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RESEARCH PAPER

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Embedded Machine Learning on ESP32 for Upper-Limb Exoskeletons Based on EMG

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ABSTRACT

Stroke remains one of the primary causes of long-term disability worldwide and frequently results in persistent impairment of upper limb motor function. To support more effective and intensive rehabilitation, there is a need for wearable devices that can interpret muscle activity and autonomously assist limb movement without relying on an external computer. This study aims to design and implement an upper-limb rehabilitation exoskeleton that is driven by electromyography (EMG) signal classification using machine learning and by real-time elbow angle monitoring, with all models deployed directly on an ESP32 microcontroller. The proposed exoskeleton is built from lightweight, ergonomic 3D-printed components and operates in both unilateral and bilateral modes. Its main contributions include: (1) embedding real-time EMG classification models on the ESP32 so that the device can function independently, (2) integrating EMG-based motor control with elbow angle feedback from an MPU6050 inertial measurement unit, and (3) incorporating a load cell to estimate biceps force during training. EMG signals from the forearm flexor muscles are processed to extract statistical features such as variance (VAR), waveform length (WL), integrated EMG (IEMG), and root mean square (RMS). These features are used to train Random Forest, Decision Tree, Support Vector Machine (SVM), and XGBoost classifiers. The trained models are converted to C code using the micromlgen library for execution on the ESP32. System evaluation involved thirty male participants aged 20–25 years with body weights between 50–85 kg. All tested models achieved 100% accuracy in distinguishing relaxed versus grasping muscle contractions, while the correlation of elbow angles between unilateral and bilateral ESP32 systems reached 0.9469, indicating highly consistent motion detection. The Decision Tree model was selected for deployment due to its superior memory efficiency on the microcontroller. These results demonstrate that the developed ESP32-based exoskeleton provides a practical, efficient, and easily integrable solution for wearable stroke rehabilitation..

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I. INTRODUCTION

Stroke remains one of the leading causes of long-term adult disability worldwide, and more than half of survivors experience persistent upper-limb motor impairment that limits independence in daily activities [1], [2]. Conventional rehabilitation can improve function but is often constrained by therapist availability, session duration, and the difficulty of providing sufficiently intensive, repetitive, and task-specific training over long periods, especially in resource-limited settings [1], [3]. Upper-limb exoskeletons have therefore been developed to deliver robot-assisted therapy and show promising gains in motor function and quality of life; however, many current systems are still bulky, expensive, and tethered to clinical environments, which restricts their use for home-based or continuous rehabilitation [3], [4]. In parallel, surface electromyography (sEMG) has emerged as a key modality for intuitive, user-intent-driven control of exoskeletons, and numerous studies have demonstrated that machine-learning classifiers can decode movement intentions and hand or arm patterns from EMG with high accuracy [5]–[7]. Nevertheless, most of these systems still rely on external PCs, workstations, or high-end embedded platforms to handle the full EMG processing pipeline acquisition, filtering, feature extraction, and classification which increases cost and complexity and reduces portability [5], [8], [9]. Soft wearable devices, such as fabric sleeves for upper-limb augmentation, offer improved comfort and lightweight actuation but typically depend on external controllers and do not yet provide fully autonomous, microcontroller-based machine-learning control integrated with joint kinematics and force sensing [7], [10]. Recent reviews also emphasize the need for mobile-health and home-deployable technologies that combine robust intention detection with sensor fusion and edge or embedded computing, so that assistance can adapt in real time without relying on continuous clinical supervision [2], [8], [9]. Consequently, there is still a clear

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gap for low-cost, upper-limb exoskeletons that embed the entire EMG-driven machine-learning pipeline directly on a compact microcontroller, while simultaneously monitoring elbow joint angles and muscle effort, to support practical unilateral and bilateral training outside the laboratory or hospital.

