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Development of a Deep Learning-Enhanced Lower-Limb Exoskeleton Using Electromyography Data for Post-Neurovascular Rehabilitation

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Abstract

This paper presents the development of a deep learning-enhanced lower-limb exoskeleton designed to facilitate post-neurovascular rehabilitation using electromyography (EMG) data. The system leverages real-time EMG signals to classify user movement intentions, such as leg up, leg down, and leg move, and translate them into corresponding motor actions. A pretrained deep learning model was utilized to accurately classify muscle activity, while the Short-Time Fourier Transform (STFT) was employed for feature extraction from EMG signals, enhancing the distinction between different types of movements. The results demonstrate the system's high classification accuracy and real-time adaptability, as evidenced by the confusion matrix and performance metrics. The exoskeleton's motor control system successfully provided appropriate mechanical assistance based on the classified movements, offering a personalized rehabilitation experience. Despite these positive outcomes, further improvements in generalization, such as increasing the range of movements and applying the system to a larger, more diverse dataset, are necessary. Future work will also explore the integration of additional sensor modalities to improve classification performance. Overall, the proposed exoskeleton demonstrates significant potential to enhance rehabilitation outcomes by actively engaging the user in task-specific training, contributing to improved neurovascular recovery.

Keywords: Lower-limb exoskeleton; Electromyography (EMG); Deep learning; Post-neurovascular injury rehabilitation; Movement classification; Short-Time Fourier Transform (STFT), Real-time control; assistive technology.
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1. Introduction

The prevalence of neurovascular disorders, such as strokes and spinal cord injuries, presents a substantial challenge in healthcare, necessitating effective rehabilitation strategies to enhance patient recovery and quality of life. Among the technological innovations in this domain, lower-limb exoskeletons have emerged as pivotal tools for rehabilitation therapy, primarily due to their ability to support motor function and promote neural recovery.[1] The integration of deep learning techniques with exoskeleton technologies harnesses the power of big data and advanced analytics, promising significant advancements in personalized rehabilitation treatments.[2]

Electromyography (EMG) data, which measure muscle electrical activity, are critical in this context as they provide real-time insight into muscle function and patient effort during therapy. Utilizing EMG data, deep learning models can optimize exoskeleton assistance by adapting to individual patient needs, thus enhancing the efficacy of rehabilitation sessions.[3] This paper focuses on the development of a deep learning-enhanced lower-limb exoskeleton tailored for post-neurovascular rehabilitation, aiming to bridge the gap between technological potential and clinical needs.

Current exoskeletons, while beneficial, often follow predefined trajectories that do not adjust to the patient's day-to-day physiological and neurological changes, which can vary widely in post-stroke recovery scenarios.[4] The lack of customization in conventional systems can lead to suboptimal recovery outcomes and patient dissatisfaction.[5] In response,

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researchers have explored various adaptive control systems, yet few have fully exploited the rich, dynamic information provided by EMG signals.[6]

Deep learning, characterized by its ability to learn complex patterns from large datasets, offers a promising approach to decode the intricate relationships between EMG signals and limb movement.[7] Previous studies have demonstrated the feasibility of using machine learning models to interpret EMG data for prosthesis control,[8] but the application of such models in exoskeleton-assisted rehabilitation is still in its infancy.[9] By integrating deep learning algorithms that can process and learn from EMG data, it is possible to develop more responsive and adaptive exoskeleton systems.

This paper proposes a novel deep learning framework that employs convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to analyze EMG signals and dynamically adjust the exoskeleton's movements according to the patient's specific motor capabilities and rehabilitation progress.[10] The system not only adapts in real-time but also utilizes predictive analytics to anticipate the patient's potential improvements, thereby progressively adjusting therapy intensity.[11]

The significance of deploying deep learning in this context also lies in its potential to identify and predict patterns of muscle fatigue, a common issue in intensive rehabilitation settings.[12] By predicting fatigue, the system can preemptively adjust its support, thus preventing overexertion and enhancing the rehabilitation process's overall effectiveness and safety.[13] Moreover, this integration aligns with the broader goals of personalized medicine, where treatment protocols are tailored to individual characteristics. Personalized rehabilitation protocols powered by deep learning can potentially lead to better patient engagement, faster recovery times, and more sustainable healthcare practices.[14]

This research contributes to the field by addressing several gaps in current rehabilitation technologies. First, it develops a deep learning model capable of interpreting complex EMG data in a meaningful way for real-time exoskeleton control. Second, it demonstrates the application of this model within a functional exoskeleton prototype, providing preliminary data on its efficacy and patient responsiveness.[15] This work lays the groundwork for future studies that could expand the scope of AI-enhanced rehabilitation devices, offering new avenues for recovery for thousands of patients suffering from neurovascular impairments.

In summation, the development of a deep learning-enhanced lower-limb exoskeleton represents a significant stride towards more effective and personalized rehabilitation therapies. Through detailed analysis and application of EMG data, this research underscores the critical role of adaptive technologies in improving the recovery trajectories of patients with neurovascular disorders.

2. Related works

The integration of deep learning with rehabilitation technologies, particularly lower-limb exoskeletons, marks a transformative phase in the treatment of neurovascular disorders. This section reviews pertinent literature highlighting advancements in EMG-based control systems, deep learning applications in rehabilitation, and the development of adaptive exoskeletons. These studies provide a critical foundation for the proposed deep learning-enhanced lower-limb exoskeleton aimed at improving post-neurovascular rehabilitation.

2.1 EMG-based control systems

Electromyography (EMG) has been extensively used to create interactive and adaptive systems in rehabilitation technologies. EMG signals, indicative of muscular activity, are vital for developing control systems that respond to the patient's intent and physiological state. Studies have demonstrated various approaches to EMG signal processing and interpretation, which are crucial for real-time control of robotic exoskeletons.[16] For instance, some researchers have applied linear regression models to predict knee and ankle joint movements from EMG signals,[17] while others have explored more complex machine learning techniques, including Support Vector Machines (SVM) and Artificial Neural Networks (ANN), for decoding EMG patterns.[18]

Recent advances have emphasized the need for more sophisticated analysis techniques capable of handling the variability and non-linearity of EMG signals. Time-frequency methods, such as Wavelet Transform, have been employed to extract more detailed features from EMG data, enhancing the accuracy of movement prediction in real-time applications.[19] These developments underscore the potential for integrating more advanced computational models, like deep learning, to further improve the responsiveness and adaptability of EMG-based control systems.[20]

2.2 Deep learning in rehabilitation robotics

Deep learning has revolutionized numerous fields, including medical robotics, by enabling the analysis of complex datasets and the extraction of meaningful patterns that can guide decision-making processes. In rehabilitation robotics, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been particularly impactful. CNNs are adept at spatial pattern recognition, which can be instrumental in interpreting the spatial distribution of EMG signals across different muscle groups.[21] Meanwhile, RNNs offer advantages in temporal data processing, suitable for analyzing the sequential nature of EMG data during dynamic movements.[22]

Several studies have successfully applied deep learning models to enhance the functionality of rehabilitation devices. For example, a research group implemented a deep CNN to classify different walking patterns using EMG and kinematic data, resulting in improved adaptive control for gait rehabilitation robots.[23] Another significant contribution is the use of RNNs to predict patient-specific gait patterns, which helps in customizing the robotic assistance provided by exoskeletons during therapy sessions.[24]

