A deep learning approach for surface electromyographic signal analysis: toward robotic elbow orthosis control

Un enfoque con aprendizaje profundo para el análisis de señales electromiográficas de superficie: hacia el control de órtesis robótica de codo

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Abstract

Motor disabilities resulting from neuromuscular diseases severely impact patients' quality of life. This study proposes a hybrid CNN-LSTM regression-based model to estimate elbow joint angles in real-time using surface electromyographic (sEMG) signals, aiming for precise and continuous control of robotic orthosis. sEMG signals from the biceps and triceps, obtained from a validated public database, were preprocessed rigorously. The model was trained and evaluated using the following metrics: MAE (0.0828), RMSE (0.1132), R^2 (0.9517), and Pearson correlation (0.9757), demonstrating high accuracy and robustness. A graphical user interface was developed to display real-time sEMG signals and predictions. Results confirm the feasibility of the proposed approach for clinical applications, highlighting its potential to enhance upper-limb rehabilitation and promote patient autonomy through intuitive control of active orthotic devices.

Keywords: EMG, artificial intelligence, orthosis

Resumen

Las discapacidades motoras derivadas de enfermedades neuromusculares afectan significativamente la calidad de vida de los pacientes. En este trabajo se propone un modelo híbrido CNN-LSTM con enfoque regresivo para estimar en tiempo real el ángulo articular del codo a partir de señales electromiográficas superficiales (sEMG), con el objetivo de controlar de forma precisa y continua una órtesis robótica. Se emplearon señales sEMG de bíceps y tríceps de una base de datos validada, las cuales fueron sometidas a un riguroso preprocesamiento. El modelo fue entrenado y evaluado utilizando métricas como MAE (0.0828), RMSE (0.1132), R^2 (0.9517) y coeficiente de Pearson (0.9757), evidenciando alta precisión y robustez. Además, se desarrolló una interfaz gráfica para visualizar las señales y predicciones en tiempo real. Los resultados confirman la viabilidad del enfoque propuesto para aplicaciones clínicas, destacando su potencial para mejorar la rehabilitación funcional del miembro superior y promover la autonomía del paciente mediante un control intuitivo de órtesis activas.

Palabras clave: EMG, inteligencia artificial, órtesis

Introduction

Neurodegenerative and neuromuscular disorders, including multiple sclerosis, amyotrophic lateral sclerosis, muscular dystrophy, spinal muscular atrophy, spinal cord injury, and stroke, ultimately lead to a progressive loss of motor function, rendering individuals unable to perform even the simplest of tasks. Consequently, patients often experience a substantial decline in independence, quality of life, and self-esteem due to their constant reliance on external assistance. This issue is particularly critical in upper limb function, as autonomy in these muscle groups is not only essential for basic activities but also for performing everyday actions that, although not vital, play an essential role in maintaining emotional well-being and overall life quality.[1,2]

Motor training-based physical rehabilitation, centered on the repetition of isolated movements, has been proven to be highly effective in restoring upper limb functionality.[2-6] Despite its proven benefits, conventional rehabilitation approaches still rely heavily on the continuous involvement of trained therapists. This dependence can significantly hinder patient recovery due to several factors, including the time-consuming and labor-intensive nature of therapy, as well as limited access to therapist-mediated care and specialized equipment; barriers that are especially pronounced in resource-limited settings.[2,3,7] Furthermore, rehabilitation success is highly dependent on the patient's ability to attend therapy consistently. However, these limitations often result in persistent upper limb impairment among patients.[2,3]

Given this context, autonomous recovery of lost motor function represents a meaningful step towards achieving greater independence in daily life. Technological advances in rehabilitation engineering introduce promising alternatives to address muscle weakness, notably through the development of assistive devices (ADs). These devices are specifically designed to assist users in performing both particular or everyday activities, while maintaining or enhancing their functional abilities despite physical impairment.[1,8-10]

Among ADs, myoelectric orthoses stand out for their capacity to partially restore lost motor function. These devices function by detecting surface

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electromyographic (sEMG) signals generated by the user's muscle contractions using integrated electrodes. The recorded action potentials from groups of muscle fibers are subsequently processed to perform movement.[11-17] However, similar to conventional rehabilitation, these technologies remain limited in many resource-constrained settings, where an estimate of only 5-15 % of individuals in need of ADs have access to them, primarily due to factors such as low production volumes, substandard quality and a lack of a qualified specialist to instruct patients in the operation of these devices.[18]