Contemporary research on upper-limb rehabilitation exoskeletons shows a rapid transition from purely mechanical assistance toward systems that tightly integrate biomechanics, sensing, and machine learning–based control. Early EMG-driven designs for hand exoskeletons, such as the multi-joint device proposed by Li et al., demonstrated that surface EMG signals can reliably encode user intent; their system employed six linear actuators to provide high degrees of freedom for coordinated thumb and finger motion, while comparing several pattern-recognition models SVM, KNN, Decision Tree, MLP, and multi-channel CNN and achieved up to 99% offline classification accuracy and over 80–90% online accuracy for most subjects, highlighting the feasibility of EMG-driven control but still relying on external computational resources for signal processing and model execution [1]. Extending the use of EMG, Trigili et al. focused less on continuous trajectory tracking and more on robust detection of motion onset, collecting EMG data from healthy participants performing random reaching tasks while wearing an exoskeleton; by extracting time-domain features and modeling their distribution with Gaussian Mixture Models, they designed detectors that identified transitions between rest, “Go-forward,” and “Go-backward” states with sensitivities up to 89.3% and specificities above 94%, underscoring the potential of probabilistic machine learning for detecting user intention in real time [2]. More recent developments have explored soft robotics to improve comfort and safety; Hoang et al. designed a fabric-based sleeve that uses fiber-reinforced hydraulic actuators and liquid-metal strain sensors embedded in textiles, then introduced an asymmetric hysteresis model with only a few parameters to compensate for nonlinearities and hysteresis in actuator behavior, demonstrating that their sleeve can generate meaningful assistive forces while significantly reducing muscle activation, though the system still depends on PC-based control rather than embedded intelligence [3]. Focusing specifically on elbow motion, Triwiyanto et al. proposed an embedded prediction system in which EMG signals from the biceps are amplified, filtered, and processed by an ARM-based STM32F429 microcontroller to estimate elbow joint angles; by using zero-crossing features and Butterworth low-pass filtering, they obtained root mean square errors between 8° and 16° and correlation coefficients of 0.94–0.99, proving that accurate angle estimation from EMG is possible on a resource-constrained embedded platform but without yet combining this capability with multi-sensor feedback or integrated machine learning models [4]. To improve wearability and daily usability, Malvezzi et al. introduced a lightweight hand exoskeleton that leverages postural synergies so that each finger is driven by a single motor with coupled joint motions; the prototype weighed about 40 g per finger yet could generate up to 15 N, illustrating that mechanical optimization alone can deliver compact devices suitable for rehabilitation and activities of daily living, though the control strategy remained relatively simple and did not exploit embedded learning-based adaptation [5]. Complementary to these hardware-oriented works, Triwiyanto et al. systematically analyzed electrode placement and forearm posture for a wearable hand exoskeleton trainer, showing that selecting the flexor digitorum superficialis as the primary recording site yields classification accuracies around 96.6% and that windowing strategies strongly affect angle estimation performance, thereby emphasizing the importance of signal acquisition and feature-window design for robust EMG classification across users [6]. At the system level, Meng et al. integrated an upper-limb exoskeleton with a wheelchair, designing a six-DOF mechanism whose kinematics were based on seated ranges of motion at the shoulder, elbow, forearm, and wrist; their pilot study demonstrated acceptable joint errors (~15% in flexion–extension) and successful support of functional tasks such as drinking, yet the architecture constrained user mobility due to wheelchair dependence and provided limited active, muscle-driven control [7]. To enrich interaction and remote guidance, Lanini et al. interconnected two ARMin exoskeletons in a master–slave teleoperation configuration with six DOF each, comparing proportional–derivative control for unilateral teleoperation with compliance-based bilateral control that leverages torque feedback; experimental results showed that participants could learn and replicate trajectories and infer the partner’s engagement state (active, passive, resisting), but the approach demanded high-end hardware and communication bandwidth, resulting in cost and latency challenges that reduce practicality for widespread, home-based rehabilitation [8]. Secciani et al. further addressed the need for portability by designing a fully wearable hand exoskeleton capable of both assistive support and telerehabilitation; their mechatronic architecture emphasized comfort, compactness, and real-time intent detection using surface EMG, and early trials with spinal muscular atrophy patients confirmed that users could perform independent and remotely supervised exercises, although the system neither incorporated elbow rehabilitation nor deployed machine learning models directly on a microcontroller for autonomous adaptation [9]. A broader perspective is provided by recent reviews, such as that by Fairuz et al., who survey upper-limb exoskeletons designed to support elderly individuals in activities of daily living and highlight trends toward multi-joint assistance, richer assessment metrics, and the incorporation of sensor fusion for better user-state estimation, while also noting that many devices still rely on desktop-class computing for signal processing and lack integrated, on-board intelligence that would enable low-cost, untethered operation [10]. Collectively, these state-of-the-art contributions demonstrate substantial progress in EMG-driven control, soft actuation, teleoperation, and ergonomic design, but they also reveal persistent gaps: hand-focused systems rarely

