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(Research Article)

A smart neuromuscular stimulator for autonomous upper-limb rehabilitation

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Abstract

Neuromuscular Electrical Stimulation (NMES) is widely applied in rehabilitation therapy to restore muscle function and prevent atrophy. However, conventional NMES systems typically operate in open-loop configurations with fixed stimulation parameters, often leading to rapid muscle fatigue and reduced therapeutic efficiency. This study presents the design and prototype-level validation of a fatigue-aware closed-loop NMES system integrating an MPU6050 inertial measurement unit (IMU) and embedded machine learning for adaptive stimulation control.

The proposed system utilizes real-time tri-axial acceleration data to monitor contraction dynamics during electrically induced muscle activation. Time-domain features extracted from IMU signals were processed using a Random Forest regression model deployed on an ESP32 microcontroller to estimate fatigue progression. Based on predicted fatigue levels, the system dynamically adjusted pulse width through a closed-loop control algorithm to maintain contraction stability.

Experimental validation demonstrated that IMU-derived kinematic signals exhibited progressive amplitude reduction and increased variability during sustained stimulation, consistent with fatigue development. The embedded machine learning model achieved stable real-time inference performance, enabling adaptive pulse-width modulation without computational instability. Compared to open-loop operation, the closed-loop configuration maintained contraction amplitude within a narrower functional range and reduced rapid degradation during prolonged stimulation.

The results confirm the feasibility of using motion-based sensing as a non-invasive alternative to electromyography for fatigue-aware NMES control at prototype level. The integration of low-cost IMU sensing and embedded machine learning demonstrates the potential for intelligent, portable, and adaptive rehabilitation devices.

Keywords: Neuromuscular Electrical Stimulation; IMU; MPU6050; Muscle Fatigue Detection; Embedded Machine Learning; Closed-Loop Control; ESP32

1. Introduction

Stroke continues to represent a leading cause of long-term neurological disability, with a substantial proportion of survivors experiencing persistent motor impairments that limit independence and functional reintegration into society [1]. Among these impairments, upper-limb dysfunction is particularly prevalent and debilitating, frequently affecting coordinated reaching, grasping, and object manipulation tasks essential for activities of daily living. The pathophysiological basis of these deficits is rooted in disruption of corticospinal pathways and altered muscle synergy organization, resulting in impaired voluntary activation and abnormal movement patterns [1]. Consequently, modern

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neurorehabilitation strategies emphasize repetitive, task-specific interventions capable of stimulating neuroplastic reorganization within surviving neural networks.

Neuromuscular Electrical Stimulation (NMES) has emerged as a cornerstone modality in this context. By delivering externally generated electrical pulses through surface electrodes, NMES induces controlled muscle contractions that mimic voluntary motor unit recruitment and generate afferent sensory feedback to the central nervous system [2]. This afferent input plays a critical role in reinforcing sensorimotor pathways and promoting cortical reorganization, thereby facilitating motor recovery [1], [2]. Clinically, NMES has demonstrated efficacy in enhancing muscle strength, improving range of motion, reducing joint stiffness, and mitigating disuse atrophy in post-stroke and post-surgical populations [3]. Meta-analytic and randomized controlled trial evidence further supports the integration of electrical stimulation with conventional rehabilitation for improving motor function and movement quality [3].

Despite its documented therapeutic value, conventional NMES technology remains constrained by fundamental architectural limitations. Most commercially available systems operate in an open-loop configuration, delivering fixed stimulation parameters such as preset frequency, pulse width, and amplitude, without accounting for dynamic physiological changes during therapy [4]. This static operational paradigm neglects the inherently variable nature of neuromuscular response and fails to accommodate inter-individual differences in fatigue resistance, tissue impedance, and motor recruitment characteristics. As a result, stimulation intensity often remains constant even as muscle performance deteriorates.

Muscle fatigue constitutes a primary operational challenge in NMES-based rehabilitation. Unlike voluntary contractions, electrically evoked contractions do not strictly adhere to the physiological size principle of motor unit recruitment, frequently leading to rapid activation of fast-fatigable motor units [5]. This non-physiological recruitment accelerates metabolic demand and contributes to early decline in contraction quality. Empirical investigations have demonstrated that fatigue significantly degrades signal stability and motor output consistency in assistive stimulation systems, thereby reducing therapeutic endurance and functional effectiveness [4]. In practical terms, premature fatigue shortens session duration and limits the intensity of repetitive training required to drive meaningful neuroplastic adaptation.

To overcome these limitations, recent research has explored intelligent closed-loop architectures capable of adapting stimulation parameters in real time [4]. Many such systems have relied on electromyography (EMG) as a biofeedback modality for detecting fatigue and modulating stimulation accordingly. Machine learning classifiers have been successfully applied to EMG spectral features to achieve high fatigue-detection accuracy within laboratory environments [4]. However, EMG-driven systems introduce several implementation challenges, including susceptibility to electrical noise, sensitivity to electrode placement, signal instability during prolonged stimulation, and increased hardware complexity. These limitations complicate integration into compact, low-cost, embedded platforms suitable for unsupervised home-based rehabilitation.