Machine learning (ML), a subset of artificial intelligence (AI), has been introduced and applied in the extraction of relevant features from sEMG signals, generating improved control strategies for ADs. Various studies have demonstrated the feasibility of ML models to classify tasks and enhance the accuracy and robustness of human movement recognition. The incorporation of AI in the development of robotic orthoses optimizes their functionality and adaptability to user needs.[3,11,19]

Notably, deep learning (DL) algorithms are capable of autonomously learning representations directly from raw data with minimal human intervention. These DL models present a layered architecture that incorporates artificial neural networks, enabling them, in principle, to function similarly to the human brain.[19]

Convolutional neural networks (CNNs), an animal visual cortex-inspired DL architecture,[14,20] have vast applications such as image processing, computer vision, and text classification, due to the capability to process structured arrays of data.[19,20] In contrast to handcrafted features, CNNs are capable of autonomously learning relevant features from sEMG signals, requiring relatively small quantities of data for model optimization.[14,21,22] When applied to sEMG signals, CNN processes sequences of muscle potential values, enabling the extraction of features such as muscle burst, wave patterns, and muscle activation dynamics.

Long short-term memory (LSTM), a specialized type of recurrent neural network (RNN) and a biologically inspired neural network, is a widely used DL model with the capability of recognizing patterns and temporal dependencies in sequential data.[23] Proven effective in applications such as numerical time series, texts, and audio recordings, the LSTM architecture allows for enhanced modeling of the long-term dependencies in time-dependent data. Given the sequential nature of the sEMG signals, LSTM models are well-suited for identifying the timestamps of muscle activity. [19,23-27]

The primary objective of this work is the development and validation, through simulations, of a hybrid deep learning model that integrates convolutional and recurrent neural networks, CNN and LSTM respectively, for real-time estimation of the elbow joint angle using surface electromyography (sEMG) signals. This work aims to establish a foundation for future implementation of DL models in the control of robotic orthoses for assistance or rehabilitation.

Materials and methods

No experimental procedures involving human participants were performed in this study. All analyses were conducted using a publicly accessible, previously validated dataset, which possesses prior ethical approval for its use and distribution.[28]

The proposed methodology focuses on four main stages: dataset selection, signal preprocessing and processing, CNN-LSTM hybrid architecture, and deep learning model predictions.

Database selection

The selected dataset used contains surface electromyography (sEMG) and kinematic data (elbow joint angles) from ten subjects (six males and four females) performing various flexion–extension

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and pronation–supination exercises. For flexion–extension movements, data were collected with the subjects standing and performing the movement with their arm alongside the body. For pronation–supination movements, subjects were seated with the forearm supported on a table.

The sEMG signals were acquired using a Shimmer3 EMG device, while joint angles were estimated using the integrated inertial measurement units (IMUs) in the same device. Each subject performed the following exercises: flexion–extension without load, with a 3 lb dumbbell, and with a 5 lb dumbbell; as well as pronation–supination under the same load conditions.

For this study, only the data corresponding to the flexion–extension movement without additional loads were used. These signals were acquired at a sampling frequency of 1024 Hz while subjects followed a controlled rhythmic pattern.

Elbow joint angles, ranging from 0° (full extension) to 120° (maximum flexion), were defined as the target variable for the regression model. These values were obtained from the IMUs during sEMG data acquisition, providing a reliable and continuous ground truth. This dataset was selected due to its public availability, inclusion of raw signals for all subjects, and sex-based variability.

Signal preprocessing and processing

Accurate and meaningful extraction of muscle activity data relies heavily on the effective processing of EMG signals. Raw signals, due to their low amplitude and susceptibility to noise, are not suitable for direct analysis or practical applications without proper preprocessing.[29]

According to this, in the preprocessing stage, a notch filter at 60 Hz was applied to remove power line interference. This was followed by the Teager–Kaiser Energy Operator (TKEO),[30] to enhance the detection of muscle activation. A band-pass filter with cutoff frequencies of 15 Hz and 350 Hz (the recommended approach according to recent studies)[31] was then used to eliminate irrelevant frequency components.

After filtering, the signals and corresponding joint angles from all subjects were concatenated and truncated to the same length, using the shortest signal as a reference. A feature matrix was then constructed using a sliding window approach.