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address elbow joint training or force feedback; soft sleeves and teleoperated platforms typically depend on external computers; and even when embedded controllers are used, machine learning is often trained offline and executed on PCs rather than being fully ported to microcontroller environments. This motivates the development of an upper-limb exoskeleton that not only performs EMG-based classification with modern algorithms but also embeds the trained model directly on a low-cost microcontroller, while simultaneously acquiring elbow angle and biceps force via inertial and load-cell sensing, thereby closing the gap between high-performance machine learning and truly portable, sensor-rich, and standalone rehabilitation devices suitable for routine clinical and home use [1]–[10].

Despite substantial progress in EMG-driven exoskeletons and wearable robotics, several gaps remain before truly portable, intelligent upper-limb devices can be widely deployed. Existing embedded systems have predicted elbow angle from EMG on microcontrollers, but typically without modern pattern-recognition pipelines or multi-sensor fusion [1]. Many EMG-controlled hand and upper-limb exoskeletons still rely on PCs, single-board computers, or high-end hardware for signal processing and classification, limiting portability and cost-effectiveness [2], [7]. Soft fabric sleeves and portable devices improve comfort but often lack integrated, on-board machine learning and comprehensive sensing of joint kinematics and muscle effort [3], [8]. Recent reviews highlight a need for upper-limb exoskeletons that combine low-cost embedded intelligence, multi-joint assistance, and home-based usability in real-world contexts [4]–[6].

This study aims to develop a low-cost, wearable upper-limb exoskeleton that can operate as an autonomous rehabilitation device by embedding the entire electromyography (EMG)–based machine learning pipeline directly on an ESP32 microcontroller, while simultaneously monitoring elbow joint motion and muscle effort. To realize this goal, the paper makes several key contributions. First, it implements an on-device machine learning framework in which EMG signals are acquired, filtered, and transformed into time-domain features, and multiple classifiers are trained and then converted into C code for real-time execution on the ESP32; this eliminates the need for an external PC and demonstrates that modern pattern-recognition models can run effectively on a resource-constrained microcontroller. Second, it presents the design of a multi-sensor exoskeleton architecture that integrates EMG electrodes for intention detection, an inertial measurement unit for continuous elbow angle tracking, and a load cell for estimating biceps force, all embedded in a lightweight, 3D-printed structure that supports both unilateral and bilateral training configurations. Third, it provides a comparative evaluation of different classifiers in terms of accuracy, memory footprint, and inference time, and validates the selected embedded model through experiments with human participants, showing high EMG classification performance and a strong agreement between unilateral and bilateral elbow angle measurements. Together, these contributions offer a concrete step toward practical, portable, and sensor-rich rehabilitation exoskeletons that can be deployed in home or community settings without permanent dependence on clinical infrastructure.

II. MATERIAL AND METHODS

A. Dataset

The dataset in this study was obtained from thirty male student volunteers at Poltekkes Kemenkes Surabaya, with ages ranging from 21 to 25 years, body weights between 50 and 90 kg, and heights from 150 to 180 cm. Each participant was instructed to perform two distinct muscle activities relaxation and grasping which were encoded as class 0 and class 1, respectively, to form a binary EMG classification problem. Surface EMG signals were acquired using an OYMotion Analog EMG Sensor (Type SEN0240, OYMotion, China) equipped with dry electrodes, which were positioned over the flexor muscles of the forearm to capture activity related to hand closing. Every EMG recording was synchronized with the motion of the upper-limb exoskeleton, operated either in unilateral mode or in a bilateral configuration, so that muscle activity, joint motion, and interaction with the device could be analyzed together. In addition to EMG, kinematic and force-related data were collected by integrating an MPU6050 inertial measurement unit to measure elbow joint angles and a load cell to estimate biceps force during flexion tasks. This combination of EMG, joint angle, and force measurements provides a comprehensive dataset for training and evaluating embedded machine learning models as well as for assessing the biomechanical performance of the exoskeleton system.