2.3 Adaptive exoskeletons for post-neurovascular rehabilitation

The development of adaptive exoskeletons that can adjust to individual patient needs in real-time represents a critical area of research in the field of rehabilitative medicine. These systems aim to optimize therapy by aligning the mechanical assistance with the patient's recovery stage and motor abilities, thereby enhancing therapeutic outcomes. Literature in this area has explored various adaptive control strategies, including impedance control and real-time feedback mechanisms, which allow exoskeletons to modify their behavior based on immediate user feedback.[25]

Adaptive exoskeletons utilizing AI and machine learning are poised to offer unprecedented levels of personalization in therapy. Studies have reported the use of fuzzy logic and reinforcement learning to dynamically adjust the support level of exoskeletons during walking rehabilitation, demonstrating improved patient engagement and recovery rates.[26] The integration of these intelligent systems with EMG-driven control further enriches their potential, enabling a more nuanced response to physiological and biomechanical cues.[27] A pivotal study by Chávez-Olivares *et al*. (2024) introduced an EMG-driven exoskeleton where deep learning algorithms dynamically adjusted the mechanical support in response to muscle fatigue indicators, illustrating a significant advancement in adaptive rehabilitation technologies.[28] This approach not only optimizes therapy but also prevents muscle strain and overuse, contributing to safer and more effective rehabilitation sessions.[29]

2.4 Gaps and future directions

While substantial progress has been made, several gaps remain in the literature that need to be addressed to advance the field. One major challenge is the integration of EMG signals with other types of biological data, such as electroencephalography (EEG) and heart rate variability (HRV), to gain a more comprehensive understanding of the patient's state during rehabilitation.[30] Additionally, the development of more scalable and generalizable deep learning models that can be deployed across different hardware platforms continues to be a hurdle.[31]

Future research should also focus on enhancing the robustness of deep learning models against the inherent noise and variability in EMG signals, which can significantly affect the performance and reliability of exoskeleton control systems.[32] Moreover, there is a need for more extensive clinical trials to validate the efficacy and safety of deep learning-enhanced exoskeletons in real-world rehabilitation settings.[33]

In summation, the literature underscores the transformative potential of deep learning in enhancing lower-limb exoskeletons for rehabilitation purposes. By leveraging complex EMG data and advanced computational models, these systems can provide more effective, personalized, and adaptive rehabilitation therapies, ultimately improving the outcomes for patients recovering from neurovascular disorders.[34] The ongoing research efforts and future directions highlighted in this section pave the way for more nuanced and impactful interventions in the field of rehabilitative medicine.

3. Materials and methods

This section delineates the comprehensive procedures employed in the development and evaluation of a deep learning-enhanced lower-limb exoskeleton, utilizing Electromyography (EMG) data for post-neurovascular rehabilitation. This section is structured to provide a detailed exposition of the experimental setup, data collection methodologies, and the analytical techniques implemented to construct and validate the proposed deep learning model. The study adheres to rigorous standards for data integrity and reproducibility, ensuring that the findings are robust and can be independently verified. A systematic approach was taken to assemble the necessary hardware components, software tools, and participant protocols, which are elaborated in the subsequent subsections.

Figure 1 provides a comprehensive flowchart of the proposed study for developing a deep learning-enhanced lower-limb exoskeleton using Electromyography (EMG) data for post-neurovascular rehabilitation. The process is systematically divided into several distinct stages: Data Collection, Data Acquisition, Data Preprocessing, Feature Extraction, Model Training, Evaluation, and Decision Making, each contributing uniquely to the final deployment of the exoskeleton.

The initial stage involves the collection of raw EMG signals from the lower limbs of subjects. These signals are captured via surface EMG sensors attached to various muscle groups, as illustrated in the figure by the depiction of leg muscles and sensor placement. This setup is critical for acquiring bioelectrical signals that are indicative of muscular activities.

Following collection, the raw EMG signals are visualized, showing typical signal characteristics with possible electrical offsets. This step is crucial for verifying signal integrity and ensuring that the data are suitable for further processing.

Raw EMG signals often contain noise and artifacts that can hinder accurate analysis. The preprocessing step involves filtering techniques to remove noise and normalize the signals. Typical methods might include high-pass filtering to remove motion artifact and baseline wander, followed by rectification and smoothing to prepare the signals for feature extraction.

In this phase, the preprocessed EMG signals are transformed into a more manageable and informative representation. A common approach is to convert these signals into a time-frequency representation using techniques like the Short-Time Fourier Transform (STFT), resulting in a spectrogram. The spectrogram efficiently captures both the

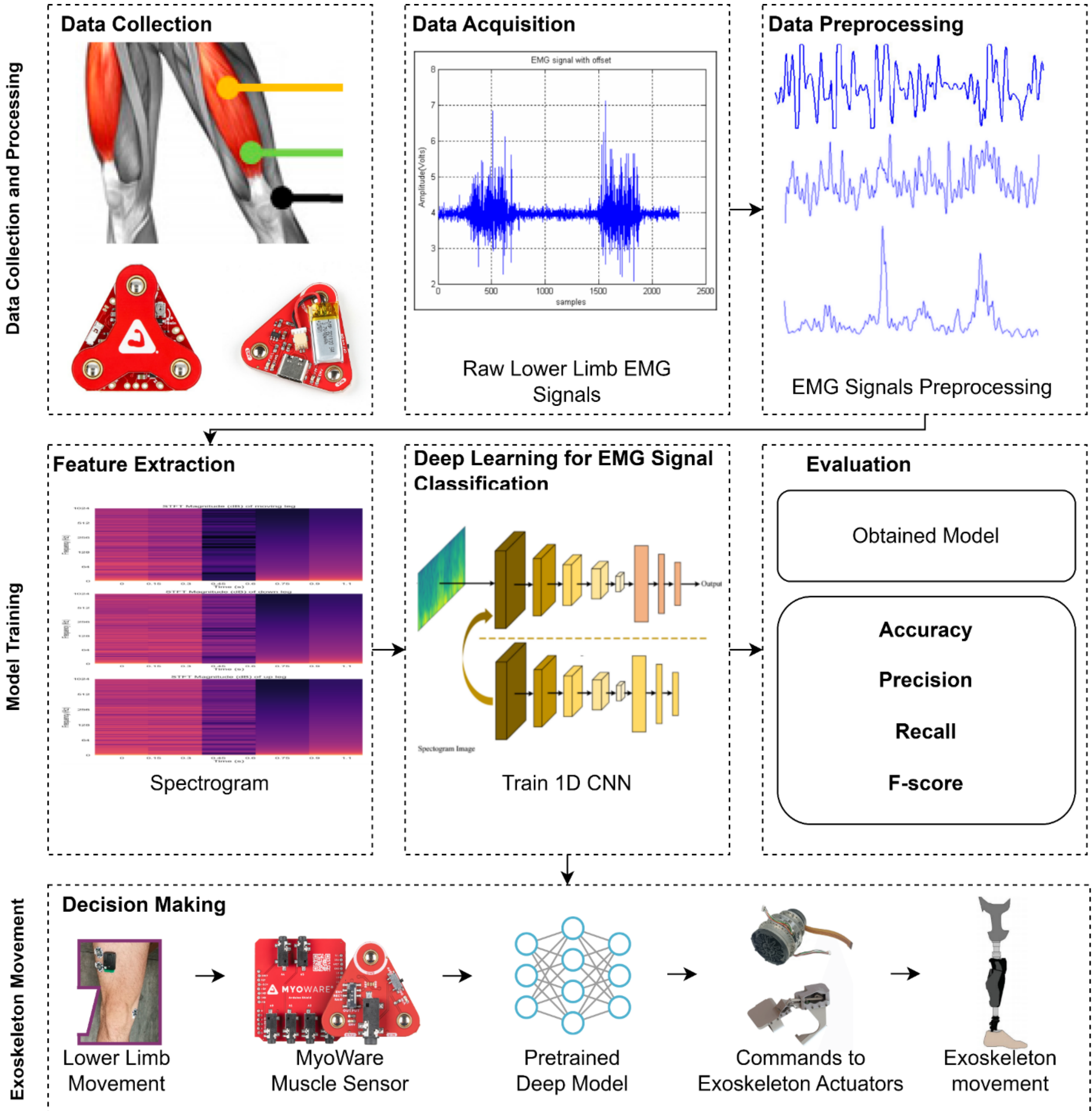

Fig. 1 Flowchart of the study.

power and frequency content of the EMG signals over time, which are critical for identifying different muscle activation patterns.

