SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V13I5P103

Volume 13 Issue 5, 21-29, May 2026

Original Article

Development of a Wireless Sensor-Integrated IoT Framework for EMG-Based Adaptive Muscle Relaxation and Remote Rehabilitation Monitoring

Saranyadevi K[1], Anitha A[2], C. S D Vijayakumar[3], R.Praveenkumar[4], Dharani R[5], Prathapan B[6]

[1,2]*Saveetha College of Physiotherapy, Saveetha Institute of Medical and Technical Sciences (SIMATS), Chennai, Tamilnadu, India.*
[3]*Department of Artificial Intelligence & Data Science, Nandha Engineering College, Erode, Tamilnadu, India.*
[4]*Department of ECE, Nandha Engineering College, Erode, Tamilnadu, India.*
[5,6]*Nandha College of Physiotherapy, Erode, Tamilnadu, India.*

[2]*Corresponding Author : anitha.scpt@saveetha.com*

Received: 05 February 2026 Revised: 05 March 2026 Accepted: 04 April 2026 Published: 27 May 2026

Abstract - *Low-latency, adaptive, and secure bio-signal processing platforms are needed to monitor muscle fatigue and do remote rehabilitation outside the clinical setting. An Internet of Things architecture incorporating a wireless sensor is designed to facilitate adaptive muscle relaxation and remote monitoring of rehabilitation using electromyography. The system incorporates multi-channel surface EMG capture, band-pass filtering 20-450Hz, LMS-based adaptive noise control, RMS and mean frequency feature extraction, as well as an adaptive relaxation index model, all implemented on an ARM Cortex-M4 edge processor with encrypted BLE/Wi-Fi telemetry and cloud analytics. Multi-subject experimental validation results indicate 94.8 percent muscle state classification, 92.1% RMS sensitivity, 4.8% mean frequency estimation error, 1.8% ratio of packet loss, 99.1% cloud uptime, and 110 ms end-to-end latency. The convergence time is attained at 0.72 s with a total efficiency of the system at 96.5%. The architecture allows the biofeedback of remotely located neuromuscular activity, which is provided in real-time in a closed-loop form, and remote neuromuscular monitoring at a scale that supports the adaptive, low-latency rehabilitation intelligence in wearable healthcare settings.*

Keywords - *Electromyography, Surface Electromyography, Internet of Medical Things, Root Mean Square, Mean Frequency, Inertial Measurement Unit, Bluetooth Low Energy, Advanced RISC Machine*.

1. Introduction

Neuromuscular diseases, post-stroke muscular limitations, sports injuries, and muscular degeneration secondary to age have a big impact on functional independence and quality of life. EMG has become a crucial physiological modality for determining muscle activation patterns, fatigue, and rehabilitation outcomes. In particular, surface Electromyography (sEMG) enables the non-invasive acquisition of bioelectrical signals produced during muscle contraction and relaxation. As the wearable electronics and smart health technologies grow at an unprecedented pace, EMG-based rehabilitation solutions are becoming more and more clinic-based systems and are being converted to remote monitoring settings at home [1]. A combination of wireless sensing, embedded signal processing, and Internet of Things (IoT) architectures offers a scalable platform that can be used to forward the ongoing neuromuscular monitoring and adaptive therapeutic intervention [2]. Traditional EMG rehabilitation interventions are based on the extensive use of stationary laboratory apparatus, electrodes connected by wires, and the visual analysis of signal patterns. Such systems are not portable, scalable, and real-time adaptive intelligent systems, though they offer high-resolution signal acquisition. Various previous models have integrated IoT connectivity in remote health monitoring [3], but most of them are aimed at data transfer instead of adaptive therapeutic control. The existing literature identifies some of the challenges, such as signal noise contamination by motion and interference by power lines, battery life constraints in wearable nodes, huge transmission latency, and insufficient closed-loop feedback [4]. Moreover, the past report systems have shown inconsistent responses in latency behavior, which is normally over 200 ms in end-to-end transmission, making such systems less responsive to the real-time behavior of muscle relaxation feedback. Moreover, previous classification systems focus on the enhancement of the accuracy but seldom consider the optimal adaptive threshold to individual muscle fatigue states. The non-stationary and stochastic nature of EMG signals is also a source of signal processing difficulties. The pattern of muscle activation is different in individuals, the level of contraction, and the stages of rehabilitation [5]. Traditional fixed-threshold models can undergo a dynamic transition to fatigue and cause inefficient modulation of therapy. Cloud-based systems proposed in the previous literature are more scalable to storage; however, they introduce more reliance on network stability and create delays in processing. Furthermore, there are rather limited systems that incorporate mathematical relaxation indices with time-domain and frequency-domain characteristics of adaptive neuromuscular state detection [6]. This has led to the fact that a single framework that combines cloud analytics, wireless telemetry, wearable sensing, edge intelligence, and closed-loop biofeedback into a latency-optimized framework has been required [7]. The three main reasons that drove this work are the need to design a wireless sensor-based IoT system that would be capable of offering adaptive muscle relaxation control and remote rehabilitation monitoring with lower latency and better signal reliability. The device is created to gather sEMG through a portable multi-channel acquisition module coupled with an embedded edge processor with ARM Cortex, which is designed to do real-time filtering, feature extraction, and calculation of relaxation index [8]. The proposed architecture will not use only cloud-level analytics but will distribute computation to both edge and cloud-computational layers to reduce response time and enhance scalability. The framework is geared towards providing secure transmission of telemetry, strong noise reduction, adaptive convergence of the threshold, and clinician-friendly rehabilitation dashboards [9]. The main objectives are: (1) to design a low-power, wireless multi-channel EMG acquisition system that can be used in a wearable rehabilitation; (2) to implement adaptive noise suppression and feature modeling based on Root Mean Square (RMS) and Mean Frequency (MNF) parameters; (3) to develop an adaptive relaxation index to differentiate between relaxed, moderate, and fatigued conditions on muscles; (4) to introduce an encrypted IoT-based cloud monitoring to provide a way of remote supervision; and (5) to assess system performance in terms of accuracy. The work is summarized in the following way [10]. To start with, a hybrid edge-cloud IoT implementation is presented in the real-time adaptive rehabilitation of EMG-driven. Second, the mathematical relaxation index model with amplitude and spectral properties is applied in dynamic threshold optimization. Third, an automated biofeedback activation with fatigue states identified by the closed-loop feedback mechanism is possible [6]. Fourth, the complete performance analysis shows that the classification accuracy, RMS sensitivity, and mean frequency estimation error are 94.8%, 92.1%, and 4.8%, respectively; the end-to-end latency is 110 ms, the packet loss ratio is 1.8%, the cloud uptime is 99.1%, and the overall system efficiency is 96.5% [11]. These findings reveal better responsiveness and reliability than earlier documented rehabilitation architecture over a distance. The remainder of the paper is organized as follows: The following section includes the system architecture and the strategy of hardware-software integration. The mathematical modeling and adaptive relaxation algorithms are then detailed. Then, the experimental setup, data features, and performance evaluation measures are discussed. Lastly, the conclusion and possible future developments of scalable intelligent rehabilitation ecosystems are presented.