B. Data Collection

The data collection procedure involved thirty male student volunteers from Poltekkes Kemenkes Surabaya, who each wore the developed upper-limb exoskeleton mounted along the shoulder and forearm while surface EMG electrodes were placed over the forearm flexor muscles using an OYMotion dry-electrode sensor module connected to the EMG conditioning circuit via audio jack cables, following common practices in EMG-driven exoskeleton studies [1]–[3]. Participants were instructed to repeatedly perform two distinct hand gestures relax and grasp which were encoded as class 0 and class 1, respectively, to form a binary classification task for muscle activity (Fig. 1). During each trial, EMG signals were recorded simultaneously with measurements from the MPU6050 inertial measurement unit, used to track elbow joint angles, and from a load cell installed to estimate biceps force, yielding synchronized neuromuscular and biomechanical data streams. Data were acquired under two operational modes of the exoskeleton: in the unilateral mode, EMG signals were processed on the local microcontroller to directly drive the motor that actuates finger movement; in the bilateral mode, EMG classification was executed on a separate unit and the predicted movement intention was transmitted wirelessly via Bluetooth to control the contralateral exoskeleton, as commonly explored in bilateral rehabilitation architectures

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[2], [4]. In both modes, all sensor readings including EMG envelopes, estimated elbow angles, and biceps force were logged in a time-synchronized manner to enable subsequent analysis of system responsiveness, classification performance, and the agreement between unilateral and bilateral configurations.

C. Data Processing

In this study, the raw EMG signals recorded from the forearm flexor muscles are first segmented into analysis windows and then processed to extract several statistical features[20], [21], [22]. These features include Variance (VAR), Waveform Length (WL), Integrated EMG (IEMG), and Root Mean Square (RMS). Each of these features provides unique information about the signal characteristics and muscle activity[23], [24], [25]. The variance quantifies the spread of the EMG signal values over a window[25]. Mathematically, variance is calculated as:

$$Variance = \frac{1}{N-1}\sum_{i=1}^{N} xi^2$$

where *n* is the total number of samples in the window, *i* is the signal value at the *i-th* sample, and *xi* is the mean value of the samples in that window.

The waveform length (WL) measures the cumulative length of the EMG waveform within a segment[22], [24], [26]. It represents the complexity of the signal and is computed by summing the absolute differences between consecutive signal samples:

$$Waveform\ Length = \sum_{i=1}^{N-1} |x_{i+1} - x_i|$$

The integrated EMG (IEMG) represents the total signal strength within the window and is calculated as the sum of the absolute values of all samples[22], [27]:

$$IEMG = \sum_{i=1}^{N} |x_i|$$

Lastly, the root mean square (RMS) provides an estimate of the power content of the EMG signal[24], [28]. It is calculated using:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} xi^2}$$

Together, these statistical features are used to transform raw EMG signals into numerical representations suitable for training the machine learning classifiers, ensuring that the models can accurately distinguish between relaxed and grasp states. In this study, four machine learning algorithms were used to classify EMG signals into relax and grasp.

1. Decision Tree

A Decision Tree classifier splits the dataset based on feature values using criteria such as Gini index or entropy. Each node represents a decision rule, and the tree recursively partitions data until it reaches a leaf node:

$$Gini = 1 - \sum_{i=1}^{n} {p_i}^2$$

where p_i is the proportion of samples belonging to class i at node t.

2. Random Forest

Random Forest is an ensemble learning method that builds multiple decision trees and outputs the majority vote of the trees. It reduces overfitting and improves generalization:

$$\hat{y} = mode(\{h1(x), h2(x), \ldots, hn(x)\})$$

where $h_k(x)$ is the prediction of the k-th decision tree.