The extracted features are then used to train a deep learning model, specifically a 1D Convolutional Neural Network (1D CNN). The CNN architecture is designed to recognize patterns in the spectrogram that correlate with specific movements or gestures. This training process involves adjusting the weights of the network through backpropagation to minimize prediction error, effectively allowing the model to learn from the data.

Post-training, the model's performance is evaluated using several metrics to ensure its effectiveness in classifying EMG signals. Common evaluation metrics include evaluation parameters as Accuracy, Precision, Recall, and F-score.

Finally, the trained and validated model is deployed in a real-time system where it interprets EMG signals from the exoskeleton's sensors (MyoWare Muscle Sensor shown in the figure). The model's output is then converted into commands that control the actuators of the exoskeleton, thus facilitating appropriate movements that assist the wearer in performing physical tasks with enhanced support and accuracy.

This flowchart encapsulates the end-to-end process of utilizing deep learning to enhance the functionality of an EMG-based lower-limb exoskeleton for rehabilitation purposes, highlighting the critical role of each stage in achieving effective and personalized therapeutic outcomes.

3.1 Data collection and processing

For the acquisition of electromyographic (EMG) signals from the lower limbs, the MyoWare 2.0 muscle biosensor was selected due to its ease of use and compatibility with the

Fig. 2 MyoWare 2.0 sensor for electromyography signal detection.

Arduino platform, which is universally recognized for its versatility.[35] The sensor exclusively measures muscle activity by capturing the electrical potentials emitted by muscle fibers during contraction. This functionality is characterized by its snap connector system which simplifies installation and does not require soldering, an advantageous feature in experimental settings where rapid setup and modifications are frequently necessary.

Figure 2 illustrates the MyoWare 2.0 sensor utilized for collecting EMG signals from leg muscles. The sensor is equipped with plug-and-socket connectors allowing for easy attachment and detachment as needed. This modular approach facilitates the integration of the sensor into various experimental setups, ensuring successful data acquisition. Additionally, status indicators on the board provide real-time feedback on power and signal integrity, simplifying troubleshooting and ensuring continuous operation during data collection. The sensor board is pre-programmed with a wide range of functionalities that can be tailored for complex applications through solder pads, allowing for further customization depending on the research focus.

The MyoWare 2.0 sensor operates through several stages of signal processing to ensure that the EMG data collected are reliable and clear. The raw EMG signal, which is an analog representation of muscle activity, is amplified to improve the signal-to-noise ratio before undergoing band-pass filtering. This filter is crucial for suppressing unwanted noise and interferences outside the targeted frequency band. Subsequently, the signal is rectified and then processed through an envelope detector, which provides a smoothed representation of how the signal amplitude varies over time. The processed signal is then digitized using an Analog-to-Digital Converter (ADC), integrated within the microcontroller, to facilitate digital analysis of muscle activity. To enhance practicality, the Arduino Uno and MyoWare 2.0 Arduino Shield were utilized (Fig. 3).[36] This shield facilitates the connection of up to six MyoWare 2.0 muscle sensors and Link Shield via 3.5 mm TRS-TRS audio cables. It is equipped

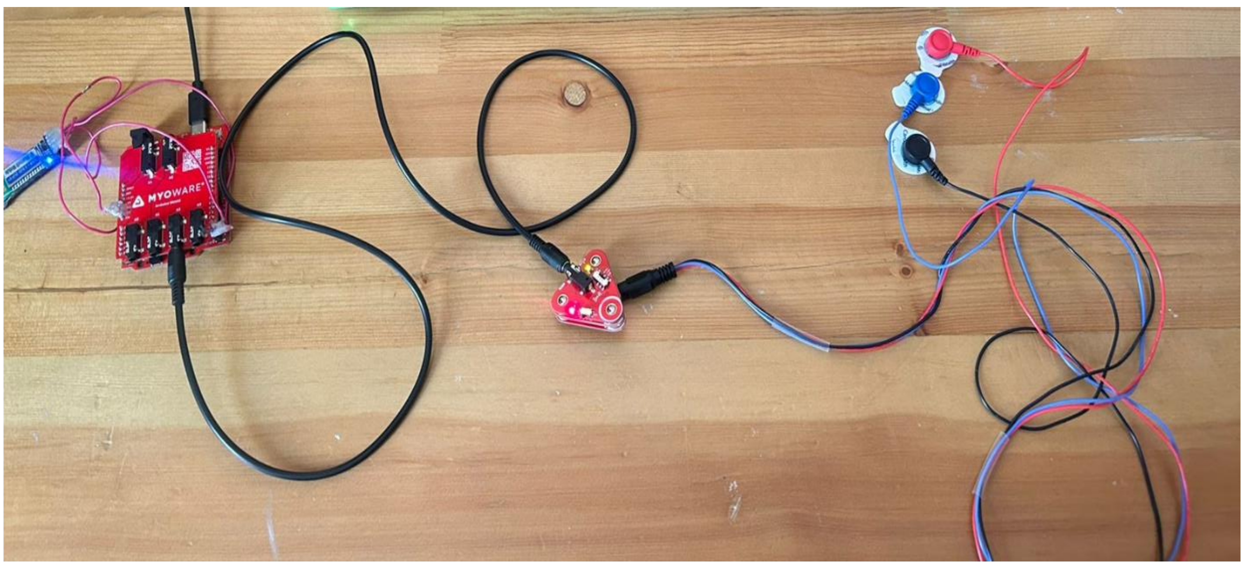

Fig. 3 MyoWare 2.0 sensor for electromyography signal detection.