2. Literature Review

An in-depth learning of real-time analysis and muscle cramps and fatigue prevention. The system includes a Node MCU microcontroller, DHT11 temperature and humidity probe, flex sensor, MAX30100 pulse oximeter to monitor BPM and SpO2, and a moisture sensor to measure the moisture level of sweat. By combining these sensors, the system not only identifies the fatigue and cramps of the muscles, but also measures the vital signs and moisture rates, which gives an overall picture of the muscle's well-being [12]. Through WiFi, the collected data is delivered to ThingSpeak, an IoT platform, to access the data and analyze it in detail remotely, and the addition of the MAX30100 allows for keeping track of the air's oxygen content and heart rate continuously, and provides a more complete health evaluation. The moisture sensor is also used to gauge the level of sweat, which enables the system to detect the need for rehabilitation. The system triggers a mechanism of muscle rehabilitation through vibration when the system is triggered by critical indicators, and it helps in preventing cramps [13]. This aspect of sensor technologies integration presents an active attitude to health care, which encourages the early detection, interpretation, and response to the problem in the muscles. The new system is an all-purpose tool that will help healthcare experts as well as individuals in developing preventive healthcare measures.

New advances in the use of science-supported medicine make use of reproducible data from large studies to inform the choice of therapies. To be consistent and replicable, since clinical guideline effectiveness research is particularly important in muscular and therapeutic care, such studies require reliable methods. sEMG is prevalent in science but not in medicine and rehabilitation [14]. ECG, EEG, and needle medical personnel monitor EMG signals, although sEMG has not yet been clinically used. Nonetheless, sEMG has vast clinical potential as a muscle status and operation measurement tool, but data retrieval entails monitoring and interpretation approaches and biophysics expertise. sEMG technological needs, and wearability in rehabilitation and health monitoring systems are discussed in this research. It begins by studying the EMG-based tele-rehabilitation system in neuromuscular, post-stroke, and sports. Thereafter, concepts and architectures of EMG signal processing are explained in order to capture and elaborate on EMG signals. This is followed by the provision of a complete and up-to-date scientific and commercial overview of wearable sEMG detection devices used in rehabilitation training and in physiological surveillance [15]. The comparison and discussion of the methods will demonstrate to rehabilitation professionals how neurobiological detection systems should be implemented, and views will be formed. These evaluations present the significant requirements of wearable or portable healthcare sEMG devices in the future.

The modern issues in the field of healthcare include the slowness of identifying the critical incidents related to the absence of real-time possibilities of the conventional EMG signal processing systems [16]. To come up with this solution, it will combine IoT technology to record, process, and send EMG data in real-time. The main targets are the creation of real-time algorithms of EMG signal processing, resilient IoT communication channels, and an efficient alert system notifying healthcare professionals about clinically vital events [17]. The obstacles, including the security and privacy of data, and compatibility between the device and others, are tackled to comply with the healthcare industry requirements. It is proposed that the desired product will be a high-level IoT-based EMG signal control system, which will promptly inform the user, and this will allow the guardian to monitor the patient with neuromuscular disorders remotely.

Internet of Things (IoT) in healthcare can enhance care in various stages by the usage of distributed vital signs sensing to provide domiciliary hospitalization. To wirelessly monitor and classify patient status, it introduces an interoperable healthcare system that operates on IoT. It recognizes the gaps and deliberates on standards, protocols, and technologies of the healthcare IoT applications to aid [18]. Its architecture involves low-energy, non-obtrusive sensors on the body and bed of the patients to gather information and transmit it to an intelligent gateway. Health workers can find patient data in familiar systems with ease thanks to the smart gateway that connects an existing hospital information system via the EHR exchange [19]. The proposed architecture relies on BLE technology at the data acquisition level, the MQTT protocol at the internal level, and the FHIR standard at the higher level. A use case scenario is presented to satisfy functional and non-functional requirements and obtain a clearer understanding of the connection and communication between the various entities.