3. SVM

SVM is a supervised learning algorithm that finds the optimal hyperplane to separate two classes by maximizing the margin:

$$min\frac{1}{2}\|w\|^2\ subject\ to\ y_i(w\, x_i + b) \geq 1$$

where *w* is the weight vector, x_i is the input feature, and $y_i \in \{-1,1\}$ is the class label.

4. XGBoost

XGBoost is a gradient boosting algorithm that builds trees sequentially by minimizing a regularized objective function:

$$L = \Sigma\, l(y, y\_pred) + \gamma T + (\lambda / 2)\Sigma\, w^2$$

where *l* is the loss function and $\Omega(f_k)=\gamma T+\frac{1}{2}\lambda\|w\|^2$ is the regularization term penalizing the complexity of the kkk-th tree. To evaluate the performance of the machine learning models, a confusion matrix is generated to calculate classification accuracy and other related metrics[29], [30]. The accuracy represents the proportion of correctly classified instances among all predictions. It is defined by the formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where True Positive (TP) refers to the number of samples that are correctly predicted as grasping (class 1), while True Negative (TN) denotes the number of samples correctly predicted as relaxed (class 0). On the other hand, False Positive (FP) represents the number of samples that are incorrectly classified as grasping when they are actually in a relaxed state, and False Negative (FN) refers to samples that are wrongly predicted as relaxed when they are in fact performing a grasping gesture. These metrics provide a detailed insight into the system's ability to detect the intended muscle state and minimize misclassification. High true positive and true negative values, along with low false positives and false negatives, indicate a reliable and robust classification model suitable for real-time exoskeleton control.

III. RESULTS

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The classification results show that all four evaluated machine learning models Decision Tree, Random Forest, SVM, and XGBoost were able to perfectly discriminate between the *relax* and *grasp* conditions, achieving 100% accuracy on the test data. This means that, for the recorded dataset, every EMG window was assigned to the correct class with no misclassification, indicating that the chosen time-domain features (VAR, WL, IEMG, RMS) provide a very clear separation between the two muscle states. Embedding these trained models into the ESP32 using the *micromlgen* library did not degrade performance: the on-device predictions matched the offline results, demonstrating that quantization, code generation, and execution on a resource-constrained microcontroller can still preserve full classification fidelity.

From a deployment perspective, all models could technically run on the ESP32, but their computational and memory footprints differed, which is critical for a real-time embedded system. Among the tested algorithms, the Decision Tree model provided the best balance between accuracy, memory usage, and execution time. When implemented on the ESP32, it occupied only a modest portion of the available flash and dynamic memory, leaving sufficient resources for sensor acquisition, wireless communication, and control tasks. In addition, its inference time per window was short enough that the system could respond within a single control cycle, ensuring there was no perceptible delay between muscle activation, classification, and motor actuation. This combination of perfect accuracy and lightweight implementation justified selecting the Decision Tree as the primary embedded model for the final prototype.

The multi-sensor evaluation further confirms the reliability of the overall system. The elbow joint angles measured from the MPU6050 sensors in unilateral and bilateral modes exhibited a correlation coefficient of 0.9469, indicating a very strong linear relationship between the two configurations. In practical terms, this shows that the bilateral exoskeleton can mirror elbow motion with high consistency relative to the unilateral reference, which is essential for symmetric training and rehabilitation scenarios. Moreover, the temporal patterns from the load cell (biceps force) and the IMU (elbow angle) evolved coherently during flexion–extension tasks, supporting the validity of the force estimation mechanism and demonstrating that the integration of EMG, kinematic, and force sensing provides a physically meaningful representation of user effort. Together, these findings show not only that the classifier is accurate, but also that the embedded system delivers synchronized, reliable measurements across all sensing modalities, making it suitable for real-time, wearable rehabilitation applications.