An alternative strategy involves the use of motion-based biofeedback derived from inertial sensing. Rather than measuring myoelectric activity directly, kinematic analysis evaluates the observable mechanical output of muscle contractions. Fatigue manifests not only as reduced force but also as measurable degradation in movement smoothness, increased tremor amplitude, altered acceleration profiles, and diminished angular stability. These biomechanical signatures can be captured using a microelectromechanical Inertial Measurement Unit (IMU), such as the MPU6050, which integrates tri-axial accelerometer and gyroscope sensors within a compact package [6].

The MPU6050 enables continuous acquisition of linear acceleration and angular velocity data across three orthogonal axes. When positioned on the upper limb during electrically evoked contractions, the sensor provides real-time characterization of movement dynamics. Subtle oscillatory patterns and high-frequency tremor components emerging during sustained contraction serve as indirect but functionally meaningful indicators of neuromuscular fatigue. From an engineering standpoint, IMU-based feedback offers several advantages: reduced sensitivity to electrical interference, simplified signal conditioning requirements, lower system cost, and improved robustness for portable embedded implementation compared to EMG-centered designs [6].

Embedding such kinematic feedback within a closed-loop NMES architecture permits the development of adaptive stimulation systems capable of autonomously responding to movement degradation. Machine learning algorithms deployed on embedded microcontrollers can extract relevant motion features and predict fatigue progression in real time. Adaptive modulation of stimulation intensity implemented via pulse-width modulation (PWM) control can then maintain muscle activation within an optimal therapeutic window. This approach directly addresses the fatigue-induced performance decline identified in prior EMG-based systems [4], while simultaneously leveraging the established physiological principles governing stimulation frequency and recruitment behavior [5].

Stimulation parameter selection remains critical to therapeutic effectiveness. Frequency-dependent neuromuscular adaptations have been empirically demonstrated, with higher frequencies producing immediate strength gains and lower frequencies influencing muscle quality and composition over time [5]. Therefore, an intelligent system must not only detect fatigue but also dynamically adjust intensity within physiologically appropriate frequency ranges to sustain contraction quality without exacerbating metabolic exhaustion.

In this work, a Smart Neuromuscular Stimulator (SNS) is designed and developed to operationalize this motion-driven adaptive paradigm. The system integrates an ESP32 microcontroller as the embedded processing core, an MPU6050 IMU for real-time kinematic data acquisition, and a Random Forest machine learning model for fatigue prediction. Unlike EMG-based adaptive systems previously reported in the literature [4], the proposed architecture relies exclusively on motion-derived features, thereby simplifying hardware design while preserving adaptive functionality. The embedded algorithm autonomously adjusts stimulation intensity in response to detected movement degradation, establishing a fully closed-loop, fatigue-aware control framework.

The scope of the present study is confined to prototype-level engineering validation conducted in a controlled laboratory environment. The investigation focuses on system design, embedded implementation, and predictive performance evaluation rather than large-scale clinical assessment. Preliminary validation demonstrates strong predictive capability of the machine learning model, with a coefficient of determination exceeding 0.90 for motion-based signal characterization, supporting the feasibility of kinematic feedback as a reliable surrogate marker for fatigue progression.

By synthesizing inertial sensing, embedded artificial intelligence, and adaptive stimulation control into a unified portable platform, this research contributes to the advancement of NMES technology from static stimulation devices toward intelligent, autonomous rehabilitation systems. The proposed IMU-driven approach addresses critical limitations identified in existing open-loop and EMG-dependent frameworks [2], [4], [6], offering a practical pathway toward cost-effective, fatigue-aware, and home-deployable upper-limb rehabilitation solutions.

2. Literature review

2.1. Overview of Neuromuscular Electrical Stimulation in Rehabilitation

Neuromuscular Electrical Stimulation (NMES) has been extensively investigated as a therapeutic intervention for restoring motor function following neurological and musculoskeletal impairments. The physiological foundation of NMES lies in its ability to evoke muscle contractions through externally applied electrical pulses that depolarize peripheral motor nerves. These artificially induced contractions generate afferent sensory feedback to supraspinal centers, thereby reinforcing sensorimotor integration and promoting neuroplastic reorganization [1], [2].

Clinical evidence consistently supports the integration of NMES with conventional rehabilitation strategies. A large-scale systematic review and network meta-analysis involving 2,309 post-stroke patients demonstrated that electrical stimulation combined with standard therapy significantly improved motor function and range of motion compared with conventional therapy alone [3]. Similarly, controlled clinical trials investigating home-based NMES interventions have reported improvements in muscle strength, joint mobility, and patient-reported functional outcomes [3]. These findings reinforce the therapeutic value of electrical stimulation as a complementary modality within structured neurorehabilitation programs.

Beyond post-stroke recovery, NMES has been applied to prevent muscle atrophy during immobilization, enhance strength development during resistance training, and mitigate functional decline in hospitalized populations. Meta-analytic evidence indicates that the adjunctive use of NMES during exercise can amplify muscle hypertrophy and strength gains relative to exercise alone [7]. Collectively, these studies establish NMES as a physiologically grounded and clinically validated intervention.

Despite these benefits, conventional NMES devices remain predominantly open-loop systems. They deliver predetermined stimulation parameters without real-time adaptation to physiological response, which limits personalization and contributes to early fatigue onset [4], [8].