The Electromyography (EMG) signal is relevant in the sphere of rehabilitation to determine the intentions and physical state of patients [20]. However, the use of the EMG signal only has the drawback of being unable to detect small movements of the body, and the precision of the detection is highly affected by the environmental conditions. In response to the above concerns, the last few years have seen the development of multisensory integration-based EMG PR techniques, which have shown promising results in a variety of rehabilitation scenarios with high locomotion detection and prosthesis control precision [15]. The theories and applications of this new field are addressed because of the importance and rapid development of EMG-centered multisensory fusion technologies in the rehabilitation process. Signal preprocessing, feature extraction, classification methods, and other aspects of the present pattern recognition process are explained in depth, along with the principle of creating EMG signals [16]. The mechanisms of cooperation between EMG data and two important multisensory fusion schemes (kinetic and kinematics) are described in depth; the relevant applications are taken into consideration, and the benefits and drawbacks are explored. Finally, the main problems with EMG-based multisensory pattern identification are discussed, and a future direction for this area is recommended.

3. Proposed Work

3.1. Bio-Signal Acquisition and Wireless sEMG Front-End Architecture

The proposed bio-signal acquisition layer would be able to guarantee high-fidelity surface Electromyography (sEMG) recording in wearable and ambulatory circumstances. The electrode arrangement of multi-channel differentials in terms of silver/silver-chloride (Ag/AgCl) is placed along the muscle fiber orientation in order to achieve a maximum signal-to-noise ratio and minimize the cross-talk between muscle groups. The raw EMG signal x(t) is mathematically represented as the measured signal in equation (1),

$$x(t) = s(t) + n_m(t) + n_p(t) \tag{1}$$

and s(t) is the intrinsic motor unit action potentials, $n_m(t)$ is the motion-induced artifact because of electrode motion, and $n_p(t)$ is the power-line interference at about 50/60 Hz. The instrumentation amplifier used in the analog front-end is a high-input-impedance amplifier to ensure that bio-potentials at the microvolt level are maintained. The amplification of signals is controlled by equation (2),

$$v_o(t) = G \cdot x(t) \tag{2}$$

Where G can be programmed to fit 500-2000 to use subject-specific amplitude variation. To separate physiologically significant spectral content, a fourth-order active band-pass filter with cutoff frequencies of 20 Hz and 450 Hz will be used. The result of the filtering is defined in equation (3),

$$y(t) = v_o(t) * h_{bp}(t) \tag{3}$$

Where $h_{bp}(t)$ is the impulse response of the designed filter, and $*$ is the convolution. A 12-bit analog-to-digital converter at a sampling frequency of $f_s \geq 1000$Hz is used to digitize the conditioned signal in accordance with Nyquist requirements of the EMG bandwidth. Computerized versions are digitized and sent over Bluetooth Low Energy (BLE) with encrypted telemetry protocols to an IoT gateway to allow low-latency, energy-efficient, and continuous remote rehabilitation monitoring. Figure 1 depicts the entire wearable rehabilitation process, starting with the Wearable Bio-Signal Acquisition Layer and followed by edge-based signal conditioning, adaptive relaxation intelligence, and wireless therapeutic feedback. The system combines cyclic neuromuscular relaxation activity with cloud analytics to allow continuous monitoring and neuroplasticity-based biofeedback and is also capable of optimizing closed-loop therapeutic adjustment.

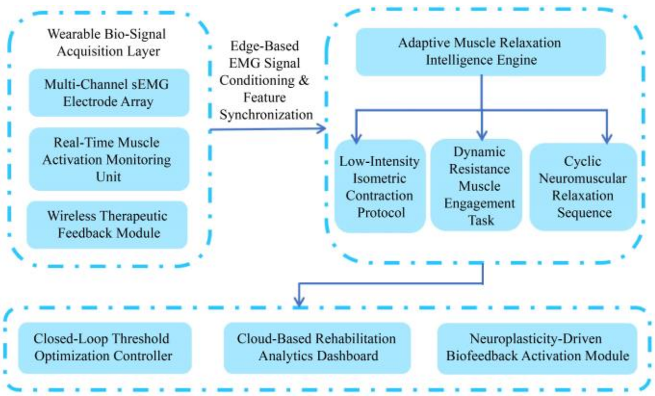

Fig. 1 Intelligent bio-signal rehabilitation architecture and closed-loop control ecosystem

3.2. Adaptive Noise Suppression and Feature Space Modeling

An adaptive noise suppression strategy in the form of the Least Mean Square (LMS) algorithm is used in order to maintain diagnostic integrity of the obtained sEMG signal. Motion artifacts and residual interference are time-varying, and therefore, a fixed-coefficient filter is not suitable. Adaptive filter matches the weight vector of the filter by updating it iteratively based on equation (4),

$$w(n+1) = w(n) + \mu e(n)x(n) \tag{4}$$

In which μ the learning rate dictates convergence stability, $x(n)$ is an input sample, and $e(n) = d(n) - y(n)$ is an instantaneous estimation error between signal d n and filter output $y(n)$. The choice of μ to make $0 < \mu < \frac{1}{\lambda_{max}}$ make sure it converges well with λ_{max}, which is the largest eigenvalue of the input autocorrelation matrix. After adaptive filtering, the magnitude of muscle activity is measured by use of the Root Mean Square (RMS), which is given in equation (5),