IV. DISCUSSION

The findings of this study show that the proposed exoskeleton system can robustly distinguish between relaxed and grasp muscle states, with all four evaluated classifiers Decision Tree, Random Forest, SVM, and XGBoost achieving 100% accuracy on the recorded EMG dataset. This perfect separation indicates that the selected time-domain features (VAR, WL, IEMG, RMS) and the windowing strategy are highly discriminative for this specific binary task and electrode placement, enabling a very clear mapping between muscle activation patterns and the two intended gestures. From an embedded-systems perspective, the fact that these models could be converted into C code via the micromlgen library and executed on the ESP32 without loss of accuracy confirms that the computational and numerical constraints of a low-cost microcontroller do not necessarily compromise pattern-recognition performance, at least for problems of comparable complexity. The Decision Tree model, in particular, offers a favorable trade-off between interpretability, memory footprint, and inference time, occupying around 86% of flash and 12% of dynamic memory while still leaving headroom for sensor acquisition, Bluetooth communication, and control routines. This resource profile suggests that the chosen architecture is already near the upper bound of complexity for this hardware and that adding more gesture classes or more sophisticated models would require careful optimization or memory expansion.

The developed exoskeleton system successfully classified EMG signals into two muscle conditions relax and grasp with 100% accuracy across all tested machine learning classifiers (Decision Tree, Random Forest, SVM, and XGBoost). The Decision Tree classifier was selected for deployment on the ESP32 microcontroller due to its superior memory efficiency, occupying only 86% of flash memory and 12% of dynamic memory, allowing real-time classification and motor actuation without reliance on a PC. The bilateral control system achieved a high elbow angle correlation of 0.9469 compared to the unilateral system, indicating consistent and reliable mirroring of movement. Additionally, synchronous readings from the IMU and load cell showed aligned patterns, reinforcing the fidelity of sensor integration in representing biceps muscle force and joint angle during rehabilitation exercises.

Compared to prior works, this system addresses several key gaps. For instance, Meng et al. and Secciani et al. developed systems that were either limited to wheelchair-bound applications or lacked direct microcontroller-based classification, making them less practical for portable and independent rehabilitation[17], [19]. Meanwhile, Hoang et al. and Lanini et al. implemented assistive systems with soft actuators or bilateral control but still depended on external computing resources[14], [18]. Unlike those studies, this research fully embeds the classification model into the wearable unit itself, enabling standalone operation and greater flexibility for at-home therapy.

Nonetheless, the proposed system has limitations. It only supports two basic gestures (grasp and relax), limiting its applicability in more complex rehabilitation scenarios. Additionally, although sensor placement and system calibration were standardized, inter-user muscle differences may introduce variability in EMG patterns, potentially affecting generalization. The dataset used was

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also limited to male subjects within a narrow age and weight range.

Despite these constraints, the system's real-time classification, dual-mode functionality (unilateral and bilateral), and embedded intelligence present a significant advancement toward personalized, adaptive rehabilitation tools. Its low cost and standalone operation make it especially valuable for resource-limited settings and daily home-based therapy.

When the multi-sensor aspects of the system are examined, the high correlation coefficient (0.9469) between elbow joint angles measured in bilateral and unilateral modes indicates that the bilateral configuration can mirror the reference motion with strong fidelity, which is essential for symmetric training paradigms and for using the unimpaired limb as a template in stroke rehabilitation. This performance compares favorably with previous embedded elbow-control studies that relied on EMG-based estimation alone, such as Triwiyanto et al. who reported correlation values between 0.94 and 0.99 but did not integrate bilateral mirroring or on-board multi-class machine learning in a single platform [16]. The coherent temporal evolution between IMU-based elbow angles and load-cell–derived biceps force further supports the internal consistency of the sensing chain and indicates that the system can capture both kinematic and kinetic aspects of movement, which is relevant for monitoring patient effort and tailoring assistance levels over time.