A window size of 600 ms and a step size of 40 ms were selected. This configuration allows the model to capture complex patterns of muscle activation while maintaining high temporal resolution. The resulting 93.33 % overlap between windows smooths the predictions and increases the amount of effective training data.

CNN + LSTM hybrid architecture

The proposed model comprises two one-dimensional convolutional layers (Conv1D), which are responsible for extracting both spatial and temporal features from raw sEMG signals. These layers enable the identification of relevant patterns within temporally segmented windows. Subsequently, two LSTM layers are incorporated to capture the temporal dependencies inherent in the EMG signals. Finally, a dense output layer with linear activation is used to perform regression on the elbow joint angle.

Deep learning model predictions

Dividing data into training, validation, and test sets is critical for preventing overfitting and for reliably evaluating the performance of machine learning models in medical applications. According to Amazon Machine Learning documentation, a commonly adopted strategy is to divide labeled datasets into training and evaluation subsets, typically allocating 70-80 % for training and 20-30 % for evaluation.[32]

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In this work, the dataset was partitioned into 70 % for training, 20 % for validation, and 10 % for testing. The hybrid model was trained using the preprocessed sEMG signals, and its performance was assessed on the test dataset.

Model evaluation was performed using the following statistical metrics: coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE), and Pearson's correlation coefficient. These metrics provide a comprehensive assessment of the model's regression capabilities.

Graphic User Interface (GUI)

Finally, the trained model was integrated into a GUI to facilitate real-time operation and user interaction. The GUI displays a simulation of real-time sEMG signal input, the corresponding joint angle prediction, and statistical metrics, allowing users to monitor the model's performance during execution.

In this regard, GUIs allow researchers to gain a deeper understanding of EMG signals and their analysis procedures, which can be leveraged for more powerful and flexible applications in the future. These interfaces not only facilitate interaction between the user and the system but also enhance patient motivation, enable real-time monitoring, and provide visual feedback that can optimize the rehabilitation process.[33,34]

Results

This section presents the performance evaluation of the CNN+LSTM model, including the calculation of various standard statistical metrics and graphical analyses. The results demonstrate the model's capability and accuracy in predicting elbow joint angles from surface electromyography (sEMG) signals.

Metric evaluation

The root mean squared error (RMSE) and the mean absolute error (MAE) are two standard metrics widely used in the performance assessment of predictive models. The MAE represents the average of the absolute differences between actual and predicted values, while the RMSE is the square root of the mean squared error (MSE). Although taking the square root does not change the relative ranking of evaluated models, it allows for the metric to be expressed in the same units as the target variable "$\hat{y}$", which is useful since it conveniently represents the typical or "standard" error when errors follow a normal distribution.[35] The values obtained by the model were MAE = 0.0828 and RMSE = 0.1132.

Table 1. *Evaluation metrics of the CNN-LSTM model for elbow joint angle estimation*

Metrics	Results
MAE	0.0828
RMSE	0.1132
R^2	0.9517
PCC	0.9757

The table summarizes the model's performance metrics, computed using the Scikit-learn library in Python. These metrics assess the accuracy of the elbow joint angle predictions, where lower MAE and RMSE values indicate smaller errors, and higher R^2 and Pearson's Correlation Coefficient (PCC) values reflect a strong alignment between predicted and actual values.

These values reflect an acceptable model performance, considering that both errors are relatively low and close to each other. The RMSE being slightly higher suggests the presence of some larger errors, as this metric penalizes larger deviations more heavily due to its quadratic nature.

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The coefficient of determination (R^2) indicates the proportion of variance in the response variable that is explained by the independent variables in a linear regression model. Higher R^2 values reflect greater explanatory power of the model.[36]

In this study, a R^2 value of 0.9517 was obtained, indicating that 95.17 % of the variability in joint angles can be explained by the model based on electromyographic signals. This result is considered favorable, as it indicates a highly accurate fit between the model's predictions and the actual data.

It is important to emphasize that, although a high R^2 value indicates strong model performance, it does not guarantee that the model is completely error-free; it does strongly suggest that the model has successfully captured the relationship between input and output variables.[37]

The Pearson correlation coefficient (PCC) is a fundamental statistical metric for quantifying the linear relationship between a model's predictions (output variables) and the actual observed values (input variables).[38] The generated model shows a PCC of r = 0.9757.