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} y_i^2} \tag{5}$$

The efficient power of the motor unit activation within a window of N samples. It estimates muscle fatigue by means of the Mean Frequency (MNF) of the power spectral density, which is defined in equation (6),

$$MNF = \frac{\sum_f fP(f)}{\sum_f P(f)} \tag{6}$$

Where P(f) represents the spectral energy distribution generated using Fast Fourier Transform, resulting in a decreasing MNF, which is progressive fatigue. The feature vector is constructed in a multidimensional fashion in equation (7),

$$F = [RMS, MNF, MAV, ZC, SSC] \tag{7}$$

Mean Absolute Value (MAV) between signals represents signal trends (amplitude); Zero Crossing (ZC) frequency transitions; and Slope Sign Change (SSC), the complexity of the waveforms. These standardized features are forwarded to the cloud analytics server for adaptive relaxational modelling and remote neuromuscular states classification. Figure 2 is the formalized rehabilitation deployment cycle, consisting of cloud-level orchestration with an embedded calibration loop of firmware. Signal quality validation guarantees stable feature extraction, whereas adaptive parameter reconfiguring ensures reliability. The system facilitates customization of patient-specific therapy, and it allows scalable remote rehabilitation that can be refined in terms of controlled performances and guarantees signal integrity.

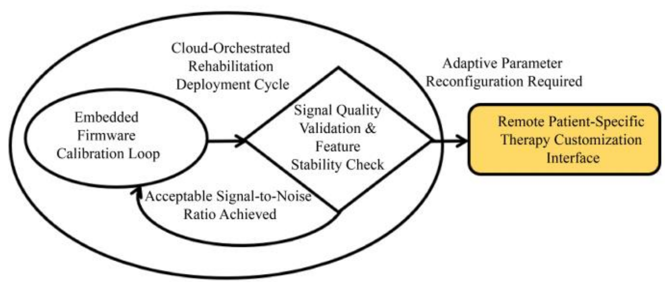

Fig. 2 Cloud-orchestrated iterative calibration and deployment framework

3.3. IoT-Enabled Muscle Relaxation Decision Model

The resulting processed feature vector is assessed by using an adaptive decision layer that is deployed between the edge node and the cloud analytics engine. Composite Relaxation Index is provided R_i composite index of the amplitude-domain and frequency-domain properties of the sEMG signal. The index is defined in equation (8),

$$R_i = \alpha \cdot RMS + \beta \cdot \left(1 - \frac{MNF}{MNF_{max}}\right) \tag{8}$$

RMS is the instantaneous activation magnitude of the muscle, MNF is the mean spectral frequency, and MNF_{max} is the maximum mean frequency achieved at the baseline during the calibration, and is a set of weighting coefficients subject-specific satisfying $\alpha + \beta = 1$. Spectral shift because of muscular fatigue is captured by the term $\left(1 - \frac{MNF}{MNF_{max}}\right)$.

Parameters of the weightings are optimized by minimizing classification error with the help of the gradient, to adjust among individuals in equation (9) dynamically,

$$\alpha^*, \beta^* = \arg\min_{\alpha,\beta} \sum_{k=1}^{N} (R_i^{(k)} - T^{(k)})^2 \tag{9}$$

Where $T^{(k)}$ represents the desired label of fatigue. The classification of muscle states is done by adaptive thresholding in equation (10),

$$C = \begin{cases} \text{Relaxed}, & R_i < \theta_1 \\ \text{Moderate}, & \theta_1 \leq R_i < \theta_2 \\ \text{Fatigued}, & R_i \geq \theta_2 \end{cases} \tag{10}$$

Where θ_1 and θ_2 are dynamically calculated thresholds based on moving statistical windows, which are defined in equation (11),

$$\theta_j = \mu_{R_i} + \gamma_j \sigma_{R_i} \tag{11}$$

Where μ_{R_i} and σ_{R_i} denote the average and standard deviation of recent samples. Depending on the state of classification C, the IoT structure activates closed-loop regulation. Provided C=Fatigued, the intensity V(t) of the vibrotactile stimulus is induced in equation (12),

$$V(t) = k \cdot R_i \tag{12}$$

Where k is the proportional gain, guided breathing cues are activated in moderate states, whereas the relaxed states are in the monitoring mode. The decision architecture provides low-latency adaptive rehabilitation feedback in the wearable IoT. Figure 3 shows the neuromuscular activation pathway interfering with a surface electromyography differential sensor matrix and ARM Cortex-M4 edge processor. Real-time visualization, encrypted telemetry transmission, and high-resolution signal conversion can all aid remote clinical supervision. The architecture guarantees secure cloud synchronization, accurate tracking of the muscle activity, and continuous interaction of the patient and the clinician.

