CNN) was employed for detecting three classes: no activity, walking and walking with weight. Our evaluation shows that the CNN model was able to detect the activities with similar accuracy in the presence and absence of an exoskeleton. An average accuracy of 85.66% was observed for the condition without the exoskeleton, and an average accuracy of 86% was observed for the exoskeleton-assisted condition. Also, when the CNN model was trained on exoskeleton-assisted data and tested on EMG data without exoskeleton (and vice versa), a notable reduction in accuracy was observed. This suggests that the machine learning model performs reliably under in-domain evaluation and struggles to generalise across conditions. This highlights the need for domain adaptation to mitigate the exoskeleton-induced distribution shift in EMG.

Keywords: EMG · 1D CNN · Exoskeleton assistance · Rehabilitation · Occupational assistance.

1 Introduction

Wearable assistive robotic technologies are increasingly recognised as suitable tools for rehabilitation, assistive mobility, and occupational assistance. These technologies can provide external torques or support to assist movements, thereby reducing muscular strain and metabolic energy expenditure while maintaining task performance. As a result, they have emerged as promising solutions to mitigate physical demands experienced by workers [21,26]. The human performance augmentation exoskeletons are designed to enhance strength and endurance in able-bodied individuals. These facilitate lifting and transporting heavy loads across extended distances [28]. Typical applications include warehouses, construction sites, emergency relief operations, and military settings. Exoskeletons are generally categorised as passive or active, based on their power source. Passive exoskeletons rely on simple and less expensive parts like metal or gas springs and elastic elements to support a posture or movement. In contrast, an active exoskeleton is powered by electric motors, pneumatic muscles, or hydraulic actuators [17,5,1]. With the help of sophisticated actuators, these wearable devices can enhance human capabilities by providing mechanical support, augmenting strength, and facilitating movement.

Surface Electromyography (sEMG) is an important sensing modality for exoskeleton control, motion intention detection, and rehabilitation robotics. Different activities can be identified and classified with the help of features extracted from EMG signals, which can help in controlling exoskeletons. Exploring the muscle activity also helps to address the challenge of accurately predicting users' intentions to perform various tasks. With the advancements in machine learning and deep learning technologies, various movements were easily recognised with the help of extracting useful features from EMG. Convolutional neural networks(CNNs) enable effective extraction of deep spatiotemporal features from EMG. They exhibit superior performance over traditional handcrafted feature extraction methods [22].

The application of sEMG technology not only allows for real-time monitoring of muscle activation patterns but also aids in the assessment of ergonomic risks associated with manual material handling tasks [24]. Integrating bipolar EMG-based activity prediction with exoskeleton systems can help in developing robust, data-driven assistive technologies capable of adapting to dynamic neuromuscular patterns.

The objective of this work is to investigate and compare the model performance of a 1D CNN in predicting lower limb activities in the presence and absence of a robotic exoskeleton. This is motivated by the increasing use of wearable robots in gait rehabilitation and mobility assistance, where reliable and domain-robust intention-recognition algorithms are critical for safe and seamless human–robot interaction. This study presents a preliminary pilot investigation based on EMG data collected from four healthy subjects who were instructed to walk while holding a weight with and without wearing an exoskeleton.

2 Related work

The advancements in machine learning and deep learning techniques significantly improved the EMG-based activity detection, which in turn improved the performance and functionality of robotic exoskeletons. With the help of sophisticated algorithms and large datasets, researchers can develop systems that more effectively interpret the electrical signals generated by muscle activity, enabling more accurate and responsive control of exoskeletons. This integration of deep learning enables adaptive responses to various movements, improving user experience and facilitating better rehabilitation efforts for individuals with mobility impairments [23]. Recent studies show that using convolutional neural networks(CNN) and recurrent neural networks(RNN) can improve the accuracy of movement detection and device responsiveness, leading to a better interface between users and assistive devices [2]. These advancements do not only apply to rehabilitation scenarios; they can also extend to occupational assistance, particularly where assistance is needed for lifting heavy objects.