Graphical analysis

Figure 1 displays blue dots representing data pairs (actual value, predicted value) and a red dashed line representing the ideal line. A high concentration of points near this line is observed, indicating a precise match between the model's predictions and the actual values. The strong visual correlation supports the previously reported PCC value.

As shown in Figure 1, the angle predicted by our model is consistent with the actual angle provided by the dataset. The overlap of both curves demonstrates that the model accurately captures both the general shape of the signal and the dynamic transitions between different phases of movement. This agreement is especially noticeable in the flexion and extension peaks, where prediction challenges typically arise due to the rapid joint movement.

Moreover, the low dispersion between both curves suggests a robust generalization capability of the model, which is essential for its implementation in a real-time assistive system, always considering that new signals must be processed using the same algorithm with which the model was trained and must follow a signal acquisition protocol similar to that used in the employed dataset.

The observed accuracy (95.17 %) in the predicted signal quantitatively supports the previously analyzed metric values and reinforces the feasibility of the CNN-LSTM approach as an effective tool for continuous joint angle estimation from EMG signals.

Overall, these results suggest that the model can predict the joint angle with adequate accuracy, which represents a significant step towards the implementation of control systems for the proposed application.

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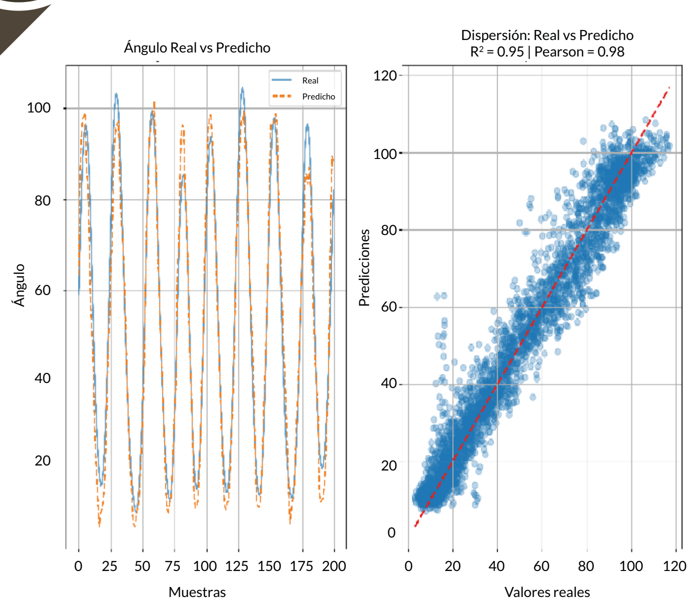

Figure 1. *Graph of actual vs. predicted angle by the CNN-LSTMmodel, with samples vs. angle*

Note: *the figure illustrates the model's performance through two visualizations. On the left, the comparison between real and predicted joint angles over time shows a strong overlap of both signals, especially at flexion and extension peaks, confirming the model's ability to follow the dynamics of movement. On the right, the scatter plot shows predicted vs. actual values, with most points concentrated near the ideal red dashed line, visually supporting the high R^2 (0.95) and PCC (0.98) previously reported.*

Discussion

The hybrid CNN-LSTM architecture represents a significant methodological advancement in the preprocessing of sEMG signals for the control of robotic orthoses, outperforming conventional AI-based approaches that are limited to discrete movement classification.[39] In contrast to these methods, the proposed model generates continuous estimations of joint angles, which enables proportional control and high kinematic fidelity, particularly valuable in clinical contexts where natural motion patterns need to be replicated with high accuracy (95.17 %). This angular regression capability positions the architecture as a technically superior solution for rehabilitation applications that demand accuracy and smoothness in robotic actuation, thus establishing a new paradigm in the integration of deep neural networks for biomedical signal processing.

In previous studies,[40] it has been demonstrated that hybrid models based on CNN-LSTM architectures exhibit superior performance compared to traditional pure approaches, such as those relying solely on CNN, LSTM, SVM, or KNN. This advantage is particularly evident in regression tasks applied to the processing of sEMG signals, positioning these hybrid models as a more robust and efficient alternative for the development of targeted applications in this field.