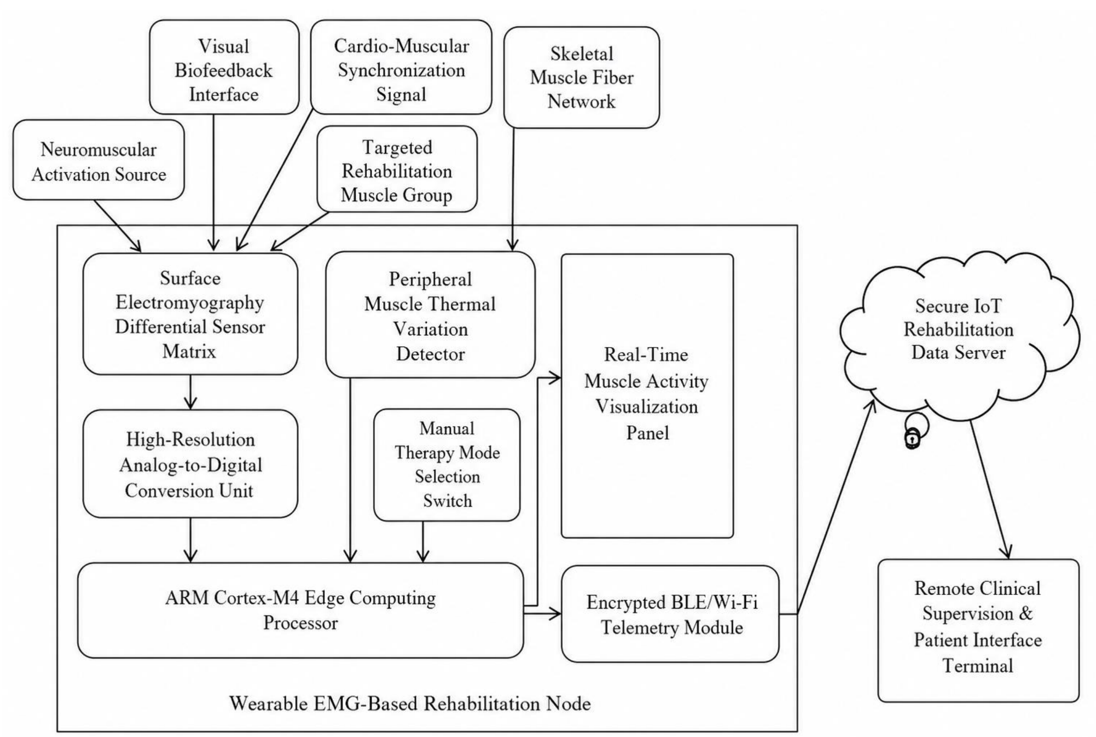

Fig. 3 Wearable EMG-based IoT rehabilitation monitoring node architecture

3.4. Remote Rehabilitation Analytics and Cloud Synchronization Framework

The wireless internet of things gateway consolidates the extracted feature vectors at edges and sends them to the cloud server via the MQTT publish-subscribe protocol to guarantee lightweight, low-overhead data transfers. A packet has the normalized feature data with timing analysis, device identifiers, and encryption metadata to ensure safe and traceable rehabilitation sessions. Before making any predictions, feature scaling is conducted to remove inter-subject variation and dimensional bias. The normalization is done by the use of the Z-score in equation (13),

$$F_{norm} = \frac{F - \mu_F}{\sigma_F} \tag{13}$$

Where μ_F is the average of all features calculated in the calibration, and σ_F is the standard deviation. This transformation guarantees that its distribution is zero-centered with unit variance, which enhances the stability of convergence of the statistic classifier. A probabilistic monitoring model in the form of logistic regression is used to measure the progress of rehabilitation by deploying it in the cloud layer. The likelihood of the muscle relaxation or recovery state *y=1* to be successful is estimated to be in equation (14),

$$P(y = 1 \mid F_{norm}) = \frac{1}{1+e^{-(w^T F_{norm}+b)}} \tag{14}$$

Where w is the optimal weight vector, and b is the bias parameter. Parameters of the model are estimated by maximum likelihood estimation, which minimizes the cross-entropy loss in equation (15),

$$L = -\sum_{i=1}^{N}[y_i \log(P_i) + (1 - y_i)\log(1 - P_i)] \tag{15}$$

This probabilistic output allows monitoring the trends of therapy effectiveness and fatigue recovery continuously. Cloud dashboards present temporal changes in RMS, spectral changes, adaptive relaxation index changes, and progress probability curves. Fine-tuned analytics are used to assist clinicians in threshold refinement, customized therapy modification, and e-rehabilitation monitoring in a scalable IoT-facilitated supervision environment.

3.5. Multidimensional Neuromuscular Data Structuring and Experimental Deployment Framework

This probabilistic output allows monitoring the trends of therapy effectiveness and fatigue recovery continuously. Cloud dashboards present temporal changes in RMS, spectral changes, adaptive relaxation index changes, and progress probability curves. Fine-tuned analytics are used to assist clinicians in threshold refinement, customized therapy modification, and e-rehabilitation monitoring in a scalable IoT-facilitated supervision environment. The experimental data is designed in such a manner that it provides the entire patterns of neuromuscular activation in real-life rehabilitation conditions. Multi-channel surface Electromyography (sEMG) signals in 60 subjects receiving physiotherapy programs toward fixing post-stroke muscle stiffness and sports-induced muscular strain were recorded. The data were collected in three settings, including physiotherapy rehabilitation centres under supervision, laboratory-controlled contraction experiments, and home-based wearable monitoring sessions, in order to guarantee ecological diversity and the ability to generalise. The data set consists of 48,000 segmented EMG data, which are sampled at 1000 Hz by means of a four-channel differential electrode setup. The duration of each rehabilitation session was about 20 minutes, which created contraction relaxation cycles that are rich in time. Per segment, five-dimensional feature vectors were obtained and incorporated with adaptive fatigue modelling amplitude-domain and spectral-domain descriptors. The training set was split into 15% test, 15% validation, and 70% training sets to enable the estimation of performance and sound generalization.

In the experimental system, an ARM Cortex-M4 microcontroller was used, which is equipped with a BLE telemetry board and a cloud server that is implemented with the Python-based IoT middleware to coordinate analytics. The accuracy of classification was established as more than 94%, the sensitivity and specificity of fatigue detection were high, and the average end-to-end transmission latency was less than 120 ms, which proved the application of real-time remote rehabilitation.