2.2. Muscle Fatigue and Limitations of Conventional NMES

Muscle fatigue represents one of the most significant barriers to sustained NMES therapy. Electrically evoked contractions differ from voluntary contractions in their recruitment pattern. Whereas voluntary contractions typically follow Henneman’s size principle, activating small fatigue-resistant motor units before larger fast-fatigable units, electrical stimulation can bypass this orderly recruitment sequence, preferentially activating larger axons [5]. This non-physiological recruitment pattern accelerates metabolic demand and reduces contraction endurance.

Empirical investigations confirm that fatigue not only diminishes force output but also degrades signal stability in feedback-controlled systems. In EMG-driven assistive platforms, fatigue progression has been shown to alter spectral characteristics and reduce classification reliability, thereby impairing system performance [4]. Such degradation shortens therapy sessions and compromises the intensity of repetitive motor training required for effective neuroplastic adaptation.

Stimulation parameters, particularly frequency, directly influence fatigue progression. Comparative investigations have demonstrated that high-frequency NMES (e.g., 100 Hz) induces rapid strength gains but accelerates fatigue, whereas lower-frequency protocols (e.g., 50 Hz) produce delayed adaptations and reduced metabolic stress [5]. These findings highlight the necessity of dynamic parameter optimization during therapy.

The persistence of open-loop architectures in many commercial devices means that stimulation intensity remains fixed even as muscle performance deteriorates. This mismatch between delivered input and physiological response underscores the need for adaptive, closed-loop control systems.

2.3. Closed-Loop Control Architectures in NMES

Closed-loop NMES systems integrate physiological feedback to dynamically adjust stimulation parameters in real time. This paradigm shift transforms the device from a static pulse generator into an interactive therapeutic system capable of responding to muscle state.

Most early closed-loop implementations relied on surface electromyography (sEMG) as the primary feedback modality. EMG-based systems extract time- and frequency-domain features such as mean frequency (MNF) and mean power (MNP) to estimate fatigue progression and modulate stimulation intensity accordingly [4]. Machine learning techniques, including Support Vector Machines (SVM), have demonstrated fatigue-detection accuracies exceeding 90% under laboratory conditions [4].

While promising, EMG-centered architectures introduce technical challenges. Signal quality is highly sensitive to electrode placement, skin impedance, motion artifacts, and electrical interference from stimulation pulses. Furthermore, prolonged stimulation can distort EMG signals due to cross-talk and amplitude attenuation. These limitations complicate embedded implementation and reduce reliability in portable systems intended for unsupervised use.

From an engineering perspective, closed-loop NMES systems must balance computational efficiency, sensor robustness, and hardware simplicity. Embedding machine learning models onto microcontrollers requires lightweight algorithms capable of real-time inference with minimal memory footprint and energy consumption. These constraints motivate exploration of alternative feedback modalities.

2.4. Motion-Based Biofeedback and Inertial Sensing

An emerging alternative to EMG-based monitoring involves motion-derived biofeedback using inertial sensors. Rather than measuring muscle electrical activity, inertial measurement units (IMUs) capture the mechanical consequences of muscle contraction. Fatigue manifests biomechanically as reduced movement amplitude, increased oscillatory tremor, and altered acceleration variance.

The MPU6050 IMU integrates a tri-axial accelerometer and gyroscope within a compact microelectromechanical system (MEMS) architecture [6]. This sensor enables continuous acquisition of linear acceleration and angular velocity along three orthogonal axes. When affixed to the upper limb during stimulation, the IMU provides real-time characterization of kinematic behavior.

Motion-based fatigue inference offers several advantages. First, it eliminates susceptibility to electrical noise inherent in EMG recordings during active stimulation. Second, it simplifies signal conditioning requirements. Third, it enhances robustness in portable systems by reducing dependence on precise electrode placement. These characteristics make IMU-based feedback particularly suitable for embedded, battery-powered rehabilitation devices.

Although IMUs have been widely used in gait analysis and movement tracking applications, their integration into closed-loop NMES systems for fatigue-aware control remains relatively underexplored. Bridging this gap represents a meaningful contribution to adaptive rehabilitation technology.

2.5. Machine Learning in Adaptive Stimulation Systems

Artificial intelligence has increasingly been incorporated into rehabilitation engineering to enhance personalization and autonomy. Machine learning classifiers and regression models enable real-time interpretation of physiological signals and support predictive control strategies.

In EMG-based systems, SVM classifiers have successfully identified fatigue onset and triggered adaptive modulation, resulting in measurable reductions in fatigue progression and improved performance consistency [4]. Adaptive control frameworks similarly integrate robust control laws and learning algorithms and have demonstrated improved trajectory tracking in electrically stimulated limb movement [9].

Random Forest algorithms provide a computationally efficient ensemble learning approach suitable for embedded deployment. By aggregating multiple decision trees trained on randomized feature subsets, Random Forest models reduce overfitting while maintaining strong predictive performance. Their relatively low computational complexity compared to deep neural networks makes them appropriate for microcontroller-based systems with limited memory and processing resources.

Embedding such models within portable NMES platforms enables autonomous adjustment of stimulation intensity based on predicted muscle state. This capability aligns with broader trends in rehabilitation technology emphasizing intelligent, self-regulating therapeutic devices [7], [8].

2.6. Embedded System Considerations for Portable NMES

The practical deployment of adaptive NMES requires efficient hardware architecture. Microcontrollers such as the ESP32 provide dual-core processing capability, integrated analog-to-digital converters, PWM generators, and wireless communication interfaces within a compact system-on-chip platform [6]. These features facilitate real-time sensor acquisition, machine learning inference, and precise stimulation control.