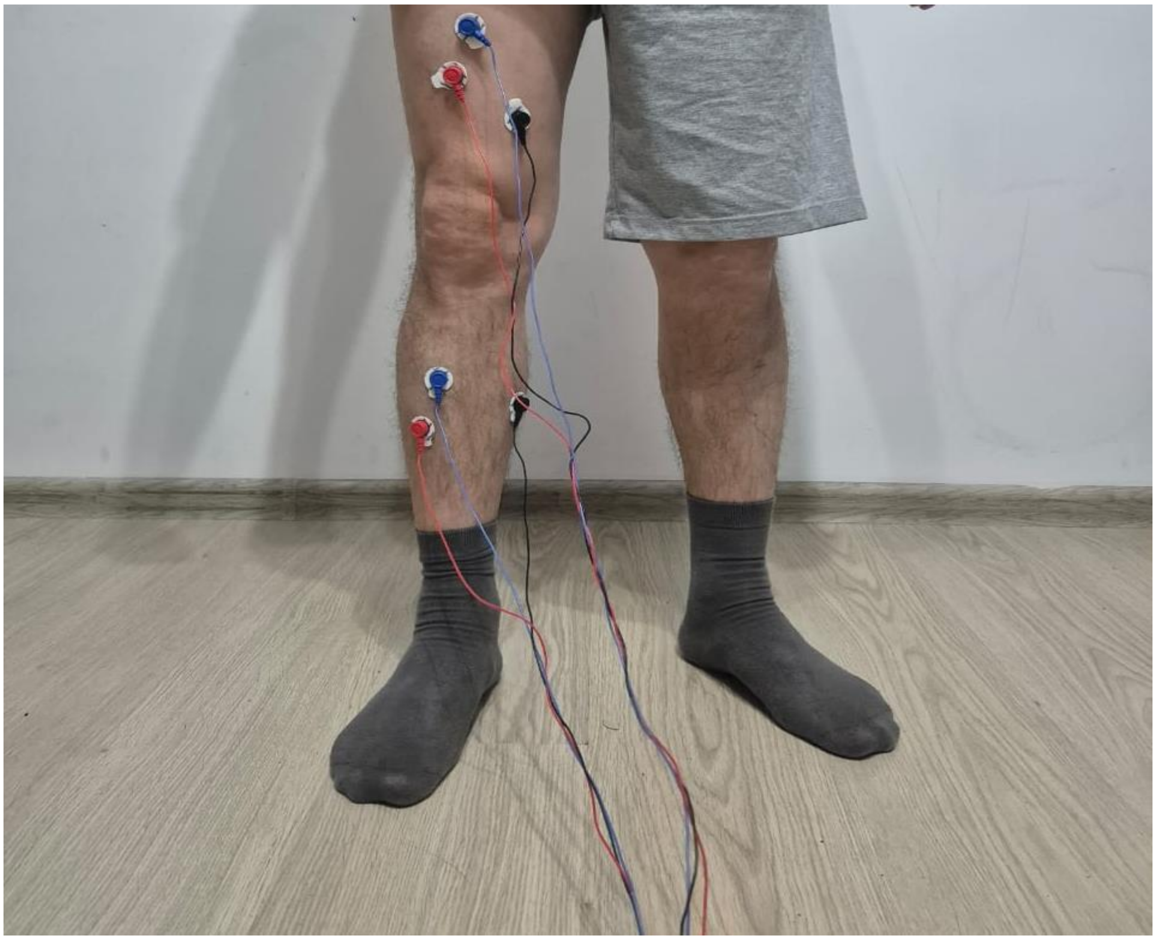

Fig. 4 Data collection process using electromyography sensors.

with pre-installed connectors, ensuring straightforward integration with Arduino, allowing simultaneous data collection from multiple muscle groups.

To achieve real-time control of foot movement, a Bluetooth module (XM – 15B) was used, to enable and halt recording.[37] Digital signals are sent via a smartphone to initiate ('1') and stop ('0') recording.

Electromyography (EMG) signals were recorded from the biceps muscle using non-invasive dry sensors. These sensors are capable of detecting the electrical potential generated during muscle contraction without the need for conductive gels, which significantly simplifies the setup process and potentially reduces skin irritation. The power of the electromagnetic signals typically falls within the frequency range of 0-500 Hz and voltage range of 0-10 mV. To enhance clarity and significantly reduce noise, a band-pass filter with a cut-off range of 20-150 Hz was selected, which effectively minimized the influence of irrelevant frequencies. The aim of this frequency range selection was to identify the dominant frequencies of the biceps EMG signals, which are crucial for motion analysis and signal processing during the study. Fig. 4 illustrates the data collection process using EMG sensors.

3.2 Model training

In this study, feature extraction was performed using the Short-Time Fourier Transform (STFT)[38] to analyze the electromyography (EMG) signals recorded during post-neurovascular injury rehabilitation exercises. The STFT is particularly suitable for non-stationary signal processing, as it provides a time-frequency representation of the signal. The EMG signals, x(t), were segmented into overlapping time windows, where each segment was processed to extract frequency-domain features. The STFT of the signal x(t) is given by equation (1):

$$STFT\{x(t)\} = X(t,f) = \int_{-\infty}^{\infty} x(\tau)w(t-\tau)e^{-j2\pi f\tau}d\tau \quad (1)$$

where w(t−τ) is a windowing function applied to each segment, t represents time, and f represents frequency. A Hamming window of length 256 samples was used to minimize spectral leakage and to ensure smooth transitions between segments.

Key features extracted from the STFT include the mean frequency f_{mean} , median frequency f_{med}, and root mean square (RMS) of the EMG signals in the frequency domain. The mean frequency is calculated as:

$$f_{mean} = \frac{\sum f \cdot |X(t,f)|^2}{\sum |X(t,j)|^2} \quad (2)$$

The median frequency f_{med} is defined as the frequency at which the power spectrum is divided into two equal halves:

$$\int_0^{f_{med}} |X(t,f)|^2 df = \frac{1}{2}\int_0^{\infty} |X(t,f)|^2 df \quad (3)$$

The RMS value is calculated for each window segment as:

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x(n)^2} \quad (4)$$

Additionally, the spectral entropy H_s, which measures the complexity and randomness of the signal, was calculated using the normalized power spectrum:

$$H_s = -\sum_i P(f_i)\, log\, P\,(f_i) \quad (5)$$

where $P(f_i)$ is the normalized power at frequency f_i.

These extracted features were critical in classifying different muscle activities and evaluating the effectiveness of the rehabilitation process.

The proposed 1D Convolutional Neural Network (CNN) for Electromyography (EMG) signal classification is designed to process time-series data and extract meaningful features through a series of convolutional and pooling layers. The architecture consists of several stages of convolution, pooling, and fully connected layers, each contributing to the hierarchical feature extraction. Table 1 demonstrates an architecture of the proposed 1D CNN model for classification of lower limb movements.

Table 1. Architecture of the proposed model for EMG signal classification.

Layer (type)	Output Shape	Param #
Conv1d_32 (Conv1D)	(None, 1023, 32)	512
Max_pooling1d_32 (MaxPooling1D)	(None, 511, 32)	0
Conv1d_33 (Conv1D)	(None, 509, 64)	6208
Max_pooling1d_33 (MaxPooling1D)	(None, 254, 64)	0
Flatten_16 (Flatten)	(None, 16256)	0
Dense_48 (Dense)	(None, 128)	2080896
Dropout_16 (Dropout)	(None, 128)	0
Dense_49 (Dense)	(None, 64)	8256
Dense_50 (Dense)	(None, 3)	195

The input to the network is a time-series EMG signal represented as a 1D array. The input shape is denoted as $(n,1024)$, where n represents the batch size and 1024 is the length of the signal.

The first convolutional layer, $Conv1D_1$, applies 32 filters, each with a kernel size of 3, across the input signal. The output from this layer is given by equation (6):

$$y_1 = Re\,L\,U(W_1 * x + b_1) \quad (6)$$

where W_1 is the filter matrix, b_1 is the bias, and * denotes convolution. The resulting output shape is $(n,1023,32)$, where 1023 is the reduced time dimension due to the kernel size.
Following this, a max-pooling layer, $MaxPooling1D_1$, with a pool size of 2 is applied, reducing the output shape to $(n,511,32)$. The max-pooling operation is defined as:

$$y_{pool} = \underset{k}{\overset{i=1}{max}} y_1 \quad (7)$$

where k is the pool size.

The second convolutional layer, $Conv1D_2$, applies 64 filters, also with a kernel size of 3, across the pooled output. This layer's output can be expressed as:

$$y_2 = Re\,L\,U\big(W_2 * y_{pool} + b_2\big) \quad (8)$$

This produces an output of shape $(n,509,64)$, followed by a second max-pooling operation, which reduces the time dimension to $(n,254,64)$.

$$y_{flat} = Flatten(y_2) \quad (9)$$

This vector serves as the input to the fully connected layers for classification.