Supervised learning methods such as support vector machines (SVMs) and neural networks have shown promise in distinguishing between different muscle patterns, which is crucial for developing prosthetic control systems that respond to user intent in real-time [14]. A hybrid regression model comprising a parallel CNN-LSTM architecture managed to capture spatial and temporal features of the EMG signals, which can generate a trajectory for the upper extremity movements [22].

Recent research integrating EMG technology with exoskeleton systems emphasises the importance of user-centred design in improving system performance [7] [8]. By focusing on user experience, these studies try to develop exoskeletons that can address the varied physiological, ergonomic, and psychological requirements of users. Such systems can enhance comfort, adaptability, user acceptance, and overall system usability, leading to more effective human–machine interaction. Implementing adaptive control strategies that learns from users' movements could significantly enhance the responsiveness of exoskeletons, making them more intuitive during rehabilitation [19]. A recent study suggests that a passive exoskeleton has the potential to reduce muscular loading at the lower back level during static forward bending [6].

By analysing the muscle activation patterns during lifting movements, tailored exoskeleton systems can be developed that provide real-time support, which reduces the risk of injury and improves performance outcomes for individuals with mobility impairments. Integrating EMG data with advanced motion sensors can create a feedback loop that can adapt to the user's lifting techniques, promoting safer and more efficient movement strategies [27]. Significant reductions in muscle activation (30–60%) and perceived lower-limb effort were observed while using a hip and knee joint actuated exoskeleton developed for repetitive manual lifting and carrying tasks [20]. EMG-based prediction and control allow exoskeletons to assist lifting and movement, substantially reducing muscular effort and enabling users to perform daily tasks more independently. However, limited research has investigated whether EMG-based activity clas-

Fig. 1: Lateral and posterior view of MATE-XB exoskeleton.

sification models maintain their robustness and reliability across both assisted and unassisted conditions, highlighting the need for systematic evaluation under varying mechanical support scenarios. Translating this potential into routine everyday use still requires more robust, low-calibration systems and long-term field studies.

3 Methodology

This study involved collecting bipolar EMG data from four healthy participants while they were asked to walk with and without holding a 10 kg box.

3.1 MATE - XB

The MATE-XB (Comau, Italy), shown in Figure 1, is a passive back exoskeleton specifically developed to reduce muscular effort in the lumbar region during manual handling tasks. The device is intended to support workers engaged in activities such as squatting, stooping, or performing repetitive lifting, thereby reducing spinal load and improving task execution quality.
It provides extensor assistance at the hip–spine complex through a stiff, H-shaped carbon-fibre backbone coupling three subsystems: (i) the human–machine interface (HMI), (ii) passive degrees of freedom (pDOFs), and (iii) bilateral passive actuation units at the hips. The HMI, comprising thigh cuffs, trunk vest, pelvic belt, and lower pelvic stability belt, ensures mechanical coupling and bidirectional force transmission between the user and the device. The pDOFs, provided by flexible trunk straps and hip ab/adduction hinges, allow natural motion without imposing rigid trajectories, thereby preserving mobility, alignment, and comfort during prolonged use. The device relies on two lateral spring-based actuators that store energy during trunk flexion and release it during extension, thereby assisting the return to an upright posture. Five selectable assistance levels are available, corresponding to different torque outputs delivered to the user, with a

peak torque ranging from 50 to 80 Nm. The structural configuration allows effective mechanical coupling with the user while preserving mobility and alignment during dynamic tasks.
The device is produced in two sizes (L and XL), but its adjustable components enable use across a wide range of body dimensions. Given the participants' anthropometrics, an L-size exoskeleton was used. The device's weight was approximately 4.1 kg