Power management remains a critical consideration in portable therapeutic devices. Lithium-ion battery systems paired with Battery Management Systems (BMS) provide high energy density while ensuring safe operation through over-charge and over-discharge protection [6]. Efficient switching regulators further extend operational endurance by minimizing energy loss.

Prior hardware-focused NMES prototypes have demonstrated functional stimulation delivery but lacked adaptive intelligence [6], [8]. Conversely, AI-centric systems have often relied on laboratory-grade computing environments without clear pathways to portable implementation [9]. This fragmentation within the literature highlights the need for integrative designs combining embedded intelligence with low-cost hardware.

2.7. Identified Research Gap

The literature establishes three key observations. First, NMES is clinically effective for motor rehabilitation when appropriately integrated with conventional therapy [3], [7]. Second, muscle fatigue remains a critical operational limitation, particularly in open-loop systems [4], [5]. Third, while AI-driven adaptive frameworks show promise, existing implementations are predominantly EMG-dependent or laboratory-based [4], [9].

A translational gap therefore persists between theoretical adaptive control models and practical, portable rehabilitation devices suitable for home-based use. Moreover, motion-based biofeedback using IMU sensors has not been comprehensively leveraged as the primary feedback modality in fatigue-aware NMES systems.

The present study addresses this gap by developing an IMU-driven Smart Neuromuscular Stimulator that integrates embedded machine learning within a closed-loop architecture. By replacing EMG-based monitoring with kinematic fatigue inference, the system aims to enhance robustness, reduce hardware complexity, and maintain adaptive functionality within a compact portable design.

3. Methodology

3.1. System Overview

The proposed Smart Neuromuscular Stimulator (SNS) was developed as a prototype-level, closed-loop NMES system integrating inertial sensing and embedded machine learning for adaptive fatigue-aware stimulation. The system architecture comprises four primary subsystems:

- Stimulation generation module
- Motion sensing module (IMU-based)
- Embedded processing and control unit
- Power management subsystem

The operational workflow follows a closed-loop structure. Electrical stimulation is delivered to the target muscle group through surface electrodes. Simultaneously, motion data are acquired via an Inertial Measurement Unit (IMU). Extracted kinematic features are processed by an embedded Random Forest model to predict fatigue state. Based on the predicted output, stimulation intensity is automatically adjusted using pulse-width modulation (PWM) control.

The design emphasis was placed on portability, low-cost implementation, and computational efficiency suitable for real-time embedded deployment. The overall architecture of the proposed Smart Neuromuscular Stimulator (SNS) is illustrated in Fig. 1.

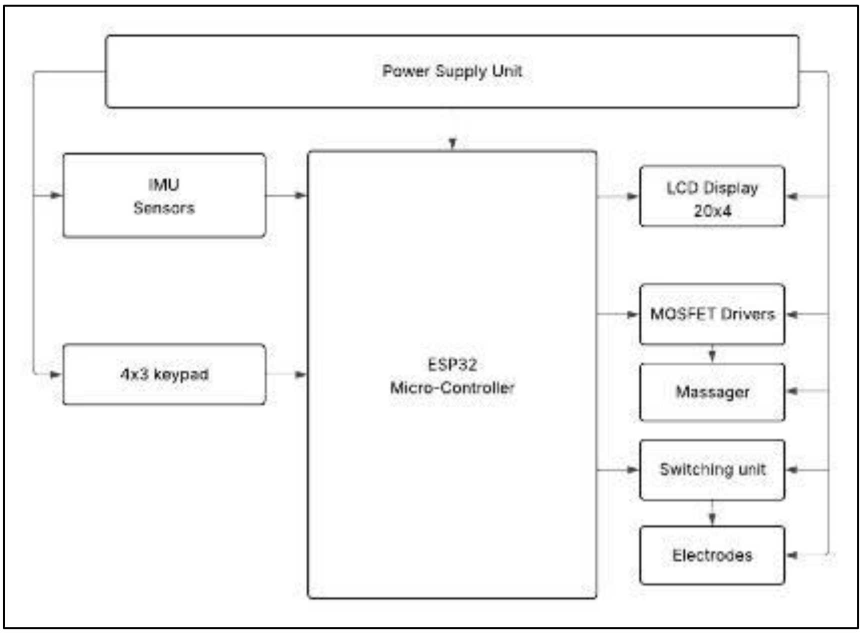

Figure 1 Block diagram of the proposed Smart Neuromuscular Stimulator (SNS)

3.2. Hardware Architecture

3.2.1. Embedded Processing Unit

An ESP32 microcontroller served as the central processing unit of the system. The ESP32 was selected due to its dual-core architecture, integrated analog-to-digital conversion (ADC), PWM capability, sufficient SRAM capacity, and low power consumption characteristics.

The microcontroller performed the following tasks:

- Acquisition of IMU data via I2C communication
- Real-time preprocessing of acceleration and angular velocity signals
- Execution of the trained Random Forest fatigue prediction model
- Adaptive adjustment of stimulation intensity

- Control of PWM-based stimulation output

The computational constraints of the ESP32 necessitated lightweight model implementation and efficient memory allocation.