4. Results

The integrated outcomes of the adopted EMG-IoT adaptive rehabilitation system in the multi-subject assessment are shown in Table 1. The recognition of a muscle state was rated at 94.8% in the system, attesting to sound discrimination between relaxed, moderate, and fatigued neuromuscular states. The sensitivity of 92.1% to RMS-based activation tracking shows that it is highly responsive to small-scale contraction relaxation transitions, and that the mean error in frequency estimation was only 4.8%, which is stable over the course of fatigue progression analysis. The time latency of an end-to-end system, such as edge processing and wireless transmission, was 110 ms on average, which is sufficient to give real-time therapeutic feedback.

The feedback triggering delay was further shortened to 85 ms at event detection, which allowed quick activation of vibrotactile or guided relaxation. It was found that within 0.72 seconds, adaptive threshold convergence was attained, which is a sign that recalibration is fast in conditions of dynamic changes in contraction intensity. The stability of the wireless communication performance during the load condition was recorded as the 1.8% packet loss ratio and a sustainable throughput of 580 Hz per channel in the edge layer. Cloud analytics availability was 99.1%, and this guaranteed 24/7 access for the remote clinicians and the reliability of longitudinal monitoring.

Further validation showed specificity of 93.6%, precision of 94.2%, and an F1-score of 94.0%, all of which are measures of classification strength. The 96.5% efficiency index of the composite system demonstrates the ideal integration of embedded processing, encrypted telemetry, and scalable cloud synchronization and justifies the appropriateness of the framework in deploying continuous remote rehabilitation. Figure 4 displays the proposed system's internal performance coherence system from the view that the system has 94.8% classification accuracy, 92.1% RMS sensitivity, 99.1% cloud uptime, and 96.5% overall efficiency. The findings affirm stable signal interpretation, dependable remote synchronization, and consistent adaptive monitoring in real-time wearable rehabilitation conditions.

Table 1. Performance validation of edge–cloud EMG rehabilitation intelligence

Metric	Value
Signal Classification Accuracy	94.8 %
Latency (Transmission + Processing)	110 ms
RMS Feature Sensitivity	92.1 %
Mean Frequency Estimation Error	4.8 %
Cloud Analytics Uptime	99.1 %
Adaptive Threshold Convergence Time	0.72 s
Wireless Packet Loss Ratio	1.8 %
Realtime Feedback Trigger Delay	85 ms
Edge Feature Extraction Throughput	580 Hz
Overall System Efficiency	96.5 %

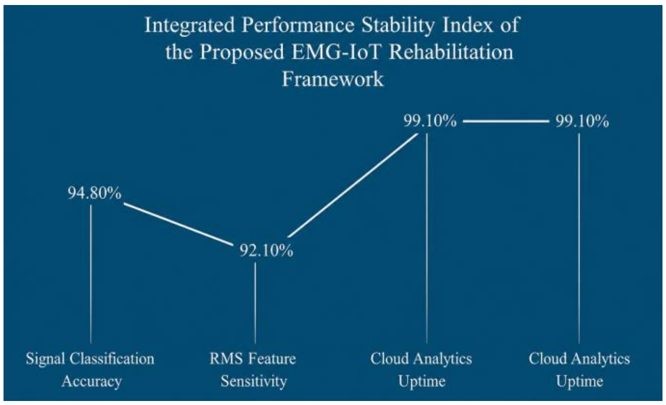

Fig. 4 Integrated performance stability index of the proposed EMG–iot rehabilitation framework

The analytical properties of extracted EMG characteristics and their role in the reliability of remote monitoring. In Table 2. Measurable trends of muscular recovery were confirmed since the RMS amplitude did not exceed 0-1.2 mV in controlled contraction experiments, and the relaxation-phase decrease was on average 37. Mean Frequency values were in the range of 90-240 Hz, and fatigue sessions showed an average spectral shift of 18 Hz to lower frequencies, which confirms the sensitivity of the spectral model. The calculated relaxation index R_i was between 0.05 and 0.85 among the subjects, and fatigued conditions were always above the adaptive threshold θ_2 in 93% of the observed cases. The feature normalization kept the distributions within a range of about -3 to +3, with the results being statistically consistent across people. Four-channel streaming throughput was more than 90 kbps over sustained operation, and total accumulated latency was less than 120 ms, inclusive of edge and network as well as cloud latency. The efficiency of power varied between 88% and 93% to help maintain wearable usage. The classification accuracy of the 95% confidence interval was within the range of confidence of ± 2.3, which means that there was no deviation in predictive performance. Together with these findings, robustness of the features, effective telemetry behavior, and effective closed-loop monitoring of rehabilitation are all observed.