3.2 Experiment Protocol

Participants carried out a semi-realistic manual handling task developed to resemble a typical industrial lifting activity. The task involved the repeated lifting, carrying, and repositioning of a 10 kg box according to a predefined sequence. The sequence began with the box placed on a shelf at a height of 25 cm (location A). From this position, the participant lifted the box and transferred it to a second shelf located at 45 cm height (location B). Subsequently, the participant turned around a cone positioned behind them (location C), returned to shelf B, lifted the box once more, and placed it back onto the initial shelf at location A. A schematic illustration of the experimental setup and task sequence is provided in Figure 2. Each trial consisted of ten continuous repetitions of the described sequence, with a duration of approximately 6 minutes. Participants completed a total of five trials consecutively, resulting in an overall task duration of about 30 minutes. The experiment was performed under two experimental conditions: wearing the exoskeleton (YesExo) and without the exoskeleton (NoExo). To minimise potential order effects, the sequence of conditions was randomised across participants.
In addition to the dynamic trials, a static calibration trial was acquired. During this trial, participants stood upright with a neutral posture, arms slightly abducted and palms facing forward.
At the start of the experimental session, participants were equipped with the exoskeleton to ensure appropriate fit, comfort, and correct functioning. They were allowed a familiarisation period, during which they walked and performed several practice lifting movements to become accustomed to the device and its assistance. Following this familiarisation phase, the exoskeleton was removed, and anthropometric measurements were collected prior to the execution of the experimental protocol.

sEMG data were collected using 16 wireless bipolar Mini Wave sensors (Cometa, Italy), with a sampling frequency of 2000 Hz. Electrodes were positioned bilaterally over the main trunk extensor muscles, including the Longissimus Thoracis pars thoracis (located 4 cm lateral to the T10 vertebra), the Longissimus Thoracis pars lumborum (3 cm lateral to L1), and the Iliocostalis lumborum (6 cm lateral to L2). Further sensors were placed on the abdominal muscle groups, namely the Internal Oblique, External Oblique, and Rectus Abdominis, as well as on selected lower-limb muscles relevant to lifting tasks, specifically the Rectus Femoris and Biceps Femoris. Electrode placement was mirrored on both sides of the body to allow for reliable bilateral comparisons of muscle activity.

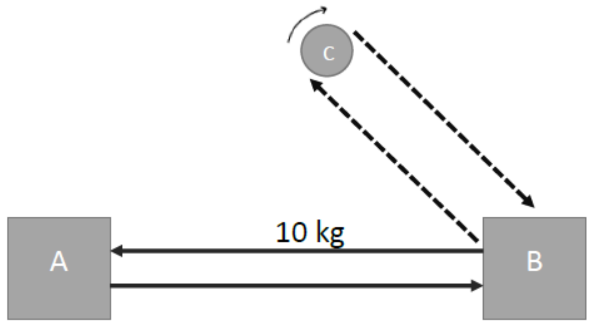


Fig. 2: Schematic representation of the task.

3.3 Feature extraction and classification

Removing artefacts from the recorded EMG is a crucial step in the pre-processing stage. The EMG signals were band-pass filtered between 20 Hz and 400 Hz using a 4th-order Butterworth filter to remove low-frequency motion artefacts and high-frequency instrumentation noise. Additionally, a notch filter was designed at 50Hz to remove power line interference. This preprocessing ensures that the EMG signals are of good quality, enabling effective classification using machine learning models. The choice of features plays a vital role in designing an effective EMG-based classification system. Well-selected features can enhance the ability of the model to distinguish between different activities. Six time-domain features were used here for the classification of activities. The features used are Mean Absolute Value (MAV), Root Mean Square (RMS), Zero Crossing (ZC), Variance (VAR), Waveform Length (WL) and Integrated EMG (IEMG). These features can efficiently capture the elements of muscle activity which are needed for accurate movement prediction and are effective in real-time applications like prosthetic control, exoskeletons, and gesture recognition [13,3,9]. Each feature was calculated for a window length of 100ms.