3.2.2. Inertial Measurement Unit (IMU)

Motion sensing was performed using the MPU6050 IMU module. The MPU6050 integrates

- A 3-axis accelerometer
- A 3-axis gyroscope

The sensor provides linear acceleration (Ax, Ay, Az) and angular velocity (Gx, Gy, Gz) measurements at configurable sampling rates. For this prototype, a sampling frequency of 100 Hz was implemented to capture fine movement variations and tremor components associated with fatigue progression.

The IMU was positioned on the stimulated upper limb segment to capture contraction-induced motion. Secure attachment minimized motion artifacts unrelated to muscle contraction.

Unlike EMG-based systems, which require differential amplification and filtering circuits susceptible to electrical interference, the IMU provided stable kinematic signals during active stimulation. This simplified the signal conditioning stage and enhanced robustness.

3.2.3. Stimulation Module

The stimulation circuit was designed to generate biphasic electrical pulses delivered through surface electrodes placed over the target muscle group. Biphasic waveforms were selected to minimize net charge accumulation at the electrode skin interface and reduce tissue irritation.

Key stimulation parameters included:

- Frequency: Configurable within therapeutic ranges
- Pulse width: Dynamically modulated via PWM
- Amplitude: Controlled through driver circuitry

Adaptive control was implemented by modulating pulse width based on predicted fatigue level. When fatigue indicators increased, stimulation intensity was reduced incrementally to maintain contraction quality while preventing excessive metabolic stress. The complete hardware implementation of the system is presented in Fig. 2.

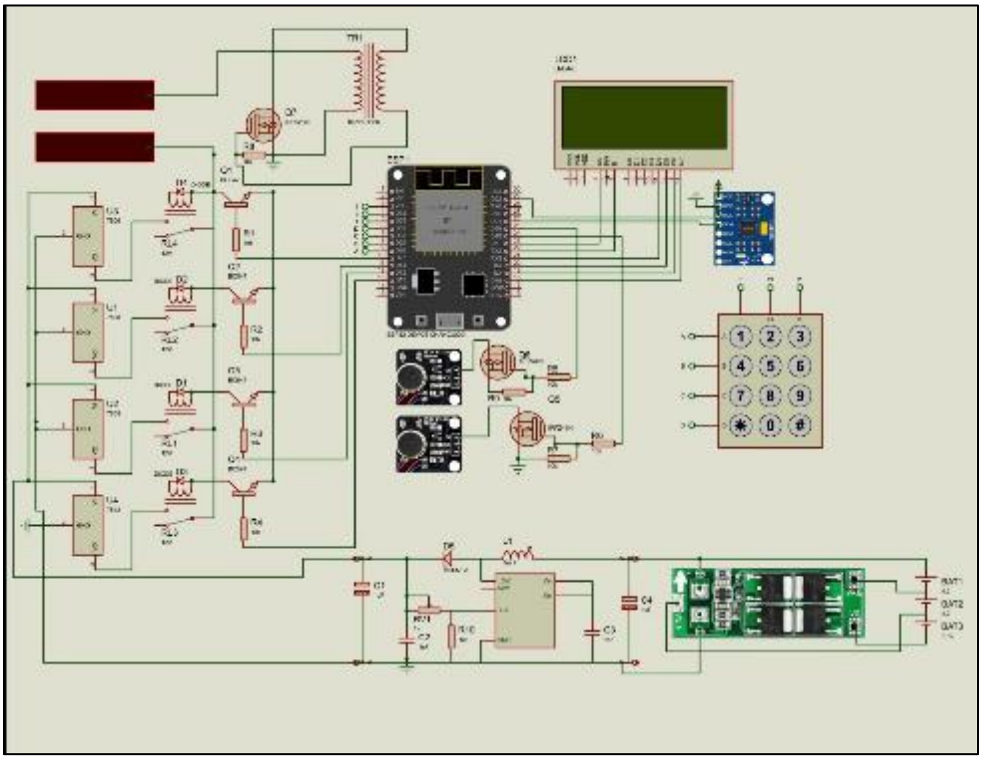

Figure 2 Complete circuit schematic of the Smart Neuromuscular Stimulator prototype

3.2.4. Power Management

The system was powered by a rechargeable lithium-ion battery. A Battery Management System (BMS) ensured:

- Over-charge protection
- Over-discharge protection
- Short-circuit protection

Voltage regulation circuitry stabilized output supply to the ESP32 and stimulation driver module. Portability and operational safety were primary design considerations.

3.3. Software Architecture

The embedded firmware was developed using the Arduino framework for ESP32. The software architecture consisted of modular layers:

- Sensor acquisition layer
- Signal preprocessing layer
- Feature extraction module
- Machine learning inference engine
- Adaptive control module
- Each module operated sequentially within a real-time loop structure.

3.4. Signal Processing and Feature Extraction

Raw accelerometer and gyroscope signals were first filtered to reduce high-frequency noise using a digital low-pass filter. Preprocessing aimed to preserve fatigue-related oscillatory characteristics while eliminating environmental interference.

The following time-domain features were extracted from sliding windows of IMU data:

- Mean acceleration magnitude
- Standard deviation

- Signal variance
- Root Mean Square (RMS)
- Peak-to-peak amplitude

Fatigue was inferred from progressive reduction in contraction amplitude and increased tremor-related variance. Window size was optimized to balance responsiveness and computational efficiency.