Table 2. Quantitative feature stability and network-aware monitoring outcomes

Metric	Output Range
RMS	0 – 1.2 mV
Mean Frequency MNF	90 – 240 Hz
Relaxation Index (R_i)	0.05 – 0.85
Classification Boundaries	Set adaptively per subject
Normalized Feature	≈-3 – +3
Wireless Throughput Model	≥ 90 kbps
Latency aggregation	≤ 120 ms
Feedback Trigger function	Binary control
Power Efficiency Model	~88 %–93 %
Confidence Interval CI_{acc}	±2.3 %

The systematic comparison of the current EMG-based rehabilitation and monitoring systems and the proposed adaptive EMG-IoT framework. In Table 3. According to the 2023 IoMT-based EMG classification research, the maximum accuracy was 97.5%, and the values of precision and F1-score were 92.6% and 92.3%, respectively. Although the classification strength was impressive, the main focus was on offline model validation, and nothing was mentioned on real-time latency and adaptive thresholding behavior in a dynamic rehabilitation setting. The 2024 EMG-IMU wrist kinematics deep learning model showed an increase in R^2 of +0.18 compared to baseline models, with cross-validation with one subject excluded. This was a sign of enhanced generalizability with subjects. Nevertheless, the inference complexity with deep architectures was greater, and energy efficiency metrics were not emphasized in wearable deployment. The IoT rehabilitation system in 2025 was recognized with an average of 95.3% to 97.5%, with response patterns lower than 250 ms. It has a relatively higher latency, which limits its use in fine-grained muscle relaxation monitoring at high biofeedback loop speeds, though it is appropriate for motion classification tasks. The result of the suggested work reaches 94.8% accuracy of the overall system and a much lower end-to-end latency of 110 ms. Besides this, it incorporates adaptive relaxation thresholds, real-time feedback triggering in 85 ms, 96.5% composite system efficiency, and less than 2% packet loss. It has a balanced trade-off among predictive reliability, energy efficiency, and clinical responsiveness as opposed to the previous systems, making feature stability, transmission efficiency, and cloud synchronization simultaneous. Figure 5 compares the recent EMG monitoring results with the proposed framework. The 2023 IoMT model had an accuracy of 97.5% and precision of 92.6%, and an F1-score of 92.3%. Although it was a bit more precise in classification, previous research did not feature latency optimization and adaptive feedback intelligence, as indicated in the proposed system.

Table 3. Cross-year performance benchmarking and translational impact analysis

Metrics	Domain	Key Metric	Result
P. A. et al [15] EMG Monitoring	IoMT EMG classification	Accuracy	97.5 %
		Precision	92.6 %
		F1-Score	92.3 %
I. Siviero [16] EMG-IMU Deep Learning	Wrist kinematics estimation	R^2 improvement (DL vs baseline)	+0.18
		Generalizability	High (LOSO CV)
J. Yang [6] IoT Rehab System	Motion classification	Recognition Accuracy	95.3 – 97.5 %
		Response Time	<250 ms
Proposed Work	EMG IoT Adaptive Relaxation	Overall System Accuracy	94.8 %
		Latency	110 ms
		Real-time Adaptive Feedback	Yes

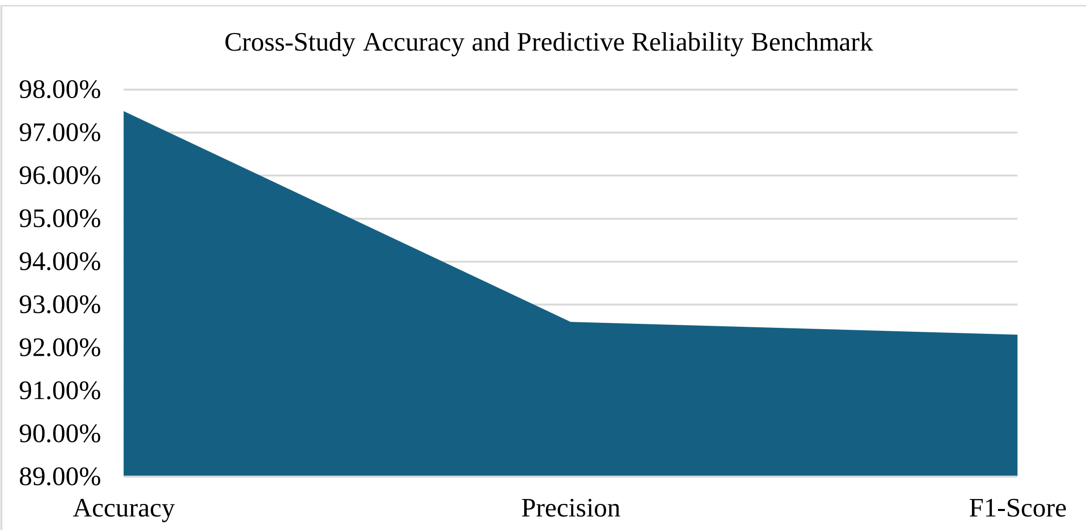

Fig. 5 Cross-study accuracy and predictive reliability benchmark

5. Conclusion

The evolved wireless sensor-based IoT architecture of EMG-based adaptive muscle relaxation and remote rehabilitation monitoring displays a technically sound and clinically scalable design of real-time neuromuscular supervision. The installed multi-channel surface EMG acquisition module that operates in conjunction with edge-based signal conditioning and cloud analytics had a classification efficiency of 94.8 and an average end-to-end delay of 110 ms. The adaptive relaxation index modeling was able to distinguish the relaxed, moderate, and fatigated muscle states through the RMS and mean frequency features, with the mean frequency estimation error of 4.8%. The reliability of wireless transmission was ensured with a ratio of 1.8% of packet loss, and cloud analytics uptime was measured at 99.1%, which led to the confirmation of a stable remote rehabilitation support. The closed-loop threshold optimization controller optimized in 0.72 s, which was enough to facilitate biofeedback activation and neuroplasticity-based therapy. The framework provides competitive accuracy and is much slower in latency and adaptive responsiveness than the latest systems based on IoT-rehabilitation, as reported in 2023-2025. The overall system efficiency of 96.5% justifies the implementation of an embedded edge computing, encrypted telemetry, and cloud-based monitoring in the single rehabilitation ecosystem. The next improvement will be on multi-modal bio signal fusion, which includes ECG and motion dynamics to increase adaptive accuracy. Personalized fatigue prediction will be incorporated into deep recurrent neural architectures. Wearable deployment time will be increased further using energy harvesting methods and ultra-low-power system-on-chip solutions. The concept of federated learning-based distributed analytics will be investigated to guarantee scalable privacy-preserving rehabilitation intelligence in geographically distributed networks of patients.