Considering EMG as a time series $x(t)$, $t = 1, 2, 3, \ldots, T$, then the above time-domain features are defined as follows:

Mean Absolute Value: It is calculated by taking the average of the absolute value of the signal for a particular window [25]:

$$MAV = \frac{1}{T}\sum_{t=1}^{T}|x(t)| \tag{1}$$

Root Mean Square: This is calculated by finding the square root of the average power of the EMG signal for the analysis window [12]:

$$RMS = \sqrt{\frac{1}{T}\sum_{t=1}^{T}x(t)^2}. \tag{2}$$

Zero Crossing: This is calculated by counting the total number of sign changes from a positive to negative amplitude and vice versa:

$$ZC = \sum_{t=1}^{T-1} \mathbb{I}\left(x[t] \cdot x[t+1] < 0\right), \tag{3}$$

where $\mathbb{I}(\cdot)$ is an indicator function that evaluates to 1 if the condition inside is true, and zero otherwise.

Variance: Variance is defined as the average of the squared values of the deviation of the signal around its mean:

$$VAR = \frac{1}{T} \sum_{t=1}^{T} \left(x(t) - \bar{x}\right)^2 \tag{4}$$

where $\bar{x}$ is the mean of the signal.

Waveform Length: Measures signal complexity as the cumulative length over the window [15]:

$$WL = \sum_{t=2}^{T} |x(t) - x(t-1)|. \tag{5}$$

Integrated EMG: It represents the summation of the absolute values of the sEMG signal amplitude and is given as

$$IEMG = \sum_{t=1}^{T} |x(t)|. \tag{6}$$

Network Architecture A one-dimensional CNN (1D-CNN) model was employed to predict three activities using the extracted time-domain features from bipolar EMG. CNN architectures are well suited for EMG-based activity recognition because they can capture local temporal patterns in the signal through convolutional filters. Compared with traditional feedforward neural networks, CNNs are able to automatically learn discriminative features from sequential data while preserving temporal relationships between signal samples[18]. The network architecture consists of four convolutional layers followed by two fully connected layers. Each convolutional layer was activated using the ReLU activation function and is followed by a maxpooling layer of pool size 2.

Integration into CNN Pipeline The CNN model was implemented using PyTorch with the dataset split into 70% training, 15% validation, and 15% testing to ensure sufficient data for training while maintaining separate subsets for tuning model evaluation. Training was conducted with a batch size of 32 over a maximum of 100 epochs, with early stopping applied to prevent overfitting. The learning rate was set to 0.0001, and a dropout rate of 0.2 was used to enhance generalisation.

A non-overlapping window of 100 samples was used to extract the time-domain features of EMG. These features were then input into the 1D-CNN to predict the following functional tasks: No activity, walking and walking with weight.