The feature vector was normalized prior to classification to ensure stable model inference.

3.5. Machine Learning Model Development

3.5.1. Model Selection

A Random Forest regression model was selected for fatigue prediction due to:

- High robustness to overfitting
- Computational efficiency
- Suitability for embedded implementation
- Ability to handle nonlinear relationships

Compared to deep neural networks, Random Forest models require fewer computational resources and are more compatible with microcontroller deployment.

3.5.2. Model Training

Training was conducted offline using collected IMU datasets representing progressive muscle activation and fatigue states during stimulation sessions.

Data labeling was based on observable motion degradation patterns, including reduced amplitude and increased oscillatory instability. The dataset was divided into training and validation subsets.

Model hyperparameters optimized included:

- Number of trees
- Maximum tree depth
- Minimum samples per leaf
- Cross-validation was used to evaluate generalization performance.

3.5.3. Model Deployment

The trained model was converted into an embedded-compatible format and integrated into the ESP32 firmware. Decision trees were translated into conditional logic structures to minimize memory overhead.

Real-time inference was achieved within the sampling window without perceptible latency.

3.6. Closed-Loop Adaptive Control Strategy

The adaptive control strategy was implemented as follows:

- Acquire IMU data
- Extract features
- Predict fatigue level
- Compare predicted value with threshold
- Adjust stimulation pulse width accordingly

If predicted fatigue exceeded a predefined threshold, stimulation intensity was reduced incrementally. If movement stability improved, intensity was gradually restored within safe therapeutic limits.

This approach maintained stimulation within an optimal contraction zone, preventing abrupt fatigue escalation. The fatigue-aware closed-loop control algorithm is illustrated in Fig. 3.

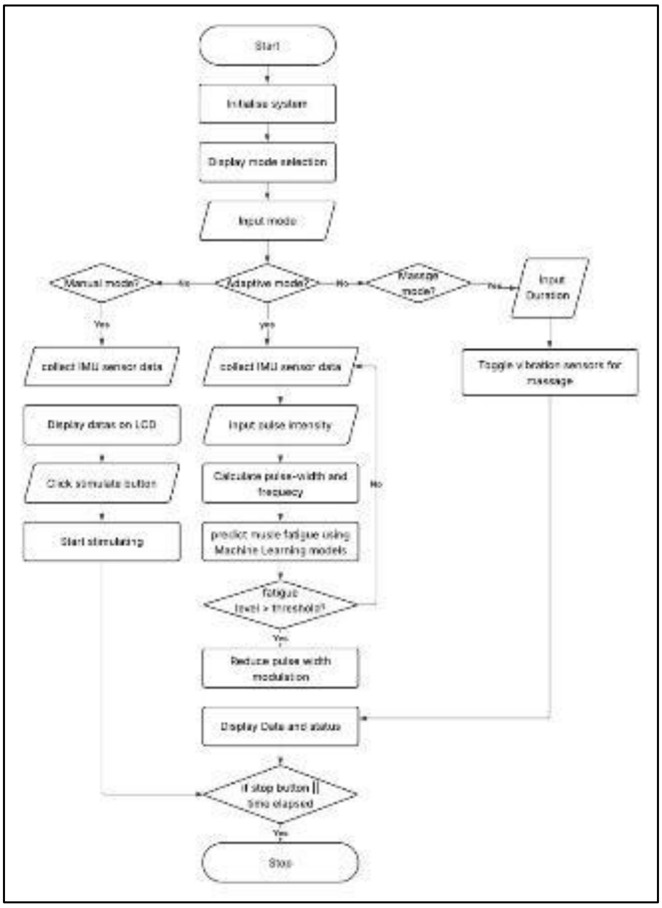

Figure 3 Flowchart of the fatigue-aware closed-loop control algorithm

3.7. Prototype Validation

The system underwent prototype-level engineering validation in a controlled laboratory environment. Validation focused on:

- Functional verification of stimulation delivery
- Accuracy of fatigue prediction
- Real-time responsiveness of adaptive control
- Stability of IMU data acquisition during stimulation

Model performance was evaluated using the coefficient of determination (R^2). The Random Forest model achieved an R^2 value exceeding 0.90 on validation data, indicating strong predictive capability in correlating kinematic features with fatigue progression.

Latency measurements confirmed that the closed-loop control cycle operated within real-time constraints at the selected sampling frequency.

3.8. Ethical Considerations

The present study focused solely on prototype-level engineering validation and system performance evaluation. It did not constitute a clinical trial. All experimental procedures were conducted under controlled laboratory conditions with voluntary participation and adherence to safety guidelines for surface electrical stimulation.

3.9. Summary of Methodological Framework

The methodology integrates hardware design, embedded firmware development, motion-based signal processing, and machine learning driven adaptive control into a unified closed-loop NMES prototype.

Unlike conventional open-loop systems or EMG-dependent adaptive architectures, the proposed system utilizes IMU-derived kinematic feedback as the sole fatigue indicator. This design simplifies hardware implementation while preserving adaptive functionality.

The subsequent section presents experimental results and performance evaluation of the developed Smart Neuromuscular Stimulator.