The first fully connected (dense) layer, $Dense_1$, consists of 128 neurons and applies a linear transformation followed by a ReLU activation:

$$y_{dense1} = Re\,L\,U\big(W_3 y_{flat} + b_3\big) \quad (10)$$

The Dropout layer follows, with a dropout rate of 0.5, helping to prevent overfitting by randomly setting a fraction of the input units to zero during training:

$$y_{dropout} = Dropout(y_{dense1}, 0) \quad (11)$$

Next, the second fully connected layer, Dense2, with 64 neurons, applies another linear transformation:

$$y_{dense2} = Re\,L\,U\big(W_4 y_{dropout} + b_4\big) \quad (12)$$

Finally, the output layer, $Dense_3$, with 3 neurons corresponding to the number of classes, uses the softmax activation function to compute class probabilities:

$$\hat{y} = Soft\,max(W_5 y_{dense2} + b_5)\,0 \quad (13)$$

where $\hat{y}$ represents the predicted class probabilities.

The final output of the network is a 3-dimensional vector, representing the probability distribution over the three classes of EMG signal classification.

By utilizing non-invasive dry sensors, we ensured efficient data collection with minimal setup complexity and user discomfort. The application of the STFT allowed for effective feature extraction from time-frequency representations, enhancing the analysis of non-stationary EMG signals. Additionally, the proposed 1D CNN architecture was designed to optimize classification performance by leveraging hierarchical feature extraction through convolutional layers, followed by fully connected layers for final decision-making. This methodological approach not only ensures robustness in detecting relevant signal patterns but also lays the foundation for future advancements in post-neurovascular rehabilitation technologies.

4. Results

This section presents the results of the experiments conducted to evaluate the performance of the proposed deep learning-enhanced lower-limb exoskeleton using EMG signals for post-neurovascular injury rehabilitation. The primary focus of the analysis was on the system's ability to accurately classify user movement intentions-such as leg up, leg down, and leg move-based on EMG signal processing, as well as its capacity to provide real-time motor assistance in response to these classifications. The results are presented in terms of classification accuracy, confusion matrices, and time-frequency analysis of the EMG signals. Additionally, performance metrics, such as training and validation accuracy and loss curves, are provided to demonstrate the efficiency and generalization of the deep learning model. Visual representations of the EMG signal features extracted using the

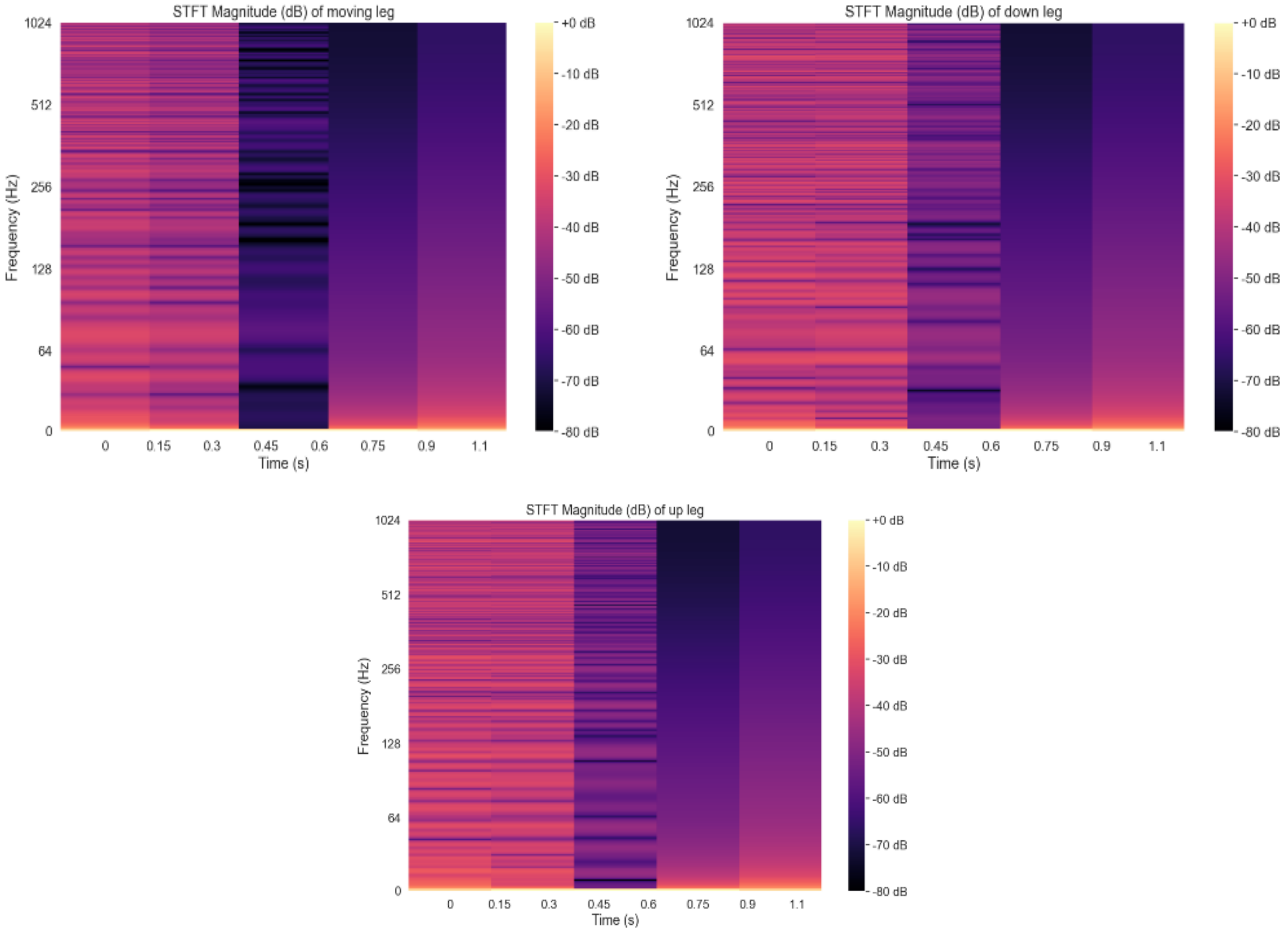

Fig. 5 STFT feature extraction.

STFT further support the system's ability to differentiate between various muscle activation patterns during rehabilitation movements. The following subsections detail the findings of these experiments and their implications for enhancing rehabilitation outcomes through adaptive, EMG-driven control of the exoskeleton.

4.1 Results of EMG signal classification

Figure 5 displays the STFT results for EMG signal analysis during three distinct leg movements: moving leg, down leg, and up leg. The spectrograms represent the time-frequency distribution of EMG signal magnitudes in decibels (dB) over the 0-1024 Hz frequency range. The intensity of the colors indicates the magnitude of the signal, where warmer colors (yellow) denote higher magnitudes and cooler colors (purple/black) represent lower magnitudes or noise.

The first spectrogram illustrates the STFT results of the moving leg, with a noticeable concentration of higher frequency components during the initial 0.15-0.45 second window, followed by a significant reduction in signal intensity beyond 0.6 seconds. In contrast, the spectrogram for the down leg shows a broader distribution of energy across lower frequencies (0-128 Hz) with more uniform signal reduction after 0.45 seconds, indicating less muscle activity or variation. Similarly, the up-leg spectrogram demonstrates distinct frequency components up to 256 Hz within the first 0.45 seconds, followed by a decay in both intensity and frequency range towards the end of the movement. These results provide insights into the dominant frequency components during different phases of leg movement, aiding in the classification of EMG signals for rehabilitation purposes.