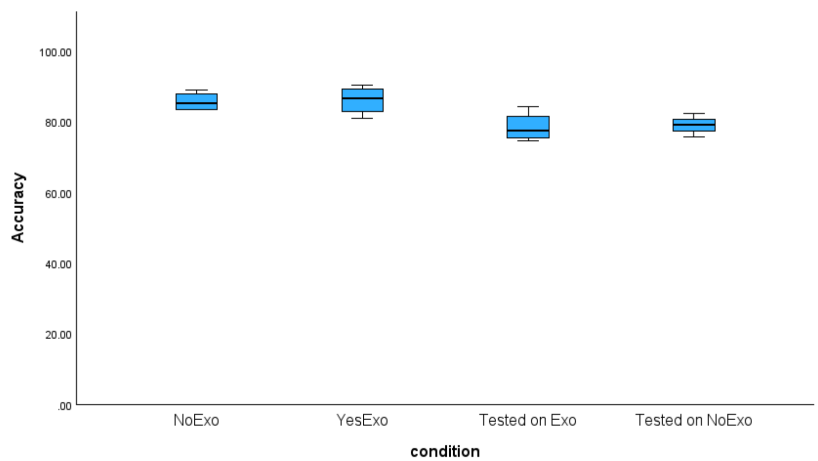
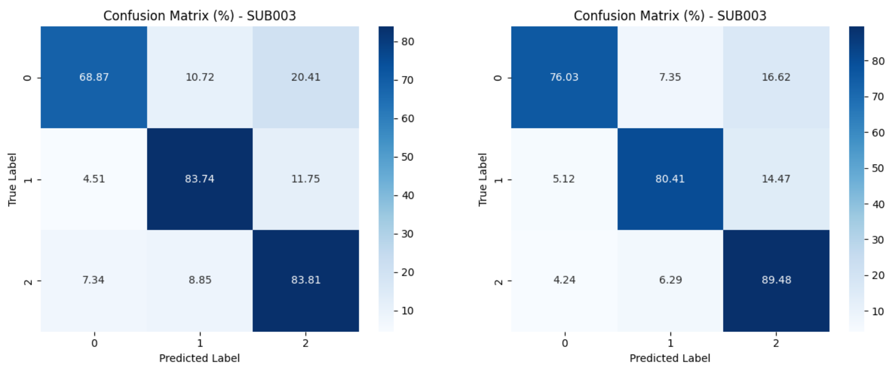


Fig. 3: Boxplot comparing the accuracy of CNN for different conditions. The first boxplot shows the accuracy for the No EXO condition. The second one is for the YesExo condition. Third is the accuracy obtained when training is done on data from No Exo and testing is done on Exo assistance data. The fourth boxplot shows accuracy when training is done on YesExo data and testing is done on NoExo data.

4 Results

A 1D CNN was employed to predict three classes: no activity, walking with weight and walking without weight. No activity corresponds to the task where the participant is not doing anything. During walking activity, the participant is walking from location B turned around C and back to position B. Walking with weight is when the participant moves from A to B or B to A carrying the weight. The tasks were predicted upon four conditions: one while performing the activity with the exoskeleton assistance (YesExo), second while performing activities without the exoskeleton assistance (NoExo), third condition was to predict the activities when the model is trained on EMG data from no exoskeleton and tested on exoskeleton-assisted data, and fourth, the model is trained on exoskeleton assisted EMG data and tested on data without exoskeleton. The first two conditions are referred to as in-domain evaluation, whereas the last two conditions are referred to as cross-domain evaluation throughout this paper..

A box plot comparing the accuracy of the model between the four conditions is presented in Figure 3. It is observed that across both No Exo and Yes Exo conditions, the CNN exhibited consistently similar classification performance. The same can be observed for cross-domain evaluation, too, even though the accuracy is reduced. The model was employed on four subjects' data, and an average accuracy of 85.66% was obtained in the condition without using an exoskeleton. In the exoskeleton-assisted condition, the model was able to predict the activities with an average accuracy of 86%. This minor variation in accuracy was statistically insignificant and fell within the expected variability range of the cross-validation process. For the cross-domain evaluation, the model was able to predict the activities with an average accuracy of 78.12% when trained on exoskeleton-assisted data and tested on NoExo data, 77.41% when trained on No exo and tested on YesExo EMG.



(a) Exoskeleton assisted (b) No Exoskeleton

Fig. 4: Confusion matrices comparing activity recognition performance under exoskeleton-assisted (exo) and no-exoskeleton (no exo) conditions for a single subject. The labels are 0 = No activity; 1=Walking; 2=Walking with weight.