In an article,[41] a hierarchical dynamic Bayesian model is introduced, integrating Gaussian mixture models (GMM) and hidden Markov models (HMM) to classify movement states based on sEMG signals. Although Bayesian networks demonstrated notable effectiveness in state classification tasks, achieving an accuracy of 93.83 % when including the resting state, the proposed model is outperformed in regression tasks by alternative approaches. These regression tasks are essential for continuous and smooth control of robotic orthoses, as they enable more precise and dynamic estimation of motor intentions. Nevertheless, it is important to emphasize that both architectures can be regarded as complementary, since their integration could leverage the individual strengths of each model across different aspects of sEMG signal processing and analysis.

The CNN-LSTM hybrid model demonstrates exceptional performance, as evidenced by key metrics such as a coefficient of determination (R^2) of 0.9517 and a Pearson correlation coefficient of 0.9757. This high level of accuracy can be attributed to the synergy between its architectural components and a rigorous signal processing pipeline.

On one hand, the convolutional layers (Conv1D) perform automatic extraction of hierarchical features, with the first layer identifying simple local patterns in the sEMG signals, such as abrupt amplitude changes, while the second layer cap-

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tures more complex combinations of muscle activation. On the other hand, the LSTM layers incorporate temporal memory, preserving information from previous 600-ms windows, which is critical for modeling the temporal dynamics of joint movements, particularly during transitions between flexion and extension phases.

Additionally, the optimized signal preprocessing pipeline, which includes the application of a notch filter, a band-pass filter, and the TKEO, enables the effective extraction of genuine neuromuscular components while systematically mitigating various artifacts inherent to signal acquisition in real-world environments. This rigorous denoising process allows the convolutional layers of deep architecture to more accurately discriminate authentic spatiotemporal patterns of muscle activation, establish statistically robust correlations between electromyographic features and reference joint angles, and minimize the learning of spurious features that could compromise the validity of predictions. Consequently, the integrity of the input signal is preserved as a critical determinant of the model's outstanding performance in continuous regression of kinematic parameters.

The implemented GUI is not merely a supplementary feature but rather plays a pivotal role as a critical enabler for the clinical adoption of this technology. It allows for real-time visualization of both sEMG signals and predicted joint angles, thereby enabling therapists to immediately assess the relationship between muscle activation and movement patterns. This capability is essential for optimizing rehabilitation protocols through personalized adjustments. Furthermore, the GUI has been designed with an emphasis on ergonomic and functional optimization, ensuring a minimal learning curve and facilitating its deployment in resource-constrained settings, where operational simplicity and efficiency are crucial for clinical viability.

According to the document published by INEGI,[42] it is evident that 15.9 % of women and 18.1 % of men with disabilities have difficulties in moving or using arms or hands, with the main causes being diseases (43.9 %) and advanced age (27.2 %). Although the study does not specify the percentage of individuals receiving physical rehabilitation, the data indicate that 67.2 % of this population is affiliated with social security institutions, while 17.9 % have access to public health services, suggesting that, in theory, a significant proportion could be covered for rehabilitation therapies. However, lacking accurate information on their effective implementation, a critical gap in care is evident. In this context, the adoption of the proposed technology, based on AI for personalized medicine, adaptive rehabilitation with automatic calibration, and the development of low-cost robotic elbow orthoses through open-source hardware and software solutions, would represent a substantial advance by offering an accessible, scalable and highly adaptable system to the individual needs of patients, thus optimizing the resources available in healthcare institutions.

The presented DL model was developed and validated using data from healthy subjects, without taking into consideration significant physiological characteristics (e.g., age, body mass index, arm length, lateral dominance), representing a significant limitation in extrapolating the results to clinical populations. Consequently, it is suggested that future research incorporate adaptive preprocessing protocols that allow the inclusion of electromyographic signals contaminated by clinical factors such as the influence of drugs or the presence of involuntary movements. Also, it is recommended to initiate clinical validation through pilot studies in populations under controlled neurological conditions, such as patients with relapsing-remitting multiple sclerosis, before extending its application to cohorts with more complex and advanced pathologies, such as advanced amyotrophic lateral sclerosis.