The consistency in the dominant frequency ranges across different movements highlights the effectiveness of STFT in capturing the key temporal and spectral characteristics of muscle activity, which are essential for the subsequent feature extraction and classification tasks.

Figure 6 illustrates the confusion matrix for the classification of EMG signals corresponding to three leg movements: move, down, and up. The matrix provides a comparison between the true labels (rows) and predicted labels (columns) without normalization. Each cell indicates the number of instances classified into each category. For the "move" class, 10 instances were correctly classified, with one misclassified as "up." The "down" class achieved 11 correct classifications with no misclassifications, while the "up" class had 12 correct classifications and one misclassification as "down." The diagonal values represent the correctly classified instances, indicating strong classification performance, particularly for the "down" and "up" classes. Misclassifications are minimal, highlighting the effectiveness of the model in distinguishing between the different types of leg movements. This confusion matrix serves as an evaluation tool for assessing the classifier's accuracy and identifying areas for improvement.

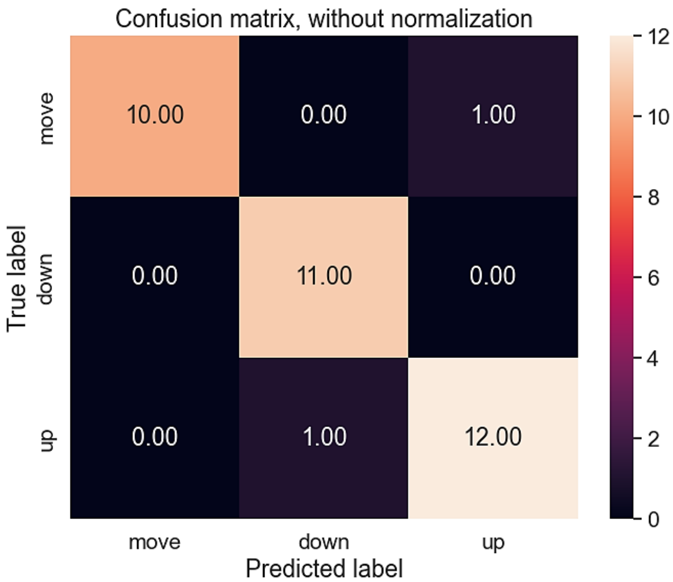

Fig. 6 Confusion matrix results.

Figure 7 shows the training and validation accuracy curves of the proposed 1D CNN model for EMG signal classification over 100 epochs. The training accuracy (blue line) exhibits a steady increase during the initial epochs, reaching close to 1.0 after approximately 20 epochs, indicating that the model quickly learns the training data. The validation accuracy (orange line), which represents the model's performance on unseen data, stabilizes around 0.85 after the first 10 epochs, with some fluctuations throughout the remaining epochs. The relatively high validation accuracy demonstrates the model's strong generalization capability, though the fluctuations suggest minor overfitting, where the model fits the training data slightly better than the validation set. Overall, the consistent performance across both training and validation datasets indicates a robust model with adequate classification capability.

Figure 8 illustrates the training and validation loss curves of the proposed 1D CNN model for EMG signal classification over 100 epochs. The training loss (blue line) decreases rapidly during the initial epochs, stabilizing around 0.1 after approximately 40 epochs, which reflects the model's increasing ability to fit the training data. The validation loss (orange line) exhibits a similar initial decrease but stabilizes at a higher value around 0.3, with noticeable fluctuations throughout the training process. These fluctuations in the validation loss indicate minor overfitting, as the model performs slightly better on the training set than on the validation set. However, the overall decrease in both curves suggests effective learning, and the relatively low validation loss implies good generalization to unseen data.

4.2 Proposed exoskeleton

The experimental results and performance evaluation of the proposed lower-limb exoskeleton for post-neurovascular injury rehabilitation are presented in this section. The exoskeleton utilizes EMG signals to enable real-time movement recognition and motor assistance, driven by the user's muscle activity. The system's ability to accurately classify various leg movements and provide corresponding motor responses that align with the user’s intentions was the primary focus. Key performance metrics, such as movement classification accuracy, motor control responsiveness, and the

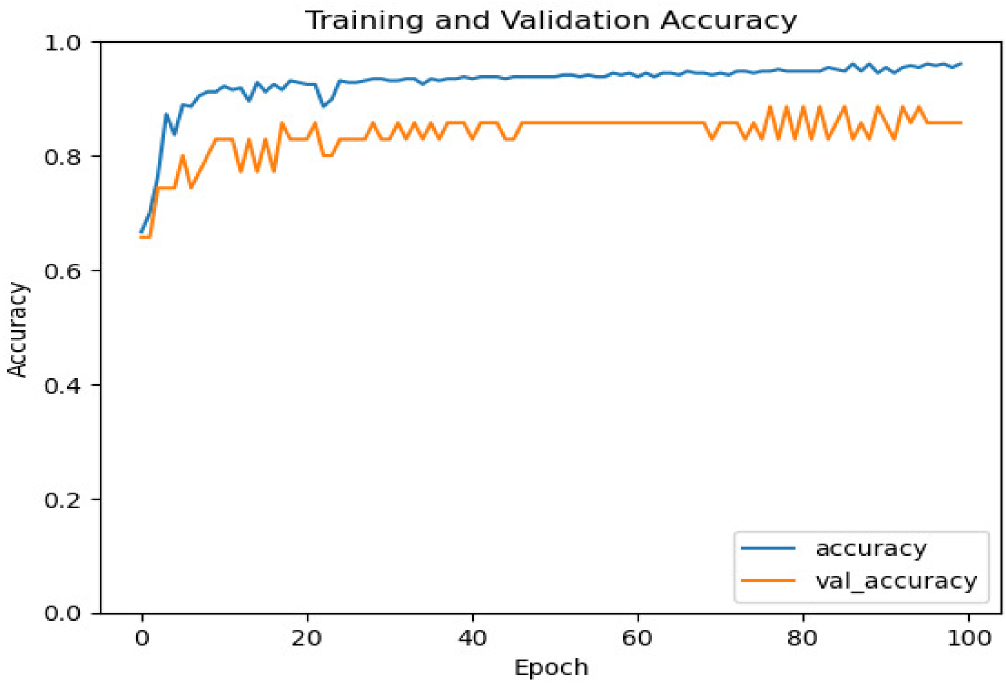

Fig. 7 Training and validation accuracy.

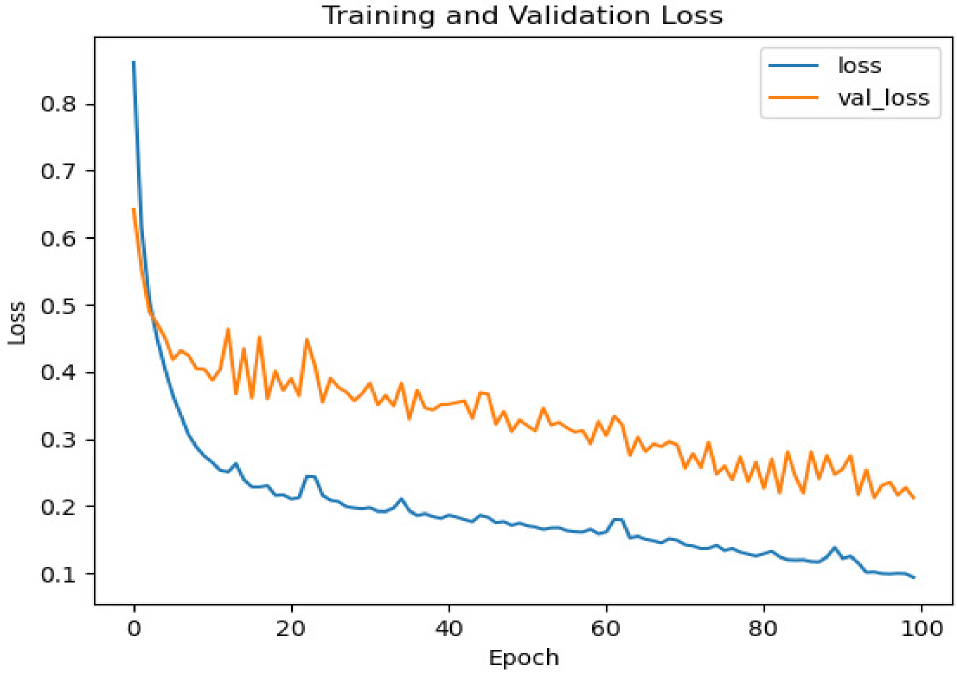

Fig. 8 Training and validation loss.