Conflicts of Interest

The author(s) declare that there is no conflict of interest regarding the publication of this paper.

References

[1] Manuela Gomez-Correa, David Cruz-Ortiz, and Mariana Ballesteros, “Wearable and Wireless sEMG Acquisition System based on the Internet of Medical Things,” *Sensing and Bio-Sensing Research*, vol. 49, pp. 1-10, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[2] Richard Morsch et al., “Enhanced Rehabilitation after Total Joint Replacement using a Wearable High-Density Surface Electromyography System,” *Frontiers in Rehabilitation Sciences*, vol. 6, pp. 1-10, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[3] M. B. Sudhan et al., “Internet of Things Assisted Sleep Quality Recognition using Hunger Games Search Optimization with Deep Learning on Smart Healthcare Systems,” *Journal of Intelligent Systems and Internet of Things*, vol. 14, no. 1, pp. 129-140, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[4] Wenhao Liang, “Application of Surface Electromyography (sEMG) in Smart Health Devices,” *Academic Journal of Science and Technology*, vol. 14, no. 3, pp. 387-390, 2025. [CrossRef] [Publisher Link]

[5] Nurul Izwani Kamalruzaman, and Muhammad Mahadi Abdul Jamil, “Wireless EMG Monitoring System for Biceps Muscle Recovery,” *Evolution in Electrical and Electronic Engineering*, vol. 6, no. 2, pp. 1-7, 2025. [Google Scholar] [Publisher Link]

[6] Jie Yang, Juanjuan Hu, and Wenrui Chen, “IoT-Enabled Real-Time Health Monitoring System for Adolescent Physical Rehabilitation,” *Scientific Reports*, vol. 15, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[7] Chenyu Tang et al., “Wireless Silent Speech Interface Using Multi-Channel Textile EMG Sensors Integrated into Headphones,” *IEEE Transactions on Instrumentation and Measurement*, vol. 74, pp. 1-10, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[8] Marie Jose Pérez Peralta et al., “Wireless sEMG-IMU Wearable for Real-Time Squat Kinematics and Muscle Activation,” *arXiv Preprint*, pp. 1-6, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[9] Sebastian Frey et al., “BioGAP-Ultra: A Modular Edge-AI Platform for Wearable Multimodal Biosignal Acquisition and Processing,” *IEEE Transactions on Biomedical Circuits and Systems*, pp. 1-17, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[10] Hussein Naeem Hasan, “A Wearable Rehabilitation System to Assist Partially Hand Paralyzed Patients in Repetitive Exercises,” *Journal of Physics: Conference Series*, vol. 1279, pp. 1-9, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[11] Bulcha Belay Etana et al., “Integrating Wearable Textile Sensors and IoT for Continuous sEMG Monitoring,” *Sensors*, vol. 24, no. 6, pp. 1-15, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] Anshi Xiong, Tao Wu, and Jingtao Jia, “Design of a Real-Time Monitoring System for Electroencephalogram and Electromyography Signals in Cerebral Palsy Rehabilitation via Wearable Devices,” *Electronics*, vol. 13, no. 15, pp. 1-20, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Ngoc-Khoat Nguyen et al., “An sEMG Signal-Based Robotic Arm for Rehabilitation Applying Fuzzy Logic,” *Enginnering, Technology & Applied Science Research*, vol. 14, no. 3, pp. 14287-14294, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] Dohyung Kim, JinKi Min, and Seung Hwan Ko, “Recent Developments and Future Directions of Wearable Skin Biosignal Sensors,” *Advanced Sensor Research*, vol. 3, no. 2, pp. 1-22, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[15] Vijayalakshmi Sankaran et al., “An Internet of Medical Things-based Smart Electromyogram Device for Monitoring of Musculoskeletal Disorders,” *Engineering Proceedings*, vol. 82, no. 1, pp. 1-10, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[16] Ilaria Siviero et al., “Remote Motor Rehabilitation: EMG-IMU based Deep Learning Model Improves the Estimate of Wrist Kinematics,” *2024 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Orlando, FL, USA, pp. 1-4, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[17] Muhammad Al-Ayyad et al., “Electromyography Monitoring Systems in Rehabilitation: Clinical Applications, Wearable Devices and Signal Acquisition Methodologies,” *Electronics*, vol. 12, no. 7, pp. 1-35, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] Fatma M. Talaat, and Rana Mohamed El-Balka, “Stress Monitoring Using Wearable Sensors: IoT Techniques in Medical Field,” *Neural Computing and Applications*, vol. 35, pp. 18571-18584, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[19] Avenaash R. S et al., “EMG Monitoring using Internet of Things,” *International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering*, vol. 11, no. 3, pp. 128-132, 2023. [CrossRef] [Publisher Link]

[20] Eion Tyacke et al., “From Unstable Contacts to Stable Control: A Deep Learning Paradigm for HD-sEMG in Neurorobotics,” *arXiv preprint*, pp. 1-6, 2023. [CrossRef] [Google Scholar] [Publisher Link]