In relation to other state-of-the-art exoskeletons, this work addresses several practical limitations. Meng et al. designed a powered upper-limb exoskeleton integrated with a wheelchair, achieving acceptable joint tracking errors for shoulder and elbow movements, but the system's dependence on the wheelchair chassis constrained mobility and did not emphasize embedded machine-learning–based intent detection [17]. Lanini et al. implemented a sophisticated bilateral teleoperation framework connecting two multi-DOF ARMin exoskeletons; although their approach enabled rich interaction and partner-state inference, it relied on high-end hardware and networked communication, leading to latency and cost issues that hinder everyday, home-based deployment [18]. Secciani et al. proposed a fully wearable hand exoskeleton suitable for telerehabilitation, with a strong focus on ergonomics and remote supervision, yet their control strategy was not centered on microcontroller-embedded classification nor did it extend to elbow rehabilitation [19]. Hoang et al. introduced a soft fabric sleeve with hydraulic actuators and liquid-metal strain sensors that significantly reduced muscle workload and improved comfort, but their system still depended on PC-based control and did not perform EMG-driven machine learning directly on the embedded device [14]. Compared to these studies, the present work brings the decision-making layer directly onto a low-cost ESP32, combining EMG classification, elbow angle sensing, and force estimation in a single, self-contained platform that can operate without tethering to a computer, which is a critical step toward affordable, portable, and daily-use rehabilitation technology.

Nevertheless, several limitations must be acknowledged. First, the classification problem is restricted to two gestures relax and grasp so the current system cannot yet support richer hand functions (e.g., pinching, lateral pinch, graded grasp strength) or complex multi-step rehabilitation protocols. Extending the gesture set will likely increase feature-space overlap and may reduce accuracy, particularly under embedded memory constraints; this will require exploring more compact features, model pruning, or incremental learning strategies. Second, the study involved only 30 male participants within a narrow age, height, and weight range, all of whom were healthy; as a result, the trained models may not generalize directly to older adults, women, or stroke survivors whose muscle activation patterns, fatigue characteristics, and spasticity differ markedly from those of young, healthy subjects. Third, although electrode placement and calibration procedures were standardized, residual inter-subject variability and day-to-day changes in skin impedance or electrode contact can affect EMG signal quality; robustness to such variability was not explicitly quantified here. Finally, the mechanical design and control experiments focused mainly on proof-of-concept performance rather than long-term usability, comfort, and safety in real clinical environments.

Despite these constraints, the combination of real-time embedded classification, dual unilateral–bilateral operation, and integrated sensing in this system represents a meaningful advance toward personalized and adaptive rehabilitation devices. It demonstrates that it is technically feasible to bring machine learning out of the laboratory and onto a compact microcontroller within a wearable exoskeleton, laying the groundwork for future studies that incorporate more diverse user populations, richer movement repertoires, adaptive control algorithms, and long-term clinical trials.

V. CONCLUSION

The present study set out to design and implement a wearable upper-limb exoskeleton that embeds machine learning directly on an ESP32 microcontroller to classify EMG signals in real time and to monitor elbow joint motion, with the overarching goal of supporting stroke rehabilitation therapy in a portable and low-cost form factor. This objective was achieved by implementing four classifiers Random Forest, Decision Tree, SVM, and XGBoost on the microcontroller and demonstrating that all of them can reliably distinguish between relaxed and grasping muscle conditions with 100% classification accuracy, confirming that the selected EMG features and processing pipeline are highly effective for this binary task. In parallel, the system successfully integrated an MPU6050 IMU for elbow angle measurement and a load cell for biceps force estimation, with the bilateral configuration achieving a correlation of 0.9469 relative to the unilateral reference, indicating highly consistent mirrored motion and validating the robustness of the sensing and control architecture. An important additional finding is that, among the tested algorithms, the Decision

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Tree model provided the most favorable trade-off between accuracy, memory usage, and inference time, making it the most suitable candidate for deployment on the resource-constrained ESP32 and demonstrating the practical feasibility of on-device machine learning in a fully wearable exoskeleton. Looking ahead, future work will focus on refining the mechanical design particularly redesigning the finger mechanism to better accommodate a wider range of arm sizes and improving the integration of gears and belts for smoother, quieter actuation as well as extending the control strategy with adaptive algorithms that can automatically tune assistance levels to individual muscle strength, fatigue, and rehabilitation progress, and validating the system in broader, long-term clinical studies with diverse stroke populations

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