Figure 4 presents the confusion matrices for exo-assisted and exo-unassisted conditions for the selected activities. Labels 0,1 and 2 are used for no activity, walking and walking with weight, respectively. In the assisted condition, the model achieved the classification rates of 68.87% for no activity, 83.74% for walking without weight, and 83.81% for walking with weight. Similarly, when there was no exoskeleton present, accuracies were 76.03%, 80.41%, and 89.48% for Classes 0, 1, and 2, respectively. In both conditions, walking with weight class was classified better, while the no-activity class showed relatively lower accuracy, particularly during exoskeleton-assisted trials. Misclassifications were predominantly observed between walking with and without weight in the exoskeleton-assisted condition, likely due to the similarity in gait-related EMG activation patterns. In the assisted condition, noticeable confusion is observed between no

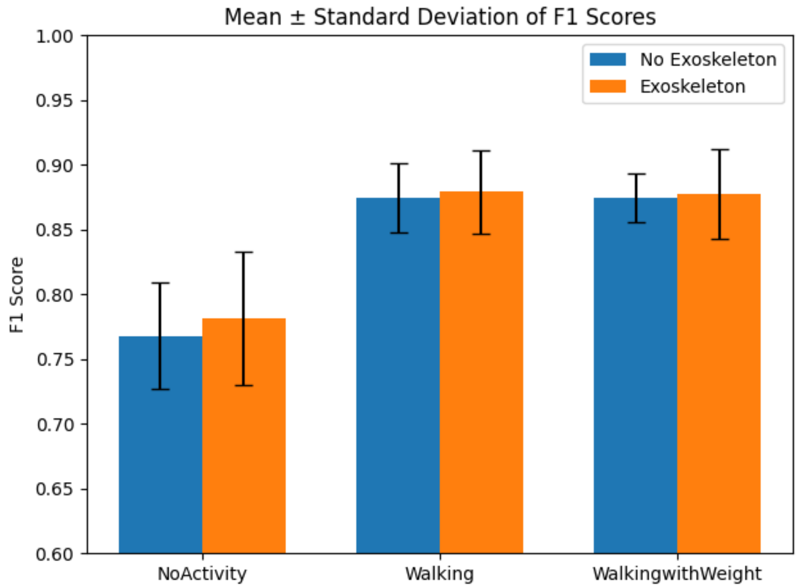


Fig. 5: Comparison of mean ± standard deviation F1-scores under exoskeleton-assisted and no-exoskeleton conditions

activity and walking, as well as between walking and walking with weight. This indicates that, under exoskeleton assistance, the model occasionally struggles to clearly separate resting states from low-intensity walking and to distinguish between the two walking conditions, likely due to overlapping or reduced EMG activation patterns introduced by mechanical support. Importantly, the overall structure and magnitude of the diagonal elements remain consistent across both matrices, indicating that the presence of the exoskeleton does not substantially affect the discriminative capability of the EMG-based CNN model. These findings further support the robustness of the proposed approach for activity recognition under varying mechanical assistance conditions. The model demonstrated strong performance in identifying walking with weight in the no-exoskeleton condition. However, in the assisted condition, both walking with weight and walking were classified with similar accuracy. This suggests that exoskeleton assistance may reduce the relative differences in EMG activation magnitude between the two walking tasks, thereby making their neuromuscular patterns more similar and slightly reducing class separability.

A paired sample t-test was conducted to compare the accuracy of task prediction between exoskeleton-assisted and unassisted conditions. There was no significant difference in accuracy observed between the two conditions ($p=0.748$). Figure 5 presents the mean ± standard deviation of the F1-scores for the three activity classes under exoskeleton-assisted and unassisted conditions for all four subjects. Overall, comparable performance is observed during in-domain evaluations, indicating that exoskeleton assistance does not significantly affect classification performance. For the no Activity class, the mean F1-score slightly improves in the assisted condition, although variability across subjects remains noticeable. For both Walking and Walking with Weight, the mean F1-scores are consistently high (above 0.87) in both conditions, with overlapping standard deviation ranges. The small differences between assisted and unassisted cases, together with overlapping error bars, suggest that the EMG feature representations remain discriminative even in the presence of mechanical assistance. A similar pattern was observed for the F1 scores of cross-domain evaluation too, but with a reduced value.