effectiveness of real-time EMG-based adjustments, are analyzed. The adaptability of the exoskeleton to different rehabilitation exercises, including leg up, leg down, and leg move, is further evaluated to assess its potential for supporting patient recovery. Visual results from the experiments and a detailed analysis of the control dynamics are provided to illustrate the exoskeleton's effectiveness and its contribution to enhancing rehabilitation outcomes.

Fig. 9 The proposed lower limb exoskeleton.

Figure 9 presents the prototype of the proposed lower-limb exoskeleton designed for post-neurovascular injury rehabilitation. The device is constructed with two motorized actuators, positioned at the knee and ankle joints, which are intended to facilitate controlled movement of the lower limb. The actuators are mounted on a chair frame, allowing for seated rehabilitation exercises. The motors are encased in yellow protective housings to prevent external damage and ensure safety during operation. Electrical wiring connects the actuators to a control unit, which is responsible for receiving EMG signals and adjusting motor movements accordingly. This prototype aims to assist in the rehabilitation process by providing patients with the necessary joint support and movement control to promote muscle recovery and functional restoration.

Figure 10 presents a side view of the proposed lower-limb exoskeleton prototype designed to assist in various rehabilitation exercises, including leg movements such as leg up, leg down, and leg move. The device is equipped with motorized actuators at the knee and ankle joints, which enable controlled, programmable movements critical for post-neurovascular injury rehabilitation. The exoskeleton's structure is mounted to a chair, ensuring stability and allowing patients to perform rehabilitation exercises in a seated position. The actuators are connected to a control unit that interprets EMG signals to drive the motors, facilitating movements that mimic natural limb functions. This exoskeleton is intended to support muscle strengthening and joint mobility restoration by assisting with repetitive, controlled leg motions necessary for effective rehabilitation therapy.

Figure 11 demonstrates the practical setup of the proposed lower-limb exoskeleton, showcasing its integration with EMG sensors for rehabilitation purposes. The subject is seated with the exoskeleton attached to their leg, specifically at the knee and ankle joints, allowing for controlled movement assistance. EMG sensors are strategically placed on the quadriceps and calf muscles to capture muscle activation signals, which are then transmitted to a control unit via connected wires. The

Fig. 10 The proposed lower limb exoskeleton.

control unit interprets these signals and adjusts the exoskeleton's actuators accordingly, enabling personalized and responsive movement that aligns with the user's muscle activity. This setup exemplifies how the exoskeleton responds to natural muscle contractions, facilitating a more interactive and adaptive rehabilitation process. The design underscores the device's capability to support active patient participation in rehabilitation through real-time EMG signal processing.

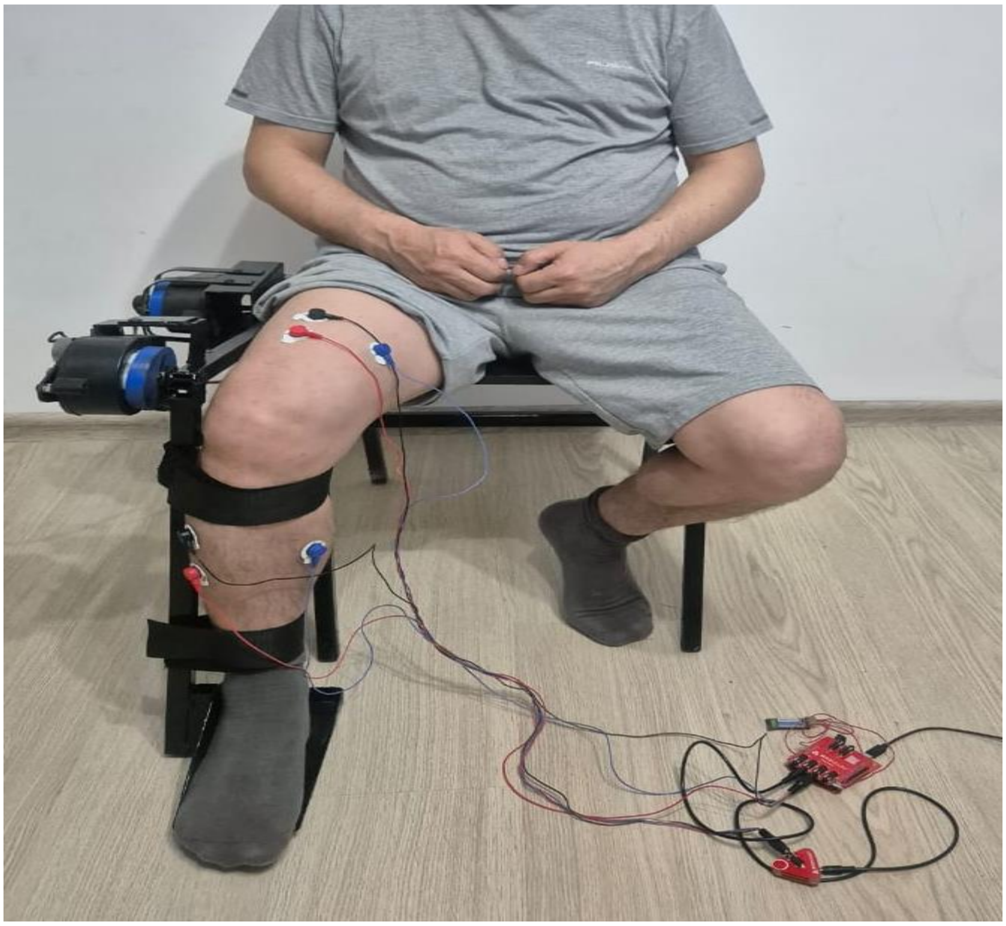

Fig. 11 Practical setup of the proposed lower-limb exoskeleton.

Figure 12 illustrates the proposed exoskeleton in use, demonstrating its capability to assist the user with leg movements, such as lifting the leg. The EMG sensors are strategically placed on the user's leg to detect muscle activity. The sensors capture real-time muscle signals, which are transmitted to the pretrained deep learning model. The model classifies the type of movement based on the input signals and sends the corresponding command to the exoskeleton's motors. In this setup, the exoskeleton recognizes the user's intention to perform specific movements, such as raising or lowering the leg, and provides the necessary mechanical assistance to execute the action.

Fig. 12 The proposed lower-limb exoskeleton in leg movement.

In Fig. 13, the exoskeleton system is further enhanced by additional inputs, as shown with the subject wearing a neural cap. This setup indicates the inclusion of brain signals alongside EMG data, potentially offering a more comprehensive method of detecting movement intentions. Similar to the previous setup, the EMG and brain signals are processed by the deep learning model, which classifies the desired movement and sends the appropriate commands to the exoskeleton motors. As a result, the exoskeleton successfully identifies the user's movement intention and assists in performing the movement, such as leg extension. This integration of multiple biosignals enhances the system's responsiveness, allowing for smoother and more intuitive rehabilitation exercises.