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During the acquisition of a patient's muscle action potentials, several technical improvements could significantly enhance system performance. One key enhancement would be the use of portable, high-precision electrodes, which offer better signal quality, increased comfort for the user, and greater robustness against motion artifacts and electrode displacement—common issues in long-term or real-world applications. Other potential improvements include the implementation of wireless data transmission to increase the system's portability and reduce cable-induced noise, as well as the use of adaptive filtering techniques to dynamically adjust to changing noise conditions. Finally, personalized calibration procedures and online learning algorithms could allow the model to adapt to individual users and improve performance over time, particularly in rehabilitation scenarios where muscle activation patterns may change during recovery.

Finally, we propose the implementation of a quantized architecture on low-power microcontrollers, combining a hybrid CNN+LSTM model for the prediction of the desired angle, together with a PID controller in charge of the precise torque correction, integrating also an emergency stop module based on critical thresholds of sEMG activity, to guarantee both the safety and the operational stability of the system in real time.

Critical analysis of related works

A critical analysis underscores the advantages and trade-offs of the proposed CNN-LSTM approach. Velásquez *et al*. (2023)[19] demonstrated that hybrid CNN-LSTM architectures outperform single-architecture models in classification tasks by effectively capturing both spatial and temporal features of sEMG signals. While their work was focused primarily on discrete classification, our study extends the applicability of this hybrid architecture to continuous regression, achieving high kinematic fidelity (R^2 = 0.9517) necessary for real-time orthosis control. Similarly, Cai and Zhu (2021) [40] reported significant improvements in gesture recognition accuracy when integrating CNN and LSTM, but their experiments did not address regression-based control, leaving a gap that our model addresses. In contrast, Chen *et al*. (2023)[41] employed a hierarchical dynamic Bayesian model (GMM + HMM) for movement state classification, obtaining notable accuracy (93.83 %), yet their framework lacks the capability for continuous estimation. This limitation makes it less suitable for smooth, proportional control in assistive devices, where our CNN-LSTM approach demonstrates clear advantages.

Table 2. *Performance analysis of selected models for sEMG-based robotic orthosis control*

Model	Performance	Applicability
SVM	Accuracy = 93.35 % in gesture classification [3]	Discrete movement classification
CNN	Accuracy = 91.30 % in movement classification [14]	Movement classification and muscle activation detection
LSTM	Accuracy = 91.30 % in real.[24]	Sequence prediction and time-series modeling
CNN + LSTM	R^2 = 0.95 (this study)	Continuous and precise control of orthoses

Note: *the table summarizes the performance and applicability of various machine learning and deep learning models commonly employed for sEMG signal analysis. The comparison includes traditional approaches, such as SVM, and advanced architectures, such as CNN, LSTM, and the proposed CNN+LSTM hybrid model, highlighting their reported accuracy and primary use cases in movement classification, time-series prediction, and continuous control of orthoses.*

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Conclusion

This study presents a hybrid CNN-LSTM model designed to estimate elbow joint angles in real time from surface electromyographic (sEMG) signals, to enable intuitive control of robotic orthoses. The proposed architecture successfully integrates the spatial feature extraction capabilities of convolutional layers with the temporal sequence modeling strengths of recurrent layers. The model achieved a high predictive performance, with a Pearson correlation coefficient of 0.9757, a coefficient of determination (R^2) of 0.9517, and low error rates (MAE = 0.0828, RMSE = 0.1132), validating its efficacy in mapping EMG signals to biomechanical variables. These results support the central hypothesis that EMG-based AI models can provide accurate, continuous estimations of joint motion, offering a promising avenue for the development of intelligent assistive technologies. The model's robustness and precision make it a strong candidate for future integration into portable and adaptive rehabilitation systems. Compliance with national and international medical device regulations has been considered in additional research, laying the groundwork for clinical translation and potential commercialization.

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Conflict of interest statement

The authors declare no conflicts of interest.

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Contribution statement

Lennin Eduardo Figueroa Gil - Departamento de Ingeniería Química y Metalurgia, Universidad de Sonora: Design of deep learning architecture and model training.

Juan Guzmán García - Departamento de Ingeniería Química y Metalúrgia, Universidad de Sonora: Signal preprocessing, development of the graphical user interface and integration of the predictive system.

Joshua Alan Romero Andrade - Departamento de Ingeniería Química y Metalurgia, Universidad de Sonora: Data collection process, writing and preparation of the manuscript.

Edwin Alain Ruelas Estrada - Departamento de Ingeniería Química y Metalurgia, Universidad de Sonora: Literature review, documentation, and analysis of results.

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