A repeated measures ANOVA was performed to compare model accuracy across the four conditions. The results indicated that in-domain models (trained and tested on data from the same condition) achieved significantly higher accuracy than cross-domain models (trained on one condition and tested on the other) ($p < .05$). No significant difference was found between the two in-domain models or between the two cross-domain models.

5 Discussion

The main objective of this paper was to explore whether robotic exoskeleton assistance influences the performance of a machine learning model for the prediction of human activities related to walking. The results demonstrated that classification performance remains largely consistent across exoskeleton-assisted and unassisted conditions for in-domain evaluations. The comparable F1-scores and overlapping standard deviations indicate that the discriminative capability of the extracted EMG features is preserved even in the presence of mechanical assistance. However, when the same machine learning model is used for cross-domain evaluation, the accuracy of prediction is significantly reduced.

A window size of 100 ms is selected as a compromise between responsiveness and classification performance. A shorter window size allows faster system response and improves real-time control capabilities, but it may lead to reduced feature stability due to limited signal information. Conversely, a larger window size provides more stable statistical features but increases system latency. The system's response time should remains below 300 ms, to minimise any perceived lag [10]. This trade-off is particularly important for rehabilitation and assistive exoskeleton systems, where timely detection of user intention is essential for effective human–robot interaction.

Identification of walking-related activities (walking and walking with weight) consistently achieved higher F1-scores than the no-activity class. This suggests that the CNN architecture effectively captured dynamic muscle activation patterns during gait. While walking with weight showed slightly better performance in the unassisted condition, this difference diminished under exoskeleton assistance. This may be explained by reduced separability in the EMG feature space. Since several extracted EMG features are amplitude-dependent, mechanical assistance likely attenuates the relative differences in muscle activation between loaded and unloaded walking [4]. This might cause the feature distributions of the two walking classes to become more similar, leading to comparable classification performance.

Although exoskeleton assistance may reduce muscle activation amplitude due to partial load compensation, the relative temporal structure and coordination patterns among muscles appear to remain sufficiently informative for classification [11] [16]. The convolutional layers likely captured invariant temporal features that generalise across both assisted and unassisted scenarios. The findings also suggest that EMG remains a reliable sensing modality for activity recognition even in the presence of external mechanical support. This suggests that a single trained model may be effective under both assisted and unassisted conditions.

Moreover, consistent performance across subjects demonstrates the generalisation capability of the proposed 1D-CNN framework. Maintaining high F1-scores across various individuals and conditions further supports the feasibility of integrating deep learning-based EMG classification into adaptive exoskeleton control strategies.

The results indicate that although EMG-based models achieve high accuracy under the same operating conditions, cross-condition evaluation between exoskeleton-assisted and non-assisted scenarios leads to reduced performance. This finding suggests that exoskeleton assistance alters underlying EMG patterns, emphasising the need for domain-adaptive learning approaches to enable reliable human–robot interaction and adaptive control in assistive exoskeleton systems.

6 Conclusion

This study investigated the effectiveness of a 1D CNN to predict the three activities with the help of features extracted from Electromyogram signals under exoskeleton assisted and non-assisted conditions. The predicted classes include no activity, walking and walking without weight. These were predicted using the EMG data collected from four subjects. The findings demonstrate that the model performs consistently within both exoskeleton-assisted and non-assisted conditions; however, reduced accuracy during cross-condition evaluation suggests that exoskeleton assistance alters EMG signal characteristics, highlighting the need for adaptive learning approaches in assistive robotic systems.

However, a major limitation of the study was the small number of participants, which may constrain the generalisability of the results. Future studies should focus on developing domain adaptation and transfer learning strategies to improve the model's ability to generalise across exoskeleton-assisted and non-assisted conditions, thereby mitigating the exoskeleton-induced shifts observed in EMG signal patterns. These adaptive learning strategies enable robotic systems to keep stable performance across users and rehabilitation stages, which is important for clinical deployment of exoskeletons, prostheses, and socially assistive rehabilitation robots.

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