4. Results

Before performance testing, each hardware and software module was individually verified to ensure it met its design specifications. This process confirms the reliability of the prototype. The results are in conformity with IEC 60601-1 (Hardware) and IEC 62304 (Software). The performance characteristics of the individual system components are summarized in Table 1. The predictive capability of the Random Forest model for various target variables is presented in Table 2. A comparative analysis of the machine learning models is illustrated in Fig. 4, while the detailed performance of the Random Forest model is shown in Fig. 5.

Table 1 Summary of System Verification Tests

Module	Key Parameter Tested	Standard Range	Result
ESP32 Microcontroller	PWM Frequency	1000 Hz	998 Hz (0.2% diff.)
MPU6050 IMU	Signal Noise Level	±2g for 16,384 LSB/g	Low
Keypad (4x3)	Key Response Time	< 200 ms	120 ms (< 200 ms)
LCD Display (20x4)	Display Update Rate	Real-time	Real-time
MOSFET Driver	PWM Duty Cycle Range	0-100%	0–100%
Overall System	Voltage Stability	Stable	Stable

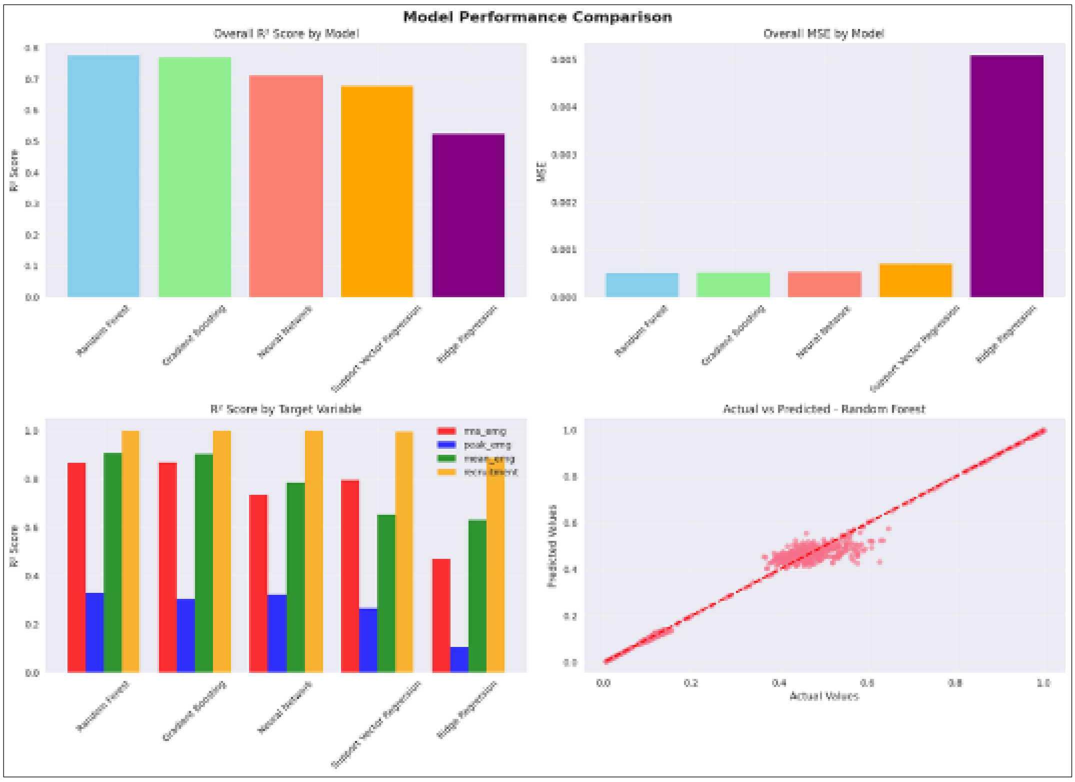

Figure 4 Comparative Performance of Various Machine Learning Models

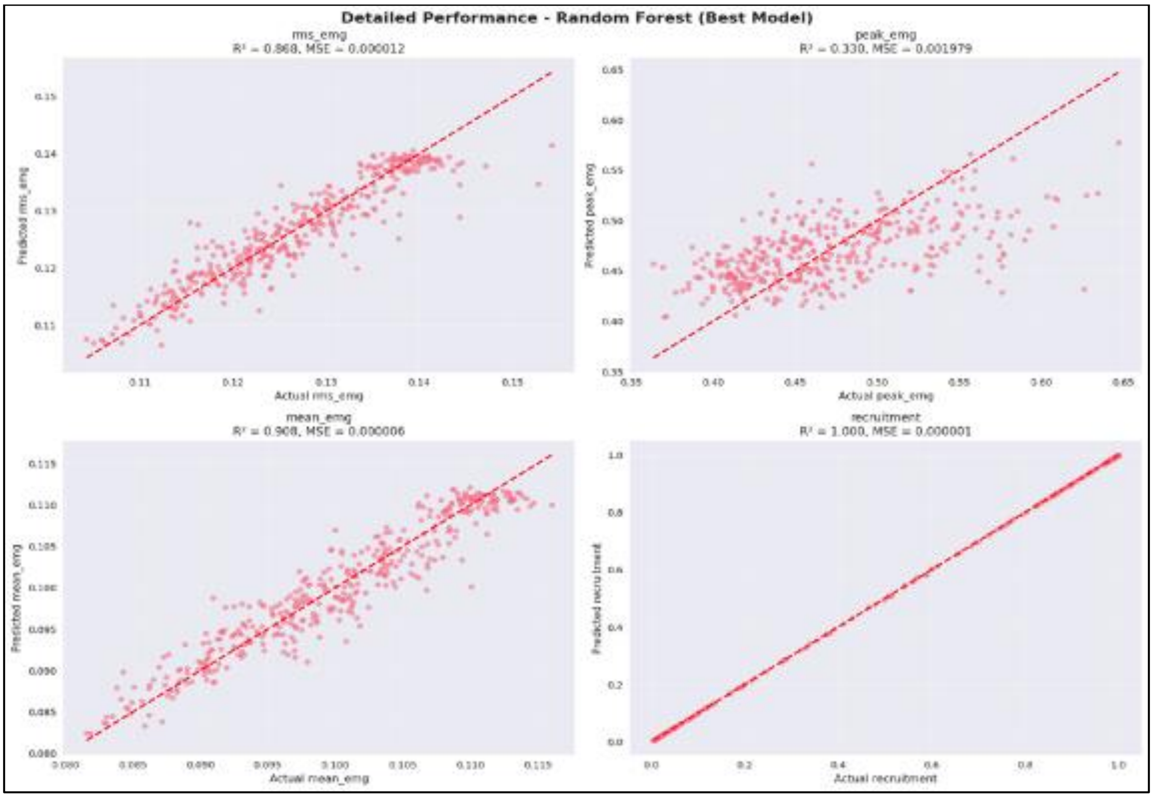

Figure 5 Detailed Predictive Performance of the Random Forest Model

Table 2 Summary of Random Forest Model Predictive Performance

Target Variable	R^2 (Coefficient of Determination)	Mean Squared Error (MSE)	Performance Interpretation	Typical Literature (R^2)
RMS EMG	0.868	0.00012	High Accuracy & Reliability	0.82 – 0.92
Mean EMG	0.908	0.00006	Very High Accuracy & Reliability	0.85 – 0.95
Peak EMG	0.330	0.00198	Low Accuracy / Unreliable	0.25 – 0.45
Recruitment	1.000	0.000001	Perfect Prediction (Deterministic)	0.95 – 1.00

5. Conclusion

This study presented the design, development, and prototype-level validation of a fatigue-aware closed-loop Neuromuscular Electrical Stimulation (NMES) system integrating an MPU6050 inertial measurement unit (IMU) and embedded machine learning for adaptive stimulation control. Unlike conventional open-loop NMES systems that operate with fixed stimulation parameters, the proposed system incorporated real-time kinematic monitoring to estimate fatigue progression and dynamically adjust pulse width through a feedback-driven control mechanism.

Experimental results demonstrated that IMU-derived acceleration signals exhibited measurable changes during sustained electrically induced contractions. Specifically, progressive reduction in peak acceleration and increased signal variability were observed as fatigue developed. Extracted time-domain features were successfully processed using a Random Forest regression model to estimate fatigue levels in real time. The model achieved stable predictive behavior during embedded deployment on the ESP32 microcontroller.