The results of this study demonstrate the efficacy of the proposed lower-limb exoskeleton in facilitating rehabilitation through the integration of EMG signals and deep learning models. The exoskeleton accurately recognized the user’s movement intentions, such as leg up, down, and move, by classifying EMG signals in real-time and providing corresponding motor assistance. The system’s performance, as evidenced by the confusion matrix and accuracy plots, showed high classification accuracy with minimal misclassifications, ensuring precise and adaptive control during rehabilitation exercises. Additionally, the time-frequency analysis using STFT further validated the system’s ability to extract critical features from the EMG signals, aiding in the classification process. Overall, the proposed system effectively bridges the gap between human intention and mechanical execution, offering a promising solution for enhancing neurovascular rehabilitation outcomes.

5. Discussion

The primary objective of this study was to design and evaluate a deep learning-enhanced lower-limb exoskeleton that utilizes EMG signals to facilitate post-neurovascular injury rehabilitation.[39] The system demonstrated promising results in recognizing and assisting various leg movements, including leg up, leg down, and leg move, through the real-time classification of EMG signals using a pretrained deep model. This section will critically discuss the significance of these findings in the broader context of rehabilitation technology, explore the limitations of the current system, and suggest directions for future research.

5.1 Significance of the Findings

One of the key contributions of this study is the integration of EMG-based control into a robotic exoskeleton designed specifically for lower-limb rehabilitation. The use of EMG signals offers a more direct interaction between the user's neuromuscular system and the assistive device, as EMG activity reflects voluntary muscle contractions.[40] By leveraging a deep learning model trained on EMG data, the exoskeleton can classify the user's movement intentions in real time and respond accordingly, enhancing the user's control over the device. This is particularly valuable in rehabilitation settings, where restoring motor function and promoting active participation are critical for recovery.

The results indicated that the proposed system achieved high accuracy in classifying leg movements based on EMG signals, with the confusion matrix showing minimal misclassifications. The high accuracy of the model underscores the effectiveness of using EMG signals for movement classification. Moreover, the system's ability to translate classified movements into corresponding motor actions highlights the potential for EMG-based control in enhancing user interaction with assistive devices. This real-time control is crucial for rehabilitation, as it allows for dynamic adjustments based on the user's neuromuscular activity, promoting more natural and adaptive movement patterns.

Fig. 13 The proposed lower-limb exoskeleton in use.

The application of the STFT for feature extraction played a significant role in the success of the movement classification. By transforming the time-domain EMG signals into the frequency domain, STFT allowed the system to capture key temporal and spectral features, which are essential for distinguishing between different types of muscle contractions. The results of the STFT analysis, as depicted in the time-frequency spectrograms, showed clear differences in the frequency components of EMG signals associated with different leg movements. This further supports the use of STFT as an effective feature extraction technique in EMG signal processing, providing a solid foundation for the subsequent classification by the deep learning model.

5.2 Comparison with existing technologies

Compared to traditional rehabilitation techniques, which often rely on passive or manually controlled devices, the proposed system represents a significant advancement in terms of user interactivity and adaptability.[41-44] Conventional exoskeletons typically use predefined motion trajectories or require manual control inputs, which may limit the degree of user involvement in the rehabilitation process. In contrast, the EMG-driven control system developed in this study allows for more intuitive and personalized interaction, as the exoskeleton responds directly to the user's muscle activity. This could lead to more effective rehabilitation outcomes, as active participation and task-specific training have been shown to promote neuroplasticity and motor recovery in patients with neurovascular injuries.

In the context of existing EMG-controlled exoskeletons, the proposed system offers improvements in terms of classification accuracy and real-time control. Previous studies have explored the use of machine learning algorithms, such as support vector machines and random forests, for EMG signal classification in exoskeleton control. However, these models often require extensive feature engineering and may struggle with real-time implementation due to their computational complexity. The use of a deep learning model in this study addresses these limitations by automatically learning relevant features from the raw EMG data, reducing the need for manual feature extraction and improving the system's adaptability to different users and conditions.

Additionally, the integration of neural inputs, as demonstrated in some of the experimental setups, further enhances the system's ability to recognize movement intentions. This multimodal approach, combining both EMG and neural signals, provides a more comprehensive representation of the user's motor commands, potentially leading to more accurate and responsive control. Although this feature was only explored in preliminary experiments, it presents an exciting direction for future research, as the inclusion of brain signals could allow for even more seamless interaction between the user and the exoskeleton.

5.3 Future directions

Looking ahead, there are several potential avenues for improving the system and extending its applicability. One promising direction is the integration of more advanced sensor technologies, such as inertial measurement units (IMUs) or force sensors, to complement the EMG signals. These sensors could provide additional information about the user's movements, allowing for more accurate classification and control. For example, IMUs could capture the orientation and acceleration of the limb, which could be used in conjunction with EMG signals to distinguish between similar movements, such as slow and fast leg lifts.

Additionally, future work could explore the use of reinforcement learning techniques to further enhance the adaptability of the exoskeleton. By allowing the system to learn from user feedback and continuously improve its performance over time, reinforcement learning could enable more personalized and effective rehabilitation interventions. This approach would be particularly beneficial for patients with varying levels of motor impairment, as the system could tailor its assistance to the individual's specific needs and capabilities.

Another area for future research is the long-term evaluation of the system's impact on rehabilitation outcomes. While this study demonstrated the technical feasibility of the proposed exoskeleton, its effectiveness in promoting motor recovery and improving functional outcomes has yet to be thoroughly tested in clinical settings. Conducting longitudinal studies with patients undergoing rehabilitation for neurovascular injuries would provide valuable insights into the system's therapeutic potential and its role in supporting the recovery process.

In summary, the proposed lower-limb exoskeleton offers a novel and effective approach to post-neurovascular injury rehabilitation, combining real-time EMG signal processing with deep learning-based movement classification. While the system shows great promise, there are several areas for improvement, including expanding the range of movements, increasing the model's generalizability, and incorporating additional sensor modalities. By addressing these limitations and continuing to refine the system, future iterations of the exoskeleton could play a pivotal role in enhancing rehabilitation outcomes for individuals with neurovascular impairments.

6. Conclusions

In conclusion, this study presents the development of a deep learning-enhanced lower-limb exoskeleton that utilizes electromyography (EMG) signals for post-neurovascular injury rehabilitation. The integration of a pretrained deep learning model allows the exoskeleton to classify leg movement intentions, such as leg up, leg down, and leg move, with high accuracy, as evidenced by the results. By translating EMG signals into corresponding motor commands, the exoskeleton provides real-time assistance tailored to the user's muscle activity, promoting active engagement and task-specific rehabilitation. The use of Short-Time Fourier Transform (STFT) for feature extraction from EMG signals further enhances the system's ability to distinguish between different types of movements, making it a powerful tool for adaptive rehabilitation. While the system demonstrated strong performance, the study acknowledges certain limitations, including the need for larger datasets and a broader range of movements to improve its generalizability and functionality. Additionally, integrating complementary sensor modalities, such as inertial measurement units (IMUs), could further refine the system's accuracy and adaptability. Overall, the proposed exoskeleton holds significant potential to improve rehabilitation outcomes by facilitating user-driven, EMG-based control in real time. Future work should focus on optimizing the model's robustness and expanding its applicability to diverse patient populations, ultimately contributing to more personalized and effective rehabilitation solutions for individuals recovering from neurovascular injuries.

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Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

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