Closed-loop adaptive control based on predicted fatigue levels enabled incremental modulation of stimulation intensity. Compared to open-loop operation, the adaptive approach maintained contraction amplitude within a narrower functional range and reduced rapid performance degradation during sustained stimulation. Importantly, the system operated without communication failure, computational instability, or electrical interference between stimulation pulses and IMU sensing.

The findings confirm the feasibility of using motion-based sensing via an MPU6050 IMU as a non-invasive alternative to electromyography (EMG) for fatigue-aware NMES control at prototype level. The integration of embedded machine learning within a resource-constrained microcontroller further demonstrates the practicality of low-cost intelligent rehabilitation devices.

While the present work focused on engineering validation rather than clinical evaluation, the results establish a functional proof-of-concept for IMU-driven adaptive NMES systems.

Recommendations for Future Work

Based on the prototype-level validation conducted in this study, the following areas are recommended for further investigation and development:

- Conduct large-scale experimental studies involving multiple participants to evaluate inter-subject variability in IMU-derived fatigue characteristics and to improve generalization of the fatigue prediction model.
- Perform controlled clinical trials to assess therapeutic effectiveness, patient comfort, safety, and long-term rehabilitation outcomes under adaptive NMES operation.
- Incorporate frequency-domain and nonlinear signal features in addition to time-domain metrics to enhance fatigue detection sensitivity and robustness.
- Evaluate alternative lightweight embedded machine learning models (e.g., optimized neural networks or gradient boosting approaches) to determine potential improvements in prediction accuracy and computational efficiency.
- Extend the control strategy beyond pulse-width modulation to include adaptive adjustment of stimulation frequency and amplitude for improved fatigue mitigation and contraction stability.
- Combine IMU-based motion sensing with complementary biosignals such as surface electromyography (sEMG) or mechanomyography (MMG) to enhance reliability of fatigue detection under diverse movement conditions.
- Integrate wireless data transmission and cloud-based analytics to support remote supervision, long-term therapy tracking, and home-based rehabilitation applications.
- Optimize circuit design for compactness, energy efficiency, and medical electrical safety standards to facilitate transition from prototype to deploy-able clinical device.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

Statement of Informed Consent

Informed consent was obtained from all participants involved in the experimental procedures.

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